

The impact of Federal Reserve Interest Rate Hikes on the Systemic Risk of the U.S. Banking Industry: Based on Semi-Parametric Vine Copula SCCA Model

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Abstract. We use the Vine Copula SCCA model to measure the systemic risk of the US banking industry, and compares the impact of two different events, external risk and Fed rate hike on systemic risk. The results demonstrate that the systemic risk of the US banking industry reached its peak when affected by external shocks (2020) but was quickly released by market rescue measures. When the Fed raised interest rates consecutively in 2022, large banks showed good resistance to risk, but the joint default risk of small and medium-sized banks remained at a significant level for a long time, indicating that interest rate hikes may have increased the systemic risk of the US banking industry. US banking industry should maintain good risk management and prudent operation, and the regulatory intensity they receive also needs to be strengthened.

Keywords: Vine Copula; SCCA; Banking Systemic Risk.

1. Introduction

In 2022, the Federal Reserve implemented eight interest rate hikes, raising its target range for the federal funds rate to 4.5% to 4.75%. As the world's largest economy, the United States' monetary policy and interest rate adjustments have had profound implications for global financial markets and the banking industry. In particular, under the backdrop of the Federal Reserve's rapid interest rate hikes, the banking sector faced pressures such as asset depreciation and deposit outflows. Silicon Valley Bank declared bankruptcy just two days after receiving the Best Bank award, which strongly reflected the adverse impact of the Federal Reserve's tightening monetary policy. This event also posed significant challenges to traditional risk assessment metrics. This paper will employ a non-parametric modeling approach to measure systemic risk in the U.S. banking industry and explore the impact of Federal Reserve interest rate hikes on systemic risk.

2. Literature Review

Individual financial institutions as well as to gauge the risk level of macroeconomic sectors. This method provides a comprehensive framework for assessing and quantifying the risk associated with corporate debt and financial institutions.

Gray et al. (2010)[4] introduced Systemic Contingent Claims Analysis (SCCA), which incorporates Copula functions and the concept of generalized extreme value distributions into the CCA framework. This enhancement allows for the consideration of risk interdependencies among financial institutions, making SCCA more suitable for applications. Early research defined systemic risk as follows: when a single financial institution experiences extreme events, typically referring to bankruptcy or collapse, it represents the maximum possible risk or loss faced by other financial institutions or the entire financial system. For instance, Adrian et al. (2008)[1] introduced the concept of Conditional Value at Risk (CoVaR), which measures the risk contribution of an individual financial institution to the entire financial system by estimating the difference between the Value at Risk (VaR) of the institution under crisis conditions and normal conditions. This difference is defined as ΔCoVaR . Although CoVaR takes into account the interconnections and risk

transmission among financial institutions, the risk values of individual institutions are not additive, making it challenging to accurately estimate systemic risk.

In order to more effectively quantify systemic risk and address the challenge of non-additivity of risks, Acharya et al. (2010)[2] proposed two indicators to assess the level of systemic risk: Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES). MES is an indicator used to measure the systemic risk of financial institutions. It evaluates an institution's marginal risk contribution to the entire financial system by measuring its expected losses during extreme market downturns. MES is widely used in empirical and is applicable even when significant financial risk exposure has not occurred. SES is a method used to assess the contribution of individual financial institutions to systemic risk within the financial system. SES takes into account the weighted losses of individual stocks, meaning that increasing the weight of a particular financial institution will lead to an increase in overall market risk. When measuring systemic risk in the banking industry, SES can comprehensively consider multiple risk factors, such as asset returns, non-performing loan ratios, capital adequacy ratios, and others, providing a more comprehensive risk assessment capability. However, both of these methods have certain limitations. For instance, MES does not consider factors like a financial institution's leverage, size, and market factors. SES calculations involve estimating and synthesizing multiple risk factors, which require high data quality and reliability. In complex financial markets, the assessment of SES may not be robust and could be influenced by model assumptions and parameter choices.

Gray et al. (2007)[3] introduced Contingent Claims Analysis (CCA), which is a method based on market prices and option pricing principles. It is used for valuing risky corporate debt and assessing default probabilities. This approach incorporates a wider range of data, considering both a financial institution's balance sheet data and stock market information. CCA calculates the expected returns of assets under risk-neutral conditions and uses risk-free interest rates to measure the likelihood of a company defaulting. CCA has found widespread application among financial market participants. It can be employed to measure the default risk level of or researching risk measurements at the industry or overall systemic level. However, it's important to note that SCCA assumes that the loss distributions of each financial institution are identical and can only fit a single two-dimensional risk dependency structure. On the other hand, Vine Copula models are used to model dependencies among multi-dimensional random variables. These models break down the multivariate joint distribution into a series of conditional joint distributions, enabling flexible modeling of complex multi-dimensional dependency structures.

In summary, while SCCA improves upon CCA by considering risk interdependencies, Vine Copula models offer even more flexibility in modeling complex, multi-dimensional dependency structures among financial variables. Schepsmeier U (2015)[5] proposed a new goodness-of-fit test for Regular Vine (R-vine) copula models, which aims to assess how well R-vine copula models fit observed data, providing a valuable tool for model evaluation and selection in multivariate analysis. R-vine copula model allows for the simulation and analysis of complex multivariate dependency structures, making it widely applicable in the field of finance and other multivariate data analysis tasks. Gong (2022)[6] proposed the semi-parametric Vine Copula SCCA model, which incorporates the R-Vine Copula model and semi-parametric modeling, relaxes the assumptions of the SCCA model on the risk dependence structure and marginal distribution, enhances the adaptability of the systemic risk measurement of the banking industry, and thus measures the evolution characteristics of the systemic risk of the banking industry more scientifically.

The risk interdependency structure within the U.S. banking system is influenced by variations among different types, sizes, and geographical locations of banking institutions. Large national commercial banks may exhibit significant risk transmission relationships among themselves. Regional banks are impacted by the regional economy and market competition. The openness of financial markets leads to risk interdependencies formed through market transactions among different banks, and specific types of banking institutions are influenced by regulatory requirements and market environments tailored to their characteristics. The regulatory framework of the U.S.

banking industry is complex, involving multiple regulatory agencies, which also affect the risk interdependency structure. Therefore, this paper will employ the Vine Copula SCCA to measure systemic risk within the U.S. banking industry.

3. Methodology

3.1 Bank Potential Loss and Default Probability

Contingent Claims Analysis (CCA) is a financial analysis method based on the Black-Scholes-Merton option pricing theory. It provides a framework rooted in stochastic processes and probability distributions to evaluate the value and risk of financial assets. CCA treats a company's assets and liabilities as a series of contingent claims, which are equity interests triggered under specific conditions. These contingent claims can include stocks, bonds, options, and other financial instruments. In the Merton model, the company's equity value E_t is seen as a call option on the company's asset value A_t and debt B_t . According to this model, the relationship between equity value and company asset value and debt can be expressed by the following formula:

$$E_t = A_t N(d_1) - B_t e^{-rT} N(d_2) \quad \#(1)$$

Where $N(d)$ is the standard normal distribution function, r is the risk-free interest rate, T is the time to maturity, B_t is the face value of the bank's debt at time t , $(T - t)$ is the time to debt maturity, and d_1 and d_2 are two intermediate variables given by:

$$d_1 = \frac{\left(\ln \frac{A_t}{B_t} + \left(r + \frac{\sigma_A^2}{2} \right) \times (T - t) \right)}{(\sigma_A \times \sqrt{T})}$$

$$d_2 = \frac{\left(\ln \frac{A_t}{B_t} + \left(r - \frac{\sigma_A^2}{2} \right) \times (T - t) \right)}{(\sigma_A \times \sqrt{T})}$$

The relationship between equity value volatility σ_E and implied asset volatility σ_A can be derived from Ito's Lemma, expressed mathematically as follows:

$$\sigma_E = \frac{\sigma_A A_t N(d_1)}{E_t} \quad \#(2)$$

The expression for the bank's asset value A_t following a geometric Brownian motion at time t is:

$$d(A_t) = \mu_A A_t dt + \sigma_A A_t dW_t \quad \#(3)$$

Here, μ_A represents the bank's asset return rate, σ_A is the standard deviation of asset returns, and dW_t is a stochastic process following a standard Brownian motion.

Potential loss L_t is an important risk indicator that measures the risk level of an individual bank in the CCA method. It mainly reflects the severity of the consequences that may be caused by a potential default event of an individual bank institution. Under the assumptions of the Black-Scholes-Merton option pricing theory, the potential loss of each bank can be regarded as the value of a European put option. The expression for potential loss is:

$$L_t = B_t e^{-r(T-t)} N(-d_2) - A_t N(-d_1) \quad \#(4)$$

In addition, in the Merton model, the value of a firm's assets is considered as a tradable financial asset, which fluctuates with time and market changes. When the value of a firm's assets falls below the value of its debt, the firm is considered to be in default. The default probability $PD = N(-d_2)$.

3.2 Bank risk dependence structure based on Vine Copula model

Let F be the joint distribution function of the n -dimensional random variable (X_1, X_2, \dots, X_n) , with marginal distribution functions F_1, F_2, \dots, F_n respectively. According to

the copula theory proposed by Sklar (1959)[7], there exists an n-dimensional copula function $C: [0, 1]^n \rightarrow [0, 1]$, such that for all $(x_1, x_2, \dots, x_n) \in R^n$, we have:

$$F(x_1, x_2, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)) \quad \#(5)$$

Based on this theory, Bedford et al. (2002)[8] introduced the Vine Copula model. It represents the high-dimensional dependence by decomposing the n-dimensional copula function C into a series of conditional bivariate copulas. Specifically, the Vine Copula constructs a hierarchy, where each level contains a set of conditional bivariate copulas. These conditional bivariate copulas describe the dependence structure between individual random variables, and by combining these dependencies layer by layer, we can obtain the entire high-dimensional dependence structure.

SCCA may neglect the nonlinear relationship between the potential losses of financial institutions, and thus fail to capture the interdependence and joint default probability of financial institutions. Vine Copula SCCA, by introducing the Vine Copula model, can capture the complex nonlinear and heterogeneous correlation among financial institutions. The Vine Copula model can decompose the high-dimensional joint distribution into multiple conditional bivariate Copulas, which describe the dependence structure between pairs of financial institutions, and can better fit the systemic risk.

Vine Copula models can be classified into three categories according to their structure: R-Vine, C-Vine, and D-Vine. These three types of Vine Copula can all be used to represent the dependence relationships among multivariate random variables. In R-Vine, various complex dependence structures can be captured by changing the tree structure and the bivariate Copula between each layer, making it more suitable for high-dimensional data. In contrast, the structures of C-Vine and D-Vine are more restricted and may not be able to capture some complex dependence structures. Therefore, this paper adopts the R-Vine structure to fit the risk dependence relationships between pairs of banks. In terms of determining the specific function structure, this study follows the maximum spanning tree method, which calculates the Kendall rank correlation coefficient τ between pairs of variables and selects the tree structure that maximizes the sum of absolute values of τ at each layer. After establishing the R-Vine function structure, the AIC criterion is used to screen the Pair Copula functions corresponding to each edge, and the Pair Copula function with the smallest AIC value is selected as the function for the corresponding edge. The parameters of each Pair Copula function are estimated by the maximum likelihood method.

3.3 Systemic risk indicators of the banking industry

This paper follows the approach of Wang Qing et al. (2016)[9] and others, measuring the bank default correlation in the rolling window, and setting the window length and step size to one year. Kim et al. (2007)[10] found that the semi-parametric estimation method based on empirical distribution function performed relatively well in practical applications, especially when the marginal distribution was unknown or difficult to estimate. Therefore, this paper uses the empirical distribution function to transform the potential losses of each bank institution into pseudo-sample observations \hat{u}_j , and obtains the joint expected loss distribution G_t , as follows: where $C_t(\cdot)$ is the R-Vine Copula function corresponding to the t-th rolling period, $\hat{\theta}$ is the estimated value of the parameters in the Copula function. This paper constructs a joint extreme potential loss JEPL as an indicator to measure the systemic risk of the banking industry, as follows:

$$G_t(l_1, l_2, \dots, l_n) = C_t(\hat{u}_1, \dots, \hat{u}_n; \hat{\theta}) \quad \#(6)$$

Where $C_t(\cdot)$ is the R-Vine Copula function corresponding to the t-th rolling period, θ is the estimated value of the parameters in the Copula function. This paper constructs the joint

extreme potential loss JEPL as an indicator to measure the systemic risk of the banking industry, as follows:

$$\text{JEPL} = E[\sum l_{it} | H(\sum l_i) \geq \alpha] \#(7)$$

Where $H(\cdot)$ represents the distribution function of $\sum l_i$. The joint distribution of l_1, l_2, \dots, l_n , $G(l_1, l_2, \dots, l_n)$ is fitted by the R-Vine Copula function $(u_1, u_2, \dots, u_n; \theta)$, so there is no explicit analytical expression. This paper uses the Monte Carlo simulation method to estimate the JEPL indicator, with the following steps:

Step 1: Generate pseudo-sample observations $(u_1, u_2, \dots, u_n)^*$ based on the joint potential loss distribution $C_t(\widehat{u}_1, \dots, \widehat{u}_n; \widehat{\theta})$;

Step 2: Convert each set of pseudo-sample observations $(u_1, u_2, \dots, u_n)^*$ into simulated potential loss sequences of each bank $(l_1, l_2, \dots, l_n)^*$. $\xi = \sum l_i$ is a simulated sample of the sum of potential losses of n banks;

Step 3: Repeat steps 1 to 2 to simulate m times, and obtain the simulated sample of the sum of expected losses $(\xi_1, \xi_2, \dots, \xi_m)$, whose rank statistics are $\xi_{[t]}$;

Step 4: This paper sets the confidence level $\alpha=95\%$, the number of repeated simulations $m=10000$, and JEPL is estimated by equation (8);

$$\text{JEPL} = \frac{\sum_{t=m-\alpha}^m \xi_{[t]}}{m(1 - \alpha) + 1} \#(8)$$

The JEPL indicator is mainly used to calculate the expected value of the total extreme losses that may occur at a given confidence level for different types of bank institutions during the research period. Since it is also necessary to classify the sample banks for research, this paper defines the joint default probability, which makes the samples with different market values comparable and can study the temporal characteristics of systemic risk, as follows:

$$\text{JDP} = 1 - \prod \text{DP}_i \#(9)$$

Where DP_i is the default probability of a single institution at time t.

4. Findings

4.1 Data description

This paper selected 26 banking giants in the United States with significant asset and market capitalization as the research sample. They were divided into three tiers based on total assets in descending order: The first tier comprised ten banks, including JPMorgan Chase, Bank of America, and others. The second tier included nine banks, such as U.S. Bancorp, Capital One, and others. The third tier consisted of seven banks, including Fifth Third Bank, Valley Bank and others. Additionally, this paper defined "risk banks", which included banks that either faced distress or bankruptcy as of March 2023 (Silicon Valley Bank, Crypto-Friendly Bank, Signature Bank, Credit Suisse, and First Republic Bank) or three banks with significantly fluctuating default probabilities in 2022 (HSBC, Capital One, and UBS). According to the legislative reforms in the United States in 2018, banks with assets below \$250 billion were exempt from the stricter regulations applied to large banks, including capital and stress tests. Furthermore, the Trump administration's new laws significantly eased regulatory standards for small and medium-sized banks. Based on these criteria, this paper defined banks with assets exceeding \$250 billion as large banks.

The financial data in this paper is sourced from Alpha Vantage. The debt face value, denoted as B_t , is derived from quarterly data of the institutions. It is transformed into daily data using cubic interpolation and defined as the sum of short-term debt and half of long-term debt. Equity value is calculated from shares outstanding and daily stock price data, and its

volatility is estimated through fitting a GARCH(1,1) model. For this study, the daily updated ten-year Treasury bond yield provided by the Federal Reserve Economic Database is employed as the risk-free rate r .

4.2 The Time-Varying Risk Characteristics and Joint Default Probabilities

This paper utilized CCA to calculate the time series of potential losses for the sample banks. Overall, although potential losses are positively correlated with a bank's total assets, the time series of potential losses for different banks exhibit similar trends in the same direction. This was most notable during the early stages of the global outbreak of the COVID-19 pandemic, where potential losses accurately captured the systemic impact of external shocks on banks, and extreme values of potential losses were positively correlated with a bank's total assets. Throughout the year 2020, the time-varying risk characteristics of the three tiers were very similar. Starting in 2021, large banks experienced a significant reduction in potential losses, with less noticeable fluctuations, while some medium-sized banks still exhibited pronounced volatility.

Relying solely on potential losses for assessing systemic risk has limited effectiveness, but its time series still reveals certain economic phenomena. During the initial outbreak of the global pandemic, potential losses for all banks exhibited significant fluctuations, indicating that external shocks in the market may have had a similar impact on all banks, leading to increased market uncertainty and elevated credit risk. This is because the banking sector, as a core part of the financial system, is subject to similar influences from macroeconomic conditions and market factors. Larger banks, often with more assets and liabilities, may bear greater losses in absolute terms.

However, after the peak of the pandemic, larger banks demonstrated greater resilience during the economic recovery process due to factors such as diversification of their business operations, higher capital adequacy ratios, and stronger risk management capabilities. As a result, relative to their total assets, potential losses for large banks exhibited smaller fluctuations. In contrast, smaller banks may have been relatively vulnerable in these aspects, leading to greater risk volatility.

In 2022, as the Federal Reserve embarked on a tightening cycle, the potential loss volatility for some medium-sized banks became notably pronounced. When market interest rates rise, the banking industry's net interest margin, credit risk, and market risk can all be affected. However, medium-sized banks may exhibit relatively weaker resilience in these aspects. This could be attributed to challenges they face in managing interest rate risk, asset-liability structures, sensitivity to credit risk, and market competition, which collectively contribute to an increase in potential loss volatility.

Due to significant variations in the magnitude of potential losses among banks of different sizes, the joint default probability serves as a more effective indicator to encapsulate the risk profiles of banks with varying scales. The time series of joint default probabilities is depicted in Figure 1, highlighting the dynamics of these probabilities over time. From left to right, the sequence represents Tier 1, Tier 2, and Tier 3, respectively.

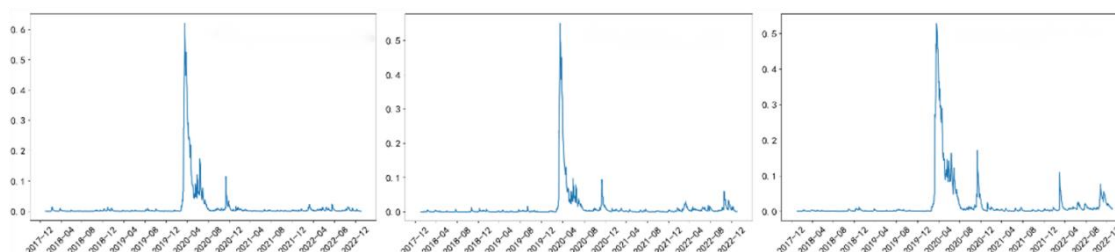


Fig. 1 Joint default probabilities

It is evident that the external shock induced by the COVID-19 pandemic was extremely impactful, placing significant pressure on the American banking sector. This pressure resulted from economic stagnation, rising unemployment rates, and credit contractions, all contributing to an increase in default risk. In the time series chart, this increase is reflected in a sharp rise in the joint default probabilities for each group of banks at the onset of the pandemic. At its peak, these probabilities even reached around 60%.

However, in 2020, the American banking sector did not experience substantial defaults. This outcome could be attributed to the swift implementation of a series of government relief measures, such as interest rate cuts and quantitative easing policies. As a result, the joint default risk swiftly receded to lower levels.

In 2022, as the Federal Reserve entered an interest rate hiking cycle, the time series chart shows distinct patterns for different tiers of banks. During this period, Tier 1 banks exhibited the lowest joint default probabilities, with peak values not exceeding 3%. In contrast, Tier 3 banks experienced fluctuating joint default probabilities, influenced by the interest rate tightening measures, with peak values reaching 10%. Although the joint default probabilities for Tier 3 banks and risk banks in 2022 were lower than in 2020, they remained relatively elevated in the long term. This could be attributed to a lack of emphasis on potential risks by relevant authorities and the absence of measures similar to those taken in 2020 to mitigate risks. Medium-sized banks, with their inherently weaker risk resilience, coupled with lenient regulatory policies, may not have had sufficient motivation to maintain robust risk management and prudent operations during the interest rate hiking cycle, thus facing heightened joint default risk. In summary, the varying patterns of joint default probabilities across different tiers of banks in 2022 reflect the complex interplay of regulatory policies, risk management practices, and market dynamics, which have implications for their respective risk profiles.

4.3 Joint extreme potential losses

The right side of Figure 2 presents the jointly estimated extreme potential losses (JEPL) derived from SCCA (fitted using the R-vine copula model). Despite the relatively modest scale of risk banks, their JEPL in 2022 exceeds that of any other grouping. On the left side of Figure 2, we observe the joint default probabilities for these risk banks. Although the peak default probabilities are lower compared to the outbreak of the COVID-19 pandemic, they persist at a noteworthy level over an extended timeframe. This observation suggests that the Federal Reserve's series of interest rate hikes have amplified the default risk for banks with limited risk resilience, subsequently increasing the potential losses across the entire banking sector.

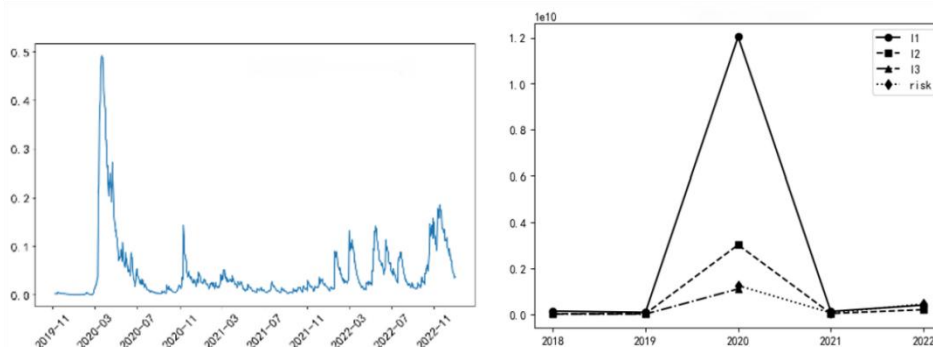


Fig. 2

5. Conclusions and suggestions

This study has assessed the systemic risk within the U.S. banking industry in recent years. The results indicate that the U.S. banking sector faced an exceptionally high joint default

probability during the outbreak of the pandemic. However, no significant market defaults occurred, which may be attributed to the rapid and effective measures implemented by the Federal Reserve and the U.S. government to mitigate these risks. It could also be due to the existence of more intricate and profound mechanisms of risk transmission among banks of different types. Subsequent to 2020, the default risk and potential losses for large U.S. banks decreased, while the risk for medium-sized and small banks remained persistently elevated. This highlights a substantial disparity in risk resilience among banks of varying sizes. The data from 2022 reveals that the Federal Reserve's interest rate hikes primarily escalated the default risk for smaller-scale banks, subsequently impacting the systemic risk and potential losses across the entire banking sector. In today's increasingly complex and dynamic economic landscape, it is imperative to formulate more rational and scientifically grounded regulatory standards for medium-sized and small banks. Such standards should avoid the direct application of regulatory requirements designed for large banks to their smaller counterparts. Additionally, exemptions for certain obligations of medium-sized and small banks should not be granted arbitrarily. Instead, these banks can be encouraged to provide more transparent disclosure of their financial and risk information. This approach would enable regulatory authorities, investors, and other stakeholders to gain a better understanding of the operational status of these banks.

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