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Indispensable Source of Risk Contagion With Big Data Analysis From a More Comprehensive View on Shadow Banking

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ABSTRACT

Although shadow banking widely exists in the financial systems of various countries, their definitions vary significantly due to specific economic and financial characteristics. This paper classifies Chinese shadow banking into six categories: securities, trust, private lending, banking, fund, and insurance. The AR-GARCH-DCC model is used to measure systemic risk spillover through from an industrial and institutional perspective. The network topology index is employed to analyze risk contagion and further explore influencing factors. Firstly, based on the results of the AR-GARCH-DCC, the estimated dynamic volatility (σ) indicates that shadow banking risk spillover is time-varying, especially in trust and securities. Second, according to the static risk spillover analysis, various institutions play different roles and can transform between risk spillovers and overflowers. Thirdly, eigenvector centrality, leverage, assets, CPI, and macroeconomic prosperity significantly impact shadow banking systemic risk spillover.

KEYWORDS

AR-GARCH-DCC, Shadow Banking, Systemic Risk Spillover

The outbreak of the financial crisis in 2008 significantly impacted both financial and economic systems in the world. Since then, scholars have increased their attention to systemic risk measurement (Adrian et al., 2008; Girardi et al., 2013; Gary et al., 2007; Acharya et al., 2017; Brownless et al., 2017). The inherent instability of the financial system depends on financial fragility, bounded rationality of market entities, and asset price volatility. Financial risks arise successively among institutions, economies, and regions based on the payment and clearing systems among financial institutions, interbank exposure, and common exposure formed by holding the same assets. While much research has traditionally concentrated on the banking system, which is the core of the financial system, shadow

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banking, often dissociated from the regulatory framework, poses substantial risks. Moreover, shadow banking spans multiple industries and institutions horizontally, increasing its infectivity. If high-risk shadow banking becomes uncontrollable, it may lead to systemic risk. Therefore, shadow banking is an indispensable component of the financial system when comprehensively measuring systemic risk.

While shadow banking is widespread, its definition varies among different countries. Scholars closely monitor the development of shadow banking and strive to formulate definitions based on theoretical frameworks and observational findings (McCulley, 2007; Krugman, 2008; Adrian & Shi, 2009; Gorton, 2009; Tucker, 2010; Pozsar et al., 2010). Various countries have different views on shadow banking due to differences in their financial structures resulting from distinct levels of financial development. The Financial Stability Board (FSB) offers a general definition of shadow banking as credit intermediaries operating outside regulatory frameworks, capable of causing arbitrage and systemic risks. However, China's shadow banking exhibits unique characteristics beyond the general situation. It has three main aspects: (a) credit intermediaries without financial licenses or supervision, such as third-party financial institutions; (b) credit intermediaries without financial licenses and subject to limited supervision, such as financing guarantee companies; and (c) instruments within financial licenses but lacking adequate supervision, such as securitization. An accurate definition of shadow banking, which serves as the cornerstone for subsequent measurement, is urgently needed.

Shadow banking can alleviate the financial pressure of small and medium-sized enterprises. Research on this issue mainly focuses on scale measurement (Harutyunyan et al., 2015; Sheng & Soon, 2015; Chen et al, 2018; Zhu, 2018; Allen et al., 2018; Acharya et al., 2020), macro-prudential supervision (Jeanne & Korinek, 2014; Cizel et al., 2016; Fève et al., 2019), correlation with monetary policy (Gertler & Karadi, 2013; Illes & Lombardi, 2013), maturity mismatch (Crotty & Epstein, 2008), and the positive and negative impacts on economic development (Allen et al., 2019; J. Du et al., 2017). However, studies have disregarded comprehensively monitoring and controlling various risks in real time. To fill in this gap, this research aims to use the 2020 China Shadow Bank Report to construct a framework containing traditional institutions like banking, insurance, securities, and also shadow banking entities, including trust, private lending, and fund. Systemic risk is measured by indicators such as $\triangle CoVaR$ according to the AR-GARCH-DCC model. Regarding the suitable regulatory system, few studies have concentrated on risk transmission from the perspective of a complex network. In this regard, this research constructs the spillover network using the generalized variance decomposition method (Diebold & Yilmaz, 2012), describing the scale and direction of risk contagion among institutions in detail. Using network topology indicators, it explores the impact of macro and corporate-level variables, thereby establishing a panel regression model to identify the factors.

This paper has the following contributions. First, in alignment with the 2020 China Shadow Bank Report, it provides a more critical, reliable, and applicable classification of shadow banking. It defines the main categories of securities, trust, insurance, private lending, fund, and banking to construct systemic risk spillover measurements at both industrial and institutional levels. Second, it accurately estimates the risk spillover using the AR-GARCH-DCC, unlike the quantile regression with its incomplete analysis of the residual hypothesis, ignoring the GARCH effect. Therefore, the nonlinear structure would fail in timely identification by mistakenly describing the correlation between the series. The AR-GARCH-DCC model can thus be used to determine $\Delta CoVaR$ systemic risk value, compensating for the defects of traditional models. Third, the measurement of risk spillover indicators covers the volatility and correlation of asset yields. Previous studies have mostly adopted $\Delta CoVaR$ and MES. This paper calculates the volatility and correlation at the same time for comparative analysis. Fourth, the topology of spillover and factors of spillover are explored to form regulatory opinions and recommendations.

The paper is organized as follows: Section 2 summarizes the literature. Section 3 describes the boundary, mechanism, and risk characteristics composition of shadow banking. Section 4 covers the methodology, and Section 5 presents the data and descriptive statistics. Section 6 discusses the empirical results on the spillover network topology and, finally, Section 7 concludes the research and provides policy implications.

LITERATURE

Despite the widespread presence of shadow banking around the globe, its definition varies in different countries. At the beginning of the 2008 financial crisis, McCulley (2007) introduced the concept of the "shadow banking system." This concept primarily refers to financial institutions that are separated from traditional sovereign regulatory banks. It is loosely defined as MMFs, structural investment vehicles, and channels among financial intermediaries that leverage the overall financial landscape. Krugman (2008) considered it as nonbank financial institution that makes various complicated financial arrangements to escape supervision. Gorton (2009) described it as institutions that combine repo with securitization or other information-insensitive debt to accomplish the same function for firms but differ from depository institutions by involving the repo market. Tucker (2010) focused on the instruments, structures, firms, or markets that replicate the core features of commercial banks on liquidity services, maturity mismatch, and leverage alone or in combination. Pozsar et al. (2010) defined shadow credit intermediation to include all credit intermediation activities that are implicitly and indirectly enhanced or unenhanced by official guarantees, including finance companies, asset-backed commercial paper (ABCP) conduits, structured investment vehicles (SIVs), credit hedge funds, money market mutual funds, securities lenders, limited-purpose finance companies (LPFCs), and government-sponsored enterprises (GSEs). Financial Stability Board (2011) believed that shadow banking should be interpreted from two aspects. In a broad sense, shadow banking involves the financial system and credit intermediaries excluded from the banking system. In a narrow sense, it refers to businesses executed by financial institutions that may lead to systemic risk, as regulatory blind spots exist—especially institutions whose business scope is limited to maturity or liquidity transformation and leverage trading. In summary, the definition of shadow banking has focused on financial or nonfinancial institutions that are outside the supervision of the traditional banking system and mainly engaged in traditional liquidity conversion and credit risk management. However, various countries have different definitions of shadow banking due to variations in financial structure caused by different levels of financial development. Therefore, for each country, the study should follow the special definition given by the government. Before the financial crisis, research on systemic risk mainly focused on a single institution, using VaR to measure the risk. However, certain limitations arose, particularly in ignoring the correlation between institutions. Adrian & Brunnermeier (2011) introduced CoVaR as a measure of systemic risk—an effective indicator representing the value at risk for financial institutions when exposed to risk. Based on this measurement, scholars developed methods for measuring and expanding indicators. Girardi et al. (2013) utilized GARCH to calculate CoVaR and introduced ΔCoVaR, defining systemic risk contribution. Then, Acharya et al. (2017) introduced the systemic expected shortfall (SES), calculated as the expected loss of a single institution during a crisis based on leverage, and marginal expected shortfall (MES). Brownless & Engle (2017) used SRISK to overcome the shortcomings of SES in reflecting risks. The contingent claims approach (CCA), based on the Black-Scholes option pricing formula, was employed by Gray et al. (2007) to measure sovereign risk, quantifying the degree of asset-liability mismatch and capturing the "nonlinear" aspects. Gray & Jobst (2013) proposed the system contingent claims approach (SCCA) by calculating tail risk. Despite continuous measurement development, research on systemic risk mainly excludes shadow banking, whose systemic risk is significant, disregarding the triggering factors of shadow banking systemic risk.

Shadow Banking in China Boundary

The general definition of shadow banking typically considers the following criteria: (a) inclusion in financial supervision, (b) existence of mismatch and high leverage operations, (c) embedding of infectivity, and (d) impact on the sound development of the system. However, there are differences in China. In 2013, the State Council divided shadow banking into three categories: (a) financial institutions outside the regulatory system without financial licenses, (b) credit intermediaries not properly regulated due to the lack of financial licenses, and (c) institutions with financial licenses engaging in asset securitization and other related businesses outside supervision. Some key insights have been offered by the 2013 Notice of the General Office of the State Council on Issues Related to Strengthening the Supervision of Shadow Banking and the 2020 “China Shadow Bank Report” (China Banking and Insurance Regulatory Commission, 2020). The report specifies that shadow banking can be identified based on the following criteria: (a) credit intermediation outside of bank supervision, accompanied by significantly lower credit standards, (b) financial products with complex and highly leveraged business structures, (c) financial products with incomplete information disclosure, and (d) financial products with high cashing pressure caused by the inherent high correlation and contagion of the financial system. Accordingly, shadow banking should broadly include interbank special purpose vehicle investment, fund trust, insurance asset management, and commercial factoring company. Accordingly, we classify shadow banking into six categories: securities, trust, insurance, private lending, fund, and banking based on standards that also consider intensity, complexity of structure, leverage, information disclosure, and centralized cashing pressure. The temporal framework covers landmark events such as the financial crisis in 2008, the “money shortage” in 2013, the stock market crash in 2015, and the COVID-19 pandemic in 2020.

Mechanism of Shadow Banking

1. Bank-security cooperation mainly refers to the integration degree of the money market, the combination and allocation of funds in innovative business, and the continuous improvement of utilization, for example through inter-bank lending and bank-securities transfer. The original intention is to help securities companies raise funds.
2. Bank-credit cooperation implies the financial management plan based on professional qualifications to strictly follow the agreement signed between the two parties for supervision through financial products and trust loans. The goal is to encourage qualified customers to establish business relations with banks through trust institutions and obtain the required funds.
3. Asset management refers to institutions, including securities companies, that strictly follow agreements to supervise and dispose of customer assets. They recommend corresponding financial products and provide targeted investment management services for customers, mostly focusing on outsourcing business. Outsourcing can alleviate the contradiction between the growing scale of banks’ own funds and insufficient investment capacity to a certain extent.
4. Private lending means financing between natural persons, legal persons, organizations, and other related entities. This lending behavior can be roughly divided into interpersonal and between

Table 1. Classification of Shadow Banking

Types	Coverage
Banking	Inter-Bank Special Purpose Vehicle Investment, Entrusted Loan, Bank Financing
Securities	Asset Management, Asset Securitization in The Securities Industry
Insurance	Insurance Asset Management
Trust	Capital Trust, Trust Loan
Private Lending	P2P Loans, Microloans, Commercial Factoring, Financing Guarantees, Consumer Loans Issued by Non-Licensed Institutions
Fund	Non-Equity Public Offering Fund, Non-Equity Private Placement Fund

citizens and non-bank financial institutions, mainly including pawn and small loan companies. Small and medium-sized enterprises are generally faced with inadequate funding channels. Private lending can alleviate the financial challenges for enterprises, but it is accompanied by disturbingly high interest rates.

5. Securitization refers to instruments that integrate a batch of illiquid credit assets and guarantee them in the form of an asset pool, promoting future cash flow into marketable securities. Commercial banks can realize the assets with poor quality and bad liquidity in advance, thus improving the capital adequacy ratio, reducing liquidity risk, and enhancing the asset-liability structure.

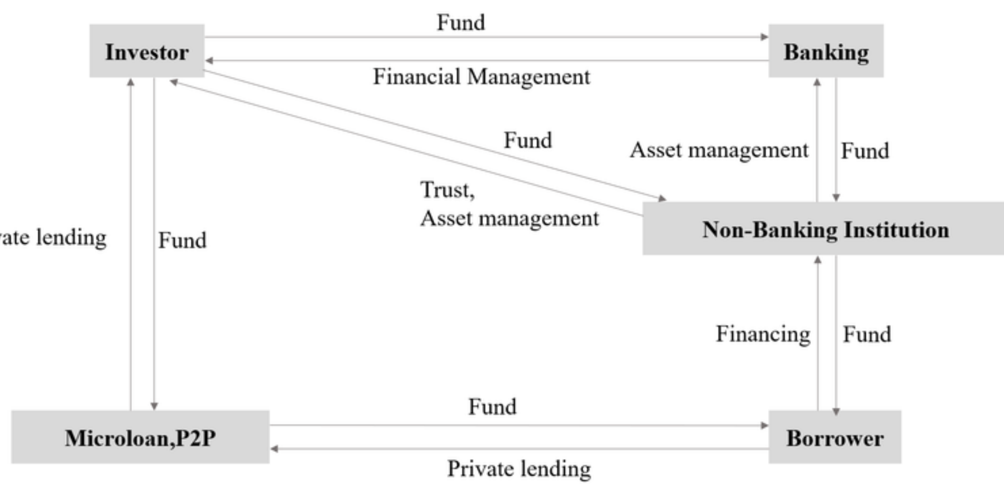
METHODOLOGY

Systemic Risk

$\triangle CoVaR$

Accumulation of an institute's risk to a certain extent can cause obvious risk spillover to other institutions, and then affect the whole system, forming systemic risk. $r_{a,t}$ represents the yield rate of institution a at time t, $r_{a,t} = 100 \times \left(lnP_{a,t} - lnP_{a,t-1}\right)$, where $P_{a,t}$ denotes the closing price of a. While the confidence level is $1-q$, VaR is defined as $Pr\left(r_{a,t} \leq VaR^{a}_{q,t}\right) = q$ to reflect the risk level of a financial institution, where $VaR^{a}_{q,t}$ represents the q quantile of the yield rate on assets of financial institutions a at time t, which is expected to be negative. Based on VaR, conditional $CoVaR$ indicates the risks faced by other institutions or systems when an institution is in crisis. If the risk event $C\left(X^{b}\right)$ of institution b occurs and b causes risk spillover to a, it can be expressed as the q quantile of the conditional risk value $CoVaR^{a|b}_{q,t}$. Formula 1 represents the yield on assets of a when the loss of b equals $VaR^{b}_{q,t}$.

Figure 1. Operation Mechanism of Shadow Banking in China



$$Pr(r_{a,t} \leq CoVaR_{q,t}^{a|b} \mid r_{b,t} = VaR_{q,t}^{b}) = q \tag{1}$$

Equation 2 shows marginal spillover effect, $\Delta CoVaR$, at time t, with a confidence level of $1-q$, which is equal to the conditional risk value of a minus the conditional risk value of a when b is in the normal state and the risk event $C\left(X^b\right)$ occurs.

$$\Delta CoVaR_{q,t}^{a|b} = CoVaR_{q,t}^{a|r_{b,t}=VaR_{q,t}^{b}} - CoVaR_{q,t}^{a|r_{b,t}=VaR_{50\%,t}^{b}} \tag{2}$$

$\Delta CoVaR$ is expected to be a negative value, which can be used to indicate the spillover of an institution to other institutions or the system. The greater the absolute value, the greater the contribution.

MES

ES refers to the expected loss when the asset income loss of an institution exceeds the α quantile. Equation 3 represents the expected loss ES at time t, if event $C\left(X^b\right)$ is defined as a stress event, and the financial system s is in a systemic crisis state.

$$ES_{s,t-1}\left(C\right) = E_{t-1}(r_{s,t} \mid r_{s,t} < C) = \sum_{b=1}^{N} \omega_{b,t} E_{t-1}(r_{b,t} \mid r_{s,t} < C) \tag{3}$$

The marginal expected loss MES is the partial derivative of the weight of ES to institution b, indicating the change in ES caused by the weight change of institution b by 1 unit, reflecting the marginal contribution to risk. In general, the higher the MES, the greater the risk contribution.

$$MES = \frac{\partial ES_{s,t-1}\left(C\right)}{\partial \omega_{bt}} = E_{t-1}(r_{b,t} \mid r_{s,t} < C) \tag{4}$$

MES evaluates the ability of institutions to resist market risks and to reflect the expectations of financial markets on whether financial institutions can make profits in the crisis.

AR-GARCH-DCC

$\Delta CoVaR$ can be measured by the AR-GARCH-DCC model. Despite the wide usage of quantile regression, the GARCH effects of the financial series are neglected, leading to the misevaluation of the correlation and the ignorance of volatility agglomeration. However, the GARCH-DCC model can identify the time-varying systemic risk more accurately and timelier. For this advantage, this paper uses the AR-GARCH-DCC model to describe the nonlinear risk correlation and aggregation among institutions. This model decomposes the conditional covariance matrix into a conditional variance and a conditional correlation coefficient matrix. In addition, it parameterizes the model according to relevant standards to reduce the number of moderate parameters. Assuming that the yields follow the AR(1) process, the bivariate GARCH-DCC model can be expressed as:

$$r_t = \mu_t + e_t$$

$$
\begin{aligned}
e_t &= H^{1/2}\varepsilon_t \\
H_t &= D_t R_t D_t \\
R_t &= diag\left(Q_t\right)^{-1/2} Q_t diag\left(Q_t\right)^{-1/2} \\
Q_t &= \left(1-\alpha-\beta\right)\bar{Q} + \alpha\left(\varepsilon_{t-1}\varepsilon'_{t-1}\right) + \beta Q_{t-1}
\end{aligned}
\tag{5}
$$

$r_t = \left(r_{a,t}, r_{b,t}\right)^T \sim N\left(0, H_t\right)$ represents the yields of financial institutions a and b, $\varepsilon_t = \left(\varepsilon_{t-1}\varepsilon'_{t-1}\right)^T$ represents the standardized residual subject to multivariate normal distribution. Q_t represents the covariance matrix, and $\bar{Q}$ is the unconditional covariance matrix. α, β of Q_t are the dynamic conditional correlation parameters. H_t is the variance-covariance matrix, which can be expressed as $H_t = D_t R_t D_t$, where the conditional variance matrix $D_t = diag\left\{h_{a,t}{}^{1/2}, h_{b,t}{}^{1/2}\right\}$ is fitted by the univariate model $GARCH\left(p,q\right)$, and R_t represents the conditional correlation coefficient matrix. Make the sum of the squares of the residuals and the sum of the conditional variances of the q-order lag term fit the D_t in $H_{a,t}$ with the single variable $GARCH\left(p,q\right)$, that is:

$$
h_{a,t} = \omega_\alpha + \sum_{m=1}^{p}\alpha_{am}\varepsilon^2_{a,t-m} + \sum_{n=1}^{q}\beta_{an}h_{a,t-n}
\tag{6}
$$

$R_t = \begin{pmatrix} 1 & \rho_{ab,t} \\ \rho_{ab,t} & 1 \end{pmatrix}$, $\rho_{ab,t}$ is the dynamic conditional correlation coefficient between institutions. The greater the $\rho_{ab,t}$, the stronger the spillover effect. It is assumed that the standardized residual is subject to multivariate normal distribution. The conditional distribution of the yield of institution a is also subject to normal distribution once a risk in institution a event occurs, namely:

$$
r_{a,t} \mid r_{b,t} \sim N\left(\frac{r_{b,t}\sigma_{aa,t}\rho_{ab,t}}{\sigma_{bb,t}}, \left(1-\left(\rho_{ab,t}\right)^2\right)\sigma_{aa,t}{}^2\right)
\tag{7}
$$

From the definition of $CoVaR$, we can get:

$$
Pr\left(\frac{r_{a,t} - r_{b,t}\sigma_{aa,t}\rho_{ab,t} / \sigma_{bb,t}}{\sigma_{aa,t}\sqrt{1-\left(\rho_{ab,t}\right)^2}} \le \frac{CoVaR^{a|b}_{q,t} - r_{b,t}\sigma_{aa,t}\rho_{ab,t} / \sigma_{bb,t}}{\sigma_{aa,t}\sqrt{1-\left(\rho_{ab,t}\right)^2}} \mid r_{b,t} = VaR^b_{q,t}\right) = q
\tag{8}
$$

$$
\frac{r_{a,t} - r_{b,t}\sigma_{aa,t}\rho_{ab,t} / \sigma_{bb,t}}{\sigma_{aa,t}\sqrt{1-\left(\rho_{ab,t}\right)^2}} \sim N\left(0,1\right)
$$

Then we can get the dynamics $CoVaR^{a|b}_{q,t}$ of financial institution b when the risk event occurs in institution a,

$$CoVaR_{q,t}^{a|b} = \Phi^{-1}\left(q\right)\cdot\sigma_{aa,t}\sqrt{1-\left(\rho_{ab,t}\right)^2} + VaR_{q,t}^{b}\cdot\frac{\sigma_{aa,t}\rho_{ab,t}}{\sigma_{bb,t}} \tag{9}$$

$\Delta CoVaR$ of institution b to a is calculated as follows:

$$\Delta CoVaR_{q,t}^{a|b} = \frac{\sigma_{aa,t}\rho_{ab,t}}{\sigma_{bb,t}}\left(VaR_{q,t}^{b} - VaR_{50\%,t}^{b}\right) \tag{10}$$

$\Delta CoVaR$ is proportional to VaR. Based on the ES, MES which is a nonlinear combination of volatility $\sigma_{b,t}$, $\rho_{ab,t}$ and expectation E_{t-1} can be deduced as:

$$MES\left(C\right) = \sigma_{b,t}\rho_{b,t}E_{t-1}(\varepsilon_{a,t} \mid \varepsilon_{a,t} < C / \sigma_{a,t}) + \sigma_{a,t}\sqrt{1-\left(\rho_{ab,t}\right)^2}E_{t-1}(\varepsilon_{a,t} \mid \varepsilon_{a,t} < C / \sigma_{a,t}) \tag{11}$$

The Diebold-Yilmaz Network

According to Diebold & Yilmaz (2014), the variance decomposition method can reflect the risk contagion between variables. Build an N-dimensional VAR, $x_t = \sum_{a=1}^{p}\varnothing_a x_{t-a} + \varepsilon_t$, x_t represents the volatility of stock price, which is a covariance stationary process, and its moving average form:

$$x_t = \sum_{a=0}^{\infty}A_a\varepsilon_{t-a} \tag{12}$$

Where $\varepsilon \sim i.i.d\left(0,£\right)$ is the disturbance vector with independent and identically distributed components. A_a is the coefficient matrix of $N \times N$ order and follows the recursive process:

$$A_a = \varnothing_1 A_{a-1} + \varnothing_2 A_{a-2} + \cdots + \varnothing_P A_{a-P} \tag{13}$$

A_a is the N-order unit matrix. When $a < 0$, $A_a = 0$.

Variance contribution means that when x_a is subject to external shocks, $d_{ab}^{H} = \frac{\sigma_{bb}^{-1}\sum_{h=0}^{H-1}\left(e_a^{'}A_h\Sigma e_b\right)^2}{\sum_{h=0}^{H-1}\left(e_a^{'}A_h\Sigma A_h^{'}e_b\right)}$ of the variance of the H step prediction error explained by shocks reflects the change by itself or other variables. Therefore, the direction and intensity of the risk spillover can be measured. Among them, Σ is the covariance matrix of the ε_t, σ_{bb} is the diagonal element, e_b is the selection vector. $D_{ab}\left(h\right) = \begin{pmatrix} d_{11} & \cdots & d_{1N} \\ \vdots & \ddots & \vdots \\ d_{N1} & \cdots & d_{NN} \end{pmatrix}$ can reflect the risk spillover effect between institutions. Standardize the variance decomposition table $\tilde{d}_{ab}\left(H\right) = \frac{d_{ab}\left(H\right)}{\sum_{b=1}^{N}d_{ab}\left(H\right)}$ where $\sum_{b=1}^{N}\tilde{d}_{ab}\left(H\right) = 1$, $\sum_{a,b=1}^{N}\tilde{d}_{ab}\left(H\right) = N$.

The spillover index of institution a to other institutions is $S_{to}\left(H\right) = 100 \times \sum_{a=1, a \neq b}^{N} \tilde{d}_{ba}\left(H\right)$, and the spillover risk tolerance index of other institutions to institution a is $S_{from}\left(H\right) = 100 \times \sum_{b=1, a \neq b}^{N} \tilde{d}_{ab}\left(H\right)$. Net spillover effect $S_{net} = S_{to}\left(H\right) - S_{from}\left(H\right)$ measures the net spillover effect. $S_{net} > 0$ means that the institution is risk infectious to the system, while $S_{net} < 0$ means that the institution is risk infectious. $S\left(H\right) = 100 \times \frac{\sum_{a,b=1, a \neq b}^{N} \tilde{d}_{ab}\left(H\right)}{\sum_{a,b=1}^{N} \tilde{d}_{ab}\left(H\right)} = 100 \times \frac{\sum_{a,b=1, a \neq b}^{N} \tilde{d}_{ab}\left(H\right)}{N}$. A node's degree is the number of links to other nodes, out-degrees is $CD_a = \sum x_{ab}$ and in-degrees is $RD_a = \sum x_{ba}$.

DATA AND DESCRIPTIVE STATISTICS

Data

Based on the definition, Insurance II (Shenwan), Securities II (Shenwan), Wind Bank Industry Index, Multi-Financial (Shenwan), and Shanghai Securities Fund Index are selected to represent the insurance, securities, banking, private lending, and fund, respectively, referring to the industry classification and data availability. In view of the vacancy of suitable index to the trust, the Shanghai and Shenzhen 300 is taken as the representative; 11 banks, 7 securities, 5 trusts, 4 insurance, 10 private lending institutions, 10 funds, which are selected according to the ranking of asset size, are good representatives. The sample period is from January 2, 2008, to December 31, 2021, totaling 3,407 trading days, to cover such extreme events as “2008 financial crisis,” “2013 money shortage,” “2015 stock market crash,” “2018 Sino US trade war,” and “2020 COVID-19.” All data are from the Wind database. The natural logarithmic rate of daily closing price is processed as $R_t = 100 \times ln\left(P_t / P_{t-1}\right)$, $t = 2, 3, \cdots, 3407$, except that the data of the fund are the net value of the restoration unit.

Descriptive Statistics

Yield Rates

Table 2 shows the skewness of all industries. The kurtosis of all industries is greater than 3, indicating the “peak and thick tail.” The yield distribution of 47 institutions also presents the same characteristics. JB test shows that the yield series does not obey the normal distribution. Limited by space, specific data of institutions are not presented. The following contents are treated similarly.

Table 2. Descriptive Statistics of Yield Rates

Industries	Mean	Median	Max	Min	Std	Skewness	Kurtosis	JB Statistics
Insurance	-0.004	-0.020	4.146	-4.576	0.955	0.003	3.132	1395.36***
Securities	-0.005	-0.019	4.139	-4.576	1.106	-0.060	3.118	1385.22***
Banking	0.003	-0.021	4.148	-4.562	0.752	-0.032	6.031	5171.26***
Private Lending	-0.013	0.011	4.147	-4.576	0.975	-0.567	3.699	2128.61***
Fund	0.005	0.005	4.087	-3.774	0.557	-0.133	7.642	8312.40***
Trust	-0.006	0.052	4.138	-4.585	1.040	-0.743	3.421	1978.55***

The average daily yield of both industries and institutions tends to 0, and the standard deviation is relatively high, indicating that the volatility of the series is high and strong. The degree of deflection is low, and most of them are between plus and minus 0.5. The ADF test in Table 3 shows that the yield series are stable. Based on the LM test in Table 4, which shows significant ARCH effect, the AR-GARCH model should be used to model the yield series.

Dynamic Volatility

By using the yield rate, the parameters are estimated by the AR-GARCH-DCC model. The AR-GARCH model is used to estimate the yields to obtain the residual series and dynamic volatility. The DCC model is used to obtain the time-varying correlation coefficient between the yields of various industries. According to Table 5, all parameters in the GARCH are significant, and the sum of all yield series is significant at the level of 1%, which meets the condition of $\alpha + \beta < 1$ and close to 1, indicating that the volatility of all yield series is persistent. According to Table 6, the dcca1+dccb1 between industries and financial markets are less than 1.

Figure 2 shows the dynamic volatility σ from 2008 to 2021 according to the AR-GARCH-DCC model. Although σ is mostly at a relatively stable low level during the sample period, it peaks in the extreme events such as the 2008 financial crisis, stock market crash in 2015, and COVID-19 in 2020. From the perspective of industries, σ of the trust and the securities is relatively high, while σ of the fund and banking are relatively low and stable, indicating that which can play the role of "stabilizer."

Dynamic Correlation

ρ is the dynamic correlation between the market. ρ of the fund is the highest, reaching 0.97, while between the market and the trust is the lowest, only 0.72. The largest ρ is between fund and securities, up to 0.84, and the lowest is between trust and banking, only 0.48, showing that the investment target

Table 3. ADF Test for Industry Yield Rates

Industries	ADF Test	P-Value	Whether Pass the Inspection
Insurance	-14.36**	0.01(<2.2e-16)	Y
Securities	-14.58**	0.01(<2.2e-16)	Y
Banking	-15.20**	0.01(<2.2e-16)	Y
Private Lending	-14.89**	0.01(<2.2e-16)	Y
Fund	-14.76**	0.01(<2.2e-16)	Y
Trust	-14.60**	0.01(<2.2e-16)	Y

Table 4. ARCH Effect Test for Industry

Industries	LM Test	P-Value
Insurance	199.17***	0
Securities	308.67***	0
Banking	302.65***	0
Private Lending	388.25***	0
Fund	400.91***	0
Trust	640.19***	0

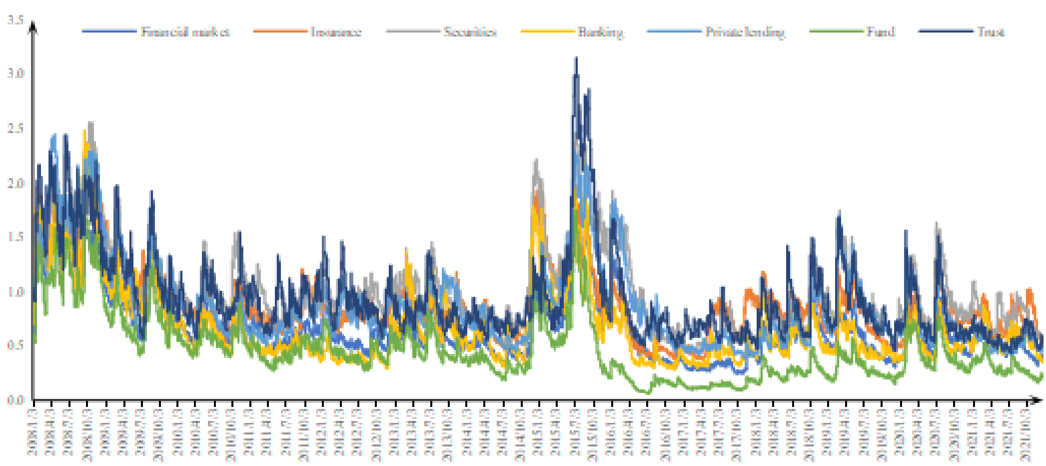
Table 5. Results of GARCH Model

	Financial Markets	Insurance	Securities	Banking	Private Lending	Fund	Trust
E	0.0022**	0.0058**	0.0085*	0.0045**	0.0070*	0.0003***	0.0154***
Std	0.0011	0.0027	0.0044	0.0019	0.0036	0.0002	0.0055
±	0.0680***	0.0625***	0.0591***	0.0881***	0.0681***	0.0839***	0.0902***
Std	0.0149	0.0129	0.0144	0.0238	0.0182	0.0127	0.0165
2	0.9303***	0.9325***	0.9347***	0.9071***	0.9245***	0.9151***	0.8951***
Std	0.0144	0.0132	0.0162	0.0230	0.0205	0.0116	0.0196

Table 6. Results of DCC Model

Financial Markets	Industries	dcca1	Std	dccb1	Std
Financial Markets	Insurance	0.0193***	0.0043	0.9744***	0.0052
	Securities	0.0301***	0.0052	0.9596***	0.0077
	Banking	0.0504***	0.0072	0.9280***	0.0116
	Private Lending	0.0259***	0.0043	0.9686***	0.0055
	Fund	0.0529***	0.0085	0.9346***	0.0100
	Trust	0.0344***	0.0065	0.9574***	0.0087

Figure 2. Dynamic Volatility Calculated by DCC-GARCH Model



of the fund is broad and thus causes strong correlation with other industries. As an important part, the bank-credit cooperative financing has a weak correlation due to its small proportion of capital.

Both ρ between the market and industries, and within the industries, showed a downward trend from 2017, which can be considered as the watershed. ρ between the trust and the financial market, insurance and banking dropped significantly, while the trust and banking present negative correlation. The year 2017, with the most stringent regulatory policies focused on banking, causing a declining interbank business, thus weakening the correlation between the balance sheets of industries. And 2017 is also the first year that the CSRC proposed the comprehensive ban on channel business, which led to a reduction between industries. Moreover, the issuance of the Guiding Opinions on Regulating the Asset Management of Financial Institutions, in cooperation with the MPA assessment, led to a slowdown in the growth of off-balance-sheet assets. By strengthening supervision and preventing risks, the process of deleveraging has been accelerated, which greatly reduced the possibility of systemic risk.

$\Delta CoVaR$

Substituting ρ, σ and other parameters into the calculation of $\Delta CoVaR$, the relationships between shadow banking industries are significant at 95% confidence level. We calculate MES as a reference. Although $\Delta CoVaR$ and MES measure risks from a "bottom-up" or "top-down" perspective, it can be found that the trends of $\Delta CoVaR$ are almost the same, with large fluctuations in the 2008 financial crisis, 2015 stock market crash, and 2020 COVID-19, respectively. The contribution of systemic risk spillover is from large to small securities, insurance, trust, private lending, banking, and fund. In China, securities are mainly composed of small and medium-sized investors, which have blind conformity and speculation and can cause problems such as information asymmetry, high leverage, and poor risk control, thus leading to "herd effect." The risk spillover of the insurance, which plays the role of "protector" and maintains close contact with other industries, is general. Therefore, the insurance and other industries' businesses are intertwined, which provides a channel for the risk transmission, resulting in a relatively certain risk spillover effect. Therefore, the degree of risk spillover is not as high as that of the securities. The spillover of the banking to other industries is small. On the one hand, banks are regulated by strict and complete rules, which

Table 7. Results of Dynamic Correlation Between Financial Market and Shadow Banking

	Financial Market-Insurance	Financial Market-Securities	Financial Market-Banking	Financial Market-Private Lending	Financial Market-Fund	Financial Market-Trust	Insurance-Securities
Mean	0.777	0.834	0.758	0.760	0.970	0.718	0.687
Max	0.896	0.933	0.948	0.928	0.995	0.923	0.839
Min	0.352	0.429	0.282	0.289	0.755	0.247	0.098
Std	0.083	0.063	0.108	0.124	0.025	0.140	0.133
	Insurance-Banking	**Insurance-Private Lending**	**Insurance- Fund**	**Insurance-Trust**	**Fund-Securities**	**Fund-Banking**	**Fund-Private Lending**
Mean	0.757	0.573	0.761	0.512	0.836	0.752	0.761
Max	0.929	0.745	0.892	0.752	0.933	0.952	0.927
Min	0.200	0.169	0.323	0.020	0.518	0.222	0.417
Std	0.097	0.114	0.096	0.144	0.052	0.125	0.096
	Fund-Trust	**Private Lending-Securities**	**Private Lending-Banking**	**Private Lending-Trust**	**Trust-Securities**	**Trust-Banking**	**Banking-Securities**
Mean	0.715	0.753	0.556	0.799	0.680	0.481	0.653
Max	0.912	0.904	0.843	0.974	0.903	0.814	0.868
Min	0.310	0.529	0.137	0.252	0.313	-0.059	0.284
Std	0.119	0.078	0.115	0.118	0.122	0.153	0.094

are subject to more comprehensive supervision by the government and the CBRC. On the other hand, the overall scale of the banking is relatively large, the operating conditions are relatively stable, and the ability to resist risks is relatively strong. The fund does exist with the least risk spillover, as the target of fund investment is relatively scattered, which can greatly play the role of risk diversification. The contribution of MES in various industries are consistent.

CHINA'S SHADOW BANKING RISK SPILLOVER NETWORK

Static Risk Spillover

Industrial Analysis

Based on the static perspective, VAR (1) is established for the volatility calculated by the GARCH (1,1). According to Diebold & Yilmaz (2014), to decompose the variance of the generalized prediction error, we select a two-week prediction period (10 days), to calculate the risk spillover matrix between industries, which is similar to the industry. The nonprimary diagonal represents the spillover between the industries. FROM represents the sum of the spillovers of other industries to it, while the TO represents the sum of the spillovers of the industry to others.

The level of risk spillover reached 67.13%. Each industry is most affected by its own lag period, while the banking is affected by its own lag period by 35.57%. The fund is the industry with the largest risk spillover and risk spillover, with an external spillover of 85.73% and a risk exposure of 70.35%. It can be seen that the diversity of investment objects in the fund can effectively absorb the risks of other industries. The securities ranks second, and the insurance ranks last. The second industry with risk spillover is the private lending, while the smallest is the banking. Only the fund and private lending have a net risk spillover over 0. The insurance has the smallest net risk spillover of -7.61%. Owning to the development of the insurance, its own attributes and more protective and social role, the risks of other industries are easily transmitted through the insurance.

During the financial crisis in 2008, the spillovers rose to 69.6%. banking is still highly affected by its own lag, up to 38.4%. At this stage, it ranked first in risk spillover, reaching 85.64%. The trust ranked second, while the insurance was the smallest. Consistent with the whole sample period, the first and second industries of risk spillover are still the fund and securities. At the same time, banking is also the industry with the highest net risk spillover, reaching 24.05%. Due to the lack of current regulatory norms, mixed operation is a common phenomenon. The banking and other industries are intertwined, with strong risk infectivity, which has an impact on the systemic risk of the entire system.

During the 2015 stock market crash, the overall risk spillover was 68.48%. The trust has become highly affected by its own lag period, up to 37.23%. At this stage, the fund surpassed the banking and up to 101.89%. The private lending and securities rank first and second in risk spillover. The fund has become the highest net risk spillover, reaching 34.28%, followed by the banking of 8.82%, and other industries are all net risk spillovers, only the private lending with the highest risk tolerance and net risk overflow. Bank financial products enter the stock market through structured trust products, funds, asset management products of securities, graded funds, private lending, internet financing, and other capital managements. As a source of fresh water, bank financial products provide support for the shadow banking. Through various financial innovative products and tools, huge amounts of funds are invested in the stock market, bringing a leveraged and speculative crisis.

During COVID-19 in 2020, the spillover rose to the highest point of 77.54%. The securities have become highly affected by its own lag period, up to 25.87%. At this stage, the trust and the securities have become the top two risk spillovers, and the smallest is the insurance. The fund and insurance rank first and second in risk spillover. The securities has become the industry with the

Table 8. $\Delta CoVaR$ and MES of Financial Market and Shadow Banking

Industries		$\Delta CoVaR$				MES			
	Risk Source	Mean	Max	Min	Risk Contribution	Mean	Max	Min	Risk Contribution
Financial Markets	Insurance	1.162	2.951	0.479	0.189	0.521	1.324	0.215	0.187
	Securities	1.322	3.262	0.562	0.216	0.631	1.556	0.268	0.227
	Banking	0.871	3.176	0.364	0.142	0.328	1.194	0.137	0.118
	Private Lending	1.105	3.052	0.483	0.180	0.512	1.415	0.224	0.184
	Fund	0.562	2.158	0.083	0.092	0.196	0.753	0.029	0.071
	Trust	1.114	3.696	0.514	0.182	0.595	1.974	0.274	0.214
Insurance	Insurance	1.184	2.920	0.503	0.259	0.738	1.821	0.314	0.280
	Securities	0.779	2.839	0.325	0.170	0.386	1.408	0.161	0.147
	Banking	1.019	2.813	0.445	0.222	0.597	1.648	0.261	0.227
	Private Lending	0.530	2.035	0.078	0.116	0.234	0.897	0.034	0.089
	Fund	1.069	3.547	0.493	0.233	0.680	2.255	0.314	0.258
Fund	Insurance	1.139	2.892	0.469	0.215	0.439	1.114	0.181	0.198
	Securities	1.288	3.176	0.547	0.243	0.540	1.331	0.229	0.244
	Banking	0.852	3.104	0.356	0.161	0.264	0.962	0.110	0.119
	Private Lending	1.027	2.837	0.449	0.194	0.442	1.221	0.193	0.200
	Fund	1.001	3.321	0.462	0.189	0.529	1.754	0.244	0.239
Private Lending	Trust	0.863	2.190	0.355	0.227	0.601	1.525	0.248	0.233
	Insurance	0.969	2.391	0.412	0.255	0.728	1.796	0.309	0.282
	Securities	0.636	2.319	0.266	0.168	0.365	1.330	0.152	0.142
	Banking	0.435	1.671	0.064	0.115	0.215	0.825	0.032	0.083
	Private Lending	0.894	2.966	0.412	0.235	0.671	2.226	0.309	0.260
Trust	Insurance	0.777	1.972	0.320	0.232	0.621	1.576	0.256	0.242
	Securities	0.888	2.189	0.377	0.265	0.754	1.859	0.320	0.294
	Banking	0.587	2.141	0.245	0.175	0.379	1.380	0.158	0.148
	Private Lending	0.740	2.043	0.323	0.221	0.600	1.658	0.262	0.234
	Fund	0.363	1.392	0.053	0.108	0.213	0.819	0.031	0.083
Banking	Insurance	1.141	2.895	0.470	0.218	0.503	1.277	0.207	0.213
	Securities	1.304	3.216	0.554	0.249	0.610	1.503	0.259	0.258
	Banking	1.126	3.109	0.492	0.215	0.489	1.349	0.213	0.207
	Private Lending	0.548	2.103	0.081	0.105	0.185	0.710	0.027	0.078
	Fund	1.122	3.722	0.517	0.214	0.573	1.901	0.264	0.243
Securities	Trust	1.032	2.620	0.425	0.233	0.643	1.631	0.265	0.244
	Insurance	0.779	2.839	0.325	0.176	0.409	1.490	0.171	0.155
	Securities	1.019	2.813	0.445	0.230	0.626	1.729	0.274	0.238
	Banking	0.530	2.035	0.078	0.120	0.249	0.956	0.037	0.095
	Private Lending	1.069	3.547	0.493	0.241	0.711	2.358	0.328	0.269

Table 9. Industry Static Spillover (2008-2021)

	Insurance	Securities	Banking	Private Lending	Fund	Trust	FROM
Insurance	34.51	13.40	18.20	9.06	17.24	7.59	65.49
Securities	12.11	30.35	11.64	15.85	17.12	12.93	69.65
Banking	16.55	11.10	35.57	9.78	19.63	7.37	64.43
Private Lending	8.26	14.54	9.45	32.00	15.43	20.31	68.00
Fund	13.64	13.59	16.59	13.44	29.65	13.08	70.35
Trust	7.32	12.06	8.16	21.05	16.30	35.11	64.89
TO	57.88	64.70	64.04	69.18	85.73	61.28	402.81
NET	-7.61	-4.95	-0.39	1.19	15.38	-3.61	67.13

Table 10. Industry Static Spillover (2008)

	Insurance	Securities	Banking	Private Lending	Fund	Trust	FROM
Insurance	31.40	10.12	27.28	9.82	11.88	9.51	68.60
Securities	9.11	24.72	16.79	17.57	14.65	17.16	75.28
Banking	16.05	9.16	38.40	11.37	15.80	9.22	61.60
Private Lending	9.22	14.72	10.61	32.37	11.26	21.81	67.63
Fund	11.46	11.62	20.75	14.10	24.46	17.61	75.54
Trust	8.24	14.90	10.22	19.00	16.58	31.07	68.93
TO	54.08	60.52	85.64	71.87	70.15	75.31	417.57
NET	-14.52	-14.76	24.05	4.24	-5.39	6.38	69.60

Table 11. Industry Static Spillover (2020)

	Insurance	Securities	Banking	Private Lending	Fund	Trust	FROM
Insurance	20.99	18.14	14.89	14.46	15.63	15.89	79.01
Securities	10.02	25.87	9.3	19.35	15.59	19.88	74.13
Banking	15.26	17.31	21.86	13.59	16.50	15.48	78.14
Private Lending	8.53	19.24	9.54	23.13	17.22	22.36	76.87
Fund	10.99	17.75	12.33	19.24	19.97	19.72	80.03
Trust	9.19	18.69	10.56	21.27	17.35	22.94	77.06
TO	53.98	91.12	56.62	87.92	82.29	93.32	465.24
NET	-25.03	16.99	-21.52	11.05	2.25	16.26	77.54

highest net risk spillover, reaching 16.99%, followed by the trust of 8.82%, and only the insurance and the banking are net risk spillovers. Thus, in the face of emergencies, insurance and banking can always play the role of stabilizer.

The following is the ranking table based on the size of the net risk spillover, financial crisis period in 2008, stock market crash in 2015, and COVID-19 period in 2020, which can more intuitively show the risk spillover, risk tolerance, net risk spillover, and net risk inflow of each industry.

Table 12. Static Spillover Ranking

2008-2021	Industries	NET	TO	FROM	2008	Industries	NET	TO	FROM
1	Fund	15.38	85.73	70.35	1	Bank	24.05	85.64	75.28
2	Private Lending	1.19	69.18	68.00	2	Trust	6.38	75.31	68.93
3	Banking	-0.39	64.04	64.43	3	Private Lending	4.24	71.87	67.63
4	Trust	-3.61	61.28	64.89	4	Fund	-5.39	70.15	75.54
5	Securities	-4.95	64.70	69.65	5	Insurance	-14.52	54.08	68.60
6	Insurance	-7.61	57.88	65.49	6	Securities	-14.76	60.52	75.28
2015	**Industries**	**NET**	**TO**	**FROM**	**2020**	**Industries**	**NET**	**TO**	**FROM**
1	Fund	34.26	101.89	67.63	1	Securities	16.99	91.12	74.13
2	Banking	8.82	76.04	67.21	2	Trust	16.26	93.32	77.06
3	Trust	-0.71	62.06	62.77	3	Private Lending	11.05	87.92	76.87
4	Securities	-8.70	61.21	69.91	4	Fund	2.25	82.29	80.03
5	Insurance	-9.41	59.75	69.15	5	Banking	-21.52	56.62	78.14
6	Private Lending	-24.27	49.92	74.18	6	Insurance	-25.03	53.98	79.01

Institutional Analysis

According to the static risk spillover matrix of 47 institutions, a matrix is obtained by sorting the net spillover size. Top 10 net risk spillovers were six funds, two banks, and two securities institutions. The net overflow level of fund is relatively high. Most of the last 10 institutions with net risk overflow are private lending institutions. During the 2008 financial crisis, top 10 net risk spillovers included six banks, three funds and one private lending. Among them, the level of bank net spillover is high. The top 10 institutions are evenly distributed and have no specific directionality. During the money shortage in 2013, top 10 net risk spillovers included six banks, three funds and one security. The net spillover level of banks is still high. The last 10 institutions are still mostly private lending institutions. During the 2015 stock market crash, the top 10 included seven funds, two banks, and one insurance institutions. The overall net spillover level of the fund is high. The last 10 institutions are still mostly private lending institutions.

During the Sino-US trade dispute in 2018, top 10 net risk spillovers included three funds, two private lendings, two trusts, one bank, one insurance institution, and one security. All industries are without obvious directionality. Among the last 10 institutions with net risk overflow, there are three insurance institutions, three banks, three bonds, and two private lendings. It shows that the dispute has had a certain impact on all banks, and the insurance and banking have played a risk-bearing role due to the impact. At the same time, bonds present the characteristic of stable. During COVID-19 in 2020, top 10 net risk spillovers included three trust institutions, two banks, two securities, two funds, and one private lending. All industries are included and there was no obvious directionality. Among the last 10 institutions with net risk overflow, there are five private lendings, two banks, two funds, and one trust. Private lending is still the largest net risk spillover.

Spillover between industries shows the characteristics of heterogeneity and variability in different time periods. Whether in spillover or net spillover effect, it is constantly changing. All industries present the phenomenon of dislocation, which can effectively avoid risk resonance, and also avoid the risk spillover of a single industry leading to systemic risk.

Dynamic Risk Spillover

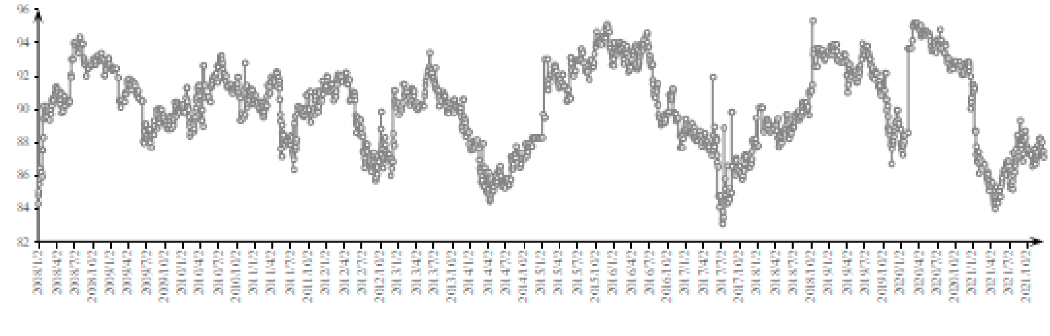
To reflect the time-varying and volatility of risk, the rolling window estimation is used to study the time-varying risk spillover effect of shadow banking. Set the observation interval as 120 days (the length of the semi-annual trading day), and the forecast period is still 10 days (the length of the two-week trading day). The dynamic spillover index is in constant fluctuation. When the risk accumulates, the dynamic spillover index continues to rise and reaches the local peak. As the risk is released, the dynamic spillover index gradually decreases. Among them, there are five obvious local peaks, 2008, June 2013, June 2015, October 2018, and February 2020, which depict the impact of extreme events on shadow banking and are conducive to the identification of systemic risk.

The volatility of the dynamic spillover index reflects the sensitivity of the market. The financial crisis in 2008 had a great impact on China's economy, and the market has suffered seriously. Risk accumulation and the total risk index have been climbing to the peak. Subsequently, the government issued a series of large-scale economic stimulus policies, resulting in a dynamic decline in the total risk index. In June 2013, overnight the lending rate soared to 13.44%, the overnight repo rate reached an unprecedented 30%, and the interest rate of funds for each term soared across the board, resulting in a serious money shortage. The stock market fluctuated sharply, and the total spillover index reached a local high again. In July 2015, the stock market experienced abnormal fluctuations, a large part of which were mainly due to highly leveraged over-the-counter capital allocation. In order to evade credit supervision and develop off-balance-sheet, banks have nurtured shadow banking. The asset management funds of banks are remitted into the stock market through various structured financial products and innovative tools, and this storm has formed. The shadow banking network is complex, and the correlation between industries is deepening, making the total index high at this stage. In 2017, the total spillover index decreased significantly because the National Financial Work Conference clearly pointed out that the prevention and control of systemic risk is of particular importance, which is not only the primary work, but also the daily work, of financial institutions. In October 2018, the total spillover index rose to the local highest, and the financial market was greatly impacted by the Sino-US trade dispute. In February 2020, due to COVID-19 in January, the expectations were still not clear, leading to a sharp decline after the spring festival holiday, and the total spillover index rose accordingly.

Net Directional Risk Spillover

Figure 4 shows the net spillover index of shadow banking from 2008 to 2021. It can be found that, the insurance and securities mostly belong to the state of net risk spillover, the banking alternates between net risk spillover and overflower. The private lending, fund and trust mostly belong to the state of net risk spillover. The insurance mainly provides medium- and long-term funds. When an impact occurs, it can often resist the impact through liquidity support. The banking showed strong net

Figure 3. Dynamic Spillover Index



risk spillover in the 2008 financial crisis, while it became a risk absorption center during COVID-19 in 2020. The volatility in other periods is relatively small, which may be due to the high correlation between the banking and other industries, while the risk has been hedged. Under the increasingly strict regulation, the original traditional model of private lending and trust is difficult to sustain and shows a large spillover. The degree of net spillover in various industries is relatively volatile and uncertain, reflecting the heterogeneity and variability of spillover in the market. Different industries have different net risk spillovers in the same time dimension, which presents dislocation phenomenon, and can avoid the risk resonance of the shadow banking.

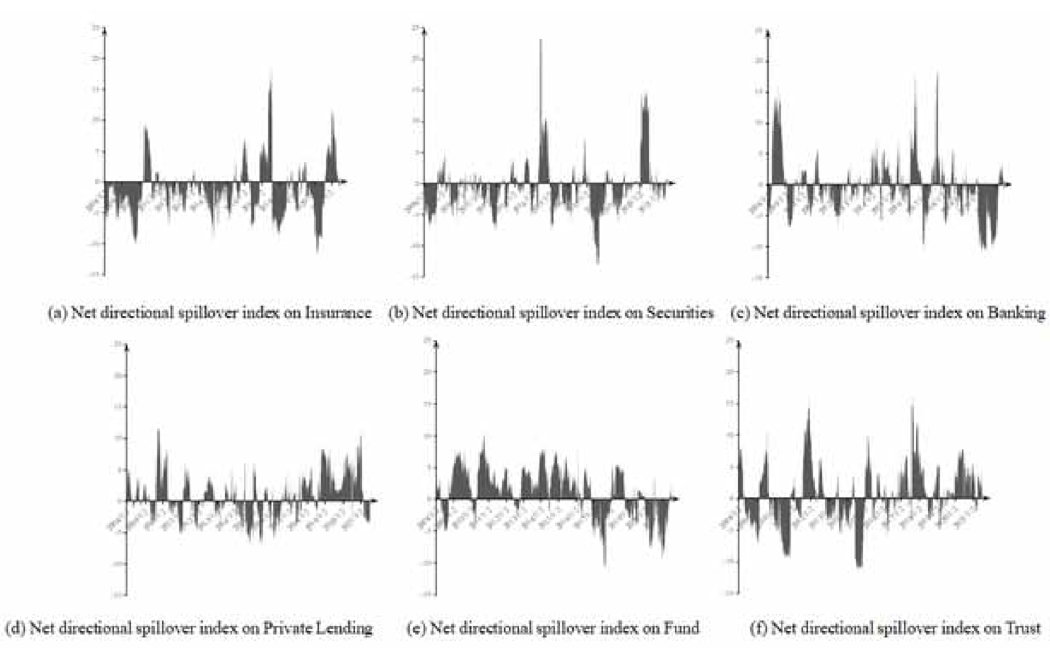
Risk Spillover Network Connection

Industrial Analysis

According to the directional dynamic spillover index, the annual inter-industry information spillover network is obtained to analyze. The node indicates the degree of connectivity, and the line between two points indicates the degree of risk spillover. In 2008, the largest risk spillovers were in the banking and trust, and the largest risk overflows were in the insurance and securities. Among them, the trust had the highest risk spillovers to the securities, followed by the banking. Various industries were closely connected, and the risk spillover between industries was significant. The banking holds huge assets and occupies a more important position compared with other industries.

In 2013, risk spillover among industries has been significantly reduced, and the fund came to be with the highest risk spillover, probably related to the broad scope of investment including the primary and secondary markets of stocks, bonds, and money market. The shortage of money was largely due to the expansion of the shadow banking and the innovation. The risk also transmitted to the insurance, securities and trust. The stock disaster in 2015 caused the risk spillover to increase sharply. The fund and securities became the main risk spillover, and the insurance was the largest risk overflower. In 2018, trust, private lending and banking were the main risk spillover, and securities became the largest risk overflower. The first year after the New Asset Management Regulations,

Figure 4. Net Directional Spillover Index



(a) Net directional spillover index on Insurance (b) Net directional spillover index on Securities (c) Net directional spillover index on Banking

(d) Net directional spillover index on Private Lending (e) Net directional spillover index on Fund (f) Net directional spillover index on Trust

Figure 5. Risk Spillover Connectedness for Industries During 2008

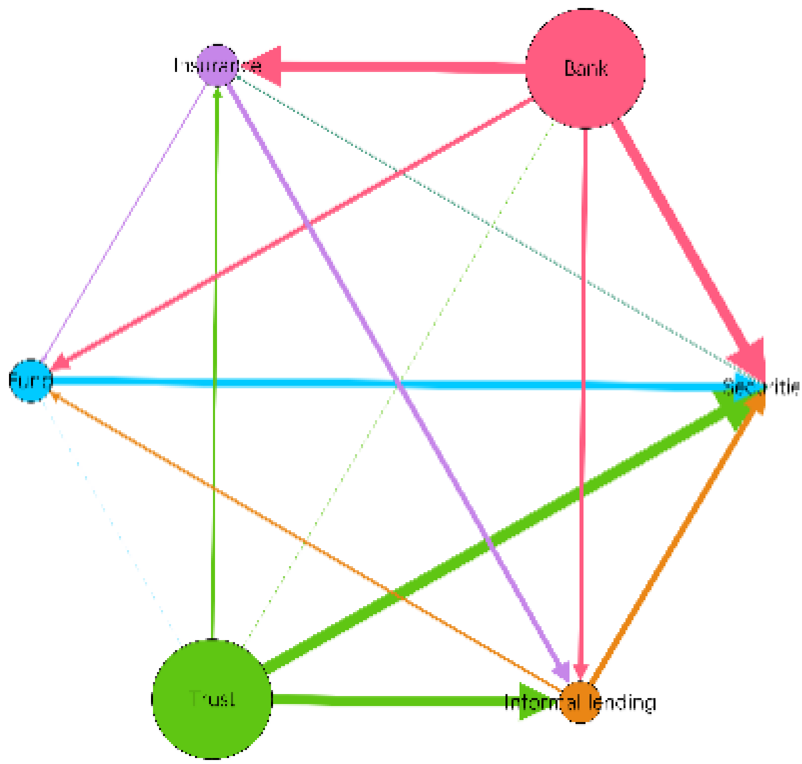
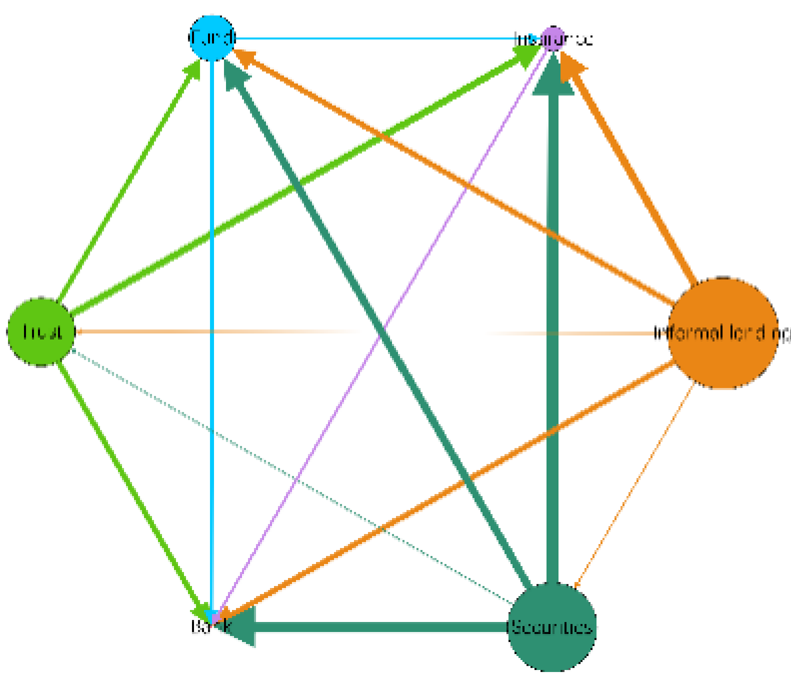


Figure 6. Risk Spillover Connectedness for Industries During 2020



accompanied by the deleveraging and tightening credit, the pressure of Sino-US trade dispute, and the tightening of financing channels, the maturity mismatch at that moment was serious. The trust and private lending have frequent thunderstorms, triggering a wave of thunderstorms, and the risk spillover increased sharply. In 2020, securities and private lending became the main risk spillover. With epidemic prevention policies by the government in the face of COVID-19, the stock market did not have multiple circuit breakers. Later, the market began to stabilize and rebound. With the support of loose fiscal and monetary policies, the expectation of recovery was strong, the market reached its peak with the tightening of policies in July, and the market tends to be stable and structured. Insurance and banking have shown the function of stabilizer.

Institutional Analysis

According to the same method, the annual inter-agency information spillover network is obtained to analyze the risk spillover between institutions. In 2008, the financial network was highly connected. CITIC Bank, Bank of Beijing, China Investment Capital, Zhejiang Orient, CNPC Capital, and Jiangsu Shuntian contributed more risk to the financial network. Guoyuan Securities, Haitong Securities, Pacific Securities, Aijian Group, and Dacheng Bonds were the main risk overflow institutions. In the face of the crisis, joint-stock banks released more risk spillover, while state-owned banks did not have too high network connection, indicating that state-owned banks have advantages in risk control, and joint-stock banks' ability to resist risks needs to be further improved.

In 2013, Tianmao Group, Bank of Communications, Shanghai Pudong Development Bank, Bank of Nanjing, Bank of China, and China Construction Bank were the main risk spillover institutions in the whole network, and Wells Fargo Tianli Growth Bond, Dacheng Bond, PetroChina Capital, Minmetals Capital, and Minsheng Holdings undertook more risk overflows. The stock disaster in June 2013 has nothing to do with the rapid expansion of banks' interbank business. A large amount of funds has been released through interbank channels, resulting in sharp fluctuations in interest rates and risk transmission across institutions, industries, and markets. In fact, it is due to the "conflict" between the rapidly expanding financing demand and money growth and the moderately supplied liquidity of the banking. Therefore, banks have become institutions with high risk spillover this year.

Figure 7. Risk Spillover Connectedness for Institutions During 2008

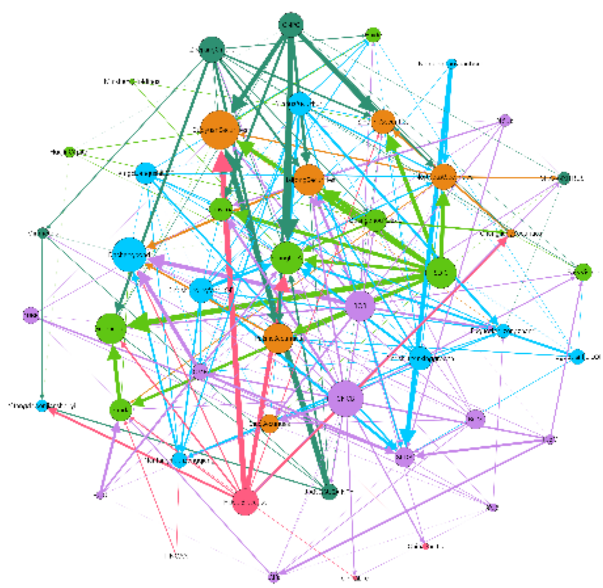
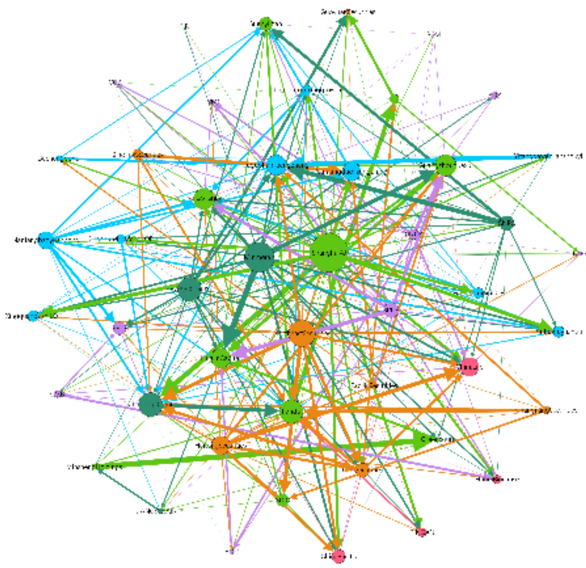


Figure 8. Risk Spillover Connectedness for Institutions During 2020



In 2015, Fuguo Tianli Growth Bond, Fuguo Tianhui LOF, Industrial Trend LOF, China Construction Bank, and Pudong Development Bank were the main risk spillover, while Minsheng Holdings, Aijian Group, Hyde, Lvting, Zhejiang Orient, and Jiangsu Shuntian were the main risk overflower, consistent with the industry. The risk spillover of the private lending and the trust reached a high level. In 2018, Minsheng Holdings, Xiangyi Rongtong, Huajin Capital, Zhejiang Oriental, Jiangsu Shuntian and CITIC Bank, China Merchants Bank, and Bank of Ningbo are the higher risk spillover, while Dacheng Bond, Fuguo Tianli Growth Bond, China Pacific Insurance, Tianmao Group, and China Life Insurance undertook major risk overflow. The risk spillovers are mostly in the trust and private lending, consistent with the industry, and the insurance still plays a stabilizing role. In 2020, the relevance of information spillover network intensified, and the risk spillover degree of Aijian Group, Northeast Securities, Haitong Securities, Minmetals Capital, and Shaanxi State Investment pretended to be higher. Yuexiu Financial Holding, Panda Financial Holding, Yijian, Fuguo Tianli Growth Bond, and Nanfang Duoli are still the main risk spillovers.

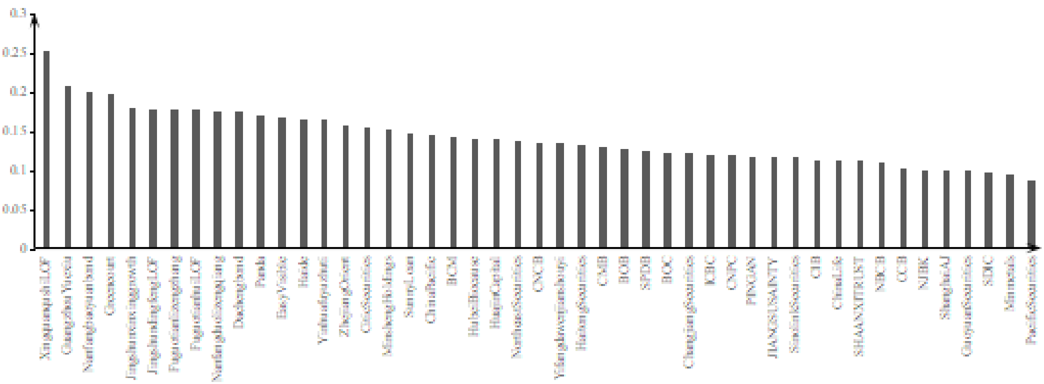
Network Topology

The eigenvector centrality and the information spillover network are used to measure the importance of the position of the institutions. The eigenvector centrality results of the whole sample period from 2008 to 2021, 2008, 2013, 2015, 2018 and 2020 are shown here.

Among the top 10 institutions with eigenvector centrality, the fund accounted for eight, and most of them were hybrid funds, and the remaining two were private lending, namely Yuexiu Financial Holding and Lvting. It can be seen that the fund occupies an extremely important position. Because of the diversity, the scale of is relatively large as a single fund is often tens of billions. Once in a risk, it will have the effect of pulling the trigger and moving the whole body, and also bring impact on other industries. By the end of 2021, the net asset value of domestic public funds reached 25.56 trillion yuan. In the current situation, it is necessary to strengthen the supervision to prevent unexpected risks.

In 2008, Guoyuan Securities, CITIC Bank, Dacheng Bond, Aijian Group, Haitong Securities, Green Court, China Investment Capital, Bank of Beijing, and Pacific ranked in the top 10 highly central institutions. The result is more consistent with the institutions with higher risk spillover reflected by the network. It showed a strong correlation between the importance of institutions and

Figure 9. Eigenvector Centrality for Institutions



the degree of risk spillover. In 2013, Tianmao Group, Bank of Communications, Pudong Development Bank, Wells Fargo Tianli Growth Bond, Minmetals Capital, PetroChina Capital, Yijian, Minsheng Holdings, and Hyde Holdings ranked in the top 10 highly central institutions. In 2015, four private lending institutions, two trust institutions, two insurances, one bank, and one fund were among the top 10 highly central institutions. It can be considered that the institutions with higher inbound and outbound degrees are also of higher importance in the whole network. In 2018, Dacheng Bond C, Xiangyi Rongtong, Minsheng Holdings, Wells Fargo Tianli Growth Bond, China Pacific Insurance, CITIC Bank, Hyde, Tianmao Group, Panda, and Bank of Ningbo rose to the top 10, without obvious industry bias, and the gap between the eigenvector centrality of institutions was weak, indicating that the important difference in the network was not significant. In 2020, there were five private lending, three trust, one security, and one fund in the top 10, which is consistent with the industry. Private lending played an extremely important role and released high risk to other industries. Although private lending has financed SMEs to a certain extent, the risk increased with the amounts of borrowers and the complex lending relationship. In 2020, the Supreme People's Court approved the scope of application of the new judicial interpretation of private lending. Seven types of local financial organizations, including small loan companies and pawnshops, started to belong to formal financial institutions. Disputes arising from financial business are not subject to the new interpretation. In the future, it is necessary to further improve the corresponding legal system of the private lending, speed up the construction of the credit reporting system, and strengthen supervision.

FACTORS OF THE RISK SPILLOVER

We analyze the factors through panel data model. Choose $\Delta CoVaR$ as the measure of risk spillover; the larger the $\Delta CoVaR$, the higher the risk spillover. Other factors are chosen, combining network topology indicators, macroeconomic, and enterprise-level factors. Eigenvector centrality is selected as the network topology indicator to be the core explanatory variable, which measures the importance of institutions in the network. Asset size, yield, and leverage are selected as enterprise-level, because the size and profitability have a great impact on the business, while leverage can also trigger risk. In terms of the macroeconomic factors, the consumer price index (CPI), which represents inflation, and the prosperity index, which represents the expectation of the macroeconomic situation, are chosen. Data of all indicators are quarterly, with a total of 56 quarters. Institutional data are taken from the Wind, and the X-12 method is used for quarterly adjustment.

Table 14. shows that the systemic risk spillovers, the centrality of feature vectors, and the extreme difference of macroeconomic indicators are small, and the extreme difference of leverage level and

Table 13. Model Indicators

Type	Name	Symbol	Description
Explained variable	Systemic Risk Spillover	$\Delta CoVaR$	5th percentile of systemic risk spillover, absolute value
Core explanatory variable	Eigenvector Centrality	Center	Spillover network indicators
Control variable	Asset Size	Size	Ln (Asset size)
	ROA	ROA	Net profit / Total asset
	Leverage	Lev	Total asset / Owner's equity
	CPI growth	CPI	Mean of monthly data
	Prosperity Index	HG	Consistency index

Table 14. Descriptive Statistics

Variable	Number	Mean	Median	Std	Min	Max
$\Delta CoVaR$	2632	1.033	0.995	0.586	0.023	3.609
Center	2632	0.142	0.138	0.034	0.063	0.355
Lev	2632	5.649	2.511	5.852	1.120	34.560
ROA	2632	1.180	0.754	2.580	-47.820	30.200
Size	2632	24.500	23.560	3.313	19.150	31.200
CPI	2632	2.476	2.183	1.854	-1.533	8.033
HG	2632	99.730	99.080	4.359	87.110	115.900

yields on assets at the institutional level is large, indicating that the financial situation of different institutions is quite different.

Set the following panel data model:

$$\Delta CoVaR = \alpha + \beta_1 Center_{i,t} + \beta_2 Lev_{i,t} + \beta_3 ROA_{i,t} + \beta_4 Size_{i,t} + \beta_5 CPI_{i,t} + \beta_6 HG_{i,t} + \varepsilon_{i,t} \qquad (14)$$

$i = 1, 2, \cdots, N$ represents the shadow banking institutions and t represents the time. First, the ADF test is used to test the stationarity. Results are stable and suitable for regression analysis. Second, through correlation analysis, it is found that there is a significant linear correlation between the eigenvector centrality and systemic risk spillovers. The VIF test result is 7.96, less than 10, indicating that there is no multicollinearity. Finally, according to the Hausman test, at the significance level of 1%, the fixed effect model is applied.

Table 15. shows the baseline results. The coefficient of eigenvector centrality is significantly positive, indicating that the more important the institution, the higher degree of its systemic risk spillover. It shows that for systematically important institutions, once they take risk, it is easy to cause more serious systemic risk. Therefore, risk awareness should be in risk prevention and control.

Among the control variables, on the enterprise-level perspective, the coefficient of leverage is significantly positive, indicating that the higher the leverage is, the stronger the degree of

Table 15. Correlation Analysis

	$\Delta CoVaR$	Center	Lev	ROA	Size	CPI	HG
$\Delta CoVaR$	1						
Center	0.049**	1					
Lev	-0.162***	-0.089***	1				
ROA	0.200***	0.0100	-0.088***	1			
Size	-0.241***	-0.117***	0.835***	-0.076***	1		
CPI	0.075***	0.00100	-0.00700	0.00300	-0.062***	1	
HG	-0.130***	0.00100	-0.00400	-0.041**	0.0280	0.040**	1

spillover, which means that shadow banking institutions, in order to pursue higher yields, generally increase leverage through inter-bank business and structure nesting and other ways, resulting in risk interweaving and aggregation among institutions. This increases the risk that the financial system will shift from real to virtual. It is still necessary to strengthen the supervision of innovation. The coefficient of yields is negative but not significant, maybe because, although the ability to resist risks will increase with the improvement of the profitability, the institution will also make high-risk investments in exchange for high yields, thus enhancing the risk spillover. The coefficient of asset size is significantly negative, meaning that the larger the asset size, the lower the systemic risk spillover. It indicates that with the increase of the asset size, the stronger the ability to resist and absorb risks is, and it is not easy to release risks to other institutions and the entire network.

Among the macroeconomic indicators, the coefficient of the CPI is significantly positive. The CPI plays a positive role in systemic risk spillover. If the price increase is too large, it will lead to inflationary pressure, thus increasing systemic risk spillover. The coefficient of the prosperity index is significantly positive. The higher the index, the greater the degree of systemic risk spillover. When the index is too high, it indicates that the macroeconomy may overheat, leading to increased risk spillovers.

It can be seen that whether it is the network topology index, the characteristics of the enterprise-level, or the macroeconomic factors, it can be an early warning on the risk spillover, helping the regulatory authorities identify the impact of risk spillover from multiple aspects and formulate corresponding policy measures to reduce the possibility of the occurrence of the shadow banking systemic risk.

To further test the robustness, MES is used as a substitution for $\Delta CoVaR$. Table 15 shows that the coefficients are positive and negative, and the significance is consistent, indicating that the conclusion of the influence of core explanatory variables on the explained variables is robust. To sum up, the greater the eigenvector centrality, the more important the position of the institution, and the higher its systemic risk spillover. The enterprise-level and the macroeconomic indicators can also influence the systemic risk spillover.

CONCLUSION AND POLICY IMPLICATIONS

Conclusion

This paper focuses on the extent of shadow banking systemic risk spillover and the risk contagion between industries and institutions of shadow banking. The sample covers 47 institutions in six shadow-banking industries within 2008-2021. First, the AR-GARCH-DCC model analyzes ΔCoVaR

Table 16. Baseline and Robustness Regression Results

Variables	$\Delta CoVaR$	MES
Center	0.4468***	0.3773***
	(2.98)	(3.57)
Lev	0.0206***	0.0096***
	(3.83)	(4.30)
ROA	-0.0020	-0.0013
	(-0.49)	(-0.45)
Size	-0.0592***	-0.0361***
	(-4.32)	(-3.84)
CPI	0.0593***	0.0379***
	(5.82)	(5.60)
HG	0.0498***	0.0292***
	(4.46)	(3.92)
Constant	-2.8877**	-1.6346*
	(-2.39)	(-2.01)
Observations	2,632	2,632
R-squared	0.629	0.580
Number	2632	2632
r2_a	0.621	0.571

and MES. Second, the research analyzes the network connectedness of shadow banking systemic risk in detail, and calculates the network topology index. Finally, it takes the systemic risk spillover as the explained variable to study the factors of the systemic risk and draw the following conclusions.

1. China's shadow banking systemic risk spillover fluctuated significantly in 2008, 2015, and 2020. The degree of shadow banking systemic risk spillover from large to small is securities, insurance, trust, private lending, banking, and fund. Among them, securities have the largest risk spillover to other industries, insurance has a moderate spillover, while banking and fund have a small risk spillover to other industries. Therefore, various types of shadow banking need different management methods. Although ΔCoVaR and MES measure risks from bottom-up and top-down perspectives, the trends are consistent overall.
2. The dynamic spillover network can more appropriately reflect the time-varying and volatility of risk than the static one. The dynamic spillover index fully depicts the impact of extreme events, which is conducive to the identification of systemic risk. The various types of shadow banking have different and uncertain roles, complicating the study of the relationship between risk spillovers and overflowers. This dislocation phenomenon can avoid the risk resonance and also prevent the spillovers of a single industry. The risk network relevance of various institutions becomes more closely related during a crisis, increasing the risk contagion. Therefore, relevant authorities need to track the development of the market and

the occurrence of emergencies in a timely manner and take targeted measures according to market events in different periods.
3. The results of the empirical research revealed that eigenvector centrality has a positive impact on spillover, reflecting that important institutions in the network contribute the most to risk. In addition, the higher the leverage of the institution, the greater the degree of spillover, while the larger the asset size, the lower the spillover. Moreover, an increase in the CPI and the prosperity index can raise the degree of systemic risk spillover. Regulators need to focus on monitoring these relevant indicators to mitigate shadow banking systemic risk.

Implications

The findings of this research highlight the crucial role of systemic shadow banking spillover in China, which needs further attention from policymakers. The degree of risk spillover varies over time, across industries, and among institutions, necessitating differentiated measures. Therefore, this paper proposes the following policy suggestions.

1. China needs a clearer definition of the shadow banking system, enhanced statistical standards and norms for shadow banking, and comprehensive monitoring of its business activities. By meeting these needs, it can enable timely tracking and disclosure of its scale, types, and characteristics. For this reason, the government should adopt some policies to accelerate the establishment and promotion of a shadow banking information platform. This platform should facilitate information sharing among consumers, investors, and platforms, ultimately reducing system instability and minimizing transaction losses for investors.
2. To more accurately and effectively measure the risks of shadow banking, the regulatory authorities, research institutions, and other entities should invest in research and development teams. This investment can develop mechanisms for early warning and effective risk management. Other researchers can emphasize the correlation characteristics to offer informed judgments on future development trends by carefully calculating indicator data for each category.
3. The findings stressed the importance of shadow banking supervision. Given that bank financing constitutes the highest proportion, banks should enhance their risk management practices. It is essential to prudently control the scale of bank-to-credit and bank-to-securities collaborations, avoiding adverse impacts on banks through capital. Simultaneously, effective management of off-balance-sheet funds and securitization is crucial to prevent further risk propagation. Private lending should be subject to regulation by clearly defining capital adequacy ratios and liquidity requirements. As for other nonbank financial institutions, efforts should be made to expand and develop their risk management capabilities. Striking a balance between risk and innovation and constructing a robust financial risk prevention and control system becomes paramount to curb the spread of risks among institutions through various channels and routes. Public and private funds should articulate investment directions clearly and strictly avoid lending in disguised forms.
4. Given the broad spectrum of industries, institutions, and businesses involved, and the diversity of participants, shadow banking should be regarded as a form of mixed operation. Consequently, regulatory departments at all levels should enhance their sense of responsibility and proactively engage in mixed supervision. The People's Bank of China, China Securities Regulatory Commission, China Banking and Insurance Regulatory Commission, and local financial regulatory authorities should reinforce cooperation and coordination. They should delineate clear responsibilities at all levels, aim for a division of labor and cooperation, implement comprehensive supervision of diverse shadow-banking activities, and collaboratively formulate pertinent and enhanced policies and measures.

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