Grande Ecole Masters in Management

Majeure Finance

Research Paper

Academic Year 2023-2024

Systemic Risk during the 2023 Banking Crisis

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24th June 2024

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1. Introduction

The 2023 banking crisis is considered the worst since 2007-2008 for the US and Europe. Right after the banks' failures, several papers were released that followed the development of the crisis, trying to identify its causes and consequences. The main cause of the crisis was the unexpected surge of interest rates, which led to significant unforeseen losses in the value of assets (government bonds) and depositors' runs.

Systemic risk is characterized by the potential of the entire system to collapse, not by individual failures. A systemic event can be defined, and its severity can be assessed by the number of institutions following the domino effect and collapsing simultaneously or sequentially shortly after one another, amplifying the instability. In the banking system, the institutions are linked and interconnected. Thus, this industry is more prone to systemic risk.

The 2023 banking crisis originated in the US – the country with the second largest (after China) amount of total assets in the banking sector worldwide (30.35tn USD as of 2022, according to Statista) and the leader by the number of G-SIBs (8 out of 30 in 2022 according to Financial Stability Board). Besides, US banks are relatively concentrated, with the three biggest banks (JPMorgan Chase, Bank of America, and Wells Fargo) holding around 25% of the nation's total assets in the banking sector. If we compare the US banking situation in 2023 to the one in the European Area, Europe presents a more fragmented picture. While it has major banks like HSBC, BNP Paribas, and Deutsche Bank (12 G-SIBs spread across seven countries), the sector is more dispersed across numerous nations, leading to lower concentration than in the US. By looking at the systemic risk indicators, such as CISS, a significant degree of co-movement can be noticed between the systemic risk levels of different countries. This fact indicates that elevated levels of systemic stress are often global phenomena. Such global stress episodes can arise from either common exposure to a similar set of shocks or through spillover effects, where stress in one country transmits to the financial systems of others. At the same time, there are instances where the financial stress is more localized[1]. Considering the arguments above and the instances of failed banks during the 2023 banking crisis, in this paper we focus our analysis mainly on the US and include some comparisons with the European Area.

Montagna, Torri, and Covi (2021), in their paper on the origin of systemic risk in the financial system define the main drivers of systemic risk: correlated economic shocks (when market or institutional failure triggers the failure of a chain of institutions or a chain of significant losses to financial institutions) and financial contagion (through solvency, liquidity, fire-sale and bank run channels), while the contribution of economic credit risk

[1] For example, during the peak of the Eurozone sovereign debt crisis in 2011 and 2012, the US financial system was relatively less affected compared to the significant impact observed in Europe (Hollo, Kremer, Lo Duca (2012))

to the systemic risk of the financial system accounts only for less than 9%. The other paper by Benoit, Colliard, Hurlin, and Pérignon (2017) that conducts a survey of the literature on systemic risk highlights three main systemic risk sources: systemic risk-taking (common exposure), contagion mechanisms, and amplification mechanisms (high leverage and low liquidity leading to the fire-sales of assets), which align with the drivers defined by Montagna, Torri, and Covi (2021). Thus, in our paper, we define two views on the systemic risk in the banking crisis 2023: external and internal. We aim to examine the effect of interconnectedness and contagion through the external view of the market by assessing the banks' stock price reaction to a bank's failure. As for the amplification mechanisms, we use the internal view of the banks' balance sheet, comparing the unrealized asset losses to different levels of depositor runs and fire sale discounts. Finally, we check if internal views impact the external view using the extended cross-sectional regression model.

The principal research question of this paper is to identify the contribution of external market reactions and internal balance sheet vulnerabilities to systemic risk in the banking sector, as evidenced by the 2023 banking crisis.

In the first part of the paper, we study the interconnectedness and contagion criteria of systemic risk through the event study methodology. We conduct several event studies to examine the effect of G-SIB, large and small bank failures during the 2023 banking crisis on the share price of other groups of banks. The event studies measuring the immediate impact of bank failures on other banks provide insights into "external" market perceptions of risk and the potential for contagion. If the failure of one bank leads to significant declines in the share prices of other banks, it suggests a high level of systemic risk and interconnectedness within the banking system. To further characterize the banks that are the most vulnerable to other banks' failures, we introduce several criteria, such as size, the level of run-prone liabilities, and available liquidity to cover the withdrawals. This is crucial for identifying the portrait of a bank that could be a potential point of failure in a systemic crisis.

The second part of the paper analyzes key aspects of the banks' balance sheets, assessing the sensitivity of the banks' assets to interest rate hikes and estimating the potential unrealized asset loss when marked to market. This helps with understanding how changes in interest rates, one of the major influences in systemic crises, can impact the stability of banks. We compute the deposit coverage ratio equilibrium (Jiang et al. (2023)) under various scenarios of depositor runs. This analysis simulates distinct stress levels in the banking system to determine how well banks can withstand sudden withdrawals by depositors, another one of the most significant factors in systemic crises. The paper provides a holistic view of systemic risk by combining interest rate sensitivity analysis with depositor-run simulations. It identifies both market risks (due to interest rate changes) and liquidity risks (due to depositor behavior) that contribute to systemic instability. Combining the analyses from part one and part two provides a comprehensive view of the banks at risk of failure and illustrates how their potential collapse could impact the financial system, thereby contributing to systemic risk.

In the third part of the paper, we use the models tested on the 2023 data to provide an analysis as of today, evaluate the current state of the banking sector, and assess whether new risk factors and market developments can be identified. By doing so, we can offer insights into potential future systemic events.

This research paper's topic is relevant and innovative. It addresses contemporary significant systemic events for the financial system, using the most recent data for analysis. In addition, this paper examines the systemic risk in the banking crisis of 2023 from different perspectives, acknowledging the dimensionality and complexity of this phenomenon.

2. Literature review

Recent economic events served as a ground for the surge of research studying the causes and consequences of systemic crises. However, the notion of systemic risk is far from being new. One of the earliest influential studies is Rochet and Tirole (1996) work developing theoretical models to explain how interbank lending could lead to systemic risk. This paper laid the groundwork for subsequent research on contagion and interconnectedness within banking networks. Academic research on systemic risk continued with the works of Allen and Gale (2000), examining financial contagion and liquidity preference shocks. Their findings indicate that interbank claims create vulnerability where a shock in one region can spread to others, leading to widespread financial instability and the appearance of correlated economic shocks. This was followed by Acharya's (2001) research, which focused on the banks' asset return correlation leading to systemic risk shifting, increasing the likelihood of simultaneous failures.

As for the early empirical research introducing the models to measure the contagion and interconnectedness of the financial system, Upper (2011), in his paper, runs a simulation and finds out that while the risk of contagion leading to widespread defaults is generally low, in some scenarios the cascade of failures across the banking system is still possible, particularly in environments with significant interbank exposures. Upper's (2011) paper is limited to testing only one channel of financial contagion – default on interbank lending. Other papers on the topic introduce new concepts such as "distance" within financial networks, which measures the likelihood of one bank's distress causing distress in another (Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015)). The paper's finding is in line with the findings of Gai and Kapadia (2010), who introduced the notion of networks being "robust yet fragile," highlighting that while interconnected systems can absorb small shocks, they are vulnerable to large, systemic events. Thus, the mentioned literature, as well as the other existing important works around systemic risk-taking, financial contagion, and interconnectedness of the banking networks, have partly answered the first part of the research question on external market reactions. In our paper, we extend the analysis of the impact of one bank's failure on the other banks using the event study approach for the 2023 bank failures to demonstrate how market perceptions and stock price reactions contribute to systemic risk.

Once the base of theoretical definitions and concepts was established, the academic research moved its focus towards examining in more detail the liquidity issue that plays a crucial role in the systemic banking crisis and bank runs. Allen and Gale (2004), in their paper on financial fragility and liquidity, discussed the liquidity-induced spiral and the notion of a fire sale of assets, highlighting that banks are forced to sell assets at significantly lower prices to meet liquidity needs, creating a vicious cycle of declining asset values and increased financial instability. The issue of liquidity spirals and loss spirals that negatively influence market prices and serve as a source of contagion was further studied by Brunnermeier and Pedersen (2009), emphasizing the role of liquidity in exacerbating systemic risk during financial crises. As for the empirical models and frameworks, we can refer to the work of Brunnermeier, Gorton, and Krishnamurthy (2014), which introduces the Liquidity Mismatch Index (LMI) that measures the difference between the liquidity of a bank's assets and liabilities under various stress scenarios. While this index offered some quantification to the liquidity matter of the systemic risk, it had some limitations, such as the accuracy of the stress test models' assumptions, static analysis that doesn't capture the moving nature of the financial markets, and evolving liquidity mismatch. Following the 2023 monetary tightening, one of the most recent working papers by Jiang et al. (2023) was released, where the authors developed a model for marking-to-market asset losses and assessing the liquidity shortage that caused the bank run in the US in 2023. In our paper, we base our analysis of the second part of the research question on the work of Jiang et al. (2023), improving the frequency of the data analyzed from a quarterly to a daily interval. We also propose a revision of the equation for extreme cases of deposit withdrawals where insured depositors also take part in initiating a bank run due to a loss of trust in the deposit insurance schemes, yielding good results for cases such as Banco Popular's run. The paper contributes to the research on systemic risk in 2023 by providing a more detailed and dynamic assessment of how internal balance sheet fragilities and liquidity issues interact with external market reactions. Thus, our research complements the existing literature by integrating the external and internal dimensions of systemic risk in the example of the 2023 banking crisis in the US.

3. Part 1: Event study

3.1. The effect of bank failures on other banks' stock prices

3.1.1. Definition of the event

As the financial system is becoming more interconnected, the failure of one bank can substantially affect the other banks and the financial system as a whole. This paper uses the event study method to examine the impact of one bank's failure on the stock prices of other banks and the factors influencing such movements.

We define an event as the announcement of a bank failure, where the event date is the announcement date. Five bank failures occurred in the US in 2023. The wave of failures started with the Silicon Valley Bank failure (the 17th largest US bank by the total asset amount as of Q4 2022) that happened on March 10, 2023 (the event date) when the California Department of Financial Protection and Innovation seized SVB and placed it under the receivership of the Federal Deposit Insurance Corporation (Barr (2023)). This was followed by the failure of Signature Bank (the 32nd largest US bank by the total asset amount as of Q4 2022) just a few days later (on March 12, 2023 (Sunday) – March 13, 2023, is the event date as the following trading day). The failure of these two large banks spread panic, especially around the banking institutions with a sizable portion of uninsured deposits. Despite all the bailing-out efforts and liquidity injections, the domino effect continued with hitting one more large US bank – First Republic Bank (the 15th largest US bank by the total asset amount), which was put under the FDIC receivership on May 1, 2023 (the event date).

Due to the high level of interconnectedness in the system, the crisis that started in the US did not take much time to arrive in Europe. The failure of Credit Suisse (a G-SIB) occurred on March 19, 2023 (Sunday; thus, March 20, 2023, is the event date), when UBS initiated the acquisition. The other two banks that failed in the US during 2023 are classified as small. One is Heartland Tri-State Bank, which failed on July 28, 2023 (the event date), and the other is Citizens Bank[2], which failed later, on November 3, 2023 (the event date). All studied events are shown in the summary below.

Table 1. Examined bank failures in the US and Europe in 2023[3]

Group	Name	Country	Event Date	Total Assets	Total Deposits
G-SIB	Credit Suisse	Switzerland	20-Mar-23	531.4 bn CHF	233.2 bn CHF
Large Banks	Silicon Valley Bank	USA	10-Mar-23	209.0 bn USD	175.4 bn USD
	Signature Bank	USA	13-Mar-23	110.4 bn USD	88.6 bn USD
	First Republic Bank	USA	01-May-23	212.6 bn USD	176.4 bn USD

[2] Citizens Bank in Sac City, Iowa (not to be confused with Citizens Bank, National Association in Providence, Rhode Island)

[3] Total assets and total deposits as of Q4 2022

Small Banks	Heartland Tri-State Bank	USA	28-Jul-23	0.139 bn USD	0.130 bn USD
	Citizens Bank	USA	03-Nov-23	0.060 bn USD	0.052 bn USD

Source: compiled by the authors from FDIC and Credit Suisse website

In 2023, we observed the failure of banks across various systemic importance levels and asset scales. This prompted our analysis of how the failure of banks from distinct categories affected others within the banking system.

We group failed banks by their total asset size, with a threshold of 1.564bn USD (following the FDIC classification): those above the threshold are categorized as large banks, while those below are considered small banks. Besides, from the large banks, we distinguish the subset of 30 banks deemed as G-SIBs at the end of 2022, following the list of the Financial Stability Board.

Regarding the event window, as the bank failures followed closely one another, it would be difficult to differentiate between the impact of each failure separately if we took larger windows. Thus, in this paper, we narrowed down the event window to one day before and one day after the event.

3.1.2. Selection criteria and data collection

As the failures described above took place in the US, we primarily studied the impact on the US banks from diverse groups defined above. Thus, using Bloomberg, we collected all the listed US banks' share price data from January 3, 2022, to calculate stock returns for the benchmark period. We cleaned the dataset for the availability of data and stock liquidity of the banks (daily traded volume and % float), eliminating banks with more than 30% of the day-to-day returns equal to zero to improve the model's accuracy. Thus, the total number of US banks (excluding American G-SIBs) examined is 286 (247 Large US Banks, 39 Small US Banks). Besides, to build a normal return model for the US banks, we obtained S&P 500 prices (SPY ETF) and, additionally, book-to-market value data and market capitalization data from Bloomberg for the same period starting from January 3, 2022.

For comparison reasons, we also studied the impact of the failures on G-SIBs and European banks. We used Bloomberg to retrieve analogical stock return data for these banks for the same benchmark period. Thus, we obtained stock returns for 30 G-SIBs and 180 Western European banks to calculate the real returns. For the normal return models for the G-SIBs, we collected MSCI Index ETF prices to benchmark against the global nature of the banks' business. As for the European banks, Stoxx Europe 600 ETF returns were gathered to benchmark the Eurozone market portfolio.

As the rise of interest rates triggered the 2023 banking crisis in the US, the banks experienced large losses on their loan and residential mortgage portfolios, even though some had high levels of liquid cash and securities. These huge unrealized losses caused panic among the depositors when announced and encouraged runs led by uninsured depositors. Thus, we want to check the impact of a bank failure on the US banks with high and low levels of run-prone liabilities (uninsured liabilities to total assets) and on the banks with high and low levels of ratio of liquid cash and available-for-sale securities to total assets.

We collected the data about assets, uninsured liabilities, cash, and securities amounts for all US FDIC-insured banks from FDIC fillings of call reports for Q4 2022.

To characterize the banks that were particularly sensitive to other bank failures during 2023, we established the following groups: size, geography, run-prone liability ratio, and liquid assets ratio (Table 2).

Table 2. Classification of the banks examined

Group	Description	Criteria
Size	G-SIB, Large, Small	List of G-SIBs, otherwise the threshold of total assets of 1.564bn USD
Geography	US, Europe	The bank's headquarters location
Run-prone liabilities	High, Medium, Low	High: above the 75th percentile of the ratio for the US banks. Low: below the 25th percentile. Medium: the remaining sample, excluding the extremes
Liquid cash and securities	High, Medium, Low	High: above the 75th percentile of the ratio for the US banks. Low: below the 25th percentile. Medium: the remaining sample, excluding the extremes

Source: defined by the authors

3.1.3. Normal performance return model

The event study methodology has two main approaches to the normal return model: the constant mean returns model (statistical) and the market model (economic). We opted for the market model approach as it better incorporates the relationship between the bank stock and the market index using economic restrictions, improving the accuracy of the normal return estimation.

We reviewed the existing literature on bank-related event studies to choose an appropriate market model to predict the normal return. It's worth mentioning that although in their work, Fama and French (2004) concluded that the CAPM is not precise and most of its uses are invalid, it is still the leading model used for normal return estimation. Barnes and Lopez (2006) discuss alternatives to the CAPM in their work and refer to the surveys of Bruner et al. (1998) and Graham and Harvey (2001) to confirm that the CAPM is indeed the prevailing model used in practice. Recent papers applying event study methodology to examine the impact of an event on banks (such as Benmelech, Yang, and Zator (2023)) also use the market model and calculate the abnormal event returns as deviations from a market model using OLS regression with the capitalization-weighted index as the market proxy.

We tested both models as data was available for the US banks. In Appendix 1 (Table A2 and Table A3), we present the regression results of CAPM and Fama-French models for all US Banks, where we aggregate the coefficients from a panel regression for all available banks and perform t-statistics to check for factor significance. Besides, we presented the results of both regressions for JP Morgan (Table A1) as an example of the output received for each of the entire sample of banks. It can be noticed that SMB and HML coefficients in the Fama-French example are not statistically significant (low t-statistics and high p-value), and the R-squared is not significantly better for the Fama-French model than for the CAPM model (0.2592 vs. 0.2454 respectively for aggregated values of the panel regressions of all the banks in the sample). Moreover, the CAPM model is more intuitive and easier to use regarding data availability, making the analysis for many banks more straightforward and comparable. Thus, considering all the arguments above, we decided to use CAPM as a market model with the market-capitalization-weighted index as a benchmark.

We build an estimate for the predicted returns through the CAPM market model where, for listed banks, historical stock returns are regressed on the market returns (ETFs tracking the S&P 500, MSCI World, and Euro Stoxx 600 indexes). The period used to estimate the benchmark regression is 365 calendar days, finishing two days prior to SVB's failure (252 trading days). This period was chosen as it represents the most similar and relevant market behavior to the one during the 2023 crisis (encompassing some instability, high volatility, and bearishness). Thus, it allows us to ensure pre-event period consistency while avoiding data contamination, as the market has not yet witnessed bank failures. Besides, our benchmarking period is quite long and provides a large sample size, which increases statistical robustness.

3.1.4. Abnormal and Cumulative Abnormal Returns

The predicted stock price from the normal performance model is then juxtaposed with the actual historical bank prices. The difference between the two on the event date is an abnormal return on the event date. The cumulative abnormal return is computed between dates -1 and +1 to gain an idea about the influence of the pre-event rumors and post-event price drifts. Besides, for the robustness check of the event studies, we computed the cumulative abnormal returns for the event window of [-5, +5].

3.1.4.1. Large Bank Failures

We first analyze the impact of a big bank failure. SVB was the first bank to collapse in the US since 2020. As can be seen from Table 3 below, SVB's failure had a significant negative impact on the other banks. The biggest negative impact was observed the day before the event, showing that the market started pricing in the failure information without significant anticipation.

The first news about the highly probable failure of SVB appeared on March 8, 2023 (2 days before the event), when SVB announced that it had sold over 21bn USD worth of its available-for-sale securities, borrowed 15bn USD and would hold an emergency sale of its stock to raise 2.25bn USD (Board of Governors of the Federal Reserve System (2023)). The announcement caused significant concern among the bank's clients and investors. It was reflected statistically as a higher negative abnormal return on day -1 for large banks, especially banks with high levels of uninsured liabilities.

Furthermore, on trading day +1, we observed bigger abnormal returns again. This is linked to Signature Bank's failure, which occurred officially on March 12th.

From Table 3, it can be seen that the announcement of the bank's failure had a negative effect not only on the geographically close banks but also on the European ones. Although the European banks experienced an adverse impact on an expectedly reduced scale compared to the US banks, we still can observe that the failure of a large bank caused wider than national level panic, worldwide concerns about contagion and stability, and reassessment of risk across the global banking sector.

Analyzing CAR [-1, +1], the results indicate that larger banks were more adversely affected by SVB's failure than smaller banks, possibly due to their higher exposure and interconnectedness within the financial system, greater market sensitivity, and systemic risk concerns. In contrast, G-SIBs' higher resilience and global diversification provide a buffer to fight the panic.

Table 3. Failure of SVB: abnormal returns[4]

	Mean -1	Mean 0	Mean +1	CAR [-1, +1]	Max 0	Min 0	St.dev. CAR
Geography							
US	-0.0358***	-0.0178***	-0.0741***	-0.1277***	0.0789	-0.2003	0.06716
Europe	-0.0040**	-0.0128***	-0.0157***	-0.0325***	0.1492	-0.1338	0.02635
Size							
Small	-0.0116***	-0.0208***	-0.0550***	-0.0873***	0.0168	-0.0804	0.00730
Large	-0.0396***	-0.0173***	-0.0771***	-0.1341***	0.0789	-0.2003	0.04178
G-SIBs	-0.0127***	-0.0204***	-0.0361***	-0.0691***	0.0405	-0.0623	0.02749
Run-prone liabilities							
High	-0.0540***	-0.0184***	-0.1025***	-0.1749***	0.0789	-0.1889	0.07782
Med	-0.0323***	-0.0171***	-0.0690***	-0.1183***	0.0335	-0.2003	0.03672
Low	-0.0244***	-0.0179***	-0.0573***	-0.0997***	0.0281	-0.0804	0.04835
Liquid cash and securities							
High	-0.0323***	-0.0181***	-0.0669***	-0.1173***	0.0281	-0.2003	0.07782
Med	-0.0387***	-0.0152***	-0.0747***	-0.1286***	0.0789	-0.1889	0.03680
Low	-0.0336***	-0.0227***	-0.0802***	-0.1365***	0.0133	-0.1288	0.01988

Source: computed by the authors

[4] *, **, *** represents statistical significance at 10%, 5% and 1% level respectively

Banks with high run-prone liabilities experienced the most significant negative abnormal returns, with a mean of -10.25% on day +1 and a CAR of -17.49%. This suggests that banks with higher proportions of liabilities susceptible to rapid withdrawal (banks in an analogous situation as SVB) faced greater concerns during the crisis and that markets were able to factor in these characteristics. Regarding liquidity, banks with high levels of liquid cash and available-for-sale securities showed less severe negative returns, with a CAR of -11.73%, compared to those with low liquidity levels with a CAR of -13.65%. These findings highlight that banks with higher levels of liquidity succumbed to panic to a lesser extent as they had more buffers to cover the depositors' run.

Compared to SVB, the failure of Signature Bank represented the most significant negative return on the day of the event and not during the pre- or post-event periods (Table 4). This highlights the difference between the two cases regarding the availability of information and the surprise effect of the event. Before its collapse on March 12, 2023, there were no significant public warnings or news reports about the potential failure of Signature Bank. The closure of Signature Bank by New York state regulators came suddenly, driven by contagious panic and a rapid loss of deposits following the collapse of SVB. On the day of the SVB failure, Signature Bank's stock collapsed by (-22.8% daily return (Figure A1 in Appendix)). Negative abnormal returns on day -1 for the Signature Bank event study can be explained by the effect of the SVB failure (the 13^{th} of March 2023 is day +1 for the SVB event, and the 10th of March is day -1 for the Signature Bank event).

One of the reasons why SVB's failure had such an impact on Signature Bank is that these two banks had similar client bases and risk profiles (exposure to technology and cryptocurrency companies). SVB's collapse led to a loss of confidence in banks with a similar exposure. Besides, Signature Bank, like SVB, had a sizable proportion of deposits that were uninsured by the FDIC (89.7% uninsured domestic deposits at Signature banks vs. 93.9% at SVB as of Q4 2022). This made depositors more likely to panic and withdraw their funds (FDIC (2023)).

The surprise effect of this failure and a change in the perception of the systemic risk by the market participants can potentially explain the fact that while having smaller total assets than SVB and less interconnectedness, the mean abnormal returns on the trading day of the failure of Signature Bank was higher than for SVB. From the market perspective, one could consider that if only a single bank fails, it could be linked to a local event with limited impact on systemic risk caused by mismanagement or particular factors of the bank in question. However, the effect of having a sequence of major banks failing within days is the trigger behind such volatility, as it signals potential effects of contagion or common exposure.

Talking about the impact of Signature Bank's failure on other banks, it can be noticed that the cumulative abnormal returns are milder for all the groups due to positive abnormal returns on the posterior day of the event. Right after the failure of SVB, the Federal

Reserve announced the creation of the Bank Term Funding Program, aiming to provide additional liquidity to eligible depository institutions, thereby helping to stabilize the banking system (Board of Governors of the Federal Reserve System (2023)). This novelty helped mitigate some of the immediate market fears following the first failure, thus potentially reducing the negative effect of the second failure and the negative cumulative abnormal returns.

The distribution of the severity of impact depending on geography, size, and high or low levels of liabilities and liquid assets ratios was the same for the Signature Bank case as in the case of SVB, just on a smaller scale. It can be observed that the difference in negative CAR between banks with low and medium levels of run-prone liabilities is not substantial. However, banks with extremely high run-prone liabilities are notably more vulnerable to failures of banks with high uninsured liabilities.

Thus, we can conclude that the effect of the failure of a big bank has been consistent so far between the two cases with the highest negative impact on a large US bank, with a high level of run-prone liabilities and a low level of liquid cash and securities.

Table 4. Failure of Signature Bank: abnormal returns

	Mean -1	Mean 0	Mean +1	CAR [-1, +1]	Max 0	Min 0	St.dev. CAR
			Geography				
US	-0.0178	-0.0741***	0.0094***	-0.0826***	0.0297	-0.6156	0.05622
Europe	-0.0128***	-0.0157	0.0048***	-0.0237***	0.1809	-0.0985	0.00651
			Size				
Small	-0.0208***	-0.0550***	0.0032***	-0.0725***	0.0297	-0.1951	0.01385
Large	-0.0173***	-0.0771***	0.0103***	-0.0842***	0.0238	-0.6156	0.03909
G-SIBs	-0.0204***	-0.0361***	0.0029	-0.0535***	0.0258	-0.0882	0.02731
			Run-prone liabilities				
High	-0.0184***	-0.1025***	0.0090***	-0.1119***	0.0038	-0.6156	0.06250
Med	-0.0171***	-0.0690***	0.0146***	-0.0714***	0.0181	-0.4348	0.03495
Low	-0.0179***	-0.0573***	0.0023***	-0.0730***	0.0297	-0.1564	0.04160
			Liquid cash and securities				
High	-0.0181***	-0.0669***	0.0064***	-0.0786	0.0297	-0.2746	0.06250
Med	-0.0152***	-0.0747***	0.0070***	-0.0830	0.0238	-0.4688	0.03116
Low	-0.0227***	-0.0802***	0.0171***	-0.0858	0.0146	-0.6156	0.01961

Source: computed by the authors

The failure of the last large bank analyzed in this paper occurred more than a month after the failures described above. The first significant news about First Republic Bank's issues appeared around mid-March 2023. On March 16th, 2023, it was reported that a consortium of 11 major US banks placed 30bn USD in deposits at First Republic Bank (FDIC (2023)). This measure served as a gesture of support for the bank and confidence in the overall banking sector, trying to slow the pace of deposit outflow to mitigate the contagion effect following the failures of SVB and Signature Bank.

Despite the effort, the depositors continued withdrawing their funds, and the bank's share price entered a very volatile period. Earnings report with a lower-than-expected level of remaining deposits and public media attention around the topic unfavorably contributed to the bank's stock price dynamics. Thus, it can be said that this failure event did not come as a surprise, which is also reflected in the CAR numbers, which are less substantial than in the two previous cases (Table 5).

The highest negative impact was observed on day +1 of the event, as the market had already expected the bank to fail since mid-March and had already partly priced in this event. However, in this case, after the official failure announcement, the market took some time to fully price the effect of this failure until the following day.

In the First Republic Bank's case, the difference in the negative CARs is more minor between the banks with high and low ratios of run-prone liabilities. This can be partly attributed to the impact of the 11 banks' uninsured deposit injection and thus slightly increased confidence in the safety of the deposits. Besides, it is interesting to see that the difference in the event effect on the banks with high and low levels of liquid cash and available-for-sale securities becomes less pronounced. One possible explanation might be the effect of the introduction of programs like BTFP that provide liquidity support to banks that lack liquidity but hold high-quality assets.

Table 5. Failure of First Republic Bank: abnormal returns

	Mean -1	Mean 0	Mean +1	CAR [-1, +1]	Max 0	Min 0	St.dev. CAR
Geography							
US	-0.0015	-0.0203***	-0.0461***	-0.0680***	0.0839	-0.1958	0.00877
Europe	-0.0108***	<0.0001	-0.0065***	-0.0172***	0.2546	-0.0893	0.01284
Size							
Small	0.0015	-0.0175***	-0.0161***	-0.0321***	0.0366	-0.0707	0.00821
Large	-0.0020	-0.0208***	-0.0509***	-0.0737***	0.0839	-0.1958	0.00911
G-SIBs	-0.0029	-0.0001	-0.0099***	-0.0130***	0.0201	-0.0247	0.00754
Run-prone liabilities							
High	-0.0054	-0.0237***	-0.0502***	-0.0793***	0.0440	-0.1096	0.04115
Med	-0.0002	-0.0204***	-0.0462***	-0.0668***	0.0839	-0.1958	0.04882
Low	-0.0013	-0.0167***	-0.0419***	-0.0599***	0.0374	-0.1747	0.02877
Liquid cash and securities							
High	-0.0065	-0.0152***	-0.0426***	-0.0643***	0.0839	-0.1530	0.04115
Med	0.0035	-0.0208***	-0.0451***	-0.0624***	0.0440	-0.1747	0.01092
Low	-0.0064	-0.0247***	-0.0517***	-0.0828***	0.0366	-0.1958	0.04061

Source: computed by the authors

To conclude, the section on the large banks' failure impact on the other bank groups, these three cases have a similar failure situation with the fast withdrawal of funds by the depositors. However, they differ in how the market learned information and the final severity of the impact. In the case of SVB, the market learned the news two days before the event compared to the surprise event of Signature Bank and compared it to the very gradual realization of the possible failure of the First Republic Bank over more than one month. This impacted the event day with the highest abnormal return. As for the scale of the impact, SVB, viewed as the most interconnected and systemic one, has the highest negative cumulative effect on all the groups of banks compared to the other two failures.

3.1.4.2. Failure of a G-SIB

For the study of the impact of the failure of a G-SIB, the paper focuses on the failure of Credit Suisse (Table 6), which is the only failed G-SIB during the 2023 banking crisis. The bank was acquired by UBS on March 19th, 2023, after having suffered a bank run the week before the acquisition.

The paper's initial hypothesis was that the announcement of a G-SIB failure should have the most significant adverse effect on the other banks due to its systemic importance, given the higher level of total assets and interconnectedness of a G-SIB compared to that of large and small banks.

For the large and small US banks, the negative effect was observed mainly on day -1. The timeline of the events of Credit Suisse's failure was similar to what happened with the First Republic Bank. Credit Suisse had been facing issues for a prolonged period before its failure. The bank had multiple scandals and legal challenges that eroded market confidence over time. The bank's stock price was extremely volatile, reflecting the ambiguity of the bank’s future (Figure A2 in appendix); the biggest negative return on Credit Suisse’s stock price before its failure was observed on the 13th of March (-9.58%) and on the 15th of March (-24.24%), firstly, due to the mounting concerns over the bank’s liquidity and solvency and afterward followed by the continued depositor outflow.

These issues were widely known, and investors had time to adjust their expectations and risk assessments, which likely mitigated the shock of the bank’s failure on day 0. Moreover, some positive news appeared about the support packages and the optimistic fate of Credit Suisse. For example, on the 16th of March, Credit Suisse’s stock saw a significant rebound (+19.15%) due to the announcement of securing an emergency credit line of 50bn CHF from the SNB, which helped bolster confidence and stabilize operations (Credit Suisse press release).

Besides, the Swiss government was quick to react and support the failing bank, facilitating the acquisition by UBS. This gave the impression to the market that the systemic risk was being managed and contained. Besides, as the failed G-SIB was not headquartered in the US, US banks had less direct exposure to the specific issues plaguing Credit Suisse.

As shown in Table 6, the CAR for large US banks following Credit Suisse's failure is -1.21%, which, opposite to our initial hypothesis, is less severe than the CARs observed following the failures of SVB, Signature Bank, and First Republic Bank. This indicates that the market did not perceive Credit Suisse's acquisition announcement as significantly disrupting the broader US financial system. Additionally, the positive mean abnormal return on day +1 for large US banks suggests some recovery in market confidence shortly after the initial shock. The abnormal return is also positive for the G-SIBs on day +1, showing that the systemic banks didn't react negatively to the acquisition announcement as it highlighted once again to G-SIBs one of the possible more or less smooth ways out of the crisis and confirmed that if the bank is too big to fail, the government will be willing to take more facilitating measures.

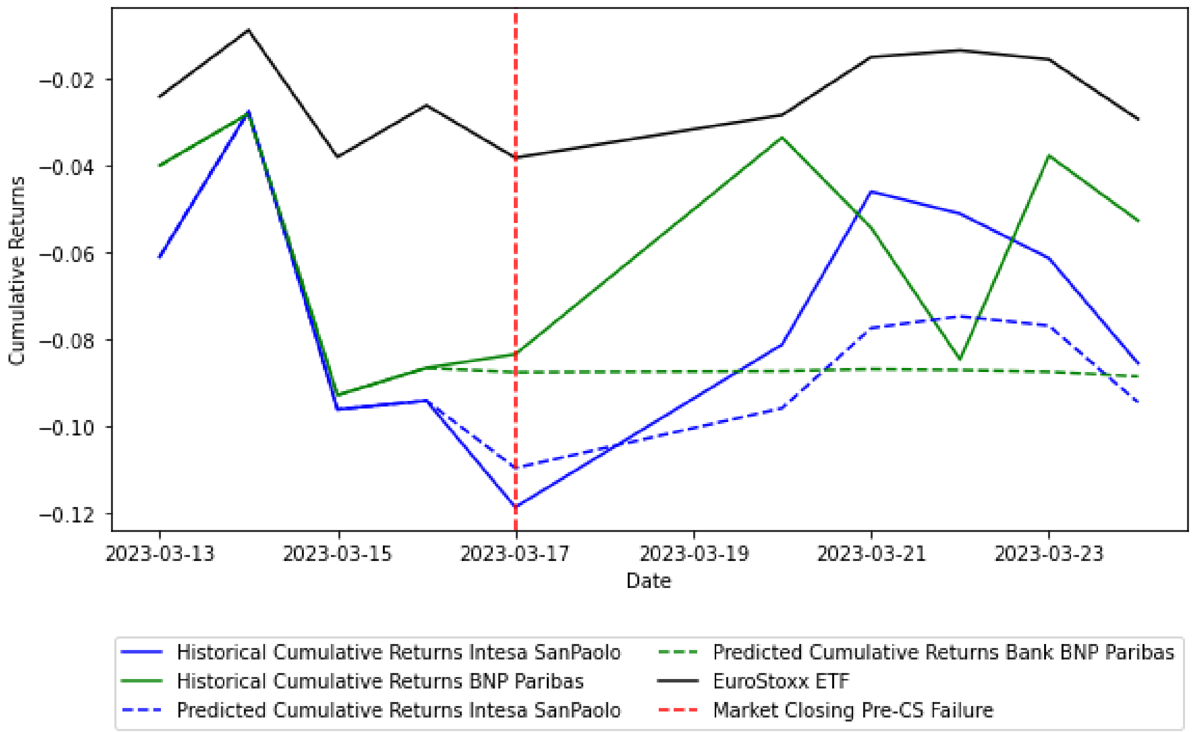
Table 6. Failure of Credit Suisse: abnormal returns

	Mean -1	Mean 0	Mean +1	CAR [-1, +1]	Max 0	Min 0	St.dev. CAR
Geography							
US	-0.0326^{***}	-0.0070^{***}	0.0264^{***}	-0.0132^{***}	0.0956	-0.4828	0.02742
Europe	-0.0046^{**}	-0.0002	0.0113^{***}	0.0066^{***}	0.1222	-0.0786	0.00796
Size							
Small	-0.0189^{***}	-0.0019^{**}	0.0090^{***}	-0.0117^{***}	0.0945	-0.0710	0.01715
Large	-0.0348^{***}	-0.0078	0.0291^{*}	-0.0134^{***}	0.0956	-0.4828	0.00839
G-SIBs	-0.0120^{***}	-0.0045^{*}	0.0165^{**}	-0.0001	0.0219	-0.0348	0.00477
Run-prone liabilities							
High	-0.0435^{***}	-0.0149^{*}	0.0370^{***}	-0.0215^{***}	0.0472	-0.4828	0.01838
Med	-0.0314^{***}	-0.0046^{***}	0.0260^{***}	-0.0100^{***}	0.0956	-0.0554	0.01497
Low	-0.0248^{***}	-0.0039	0.0164^{***}	-0.0123^{***}	0.0945	-0.0595	0.00320
Liquid cash and securities							
High	-0.0245^{***}	-0.0041	0.0165^{***}	-0.0121^{***}	0.0614	-0.1985	0.01838
Med	-0.0348^{***}	-0.0047^{**}	0.0291^{***}	-0.0104^{***}	0.0956	-0.0809	0.00591
Low	-0.0363^{***}	-0.0143^{**}	0.0310^{***}	-0.0196^{***}	0.0379	-0.4828	0.02466

Source: computed by the authors

From the result table for an expanded event window (Table A5 in appendix), it can be noticed that there was a persistent negative CAR of around 7% starting from day -5 of an event (13^{th} of March), afterward all the way to the day 0 of the event, the abnormal return fluctuated from negative to positive and back again reflecting the uncertainty in market sentiment and netting out the overall impact on CAR. Thus, the abnormal returns might seem to be low during the initially chosen 3-day event window; this can be due to the fact that the market had already priced in the shock when the first news about real liquidity problems appeared and viewed the acquisition announcement as a savior and not a system disruptive event.

Figure 1. Effect of CS failure on chosen European Banks



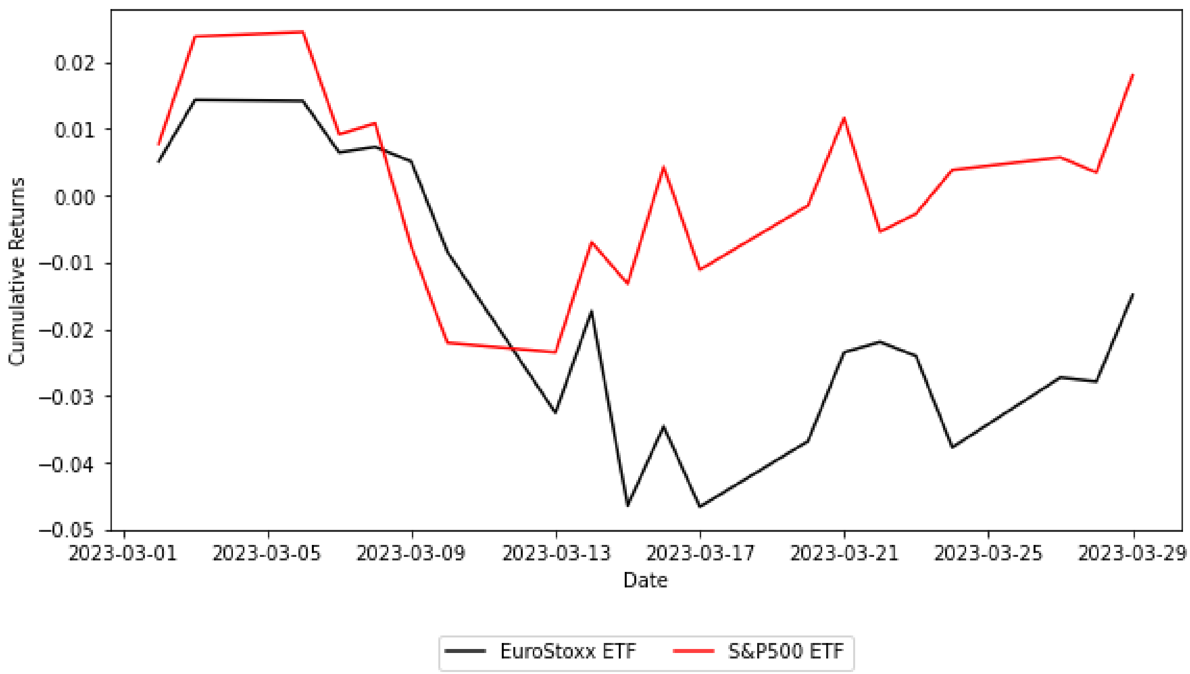
Source: computed by the authors

The impact of the anticipation effect of the Credit Suisse failure by the European banks can be observed in Figure 1. We present two examples of the historical and predicted cumulative returns for BNP Paribas and Intesa Sanpaolo, both of which had significant anticipation effects.

It can be observed that BNP Paribas suffered a decline of 6% in the days before the failure of Credit Suisse and recovered on the day of the failure 5%, well above the predicted returns using the market model.

For Intesa Sanpaolo, the Market Beta is relatively close to 1, meaning the stock is expected to trade at par regarding returns with the market index. On day -1, Intesa Sanpaolo performs worse than the market model but then recovers on days 0 and +1, in line with the results presented in Table 6. This could potentially be explained by Figure 2, which shows the cumulative returns for the S&P 500 ETF (SPY) and the Euro Stoxx 500 ETF in March. After the failures of SVB and Signature Bank, the S&P 500 recovered days before the failure of Credit Suisse, while for European stocks, the index continued falling in anticipation of Credit Suisse's problems, which led to a correction to the upside, on average, for the European Banks.

Figure 2. Cumulative returns for Euro Stoxx and S&P 500 ETFs



Source: computed by the authors

3.1.4.3. Small Bank Failures

Finally, two small banks that failed after the major wave were Heartland Tri-State Bank at the end of July and Citizens Bank at the beginning of November. The paper hypothesizes that the market does not perceive small banks as important enough to cause any distraction or systemic risk in the financial system.

Looking at the event study results for the Heartland Tri-State Bank, we could confirm the hypothesis expressed above (Table 7).

Heartland Tri-State Bank primarily served a local, rural community in Kansas. The bank's operations and customer base were geographically concentrated, meaning its failure had a limited regional impact rather than a national or international (Board of Governors of the Federal Reserve System (2024)).

Besides, this bank failure was not associated with contagion, panic, and depositors' run; it was primarily caused by internal problems, such as the bank’s CEO's accusations of fraud in cryptocurrency schemes. Thus, the market did not view this failure as a sign of broader financial instability.

Table 7. Failure of Heartland Tri-State Bank: abnormal returns

	Mean -1	Mean 0	Mean +1	CAR [-1, +1]	Max 0	Min 0	St.dev. CAR
Geography							
US	-0.0024	0.0020	-0.0057**	-0.0061***	0.0929	-0.1461	0.01942
Europe	-0.0109***	-0.0022	0.0009	-0.0122***	0.0444	-0.2883	0.00809
Size							
Small	0.0023*	0.0011	0.0094***	0.0129***	0.0765	-0.0371	0.01145
Large	-0.0031	0.0021	-0.0081***	-0.0091***	0.0929	-0.1461	0.00130
G-SIBs	-0.0004	0.0031	0.0081***	0.0108***	0.0497	-0.0243	0.00801
Run-prone liabilities							
High	-0.0075***	0.0048**	-0.0102**	-0.0128***	0.0610	-0.0406	0.02400
Med	0.0009	0.0021	-0.0027	0.0003***	0.0929	-0.1461	0.01171
Low	-0.0040	-0.0007	-0.0061*	-0.0108***	0.0380	-0.0832	0.01508
Liquid cash and securities							
High	-0.0015	0.0028	-0.0099	-0.0086***	0.0765	-0.1461	0.02400
Med	-0.0035**	0.0025	-0.0050**	-0.0060***	0.0929	-0.0596	0.00549
Low	-0.0011	0.0003	-0.0030	-0.0038***	0.0506	-0.0832	0.01072

Source: computed by the authors

Looking at the results for the Citizens Bank case (Table 8), we can observe the existence of some unusual positive abnormal returns on the day of the event that were not present in the previous cases. The bank was smaller by the size of the total assets than Heartland Tri-State Bank, with a limited national and mostly regional focus. Significant losses in the bank's loan portfolio battered the bank's equity position and led to insolvency. Thus, in this case, the problem that caused the failure was not depositor-run and lack of liquidity but realized loan losses (according to a memo of the Office of Inspector General (2024)).

Table 8. Failure of Citizens Bank: abnormal returns

	Mean -1	Mean 0	Mean +1	CAR [-1, +1]	Max 0	Min 0	St.dev. CAR
Geography							
US	0.0308***	0.0320***	-0.0047	0.0582***	1.0515	-0.0753	0.00967
Europe	-0.0001	0.0025	0.0087**	0.0110***	0.1278	-0.3384	0.00248
Size							
Small	-0.0022***	0.0072***	0.0043**	0.0093***	0.1361	-0.0362	0.00537
Large	0.0360	0.0360	-0.0061	0.0659***	1.0515	-0.0753	0.00679
G-SIBs	0.0081***	0.0092***	-0.0051**	0.0122***	0.0382	-0.0096	0.00675
Run-prone liabilities							
High	0.0241**	0.0531***	-0.0062	0.0710***	1.0515	-0.0285	0.02577
Med	0.0402**	0.0234***	-0.0049*	0.0587***	0.0844	-0.0753	0.01941
Low	0.0197***	0.0283***	-0.0026	0.0453***	0.1553	-0.0250	0.01541
Liquid cash and securities							
High	0.0488	0.0204***	0.0115	0.0807***	0.0989	-0.0753	0.02577
Med	0.0270***	0.0333***	-0.0090***	0.0513***	0.9876	-0.0362	0.00212
Low	0.0204***	0.0412***	-0.0124***	0.0492***	1.0515	-0.0285	0.01891

Source: computed by the authors

This bank's failure is unlikely to be noticed by large US banks to the extent of 6.59% of the cumulative abnormal returns. This result seems to be impacted by the other important announcements that happened during the event window. On November 2nd, 2023, after two years of fighting inflation and tightening monetary policy, the world's three major central banks (the US Federal Reserve, ECB, and BoE) kept the interest rate without increasing it (Reuters (2023)). Thus, it shows signs of possible recovery and potential for future quantitative easing. We deem this event to be the main driver of the positive abnormal returns on day -1 and day 0. This announcement was especially favorable for banks with a high level of uninsured liabilities and a high level of securities.

We can conclude the section about the impact of one bank's failure on the other banks by saying that not all of our hypotheses were confirmed by the results obtained from the event studies. We hypothesized that the impact of a G-SIB failure would be the most significantly negative one, followed by the failure of a large bank, and only then the negligent or slightly negative impact of a small bank's failure. However, as it was seen, the effect depends not only on the market perception of the systemic importance of the bank but also on the geography and nature of the bank's business, prior market expectations on the possibility of failure, and, most importantly, the surprise effect of the failure event.

With the event studies, we tested another two hypotheses about the effect of the failures on the banks with high and low runnable liabilities and available liquidity, confirming that the most significant negative impact of all the failures was observed for the banks with high run-prone liabilities. This emphasizes the importance of trust in avoiding negative systemic events in the financial system. There was a lack of trust among uninsured depositors in the SVB's case, spreading panic among the uninsured depositors of other banks, increasing the systemic risk, and hurting the financial system. As for the second hypothesis regarding the liquid cash and available-for-sale securities ratios, the results show that banks with a low level of liquid assets that could be used to cover the deposit withdrawals are more sensitive to the other banks' failures and risks in the financial system.

The efforts of the governments and the financial institutions softened the negative impact of systemic risk by injecting indispensable liquidity and supporting faith in the stability of the financial institution at risk. Moreover, the negative effects of the crisis were mitigated not only by the liquidity injections and support packages from the governments but also by their timely interventions to facilitate the sale of the assets of the failing banks. For instance, with the help of FDIC, Silicon Valley Bank's assets were sold to First Citizens Bank, Signature Bank's assets were acquired by Flagstar Bank, and First Republic Bank's assets were taken over by JPMorgan Chase. These rescues helped stabilize the affected banks and restore confidence in the financial system, thereby preventing a more severe systemic fallout.

3.2. Cross-sectional model

According to the event study methodology from Campbell et al. (1997), to investigate the relationship between the cumulative abnormal returns and the bank-specific factors defined (such as size, the ratio of run-prone liabilities, and the ratio of highly liquid assets), we run a cross-sectional regression of 3-day cumulative abnormal returns on these factors.

The cross-sectional formula used for this event study is the following:

$$CAR_i = \alpha + \alpha_A * X_A + \alpha_L * X_L + \alpha_C * X_C + \epsilon$$

Where:

- CAR_i represents the cumulative abnormal return on the day *i* of the Event window
- α_j represents the regression coefficient for each independent variable
- X_A represents the value of the bank's assets in dollars
- X_L represents the percentage of run-prone liabilities over total liabilities
- X_C is the percentage of liquid cash and securities over total assets

In Table 9, we present the cross-sectional parameters for the CAR on day +1 of the event window. From the results, it can be concluded that the failure of a large bank impacts other banks negatively, having a significant impact on larger banks (statistically significant values). Besides, the most important finding of this cross-sectional model is that the factors of larger size and especially higher levels of run-prone liabilities contributed significantly to the cumulative negative returns during the events of the large bank failures, while the factor of a high ratio of cash and available-for-sale securities partly compensates for the strong negative effect of the likely-to-be-withdrawn liabilities.

Table 9. The effect of banks' failures on CARs of tested banks on days [-1, +1]

	G-SIB	Large			Small	
	Credit Suisse	SVB	Signature	First Republic	Heartland Tri-State	Citizens
Constant	0.013292	-0.04406**	-0.05247***	-0.040054***	0.004191	0.004523
Size	4.2E-08	-2.7E-07***	-1.9E-07***	-6.4E-08	-5.6E-08	1.1E-07
Run-prone liabilities	-0.06087***	-0.22874***	-0.080886**	-0.08725***	-0.016412	0.10815
Cash and securities	-0.023706	0.040315*	0.022852*	0.031561	-0.014757	0.058654
R squared	0.0319	0.1457	0.0738	0.0412	0.0116	0.0118

Source: computed by the authors

As hypothesized above, the high levels of available liquidity could provide a buffer to the bank run and create some additional depositors' confidence in the bank's stability, highlighting the importance of managing run-prone liabilities by the levels of liquidity to lower the systemic risk of a bank run, although the results obtained had low levels of significance, indicating that the factor does not play such a key role in the behavior of the return.

Relatively high R-squared values for the large banks indicate a good model fit, while lower values for the events of Credit Suisse (discussed above), Heartland Tri-State, and Citizens Banks suggest that other factors may influence CARs for these events.

Furthermore, the three large banks have significant negative coefficients for the constant parameter; this discrepancy highlights the need to consider additional variables or context-specific factors.

Overall, the cross-sectional regression analysis in the table provides insightful evidence of how numerous factors contribute to banks' CARs during periods of financial distress. This information can be useful in characterizing the banks that are first in line to face adverse consequences of the financial system's instability. However, it is important to acknowledge limitations, such as the potential omission of other influential factors.

3.3. Significance and robustness

The last step of our event study is to verify the significance and robustness of the results. We compute a test statistic to verify if the abnormal returns of the event study are significantly different from 0. To compute the t-stat, we divide the mean abnormal return by the standard deviation divided by the square root of the number of observations $\frac{\frac{\sum AR}{N}}{\frac{\sigma_{AR}}{\sqrt{N}}}$.

We have checked the statistical significance for 1% (t-value of ±2.576), 5% (t-value of ±1.96), and 10% (t-value of ±1.645) levels. The statistical significance levels have been presented with the stars in all the abnormal return tables in the previous sections (*, **, *** represent statistical significance at 10%, 5%, and 1% levels, respectively). Thus, the abnormal returns for all three large US bank failures are significantly negative across most categories, with the majority being highly significant at the 1% level. This indicates a strong market reaction to the large bank failure events, reflecting a loss in confidence in the banking system across different bank segments. For the small banks, there is a mix of significance levels, with fewer instances of 1% significance and more at the 5% and 10% levels. The difference in significance levels underscores the varying market responses to bank failures of varied sizes, as the negative abnormal returns are statistically significantly different from zero for large bank failures and not always statistically different from zero for small bank failures.

To ensure the robustness of our event study, we have expanded the event window to encompass a wider range of trading days, specifically [−5, +5] around the event date. As explained above, the initial small event window was chosen in order to eliminate the impact on CARs of one event from the other due to the close-in-time failure events of the large banks. The expanded window allows us to capture a more comprehensive picture of market reactions, the robustness of the normal return model, and the persistence of abnormal returns. The abnormal returns and CARs are presented in Table A5 in the appendix. The data reveals that sample mean abnormal returns ($\bar{e}^*$) and CARs fluctuate significantly from 0 around the events, reflecting varied market sentiments and investor behaviors. Specifically, the results show significant negative abnormal returns immediately around the event date (day -1, day 0), with persistent effects observed on the following day (day +1). For example, the CAR for large banks such as SVB and Signature shows substantial negative returns immediately after the event (and negligent abnormal returns before the initially defined 3-day event window), indicating strong market reactions and concerns over potential systemic risk. In contrast, smaller institutions like Heartland Tri-State and Citizens exhibit more muted reactions even over the expanded event window, consistent with their lower systemic importance. Overall, the robustness of our event study is reinforced by the fact that when expanding the event window, the CARs remained statistically significant and in the expected negative direction. This approach enhances the credibility of our conclusions regarding the impact of bank failures on market stability and systemic risk.

Besides, to ensure the robustness of our normal return model for the US banks, where we employed the S&P 500 index as the primary benchmark for calculating expected returns, given its broad market representation, we conducted additional checks using alternative indices. Specifically, we compared our results with those derived from the MSCI World Index and the Dow Jones U.S. Bank Index. While the R-squared value for the MSCI World Index was lower, indicating a poorer fit and less explanatory power for our data, the Dow Jones U.S. Bank Index yielded a higher R-squared value. However, despite the better fit, the Dow Jones index was not as representative of the overall market behavior due to its narrower composition. This comprehensive validation underscores the robustness of our model, confirming that the S&P 500 index provides a reliable and representative benchmark for our event study, ensuring credible and accurate reflections of market responses to bank failures.

For the consistency check, the mean historical returns of the diverse groups of banks were presented for each of the failure events considered above (Appendix 6). It was verified that the abnormal returns remain within the reasonable deviation range from historical returns across various bank groups and event days in the event window defined. Besides, by looking at the real returns of the indexes (S&P 500 and MSCI World) that the normal return model is based on (Appendix 5), it can be said that during the event window for the large banks (SVB and Signature Bank), the indexes also performed negatively, however as there was still significant abnormal return registered during this period for the banks, this implies that the failure event had a higher impact on banks than on a broader market.

4. Part 2: Unrealized losses and bank-run equilibrium formula

Bank defaults in 2023 were triggered by a significant decline in bank assets' value due to the increase in interest rates and poor risk management. For example, SVB, the bank, held considerable positions in US government long-term bonds prior to the interest rate hikes, quickly converting into a hole worth 34bn USD in unrealized losses. As discussed above, this, coupled with the fact that almost 90% of their liabilities were unsecured, sparked a bank run that SVB could not cover by liquidating assets.

The effect of interest rate hikes on banks' unrealized losses and equilibrium has been analyzed by Jiang et al. (2023). Unrealized losses and depositor run happen due to factors out of the control of a bank as it alone cannot influence how the regulators raise interest rates and the level of depositors' confidence in the overall financial system. Thus, the systemic risk emerges and causes simultaneous distress and failure of multiple banks.

In our paper, we aim to connect the external market view (market perception and prediction) about the fragility of banks following systemic events with the internal analysis of the banks' financial health to predict the emergence of fragility in the banking system.

Previous literature studied the effects and causes of bank failures in 2023, with an article by Van Denburg and Harmelink (2024) analyzing the effect and shortcomings of the held-to-maturity approach of accounting for securities, which hides the reality of unrealized losses. Banks do not include them in their financial statements for securities classified as held-to-maturity. We test whether this effect was observed or not by the market participants applying a cross-sectional model of the computed cumulative abnormal returns.

4.1. Unrealized losses

We follow the methodology described by Jiang et al. (2023) to estimate the assets' unrealized losses. We collected bank asset repartition reporting data from the FDIC call reports for all the FDIC-insured US banks for Q1 2022 (4861 banks). This data comprises assets split by type and by maturity: RMBS, other debt securities such as US Treasury securities and non-MBS Government obligations, closed-end loans, and all other loans, each of these split by maturities of less than 3 months, between 3 and 12 months, between 1 and 3 years, between 3 and 5 years, between 5 and 15 years, and more than 15 years); CMBS split by maturities of less than 3 years and more than 3 years; debt securities with remaining maturity of 1 year or less. To account for the losses level across various maturities, we utilized the iShares US Treasury Bond ETFs and the S&P Treasury Bond Indices, reflecting price declines for different maturities. The marked-to-market loss was computed for each bank following the equation presented below:

$$MTMLoss = \sum_t \begin{matrix} RMBS\ Multiplier * (RMBS_t + Mortgage_t) * \Delta Treasury\ Price_t \\ + Treasury\ and\ Other\ Securities\ and\ Loans_t * \Delta TreasuryPrice_t \end{matrix}$$

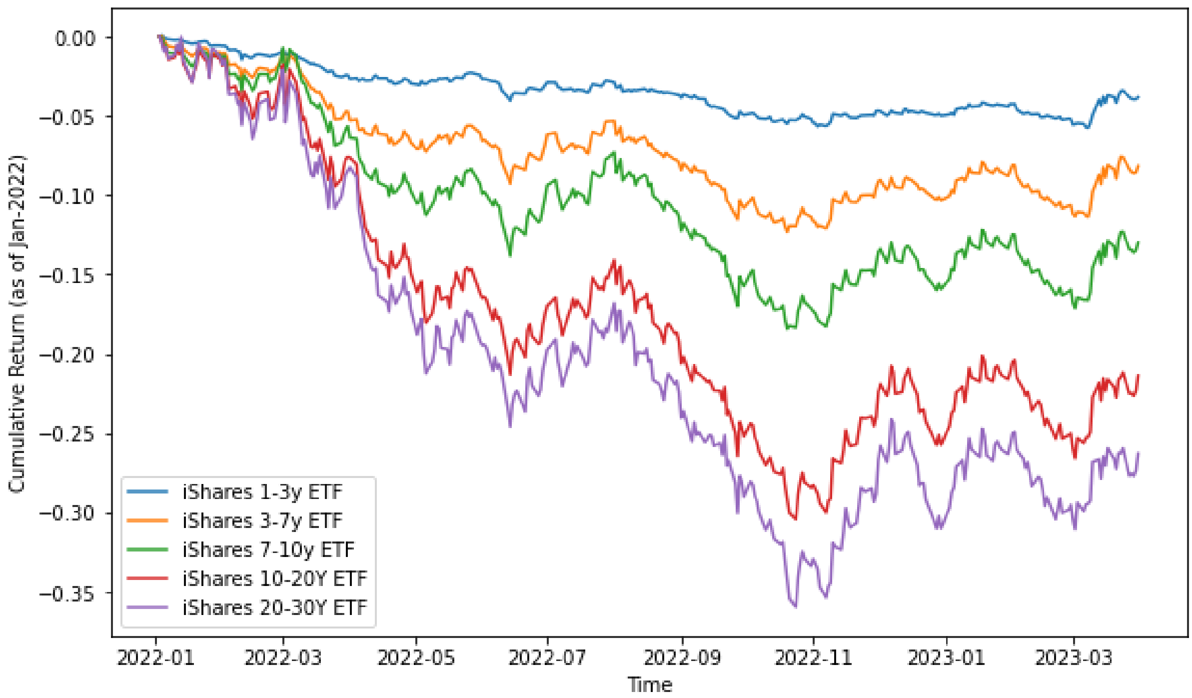
Where $RMBS\ Multiplier = \frac{\Delta iShare\ MBS\ ETF}{\Delta S\&P\ Treasury\ Bond\ Index}$

The RMBS multiplier takes the average of the market price changes for RMBS and treasury bonds across all maturities to reflect the additional risk of RMBS and residential mortgages due to prepayment risk.

Given the substantial amounts of data available, our paper computes the losses daily instead of quarterly, allowing us to identify pockets of considerable risk that would be ignored if analyzed quarterly.

Securities with longer terms incurred the largest loss, as presented by the cumulative return of the iShares US Treasury Bond ETFs across different maturities (Figure 3). Banks holding significant positions in longer-term assets as of the beginning of 2022, such as SVB, suffered a significant decline in portfolio valuation, which stresses the bank's inability to cover its liabilities.

Figure 3. Cumulative returns for iShares ETFs from Q1 2022 to Q1 2023[5]



Source: compiled by the authors from Bloomberg

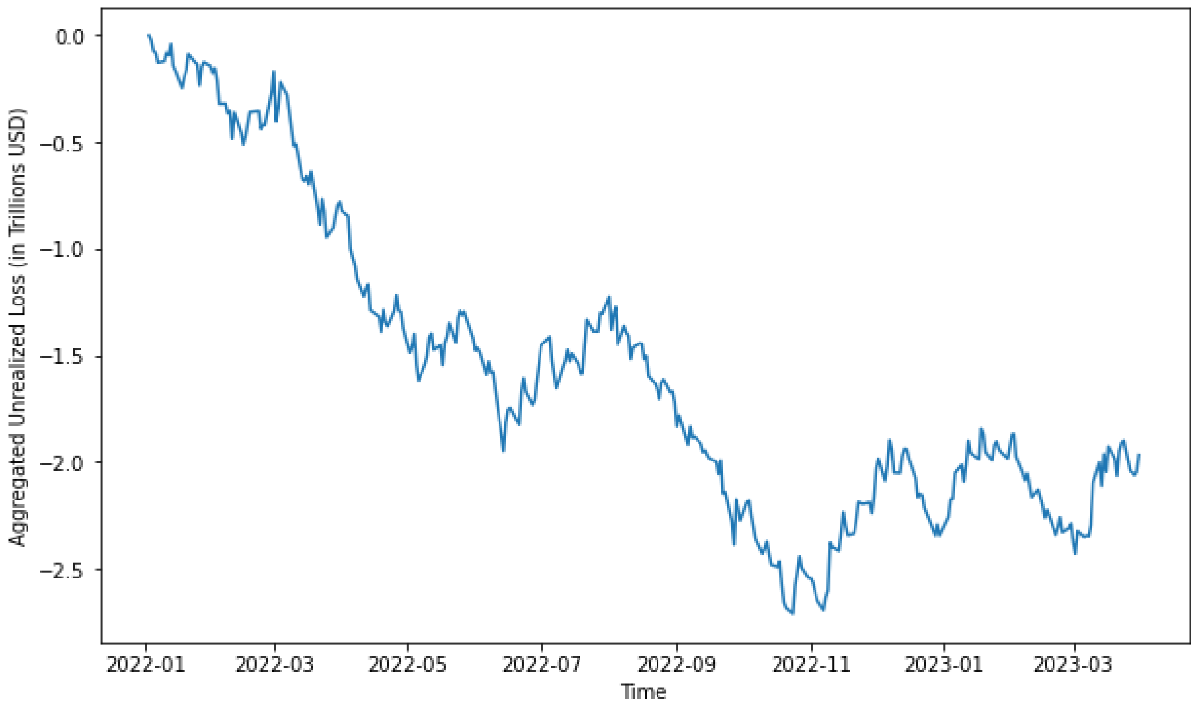
By computing the losses daily, we can identify a moment in which risk for the banks was higher than in Q1 2023, which was not presented in Jiang et al. (2023). Given the sharp recovery of bond indexes by the end of Q4 2022, following strong market sentiment and

[5] As a percentage change

the FED's dovish signals, the decline around October-November 2022 was not considered.

Our results yield the maximum of total US banks' unrealized losses estimate of around 2.6 trillion USD by the end of October 2022, which then recover to 2.0 trillion USD by late December 2022 and decline to an unrealized loss of around 2.2 trillion USD in March 2023. The findings are in accordance with Jiang et al. (2023) regarding aggregated losses of around 2.2 trillion USD by late Q1 2023, as shown in Figure 4.

Figure 4. US bank aggregate marked-to-market loss



Source: computed by authors

Having computed the unrealized marked-to-market loss, we proceed with the calculation of aggregated loss, the average loss per bank, and the number of banks at risk of failure considering four bank run scenarios: 50% of uninsured depositors run, 100% of uninsured depositors run, 100% of uninsured depositors run and 0.4% fire sale discount[6], and lastly, all asset liquidation. We identify the number of banks at risk of failure for the day of maximum unrealized losses (24 October 2022) and compare it to the same scenarios in Q1 2023 (when the failures happened).

[6] The 0.4% fire sale discount number is taken according to Jiang et al. (2023) calculation contemplating that in the SVB case, without accounting for any fire sale discount, even if all the uninsured depositors run, the bank should have been able to survive without impairing any of the insured deposit accounts. However, this was not the case in reality due to the existence of at least a slight fire sale discount, and with at least 0.4% SVB would have to impair the insured deposits. As SVB was the starting point of the bank crushes, we create a scenario with the same run characteristics: 100% of the uninsured depositor run and a 0.4% fire sale discount to identify the number of banks at risk of failing.

To perform the calculations presented below, we used FDIC call report data for Q4 2022 regarding the amounts of total assets and insured and uninsured liabilities. The reason behind using the assets as of Q1 2022 is to have a better estimate of the unrealized losses as the quantitative tightening began in March 2022, while we use the liabilities as of Q4 2022 to account for any potential deposit withdrawals prior to the failure of the first banks. This allows for a more accurate assessment of the unrealized losses that might have accumulated since the start of interest rate hikes while considering the most recent changes in deposit and total asset levels before the failure event.

The risk of failure is assessed by the bank's inability to cover its liabilities in the case of all assets liquidating or by its inability to cover its run-prone liabilities in the case of bank runs. The coverage ratios are therefore measured as follows:

In case of total liquidation:

$$Liabilities\ Coverage\ Ratio = \frac{(Total\ Assets -\ MarkedtoMarketLoss - Total\ Liabilities)}{Total\ Liabilities}$$

For the bank-run case:

$$Insured\ Deposit\ Coverage\ Ratio = \frac{(Total\ Assets -\ MarkedtoMarketLoss - s * Uninsured\ Deposits - Insured\ Deposits)}{Insured\ Deposits}$$

s is the percentage of depositors that are “awake,” meaning that they would be active in retiring their deposits in the event of a run, as defined by Jiang et al. (2023).

We find that the number of banks at risk of failure by the end of October 2022 was significantly higher than our results for Q1 2023 (Table 10 and Figure A3 in the appendix).

Table 10. Unrealized total assets losses for different run and insolvency scenarios

	24 October 2022				Q1 2023			
Scenario	All Assets Liquidate	0.4% Fire Sale	100% of depositors run	50% of depositors run	All Assets Liquidate	0.4% Fire Sale	100% of depositors run	50% of depositors run
Aggregate Loss (USD)	2.71 T	1.35 T	1.21 T	135 B	2.22 T	1.07T	1.03 T	109 B
Loss per Bank (USD)	514 M (7,712 M)	596 M (10,648M)	604 M (10,495M)	335 M (3,385 M)	458 M (6,863 M)	575 M (9,551 M)	583 M (9,586 M)	352 M (3,405 M)
Banks at risk (#)	2499	2271	2006	403	1899	1856	1770	309

Source: computed by the authors

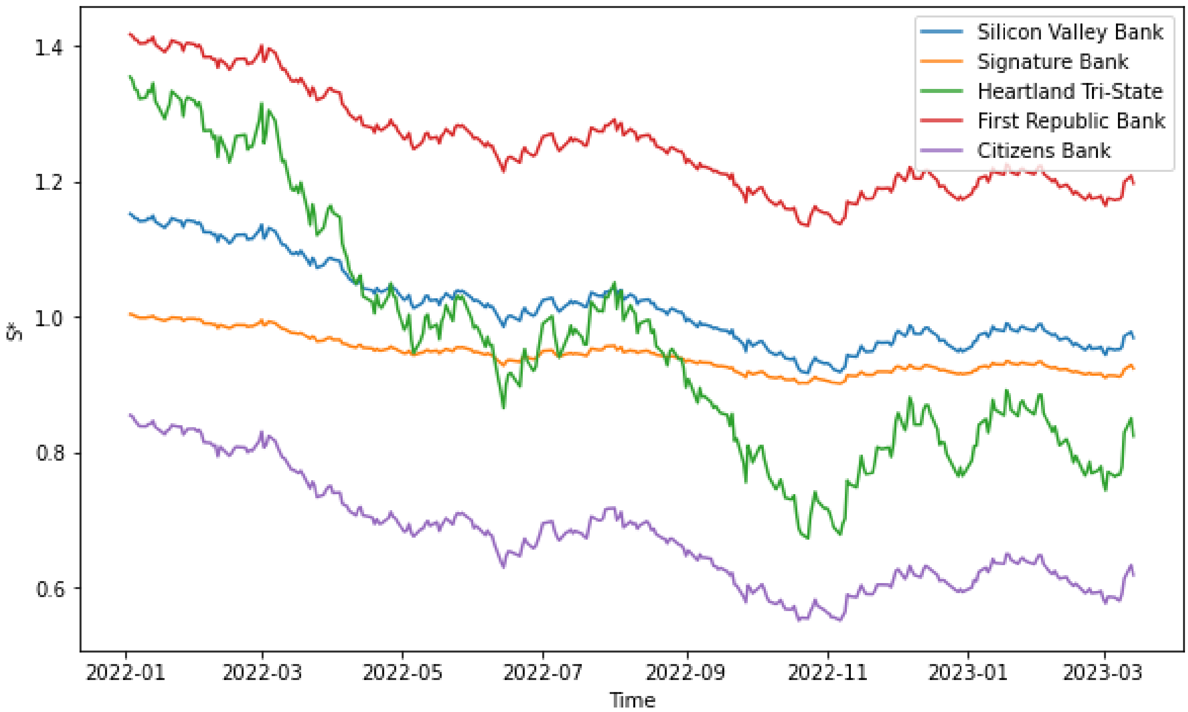
It can be concluded that the depositors take some time to adapt their behavior to the market conditions and circulating concerns among other depositors about the stability of their bank. It can be that depositors are not able to accurately assess the bank’s coverage ratio of deposits, as the failures occurred in March 2023 rather than October 2022, and only a fraction of the banks at risk suffered runs and eventual failures. Thus, it can be explained by two possible depositor behaviors. Firstly, depositors are not completely rational and run under the other (than insufficient coverage) “awakening” factors such as the influence of the general loss of trust and spreading panic around them (as the articles (such as Spitler (2024)) point out for the case of SVB and Credit Suisse). Secondly, the deposit withdrawals can be entirely rational. During market turbulence, depositors decide whether to keep or withdraw their money, considering the threshold of withdrawals, after which the bank might not have enough assets and thus defaults. If depositors believe this threshold might be surpassed, they are better off withdrawing as well, thus performing a rational bank run (Diamond and Dybvig (1983)).

To briefly analyze the matter of rational or irrational panic, we calculated an indicator of s* evolving over time for several failed banks (Figure 5). s* represents a threshold of the share of withdrawn deposits surpassing which the rational depositor should withdraw their funds (if more awake depositors s than the threshold level s* withdraw their funds (s > s*), the bank cannot survive). It is calculated according to the following formula:

$$s^* = \frac{Total\ Assets - \ MarkedtoMarketLoss - Insured\ Deposits}{Uninsured\ Deposits}$$

Figure 5 shows the periods of declining withdrawal coverage thresholds and should reflect growing depositors' concerns. Thus, for the SVB example, if the bank had the possibility to sell its assets at market fair value (marked-to-market), it could cover all of its uninsured deposits, except at the bottom in late October 2022, where s* < 1.

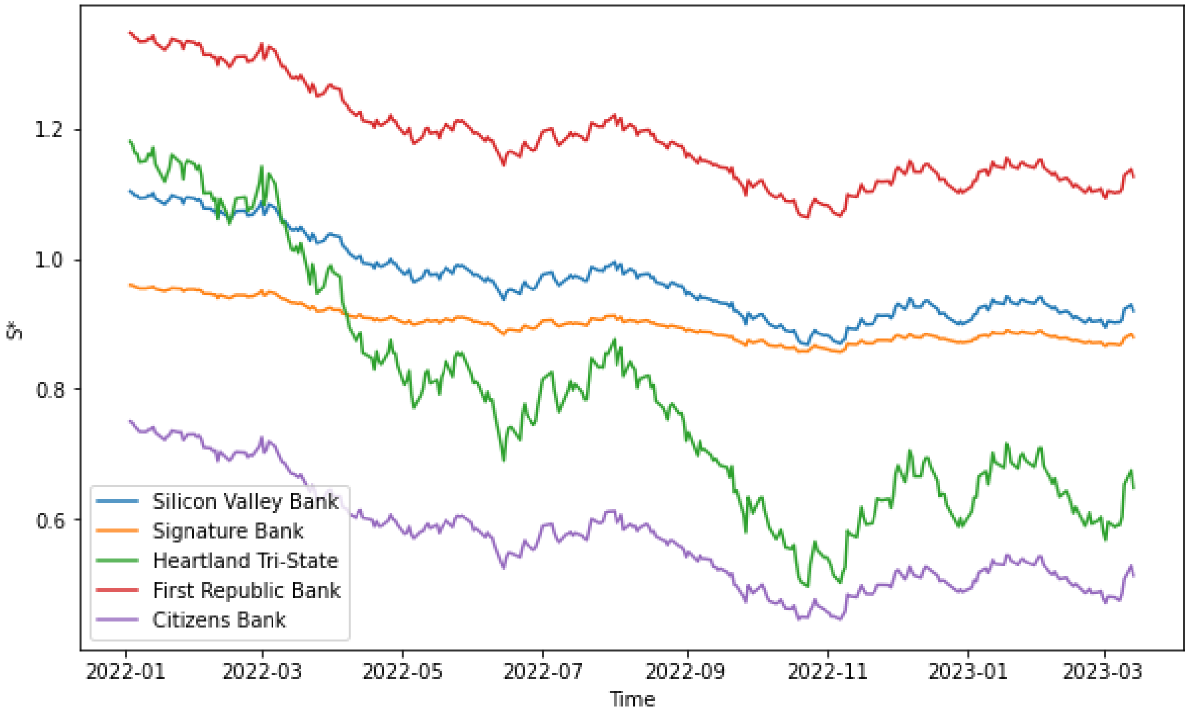
Figure 5. Evolving level of s for the failing banks during 2023*



Source: computed by the authors

If a bank is required to sell part of its assets due to liquidity concerns, it is typically the case that the market will be applying a discount over the fair market value of these assets. This discount can be substantial given the risk of the assets (uncertainty with the direction of interest rates, potential defaults, and so on) or the signaling of trouble (smelling blood in the water). Using a fire sale scenario of 0.4%, the value of s* for SVB would be under 1 for Q1 2023, as shown in Figure 6. Thus, according to our analysis, it can be said that the runs on the failed banks have been mostly rational, even with a small fire sale discount applied, except for the First Republic Bank case. This can be due to both factors: a larger amount of the fire sale discount or more panic-induced behavior of the depositors, as this failure happened a month after the first two large ones, giving the depositors a moment to reflect on the consequences SVB's and Signature Bank's depositors were facing and prompting them to act in a more protective and preventive manner, not necessarily the most rational one.

Figure 6. Evolving level of s for the failing banks during 2023 for the fire-sale scenario*



Source: computed by the authors

A scenario of 0.4% seems conservative, given that the buyers of such assets are typically other financial institutions that are well informed about the situation with potential rate hikes and understand the urgency of the liquidity requirement. Thus, there can be a lot more various scenarios built regarding the higher fire sale discount leading to a decline in the level of s*. Thus, the depositor can 'awaken' faster and rationally withdraw their funds.

To conclude this section, it can be said that a significant decline or volatility in a bank's stock price, concerns about a bank's financial health, macro environment, and so on can trigger depositors to withdraw their funds. This can force banks to liquidate positions at a loss or seek additional financing, both of which serve as stronger signals of distress and a high level of risk in the system and can lead to a self-fulfilling run. The analysis of unrealized losses on bank assets reveals how holding long-term securities in the rising interest rate environment led to significant declines in portfolio valuations, highlighting the vulnerabilities within bank balance sheets. This internal weakness made banks susceptible to liquidity issues, potential failure, and the development of systemic risk when faced with external pressures. The observed negative CARs in Part 1 for banks with higher run-prone liabilities and lower available-for-sale securities and cash indicate how markets adjust to perceived risks, reinforcing the connection between external market reactions and internal vulnerabilities.

4.2. Insured depositor runs

In the previous section, we examined the threshold s* for uninsured depositors to commit a rational bank run. Jiang et al. (2023) consider that only uninsured depositors are "awake". Nowadays, with the effects of digitalization and the velocity and accessibility of news, it is reasonable to think that some insured depositors should also be regarded as "awake". Even though their deposits are safe initially, due to a lack of information about deposit withdrawals and coverage ratios, a run can be initiated and become self-fulfilling, making the withdrawal of insured deposits reasonable.

In countries like Spain (e.g., Banco Popular) and Greece (e.g., Panellinia Bank, Piraeus Bank), banks have suffered runs on their insured depositors due to a lack of trust in the insurance scheme.

We have tested a revision to the equilibrium formula, which includes a coefficient to reflect awake insured depositors, which might be relevant for extreme cases of worsened financial environment and depositor panic or for banks with low uninsured deposits:

$$e_{run}(r_f) = e_b + (1-c)\cdot\Delta a(r_f) + \left(l_i(1-s_i) + l_u(1-s_u)\right)\cdot\Delta f(r_f)$$

With:

- e_b is the bank's equity, which is computed as $1 - l_u - l_i$
- l_u represents the uninsured leverage
- l_i represents the insured leverage
- e_b is a bank's equity, computed as $1 - l_u - l_i$
- c the fraction of safe assets
- s_i is the fraction of insured depositors that are awake. We assume that $s_i < s_u$.
- $s_u$is the fraction of uninsured depositors that are awake, which is equivalent to s in Jiang et al. (2023) formula

- $\Delta a(r_f)$ is the change in value of the assets as a function of the risk-free rate
- $\Delta f(r_f)$ is the change in deposit franchise as a function of the risk-free rate

The run equilibrium is then given as:

$$e_b + (1-c) \cdot \Delta a(r_f) + (l_i + l_u) \cdot \Delta f(r_f) < s_u l_u \Delta f(r_f) + s_i l_i \Delta f(r_f)$$

The original formula from Jiang et al. (2023) which does not include the variable s_i is sufficient to show that most of the banks that suffered bank runs in 2023 (considering fire sale for the case of SVB) were not above the run equilibrium threshold. The formula fails to capture the risk of failure of banks with high percentages of insured deposits, for example, Banco Popular's failure.

As of 2017, Banco Popular had 31.5bn EUR in securities, 92.5bn EUR in gross loans, and around 500m EUR in real estate assets (down 400m EUR year on year). Most of its deposits were insured, approximately 80% insured deposits/total deposits, with 75bn EUR and 19bn EUR in insured and uninsured deposits, respectively.

Banco Popular’s valuation report for the Single Resolution Board by Deloitte reevaluated its assets to the downside by -21.5bn EUR in the Best-Case scenario and -25.9bn EUR in the Worst-Case scenario.

Banco Popular would have remained at equilibrium event with a 100% uninsured depositor run and assets marked to market. With the equation proposed and with $s_u = 100\%, s_i > 10\%$, the bank equilibrium is breached in both the best and worst-case asset revaluation scenarios.

Thus, by revising the equilibrium formula to include a coefficient for "awake" insured depositors, the analysis acknowledges the evolving nature of the behavior of different types of depositors in a digital age. This internal factor could potentially push the average s* withdrawal threshold of insured and uninsured depositors lower, causing more instances when it can be reasonable to withdraw the funds. Thus, more banks would be at risk of a run and contribute to the development of systemic risk in banking.

The formula presented by Jiang et al. (2023) is, therefore, used to compute the equilibria threshold, given that most depositors consider the US insurance scheme trustworthy. We then don’t consider the variable s_i as relevant for computing banks at risk and for linking with the external market view, as done in the cross-sectional analysis in part 4.3.

4.3. Effect of MTM losses and equilibrium on stock returns

After analyzing factors that are less visible to the market (classified as the internal view in this paper), such as the level of unrealized losses and s* threshold of equilibrium on a bank-by-bank basis, we include them as variables in the cross-sectional model to examine their contribution to explaining cumulative abnormal returns during the failure events. We run a new cross-sectional regression of 3-day cumulative abnormal returns on the factors included before, accompanied by two more internal factors.

The modified regression equation is the following:

$$CAR_i = a + \alpha_A * X_A + \alpha_L * X_L + \alpha_C * X_C + \beta_{TL} * X_{TL} + \beta_S * X_S + \epsilon$$

Where:

- CAR_i represents the cumulative abnormal return on the day *i* of the Event window
- α_j and β_j represent the regression coefficient for each independent variable
- X_A represents the value of the bank's assets in USD
- X_L represents the percentage of run-prone liabilities over total liabilities
- X_C is the percentage of liquid cash and securities over total assets
- X_{TL} represents the value of the bank's unrealized loss over total assets
- X_S is the s* calculated as described above

Table 11. Cross-sectional regression with two additional parameters

	G-SIB	Large			Small	
	Credit Suisse	SVB	Signature	First Republic	Heartland Tri-State	Citizens
Constant	0.0131	-0.0488**	-0.0614***	-0.0478***	-0.0070	0.0103
Size	4.07E-08	-2.63E-07***	-1.88E-07***	-6.32E-08	-5.02E-08	1.03E-07
Run-prone liabilities	-0.0605***	-0.2275***	-0.0784**	-0.0840***	-0.0152	0.1099
Cash and securities	-0.0232	0.0430*	0.0293*	0.0371	-0.0067	0.0485
MTM Losses/TA	-0.0031	0.0051	0.0007	-0.0030	0.0063	0.0013
s*	0.0002	0.0023	0.0047	0.0039	0.0062**	-0.0043
R squared	0.0332	0.1469	0.0787	0.0455	0.0326	0.0124

Source: computed by the authors

Analyzing the results of Table 11, it can be seen that the MTM losses and s* are not significant for the cross-sectional model; therefore, we cannot reject the null hypothesis, and it cannot be concluded that the MTM losses and s* are observed by the market participants. Furthermore, we expected the effect of a high level of MTM losses to be negative, meaning the more losses the bank experiences, the more negative its abnormal return should be, while for most instances, it is positive instead. A plausible explanation is that the markets do not consider these factors, while the other ones are publicly available to all market participants and have proven a significant impact. The marked-to-market losses and s* are complex to retrieve and not accessible to most participants; it can be concluded that the market, in general, does not manage to read these internal signals properly.

To verify our conclusion about the statistical insignificance of the new parameters added, in Figure A4 in the appendix, we present the pairwise relationship between the six variables from the cross-sectional model to check for potential collinearity, especially between MTM losses and s* with the other variables. The variables of assets and leverage ratio have high collinearity between each other, which is in line with the results obtained across all events, with both factors contributing negatively and with significance to the CAR.

The collinearity of MTM losses and s* between each other and with other variables is very low. Therefore, we can reject the hypothesis that the effect of MTM losses and s* is reduced due to collinearity or correlation, reinforcing our initial conclusion.

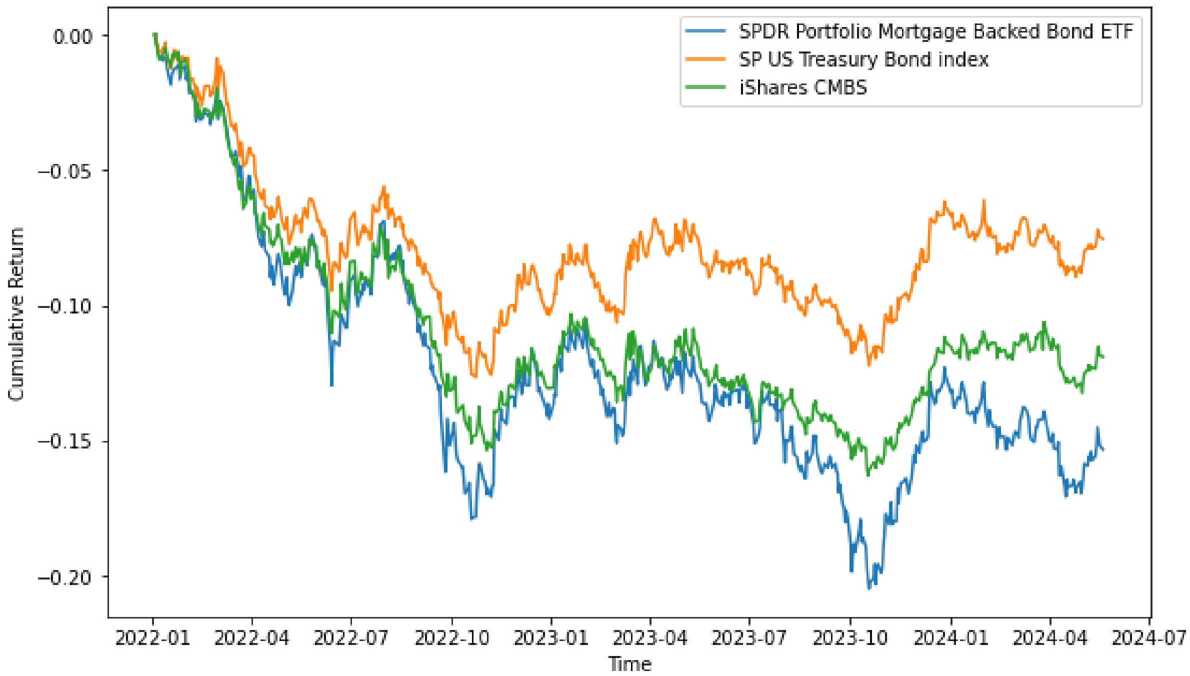
5. Part 3: Potential risks in 2024 and subsequent systemic effects

5.1. Financial events and signals up to May 2024

In this section, we study the current US banking environment as of May 2024 to assess the level of risk in case of another systemic event. We collected the same data as described in point 4.1 regarding the total assets and deposit types amounts from FDIC call reports for the latest available period of Q4 2023, the repartitioning of the assets by maturities from the FDIC reports for Q1 2023, the returns on the ETFs used for adjusting losses by asset maturity for the extended period up to May 2024 to perform the calculations displayed below.

Figure 7 presents the complete view of the three indexes used to reprice the banking assets from January 2022 to the 25th of May 2024. The cumulative returns for mortgage-backed bonds, treasuries, and CMBS ETFs demonstrate the market perception that the problems banks faced during the 2023 crisis are still inherent. For all three ETFs, prices have reached a new low again around October 2024, with mortgage-backed bonds reaching a maximum decline of 20%, while CMBS and Treasury Bonds have reached similar levels to the minimums obtained as of October 2022.

Figure 7. Cumulative return for RMBS, CMBS and Treasuries



Source: compiled by the authors from Bloomberg

The volatility of these indexes illustrates the market's expectations towards the Federal Reserve monetary policy. The year 2023 has been marked with the FED sending mixed signals regarding the fate of interest rates, pronounced sentiment swings regarding the direction of monetary policy were caused by hotter-than-expected inflationary readings, and a cooling of the jobs market and economy, given little operating window for the FED to take a firm stance.

Furthermore, we note that the failure of Heartland Tri-State Bank and Citizens Bank coincides with the decline in valuations from late Q3 up to mid-Q4 2023, the period we identified as the maximum risk. The indexes have recovered since then but have been declining again since the beginning of January 2024.

Therefore, it is relevant to assess banks' ability to meet their run-prone liabilities as of May 2024, given that most assets have significant marked-to-market down marks.

Another dawning factor we analyzed in this part is the direct effect of having prolonged periods of high interest rates, which has a key role in the level of loan delinquencies and defaults, most notably in the Real Estate mortgage ecosystem (Figure A5). According to the Mortgage Bankers Association's National Delinquency Survey (2024), as of Q1 2024, the total loan outstanding delinquency rate for 1-to-4-unit residential mortgages has increased to 3.94%, up 38bps since Q1 2023. Furthermore, according to the press release of the Federal Reserve Bank of New York (2024), credit card delinquencies are now at decade highs, reaching 9% in Q1 2024, and there is also an essential increase in auto loan defaults.

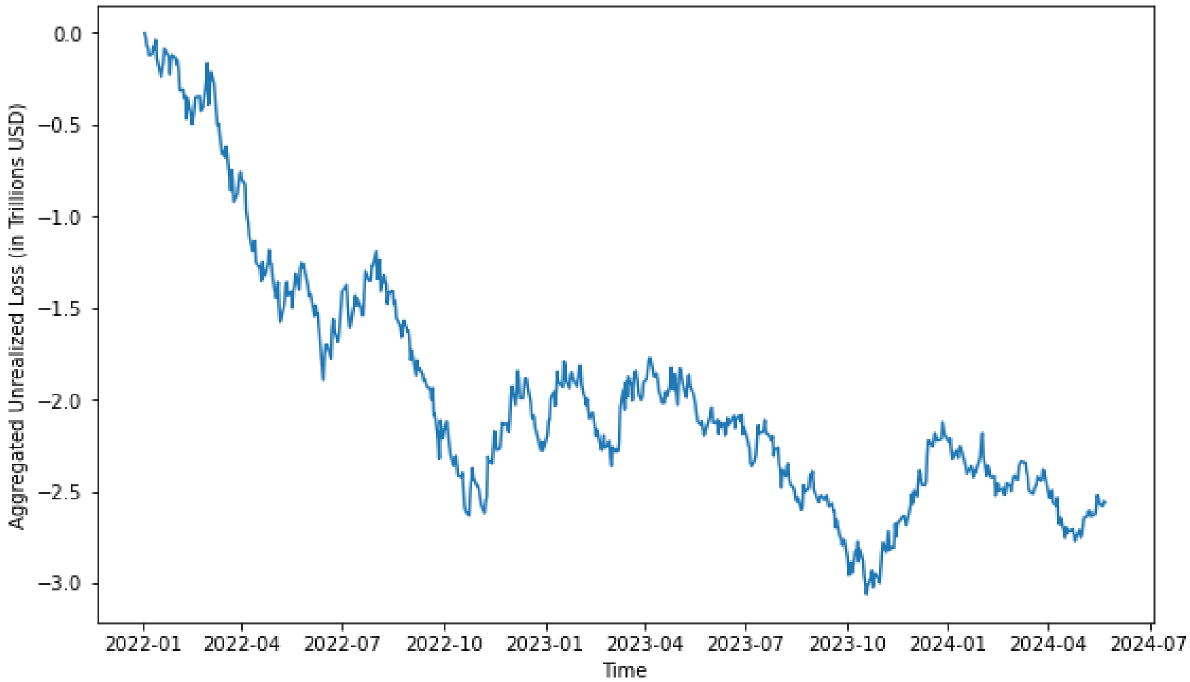
As of April 26th, 2024, the Republic First Bank (not to be confused with First Republic Bank, which failed in May 2023) had failed, with total assets around 6 billion USD and 4 billion USD in deposits. This confirms our analysis pointing at the continued existence of systemic risk in the banking sector in 2024.

5.2. Bank deposit coverage risk analysis in 2024

One of the contributing factors to the development of systemic risk in the banking sector in 2024 is the rise of loan delinquencies and defaults. To analyze this matter, we compute an estimation of the marked-to-market losses considering readjustments in assets as of Q2 2023, studying the effect of the following increase in the levels of defaults: 3%, 5%, and 7% for all loans. Our analysis of the 2024 banking system yields a negative indicator in terms of unrealized losses. The marked-to-market loss (without considering increases in delinquencies) is estimated to have reached a new minimum by late October/early November 2023, reaching approximately 3 trillion USD in unrealized losses, considering bank adjustments to account for asset liquidations (Figure 8).

From the readjustment of assets alone, it can be implied that the risk in 2024 has worsened compared to Q1 and Q2 2023; our estimations consider risks to be even higher than during the peak of bank failures in 2023. Given the computed marked-to-marked losses, we analyze the number of banks at risk of failure in the scenario with no further loan defaults. The degradation of the situation is evident in all three scenarios mentioned earlier. If all assets are liquidated as of the 25th of April, close to 1200 more banks than in Q1 2023 would be unable to repay their liabilities. For the case of a 100% depositor run, the number of banks with a negative coverage ratio is lower than for the computed case in Q1 2023, which could reflect uninsured deposit withdrawals. Overall, the risk is higher for the more conservative case of 50%, with 27 more banks at risk as of April 2024 than in Q1 2023.

Figure 8. US bank aggregate marketed-to-market loss



Source: computed by the authors

Table 12 presents the effects of increasing loan defaults for all four scenarios. Our findings show that in the event of a bank run, more banks would be at risk of failure compared to Q1 2023, given that they could not cover their insured deposits even by liquidating all their marked-to-market assets. An increase in loan defaults would have a significant adverse effect, with a scenario where 3% of loans default, thus translating into c.10% more banks at risk due to negative coverage ratios.

For comparison, the impact of these default scenarios for 2023 is detailed in Table A10 in the Appendix. Although the total number of banks that would fail in the event of liquidating all assets is higher than in mid-Q4 2022, fewer banks would be at risk of insolvency following a 100% depositor run with no fire sale discount. This reflects a change in the composition of assets and liabilities through 2023-2024, suggesting that while the overall risk of failure is increasing due to the sustained high interest rates and rising delinquencies, the specific dynamics of bank runs and asset liquidation have evolved, possibly due to adjustments in banks' asset management strategies.

Table 12. Banks at risk of failure for different scenarios

As of 25/04/2024	All Assets Liquidate	100% of depositors run	50% of depositors run	0.4% Fire sale Discount
No Loan defaults	3020	1735	336	1810
3% Loan defaults	3320	1998	423	2049
5% Loan defaults	3505	2161	498	2233
7% Loan defaults	3622	2340	572	2413
Total Banks Analyzed	4591			

Source: computed by the authors

Historically, rapid and violent increases in delinquency and default rates have been seen during the 2008 financial crisis. The current environment, marked by the significant growth in delinquencies in the commercial real estate sector, mirrors such trends. Recent articles state that delinquencies linked to commercial properties have doubled from 2022 to 2023, and estimates point to a potential 38 billion USD worth of offices under the threat of default and foreclosures, at an all-time high since Q4 2012.

Other recent bearish indicators are the status of the reserves at G-SIBs, which have declined notably in the last year, with delinquent CRE loans surpassing the reserves held to cover them. The article by Barnes (2024) in International Banker states: *"The average reserves at JPMorgan Chase, Bank of America (BofA), Wells Fargo, Citigroup, Goldman Sachs, and Morgan Stanley fell from $1.60 to $0.90 for every dollar of commercial real estate debt on which a borrower is at least 30 days late. This means that delinquent CRE loans, which tripled to $9.3 billion for the six big US banks over the last year, have now surpassed the number of reserves held at those banks to cover them".* This signals critical vulnerability in the banking system, as these banks are less equipped to manage the increasing defaults and delinquencies.

The findings of higher risks are in line with the current press and the declarations from the FDIC on May 29, 2024. At the "FDIC Quarterly Banking Profile First Quarter 2024" press conference, the FDIC described an increase in the unrealized losses amount on available-for-sale and held-to-maturity securities of 39 billion USD (+7.5% QoQ) driven by a devaluation of RMBS. On the other hand, the total amount of loans declined by 35 billion USD, driven by lower credit card loans and auto loans, while overall net interest margins declined by 10bps due to increasing funding costs led by deposit competition and lower yields on assets. All these factors translated into an increase in the number of banks in the Problem Bank List (CAMELS rating of 4 or 5) from 52 to 63, with the amount of assets held by these banks increasing from 15.8 to 82.1 billion USD.

In summary, our analysis in Part 3 highlights the worsening conditions of the banking sector, with resilient substantial unrealized losses and an increased number of banks at risk of failure due to rising loan defaults and further depreciation of securities, which could lead to potential failures in the event of the triggering of depositor runs. Banks are in a precarious spot, needing to carefully manage their actions to avoid distress signaling.

Liquidating assets at a loss and/or raising significant amounts of capital, as seen in the case of SVB, can have a substantial adverse effect on the stock returns and the depositors' perception of the safety of their deposits.

In part 2, we concluded that the markets fail to grasp these internal factors. The unrealized losses amount and the deposit coverage ratio of banks, which are not easily computable, could provide an advantage to well-informed market participants who have higher visibility and understanding of these internal signals. The computation of s* and MTM (mark-to-market) losses could yield advantageous information to hedge against the risk of bank insolvency or to benefit from the market's failure to price these factors correctly.

6. Conclusion

The banking crisis of 2023 highlighted imperfections and vulnerabilities in the financial system. This paper examined systemic risk in this crisis from the perspective of the external market and internal banks' liquidity and liabilities.

From the external perspective, it can be concluded that the markets adjust their pricing of the risks and potential effects of systemic events such as bank failures with certain efficiency for the banks with extensive media coverage, as seen with First Republic Bank and Credit Suisse. In cases where negative news or distress signals are a surprise, markets adjust violently, translating into significant effects on the sector. An explanation could be that these events trigger doubts about the financial system's health, as interconnectedness and common exposures are not atypical.

The event study part of the paper demonstrated that the banks' reaction to the news about the other banks' failures differed depending on the characteristics of both the reacting and the failing banks. The highest negative effect was observed following the failure of a large bank, and especially following the multiple consecutive large bank failures of SVB and Signature Bank, highlighting the interconnected nature of the banking sector. The paper proves that the factor that influences banks to be more prone to the domino effect is mainly the high levels of uninsured liabilities, with liquidity playing a less significant role. The combination of these two factors makes depositors doubt the safety of their funds, thus panic and run, causing the emergence of fragility in the system. With its external view, the market can factor in these characteristics when pricing in the effects of a systemic event, as shown by the cross-sectional event study.

The second part of the paper estimated the unrealized asset losses caused by the hikes in interest rates, which undermined the value of long-term loans and securities on the banks' balance sheets. It was proven that although the information about the interest rates and the approximate amounts of uninsured depositors that the bank has is openly available, the depositors cannot always correctly determine the moment of the highest asset losses and highest risk to the safety of their funds. The bank run happened in March 2023, 4 months after the highest risk of loss of the asset value. This is also evident when performing a cross-sectional model to understand the effect of these factors on the market perception of risk, showing that the unrealized losses and solvency ratios have little effect on the abnormal returns of banks after a systemic event.

Other literature (ECB (2023)) indicates that losses might not be the best measure of systemic risk. By focusing on losses or bank size, a significant portion of medium-sized banks at risk may not be accounted for as a systemic event. At the same time, the default of a single, large institution with limited effect on the rest of the system could be considered as one.

Finally, our analysis of the US banking sector as of May 2024 reveals a significant deterioration in stability compared to previous quarters. The estimated marked-to-market losses have reached an alarming 3 trillion USD by late October/early November 2023, driven by declining asset values across mortgage-backed securities, treasuries, and CMBS ETFs. This situation illustrates the persistent risks and market volatility following this period of prolonged high interest rates, which is further influenced by mixed signals from the Federal Reserve regarding their decisions on monetary policy.

Historical patterns of sharp increases in delinquencies and default rates are beginning to resurface, with notable spikes in delinquencies within the commercial real estate sector. A notorious increase in credit card and auto loan defaults further stresses the already weakened financial system.

Moreover, the failure of banks like Heartland Tri-State Bank, Citizens Bank, and the recent failure of Republic First Bank are proof of the continuous fragility. Our scenario analysis estimates the effects of an increase in loan defaults; in scenarios without further loan defaults, nearly 1200 additional banks are at risk of insolvency compared to Q1 2023. This risk amplifies under conditions of depositor runs, especially under a 50% withdrawal scenario, which sees 27 more banks at risk as of April 2024 than in Q1 2023. The diminishing reserves at systemically important banks illustrate the sector's vulnerability, leaving banks and G-SIBs more exposed to escalating defaults and delinquencies.

The banking sector urgently needs strategic measures to mitigate these risks. The next months will reveal whether recent changes in the insurance deposit scheme of Trusts, effective as of April 1st, 2024, will significantly affect the sector's market confidence.

To ensure stability, banks must navigate this environment carefully to avoid emitting any distress signals that could damage depositor confidence and trigger further systemic events.

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8. Appendices

8.1. Appendix 1. Normal return model

Table A1. Aggregate values CAPM vs. Fama-French

	CAPM	*Fama-French*
Alpha	-8.60E-05 (0.0009)	0.0319 (0.1018)
Market Beta	0.5406** (0.3428)	0.5353** (0.3417)
SMB		-0.4572 (28.6829)
HML		-0.0332 (0.0656)
R^2	0.2454 (0.1763)	0.2592 (0.1688)
R^2 adjusted	0.2423 (0.1771)	0.2502 (0.1709)

Source: computed by the authors

Table A2. CAPM model summary for JP Morgan

Dep. Variable	SPY Daily Return	R-squared	0.554
Model	OLS	Adj. R-squared	0.552
Method	Least Squares	No. of observations	252

	Coef.	*Std error*	*t*	*P value*	*[0.025*	*0.975]*
Alpha	-0.0003	0.001	-0.554	0.58	-0.002	0.001
Market Beta	0.6384	0.036	17.629	<0.0001	0.564	0.706

Source: computed by the authors

Table A3. Fama-French model summary for JP Morgan

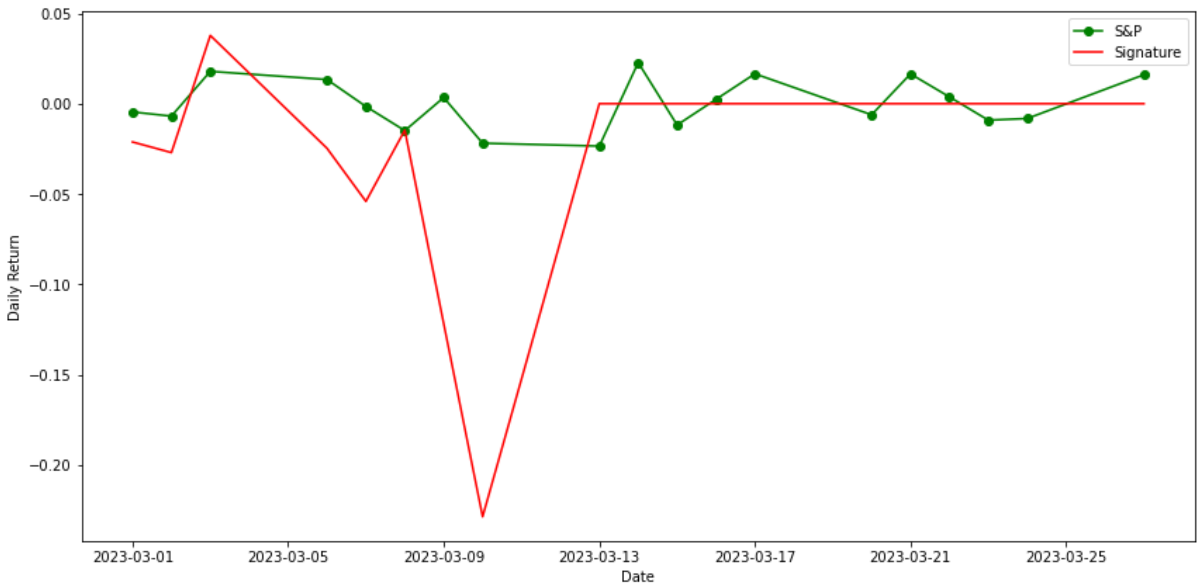
Dep. Variable	SPY Daily Return	R-squared	0.557
Model	OLS	Adj. R-squared	0.552
Method	Least Squares	No. of observations	252

	Coef.	*Std error*	*t*	*P value*	*[0.025*	*0.975]*
Alpha	-0.0383	0.073	-0.529	0.598	-0.181	0.105
Market Beta	0.6311	0.036	17.403	<0.0001	0.560	0.702
SMB	0.0015	0.002	0.644	0.52	-0.003	0.006
HML	0.0226	0.055	0.410	0.682	-0.086	0.13

Source: computed by the authors

8.2. Appendix 2. Historical stock returns

Figure A1. Historical returns for Signature Bank and S&P



Source: compiled by the authors from Bloomberg

Figure A2. Historical returns for Credit Suisse and MSCI World

Source: compiled by the authors from Bloomberg

8.3. Appendix 3. Significance in the difference of the high and low factors

Table A4. P-values of the differences between High and Low abnormal returns and CAR

	Mean -1	Mean 0	Mean +1	CAR [-1, +1]
Size Big-small				
SVB	1.02E-11	0.385	0.011	7.83E-42
Signature	0.385	0.011	0.376	6.40E-04
First Republic	0.434	0.373	0.000	1.58E-34
Credit Suisse	3.01E-03	0.272	0.000	0.561
Heartland	0.127	0.770	4.85E-05	1.63E-14
Citizens	3.00E-04	9.88E-05	0.047	4.88E-54
Run-prone liabilities				
SVB	0.002	0.920	0.001	2.03E-10
Signature	0.920	0.001	0.383	2.35E-05
First Republic	0.585	0.096	0.247	0.001
Credit Suisse	0.005	0.179	0.001	8E-05
Heartland	0.369	0.069	0.497	0.543
Citizens	0.674	0.216	0.735	5.33E-11
Liquid Cash and Securities				
SVB	0.822	0.323	0.300	0.045
Signature	0.323	0.300	0.226	0.352
First Republic	0.987	0.072	0.204	0.008
Credit Suisse	0.047	0.201	0.009	0.042
Heartland	0.948	0.513	0.402	0.125
Citizens	0.359	0.161	0.039	7.98E-14

Source: computed by the authors

8.4. Appendix 4. Abnormal returns

Table A5. Abnormal returns for the expanded event window [-5, +5]

	G-SIB		Large						Small			
	Credit Suisse		SVB		Signature		First Republic		Heartland Tri-State		Citizens	
	ē*	CAR	ē*	CAR	ē*	CAR	ē*	CAR	ē*	CAR	ē*	CAR
-5	-0.0742***	-0.0742***	-0.0037***	-0.0037***	-0.0084***	-0.0084***	-0.0066***	-0.0066***	-0.0104***	-0.0104***	-0.0043	-0.0043
-4	0.0093***	-0.0649***	-0.0084***	-0.0120***	-0.0071***	-0.0155***	-0.0251***	-0.0317***	0.0174***	0.0071***	0.0167*	0.0125
-3	-0.0030	-0.0679***	-0.0071***	-0.0190***	-0.0033***	-0.0187***	0.0001	-0.0316***	-0.0050**	0.0020	0.0000	0.0124
-2	0.0201***	-0.0478***	-0.0033***	-0.0223***	-0.0358***	-0.0546***	0.0013	-0.0303***	0.0319***	0.0339***	-0.0096**	0.0029
-1	-0.0326***	-0.0805***	-0.0358***	-0.0581***	-0.0178***	-0.0724***	-0.0016	-0.0319***	-0.0024	0.0315***	0.0307***	0.0336**
0	-0.0070***	-0.0875***	-0.0178***	-0.0759***	-0.0742***	-0.1466***	-0.0204***	-0.0523***	0.0019	0.0334***	0.0320	0.0656***
+1	0.0263***	-0.0612***	-0.0742***	-0.1500***	0.0093***	-0.1373***	-0.0462***	-0.0984***	-0.0058**	0.0276***	-0.0047	0.0608***
+2	-0.0256***	-0.0867***	0.0093***	-0.1406***	-0.0030	-0.1403***	-0.0085*	-0.1069***	-0.0055***	0.0222***	0.0099***	0.0514***
+3	-0.0218***	-0.1085***	-0.0030	-0.1436***	0.0201***	-0.1203***	-0.0272***	-0.1341***	0.0060***	0.0282***	-0.0040	0.0474***
+4	0.0168***	-0.0917***	0.0201***	-0.1235***	-0.0326***	-0.1529***	0.0279***	-01062***	0.0081***	0.0363***	-0.0020	0.0454**
+5	0.0075***	-0.0842***	-0.0326***	-0.1561***	-0.0070***	-0.1599***	-0.0148***	-0.1209***	0.0011	0.0375***x	-0.0005	0.0449**

Source: computed by the authors

8.5. Appendix 5. Mean historical returns for the benchmark indexes

Table A6. Mean historical returns for SPY ETF and MSCI World during each failure event

	SPY						MSCI World					
	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens
-5	-0.023	0.018	0.013	0.000	0.000	-0.005	-0.008	0.015	0.003	0.002	0.004	-0.002
-4	0.023	0.013	-0.002	-0.003	-0.001	-0.002	0.008	0.003	-0.007	-0.002	-0.001	0.008
-3	-0.012	-0.002	-0.015	-0.009	0.001	0.006	-0.009	-0.007	0.005	-0.008	0.005	0.008
-2	0.002	-0.015	0.003	0.001	0.001	0.007	0.014	0.005	-0.011	0.013	-0.001	0.010
-1	0.017	0.003	-0.022	0.011	0.010	0.018	-0.010	-0.011	-0.014	0.001	-0.001	0.011
0	-0.006	-0.022	-0.023	0.010	-0.007	0.015	0.006	-0.014	-0.008	0.001	0.008	0.005
1	0.016	-0.023	0.023	-0.002	0.003	0.005	0.017	-0.008	0.008	-0.007	-0.003	0.002
2	0.004	0.023	-0.012	-0.008	-0.002	0.001	-0.009	0.008	-0.009	-0.003	0.003	0.004
3	-0.009	-0.012	0.002	-0.011	-0.007	0.004	-0.002	-0.009	0.014	-0.010	-0.011	0.004
4	-0.008	0.002	0.017	0.005	-0.011	0.002	0.003	0.014	-0.010	0.005	-0.002	-0.005
5	0.016	0.017	-0.006	0.010	0.006	-0.006	0.000	-0.010	0.006	-0.001	0.001	0.010

Source: computed by the authors

8.6. Appendix 6. Mean historical returns for the groups of banks

Table A7. Mean historical returns for big and small US banks during each failure event

	Big US Banks						Small US Banks					
	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens
-5	-0.079	0.003	-0.010	-0.009	-0.015	-0.015	-0.058	-0.002	-0.003	-0.007	-0.008	-0.005
-4	0.011	-0.010	-0.018	-0.039	0.019	0.025	-0.007	-0.003	-0.006	-0.015	0.007	0.006
-3	-0.011	-0.018	-0.004	-0.007	-0.009	-0.003	-0.019	-0.006	-0.001	-0.005	-0.003	0.000
-2	0.030	-0.004	-0.051	0.010	0.034	-0.011	0.012	-0.001	-0.015	-0.006	0.011	-0.003
-1	-0.045	-0.051	-0.027	-0.005	-0.012	0.050	-0.026	-0.015	-0.024	-0.002	-0.002	-0.006
0	-0.008	-0.027	-0.079	-0.023	0.004	0.048	-0.005	-0.024	-0.058	-0.019	-0.003	0.003
1	0.036	-0.079	0.011	-0.058	-0.010	-0.011	0.008	-0.058	-0.007	-0.025	0.007	-0.001
2	-0.041	0.011	-0.011	-0.018	-0.010	-0.013	-0.012	-0.007	-0.019	-0.019	-0.005	-0.001
3	-0.023	-0.011	0.030	-0.035	-0.004	-0.015	-0.017	-0.019	0.012	-0.020	-0.012	-0.002
4	0.019	0.030	-0.045	0.041	0.001	-0.007	-0.004	0.012	-0.026	0.012	0.001	-0.008
5	0.002	-0.045	-0.008	-0.020	-0.004	-0.001	0.004	-0.026	-0.005	-0.007	-0.004	-0.001

Source: computed by the authors

Table A8. Mean historical returns for US banks with high and low levels of run-prone liabilities during each failure event

	High level of run-prone liabilities						Low level of run-prone liabilities					
	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens
-5	-0.104	0.010	-0.009	-0.003	-0.010	-0.003	-0.060	-0.002	-0.007	-0.008	-0.013	-0.011
-4	0.020	-0.009	-0.022	-0.045	0.023	0.057	0.004	-0.007	-0.009	-0.031	0.012	0.011
-3	-0.012	-0.022	-0.004	0.001	-0.004	-0.009	-0.010	-0.009	0.000	-0.006	-0.004	0.002
-2	0.033	-0.004	-0.067	0.011	0.035	-0.004	0.023	0.000	-0.032	0.008	0.024	-0.010
-1	-0.055	-0.067	-0.029	0.000	-0.013	0.037	-0.033	-0.032	-0.024	-0.003	-0.009	0.024
0	-0.008	-0.029	-0.104	-0.025	0.011	0.059	-0.004	-0.024	-0.060	-0.018	-0.002	0.025
1	0.046	-0.104	0.020	-0.059	-0.009	-0.005	0.020	-0.060	0.004	-0.051	-0.009	-0.004
2	-0.047	0.020	-0.012	-0.026	-0.012	-0.018	-0.030	0.004	-0.010	-0.016	-0.004	-0.008
3	-0.030	-0.012	0.033	-0.046	-0.001	0.019	-0.017	-0.010	0.023	-0.030	-0.006	-0.009
4	0.031	0.033	-0.055	0.056	0.005	0.014	0.010	0.023	-0.033	0.024	-0.002	-0.012
5	0.011	-0.055	-0.008	-0.015	-0.006	-0.010	0.003	-0.033	-0.004	-0.020	-0.001	0.004

Source: computed by the authors

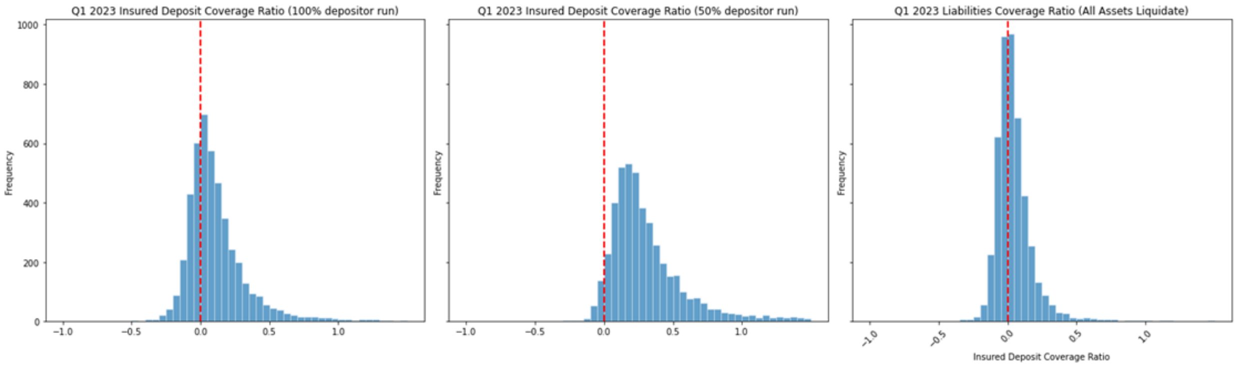
Table A9. Mean historical returns for US banks with high and low levels of liquid cash and securities during each failure event

	High level of liquid cash and securities						Low level of liquid cash and securities					
	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens	Credit Suisse	SVB	Signature Bank	First Republic	Heartland Tri-State	Citizens
-5	-0.069	0.003	-0.009	-0.012	-0.015	-0.013	-0.081	0.001	-0.010	-0.007	-0.011	-0.016
-4	0.006	-0.009	-0.015	-0.034	0.016	0.071	0.012	-0.010	-0.017	-0.033	0.020	0.014
-3	-0.013	-0.015	-0.004	-0.004	-0.004	-0.005	-0.004	-0.017	-0.002	-0.005	-0.009	0.001
-2	0.028	-0.004	-0.052	0.007	0.020	-0.023	0.028	-0.002	-0.046	0.007	0.039	-0.001
-1	-0.042	-0.052	-0.023	-0.008	-0.014	0.019	-0.042	-0.046	-0.029	0.004	-0.010	0.040
0	-0.005	-0.023	-0.069	-0.019	0.004	0.050	-0.009	-0.029	-0.081	-0.022	0.001	0.034
1	0.021	-0.069	0.006	-0.057	-0.015	-0.007	0.038	-0.081	0.012	-0.053	-0.001	-0.012
2	-0.035	0.006	-0.013	-0.014	-0.013	-0.017	-0.035	0.012	-0.004	-0.008	-0.007	-0.008
3	-0.022	-0.013	0.028	-0.025	-0.003	-0.008	-0.026	-0.004	0.028	-0.034	-0.006	-0.014
4	0.014	0.028	-0.042	0.028	-0.003	0.027	0.017	0.028	-0.042	0.035	0.003	-0.016
5	0.004	-0.042	-0.005	-0.017	-0.010	-0.015	0.001	-0.042	-0.009	-0.019	-0.002	0.002

Source: computed by the authors

8.7. Appendix 7. Liabilities coverage

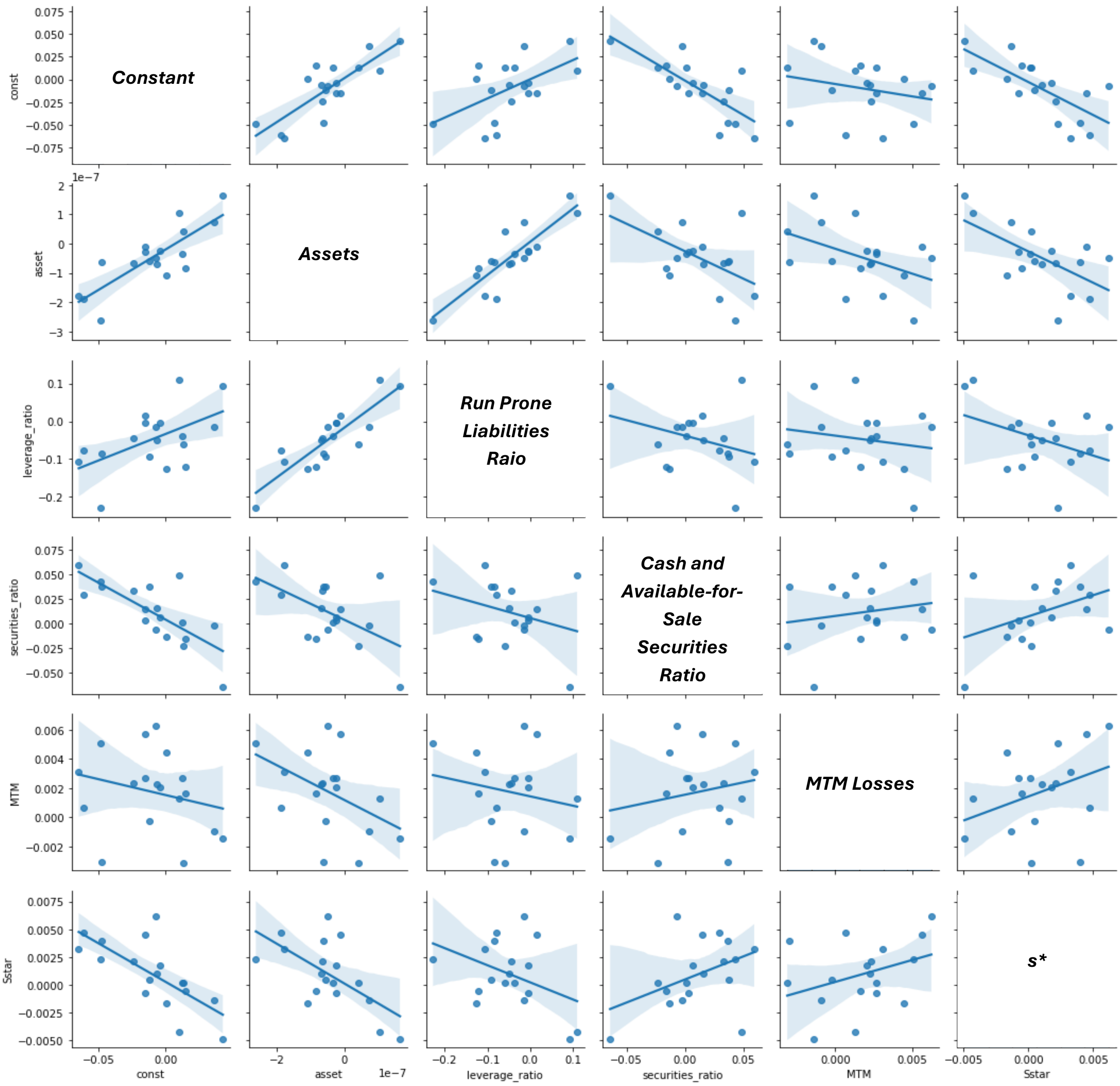
Figure A3. Distribution histograms of deposits and liabilities coverage ratios for various bank run scenarios



Source: computed by the authors

8.8. Appendix 8. Collinearity check of the variables

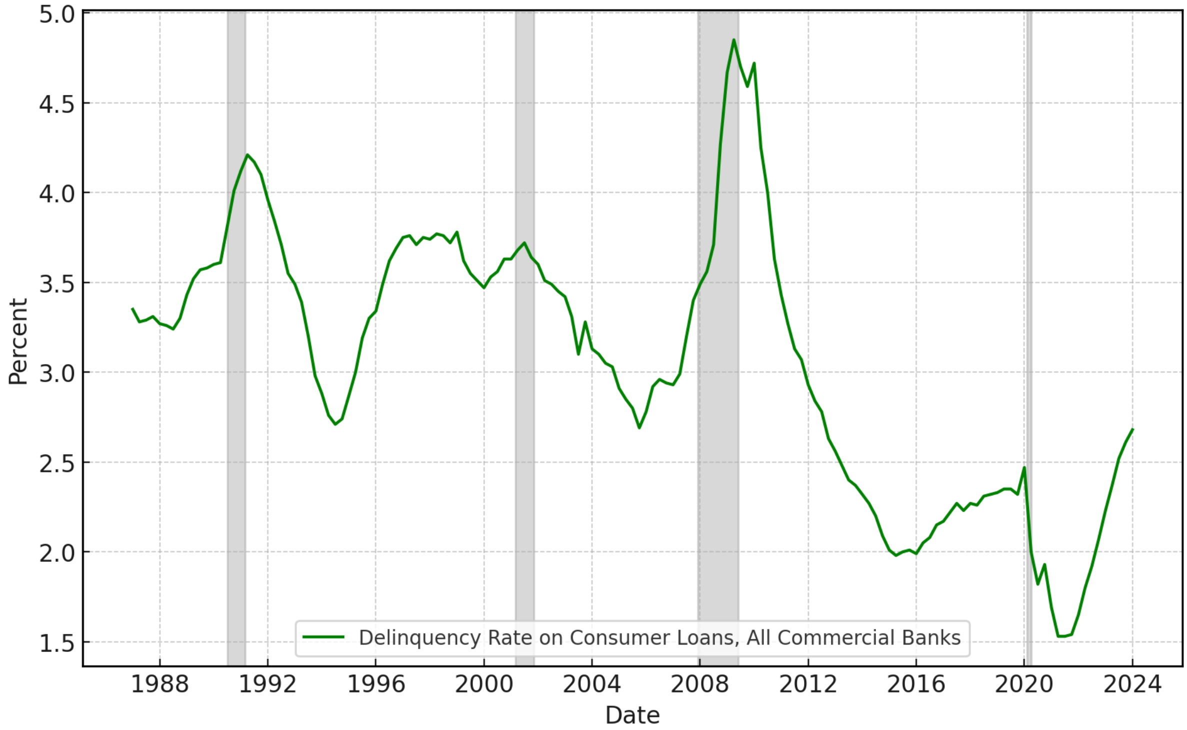
Figure A5. Plots of pairs of variables



Source: computed by the authors

8.9. Appendix 9. Loans delinquency

Figure A5. Delinquency rate on consumer loans, all commercial banks



Source: computed by the authors from the Federal Reserve of Saint Louis

8.10. Appendix 10. Bank at risk with Loan Default scenarios

Table A10. Number of insolvent banks for different run and insolvency scenarios

	24 October 2022				Q1 2023			
Scenario	All Assets Liquidate	100% of depositors run	50% of depositors run	0.4% Fire Sale	All Assets Liquidate	100% of depositors run	50% of depositors run	0.4% Fire Sale
No defaults	2499	2006	403	2271	1899	1770	309	1856
+3% defaults	2853	2381	607	2452	2366	1875	323	1944
+5% defaults	2965	2490	675	2562	2522	2015	373	2102
+7% defaults	3087	2612	753	2697	2683	2167	420	2229

Source: computed by the authors