International Review of Economics and Finance 97 (2025) 103779

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Enhancing banking systemic risk indicators by incorporating volatility clustering, variance risk premiums, and considering distance-to-capital

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ARTICLE INFO

JEL classification:
G01
G21
G28

Keywords:
Distance-to-Capital
Systemic risk
Volatility clustering
Variance risk premiums
Expected shortfall

ABSTRACT

We develop a systemic risk indicator approach using a structural GARCH option-based default risk framework incorporating volatility clustering, variance risk premiums, along with distance-to-capital features. We apply our model to the U.S. banking sector, testing its explanatory and forecasting power. Our model successfully identifies the most systemically risky banks during heightened systemic-risk episodes. Comparing our results to related approaches, especially the respected indicator of the Federal Reserve Bank of Cleveland, we evidence markedly improved performance. Given the recent implosion of Silicon Valley Bank, exploring new approaches to constructing banking systemic risk indicators should be of great interest to regulators and policy makers.

1. Introduction

Banks play a crucial role in an economy by financing businesses and households and implementing monetary policy strategies. Central banks, through control of the money supply, utilize the banking industry to achieve ultimate objectives such as economic expansion, inflation control, job creation, capital expenditures, and consumer spending. While executing these operations, banks are exposed to significant risks that can threaten the health of the overall economy. The process of allocating funds from savers to borrowers involves converting short-term deposits into long-term loans, creating a maturity mismatch. In addition to the interest rate risk from this maturity gap, banks face other exposures such as credit, liquidity, and operational risks. These risks necessitate stringent management requirements from both bank managers and regulators. Failure in a specific bank can trigger a collapse of the entire economy due to the interconnected network of funding and payment obligations across various industries. The literature on systemic risk provides substantial evidence supporting this interconnectedness and its potential consequences (see Atasoy et al., 2024; Cont et al., 2013; Li et al., 2023; Markose et al., 2023; Paltalidis et al., 2015; Qi et al., 2022).

Cascading failures within the context of systemic risk are particularly associated with the banking industry due to its operational mechanisms. Banks, which are intricately linked to the entire economic system—much like capillaries in the body—are involved in

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https://doi.org/10.1016/j.iref.2024.103779
Received 4 June 2024; Received in revised form 15 November 2024; Accepted 2 December 2024
Available online 5 December 2024
1059-0560/

raising and supplying funds and are subject to obligations managed and regulated by policy bodies. Historical failures have highlighted the importance of these regulations. The Basel Accords, developed in response to the Asian Crisis (1997), the Russian Crisis (1998), and the Global Financial Crisis (GFC) (2008–09), exemplify how new lessons have led to modifications in capital adequacy management to strengthen the industry's infrastructure. Given the critical status of the banking system in an economy, policymakers are compelled to mitigate market-wide risks and prevent potential economic catastrophes. The sophisticated role of banks in the economy not only poses risks to other counterparts in the system but also affects investor expectations and market sentiment. Deterioration in these areas can lead to panic among investors, directly impacting equity market supply and demand, and potentially resulting in stock market crashes as an aftermath of systemic risk. Considering that banking shares account for 15% of the market cap on the New York Stock Exchange, the highest of any industry, it is evident that the equity market risks originated in banking shares alone could incite panic in entire market. Furthermore, the obligations related to bank operations, particularly through credit risk management, can spread and involve other financial institutions, including the insurance sector, due to protection deals on credit derivatives like credit default swap (CDS) agreements. In Q1-2024, the notional amount insured through credit derivatives for U.S. Commercial Banks and Savings Associations reached four trillion US dollar, which is approximately 15% of the U.S. 2023 GDP (OCC, 2024). This ratio highlights the potential systemic risk in the U.S. banking sector specifically related to credit derivatives. The GFC of 2008 illustrated such risks. As reported by the Federal Reserve, the liquidity problems faced by AIG, the largest insurance company globally, were triggered by collateral calls on CDS and other credit derivatives obligations, bringing AIG to the brink of collapse. The cost of preserving the stability of the US economy, resulting from the AIG bailout, amounted to 117.5 billion US dollars under three facility programs. This shows that systemic risk in the banking industry extends beyond its operational boundaries, posing a threat to the entire economy. Thus, as noted by Cerutti et al. (2012), the banking system is often the primary focus in systemic risk analysis for any country.

The market downturns during the GFC of 2008 and the COVID-19 pandemic in 2020 demonstrate how cross-market linkages and trade channels can exacerbate the adverse effects of systemic risk. The important securitization of credit instruments, coupled with the subsequent collapse of subprime mortgage market obligations, rapidly triggered a liquidity crisis in the U.S. economy, fueled by the unforeseen interconnectedness of toxic assets. This turmoil subsequently cascaded into a sovereign debt crisis in Europe. Despite rigorous regulations enacted in response to the GFC, systemic risk remains a severe threat to market stability. During the GFC, toxic assets and off-balance sheet items were major threats to financial institutions. However, the causes of systemic risk can vary and present different drivers in each case. For instance, as discussed by Van Vo and Le (2023), overinvestment in fixed income securities and changes in Federal Reserve interest rate policy were central to the failure of Silicon Valley Bank in 2023, which led to a series of bank runs. The collapse of this relatively small bank had widespread effects; the perceived systemic risk caused a sharp decline in bank shares and incited global panic in the banking industry. The market turmoil also contributed to the failure of Credit Suisse. This time, authorities responded quickly to prevent the contagion and spread of systemic risk, resulting in short-lived risks and limited effects, as discussed by Akhtaruzzaman et al. (2023). However, the Dow Jones U.S. Banks Index reaction to this event showed that the losses in March 2023 were the second worst in the last decade, only surpassed by those experienced during the COVID-19 pandemic.

The market developments of the last two decades have exemplified the severe and unpredictable nature of systemic risk, underscoring the necessity for its proper identification, monitoring, measurement, and management. Consequently, many researchers have sought to quantify the extent of systemic risk using various methodologies. Esteemed examples of these endeavors include the models proposed by Adrian and Brunnermeier (2011) (Delta Conditional Value at Risk, ΔCoVaR), Acharya, Pedersen, Philippon, and Richardson (2017) (Marginal Expected Shortfall, MES), Banulescu and Dumitrescu (2015) (Component Expected Shortfall, CES), and Mihoci et al. (2020) (Financial Risk Meter, FRM). In this study, we propose a robust and novel approach for measuring systemic risk in the US banking sector and identify systemically risky banks. Unlike previous literature and as an alternative to the Cleveland Fed Index (CFI), we introduce a methodology that incorporates the stylized facts of financial time series with appropriate methodological support. Our method includes volatility clustering, variance risk premiums, and a distance-to-capital approach as proposed by Chan-Lau and Sy (2007), whereas the CFI utilizes Merton's (1974) distance-to-default model. Bharath and Shumway (2008) have pointed out that violations in Merton's distance-to-default model can cause significant accuracy issues, empirically demonstrating its insufficiency as a statistic for the probability of default. Chan-Lau and Sy (2007) argue that the distance-to-capital method is more robust and can account for pre-default regulatory actions. Additionally, by considering the stylized facts of financial time series, we estimate the volatility component of the probability of default through a GARCH model, specifically using the Heston, and Nandi (2000) GARCH (HN-GARCH) option valuation model. This approach allows us to account for the time-varying and clustering nature of volatility, as extensively reported in the literature (Cont, 2007; Daal et al., 2007; Lux & Marchesi, 2000; Ning et al., 2015). Furthermore, we modify the stochastic processes to account for the presence of variance risk premia, following the approach of Christoffersen, Jacobs, and Ornthanalai (2013). For consistency, we utilize the distance-to-capital methodology in estimating marginal expected shortfall in systemic risk tests and connectedness analysis across various quantiles. This comprehensive setup offers reliable and robust findings in measuring systemic risk in financial markets.

Considering the objectives of accurately measuring systemic risk and employing appropriate methodologies, we believe our study will be useful for investors, financial managers, and policymakers. Our introduced Systemic Risk Indicator (SRI) demonstrates the ability to capture growing tensions in the banking sector earlier than the CFI and VIX. The results reveal the potential of our methodology as an early risk indicator for financial markets. The cases of LTCM, Lehman Brothers, and Silicon Valley Bank illustrate the importance of accurately modeling systemic risk to select appropriate actions among alternatives. Underestimating or overestimating risk can lead to inadequate or excessive resource allocations, as evidenced by these market failures. This situation violates the fundamental economic principle of efficient resource use. Beyond the high performance of the introduced SRI, identifying systemically risky banks allows policymakers to customize actions during financial turbulence instead of relying on one-size-fits-all solutions. The network we generate to identify banks that play major roles in transmitting and receiving spillovers can be used for this purpose. For instance, authorities may prioritize banks identified in our study when adjusting the Stress Capital Buffer Requirement (SCBR). In a dynamic framework, once the SRI shows persistent growth with lower standard deviation than the predetermined threshold, the SCBR could be automatically adjusted for banks ranked with high sensitivity in the spillover network.

2. Literature review

The concept of systemic risk and its nature adapts to various markets and can be measured using alternative approaches. This flexibility allows researchers to examine systemic risk across different asset types and methodologies. In addition to contingent claim approaches, market-based methods have also garnered significant interest among researchers, as outlined below.

Estimating adequate capital is challenging as it requires both bank balance sheet data and forward-looking market-based data such as stock prices and volatilities, credit default swaps, and leverage (Singh et al., 2015). The contingent claim approach (CCA) uses risk indicators along with a comprehensive credit risk measurement using balance sheet and market-based data. In particular, distance-to-default indicators measuring default risk for monitoring the default risk of financial firms have attracted the interest of international and national institutions such as the International Monetary Fund (IMF), European Central Bank (ECB), and Office of Federal Research (OFR). Furthermore, the Financial Stability Board (2009) emphasizes the importance of this approach in terms of systemic risk analysis and determining systemically important financial institutions.

Allen et al. (2012) construct a macro index of systemic risk for the US banking sector by calculating value-at-risk CATFIN, along with expected shortfall for the monthly excess return of individual banks. CATFIN refers to measuring the collective catastrophic (tail) risk of banking systems and institutions. The authors evidence that incorporating their modeling improves CATFIN in forecasting real economic activity. Researchers at the Cleveland Fed (Craig, 2020) have introduced a systemic risk indicator application following Saldias (2013). This weekly updated indicator seeks to "represent market sentiments about the risk of extensive failure in the banking sector." The indicator calculates systemic risk as the difference between the default risk of a weighted portfolio for the same institutions (portfolio distance-to-default, PDtD) and an average default risk across individual banking institutions (average distance-to-default, ADtD). The underlying idea postulates that PDtD captures the correlations within components of the basket, unlike the ADtD (Saldias, 2013). When the interdependence among financial institutions increases, the default risk for the portfolio is higher than the average default risk of individual institutions, and hence the systemic risk increases. As it is outlined in our work, the literature provides a great deal of evidence on the existence of negative and economically large variance risk premiums in equity markets [see for example Bakshi, and Kapadia (2003), Carr and Wu (2009), and Goodell et al. (2020).] Of particular relevance, Wang et al. (2013) finds that variance risk premiums have prominent explanatory power for credit risk spreads. Kenc and Cevik (2021) find that a structural model with volatility clustering and variance risk premium produces better performance measures compared to models without such features.

There are many applications of the contingent claim approach to systemic risk measurement. Jobst and Gray (2013) produce aggregate estimates of the joint default risk of multiple institutions as a conditional tail expectation using multivariate extreme value theory based on a standard form of the Merton model. Saldias (2013) estimates individual contributions of European banks to the European financial systemic risk using a basic structural default model. Adrian and Brunnermeier (2016), Brownlees and Engle (2017), Engle and Siriwardane (2018) and Greenwood et al. (2015) incorporate the structural aspects of conditional value at risk (CoVaR), time-varying correlations, leverage adjustments, and fire sale externalities, respectively. Alternative methods in the literature have been proposed to measure systemic risk using market-based approaches. In one of the early studies, Adrian and Brunnermeier (2011) proposed the ΔCoVaR model, which captures left tail co-movements between a specific financial institution and the entire system. This methodology has garnered significant interest and has been employed by various researchers in different specifications (see Castro & Ferrari, 2014; Mensi et al., 2017; Tiwari et al., 2022; Yang & Hamori, 2021). Among these studies, Sedunov (2016) explored the performance of alternative systemic risk measures and concluded that CoVaR outperforms both causality-based and expected shortfall methods. In a different study, Liu et al. (2022) employed a high-dimensional CoVaR approach to ascertain spillovers from oil markets to G20 equity markets, comparing the results generated from Delta CoVaR and CoVaR methods. A similar comparison was conducted by Trabelsi and Naifar (2017) to investigate the exposure of Islamic equity indices to systemic tail risk. Their results demonstrated the moderate systemic risk effects experienced by GCC stock markets.

Banulescu and Dumitrescu (2015) state that a conventional market-based approach to measuring systemic risk involves using an aggregate risk measure for the entire financial system. This approach, exemplified by the expected shortfall, quantifies the contribution of each firm to the overall risk in the system, which is considered as a portfolio formed by financial institutions. Acharya et al.'s (2010) MES analysis is a notable example of this approach, as it measures the sensitivity of systemic risk to a unit change in a firm's weight within the portfolio. Derbali and Hallara (2016) applied this methodology to examine systemic risk among European banks post-GFC across 16 European economies. Banulescu-Radu et al. (2021) integrated this methodology into their backtesting procedures for systemic risk, evaluating various measures including systemic expected shortfall (SES), systemic risk measure (SRISK), and ΔCoVaR. Their results indicate that their proposed model effectively forecasts both MES and SRISK. Building on this methodology, Eckernkemper (2018) proposed a copula-based framework to estimate MES. Unlike the original approach, this alternative approach captures time-varying nonlinear dependencies, and its efficacy is empirically tested within the sectors of the Dow Jones Industrial Average.

Although MES is widely used in the literature, Banulescu and Dumitrescu (2015) argue that it fails to account for firm-specific characteristics, such as leverage, and primarily focuses on institutional connectedness. Additionally, the sum of MES values does not accurately reflect the system's aggregate expected shortfall. To address these limitations, the authors propose CES, which measures a firm's "absolute" contribution to the system's overall expected shortfall. Caliskan, Cevik, Cevik, and Dibooglu (2021) applied the CES methodology to analyze systemic risk in the Turkish stock market, focusing on 54 financial firms. Their findings indicate that the top ten systemically important financial institutions dominate nearly the entire market's systemic risk. In a study conducted for China, Liu et al. (2021) utilized CES to investigate sectoral risk contributions to the equity market. Their results showed that the banking sector was systematically the most significant contributor to systemic risk both before and during the GFC. In a more recent study, Gunay et al. (2023) assessed systemic risk in the cryptocurrency market using both CES and Granger causality for the left tail of the distribution. The results revealed that Bitcoin and Ethereum have the highest contributions to systemic risk in the cryptocurrency market, while sectoral indices exhibit limited effects compared to the dominance of these two assets.

More recently, to capture the interconnectedness of tail events between financial institutions, Mihoci et al. (2020) introduced a new market-based methodology called the FRM. This approach uses the least absolute shrinkage and selection operator (LASSO) quantile regression to capture dependencies in tail events. Wang et al. (2024) utilized this methodology to examine interconnectedness among tail events in the cryptocurrency market. Their study identified strong co-movements between CRIX and FRM@Crypto volatility and reported that FRM@Crypto has significant short-term predictive ability compared to other measures. To explore systemic risk in emerging economies, Amor et al. (2022) applied the FRM framework to Brazil, Russia, India, Mexico, South Africa, and Türkiye. Their findings indicate that systemic risk was highest during the GFC and remained significant during the global pandemic period. Ren et al. (2022) modified the FRM methodology by extending it to expectiles using LASSO-based quantile regression. This enhancement allows the model to not only estimate the probability of extreme events but also quantify the potential loss in a stressed environment within the network. The authors tested this updated model in the US equity market.

3. Methodology

3.1. Structural credit risk model

Our approach to measuring systemic risk is to estimate the default probability indicators implied by the Merton structural credit risk tradition. The Merton model starts with the conventional definition of a company (a bank in our case) default, which occurs when the value of its assets A is less than the promised debt repayment $\overline{D}$ at its maturity time $+\ T$. The probability of this default at time t, assuming $\overline{D}$ is a zero-coupon debt and does not change until $t+T$, is given by

$$P_{def,t} = Prob(A_{t+T} \leq \overline{D}_t \setminus \mathscr{F}_t) = Prob(\ln(A_{t+T}) \leq \log(\overline{D}_t) \setminus \mathscr{F}_t) \tag{1}$$

where $\mathscr{F}_t$ denotes the information available at time t.[1] To proceed, Merton (1974) assumes a geometric Brownian motion (GBM) that specifies the dynamics of A:

$$dA = [\mu_A - \delta]Adt + \sigma_A AdW \tag{2}$$

where δ is the payout rate to debt and equity holders, μ_A is the expected continuously compounded return on A, σ_A is the volatility of firm value and dW is a standard Wiener process under the physical probability measure. The GBM implied log-normal distribution for the company assets at any time t is written as:

$$\ln A_{t+T} = \ln A_t + \left[\mu_A - \delta - \frac{1}{2}\sigma_A^2\right]T + \sigma_A\sqrt{T}z_{t+T} \tag{3}$$

where $z_{t+T} = \frac{W_{t+T} - W_t}{\sqrt{T}}$ and $z_{t+T} \sim N(0,1)$.

Substituting this last Equation (3) into Eq. (1) yields the following new expression for the default probability[2]

$$P_{def,t} = N\left(\ln A - \ln(\overline{D}_t) + \left[\mu_A - \delta - \frac{1}{2}\sigma_A^2\right]T + \sigma_A\sqrt{T} \leq 0\right)$$

$$P_{def,t} = N(-DtD \geq z_{t+T}) \tag{4}$$

where DtD represents the Distance-to-Default, which is defined as

$$DtD = \frac{\ln(A/\overline{D}) + \left[\mu_A - \delta - \frac{1}{2}\sigma_A^2\right]T}{\sigma_A\sqrt{T}} \tag{5}$$

This roughly measures the number of standard deviations the firm's asset value would have to decrease to reach the default point $\overline{D}$.[3]

[1] For ease of notation, in what follows, we drop time subscripts whenever those subscripts are obvious from the context.

[2] As pointed out by Vassalou and Xing (2004) the theoretical distribution implied by the Merton model is the normal distribution. On the contrary, the KMV approach utilizes their own default database to derive an empirical distribution relating the Distance-to-Default to a default probability. In this regard, unlike the default probability calculated by KMV, the probability measure in Eq. (4) may not correspond to the true probability of default in large samples.

[3] $N(-DtD)$ is then the corresponding implied probability of default and sometimes called the expected default frequency (or EDF).

To allow for time variation in the volatility terms σ_A of the Merton model described above, we employ the Heston, and Nandi (2000) GARCH (HN-GARCH) option valuation model. They use the NAGARCH (1, 1) process of Engle and Ng (1993) to model asset value and its volatility dynamics[4]

$$\ln A_t = \ln A_{t-1} + r + \lambda h_{At} - \delta + \sqrt{h_{A,t}} z_t \tag{2a}$$

while an additional stochastic process gives the return variance $h_{A,t}$:

$$h_{A,t} = \beta_0 + \beta_1 \left(z_{t-1} - \gamma \sqrt{h_{A,t-1}}\right)^2 + \beta_2 h_{A,t-1} \tag{2b}$$

with $\beta_i > 0$ for $i = 0, 1, 2$ and λ can be interpreted as the unit risk premium.[5] This model assumes that returns are drawn from a normal distribution with time-dependent volatility. Because of this heteroscedasticity, the unconditional distribution is fat-tailed. To ensure stationarity of the variance, it is required that the parameters satisfy $\beta_1(1 + \gamma^2) + \beta_2 < 1$. The long-run unconditional variance of the process $\mathbb{E}h_t$ is then given by $(\beta_0 + \beta_1)/[1 - \beta_1\gamma^2 - \beta_2]$. The GARCH process defined in Eqs. (2a) and (2b) reduces to the standard homoscedastic lognormal process of the Merton model given in Eq. (2) if $\beta_0 = 0$ and $\beta_2 = 0$. In other words, the Merton model is obtained as a special case.

Following the method used in the derivation of Eq. (5), we obtain the Distance-to-Default under the NAGARCH (1, 1) based option pricing model:

$$DtD_G = \frac{\ln\left(\frac{A_t}{\overline{D}_t}\right) + \left[r + \lambda h_{A,t} - \delta - \frac{1}{2} h_{A,t}\right] T}{\sqrt{h_{A,t}}\sqrt{T}} \tag{5'}$$

The theoretical probability of default can then be calculated as:

$$P_{def,t} = N(-DtD_G) = -N\left(\frac{\ln(A_t/\overline{D}_t) + \left[r + \lambda h_{A,t} - \delta - \frac{1}{2} h_{A,t}\right] T}{\sqrt{h_{A,t}}\sqrt{T}}\right) \tag{4'}$$

Calculating the default probability from Eq. (4) or Eq. (4') is theoretically only possible if the Merton model or the Heston-Nandi model is used to back out A_t and $\mu_{A,t}$ or $r + \lambda h_{A,t}$ from the observed values of equity and its volatility, since the equity in both models is considered as a call option on the market value of the firm's assets. Debt is also basically a put option written on the assets of the borrowing firm. The strike price of both options is equal to the face value of the debt. Then, under the risk-neutral GBM assumption for asset values as in the Merton model the value of equity as a function of the total value of the firm can be described by the Black-Scholes-Merton formula:

$$E = e^{-\delta T} A N\left(d + \sigma_A \sqrt{T}\right) - \overline{D} e^{-rT} N(d) \tag{6}$$

where E is the market value of the firm's equity, $N(\bullet)$ is the cumulative standard normal distribution function and d is given by

$$d = \frac{\ln(A/\overline{D}) + \left[r - \delta - \frac{1}{2}\sigma_A^2\right] T}{\sigma_A \sqrt{T}} \tag{7}$$

Note that under the risk-neutral GBM assumption, the drift term parameter μ disappears in the above option pricing formula and it reduces to the risk-free rate r.

Under the NAGARCH assumption for asset values, the value of equity as a function of the total value of the firm can be described by the Heston-Nandi formula:

$$E = e^{-\delta T} A_t P_1 - \overline{D} e^{-rT} P_2 \tag{8}$$

with

$$P_1 = \frac{1}{2} + \frac{e^{-r(T-t)}}{\pi e^{-\delta T} A_t} \int_0^\infty Re\left[\frac{\overline{D}^{-i\phi} f_0(i\phi + 1)}{i\phi}\right] d\phi$$

[4] Duan (1995) also developed a GARCH option pricing model which also follows this NAGARCH(1,1) process.

[5] Note the system of equations in (2a) and (2b) takes the same forms under the physical and risk-neutral measures. The risk-neutral equations come with λ=-0.5 and modified expressions for z_{t-1} and γ.

$$P_2 = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty Re\left[\frac{\overline{D}^{-i\phi} f_0(i\phi)}{i\phi}\right] d\phi$$

where P_1 and P_2 are the probability terms corresponding to the $N\left(d + \sigma_A\sqrt{T}\right)$ and $N(d)$ terms of the Black-Scholes model, $Re[]$ is the real part of a complex number and $f_0(i\phi)$ is the conditional characteristic function of the log asset price using the risk-neutral probabilities and i is the imaginary number, $\sqrt{-1}$.

For this system of two unknowns, the solution requires a system of two equations, one of them being Eq. (6) (The basic Merton model) or (8) (the HN-GARCH model) and the second being the following option hedge formula which is derived by equating the equity volatility to the coefficient of the Brownian term obtained by applying Ito's formula to (6) or (8),

$$\sigma_E E_t = \frac{\partial E}{\partial A}\sigma_A A_t \tag{9}$$

where σ_E is the volatility of equity returns. However, in practice following the KMV method an iterative procedure is often used instead of solving the system of equations in Eq. (9). Finally, once the system has been solved for A and σ_A, the parameter μ_A can be easily approximated using the values of A.

3.1.1. Variance risk premia

In the presence of variance risk premia, we modify the stochastic processes for A and h as follows:

$$\ln(A_t) = \ln(A_{t-1}) + r + \lambda h_t^* + \sqrt{h^*} z_t^* \tag{10}$$

$$h_t^* = \beta_0^* + \beta_1^*\left(z_{t-1}^* - \gamma^*\sqrt{h_{t-1}^*}\right)^2 + \beta_2^* h_{t-1}^* \tag{11}$$

where z_t^* has a standard normal distribution and

$$h_t^* = h_t / (1 - 2\beta_0\xi)$$

$$\beta_0^* = \beta_0 / (1 - 2\beta_0\xi)$$

$$\beta_1^* = \beta_1 / (1 - 2\beta_0\xi)$$

$$\gamma^* = \gamma - \phi$$

$$\phi = -\left(\lambda - \frac{1}{2} + \gamma\right)(1 - 2\beta_0\xi) + \gamma - \frac{1}{2}$$

with ϕ and ξ being the prices of equity return risk and variance risk, respectively.[6]

3.1.2. Distance-to-Capital

So far we have used the book value of total outstanding debt as the liability determining the default barrier for a company. However, Daly et al. (2019) emphasize that the book value of total outstanding debt may not adequately gauge default risk because the leverage pattern of financial institutions is different from each other. Hence the *DtD* approach yields a greater risk score to banks regardless of their inherent leverage requirement. Also, the *DtD* employs the bank's equity as a financial buffer, which is unacceptable in modern risk management practice. Hence, Daly et al. (2019) suggest that the Distance-to-Capital (*DtC*) is a useful approach that overcomes the constraints in the *DtD* by including the required capital threshold in default risk assessments. For banks, the problem is beyond a default event and it is whether banks have adequate capital to function or not. Accordingly, we modify our distance to formulas to incorporate regulatory capital requirements. We start with modifying the Distance-to-Default measure to obtain the following Distance-to-Capital formula under time-varying volatility set up which will be explained below:

$$DtC_{i,t} = \frac{\ln\left(\frac{A_{i,t}}{\kappa \overline{D}_i}\right) + \left[\mu_{Ai} - \delta - \frac{h_{i,t}}{2}\right]T}{\sqrt{h_{i,t}}\sqrt{T}} \quad \text{where } \kappa = \frac{1}{1 - PCAR_{i,t}} \tag{13}$$

where $A_{i,t}$ is the value of bank i's assets at time t, μ_{Ai} is the return on the asset, $h_{i,t}$ is the time varying volatility of the returns, $\overline{D}_i$ is the total liabilities of the bank and T is the average maturity of liabilities. The parameter κ captures the capital requirement and hence

[6] The derivation of the above expressions is based on the following pricing kernel (M): $M(t) = M(0)\left(\frac{A_t}{A_0}\right)\phi\, exp\left(\delta t + \eta\sum_{s=1}^{t} h_s + \xi(h_t + 1 - h_i)\right)$ (12) where parameters δ and η govern the time-preference (Christoffersen, Heston, & Jacobs, 2013).

converts the widely used Distance-to-Default (*DtD*) to the new Distance-to-Capital (*DtC*). In calculating κ we take into the account capital adequacy threshold $PCAR_i$ for each bank *i*, considering accounts in pre-default regulatory state.[7]

3.2. Measuring systemic risk

As in Saldias (2013) and Craig (2020), we calculate the average-distance-to-capital ($\overline{DtC}$) as follows:

$$\overline{DtC}_t = \sum_{i=1}^{N} w_{i,t} DtC_{i,t} \tag{14}$$

where $DtC_{i,t}$ is the Distance-to-Capital of bank *i* at time *t* and $w_{i,t}$ is its weight in the average Distance-to-Capital $\overline{DtC}_t$ which may be calculated using market capitalization ratios.

Armed with the default measure, we next deal with constructing a portfolio of defaults for the whole banking system $\left(DtC^P\right)$ using the total value of the portfolio's risky debt $\left(D_t^p = \sum_{i=1}^{P} D_{i,t}\right)$, the equity market value of the portfolio $\left(E_t^p = \sum_{i=1}^{P} E_{i,t}\right)$, and the implied assets of the portfolio $\left(A_t^p = \sum_{i=1}^{P} A_{i,t}\right)$. It is straightforward to modify Eq. (13) to calculate DtC^P under the same assumptions. Finally, we calculate the systemic risk for the banking sector as a spread between $\overline{DtC}$ and DtC^P. If an economy-wide or sector-wide shock affects the entire banking sector in the US, differences between DtC^P and DtC should be positive, implying a systemic risk because the calculated credit risk for the portfolio is higher than the average credit risk of individual institutions. On the other hand, if the impact on the banking sector is coming from the failure of a specific institution, such as the collapse of the Lehman Brothers, the differences between $\overline{DtC}$ and DtC^P should be negative because while $\overline{DtC}$ will increase with the effect of the specific event, this effect on the portfolio will be limited.

3.3. Marginal expected shortfall based on distance-to-capital

To determine systemically important financial institutions in the sample, we employ the Marginal Expected Shortfall (MES) approach suggested by Banulescu and Dumitrescu (2015) using the weekly change of *DtC* (ΔDtC) for each bank in the sample.[8] To calculate the aggregate default risk of the financial system, the MES relies on the conditional Expected Shortfall (ES). Expected shortfall is also called 'conditional' value at risk, average value at risk, expected tail loss, and super quantile. The expected market default conditional on the Distance-to-Capital is less than the α quantile according to VaR determines the ES in this setting. In a more general framework with the distress event defined by a threshold *C*, the conditional ES for the whole system of the distress event can then be calculated as:

$$ES_{m,t-1} = -\mathbb{E}_{t-1}\left(\Delta DtC_{i,t} | \Delta DtC_{m,t} < C\right) \tag{15}$$

where $\mathbb{E}_t$ is the expectation operator and *C* is threshold value equals to VaR (5%). To determine the marginal contribution of an institution to the risk of the financial system using the ES, we calculate the MES as follows:

$$MES_{i,t}(C) = \frac{\partial ES_{m,t-1}(C)}{\partial w_{i,t}} = -\mathbb{E}_{t-1}\left(\Delta DtC_{i,t} | \Delta DtC_{m,t} < C\right) \tag{16}$$

where $w_{i,t}$ is the weight for institution *i* based on its market capitalization ratio. To measure how the systemic risk would change if the corresponding institution i's default risk was deleted from the portfolio we calculate the Component Expected Shortfall (CES) as:

$$CES_{i,t}(C) = -w_{i,t}\frac{\partial ES_{m,t-1}(C)}{\partial w_{i,t}} = -w_{i,t}\mathbb{E}_{t-1}\left(\Delta DtC_{i,t} | \Delta DtC_{m,t} < C\right) \tag{17}$$

where $ES_{m,t-1}(C) = \sum_{i=1}^{n} CES_{i,t}(C)$.

In terms of the multivariate GARCH framework, Banulescu and Dumitrescu (2015) showed that CES can be calculated as:

$$CES_{i,t}(C) = -w_{i,t}\left[\sigma_{i,t}\rho_{i,t}\mathbb{E}_{t-1}\left(\varepsilon_{m,t} | \varepsilon_{m,t} < C/\sigma_{m,t}\right) + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\,\mathbb{E}_{t-1}\left(\zeta_{m,t} | \varepsilon_{m,t} < C/\sigma_{m,t}\right)\right] \tag{17}$$

where $\varepsilon_{m,t}$ and $\zeta_{m,t}$ are the standardized residuals obtained from bivariate GJR-GARCH model for $\Delta DtC_{m,t}$ and $\Delta DtC_{i,t}$ respectively. $\sigma_{m,t}$ and $\sigma_{i,t}$ represent the time-varying standard deviation for the portfolio and the specific bank respectively and $\rho_{i,t}$ is the time-varying conditional correlation.

[7] See Chan-Lau and Sy (2007).

[8] Daly et al. (2019) indicated that weekly measurements of extreme financial events are more reliable in reducing noise than daily measurements. Also, using the weekly change of ΔDtC helps to ensure stationarity condition for the data.

3.4. Quantile connectedness approach based on distance-to-capital

The MES approach provides the systemically important banks in the sample, showing the impact of individual banks on market risk. On the other hand, the connectedness between the banks in the sample during the bad market conditions is important as well as systemic risk. Hence, we employ the quantile connectedness approach suggested by Ando et al. (2022) to determine the connectedness network among the banks at lower quantiles. The quantile connectedness approach depends on the estimation of the following quantile vector autoregression (QVAR):

$$\boldsymbol{y_t} = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \Phi_j(\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) \tag{19}$$

where $\boldsymbol{y_t}$ is $k \times 1$ dimensional vector of endogenous variable, τ is the quantile and lies between [0, 1] and p is the lag length of the QVAR model. In Eq. (19) $\boldsymbol{\mu}(\tau)$ indicates conditional means, $\Phi_{\boldsymbol{j}}(\tau)$ shows coefficients and $\boldsymbol{u}_t(\tau)$ is residuals with a $k\times\ k$ dimensional variance-covariance matrix, τ. The moving average representation of the QVAR (p) model is written as follows using Wold's theorem:

$$\boldsymbol{y_t} = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \Psi_{\boldsymbol{i}}(\tau)\boldsymbol{u}_{t-i} \tag{20}$$

We calculate the H-step ahead Generalized Forecast Error Variance Decomposition (GFEVD) suggested by Koop et al. (1996) and Pesaran and Shin (1998) to determine the effect of an unexpected shock in the jth variable on the ith variable. Chatziantoniou and Gabauer (2021) proposed the total spillover index at the τ-th quantile can be calculated as follows:

$$TSI(\tau) = \frac{\sum_{i,j=1,i\neq j}^{k} \widetilde{\psi}_{ij}^{g}(\tau)}{k-1} \tag{21}$$

The total directional connectedness that indicates the directional spillover from the *i-th* variable to the all-other variables j, "TO", is represented as follows:

$$C_{i\rightarrow j}^{g}(\tau) = \frac{\sum\limits_{j=1,i\neq j}^{k} \widetilde{\psi}_{ji}^{g}(\tau)}{\sum\limits_{j=1}^{k} \widetilde{\psi}_{ji}^{g}(\tau)} \tag{22}$$

The total directional connectedness "FROM," that indicates the directional spillover from the all-other variables j to the *i-th* variable is represented as follows:

$$C_{i\leftarrow j}^{g}(\tau) = \frac{\sum\limits_{j=1,i\neq j}^{k} \widetilde{\psi}_{ij}^{g}(\tau)}{\sum\limits_{j=1}^{k} \widetilde{\psi}_{ij}^{g}(\tau)} \tag{23}$$

The net total directional spillover is calculated as the difference between the directional spillovers of TO and FROM as follows:

$$C_{i}^{g}(\tau) = C_{i\rightarrow j}^{g}(\tau) - C_{i\leftarrow j}^{g}(\tau) \tag{24}$$

The positive value for the net total directional spillover indicates that *i-th* variable is the spillover transmitter otherwise it is called a spillover receiver.

4. Data

Our sample covers large U.S. bank holding companies and investment banks trading in the stock exchange market. It consists of 182 institutions for the 2000-01-01 - 2023-12-31 sample period. Appendix A presents the list of banks covered in the sample. The data set contains accounting variables such as short-term debt, long-term debt, and the number of shares outstanding and financial variables such as daily stock prices and the risk-free rates for the sample span. All data comes from DataStream except the risk-free rate and capital adequacy ratio, which are from Federal Reserve Economic Data (FRED) and the Federal Deposit Insurance Corporation (FDIC). The accounting data are quarterly as, following in many articles, we employ the cubic spline method to obtain daily values. As in Vassalou and Xing (2004) and Bharath and Shumway (2008), the face value of debt is calculated as the total of short-term debt plus half of the long-term term debt. Nevertheless, a problem arises in calculating the face value of the debt for banks as the banking sector utilizes different balance-sheet practices compared to the non-financial corporate sector, which necessitates a closer look at the distinction between the short and long-term debt of banks. For example, Harada et al. (2010) argue that maturity is not economically relevant for banks because, in the case of a bank run, the depositor tends to withdraw even if the maturity of the deposit is long-term. As in Harada et al. (2010), we calculate the short-term liabilities as the sum of the total deposit and short-term debt. We use the daily stock prices for each bank as the equity value and the one-year T-bill rate as the risk-free rate.

5. Empirical results

We start with estimation of the parameters of the NAGARCH model, for which we use the quasi-maximum likelihood method.[9] Upon the completion of this stage, we proceed to the estimation of capital shortfall (undercapitalization) probabilities using Eq. (4) together with Eq. (13) and other dependent equations using daily data to obtain daily undercapitalization probabilities for each bank. This phase of the work is quite comprehensive, involving iterative procedures to back out unobserved values and return volatility for operating assets from the observed traded prices of bank stocks via calculating the prices of the GARCH options written on their assets. In this regard, we closely follow the literature in implementing this stage except that in pricing GARCH options we use Mazzoni (2010)'s cumulant-based analytical approximation method.[10] For example, we calculate the market value of assets for each bank by iteration as in To calculate the aggregate default risk of the financial system, the MES rCrosbie and Bohn (2019) and Vassalou and Xing (2004), and convert the daily default probabilities into monthly data by using the maximum value for each month.

The critical step in calculating option prices with a variance risk premium is to estimate the variance risk premium parameter (ξ). We follow previous the empirical work pricing variance risk premiums. We follow Christoffersen, Jacobs, and Ornthanalai (2013) and adopt 117,438 for the variance risk premium parameter ξ.[11] As demonstrated in Christoffersen, Jacobs, and Ornthanalai (2013), in the presence of the time-varying GARCH volatility, the model generates time-varying variance-risk premiums despite the variance risk premium parameter taking a constant value.

After calculating DtC for each bank in the sample, we compute $\overline{DtC}$ as the weighted average of individual DtC. The next stage involves calculating the aggregated debt, equity, and asset and estimating DtC^P for the bank portfolio. Table 1 presents descriptive statistics for the average ($\overline{DtC}$) and portfolio (DtC^P) Distance-to-Capital ratios for 182 banks within the sample. More precisely, Table 1 reports the mean, median, maximum, and minimum values, the standard deviation of Distance-to-Capital for the average of individual banks and the portfolio. The results in Table 1 indicate that the mean of DtC^P is higher than the mean of $\overline{DtC}$ and this finding is consistent with the empirical results of Saldias (2013) and Craig (2020). Saldias (2013) points out that DtC^P is generally higher than $\overline{DtC}$, hence indicating the lower bound of distress.

Note that the difference between $\overline{DtC}$ and DtC^P gives us the Systemic Risk Indicator (SRI) for the aggregate US banking sector. The grey area in Fig. 2 shows the difference between $\overline{DtC}$ and DtC^P, which we call the systemic risk indicator. As seen from the figure, at the beginning of the distress periods, the gap between $\overline{DtC}$ and DtC^P narrows and significantly increases during the financial turmoil episodes. Hence, a rise in the index indicates higher systemic risk episodes because the Distance-to-Capital for the portfolio is higher than that for the weighted average of individual banks. The result depicted in Fig. 1 emphasizes four significant periods in which the systemic risk in the banking sector significantly increased, namely during the year 2000, the GFC of 2007–09, 2011–12, during 2020, and 2023. These findings are consistent with the theoretical predictions as the mentioned dates correspond to heightened fragility periods in the US financial sector. For instance, at the beginning of the sample, systemic risk increased due to the dot-com bubble in the stock market. Although the origin of the dot-com bubble is not the financial sector, the substantial drop in the stock market affected the U.S. banking sector at the beginning of the 2000s, leading to rises in the systemic risk indicator. In this vein, Bagliano and Morana (2014), Wu et al. (2021) find that the dot-com crisis led to financial fragility in the US. The second period, as mentioned above, is the global financial crisis, which was a systemic risk event in the banking sector with bankruptcies of several financial firms, including banks, during this 2007-09 episode. The rising systemic risk of the 2011–12 period is consistent with the European debt crisis. We also determine an episode corresponds to the beginning of the COVID-19 global pandemic. This finding is consistent with the empirical results of Rizwan et al. (2020). Note that the findings shown in Fig. 1 indicate that systemic risk significantly increased in the early stages of 2023 and reached levels similar to those seen during the global financial crisis. It is consistent with theoretical expectations because the systemic risk increased significantly in the U.S. banking sector in 2023, mostly because of Silicon Valley Bank and Signature Bank failing. The financial system experienced increased volatility and unpredictability as a result of this high-profile bankruptcy. Our systemic risk indicator also increased in 2002, 2004, and 2016. These dates correspond to Sarbanes-Oxley Act, the changing net capital rule by the SEC, the Chinese sell-off, and Brexit, respectively.

The time-varying volatility-associated variance risk premium is also a contributor to systemic risk. Given its richness, our GARCH option pricing model likely yields more accurate default and systemic risk indicators during high-volatility and variance risk premium episodes. In other words, the time-varying volatility and variance risk premium features better translate increasing default probabilities during the high volatility clustering episodes to increasing systemic risk indicators. In this context, while Bianconi et al. (2015) and Wu et al. (2021) identify a direct impact of the VIX on systemic risk, Stolbov et al. (2018) reveal that systemic risk increases when the economic policy uncertainty is high. Also, Patro et al. (2013) documents that correlations between stock return increases due to the idiosyncratic risk of banks during times of stress, leading to systemic risk in the banking system. In this context, the results highlighted in Fig. 2 show that our systemic risk indicator increases when the implied volatility for the market (VIX) is high and hence our results are consistent with the empirical results in the literature (the Spearman correlation between SRI and VIX is 0.590).

[9] For details see Christoffersen, Jacobs, and Ornthanalai (2013) and the references cited therein.

[10] For a detailed explanation, see Kenc and Cevik (2021).

[11] In recent years, there has been a great deal of interest in incorporating variance risk premiums into financial valuation models. Financial economists use different methods to estimate this premium, ranging from a joint estimation of variance risk premiums and return-risk premium approach to a sequential approach. See Babaoglu et al. (2018), Christoffersen, Jacobs, and Ornthanalai (2013) and Papantonis (2016) among others.

Table 1
Descriptive statistics.

	$\overline{DtC}$	DtC^P
Mean	0.484	0.579
Median	0.471	0.568
Maximum	0.972	1.235
Minimum	−0.097	−0.138
Std. Dev.	0.205	0.246
Spearman Rank Correlation		
$\overline{DtC}$	1.00	
DtC^P	0.990[a]	1.000

Notes: The table gives descriptive statistics such as mean, median, minimum, maximum, and the standard deviation for distance-to-capital (DtC) scores for the weighted average of individual banks and portfolio. In addition, the table gives the Spearman rank correlation coefficient between DtC scores for the weighted average of individual banks and portfolio.

[a] Indicates statistically significant correlation at 1% level.

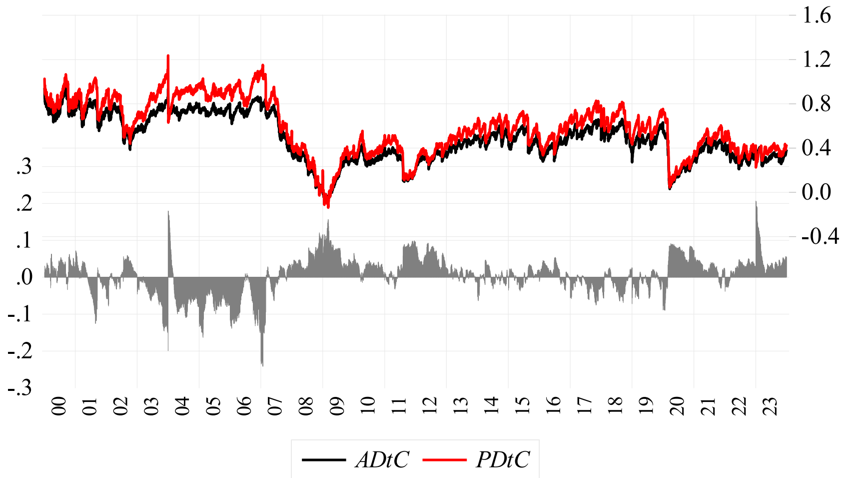

Fig. 1. Systemic Risk Indicator
Notes: The black line represents the daily weighted average of the individual distance-to-capital ($\overline{DtC}$) for each bank, while the red line illustrates the distance-to-capital for the overall portfolio (DtC^P). The shaded areas indicate the systemic risk indicator, calculated as the difference between $\overline{DtC}$ and DtC^P.

5.1. Measuring model accuracy

A well-designed systemic risk indicator should be capable of providing information for the financial distress events that occur on future dates. Hence, we first examine whether our systemic risk indicator meets this criterion, and then compare it to the Cleveland Fed systemic risk indicator.[12] We start with predicting recessions in the U.S. economy. To this end, Fig. 3 presents monthly standardized systemic risk indicators with the NBER recessions. Then, we create a recession dummy variable, taking on the value one in months of the NBER recessions dates and zero otherwise.

Comparing our empirical results to the Cleveland Fed's systemic risk indicator reveals differences in time patterns over the sample period. There are at least four reasons behind the differences. First, the number of banks in the Cleveland Fed systemic risk indicator is lower than in our systemic risk indicator. Second, while the Cleveland Fed uses a distance-to-default measure in calculating a systemic risk indicator, we employ distance-to-capital. Third, the Cleveland Fed relies on the standard Merton model to calculate distance-to-default. Finally, our time-varying volatility model also considers the priced variance risk case. The contribution of the small number of banks in the sample may be negligible. However, the conceptual differences in modeling systemic risk between our way presented in this paper and others can have significant impact on results. Using the distance-to-capital rather than a basic distance-to-default measure is a more accurate approach to measuring the default risk of financial institutions since it considers the required capital

[12] The Cleveland Fed systemic risk indicator starts from the beginning of 2008.

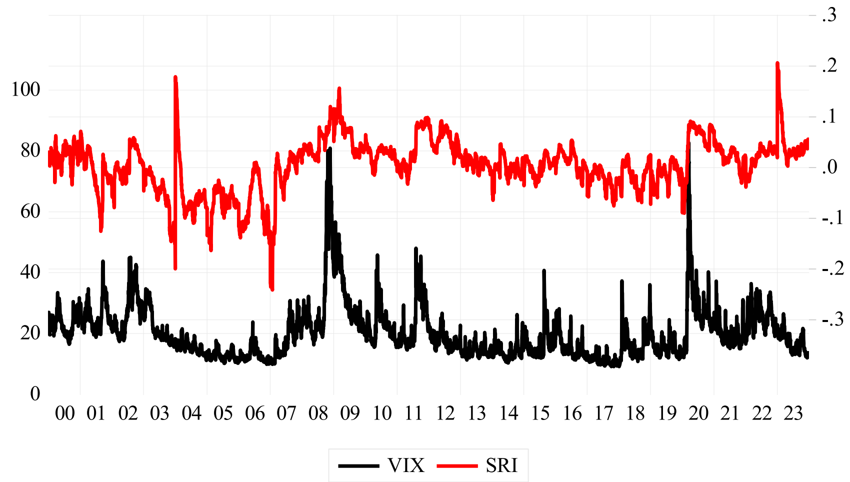

Fig. 2. Systemic Risk Indicator and VIX
Notes: The black line represents the daily VIX. The red line illustrates the systemic risk indicator, calculated as the difference between $\overline{DtC}$ and DtC^P.

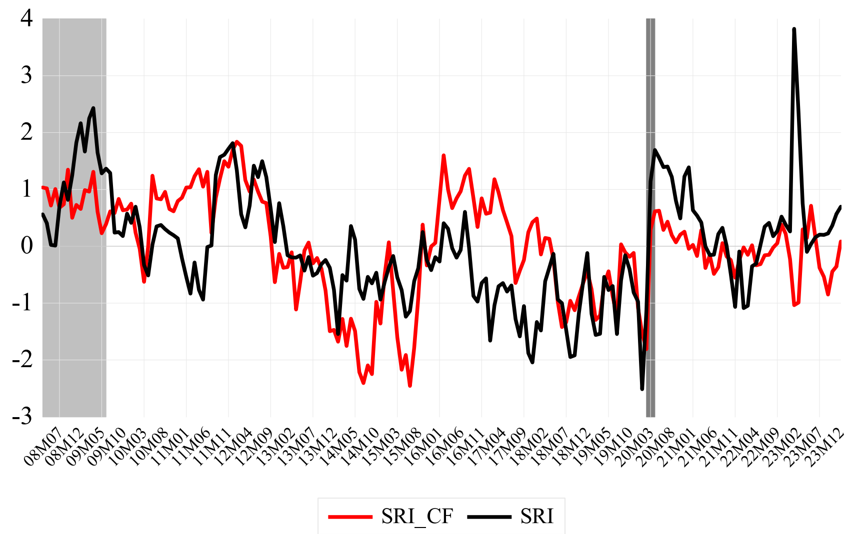

Fig. 3. Comparison of results with the Cleveland Fed Systemic Risk Indicator
Notes: The red line represents the monthly Cleveland Fed's systemic risk indicator. The black line illustrates our systemic risk indicator, calculated as the difference between $\overline{DtC}$ and DtC^P. The shaded areas are the NBER recessions.

threshold in default risk assessments. The standard Merton model does not capture the real-world phenomenon of volatility clustering. Indeed, Kenc et al. (2021) and Kenc and Cevik (2021) show that the standard Merton model underestimates the default risk during high volatility periods. The findings presented in Fig. 3 provide a vivid illustration of this pattern. Interestingly, at the start of 2023, our systemic risk index showed a notable jump that was mostly caused by Silicon Valley Bank's failure. The collapse of Silicon Valley Bank, which was the 16th-largest bank in the U.S. as of March 2023, prompted serious questions about systemic risk in the banking sector.

Next, we employ logistic regression and the Receiver Operating Characteristics (ROC) analyses. Implementing them involves treating systemic risk indicators as independent variables and the dummy variable corresponding to events as the dependent variable. The ROC analysis suggests that our model's systemic risk indicators are more capable of predicting recessions than the Cleveland Fed model. Fig. 4 depicts the ROC curves while Table 2 reports the AUC values for the respective ROC curves. Results from this figure and table indicate that our systemic risk indicator outperforms the Cleveland Fed systemic risk indicator in predicting the recessions in the U.S. Our model's AUC value of 0.845, very close to 1, testifies to this. Moreover, this score is statistically higher than the Cleveland Fed systemic risk indicator at the 5% level. This finding indicates that our systemic risk indicator provides better information about future

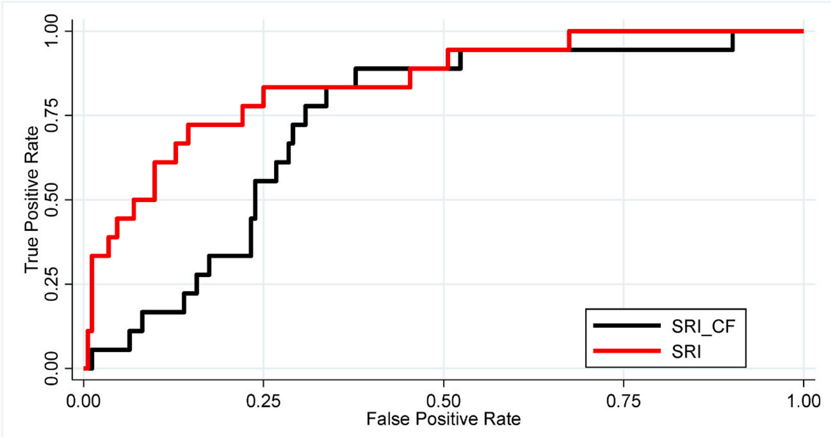

Fig. 4. ROC Curves for SRI and SRI-CF
Notes: The black line represents the ROC curve of Cleveland Fed's systemic risk indicator. The red line illustrates the ROC curve of our systemic risk indicator.

Table 2
Area under the ROC curves.

	AUC	χ^2-stat	p-value
SRI	0.845	4.630	[0.031]
SRI-CF	0.730		

Notes: The AUC values indicate the area under the ROC curve. χ^2-Stat gives the test statistic where the null hypothesis indicates that the AUC value for SRI is not different from the AUC value of SRI-CF and p-values show the probability of rejecting the null hypothesis.

recessions.[13]

Following Allen et al. (2012) and Giglio et al. (2016), we also examine the prediction performance of our systemic risk indicator for economic activity in the US. In this vein, we use the Chicago Fed National Activity Index (CFNAI) and employ bivariate time-varying parameter VAR (TVP-VAR) modeling to identify the impact of an unexpected shock in the systemic risk indicator to the CFNAI.[14] Two lags are determined as optimal lag length according to model information criteria.

Fig. 5 shows the one, three, and six periods ahead responses of the CFNAI to a one standard deviation shock in the SRI. Given estimated time-varying coefficients over the sample, we calculate monthly impulse responses. The time-series average of the stochastic volatility for each series determines the time-varying impulse responses. The impulse represents the impacts of average-sized structural shock on the VAR system. Fig. 5 indicates that the responses of the CFNAI to an unexpected shock in the SRI are negative for all periods during the sample period. These results show that our systemic risk index is successful in predicting economic activity over the 6 months ahead, with the impact of our systemic risk indicator on the CFNAI in the short term being evident. Specifically, the magnitude of calculated responses reached its highest level in 2008. This finding emphasizes the importance of systemic risk on the national activity during the GFC.

We also compare our systemic risk indicator to the Kansas City Fed Financial Stress Index and the Chicago Fed National Financial Conditions Index. Fig. 7 presents the comparison outcomes. Fig. 6 shows that our systemic risk indicator yields comparably good performance in tracking recession periods as those financial stress and conditions indices. The quality of performance of our systemic risk indicator in tracking recessions is somewhat surprising because while the systemic risk indicator is only related in its construction to the banking sector, while the financial stress and conditions indices also reflect developments in the bond market, stock market, and other asset prices. Hence, one expects that those in-dices have greater explanatory power in predicting recessions than systemic risk indicators. Also, our systemic risk indicator stands to be a successful early warning indicator because it successfully anticipates all recessions in the US.

[13] The AUC value of our systemic risk indicator for the whole sample is 0.803.

[14] 14The stochastic volatility-based TVP-VAR model proposed by Primiceri (2005) and updated by Nakajima (2011) has been widely used in the literature to obtain time-varying impulse responses between the variables. Nakajima (2011) suggested that the TVP-VAR model allows for the estimation of the prospective time-varying structure of the economy as flexible and accurate. In the model, a sample is taken from the posterior distribution of the TVP-VAR model using the Markov Chain Monte Carlo (MCMC) algorithm, and hence we use M = 10,000 samples where the first 1000 samples are just used as a burn-in period to specify prior distributions.

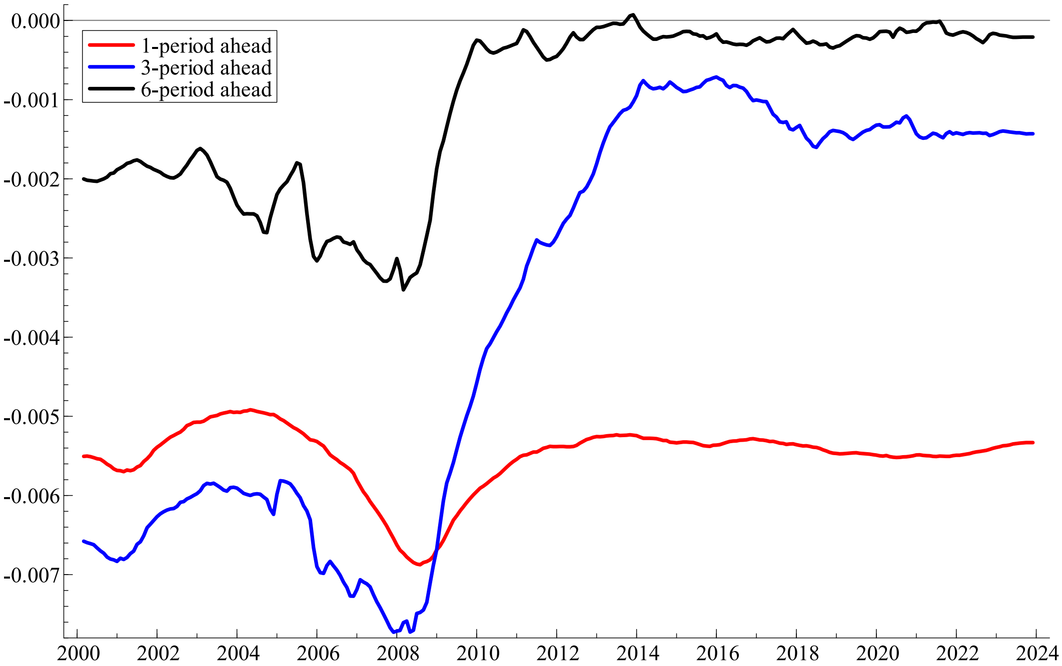

Fig. 5. Responses of CFNAI to an Unexpected SRI Shock
Notes: The figure illustrates the time-varying responses of the Chicago Fed National Activity Index to an unexpected shock in the systemic risk indicator. The red line represents the one-period-ahead response of the Chicago Fed National Activity Index to this shock. The blue line shows the three-period-ahead response, while the black line indicates the six-period-ahead response to the unexpected shock in the systemic risk indicator.

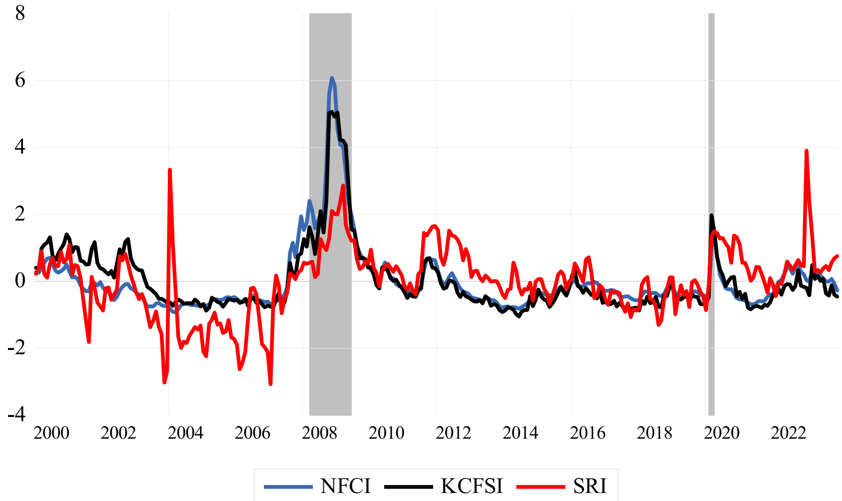

Fig. 6. Systemic Risk Indicator, Financial Stress Index and Financial Conditions Index
Notes: The figure shows Kansas City Fed Financial Stress Index (KCFSI), Chicago Fed National Financial Conditions Index (NFCI) and our systemic risk indicator (SRI). The shaded areas are the NBER recessions.

5.2. Determining systemically important institutions

After establishing the usefulness of distance-to-capital in measuring systemic risk, we deter-mine systematically important banks during the sample period. To this end, we adopt the component expected shortfall (CES) approach (Banulescu & Dumitrescu, 2015), calculating the individual contribution of each bank to the US financial systemic risk. Precisely, this work involves measuring the systemic risk for the US financial system and then assessing the contribution of individual financial institutions to the systemic risk at each point in time. Following the CES estimation procedure explained in Banulescu and Dumitrescu (2015), we forecast the

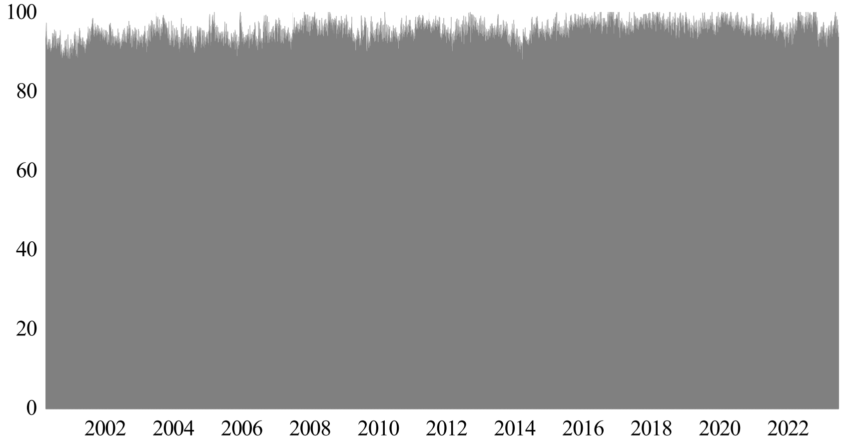

Fig. 7. The Dynamic Total Connectedness Index
Note: The figure indicates the dynamic total spillover index that is obtained from Quantile spillover analysis at a 5% quantile level.

contribution of respective institutions to this risk over a given period. Needless to say, this step is crucial for government regulation and supervision of large financial firms and markets to address systemic risks.

We estimate expected shortfalls for the end of each year from 2006 to 2023 (given in Table 3). To find out the risk profiles of financial institutions at the end of each year, we use the weekly change of distance-to-capital for each bank in the sample and then the weighted average distance-to-capital for the financial system as a whole by considering market capitalization ratios as weights.

We present the systematically important banks in the sample according to their component expected shortfall values in Tables 3 and 4. We display the 25 banks (the sum of the percentage CES of the 25 banks is higher than 90%) contributing the most to the total default of the financial system for the sample periods indicated in Table 3. The result reveals that Bank of America, Citigroup, Wells Fargo & Co, Goldman Sachs, the US Bancorp and JP Morgan were systemically important banks before the GFC with their contributions to the systemic default risk of 75.80% in 2006. The top ten systemically important banks contributed at least 78% of the overall default risk between 2007 and 2009, reaching 86.3% in 2009. Note that the contribution of Goldman Sachs, Bank of America and Citigroup to the overall default risk exceeded 43% in 2007. While the contribution of each three financial institutions (JP Morgan, Wells Fargo & Co, and the US Bancorp) to the overall default risk was higher than 10% in 2008, the four financial institutions (Bank of America, Goldman Sachs, Citigroup, and Wells Fargo & Co) came to the fore as a systemically important. During the European debt crisis in 2011, Wells Fargo & Co came to the forefront of systemic risk, and 21.61% of the overall systemic default risk was due to this financial institution. As of 2020, due to the global Covid-19 pandemic, JP Morgan, Bank of America, and Morgan Stanley have been identified as the most systemically important financial institutions, and 28.02% of the overall systemic default risk has been due to them. Note that Silicon Valley Bank has been ranked among the top 25 systemically significant banks since 2019. It initially held the 21st position in 2019, advanced to 13th in 2020, and further climbed to 11th by 2021. Its continued presence on this critical list in 2022 highlighted its growing influence within the U.S. banking sector. The summary of the CES results points out that Bank of America, Morgan Stanley, JP Morgan, Wells Fargo & Co, Citigroup, Goldman Sachs, US Bancorp, Bank of New York, Truist Financial, PNC Financial Services, State Street Corp., Fifth Third Bancorp, and Regions Financial rank among the top thirteen systemically important financial institutions. On the other hand, their rank and contribution to the overall default risk of these financial institutions vary during the sample period. These results are not surprising since the financial institutions were classified as distressed as well as global systemically important financial institutions (GSIFI) by the Financial Stability Board[15] during the Global Financial Crisis of 2008–09.

5.3. Tail connectedness among systematically important financial institutions

After identifying the top thirteen systematically important financial institutions, we also employ a quantile connectedness approach to determine the relationship among the financial institutions when distance-to-capital is low. We note that the quantile connectedness approach is related to systemic risk measurement as a strand of the systemic risk literature uses this method to determine the systemic risk indicator (Mbarki et al., 2022; Jena et al., 2022, see). We estimate the QVAR model using the weekly change of the distance-to-capital for the 13 financial institutions. In the estimation, we set the optimal lag length at 6 per the Schwarz information criterion. Using generalized error variance decomposition and considering a 10-day forecast horizon, we perform a directional spillover analysis at a 5% quantile level based on the forecast error variances. We present the analysis results in Table 4.

The results in Table 4 show that the total connectedness among the financial institutions is high during elevated default risk periods as the overall spillover index is 95.4%. The finding points out that the 13 financial institutions identified in the previous subsection

[15] The Financial Stability Board, in consultation with the Basel Committee on Banking Supervision (BCBS) and national authorities, has identified global systemically important banks (G-SIBs) since 2011.

Table 3
CES% based rankings of banks.

CES%	2006	CES%	2007	CES%	2008	CES%	2009	CES%	2010	CES%	2011	CES%	2012	CES%	2013	CES%	2014
BAC	20.977	GS	17.924	WFC	16.974	GS	19.420	WFC	17.516	WFC	21.613	WFC	23.220	WFC	25.238	WFC	17.934
C	15.368	BAC	13.628	JPM	12.586	WFC	15.811	C	14.666	USB	11.749	C	13.450	C	11.008	BAC	12.696
WFC	14.050	C	12.215	USB	10.331	BAC	10.788	BAC	11.436	JPM	11.513	USB	10.882	USB	10.018	C	11.574
GS	10.290	USB	10.220	GS	9.877	C	9.987	JPM	9.621	C	8.712	BAC	10.801	BAC	9.311	GS	9.569
USB	9.351	JPM	8.179	BAC	7.264	JPM	9.440	USB	9.512	PNC	6.681	JPM	8.048	GS	7.189	USB	9.463
JPM	5.770	MS	6.119	PNC	5.391	USB	7.459	GS	8.887	GS	5.678	GS	7.502	PNC	5.451	JPM	6.208
PNC	4.534	BK	4.940	TFC	5.022	BK	5.138	PNC	6.358	BAC	4.997	PNC	5.130	JPM	5.074	PNC	5.687
TFC	3.136	WFC	4.734	BK	4.905	MS	3.797	BK	2.057	BK	2.859	MS	3.260	MS	3.794	MS	4.326
MS	1.924	TFC	4.446	C	3.730	PNC	3.011	MS	1.920	MS	2.168	BK	2.816	BK	2.922	TFC	2.061
STT	1.465	PNC	3.169	MS	2.091	STT	1.536	NYCB	1.397	STT	1.874	FITB	2.136	FITB	2.030	BAP	1.923
ZION	1.205	STT	2.150	STT	1.617	TFC	1.266	STT	1.274	BAP	1.738	STT	1.696	NYCB	1.827	BK	1.690
FITB	1.161	FITB	1.089	CFR	1.153	NYCB	1.118	FITB	1.180	FITB	1.686	TFC	1.598	STT	1.779	STT	1.566
NYCB	1.075	NYCB	0.905	CBSH	1.137	BAP	0.821	CFR	0.991	NYCB	1.250	NYCB	1.279	MTB	1.151	NYCB	1.114
KEY	1.074	BAP	0.899	VLY	0.978	MTB	0.693	BAP	0.975	MTB	1.075	BAP	0.862	CMA	1.051	FITB	0.988
CMA	0.996	CMA	0.883	NYCB	0.831	FITB	0.627	CMA	0.960	CFR	0.994	CMA	0.669	HBAN	0.981	CMA	0.880
MTB	0.754	MTB	0.598	FITB	0.665	CFR	0.610	HBAN	0.912	CMA	0.874	HBAN	0.591	BAP	0.816	CFR	0.690
BAP	0.539	KEY	0.594	MTB	0.625	CMA	0.507	MTB	0.877	CBSH	0.809	KEY	0.492	CFR	0.777	HBAN	0.672
RF	0.495	RF	0.538	CCBG	0.570	CBSH	0.368	KEY	0.674	KEY	0.806	PB	0.307	KEY	0.646	MTB	0.605
CCBG	0.473	CFR	0.519	WABC	0.527	BOKF	0.331	CBSH	0.623	TFC	0.774	MTB	0.299	CBSH	0.558	KEY	0.590
CBSH	0.451	HBAN	0.511	UMBF	0.513	HBAN	0.314	TFC	0.553	HBAN	0.723	CCBG	0.273	ZION	0.490	CBSH	0.449
FHN	0.379	CBSH	0.446	BOH	0.496	KEY	0.285	ZION	0.552	HWC	0.466	CBSH	0.272	BOKF	0.489	ZION	0.444
VLY	0.374	ZION	0.409	KEY	0.487	HWC	0.280	WABC	0.421	ZION	0.465	FHN	0.254	TFC	0.321	SVB	0.392
SNV	0.357	ASB	0.326	CMA	0.454	TRMK	0.278	FHN	0.421	BOKF	0.436	WABC	0.240	RF	0.309	BOKF	0.357
ASB	0.305	NRIM	0.310	FULT	0.448	BOH	0.271	RF	0.412	VLY	0.376	CBU	0.239	PB	0.286	OZK	0.309

CES%	2015	CES%	2016	CES%	2017	CES%	2018	CES%	2019	CES%	2020	CES%	2021	CES%	2022	CES%	2023
WFC	19.863	WFC	19.183	BAC	19.301	WFC	25.886	BAC	14.540	JPM	14.179	BAC	15.527	BAC	15.78	JPM	14.835
C	11.073	JPM	10.224	WFC	12.932	BAC	14.536	WFC	13.140	BAC	13.844	JPM	9.019	JPM	12.12	BAC	12.092
BAC	8.640	GS	9.816	JPM	9.589	USB	11.326	JPM	12.876	MS	9.065	PNC	8.005	WFC	10.09	MS	11.383
GS	8.304	BAC	9.358	USB	9.359	JPM	8.952	PNC	8.337	TFC	7.784	MS	7.929	PNC	7.902	WFC	8.147
JPM	8.256	USB	8.689	C	8.029	C	6.432	USB	7.514	USB	7.750	WFC	7.841	USB	6.604	GS	7.145
USB	8.049	C	7.827	PNC	6.511	TFC	5.928	C	6.785	C	7.079	TFC	7.696	GS	5.142	PNC	6.265
PNC	6.094	PNC	4.309	MS	4.965	PNC	4.672	GS	5.737	GS	6.726	GS	7.015	MS	4.498	USB	5.124
MS	4.291	BK	4.136	BK	3.113	GS	4.501	MS	5.460	PNC	6.527	USB	6.153	TFC	3.541	TFC	4.668
BK	3.441	TFC	1.934	TFC	2.821	MS	2.313	TFC	4.598	WFC	5.777	C	3.678	C	3.337	C	3.489
TFC	2.865	STT	1.435	BAP	2.391	BK	1.128	BK	1.855	BK	2.296	BK	1.902	BK	2.327	BK	1.625
STT	1.678	FITB	1.432	FITB	1.641	FITB	1.117	HBAN	1.235	STT	1.331	SVB	1.654	FITB	1.809	HBAN	1.343
FITB	1.197	HBAN	1.230	STT	1.538	BAP	0.774	FITB	1.157	FITB	1.235	FITB	1.596	HBAN	1.763	FITB	1.074
NYCB	1.024	MTB	1.140	CMA	1.227	PB	0.773	STT	1.122	SVB	1.083	HBAN	1.475	CBSH	1.534	STT	1.028
MTB	0.928	NYCB	1.130	MTB	1.051	MTB	0.748	MTB	0.932	HBAN	0.938	STT	1.299	CFR	1.31	MTB	0.857
HBAN	0.667	KEY	0.768	HBAN	0.987	CBSH	0.711	CBSH	0.850	MTB	0.781	FFIN	1.124	STT	1.291	CFR	0.856
BAP	0.645	BAP	0.711	KEY	0.830	WBS	0.579	CFR	0.812	KEY	0.687	CBSH	0.887	FFIN	0.996	WBS	0.851
CMA	0.642	CMA	0.655	NYCB	0.732	KEY	0.547	KEY	0.755	CBSH	0.636	KEY	0.886	SVB	0.955	CBSH	0.769
CBSH	0.582	CBSH	0.630	GS	0.687	CFR	0.497	FFIN	0.707	CMA	0.623	CFR	0.805	MTB	0.951	WTFC	0.696
CFR	0.466	CFR	0.626	CBSH	0.677	STT	0.443	CMA	0.678	BAP	0.614	CMA	0.775	PB	0.845	BOKF	0.657
ZION	0.426	SVB	0.534	ZION	0.648	HBAN	0.421	NYCB	0.632	CFR	0.523	MTB	0.636	KEY	0.813	FBP	0.641
SVB	0.413	FFIN	0.510	WTFC	0.472	CMA	0.365	SVB	0.594	ZION	0.447	ZION	0.495	CBU	0.631	FFIN	0.603
KEY	0.389	ZION	0.509	WBS	0.468	FFBC	0.343	BAP	0.561	WBS	0.431	WTFC	0.488	CMA	0.627	FCNCA	0.567
WBS	0.348	WBS	0.490	CFR	0.465	WTFC	0.331	ZION	0.541	RF	0.386	BOKF	0.483	RF	0.621	PB	0.526
RF	0.324	UMBF	0.449	BOKF	0.396	NYCB	0.330	CBU	0.523	BOKF	0.342	OZK	0.474	NYCB	0.537	SSB	0.523

JPM: JP Morgan Chase & Co., BAC: Bank of America, WFC: Wells Fargo & Co, C: Citigroup, USB: US Bancorp, PNC: PNC Financial. Services., TFC: Truist Financial, FITB: Fifth Third Bancorp, MTB: M&T Bank, CBSH: Commerce Bancshares, GS: Goldman Sachs, STT: State Street Corporation, KEY: Keycorp, CMA: Comerica, MS: Morgan Stanley, BK: Bank of New York Mellon, HBAN: Huntington Bancshares, CFR: Cullen/Frost. Bankers, NYCB: New York Community Bancorp, BAP: Credicorp, ZION: Zions Bancorp., BOKF: BOK Financial Corporation, RF: Regions Financial Corporation, SVB: SVB Financial Group, WBS: Webster Financial, PB: Prosperity Bancshares, First Financial Bankshares Inc., WTFC: Wintrust Financial, CBU: Community Financial System, FHN: First Horizon, VLY: Valley National, Capital City Bank Group Inc., WABC: Westamerica Bancorp., ASB: Associated Banc-Corp, BOH: Bank Of Hawaii, OZK: Bank OZK, HWC: Hancock Whitney, UMBF: UMB Financial, FBP: First BanCorp., FCNCA: First Citizens Bancshares, FFBC: First Financial Bancorp., FULT: Fulton Financial, SSB: SouthState Corporation, SNV: Synovus Financial, TRMK: Trustmark, NRIM: Northrim Bancorp.

Table 4
Spillover analysis results.

	JPM	BAC	WFC	C	USB	PNC	TFC	FITB	KEY	MTB	CBSH	GS	STT	FROM
JPM	12.72	8.36	7.72	8.23	6.77	6.55	5.92	6.80	7.49	7.94	6.39	7.29	7.82	87.28
BAC	7.83	11.98	7.48	7.95	7.20	7.61	6.20	6.93	7.88	7.61	6.91	7.02	7.41	88.02
WFC	7.03	8.24	11.88	7.62	7.85	7.66	6.55	7.10	7.09	7.46	7.14	7.12	7.27	88.12
C	8.02	8.31	7.47	11.92	7.26	7.10	6.15	6.97	7.08	7.43	6.64	7.52	8.12	88.08
USB	6.59	7.78	7.63	7.33	12.49	7.85	6.73	7.53	7.07	7.62	7.30	6.74	7.34	87.51
PNC	7.03	7.84	7.83	7.38	7.69	11.68	6.66	7.01	7.23	7.71	7.59	7.00	7.36	88.32
TFC	8.09	7.54	7.39	7.65	7.22	7.18	10.36	7.22	7.78	8.14	7.08	7.03	7.33	89.64
FITB	6.43	7.67	7.41	7.28	8.27	7.69	6.66	11.36	7.17	7.79	7.54	7.14	7.59	88.64
RF	7.53	7.96	7.31	7.64	7.48	7.17	6.32	7.45	11.26	7.92	7.08	7.08	7.82	88.74
MS	7.37	7.91	7.31	7.60	7.42	7.12	6.58	7.06	7.39	12.47	7.33	6.98	7.46	87.53
GS	6.84	7.64	7.09	7.17	7.49	7.85	6.92	7.13	7.36	7.81	11.89	7.33	7.47	88.11
BK	7.69	7.81	7.47	8.11	7.23	7.33	6.36	6.64	7.18	7.48	7.24	11.69	7.77	88.31
STT	6.97	7.65	7.19	7.62	7.31	7.35	6.44	7.36	7.30	7.69	7.18	7.41	12.52	87.48
TO	87.41	94.72	89.30	91.56	89.18	88.47	77.48	85.18	88.03	92.60	85.41	85.67	90.77	1145.78
NET	0.13	6.71	1.18	3.48	1.67	0.14	−12.17	−3.46	−0.72	5.07	−2.70	−2.64	3.30	TSI: 95.48%
NPT	5	12	6	10	7	5	0	3	4	10	3	3	10	

Note: The column "FROM" shows received spillovers from others. The column "TO" indicates transmitted spillover to others. NET is the net spillover that is the difference between TO and FROM. NPT is the number of positive net pairwise spillovers for each variable. BAC: Bank of America Corp, JPM: JPMorgan Chase & Co, WFC: Wells Fargo & Co, USB: US Bancorp, TFC: Truist Financial, C: Citigroup Inc, GS: Goldman Sachs Group, PNC: PNC Financial Services Group, STT: State Street Corp, FITB: Fifth Third Bancorp, CBSH: Commerce BCSH, KEY: Key Corp, MTB: M&T Bank Corporation.

generate 95.4% of total forecast errors, implying that the systemic risk is very high among these financial institutions during extreme distress periods. In this context, the elevated default risk of one financial institution spill over to another financial institution in the sample. The results also reveal that JP Morgan, Bank of America, Wells Fargo, Citibank, the US Bancorp, PNC Financial, M&T Bank Corp. And State Street Corp. Are net default risk spillover transmitters, whereas the rest of those 13 financial institutions are net default risk spillover receivers. Furthermore, while Bank of America ranks first as a net risk spillover transmitter among the financial institutions, Truist Financial is the first as a net risk spillover receiver.

We also carry out dynamic spillover analysis using a rolling-window approach for the QVAR model in which the window size is 200. To this end, we employ a generalized variance decomposition approach to determine the variance forecast error in each subsample. The dynamic spillover index presented in Fig. 7 shows that the total connectedness among the financial markets is very high in each subsample (above 95%). During the heightened financial stress periods such as the GFC, the European Debt crisis, and the global Covid-19 pandemic, the index reached 100%, implying that these financial institutions explain all forecast error variances pointing to elevated high systemic risk.

Fig. 8 depicts the time-varying net total directional connectedness results. The figure determines whether a financial institution is a net risk transmitter, or receiver varies across the subsamples. Comparing the results reported in Table 4 and presented in Fig. 8 reveals a contrasting outcome: Goldman Sachs is a net risk receiver according to the results in Table 4 while it is a net risk during some subsamples such as the GFC, and the Covid- 19 global pandemic in Fig. 8. It reflects that the connectedness among the financial institutions represents time-varying properties.

Finally, we visualize the network topology among the financial institutions in Fig. 9 according to the difference between values in the row and column for each pairwise financial institution in Table 4. For instance, examining the relationship between Bank of America and Truist Financial, we see that although Bank of America receives 6.20 spillovers from Truist Financial, it also transmits 7.24 spillovers to the latter. Regarding the spillover relationship between Truist Financial and Bank of America, as Bank of America is a net transmitter, the arrow in Fig. 9 points in that way, from Bank of America to Truist Financial.

The financial institutions in the blue circle are the net transmitter, while the yellow-colored ones imply that the financial institutions are the net receiver, and their size increases according to the number of net pairwise transmitters. Accordingly, while Bank of America is the chief risk spillover transmitter during high default risk episodes, the Truist Financial is the major risk spillover receiver. Furthermore, in line with the results in Table 4, the results in Fig. 9 show that Citibank, Wells Fargo, JPM, US Bank, PNC Financial, State Street Bank, and M&T Bank are determined as net default risk transmitters among the 13 most systemically important financial institutions over the sample period.

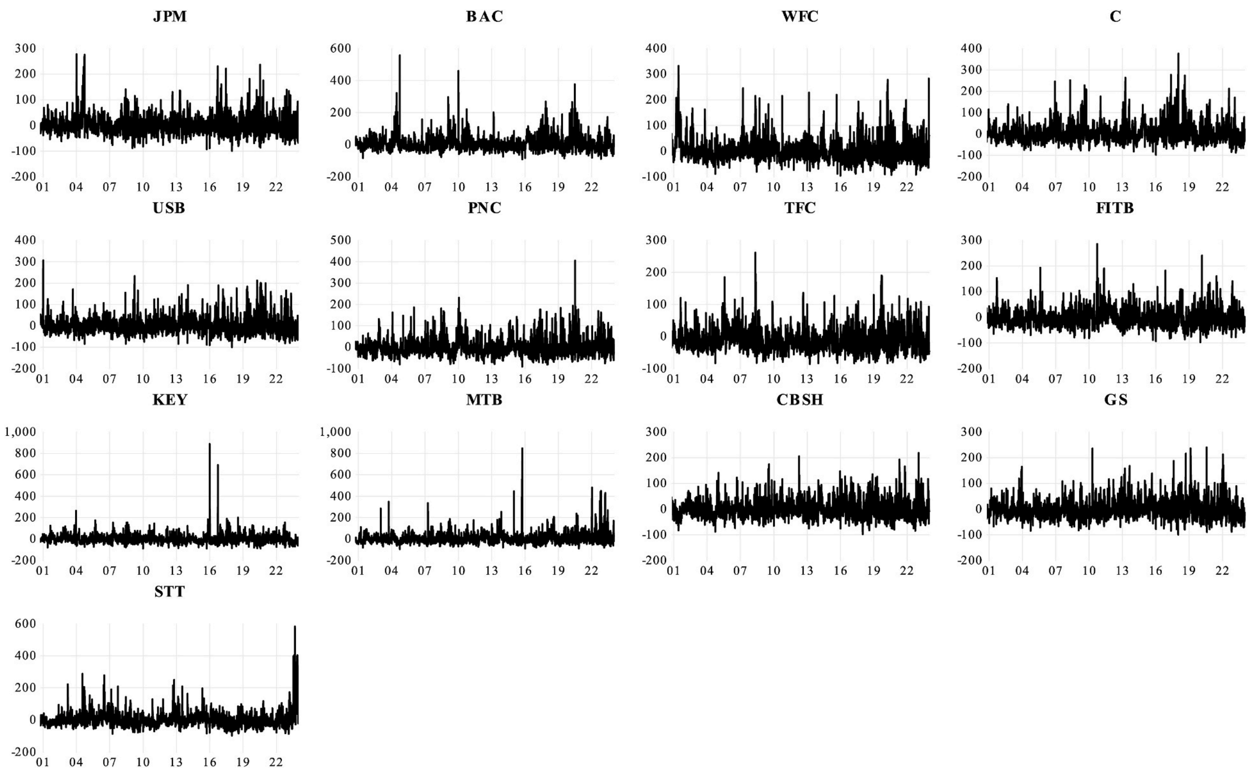

Fig. 8. The Dynamic Net Total Directional Connectedness
Note: The figure indicates the time-varying net total directional connectedness results. Positive values in the figure indicate that the bank acts as a net spillover transmitter, whereas negative values suggest that the bank is a net spillover receiver.

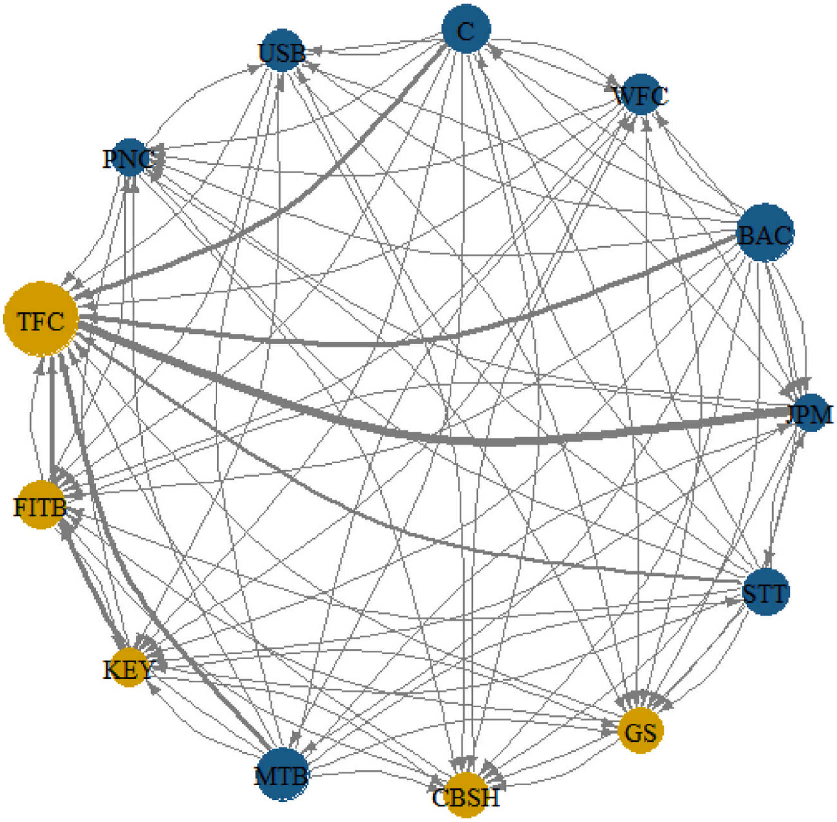

Fig. 9. Connectedness Network Results
Note: The figure shows the network topology among the financial institutions according to the difference between values in the row and column for each pairwise financial institution in the spillover analysis result. The financial institutions in the blue circle are the net transmitter, while the yellow-colored ones imply that the financial institutions are the net receiver, and their size increases according to the number of net pairwise transmitters.

These results hold significant implications for policymakers and market regulators, highlighting the need for closer monitoring of institutions like those mentioned. Enhanced scrutiny is essential to prevent a recurrence of concerns like those that emerged following the collapse of Silicon Valley Bank.

6. Conclusions

Unlike in the past, the dissemination of information through financial technologies is now considerably faster, leading to more immediate incorporation into asset prices. While this rapid information transfer enhances market efficiency during stable periods, it can exacerbate the adverse effects of panic during market downturns and heightened tension. This shows the need for accurate measurement of systemic risk in the market. An index that accurately reflects market developments would enable regulators to implement appropriate policies and allow market professionals to develop effective strategies for investment and hedging. Historical events, such as the 1998 LTCM crisis, highlight the severe consequences of failing to capture the true extent of financial risk, which led to a costly bailout operation by the Fed amounting to over three billion dollars. Similarly, despite legal limitations, the American government, through the Fed and FDIC (Federal Deposit Insurance Corporation), has provided full coverage for depositors' losses to maintain financial stability. In line with these considerations, this study introduces a systemic risk measure for the US banking sector and identifies systemically risky banks using CES and connectedness methodologies.

We develop a comprehensive framework to estimate systemic risk indicators and examine it for US banks and their contributions. The framework extends the conventional structural credit risk model to capture volatility clustering and priced variance risk premia. Our structural GARCH option pricing model also makes novel use of distance-to-capital to capture the under capitalization of bank balance sheets. We test the explanatory and forecasting power of the framework for systemic risk by applying it to US banking and market data, from the beginning of 2000 to the end of 2023. This period covers prominent heightened systemic risk episodes, including the GFC of 2007–09, the COVID-19 pandemic and recent turmoil in the U.S. banking sector. The testıng procedure involved the application of various most recent and popular financial and econometric methods to measure and predict overall systemic risk and individual systemic risk of each bank. These procedures include the difference between the portfolio and the average distance-to-capital (a measure of overall systemic risk), ES (contribution of each bank), ROC (prediction of systemic risk), and tail connectedness analysis using a QVAR model.

Our general model successfully identifies the most systemically risky banks during heightened systemic risk episodes, especially the GFC of 2008–09. Further, our expected shortfall framework determines each bank's contribution with an outcome of 25 banks accounting for more than 95 per cent of the estimated default of the financial system and with a correct identification of the institutions labelled as Systemically Important Financial Institutions at the height of the GFC by the Financial Stability Board. Finally, comparing our results to the competitor approaches, such as the Cleveland Fed systemic risk indicator, we find that our approach offers significant improvement in predicting recessions, systemic risk and default events, and systemically important financial institutions.

Although the empirical analysis in this study is grounded in a robust methodological framework and offers a thorough examination, several limitations warrant consideration for future research. Future studies might explore incorporating additional stylized facts of financial time series, such as long memory and asymmetric volatility, alongside volatility clustering in constructing systemic risk index. Additionally, applying a similar framework to other economies could provide valuable insights. While our investigation focused on the US banking sector, considering factors such as economic development level, market capitalization, and market depth, exploring systemic risk in other economies may help reveal its patterns on a global scale. Increasing the frequency of CES calculations or adapting it to a time-varying framework could offer dynamic insights into its behavior during significant market developments. Finally, a fruitful future research direction would be to allow jumps in stock prices and liquidity premium.

Author statement

The authors affirm that this work is an original work that is not published or under consideration elsewhere and is a genuine collaboration.

Appendix

Table A1
List of the Banks

Bank Name	Ticker	Bank Name	Ticker	Bank Name	Ticker	Bank Name	Ticker
JP MORGAN CHASE & CO.	JPM	COLONY BANKCORP	CBAN	RENASANT	RNST	BANK OF MARIN BANCORP	BMRC
BANK OF AMERICA	BAC	COMERICA	CMA	SANDY SPRING BANCORP	SASR	BANK OF SOUTH CAROLINA	BKSC
WELLS FARGO & CO	WFC	COMMERCE BCSH.	CBSH	SIMMONS 1ST.NAT.'A'	SFNC	BAR HARBOR BANKSHARES	BHB
CITIGROUP	C	CREDICORP	BAP	SOUTHSTATE	SSB	BROOKLINE BANCORP	BRKL
PROSPERITY BCSH.	PB	CULLEN FO. BANKERS	CFR	SYNOVUS FINANCIAL	SNV	C&F FINL.	CFFI
US BANCORP	USB	CVB FINANCIAL	CVBF	TRUSTMARK	TRMK	CAMDEN NAT.	CAC
PNC FINL.SVS.GP.	PNC	FIRST BANCORP PRICO.	FBP	UMB FINANCIAL	UMBF	CAP.CITY BK.GP.	CCBG
TRUIST FINANCIAL	TFC	FIRST CTZN. BCSH	FCNCA	UNITED BANKSHARES	UBSI	CAPITOL FED.FINL.	CFFN
FIFTH THIRD BANCORP	FITB	FIRST FINL.BANC.	FFBC	VALLEY NATIONAL	VLY	CHEMUNG FINL.	CHMG
HUNTINGTON BCSH.	HBAN	FIRST FINL.BKSH.	FFIN	WAFD	WAFD	CITIZENS HLDG.	CIZN
KEYCORP	KEY	FIRST HORIZON	FHN	WEBSTER FINANCIAL	WBS	CITY HLDG.	CHCO
M&T BANK	MTB	FIRST MERCHANTS	FRME	WESBANCO	WSBC	CIVISTA BANCSHARES	CIVB
REGIONS FINL.NEW	RF	FNB	FNB	WINTRUST FINANCIAL	WTFC	CNB FINL.	CCNE
EAST WEST BANCORP	EWBC	FULTON FINANCIAL	FULT	WSFS FINANCIAL	WSFS	CODORUS VLY.BANC.	CVLY
AMERIS BANCORP	ABCB	HANCOCK WHITNEY	HWC	ZIONS BANCORP.	ZION	COMMUNITY TRUST BANC.	CTBI
ASSOCIATED BANC-CORP	ASB	HEARTLAND FINL.USA	HTLF	1ST SOURCE	SRCE	CONNECTONE BANCORP	CNOB
ATLANTIC UNION BANK.	AUB	INDEPENDENT BANK MASS.	INDB	ACNB	ACNB	CTZN & NTHN	CZNC
BANK OF HAWAII	BOH	INTERNATIONAL BCSH.	IBOC	AMERICAN NAT.BKSH.	AMNB	DIME COMMUNITY BANC.	DCOM
BANK OZK	OZK	NEW YORK COM BANCORP	NYCB	AMERISERV FINL.	ASRV	EAGLE BANC.	EGBN
BANNER	BANR	OLD NATIONAL BANCORP	ONB	AMES NAT.	ATLO	EVANS BANCORP	EVBN
BOK FINL.	BOKF	PAC.PREMIER BANC.	PPBI	ARROW FINANCIAL	AROW	FARMERS NAT.BANC	FMNB
CATHAY GEN.BANCORP	CATY	PARK NATIONAL	PRK	AUBURN NAT. BANCORP.	AUBN	FIDELITY D&D BANC.	FDBC
COMMUNITY FIN. SYSTEM	CBU	POPULAR	BPOP	BANCFIRST	BANF	FINANCIAL INSTITUTIONS	FISI
Bank Name	Ticker	Bank Name	Ticker	Bank Name	Ticker	Bank Name	Ticker
FIRST BANCORP	FNLC	HMN FINANCIAL	HMNF	PATRIOT NAT.BANCORP	PNBK	TRUSTCO BANK NY	TRST

(continued on next page)

Table A1 (*continued*)

Bank Name	Ticker	Bank Name	Ticker	Bank Name	Ticker	Bank Name	Ticker
FIRST BUSEY	BUSE	HOPE BANCORP	HOPE	PEAPACK-GLADSTONE FINL.	PGC	UNITED BANCORP OH.	UBCP
FIRST CAP.	FCAP	HORIZON BANCORP	HBNC	PENNS WOODS BANC.	PWOD	UNITED BANCSHARES	UBOH
FIRST CMTY.	FCCO	INDEPENDENT BANK	IBCP	PEOPLES BANC.OF NOCA.	PEBK	UNITY BANCORP	UNTY
FIRST COMMONWEALTH FINL.	FCF	LAKELAND BANCORP	LBAI	PEOPLES BANCORP	PEBO	UNIVEST FINANCIAL	UVSP
FIRST COM. BANKSHARES	FCBC	LAKELAND FINANCIAL	LKFN	PLUMAS BANC.QUINCY CAL.	PLBC	WASHINGTON TST. BANC.	WASH
FIRST FINANCIAL	THFF	LCNB	LCNB	PREMIER FINANCIAL	PFC	WEST BANCORPORATION	WTBA
FIRST MID BANCSHARES	FMBH	MACATAWA BANK	MCBC	PROVIDENT FINL.HDG.	PROV	WESTAMERICA BANCORP.	WABC
FIRST NAT.CAP.STK.	FXNC	MERCANTILE BANK	MBWM	QCR HDG.	QCRH	MORGAN STANLEY	MS
FIRST OF LONG ISLAND	FLIC	MID PENN BANCORP	MPB	REP. BANCORP OF KENTUCKY	RBCAA	GOLDMAN SACHS GP.	GS
FIRST US BANCSHARES	FUSB	NATIONAL BANKSHARES	NKSH	RIVERVIEW BANCORP	RVSB	BANK OF NEW YORK MEL.	BK
FIRST UTD.	FUNC	NBT BANCORP	NBTB	S & T BANCORP	STBA	STATE STREET	STT
FLUSHING FINANCIAL	FFIC	NORTHEAST BANK	NBN	SB FINANCIAL GROUP	SBFG	AMB FINL.	AMFC
FNCB BANCORP	FNCB	NORTHRIM BANCORP	NRIM	SEACOAST BKG.OF FLA.	SBCF	CADENCE BANK	CADE
FRANKLIN FINL.SVS.	FRAF	NORTHWEST BANCSHARES	NWBI	SIERRA BANCORP	BSRR	CARVER BANCORP	CARV
GERMAN AMERICAN BANC.	GABC	NORWOOD FINANCIAL	NWFL	SOUTHERN FIRST BCSH.	SFST	CENTRAL PAC.FINL.	CPF
GLEN BURNIE BANCORP	GLBZ	OCEANFIRST FINL.	OCFC	SOUTHERN MO. BANCORP	SMBC	CF BANKSHARES	CFBK
GREAT STHN.BANCORP	GSBC	OFG BANCORP	OFG	SOUTHSIDE BANCSHARES	SBSI	COLUMBIA BKG.SYS.	COLB
GREENE COUNTY BANC.	GCBC	OHIO VALLEY BANC	OVBC	STOCK YARDS BANCORP	SYBT	COMMUNITY WEST BANC.	CWBC
HANMI FINANCIAL	HAFC	OLD POINT FINANCIAL	OPOF	SUMMIT FINL.GP.	SMMF	GLACIER BANCORP	GBCI
HERITAGE COMMERCE	HTBK	OLD SECOND BANCORP	OSBC	TIMBERLAND BANCORP	TSBK	SVB FINANCIALS	SVB
HERITAGE FINANCIAL	HFWA	ORRSTOWN FINL.SVS.	ORRF	TOMPKINS FINANCIAL	TMP		
HINGHAM INSTN.FOR SVG.	HIFS	PATHFINDER BANCORP	PBHC	TRICO BANCSHARES	TCBK		

Data availability

Data will be made available on request.

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