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Systemic Risk in the U.S. Banking Sector during the Silicon Valley Bank collapse: A Neural Network Analysis

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Abstract

The collapse of Silicon Valley Bank in 2023 exposed significant systemic risks, particularly for commercial and regional bank. This study analyzes 125 banks, categorized by size, to evaluate their contributions to systemic risks using a neural network quantile regression with Value-at-Risk and Conditional Value-at-Risk metrics. Results show that large banks remained stable, reflecting effective regulation, while commercial and regional banks experienced sharp increases in systemic risks. The findings highlight the need for enhanced supervision of smaller banks to mitigate their vulnerability to external shocks and prevent broad financial instability. The Banks with a dual risk of high vulnerability and risk exposure for the system are identified as key drivers of systemic risk.

Keywords: Systemic Risk, Neural Networks, Quantile Regression, CoVaR

1 Introduction

The failure of Silicon Valley Bank (SVB) in 2023 is representative of the largest banking crisis in the US since the 2008 financial crisis and has once again raised questions about the security of the banking sector and the dangers of a bank failure for the systemic risk, with a particular focus on medium-sized and smaller banks and their security. In this paper, the systemic risks of the banking sector are therefore estimated and analyzed based on 135 banks divided into three groups in order to analyze the impact of the banking crisis in 2023. The banks are divided into large banks, commercial banks and regional banks based on total assets, with the aim of being able to understand the effects more precisely for the different bank sizes. A neural network quantile regression is used to estimate the systemic risks based on the risk indicators Value-at-Risk (VaR) and Conditional Value-at-Risk (CoVaR). The systemic hazard and systemic fragility indices and the systemic network risk index are used as measurements to determine the risk contribution and risk exposure for the individual banks, as well as the development of the overall systemic risk within the banking groups. This model, developed by Keilbar and Wang (2022), offers the advantage that it can represent the non-linear connections within the system much better than a normal linear model, which offers advantages for analyzing the complex banking sector.

The results show that the large U.S. banks were hardly affected by the events in March 2023, which means that regulation and supervision is taking effect at these banks. Meanwhile, commercial and regional banks have shown a sharp increase in systemic risk, reinforcing the call for stronger supervision. In addition, the SFI and SHI were used to identify banks with a dual risk that are particularly dangerous to the system due to their vulnerability to external shocks and having individual risks that affect the system.

The remainder of the paper begins with a literature review of the most common methods for estimating systemic risks and the analysis of the 2023 banking crisis to date, an introduction to neural networks, an explanation of the methodology and the empirical analysis. A conclusion follows at the end.

2 Literature Review

The following literature review gives a brief overview on the literature about methods to estimate systemic risk of financial institutions and then highlights the most important literature about the Impact of the SVB collapse or the banking crises 2023 in general.
Systemic risk is the risk that the stability of the entire financial system is impaired by the spread of losses or shocks between interconnected institutions (Adrian und Brunnermeier 2016). Systemic risk can be measured using various approaches, including capital-based approaches such as Acharya, Engle, and Richardson (2012), which used the conditional capital shortage to identify systemic risk, macroeconomic models (Gertler and Kiyotaki 2010), ecologically inspired approaches (Haldane and May 2011) and also quantile-based and network-based approaches (Adrian and Brunnermeier 2016; Härdle, Wang, and Yu 2016; Hautsch, Schaumburg, and Schienle 2015). The model used by Keilbar and Wang (2022) belongs to the last group and is later used for this analysis.
Research about the banking crises 2023, and with that the SVB collapse, was done by Akhtaruzzaman, Boubaker and Goodell (2023). They investigated whether the bankruptcy of SVB promoted financial contagion to other banks and sectors. Their analysis focuses on G7 countries (excluding Russia) and the BRICS economies (Brazil, China, India, and South Africa) and compare four groups: markets, banks, non-financial firms, and financial firms. Using Dynamic Conditional Correlation (DCC-GARCH) modeling and Diebold-Yilmaz spillover analysis, they assess the intensity and direction of spillover effects. Specifically, their methodology includes a vector autoregression (VAR)-based Generalized Forecast Error Variance Decomposition (GFEVD) approach, which measures how strongly shocks to one variable influence the dynamics of others.

Their findings indicate that the strongest spillover effects occurred within the banking sector, reflecting heightened interconnectedness during the crisis. In contrast, non-banks and broader markets exhibited only marginal spillover effects. Moreover, the contagion effects were short-lived due to rapid regulatory interventions, such as the announcement by the U.S. Treasury, Federal Reserve, and FDIC to fully guarantee SVB depositors. This underscores the role of regulatory responses in containing systemic risks.

The study highlights the specificity of contagion dynamics in the 2023 banking crisis, contrasting with broader systemic disruptions observed in previous crises, such as the 2008 financial meltdown. Notably, the limited spillovers to non-banking sectors suggest that post-2008 regulatory measures, such as stricter capital requirements and enhanced risk governance, may have bolstered financial system resilience. However, the results also point to the persistent vulnerability of the banking sector as a source of systemic risk.

Nguyen et al. (2024) analyze systemic risks in European and U.S. banking systems over a period of more than 16 years, with a particular focus on the 2023 banking crisis. Their analysis is based on Credit Default Swap data from 15 banks, enabling them to examine both global (systematic) and local (idiosyncratic) channels of risk transmission. At the regional level, they identify both channels as relevant, whereas systematic factors dominate at the global level.

The study highlights that an event such as the interest rate hikes in 2022 and the 2023 banking crisis, including the collapse of Credit Suisse, had significant impacts on systemic risks. These findings are contextualized within a broader framework, also considering the 2008 financial crisis, the European debt crisis, and the COVID-19 pandemic. The method provides detailed forecasts for systemic risk measures, such as the probability of individual defaults and joint default probability.

While both papers addresses systemic risk during the banking crises 2023, banks are either seen as one large group and are not addressed in more depth as Akhtaruzzaman, Boubaker and Goodell (2023) did or focuses only on a small number of banks without a deeper focus on the U.S. market like Nguyen et al (2024). Therefore, the study in this paper is an addition to this topic.

3 Neural Networks

3.1 Basic Concept

Artificial neural networks are computational models inspired by the structure of the brain. They have several layers of interconnected nodes, similar to neurons, with each layer performing calculations (Montesinos López, Montesinos López, and Crossa 2022). Each connection has a weight that adjusts with continued training to minimize errors. Neural Networks can be structured in three layers: The Input layer, a hidden layer and the output layer. The input layer receives the raw data, the hidden layer performs computation so the network can learn complex patterns, and the output layer produces the final prediction. The approach uses backpropagation, as the weights for the computations are not given at the beginning but learned through the training process. This method optimizes the weights of the connections by minimizing the error between predicted and actual outputs using the gradient descent method (Rojas 1996; Schmidhuber 2015).

Neural networks are widely recognized as the most advanced models for prediction for several reasons. First, they can identify complicated, nonlinear patterns within data, thus, they can model complex nonlinear relationships. Secondly, their proficiency in processing and analyzing high-dimensional datasets, extracting the most important features, make them an ideal model for complex environments such as the banking sector. Thirdly, through the learning approach with the datasets, neural networks can achieve high levels of accuracy in predictions, by which they often outperform traditional statistical methods (Keilbar and Wang 2022).

A neural network with a single hidden layer is capable of approximating any continuous function h_0, if the number of hidden units is sufficiently large. As the sample size n grows, the complexity of the hidden layer, functioning as a nonparametric sieve estimator, must increase accordingly to achieve an accurate and consistent approximation of the mapping h_θ. The configuration of a neural network sieve for $t = 1,2, \ldots n$ can be expressed as follows:

$$Y_t = h_\theta(X_t) + \varepsilon_t \tag{1}$$

$$= \sum_{m=1}^{M_n} w_m^o \psi\left(\sum_{k=1}^{K} w_{k,m}^h X_{k,t} + b_m^h\right) + b_0 + \varepsilon_t \tag{2}$$

Y_t is the dependent variable, h_θ is the neural network model with (X_t), a K-dimensional vector of independent variables and ε_t is the error term. The outer summation aggregates the contributions of all M_n hidden neurons in the hidden layer with the weight w_m^o to connect each hidden neuron to the output neuron. The inner summation calculates the weighted sum of the input features $X_{k,t}$ with the weights $w_{k,m}^h$ which is then added with a bias term b_m^h. Each hidden neuron receives a linear combination of the inputs. The activation function ψ is applied to the weighted sum to have a non-linearity and to model complex functions. A common choice for the activation function is the rectifier linear unit (ReLu) function denoted as

$$\psi(z) = \max(z, 0). \tag{3}$$

A second bias b_0 is added to the final output to adjust the overall output. In the framework of sieve estimation, the sieve parameter space Θ_n expands with n continuously to $M \to \infty$ as $n \to \infty$.

3.2 Quantile regression in a neural network sieve

While neural networks can approximate highly nonlinear relationships, linear quantile regression assumes a linear relationship between the dependent variable Y_t and the independent variables X_t. Keilbar and Wang (2022) address this limitation by extending the quantile regression framework by proposed Koenker and Basset (1978) to neural networks.

In the general linear regression model:

$$Y_t = X_t\beta + \varepsilon_t, \tag{4}$$

the quantile regression for a specific quantile τ is represented as:

$$Q_\tau(\varepsilon_t|X_t) = 0. \tag{4}$$

To estimate β, a quantile loss function $\rho_\tau(z)$ is minimized. The loss function is defined as:

$$\rho_\tau = |z| \cdot |\tau - \mathrm{I}(z < 0)|. \tag{5}$$

The corresponding objective function for linear quantile regression is:

$$min_\beta \ \sum_{t=1}^{n} \rho_\tau(Y_t - X_t\beta). \tag{6}$$

This minimization problem is a linear program and can be solved efficiently using methods such as simplex algorithm or interior-pint methods. However, neural networks being inherently nonlinear, require replacing the linear predictor $X_t\beta$ with a neural network estimator$H_\theta(X_t)$ This results in the nonlinear generalization:

$$Y_t = \ H_\theta(X_t) + \varepsilon_t \tag{7}$$

The corresponding optimization problem becomes:

$$min_\theta \ \sum_{t=1}^{n} \rho_\tau\{-H_\theta(X_t)\}, \tag{8}$$

This optimization problem is nonconvex due to the nonlinear nature of the neural network and thus cannot be solved using linear programming methods. Instead, gradient-based algorithms, such as backpropagation, are typically employed to find approximate solutions.

3.3 Regularization for neural networks

With the large number of parameters, neural networks have a tendency for overfitting, meaning, that the model performs well on the training data but fails on the test data, as the model learns the noise pattern of the training data. The choice of the hyperparameters, specifically the number of hidden nodes M_n are the most effective way to reduce overfitting. Therefore, cross-validiation can be used to select the optimal tuning parameters. Furthermore, a penalty term is added on the weight parameters $w_{k,m}^h$ and w_m^o, using a elastic net regularization defined by Zou and Hastie (2005). Hereby, the L1 and L2 regularizations are combined, resulting in the optimization problem:

$$\min_{h_\theta} \sum_{t=1}^{n} \rho_\tau \{Y_t - h_\theta(X_t)\} + \lambda_1 ||\left(w_k^{h\top}, w_m^{o\top}\right)^\top||_1 + \lambda_2 ||\left(w_k^{h\top}, w_m^{o\top}\right)^\top||_2^2 \tag{9}$$

Where $||\cdot||_1$ with the regularization parameter λ_1 is the L_1-Norm and $||\cdot||_2$ with λ_2. Additionally, the dropout method by Hinton et al. (2012) and Srivastava et al. (Srivastava et al. 2014)) is used, whereby a proportion of the neurons are randomly excluded with a probability of $1 - p$. With that, the neural network does not rely too much on specific neurons and learns more robust, generalized features.

4 Systemic Risk Methodology

This section outlines the methodology used to assess systemic risks. It begins by introducing Value-at-Risk (VaR) and Conditional VaR (CoVaR) as metrics for evaluating the risk of an individual bank and its broader impact on the financial system. Next, the approach to quantify risk spillover effects using two distinct activation functions and an adjacency matrix is described. Finally, the three risk indices proposed by Keilbar and Wang (2022), Systemic Fragility Index (SFI), Systemic Hazard Index (SHI), and Systemic Network Risk Index (SNRI), are explained.

The Value-at-Risk (VaR) is widely utilized in financial risk assessment, especially since its adoption under the Basel II international framework to define capital requirements. VaR represents the maximum potential loss over a given time horizon at a specified confidence level (Basel Committee on Banking Supervision 2005). The mathematical expression for VaR at quantile level τ is as follows

$$P(X_{i,t} \leq VaR_{i,t}^{\tau}) = \tau, \tag{10}$$

with the return X for the financial institution i at time t and $\tau \in (0,1)$. This paper estimates VaR using linear quantile regression with macroeconomic variables, following the methodology of Härdle, Wang, and Yu (2016). The regression model ist:

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t}, \tag{11}$$

Where M_{t-1} is a set of macroeconomic variables with the conditional quantile of the error term $Q^{\tau}\left(\varepsilon_{i,t} \middle| M_{t-1}\right) = 0$. The VaR estimate is the fitted value of the quantile regression,

$$\widehat{\mathrm{VaR}_{\iota,t,\tau}} = \widehat{\alpha_\iota} + \widehat{\gamma_\iota} M_{t-1}. \tag{12}$$

The VaR only measures the risk of an individual institute without its impact on the systemic risk. Therefore, Adrian and Brunnenheimer (2016) propose the Conditinal VaR (CoVaR) which measures the systemic risk under the assumption, that one institute is under distress, with a conditional quantile of the return distribution. The distress-scenario is represented with the VaR of the financial institutions. Hautsch, Schaumburg, and Schienle (2015) and Härdle, Wang, and Yu (2016)) use the following notation for the CoVaR:

$$P(X_{j,t} \leq CoVaR_{j,t}^{\tau} | X_{-j,t} = VaR_{-j,t}^{\tau} = \tau, \tag{13}$$

Where $X_{-j,t}$ is a vector of returns of all firms expecjt j at time t and $VaR_{-j,t}^{\tau}$ is the corresponding vector of VaRs. CoVaR is estimated using conditional quantile regression, but the nonlinear dependencies among financial institutions make linear quantile regression unsuitable. To capture these nonlinearities, Keilbar and Wang (2022) proposed neural network-based quantile regression with activation functions introducing nonlinearity.

With the neural network defined in the previous section, the conditional quantile of banks j´s returns is regressed on the returns of all other banks:

$$X_{j,t} = h_{\theta}\left(X_{-j,t}\right) + \varepsilon_{j,t}, \tag{14}$$

$$= \sum_{m=1}^{M_n} w_m^0 \psi\left(\sum_{k \neq j}^{K} w_{k,m}^h X_{k,t} + b_m^h\right) + b^o + \varepsilon_{j,t}, \tag{15}$$

With the conditional quantile of error term $Q^\tau(\varepsilon_{j,t} | X_{-j,t}) = 0$. To calculate the CoVaR of firm j, the fitted neural network must be evaluated at the distress scenario:

$$CoVaR_{j,t}^\tau = \hat{h}_\theta(VaR_{-j,t}^\tau), \tag{16}$$

with the estimated neural network $\hat{h}_\theta$. CoVaR can be interpreted as the hypothetical τ-quantile of the loss distribution if we are in a hypothetical distress scenario, represented with all firms at their VaR.

The neural network quantile regression also enables the estimation of risk spillover effects between institutions by computing the partial derivative of the conditional quantile of one institution's returns with respect to another's:

$$\frac{\partial Q^\tau(X_{j,t}|X_{-j,t})}{\partial X_{i,t}} = \frac{\partial}{\partial X_{i,t}} \sum_{m=1}^{M_n} w_m^o \psi\left(\sum_{k \neq j}^{K} w_{k,m}^h X_{k,t} + b_m^h\right) + b^o. \tag{17}$$

With the ReLu activation function, the function is then:

$$\frac{\partial Q^\tau(X_{j,t}|X_{-j,t})}{\partial X_{i,t}} = \frac{\partial}{\partial X_{i,t}} \sum_{m=1}^{M_n} w_m^o\, w_{i,m}^h \mathrm{I}\left(\sum_{k \neq j}^{K} w_{k,m}^h X_{k,t} + b_m^h > 0\right), \tag{18}$$

Where $\mathrm{I}(\cdot)$ is the indicator function. The non-differentiability of the ReLu function is not an issue in practice, since the input of the function is zero with probability zero. Only the lower tail dependence is important in this stufy, therefore the marginal effect evaluated at the distress scenario as defined in the previous subsection is considered:

$$\left.\frac{\partial Q^t(X_{j,i} \mid X_{-j,i,t})}{\partial X_{i,t}}\right|_{X_{-j,t}=VaR_{j,t}^\tau} = \sum_{m=1}^{M_n} w_m^o w_{i,m}^h \psi'\left(\sum_{k \neq j}^{K} w_{k,m}^h \mathrm{VaR}R_{k,t}^\tau + b_m^h\right). \tag{19}$$

The marginal effect of each directed pair of firms results in an off-diagonal adjacency matrix of risk spillover effects at time t:

$$[A_t = \begin{pmatrix} 0 & a_{12,t} & \cdots & a_{1K,t} \\ a_{21,t} & 0 & \cdots & a_{2K,t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{K1,t} & a_{K2,t} & \cdots & 0 \end{pmatrix}, \tag{20}$$

Whereby the elements are defined as absolute values of marginal effects:

$$a_{ji,t} = \begin{cases} \left. \frac{\partial Q^{\tau}\left(X_{j,i} \mid X_{-j,i,t} \right)}{\partial X_{i,t}} \right|_{X_{-j,t}=VaR^{\tau}_{j,t}} , if\ j \neq i \\ 0, if\ j = 0 \end{cases}. \tag{21}$$

Hereby, it is important to note that the risk spillover effects are not symmetric in general, therefore $a_{ji,t} \neq a_{ij,t}$, since the risks the risk transmitted from one bank to another is not equal in both directions.

Keilbar and Wang (2022) propose several network measures based on the work of Diedbold and Yilmaz (2009). They measure the interconnectedness of financial institutions through variance decomposition in a vector autoregressive framework.

The connectedness is shown in three ways. First, the total directional connectedness to firm j from all firms i at time t, defined as:

$$C_{j\leftarrow\cdot,t} \sum_{i=1}^{K} a_{ji,t}. \tag{22}$$

Secondly, the total directional connectedness $from$ firm i at time t defined as:

$$C_{\cdot\leftarrow i,t} = \sum_{j=1}^{K} a_{ji,t}. \tag{23}$$

Lastly, the total connectedness of the entire system at time t is defined as:

$$C_t = \frac{1}{K} \sum_{i=1}^{K} \sum_{j=1}^{K} a_{ji,t.} \tag{24}$$

Keilbar and Wang (2022) add to this network analysis VaR and CoVaR to measure the systemic risk relevance. They propose the *Systemic Fragility Index (SFI)* and *Systemic Hazard index (SHI)* to rank financial institutions according to their relevance:

$$SFI_{j,t} = \sum_{i=1}^{K} \left(1 + \left|VaR_{i,t}^{\tau}\right|\right) \cdot a_{ji,t}, \tag{25}$$

$$SHI_{i,t} = \sum_{j=1}^{K} \left(1 + \left|CoVaR_{j,t}^{\tau}\right|\right) \cdot a_{ji,t}. \tag{26}$$

The SFI measures the risk exposure of a financial institution j which increase if those adjacency weights pointing to j are large or if the VaR of institutions i increase. Therefore, the SFI increases in periods of financial distress and can be used to identify the financial institutions that are highly influenced by the systemic risk of the system. With that, the SFI measures the vulnerability to external shocks, caused independently of its own actions.

The SHI measures the risk contribution of firm i to the system. It is calculated using the out-going adjacency weights from i, weighted by the CoVaRs of other firms. Consequently, the SHI tends to be larger if the other firms are already in distress. It identifies the banks that are systemically more important. These Indexes are advantageous as they can model asymmetries in the risk exposure and systematic impact and capture possible nonlinear relationships in the data in a network context.

The third index is the Systemic Network Risk Index (SNRI), measuring the total systemic risk in the financial system, depending on the marginal effects, outgoing VaRs, and the incoming CoVaRs with a focus for tail connectedness focusing on a lower quantile level.

$$SNRI_t = \sum_{i=1}^{K} \sum_{j=1}^{K} \left(1 + \left|\mathrm{VaR}_{i,t}^{\tau}\right|\right) \cdot \left(1 + \left|\mathrm{CoVaR}_{j,t}^{\tau}\right|\right) \cdot a_{ji,t}. \tag{27}$$

The adjusted adjacency matrix is defined as:

$$\widetilde{A_t} = \begin{pmatrix} 0 & \tilde{a}_{12,t} & \cdots & \tilde{a}_{1K,t} \\ \tilde{a}_{21,t} & 0 & \cdots & \tilde{a}_{2K,t} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{K1,t} & \tilde{a}_{K2,t} & \cdots & 0 \end{pmatrix} \tag{28}$$

With each element defines as:

$$\tilde{a}_{ij,t} = \begin{cases} a_{ji,t} \cdot (1 + |\mathrm{VaR}_{i,t}^{\tau}|) \cdot (1 + |CoVaR_{j,t}^{\tau}|), if\ j \neq i \\ 0, if\ j = i \end{cases} \quad (29)$$

These three indices are used in the next section to analyze what the systemic risk was during the 2023 banking crisis and what the risk contribution and risk exposure was for these banks during this time.

5 Empirical Study of the Systemic Risk in the U.S. Banking Sector

5.1 Data

The paper aims to analyze the systemic risk in the U.S. Banking sector within different groups of banks during the Banking Crises 2023. Therefore, the banks with the highest total assets according to q3 2022 financial reports were selected and ranked. Only Banks that are included under *Banks* in the Industry Classification Benchmark were selected and if they had returns for the full period between 2. January 2019 and 29. December 2023. Thus, Banks that delisted, merged with other banks or went bankrupt are excluded. That said, the list includes 135 Banks that then were grouped into three categories according to the Fed:

i) Large Banks, with more than 100 bn TA (14x)

ii) Commercial Banks, with TA between 10 and 100 bn (72x)

iii) Regional Banks, with TA under 10 bn (49x)

With these groups, there is a good overview over the total banking market in the U.S. and the possibility to see how these different banks reacted in the 2023. The returns are obtained from COMPUSTAT.

For the VaR-Estimation, the following set of macro-state variables were used:

(i) Implied volatility index (VIX),

(ii) The weekly S6P500 index returns,

(iii) Moody´s seasoned Baa corporate Bond Yield relative to Yield on 10-year Treasury Constant Maturity,

(iv) 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity,

(v) MarketVector Digital Assets 100 Index.

The data for the first four variables was taken from the Federal Reserve Bank of St. Louis, while the data for the last variables was taken from Refinitiv. The first four variables represent common risk factors, also used by Adrian and Brunnermeier (2016), Härdle, Wang and Yu (2016), and Keilbar and Wang (2022), while the Cryptoindex is added, since the banking failure of the Silvergate and Signature Bank was also connected to their high involvement in the crypto market and is therefore used to capture this new upcoming market but also risks for the banking sector.

5.2 Model selection

A key task in a neural network quantile regression is the tuning of hyperparameters. In this model, this includes, as described before in the neural network section, the nodes in the hidden layer, the activation function, the L1 and L2 regularization, as well as the dropout rate. The Hyperparameter Tuning is done with a recalibration at the beginning of each year within a moving-window model selection, following the approach of Keilbar and Wang (2022).

The data-sample is divided in three subsamples for several periods. The three samples are the training set T_1, which estimates the weight and bias parameter, the validation set T_2, used to evaluate the performance and choose the right model specification, and the test set T_3. The test set is used to evaluate the model with the hyperparameters on a new sample, not used in T_1 or T_2.Therefore, the performance is evaluated calculating the out-of-sample average quantile loss:

$$AQL^{oos} = \frac{1}{|T_3|} \sum_{t \in T_3} \rho_\tau \{X_{j,t} - \hat{Q}^\tau (X_{j,t} | X_{-j,t})\}. \tag{30}$$

Finally, to confirm that the model for neural network quantile regression is the right choice, it is compared to a simple baseline model based on a linear quantile regression,

$$X_{j,t} = \beta_0 + \sum_{i \neq j}^{K} X_{j,t}\, \beta_i + \varepsilon_{j,t}, \tag{31}$$

With $Q^{\tau}\left(\varepsilon_t \middle| X_{-j,t}\right) = 0$. The linear quantile regression is trained on a combined set of T_1 and T_2, and the out-of-sample performance is then evaluated using T_3. The two models are compared with the Diebold and Mariano Test (2002) that uses the difference in the quantile loss and shows that the neural network quantile regression performs better that the linear quantile regression for every bank. One Reason for that is the inability of a linear model to capture complex interdependencies of financial firms under distress (Keilbar and Wang 2022). The model selection for the neural network quantile regression is the fundament for the calculation of the CoVaR, continuing in the next section.

5.3 VaR and CoVaR Estimation.

The VaR and CoVaR are estimated with a linear quantile regression and the with a neural network quantile regression, respectively. Both regressions use a sliding window estimation framework of 233 days, as this was the number of days per year with log-returns and macro-state variables. A sliding window framework uses a fixed time window that continuously shifts across the data to account for dynamic changes in time series relationships. A 5% quantile is used.

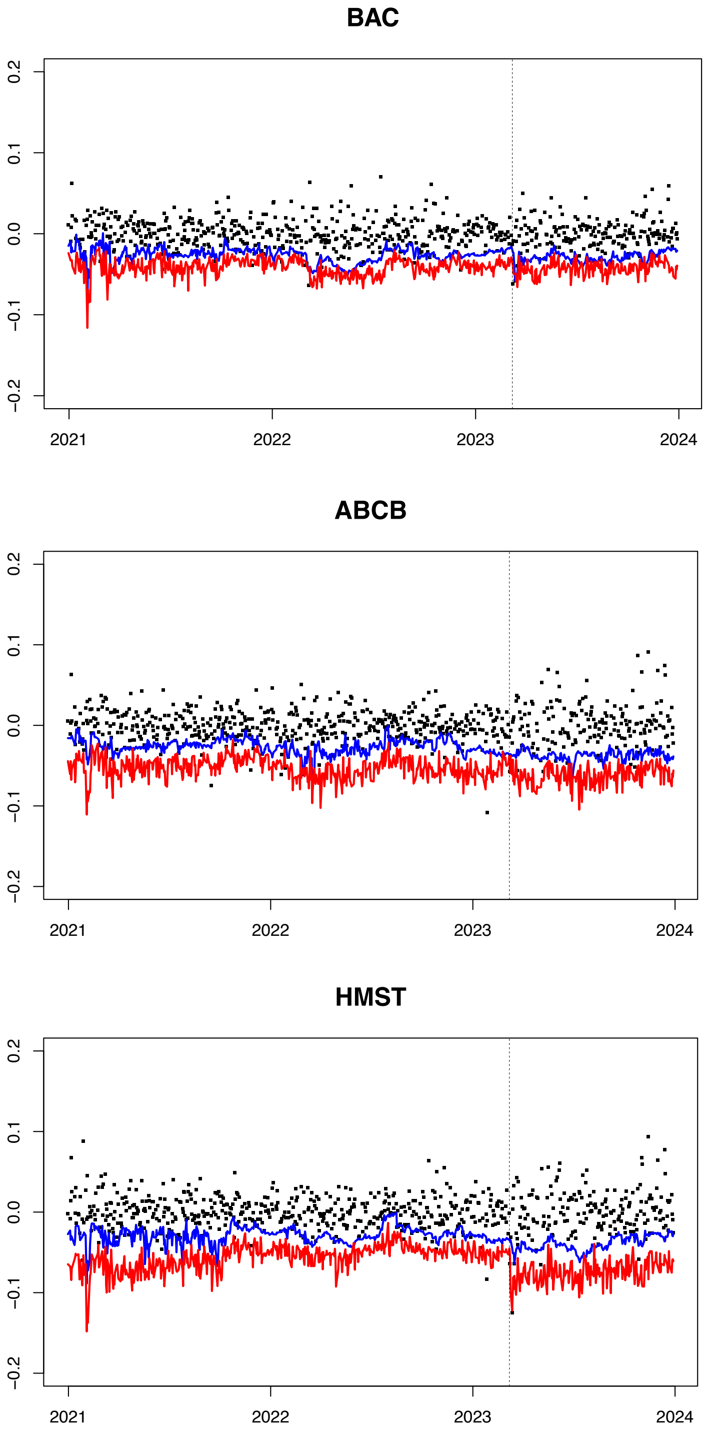

Figure 1. *Plot of one Bank per group that represents the pattern of returns (black dots), VaR (blue line) and CoVaR (Red line). Bank of Amercia (BAC), Ameris Bancorp (ABCB), HomeStreet Bank (HMST). The vertical line represents the start of the crises on the 8th of March 2023.*

The pattern of the VaR and CoVaR differs between the bank-sizes. While the largest bank did not show much affection due to the start of the crises, commercial and regional banks had a higher VaR and CoVaR from March onwards. A good comparison of the VaR and CoVaR in the time of the banking crises is the beginning for 2021, where markets where unsecure about the economy due to the COVID-19 pandemic and rising interest. Most of the Banks had higher risk parameters in this time compared to March 2023 and forwards, which indicated that the uncertainty of the economy was a stronger indicator for systemic risk than the banking failures in the own sector. However, a more precise view on the systemic risks can be given through the SNRI for the different groups as well as the SHI and SFI for individual Banks.

5.4 Network Risks

In the first step, the systemic network risk of the three groups is analyzed using the SNRI. The index reveals different dynamics compared to the individual VaRs and CoVaRs of the banks, which were higher at the beginning of 2022 compared to March 2023. Similar to the VaR and CoVaR results, banks initially exhibited elevated levels of systemic network risk, but the relative magnitude was less pronounced compared to the other measures. However, this heightened systemic network risk subsided for all three groups during the pre-crisis period, reflecting a phase of relative stability.

Among the three groups, large banks were the most stable during the pre-crisis period, showing only gradual changes in their systemic risk levels. Despite this stability, large banks consistently maintained higher systemic risk compared to their smaller counterparts, which is plausible given their size and interconnectedness within the financial system. In contrast, regional and commercial banks exhibited more noticeable fluctuations in systemic risk. Commercial banks appeared to perform better in periods of lower systemic risks, displaying relative stability during these phases. This observation contrasts sharply with their behavior during the banking crisis, where their systemic risk levels surged significantly.

With the onset of the crisis, officially marked by the shareholder letter of SVB and the liquidation of Silvergate, there is a pronounced increase in systemic risk, particularly among regional and commercial banks. However, the rise in systemic risk had already begun in early 2023, following a brief period of reduced systemic risk.

At the start of the crisis, regional banks experienced a sharper and more immediate increase in systemic risk compared to commercial banks. Yet, their risk levels also decreased more rapidly. In contrast, commercial banks demonstrated the highest levels of systemic risk during the crisis, indicating that they were the most affected by the turmoil in the banking sector. This trend suggests that commercial banks, positioned between large and regional banks in terms of total assets, may have structural vulnerabilities that render them more susceptible to systemic shocks.

Large banks, by contrast, displayed significant resilience throughout the crisis. Unlike their smaller counterparts, they did not exhibit a sharp rise in systemic risk but rather experienced a steadier systemic risk. Notably, while the systemic risks of regional and commercial banks had there peak, the systemic risk of large decreased at the same time. Importantly, the peak systemic risk of the largest banks remained substantially lower than that of the smaller groups, highlighting their relative stability in the face of systemic shocks.

This divergence in systemic risk trajectories raises questions about the robustness of regional and commercial banks to both internal sectoral shocks and external systemic disruptions. The ability of large banks to maintain relative stability underlines the effectiveness of regulatory buffers, diversified risk management strategies, and stronger capitalization requirements. In contrast, the pronounced vulnerability of smaller and mid-sized banks calls for a closer examination of their resilience and potential regulatory adjustments to mitigate systemic risk in future crises.

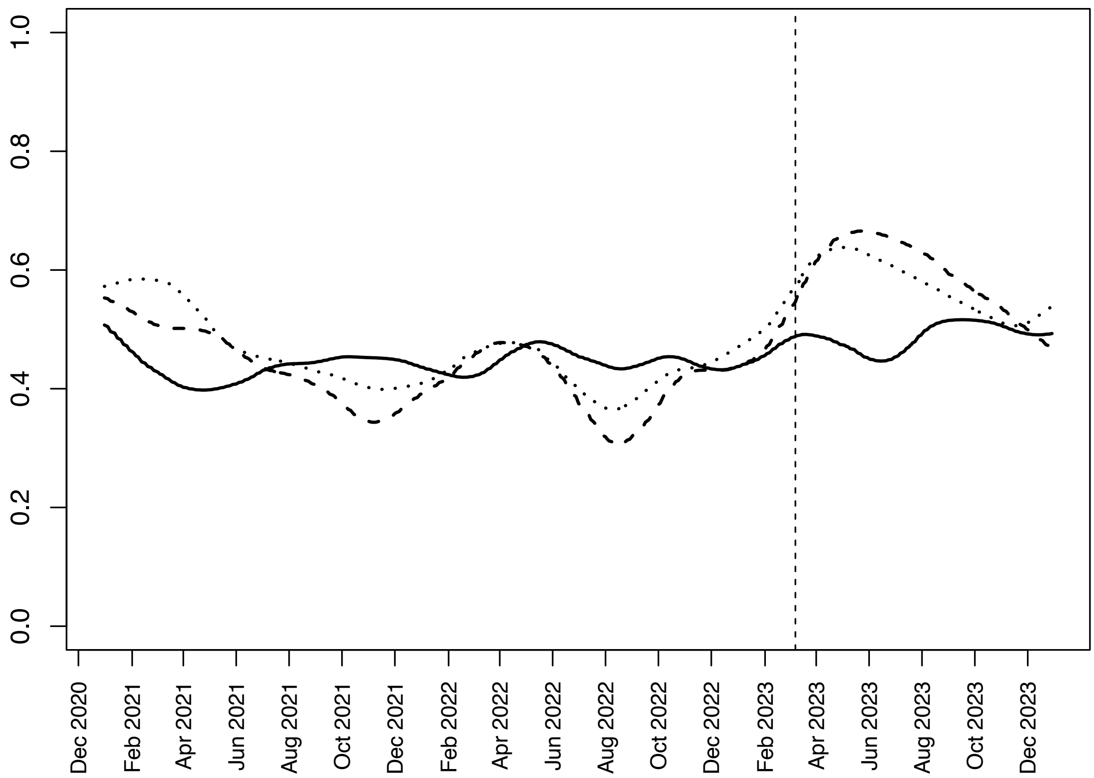

Figure 2. *The SNRI of each Group with a vertical line on the 8th of March 2023. The solid line represents the large banks, the dashed line represents the commercial banks, and the dotted line represents the regional banks.*

To further investigate these dynamics, the analysis focuses on the banks with the most notable behavior during the crisis. By examining their systemic hazard index (SHI) and systemic fragility index (SFI), a deeper understanding of their individual contributions to and vulnerabilities within the system during the crisis can be achieved. This approach highlights the specific roles these banks played in shaping the systemic risk landscape.

For the analysis of the two indices, the average value for each bank is calculated for a given period. The periods are structured as follows:

Pre- Crises: December 2022 – February 2023

Beginning of the crises: March 2023

Peak of the crises: April 2023 – June 2023

Post- Crises: July 2023 – October 2023

These different time periods can help to compare the changes in values during the time of the crises in order to determine which banks were affected by the crises and which were not and whether the crises have changed the systemic risks within the network.

The combined analysis of the SHI and SFI provides a comprehensive understanding of systemic risks and vulnerabilities during the crisis. These indices highlight not only which banks pose significant risks to the financial system but also those that are highly sensitive to external shocks. Examining both metrics together identifies key cases, such as banks with simultaneous increases in SHI and SFI, as well as those with divergent trends. Hereby, banks with an increase in both indices are the banks that show rising values in both indices or have consistently high values are particularly noteworthy here, as this is where the dangers of a bank being vulnerable to external risks meet its own risks to the system, thus showing a dual risk.

Starting with the largest banks, Fifth Third Bank (FITB) serves as a clear example of a dual-risk institution. Before the crisis, FITB held the lowest SHI and SFI values, ranking among the least systemically significant and least vulnerable banks. However, during the crisis, both SHI and SFI values rose dramatically, positioning FITB as one of the most systemically risky and vulnerable banks. After the crisis, FITB's values remain significantly above pre-crisis levels, reflecting a lasting impact on its systemic profile.

Bank of America (BAC) displays a divergent trend between SHI and SFI. At the onset of the crisis, BAC's SFI values decrease, indicating reduced vulnerability to external shocks. However, its SHI values remain elevated, reflecting its structural importance and interconnectedness within the financial system. By the peak of the crisis, BAC's SFI values rise again, aligning more closely with its SHI profile post-crisis. This duality highlights BAC's role as a stabilizer during turbulence, as they were parts of the banks that gave First Republican Bank capital, but still a structural risk carrier in more stable periods. Discover

Financial Services (DFS) also presents a unique pattern. At the peak of the crisis, DFS reaches the highest SFI value among the analyzed banks, demonstrating its heightened vulnerability. Post-crisis, its SFI values remain higher, while its SHI also increases significantly, emphasizing its potential role as a systemic risk amplifier.

Banks, such as JPMorgan Chase (JPM) and Wells Fargo (WFC), categorized as significant important financial institutions, maintain relative stability in both indices. JPM consistently holds high SHI values, underscoring its structural significance within the financial system, while its SFI values fluctuate only moderately. This stability aligns with its role as a key stabilizer during the crisis, supported by strong capitalization. Similarly, WFC exhibits stable SHI values and only moderate changes in SFI, suggesting effective risk management practices that mitigate exposure to external shocks.

KeyBank (KEY) exhibits strong volatility in both indices. During the crisis, KEY's SHI and SFI rise significantly, and the bank does not return to pre-crisis levels post-crisis. This pattern highlights structural weaknesses exacerbated by external shocks. In contrast, Regions Financial (RF) maintains relatively stable SHI rankings but experiences noticeable fluctuations in SFI, particularly post-crisis. This behavior suggests shifting external risk exposures as market conditions stabilize.

The combined analysis of SHI and SFI reveals distinct systemic dynamics during the crisis. FITB illustrates the compounding risks of simultaneous increases in both indices, while BAC and DFS highlight the complexity of divergent trends in systemic relevance and vulnerability. Stabilizers such as JPM and WFC demonstrate the importance of robust risk management and structural resilience. However, it is important to emphasize that these large banks where not as strong affected as its smaller competitors, commercial and regional banks, which are analyzed next.

The analysis of SHI and SFI values among the commercial banks reveals significant systemic risk dynamics and external vulnerability during the 2023 banking crisis. This group, consisting of a large number of banks with varying sizes and risk profiles, exhibited considerable volatility in rankings. The diverse composition of this sector contributed to the frequent shifts in risk and vulnerability, as banks reacted differently to external shocks and market conditions.

Among the systemic risk contributors, Ameris Bancorp (ABCB) stands out. Before the crisis, it was already identified as moderately risky with a SHI rank of 29, but it became a systemic risk driver during the crisis, rising to rank 4, and ended as the most significant contributor post-crisis. Similarly, Independent Bank Corp. (INDB) displayed a sharp post-crisis increase in SHI, moving from ranks 55 and 54 during the crisis to rank 2 post-crisis. Another example is Pacific Premier Bancorp (PPBI), which consistently maintained a role as a systemic risk carrier, starting with a pre-crisis rank of 12, peaking at rank 2 during the crisis, and stabilizing at rank 7 post-crisis.

In terms of external vulnerability, First Busey Corp. (BUSE), First Bancorp (FBNC), and ServisFirst Bancshares (SFBS) emerged as some of the most externally vulnerable banks post-crisis. BUSE climbed from rank 54 pre-crisis to rank 15 post-crisis, while FBNC made an even more dramatic leap from rank 59 to rank 2. SFBS, which was already among the more vulnerable banks pre-crisis (rank 15), rose to rank 1 post-crisis, becoming the most externally exposed bank in this group. Other notable examples include United Bankshares (UBSI), which climbed from rank 46 to rank 6, and Western Alliance Bancorporation (WAL), which rose sharply from rank 63 to rank 3 post-crisis.

Two banks, Customers Bancorp (CVBF) and WSFS Financial Corporation (WSFS), stand out as dual-risk cases. CVBF, which began the crisis with moderate rankings in both indices, peaked at SHI rank 12 and SFI rank 3 during the crisis, before stabilizing at relatively high levels post-crisis (SHI rank 15, SFI rank 21). WSFS displayed significant volatility, with SHI fluctuating between ranks 3 and 58 during the crisis, ultimately stabilizing at rank 6 post-crisis. In SFI, WSFS rose by 11 places to rank 26, demonstrating increasing susceptibility to external pressures alongside its systemic risk.

The crisis not only reshaped the hierarchy of systemic risk contributors but also highlighted the uncertainty within the network. Frequent shifts in SFI rankings during the crisis underscored the instability, as banks transitioned between safer and more vulnerable positions in a highly reactive environment. This volatility reflects both the diverse risk exposures of the commercial banks and the rapid changes driven by external shocks and market reactions.

The 2023 banking crisis significantly affected the commercial banks, exacerbating systemic risks and exposing the fragility within this group. The shifting relationships between systemic importance and external vulnerability during the crisis period illustrate how the network dynamics evolved under stress, with certain banks emerging as key risk drivers while others became increasingly exposed to external pressures.

The systemic risk analysis of regional banks shows a similar pattern as for the commercial banks as the crisis period reveals significant fluctuations and evolving dynamics in their roles as contributors to systemic risk and their susceptibility to external shocks.

While only Flushing Financial Corporation (FFIC) stands out as a dual-risk bank, other banks primarily influence one index. FFIC demonstrates a consistent presence in systemic risk rankings, peaking at rank 9 in SHI during the crisis and maintaining a strong position at rank 8 post-crisis. Its SFI ranking also reflects volatility, emphasizing its fragility within the system. This dual-risk profile positions FFIC as a central point of systemic vulnerability within the regional banking network, highlighting the interconnected nature of its risk exposure.

In addition to FFIC, several banks emerge as contributors to systemic risk based on their SHI rankings. First Commonwealth Financial (FCF) reaches the highest SHI ranking during the crisis at rank 1. While its ranking declines to rank 14 post-crises, FCF remains a significant contributor to systemic risk. Similarly, Univest Financial Corporation (UVSP) maintains consistent systemic relevance, ranking at rank 2 during the crisis and rank 3 post-crisis, indicating a stable but high-risk profile. Tompkins Financial Corporation (TMP) demonstrates steady relevance, peaking at rank 4 during the crisis and continuing to rank highly afterward. S&T Bancorp (STBA) also emerges as a major SHI contributor, with a notable improvement to rank 11 post-crises.

On the other hand, systemic fragility is dominated by a different set of banks. Camden National Corporation (CAC) peaks at rank 1 in SFI during the crisis, but sees a sharp decline to rank 26 post-crisis, suggesting a temporary shock. Kearny Financial Corp (KRNY) consistently ranks highly in SFI, moving from rank 2 pre-crisis to rank 10 post-crisis, reflecting persistent fragility. Similarly, Old Second Bancorp (OSBC) shows a SFI peak at rank 3 during the crisis, followed by a substantial improvement post-crisis, falling to rank 39. HomeStreet Inc (HMST) is the most fragile bank during the crisis, ranking at rank 1 in SFI, and remains vulnerable afterward at rank 2, underscoring its ongoing susceptibility to systemic shocks. Live Oak Bancshares (LOB) emerges as the most fragile institution post-crisis, achieving the rank 1 SFI ranking, after being relatively less prominent during the crisis at rank 24. Finally, Brookline Bancorp (BRKL) grows in fragility, advancing from rank 13 during the crisis to rank 4 post-crises, signaling its increasing systemic vulnerability.

Overall, the analysis reveals a diverse range of behaviors among regional banks, underscoring the complexity of systemic risk within this group. While FFIC uniquely combines high systemic risk and fragility, other banks like CAC and LOB exhibit isolated but significant vulnerabilities. Similar to the commercial banks, the crisis period also highlights the volatility within the regional bank network, as both risk contributors and fragile institutions frequently shifted ranks.

The analysis of the systemic risks of the U.S. Banking sector showed that the commercial and regional banks were much more influenced by the collapse of the Silicon Valley bank as well as the Silvergate and Signature bank then the large banks. These results provide further arguments for stronger controls and stricter regulations for smaller banks, following the example of the largest banks, which were much more resilient to this crisis. Also, the riskiest banks, having a combination of high SFIs and SHIs, are identified with the FITB, CVBF, WSFS, and FFIC. These Banks should be watched carefully by regulations to understand how to mitigate these risks in the future.

6 Conclusion

This paper aimed to analyze the systemic risk during the Silicon Valley Bank collapse and the further banking crises 2023. With the neural network quantile regression and the risk models SNRI, SFI, SHI the systemic risks for large banks, commercial banks, and regional banks were estimated and compared between these three groups as well as within these groups. The model showed that the commercial and regional banks were much more influenced by the banking crises then the large banks. This questions the current regulation for these banks and gives a more evidence for a tighter overview to make the banking sector safer in the future. In addition, banks were identified that could be particularly dangerous for the banking system due to their high vulnerability to external risks and at the same time bear high risks for the system and therefore need to be monitored with caution. This model uses only macroeconomic risk factors to estimate systemic risk, so it would be useful to include fundamental data from individual banks in further research to examine how these relate to systemic risk and to gain further knowledge of how to safeguard the banking sector.

6.1 Appendix

Table 1. *SFI Results of large banks*

Dec-Feb		March		Apr-Jun		Jul-Oct	
Ticker	Avg. SFI	Ticker	Avg. SFI	Ticker	Avg. SFI	Ticker	Avg. SFI
MTB	0,11814	CFG	0,10015	DFS	0,11923	KEY	0,11872
JPM	0,11626	BAC	0,10077	KEY	0,11588	DFS	0,11633
PNC	0,11556	DFS	0,10569	FITB	0,11435	RF	0,11584
C	0,11507	PNC	0,10598	BAC	0,11245	C	0,11469
RF	0,11266	C	0,10601	WFC	0,11188	WFC	0,11378
USB	0,11145	HBAN	0,10701	C	0,11180	BAC	0,11372
KEY	0,11003	MTB	0,10813	USB	0,11146	MTB	0,11301
BAC	0,10998	FCNCA	0,11779	CFG	0,11090	PNC	0,11240
DFS	0,10912	KEY	0,11896	PNC	0,11075	JPM	0,11113
WFC	0,10810	RF	0,11902	JPM	0,10839	FITB	0,11109
HBAN	0,10580	WFC	0,12035	RF	0,10546	FCNCA	0,11095
FCNCA	0,10505	JPM	0,12035	FCNCA	0,10436	USB	0,11067
CFG	0,10418	USB	0,12050	MTB	0,10329	HBAN	0,10922
FITB	0,09838	FITB	0,12500	HBAN	0,10081	CFG	0,10895

Table 2. *SHI results of large banks*

Dec-Feb		March		Apr-Jun		Jul-Oct	

Ticker	Avg. SHI	Ticker	Avg. SHI	Ticker	Avg. SHI	Ticker	Avg. SHI
BAC	0,11614	RF	0,12432	USB	0,11848	FITB	0,12275
FITB	0,11609	DFS	0,12031	FITB	0,11535	BAC	0,11862
WFC	0,11518	HBAN	0,11965	FCNCA	0,11509	KEY	0,11703
CFG	0,11421	C	0,11943	C	0,11464	USB	0,11700
HBAN	0,11287	WFC	0,11928	MTB	0,11360	CFG	0,11435
USB	0,11284	MTB	0,11798	DFS	0,11282	PNC	0,11400
MTB	0,11106	KEY	0,11586	BAC	0,11213	JPM	0,11386
FCNCA	0,11053	FITB	0,11441	RF	0,11164	HBAN	0,11368
JPM	0,11038	JPM	0,11390	JPM	0,11142	MTB	0,11309
RF	0,11010	PNC	0,11384	HBAN	0,11129	RF	0,11252
DFS	0,10973	CFG	0,11159	WFC	0,11053	WFC	0,11214
PNC	0,10880	USB	0,10765	CFG	0,10935	C	0,11092
KEY	0,10841	FCNCA	0,10656	KEY	0,10917	FCNCA	0,10998
C	0,10758	BAC	0,10458	PNC	0,10888	DFS	0,10745

Table 3. *SFI results for commercial banks*

Dec-Feb		March		Apr-Jun		Jul-Oct	
Ticker	Avg. SFI	Ticker	Avg. SFI	Ticker	Avg. SFI	Ticker	Avg. SFI
ABCB	6,54995	ABCB	6,09943	ABCB	6,57546	ABCB	6,63922
ASB	6,67292	ASB	7,50234	ASB	6,90444	ASB	6,81045

BANC	7,14237	BANC	6,79932	BANC	7,00302	BANC	6,61797
BANF	7,51908	BANF	7,66809	BANF	6,69045	BANF	7,09970
BANR	6,82003	BANR	6,57643	BANR	6,95755	BANR	6,61474
BHLB	6,93571	BHLB	7,13642	BHLB	6,99915	BHLB	7,12700
BKU	6,99816	BKU	7,58978	BKU	6,90235	BKU	6,88244
BOH	6,60298	BOH	7,29581	BOH	7,23864	BOH	6,80332
BOKF	7,18387	BOKF	6,85553	BOKF	6,78677	BOKF	7,13950
BUSE	6,56211	BUSE	6,96251	BUSE	7,20213	BUSE	7,07472
CATY	6,40525	CATY	6,61684	CATY	6,95102	CATY	6,78597
CBSH	6,45107	CBSH	7,01289	CBSH	7,01947	CBSH	6,78808
CBU	6,91909	CBU	6,85071	CBU	7,25773	CBU	6,97470
CFR	6,89669	CFR	7,81886	CFR	7,03919	CFR	7,04065
CMA	7,30723	CMA	7,08523	CMA	6,97689	CMA	7,13415
COLB	7,18423	COLB	6,55378	COLB	7,19994	COLB	6,57737
CUBI	7,54888	CUBI	7,49705	CUBI	7,30114	CUBI	7,07331
CVBF	6,85368	CVBF	6,54992	CVBF	7,52038	CVBF	7,01801
DCOM	6,96849	DCOM	6,95413	DCOM	7,25538	DCOM	7,17426
EFSC	6,52076	EFSC	6,64225	EFSC	7,09299	EFSC	6,92922
EGBN	6,99293	EGBN	7,38184	EGBN	7,56182	EGBN	6,82740
EWBC	6,95332	EWBC	7,39928	EWBC	6,82854	EWBC	6,89037
FBK	6,64272	FBK	7,05650	FBK	7,01179	FBK	7,05607
FBNC	6,51234	FBNC	6,56768	FBNC	7,28223	FBNC	7,25253
FFBC	6,18045	FFBC	6,55672	FFBC	6,96391	FFBC	6,76173
FFIN	7,25617	FFIN	6,97201	FFIN	7,17511	FFIN	7,18938
FFWM	7,30936	FFWM	7,17519	FFWM	7,37401	FFWM	7,15349

FHB	6,47563	FHB	6,74218	FHB	6,79564	FHB	6,99397
FHN	7,30572	FHN	7,70080	FHN	7,08352	FHN	6,77878
FIBK	6,91512	FIBK	6,76053	FIBK	7,37081	FIBK	7,01555
FNB	6,35129	FNB	6,77326	FNB	6,75665	FNB	6,71199
FRME	6,72473	FRME	7,12363	FRME	6,76967	FRME	6,59526
FULT	6,84911	FULT	6,72826	FULT	6,38003	FULT	6,61999
GBCI	6,93642	GBCI	7,14034	GBCI	6,99646	GBCI	7,08940
HOMB	6,44836	HOMB	6,92096	HOMB	6,59442	HOMB	6,64908
HOPE	7,16989	HOPE	7,15959	HOPE	6,73323	HOPE	6,68279
HTH	6,89742	HTH	6,84150	HTH	7,21352	HTH	6,98212
HTLF	6,77487	HTLF	7,29650	HTLF	7,08602	HTLF	7,00714
IBOC	6,60485	IBOC	6,99122	IBOC	6,63229	IBOC	6,64964
IBTX	6,87072	IBTX	6,54710	IBTX	7,41379	IBTX	6,99277
INDB	6,81176	INDB	6,97037	INDB	7,14736	INDB	6,94895
NBTB	6,55628	NBTB	6,91848	NBTB	7,07782	NBTB	6,87172
NWBI	6,64367	NWBI	6,95903	NWBI	6,89818	NWBI	6,50260
OCFC	6,63738	OCFC	6,39566	OCFC	6,55077	OCFC	6,63795
OFG	6,26878	OFG	6,91977	OFG	6,80616	OFG	6,73343
ONB	6,98816	ONB	6,42270	ONB	6,76003	ONB	7,07668
PB	6,32504	PB	7,29146	PB	7,21322	PB	6,93405
PFS	6,70642	PFS	6,83476	PFS	6,50082	PFS	6,67889
PNFP	6,56586	PNFP	6,56442	PNFP	6,74233	PNFP	7,04952
PPBI	6,36340	PPBI	6,69594	PPBI	6,86922	PPBI	6,40243
RNST	6,75313	RNST	6,67872	RNST	6,89094	RNST	6,75600
SASR	7,13426	SASR	7,05911	SASR	7,16339	SASR	7,05109

SBCF	6,65151	SBCF	6,56797	SBCF	6,88249	SBCF	6,94802
SFBS	7,00657	SFBS	6,89265	SFBS	7,33506	SFBS	7,25897
SFNC	6,80159	SFNC	6,63100	SFNC	7,31697	SFNC	6,95369
SNV	6,77198	SNV	6,63909	SNV	7,06152	SNV	6,98608
SSB	6,71644	SSB	6,95400	SSB	6,52688	SSB	6,70951
TCBI	7,00991	TCBI	6,71046	TCBI	7,15144	TCBI	7,14623
TFSL	7,01014	TFSL	7,42673	TFSL	7,56383	TFSL	6,98838
TOWN	6,55004	TOWN	6,51006	TOWN	6,80677	TOWN	6,64973
TRMK	6,56533	TRMK	7,27634	TRMK	7,12108	TRMK	6,98919
UBSI	6,64514	UBSI	6,42483	UBSI	7,16442	UBSI	7,16082
UMBF	7,03755	UMBF	6,84655	UMBF	6,97557	UMBF	6,89904
VBTX	6,68006	VBTX	6,71555	VBTX	7,01334	VBTX	6,74180
VLY	6,45288	VLY	7,03127	VLY	6,96646	VLY	6,60670
WAFD	6,41295	WAFD	7,34774	WAFD	6,85530	WAFD	6,85506
WAL	6,41917	WAL	6,83551	WAL	6,90357	WAL	7,21717
WBS	6,82697	WBS	6,69626	WBS	6,57979	WBS	6,81400
WSBC	6,31473	WSBC	6,83854	WSBC	6,56892	WSBC	6,77882
WSFS	6,77085	WSFS	7,00543	WSFS	6,92520	WSFS	6,99134
WTFC	6,75208	WTFC	6,82484	WTFC	7,13324	WTFC	6,87626
ZION	6,79899	ZION	6,54631	ZION	6,70895	ZION	6,81064

Table 4. *SHI Results for commercial banks*

Dec-Feb		March		Apr-Jun		Jul-Oct	

Ticker	Avg. SHI	Ticker	Avg. SHI	Ticker	Avg. SHI	Ticker	Avg. SHI
ABCB	7,01295	ABCB	7,28739	ABCB	7,39228	ABCB	7,33004
ASB	7,09660	ASB	6,98247	ASB	7,25388	ASB	6,98650
BANC	6,90381	BANC	6,99492	BANC	7,03164	BANC	6,81375
BANF	6,56784	BANF	6,78484	BANF	6,68661	BANF	6,58908
BANR	7,07405	BANR	7,09149	BANR	7,30914	BANR	7,10785
BHLB	6,70651	BHLB	6,94394	BHLB	6,81002	BHLB	6,82559
BKU	6,91354	BKU	7,21135	BKU	7,30602	BKU	7,04309
BOH	7,08418	BOH	7,35732	BOH	7,26471	BOH	7,04193
BOKF	6,64886	BOKF	6,90048	BOKF	7,04330	BOKF	6,65614
BUSE	7,12860	BUSE	7,14240	BUSE	7,17176	BUSE	7,06575
CATY	7,04140	CATY	7,19177	CATY	7,33038	CATY	7,00260
CBSH	7,13452	CBSH	7,34020	CBSH	7,11322	CBSH	6,82482
CBU	6,97820	CBU	7,37197	CBU	7,20363	CBU	6,73584
CFR	6,70998	CFR	7,12691	CFR	7,12923	CFR	6,88353
CMA	6,92997	CMA	7,01854	CMA	7,27830	CMA	6,97033
COLB	6,97067	COLB	7,21953	COLB	7,03905	COLB	6,92006
CUBI	6,98980	CUBI	7,28665	CUBI	7,20749	CUBI	6,70791
CVBF	6,76843	CVBF	7,16049	CVBF	7,31279	CVBF	7,10353
DCOM	6,77268	DCOM	6,91303	DCOM	7,18788	DCOM	6,90208
EFSC	6,94280	EFSC	7,03741	EFSC	7,00422	EFSC	6,93400
EGBN	6,84308	EGBN	6,90022	EGBN	6,83920	EGBN	6,78455
EWBC	7,09705	EWBC	7,13483	EWBC	7,34650	EWBC	7,16465
FBK	6,99048	FBK	6,98242	FBK	7,11872	FBK	6,75312

FBNC	7,03052	FBNC	7,11503	FBNC	6,98832	FBNC	6,89285
FFBC	7,07807	FFBC	7,29462	FFBC	7,33874	FFBC	7,02284
FFIN	6,97914	FFIN	7,14757	FFIN	7,22119	FFIN	6,98911
FFWM	6,60356	FFWM	7,24920	FFWM	7,11353	FFWM	6,97010
FHB	7,13210	FHB	7,11745	FHB	7,18402	FHB	7,08252
FHN	6,36898	FHN	6,82905	FHN	7,08732	FHN	6,93020
FIBK	6,91663	FIBK	6,78631	FIBK	6,99407	FIBK	6,79574
FNB	7,03621	FNB	7,09770	FNB	7,29501	FNB	7,10413
FRME	6,91532	FRME	6,93436	FRME	7,14437	FRME	7,08199
FULT	6,99639	FULT	7,00365	FULT	7,24588	FULT	6,96701
GBCI	7,24900	GBCI	7,38435	GBCI	7,35964	GBCI	6,99151
HOMB	7,09904	HOMB	6,83469	HOMB	7,10265	HOMB	6,94661
HOPE	7,26501	HOPE	7,30435	HOPE	7,27165	HOPE	7,13384
HTH	6,60250	HTH	6,89940	HTH	6,88501	HTH	6,75305
HTLF	6,90606	HTLF	6,93376	HTLF	7,16476	HTLF	6,81007
IBOC	6,89145	IBOC	6,87454	IBOC	7,08044	IBOC	6,89673
IBTX	6,93819	IBTX	7,19148	IBTX	7,26216	IBTX	7,17323
INDB	6,80121	INDB	7,01980	INDB	7,15891	INDB	7,27407
NBTB	6,70712	NBTB	6,98857	NBTB	7,05880	NBTB	6,87166
NWBI	6,96541	NWBI	7,17262	NWBI	7,22920	NWBI	6,80640
OCFC	6,92585	OCFC	7,13870	OCFC	7,34749	OCFC	7,04986
OFG	6,68859	OFG	7,07922	OFG	6,92812	OFG	6,81585
ONB	6,96945	ONB	7,17921	ONB	7,23693	ONB	7,13025
PB	7,09774	PB	7,17700	PB	6,97201	PB	6,85384
PFS	6,79960	PFS	7,13354	PFS	6,97925	PFS	7,00946

PNFP	7,20624	PNFP	7,23185	PNFP	7,21509	PNFP	7,05478
PPBI	7,11689	PPBI	7,03147	PPBI	7,41534	PPBI	7,13641
RNST	7,11746	RNST	7,14117	RNST	7,22299	RNST	7,20357
SASR	7,04948	SASR	7,13826	SASR	7,09892	SASR	6,84698
SBCF	6,81537	SBCF	7,16850	SBCF	7,47066	SBCF	7,06065
SFBS	6,56247	SFBS	6,87154	SFBS	6,85070	SFBS	6,67906
SFNC	6,94563	SFNC	7,09312	SFNC	7,05085	SFNC	6,94904
SNV	7,17405	SNV	7,22285	SNV	7,23391	SNV	7,08529
SSB	7,13585	SSB	7,06113	SSB	7,30247	SSB	7,00482
TCBI	6,87054	TCBI	7,14114	TCBI	7,18185	TCBI	7,00577
TFSL	6,64588	TFSL	6,57327	TFSL	6,73499	TFSL	6,58068
TOWN	6,97533	TOWN	7,19130	TOWN	7,09282	TOWN	7,00793
TRMK	7,02435	TRMK	7,02244	TRMK	7,20658	TRMK	6,98730
UBSI	7,18603	UBSI	7,13048	UBSI	7,07115	UBSI	6,96113
UMBF	6,89644	UMBF	7,00392	UMBF	7,10320	UMBF	7,04059
VBTX	6,82954	VBTX	7,35822	VBTX	7,24010	VBTX	7,04610
VLY	7,14602	VLY	7,09652	VLY	7,11503	VLY	6,89048
WAFD	6,65823	WAFD	6,82500	WAFD	6,78040	WAFD	6,67670
WAL	7,01496	WAL	7,26603	WAL	7,35954	WAL	7,02762
WBS	7,02284	WBS	7,35663	WBS	7,19743	WBS	7,05677
WSBC	6,99100	WSBC	7,24007	WSBC	7,19924	WSBC	7,12948
WSFS	6,92004	WSFS	7,40315	WSFS	7,03473	WSFS	7,15066
WTFC	7,03386	WTFC	7,57145	WTFC	7,38023	WTFC	7,10848
ZION	7,08203	ZION	7,45111	ZION	7,41487	ZION	7,13523

Table 5. *SFI results for regional banks*

Dec-Feb		March		Apr-Jun		Jul-Oct	
Ticker	**Avg. SFI**	**Ticker**	**Avg. SFI**	**Ticker**	**Avg. SFI**	**Ticker**	**Avg. SFI**
BRKL	5,46711	BRKL	5,60726	BRKL	5,61740	BRKL	5,55876
CAC	5,25601	CAC	6,00457	CAC	5,66217	CAC	5,31966
CASH	5,38683	CASH	5,38117	CASH	5,43745	CASH	5,22820
CCNE	5,39242	CCNE	5,62992	CCNE	5,46901	CCNE	5,40091
CFFN	5,28585	CFFN	4,84818	CFFN	5,39133	CFFN	5,48887
CHCO	5,02877	CHCO	5,66119	CHCO	5,21932	CHCO	5,23701
CNOB	5,11429	CNOB	5,56740	CNOB	5,43854	CNOB	5,38253
CPF	5,17275	CPF	5,29568	CPF	5,14415	CPF	5,44986
CTBI	5,24176	CTBI	5,24022	CTBI	5,10248	CTBI	5,00500
EQBK	5,37925	EQBK	5,57514	EQBK	5,32450	EQBK	5,34211
FBMS	5,42767	FBMS	5,73671	FBMS	5,50473	FBMS	5,24260
FCF	5,22443	FCF	5,31809	FCF	5,50268	FCF	5,30890
FFIC	5,20747	FFIC	5,33791	FFIC	5,64373	FFIC	5,44116
FISI	5,13124	FISI	5,57667	FISI	5,48764	FISI	5,41115
FMBH	5,03104	FMBH	5,64707	FMBH	5,33585	FMBH	5,16059
GABC	5,08596	GABC	5,12892	GABC	5,55026	GABC	5,20752
GSBC	5,07969	GSBC	5,31237	GSBC	5,49035	GSBC	5,25007
HAFC	4,89407	HAFC	5,07120	HAFC	5,26480	HAFC	5,13768
HBNC	5,14460	HBNC	5,13591	HBNC	5,33326	HBNC	5,38897
HFWA	4,95974	HFWA	5,25793	HFWA	5,07518	HFWA	5,22281

HMST	5,77805	HMST	5,46534	HMST	5,97695	HMST	5,56876
HTBK	5,12979	HTBK	5,34716	HTBK	5,33776	HTBK	5,53373
KRNY	5,66352	KRNY	5,99291	KRNY	5,49511	KRNY	5,43732
LKFN	5,29536	LKFN	5,49327	LKFN	5,84412	LKFN	5,40950
LOB	5,64255	LOB	5,83254	LOB	5,41892	LOB	5,59915
MBWM	5,15436	MBWM	5,00079	MBWM	4,91509	MBWM	5,33974
MOFG	5,21151	MOFG	5,41693	MOFG	5,17744	MOFG	5,38842
MSBI	5,03105	MSBI	5,06669	MSBI	5,50581	MSBI	5,12839
NBHC	5,31887	NBHC	5,56612	NBHC	5,36208	NBHC	5,55949
NFBK	5,07997	NFBK	5,19193	NFBK	5,44550	NFBK	5,39600
OSBC	5,58289	OSBC	5,91993	OSBC	5,57876	OSBC	5,17624
PEBO	5,29560	PEBO	5,48932	PEBO	5,53898	PEBO	5,26227
PFBC	5,36865	PFBC	5,15899	PFBC	5,32469	PFBC	5,20433
PGC	5,13835	PGC	4,98911	PGC	5,22115	PGC	5,36935
PRK	5,11380	PRK	5,62018	PRK	5,08562	PRK	5,49325
QCRH	5,47321	QCRH	5,87073	QCRH	5,47970	QCRH	5,29052
RBCAA	5,41875	RBCAA	5,65343	RBCAA	5,30552	RBCAA	5,40878
SBSI	5,34439	SBSI	5,47777	SBSI	5,46002	SBSI	5,14638
SRCE	5,29997	SRCE	4,78309	SRCE	5,32358	SRCE	5,28284
STBA	5,08885	STBA	5,23713	STBA	5,18375	STBA	5,42461
SYBT	5,51097	SYBT	5,45857	SYBT	5,67321	SYBT	5,03174
TBBK	5,50496	TBBK	5,58572	TBBK	5,35681	TBBK	5,08897
TCBK	5,01933	TCBK	5,45357	TCBK	5,08359	TCBK	5,13353
THFF	5,64166	THFF	5,56258	THFF	5,17063	THFF	4,99931
TMP	5,07304	TMP	5,25814	TMP	5,12492	TMP	5,10352

TRST	5,14069	TRST	5,15259	TRST	5,12725	TRST	5,35342
UVSP	5,08206	UVSP	5,15272	UVSP	5,39810	UVSP	5,28920
WABC	5,43382	WABC	5,62261	WABC	5,58037	WABC	5,41737
WASH	5,30161	WASH	5,58309	WASH	5,57421	WASH	5,33851

Table 6. *SHI results for regional banks*

Dec-Feb		**March**		**Apr-Jun**		**Jul-Oct**	
Ticker	**Avg. SHI**	**Ticker**	**Avg. SHI**	**Ticker**	**Avg. SHI**	**Ticker**	**Avg. SHI**
BRKL	5,32020	FCF	5,97193	HBNC	5,75447	TCBK	5,64537
CAC	5,37649	UVSP	5,86881	UVSP	5,73230	HAFC	5,58654
CASH	5,40125	NBHC	5,83650	STBA	5,72251	UVSP	5,57452
CCNE	5,48931	TMP	5,81024	TMP	5,69885	MBWM	5,55082
CFFN	5,46841	CPF	5,77815	FCF	5,69400	TMP	5,54331
CHCO	5,31962	GABC	5,75129	HTBK	5,66551	WASH	5,53155
CNOB	5,42537	TBBK	5,73389	WASH	5,65445	CTBI	5,51560
CPF	5,69750	CCNE	5,70821	CAC	5,64662	FFIC	5,48292
CTBI	5,61067	STBA	5,69889	FFIC	5,64369	THFF	5,48282
EQBK	5,38585	KRNY	5,65961	SRCE	5,63768	HFWA	5,47811

FBMS	5,34016	FMBH	5,65737	CPF	5,62068	STBA	5,46959
FCF	5,38516	TRST	5,65240	CNOB	5,61637	MSBI	5,46186
FFIC	5,30997	FISI	5,65052	TCBK	5,61208	BRKL	5,44731
FISI	5,48640	CFFN	5,64522	HAFC	5,60680	FCF	5,44506
FMBH	5,33553	HBNC	5,63363	QCRH	5,60049	FBMS	5,43775
GABC	5,37334	SBSI	5,62875	THFF	5,59240	GABC	5,43561
GSBC	5,53025	MBWM	5,62732	NBHC	5,57391	GSBC	5,43355
HAFC	5,46851	CTBI	5,61464	PGC	5,56975	QCRH	5,42736
HBNC	5,47121	SYBT	5,60995	GABC	5,54971	HBNC	5,41912
HFWA	5,23298	WASH	5,60464	GSBC	5,52505	NFBK	5,41457
HMST	5,25136	HAFC	5,60172	LKFN	5,51530	PGC	5,41030
HTBK	5,25399	CASH	5,56628	EQBK	5,47417	CFFN	5,39992
KRNY	5,35813	EQBK	5,54142	TRST	5,46961	OSBC	5,39822
LKFN	5,28125	HTBK	5,54018	HFWA	5,46504	HTBK	5,38691
LOB	5,09490	PGC	5,53907	FISI	5,46131	TRST	5,38098
MBWM	5,25395	FFIC	5,51190	MBWM	5,46023	CAC	5,37222
MOFG	5,26462	PEBO	5,51119	PFBC	5,45552	TBBK	5,36980
MSBI	5,33691	CHCO	5,50900	CFFN	5,44930	PEBO	5,36706
NBHC	5,29312	GSBC	5,50599	CTBI	5,43869	SRCE	5,36443
NFBK	5,40249	SRCE	5,50292	OSBC	5,43472	PFBC	5,34922
OSBC	5,28216	LKFN	5,49663	SBSI	5,42126	NBHC	5,31473
PEBO	5,39186	CAC	5,47651	FMBH	5,42045	CPF	5,30144
PFBC	5,36702	HFWA	5,46852	CASH	5,41373	CNOB	5,29891
PGC	5,13908	MSBI	5,46503	CCNE	5,40836	CCNE	5,29723
PRK	5,41909	WABC	5,45939	MOFG	5,40515	PRK	5,29426

QCRH	5,30660	NFBK	5,45269	HMST	5,40388	CASH	5,27947
RBCAA	5,18931	TCBK	5,43565	BRKL	5,40164	SBSI	5,26090
SBSI	5,41747	OSBC	5,41974	PRK	5,38456	KRNY	5,25603
SRCE	5,53503	PRK	5,41125	KRNY	5,37328	HMST	5,25585
STBA	5,65772	QCRH	5,40788	SYBT	5,36734	FISI	5,25486
SYBT	5,22247	PFBC	5,38169	MSBI	5,35785	WABC	5,24063
TBBK	5,48780	RBCAA	5,35420	NFBK	5,34507	EQBK	5,23319
TCBK	5,52595	MOFG	5,33525	TBBK	5,34462	FMBH	5,21561
THFF	5,14977	BRKL	5,33307	PEBO	5,34327	LKFN	5,21295
TMP	5,46080	HMST	5,29317	FBMS	5,33894	MOFG	5,20319
TRST	5,49189	LOB	5,28971	WABC	5,33848	SYBT	5,19022
UVSP	5,45039	CNOB	5,28576	CHCO	5,26543	CHCO	5,18693
WABC	5,23820	THFF	5,24709	RBCAA	5,22577	RBCAA	5,00784
WASH	5,35226	FBMS	5,21935	LOB	5,20783	LOB	4,98512

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