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Is Bank Failure a Risk to the Equity Market?

Abstract. *This paper analyses the effect of the Silicon Valley Bank collapse on different sectors of U.S. equities based on forecasting counterfactual market responses. The findings suggest that bank collapse has a negative impact on the US equities. The results indicate rapid divergence from counterfactual predictions, and the actual equities are consistently lower than expected in the absence of collapse. The pointwise causal effect displays an estimate of the equities that fall following the collapse. In relative terms, these equities decreased between -3% and -10%. Moreover, the intervention's causal effect estimations indicate that the impact is particularly significant for the real estate, financial, and consumer discretionary sectors. As a result, investors and policymakers should enhance their regulatory structure, investigate cutting-edge technologies, build an early warning system, and seek social media's role in predicting bank runs.*

Keywords: *stock market, bank collapse, causal inference, conflict, counterfactual prediction.*

JEL Classification: E44, E66, G18.

1. Introduction

Banking crises can significantly impact the stock market due to their close relationship with the economy (Shin 2009). This can cause panic among investors, reduce liquidity in the financial system, and tighten lending criteria, making it more difficult for businesses to raise money and cause the stock to fall. Additionally, the crisis can affect other industries that rely on bank financing and may negatively affect stock prices. Banks play critical lending and capital market roles; bank failures and financial crises have frequently occurred with stock market collapse throughout modern economic history, with turmoil spreading from one market to another. In addition, banking system distress interrupts credit flows, dampens profitability, requires public bailouts, and extends financial system losses, fuelling significant stock market falls associated with previous banking crises. Thus, large bank failures have broad effects on financial systems and economies and can lead to financial crises if not adequately managed (Shin 2009).

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The primary purpose of this study is to analyse the effect of the Silicon Valley Bank (SVB) collapse on different sectors of the US equities, including the S&P 500 Real Estate, Energy, Industrial, Financials, Consumer Staples, Information Technology, Communication Services, Health Care and Consumer Discretionary. The collapse of the SVB has been the largest bank failure in the US since 2008 (Yousaf et al., 2023), causing other bank closures and panic in the equity market. The SVB was established in 1983 to cater to emerging tech companies and became one of the largest banks in the country. In 2020, the SVB witnessed a surge of cash deposits due to the pandemic, tripling its deposits in two years to reach $189 billion, making 2021 the most profitable year. Moreover, the SVB purchased $10 billion in worth of longer-term US treasury and government-backed mortgage securities, leading to an annual increase of approximately $100 billion in its securities portfolio. However, interest rates rose, causing bond prices to fall, and SVB held onto many bonds and incurred substantial losses. Eventually, SVB's investments were worth $17 billion less than their fair value. In addition, the increase in interest rates led to a reduction in new bank deposits of nearly $30 billion from March to December 2022.

The Silvergate Capital Bank collapsed on March 8th, 2023, which had a contagion effect on the bank run. Similarly, in a regulatory filing on March 8, SVB announced that it sold a significant portion of its securities portfolio, incurring a loss of approximately $1.8 billion, to cover the decline in deposits. This statement prompted fear, with more and more startups withdrawing cash and the stock price dropping. SVB eventually ran out of cash, which forced the regulators to seize the bank. As a result, the stock price went into a freefall on March 9th, 2023, and customers withdrew $42 billion in deposits. Consequently, the S&P 500 index shows a sharp decline of more than 3% (Yousaf et al., 2023). The SVB's statement about issuing bonds at a loss to raise cash coincides with Silvergate's collapse. This caused the SVB's stock price to collapse by 60% on March 9th, 2023, and the bank to shut down on March 10th (Yousaf et al., 2023). Meanwhile, the Treasury Department, Federal Reserve, and Federal Deposit Insurance Corporation (FDIC) released a joint announcement on March 12th, 2023, to compensate uninsured depositors. In addition, the Securities and Exchange Commission (SEC) and Justice Department initiated an inquiry into the event on March 14th, 2023. These measures led to a small recovery in the US markets, but international reactions caused Credit Suisse's share price to fall and the S&P 500 to decline. Therefore, the causal inference method is used to examine the effect of the SVB collapse on the US equities.

The study offers several contributions to the literature. It was confirmed that the SVB collapse adversely affected the US equities. This demonstrates the negative impact. The study is essential for evolving effective bank management and supervision, as failures of large banks can catalyse broad effects on financial systems and even culminate in financial crises if not properly managed. In addition, the discussion aims to estimate how the US equities would react in the absence of a collapse. The pre-period relationship is demonstrated using a model, which is then utilised in the post-period to generate a counterfactual estimate. The control variables predict outcomes, as the treatment does not impact them. Additionally, although the treatment does not directly affect the covariates, it does correlate with the primary variable's outcome. Moreover, to our knowledge, the previous literature lacks studies that employed causal inferences about the impact of the banking crisis on the equity market. The market is in fear due to the crash, and the market's response has been severe. Nevertheless, the equities would not have lost value if the SVB had not collapsed. As a result, the findings are significant as a benchmark for equity markets facing similar challenges. Furthermore, in terms of technique, this study provides a more reliable means of quantifying the influence of the SVB collapse on stock prices using causal inference. Additionally, the study takes into account the role of exogenous factors in the empirical design of counterfactual prediction. The results imply that the SVB collapse had a detrimental effect on the US equity market. Additionally, there is rapid divergence from counterfactual forecasts, and the actual US equities are continually lower than those predicted in the absence of SVB collapse. Therefore, investors and policymakers should enhance their regulatory structure, investigate cutting-edge technologies, build an early warning system, and seek social media's role in predicting bank runs. Furthermore, given the new role of social media in affecting bank runs, it is critical to investigate the impact of this collapse on the US equities.

This study comprises the literature review in Section 2, which follows the Bayesian structural time-series models in Section 3. The data are elucidated in Section 4. In Section 5, the results are described. The study's conclusions are presented in the last section.

2. Literature review

The preceding literature review included studies that analysed the effects of the financial crisis and the COVID-19 pandemic on the stock market. Aharony and Swary (1983) studied the effects of bank collapse on the US banking industry. The findings showed that bank failure was caused predominantly by fraud, while no contagion effects were observed. Schwert (2011) investigated stock volatility in the aftermath of the 2008 financial crisis in the US These findings explored high levels of stock market volatility, particularly among banking sector companies. Tsay and Ando (2012) analysed the effects of the subprime financial crisis on the US stock market. The outcome confirmed the movement of stock returns when the dimension was high. Asteriou et al. (2019) suggested that banks perform significantly during collapses, indicating greater share return volatility. He et al. (2020) confirmed that COVID-19 had no impact on stock markets. Alber (2020) showed that coronavirus negatively affects stock market returns in developed countries. Acharya et al. (2021) examined why bank stock values fell during the COVID-19 pandemic. The finding that banks had a greater stock price decrease might be attributed to contingent leverage. Choi (2021) tested the efficiency of the US stock market during the global financial crisis and the COVID-19 pandemic. The outcome revealed that the average return series has nonpersistent and persistent features. Furthermore, the consumer discretionary and utility sectors had the highest and lowest levels of efficiency, respectively.

Several studies have examined the effect of banking crises on the stock market. Black et al. (2016) measured the systemic risk of European banks during the sovereign debt crisis. The findings show that the risk of European banks is increasing due to sovereign default risk. Yousaf et al. (2022) indicated the negative impact of the Russia–Ukraine conflict on stock markets in G20 countries. Furthermore, the analysis showed that this conflict adversely affects European and Asian countries. Boubaker et al. (2022) found that invasion generated negative cumulative abnormal returns for global stock market indices, but with heterogeneous effects. Yousaf et al. (2023) examined the impact of the SVB collapse on the US market. The findings identified abnormal returns on the event date only for the financial, materials, and real estate sectors. However, there were no sector reactions during the pre-event period. Köseoğlu et al. (2023) suggested that the Ukraine war negatively impacts the stock market. Yadav et al. (2023) examined how bank collapse has affected global stock indices. According to the results, failure may profoundly influence world equity markets through cross-border ripple effects. Martins (2023) concluded that a banking collapse negatively impacts European stock markets. Pandey et al. (2023) showed that bank failure causes uncertainty and panic in the market, reflecting negative returns.

The contemporary literature has studied the causal effect of bankruptcy on stock markets. Most related studies have focused on correlations rather than causal inference. The widely used event study has the drawback of estimating the impact on the stock price produced by disasters before and after the event (Köseoğlu et al., 2023). Other studies have considered time-series data to assess how conflicts affect the stock market. However, these techniques cannot directly estimate causal influence due to the use of a carefully thought-out counterfactual context. Studies have been conducted to analyse the effect of bankruptcy on stock prices. However, the literature does not examine the situation in which bankruptcy did not occur, which could provide comprehensive information on the effect of bankruptcy. Most existing studies have employed traditional methodologies to detect bankruptcy impacts on relevant stock markets, but studies that have used methods to detect causal inference are lacking. This could help us to understand the situation of bankruptcy and vice versa. This study addresses the shortcomings of previous studies by considering the impact of the SVB collapse on the US stock prices. The model also considers the condition of the stock price response if there is no collapse. The current study uses the causal inference approach to produce precise counterfactual predictions depending on the control time series that underwent no treatment, providing valuable input to stakeholders. This provides a comprehensive understanding of the conflict.

3. Causal inference method

Brodersen et al. (2015) describe the limits of using the difference-in-differences (DD) technique to analyse causal effects. First, despite the design's temporal component, the approach assumes i.i.d. data and is based on static regression. When fitted to serially correlated data, static models produce positive results with tight uncertainty ranges. Second, the technique considers only the periods before and after the intervention, ignoring the changing influence over time, which is an integral part of causal inference (Xu et al. 2023). Third, developing a synthetic control from a collection of predictor variables has proven difficult in previous studies, particularly when DD analyses are based on time series. However, this study effectively overcomes this barrier while investigating causal influence.

There are several ways to address the limitations of DD approaches, and one such solution is to use state-space models that can depict changes over time as measurable outcomes. Furthermore, utilising a fully Bayesian approach with a spike-and-slab prior makes it possible to avoid overfitting and account for posterior uncertainty regarding the relevance and impact of various variables on the study's forecasts. Hence, this study adopts the causal inference method proposed by Brodersen et al. (2015).

Bayesian structural time-series models, which can be used to define a pair of equations, serve as a starting point for this approach.

$$y_t = Z_t^T \alpha_t + \varepsilon_t \tag{1}$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \tag{2}$$

where $\varepsilon_t \sim N(0, \sigma_2)$ and $\eta_t \sim N(0, Q_t)$ are independent of all the other unknowns. The link between observed data y_t and a latent d-dimensional state vector α_t is established in Equation (1). The evolution of the state vector at αt through time is stated by Equation (2). In this study, y_t is a scalar observation, Z_t is a d-dimensional output vector, T_t is a $d \times d$ transition matrix, R_t is a $d \times q$ control matrix, ε_t is a scalar observation error with noise variance σ_2, and η_t is a q-dimensional system error with a $q \times q$ state-diffusion matrix Q, where $q \leq d$."

In the context of the applications analysed in this study, the most crucial state component is regression, which produces counterfactual predictions. A synthetic control is created using a combination of unexposed markets to achieve this. The observed responses from such markets enable the identification of variable components in the treated market that are not easily captured by more general seasonal sub models.

To generate accurate counterfactual predictions, the methodology utilised in this study relies heavily on control time series that were not subject to any treatment. These time series are valuable because they capture shared variance components, including the effects of unobserved factors that the model would otherwise overlook. A simple and effective way of incorporating control series into the model is linear regression. The coefficients of the model can either remain constant or vary over time. This study introduces contemporaneous variables with fixed coefficients, which may be expressed in state-space form by setting $Z_t = \beta_t x_t$ and$\alpha_t = 1$.

We can denote the complete set of model parameters as θ and represent the entire state sequence as $\alpha = (\alpha_1, \dots \dots \dots \dots \dots . \alpha_m)$. Brodersen *et al.* (2015)

suggested that to adapt the Bayesian inference method, specify a prior distribution $\rho(\theta)$ for the model parameters and a distribution $\rho(\alpha_0 \theta)$ for the initial state values; then, draw samples from the joint distribution $\rho(\alpha, \theta_y)$ using the Markov chain Monte Carlo technique.

Concerning the estimation (pointwise) of the impact,

$$\emptyset_t^{(\tau)} \coloneqq y_t - \sim y_t^{(\tau)} \tag{3}$$

is constructed for each draw r and for each time point $t = n + 1, \dots \dots \dots .., m$, where n is the time the treatment happens, to gather findings from the a posteriori causal effect."

It is possible to estimate the cumulative impact of the intervention over time. This is done by calculating the cumulative sum of causal increments through:

$$\sum_{t=n+1}^{t} \emptyset_t^{\tau} \ \forall \ t = n + 1, \dots \dots \dots \dots, m \tag{4}$$

Causal inference is a statistical tool used to determine the association between a treatment and an outcome. It assesses the effect of an intervention on a response variable. The technique compares the observed outcome to counterfactual estimates of what would have happened without the intervention. The two differences offer an approximation of the intervention's causal influence. Unlike previous novel causality tests, this approach focuses directly on evaluating the causal effect of an intervention rather than just testing for causation between two variables. Furthermore, we considered control factors related to the response variable to generate a more accurate forecast of what would have happened in the absence of the intervention. This approach helps eliminate any confounding factors that might impact the response variable.

4. Data

This study evaluates the causal effect of the SVB collapse on the US equity market. The equity sectors include real estate, energy, industry, financials, consumer staples, information technology, communication services, health care, and consumer discretion. These sectors of the S&P 500 index serve as a classification measure for the entire US market. The daily average return data for the nine sectors in the S&P 500 index are employed. The study period is from February 2nd, 2023, to April 20th, 2023. The pre-treatment period consisted of February 2nd, 2023, to March 8th, 2023, while the post-treatment period consisted of March 10th, 2023, to April 20th, 2023. In this study, March 9th, 2023, was selected as the event point on which the day on which the SVB collapsed.

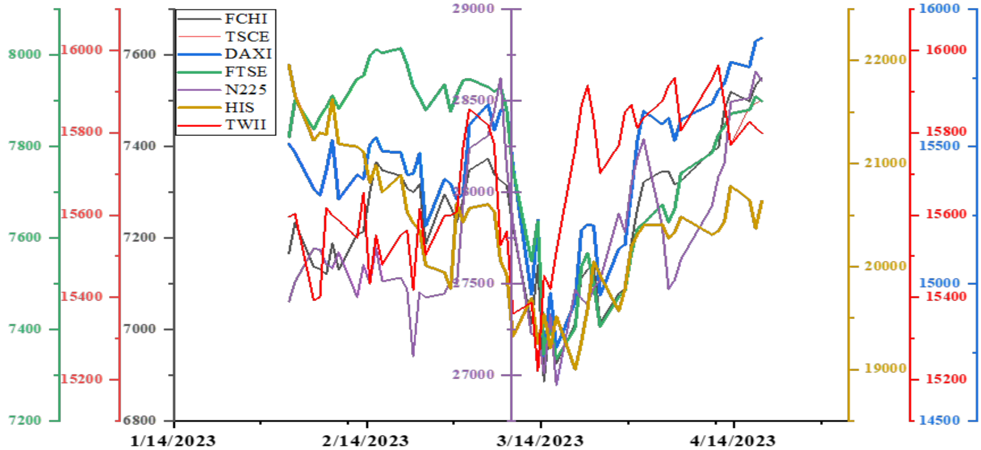

Figure 1. Trends of the covariates during SVB collapse
Source: Authors' work.

This study considers other factors that can significantly affect stock prices (see Figure 1). Thus, there are nine covariates in the form of major global stock market indices, such as the FTSE 100 index (FTSE), the French CAC 40 index (FCHI), the German DAX 300 index (GDAXI), the Nikkei 225 Index (N225), the Korea Composite Index (KS11), the Hang Seng Index (HSI), the Shanghai Stock Index and the Taiex Index (TWII). Table 1 summarises these equity sectors. This finding implies that the highest fluctuation in these equity prices is confirmed by the standard deviation. Moreover, the skewness values are positive except in the energy, industrial, and information technology sectors. However, the kurtosis value indicates that all the series are leptokurtic. The Jarque–Bera test confirmed that the series are normally distributed.

Table 1. Summary statistics

S&P 500 (sectors)	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Bera
Real Estate	235.903	9.178	0.357	2.622	1.385
Energy	643.770	27.123	-0.529	2.497	2.859
Industrial	846.843	16.481	-0.167	2.124	1.832
Financial	558.140	32.680	0.314	1.530	5.322
Consumer staple	767.205	15.834	0.366	1.886	3.705
Information Technology	2502.413	88.078	-0.053	1.657	3.781
Communication Service	183.820	7.903	0.021	1.734	3.343
Health	1511.754	37.850	0.132	1.698	3.678
Consumer Discretionary	1129.535	27.186	0.054	2.652	0.277

Source: Authors' calculation.

5. Empirical analysis

Figure 2 (a-c) shows the causal inference results obtained by employing the covariates during SVB collapse. The data are shown by a solid line in the first panel, while the dotted line represents the projected post-treatment result. The difference between the actual and projected outcomes is shown in the second panel and is known as the pointwise causal effect. The third panel depicts the intervention's cumulative impact, determined by aggregating the pointwise effects. The vertical dashed line shows the treatment dividing line. This finding offers a sharp divergence from counterfactual predictions, and the S&P 500 Real Estate, Energy, and Industrial sectors were consistently lower than expected in the absence of the SVB collapse. The two curves suggest that these sectors strongly reacted to the collapse. The pointwise causal effect indicates that the effect is close to zero before failure and decreases after collapse. These industries have relative declines of 5.9%, 3.5%, and 3%, respectively, following the SVB bankruptcy.

(a) (b) (c)

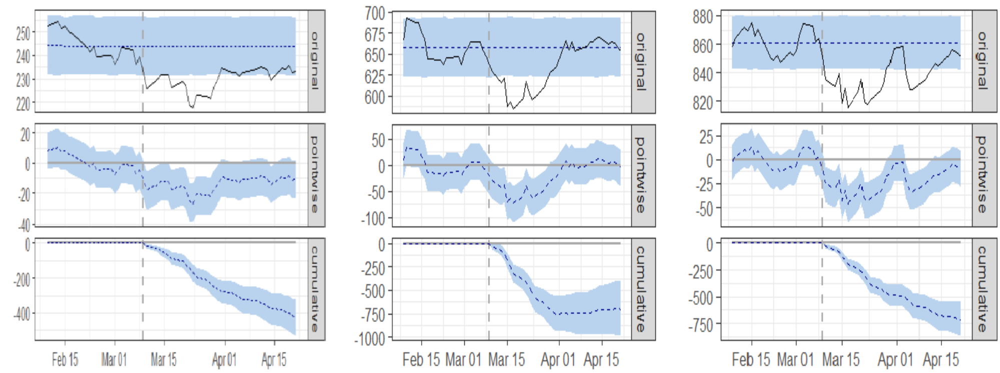

Figure 2. The time-varying causal effect of the SVB collapse on the US equity

Source: Authors' calculation.

Table 2 highlights the explanation of Figure 2. The S&P 500 real estate sector had an average value of approximately 229.89 post-intervention. On the contrary, the expected average response would be 244.35 without a collapse. The estimate of the intervention's causal effect on the real estate sector is -14.47. During the post-collapse period, the real estate sector had an overall value of 6.90K. The expected causal effect is 7.33 K in the absence of collapse. Similarly, the S&P 500 energy sector had an average value of approximately 634.59 in the post-collapse period. In contrast, the expected average response would be 657.95 without bankruptcy. The estimated causal effect of the collapse on the energy sector is -23.37. The energy sector had an overall value of 19.04 K following bank failure. The expected causal effect is 19.74 K in the absence of collapse. The S&P 500 industrial sector had an average value of approximately 837.33. However, the expected average response would be 861.01 if there was no collapse. The estimated causal effect of the collapse on the industrial sector is -23.68, with an overall value of 25.12K. The anticipated causal effect of 25.83K in the absence of insolvency.

Table 2. S&P 500 Real Estate, Energy and Industrial (Sector) Data

	Real Estate		Energy		Industrial	
	Average	**Cumulative**	**Average**	**Cumulative**	**Average**	**Cumulative**
Actual	230	6897	635	19038	837.33	25120
Prediction	244 (1.8)	7331 (54.1)	658 (5)	19739 (151)	861 (2.7)	25830 (79.5)
95% CI	[241, 248]	[7224, 7443]	[648, 668]	[19426,	[856, 866]	[25671,
Absolute	-14 (1.8)	-434 (54.1)	-23 (5)	-701 (151)	-24 (2.7)	-710 (79.5)
95% CI	[-18, -11]	[-547, -328]	[-33, -13]	[-989, -389]	[-29, -18]	[-866, -551]
Relative	-5.9% (0.69%)	-5.9% (0.69%)	-3.5%	-3.5% (0.74%)	-2.8% (0.3%)	-2.8% (0.3%)
95% CI	[-7.3%, -4.5%]	[-7.3%, -4.5%]	[-4.9%, -2%]	[-4.9%, -2%]	[-3.3%, -2.1%]	[-3.3%, -2.1%]

Source: Authors' calculation.

Figure 3 (d-f) displays causal inference results employing the covariates during SVB collapse. This result shows a sharp divergence from counterfactual predictions, and the S&P 500 financials, consumer staples, and information technology were consistently lower than expected in the absence of the SVB collapse. Moreover, the pointwise causal effect shows that these sectors fell after the SVB collapsed. In relative terms, these sectors have declined by 10%, 2.3%, and 3.4%, respectively, following bank default.

Table 3 highlights the description of Figure 3. During the post-bankruptcy period, the S&P 500 financial sector had an average value of approximately 533.76. However, without a bank collapse, the expected response would be 595.11. The estimate of the causal collapse effect is -61.36. The financial sector had an overall value of 16.01K in the post-insolvency period. The expected causal effect is 17.85K in the absence of collapse. Moreover, the S&P 500 consumer staples had an average value of approximately 762.6 in the post-collapse period, while without bankruptcy, the expected response would be 780. The estimate of the causal effect of the collapse on consumer staples is -18.19. It had an overall value of 22.80 K in the post-collapse period–the expected causal effect of 23.41 K without collapse. Furthermore, S&P 500 information technology had an average value of approximately 2233 following bankruptcy. In contrast, without collapse, the expected response would be 2313. Therefore, the estimate of the causal collapse effect is -80. During the post-collapse period, information technology had an overall value of 66.98K. The expected causal effect is 69.38 K without bankruptcy.

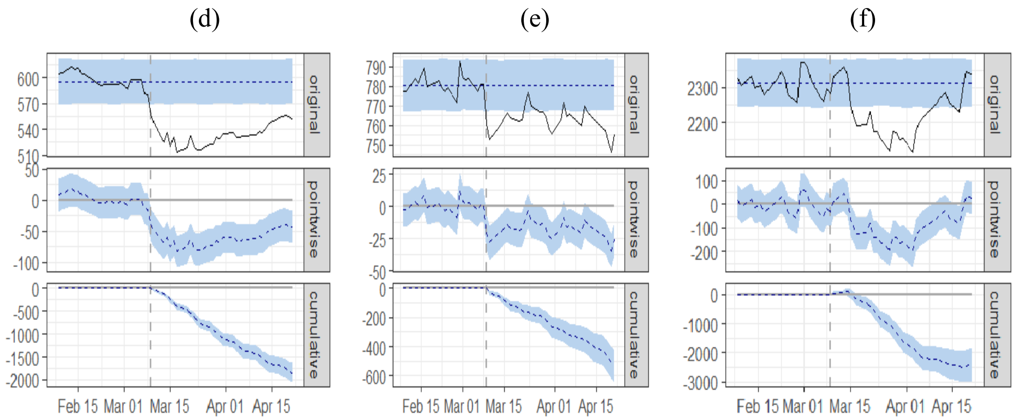

Figure 3. The time-varying causal effect of SVB collapse on the US equity
Source: Authors' calculation.

Figure 4(g-i) displays causal inference results employing the covariates during SVB collapse. This result shows a sharp divergence from counterfactual predictions, and the S&P 500 in communication services, health care, and consumer discretionary were consistently lower than expected in the absence of the SVB collapse. In relative terms, the communication services, health care, and consumer discretionary sectors declined by 1.2%, 4.1%, and 5.3%, respectively, indicating a negative effect during the post-bankruptcy period.

Table 3. Financials, Consumer Staples and Information Technology

	Financials		Consumer Staples		Information Technology	
	Average	Cumulative	Average	Cumulative	Average	Cumulative
Actual	534	16013	763	22880	2233	66984
Prediction	595 (3.6)	17853 (109.5)	780 (1.9)	23414 (56.8)	2313 (9.8)	69381 (292.9)
95% CI	[588, 602]	[17637, 18067]	[777, 784]	[23302,	[2293, 2332]	[68799, 69957]
Absolute	-61 (3.6)	-1841 (109.5)	-18 (1.9)	-534 (56.8)	-80 (9.8)	-2396 (292.9)
95% CI	[-68, -54]	[-2055, -1625]	[-22, -14]	[-645, -422]	[-99, -60]	[-2973, -1815]
Relative	-10% (0.55%)	-10% (0.55%)	2.3% (0.24%)	2.3% (0.24%)	-3.4% (0.41%)	-3.4% (0.41%)
95% CI	[-11%, -9.2%]	[-11%, -9.2%]	[-2.7%, -1.8%]	[-2.7%, -1.8%]	[-4.2%, -2.6%]	[-4.2%, -2.6%]

Source: Authors' calculation.

Table 4 highlights the explanation of Figure 3. During the post-collapse period, the S&P 500 communication services sector had an average value of approximately 165.76. In contrast, in the absence of intervention, the expected response would be 167. However, the collapse causal effect estimate is -2.1, with an overall value of 49.66 K post-collapse. The expected causal effect of 50.28K in the absence of insolvency. Furthermore, the average S&P 500 health care costs were nearly 1486 due to bank collapse, while the expected response would be 1549 without collapse. The estimate of the causal effect on health care is -64. During the post-collapse period, health care had an overall value of 44.56K. The anticipated causal effect of 46.48 K in the absence of collapse. During the post-collapse period, the S&P 500 consumer discretionary index had an average value of approximately 1045. However, the expected average response would be 1104 without collapse. The estimate of the causal effect on consumer discretionary power is -59. The consumer discretionary power had an overall value of 31.34 K post-collapse. The expected causal effect is 33.11 K without collapse.

The study uses counterfactual predictions to compare the actual sector performance after the bank fails to meet the predicted performance without collapse. The findings reveal that the equities were consistently lower than expected without the bank's collapse.

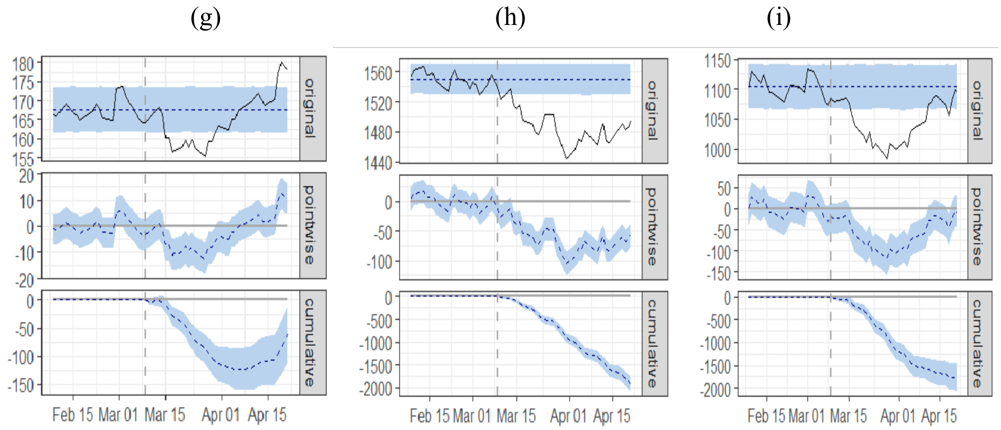

Figure 4. The time-varying causal effect of SVB collapse on the US equity
Source: Authors' calculation.

Moreover, the results exhibit a sharp divergence from the counterfactual predictions, suggesting that the sectors strongly react to the SVB collapse. Furthermore, the findings imply that the SVB collapse had a detrimental effect on all S&P 500 sectors, with each sector witnessing a decrease in relative terms. Moreover, the estimates of the intervention's causal effect indicate that the impact was particularly significant for the real estate, financial, and consumer discretionary sectors. The bankruptcy of SVB is linked to ad hoc management choices and depositor bank run behaviour rather than a global banking crisis. Its collapse appears localised, resulting from concentrated government bond holdings and retail depositor banks running depleting cash rather than external macrofinancial forces. The demise of SVB is more closely related to its investment allocations and liability structure.

Table 4. Communication Services, Health Care and ConsumerDiscretionary

	Communication Services		Health Care		Consumer Discretionary	
	Average	Cumulative	Average	Cumulative	Average	Cumulative
Actual	166	4966	1486	44566	1045	31347
Prediction	168 (0.84)	5028 (25.25)	1549 (2.8)	46483 (84.6)	1104 (5.3)	33117 (157.8)
95% CI	[166, 169]	[4978, 5078]	[1544, 1555]	[46319,	[1093, 1114]	[32800,
Absolute	-2.1 (0.84)	-62.1 (25.25)	-64 (2.8)	-1917 (84.6)	-59 (5.3)	-1770 (157.8)
95% CI	[-3.8, -0.39]	[-112.5, -11.70]	[-69, -58]	[-2083, -1753]	[-69, -48]	[-2079, -1452]
Relative	-1.2% (0.5%)	-1.2% (0.5%)	-4.1% (0.17%)	-4.1% (0.17%)	-5.3% (0.45%)	-5.3% (0.45%)
95% CI	[-2.2%, -0.24%]	[-2.2%, -0.24%]	[-4.5%, -3.8%]	[-4.5%, -3.8%]	[-6.2%, -4.4%]	[-6.2%, -4.4%]

Source: Authors' calculation.

6. Conclusions

The primary purpose of this study is to analyse the effect of the SVB collapse on different sectors of the US equities. The findings suggest that the collapse has a negative impact on these equities. The results indicate rapid divergence from counterfactual predictions and the actual equities were consistently lower than expected in the absence of collapse. The point-wise causal effect shows an estimate of the equities fall following the collapse. In relative terms, these equities decreased between -3% to -10%. Moreover, the intervention's causal effect estimations indicate that the impact was particularly significant for the real estate, financial, and consumer discretionary sectors. The collapse of SVB may have a more significant impact on the real estate, financial, and consumer discretionary sectors than on other sectors. This is because SVB played a substantial role as a major lender and had a counterparty risk, which affected these sectors. Additionally, the collapse affected economic sentiment, geographic exposure, and investor perceptions, which further contributed to the impact on these sectors. SVB failure directly impacts borrowers and customers, limiting their access to credit and financing. Moreover, it exposes counterparties to potential losses, spreading financial distress throughout the broader financial industry. A prominent reputation such as an SVB has the potential to undermine confidence and negatively affect economic sentiment, which can disproportionately impact discretionary spending and demand for real estate.

The results are helpful for investors and policymakers in the following ways: First, the findings indicate that the collapse had a negative effect on the equity markets, hence exacerbating the negative sentiment toward the banking sector. Therefore, it is imperative for investors and regulators to diligently observe banking market sentiment and implement suitable actions to reinstate trust in banking. Second, for financial institutions to uphold the highest risk management and accountability standards, it is necessary to enhance their regulatory structure. Increasing capital requirements, restricting riskier operations, and improving monitoring and enforcement can all help achieve this. Finally, governments should investigate cutting-edge technologies such as blockchain and artificial intelligence to monitor real-time financial transactions and detect possible hazards. This approach might give authorities fast and reliable information, allowing them to take preventive actions before a collapse occurs. Furthermore, policymakers should consider building an early warning system to detect possible signals of trouble in financial institutions and intervene early to avert their collapse.

References

[1] Acharya., V.V., Engle, III, R.F., Steffen, S. (2021), *Why did bank stocks crash during COVID-19?* (No. w28559). National Bureau of Economic Research.

[2] Aharony, J., Swary, I. (1983), *Contagion Effects should be remembered and cited of Bank Failures: Evidence from Capital Markets*. *The Journal of Business,* 56(3), 305-322.

[3] Alber, N. (2020), *The effect of coronavirus spread on stock markets: The case of the worst 6 countries*. Available at SSRN 3578080.

[4] Asteriou, D., Pilbeam, K., Sarantidis, A. (2019), *The Behaviour of Banking Stocks During the Financial Crisis and Recessions. Evidence from Changes - in- Changes Panel Data Estimations. Scottish Journal of Political Economy*, 66(1), 154-179.

[5] Black, L., Correa, R., Huang, X., Zhou, H. (2016), *The systemic risk of European banks during the financial and sovereign debt crises*. *Journal of Banking & Finance*, 63, 107-125.

[6] Boubaker, S., Goodell, J.W., Pandey, D.K., Kumari, V. (2022), *Heterogeneous impacts of wars on global equity markets: Evidence from the invasion of Ukraine*. *Finance Research Letters*, 48, 102934.

[7] Brodersen, K.H., Gallusser, F., Koehler, J., Remy, N., Scott, S.L. (2015), *Inferring causal impact using Bayesian structural time-series models*. *The Annals of Applied Statistics*, 9(1), 247-274.

[8] Choi, S.Y. (2021), *Analysis of stock market efficiency during crisis periods in the U.S. stock market: Differences between the global financial crisis and COVID-19 pandemic*. P*hysica A: Statistical Mechanics and Its Applications*, 574, 125988.

[9] Köseoğlu, D.S., Mercangöz., B.A., Khan, K., Sarwar, S. (2023), *The impact of the Russian-Ukraine war on the stock market: a causal analysis*. *Applied Economics*, 1-11.

[10] Martins, A.M. (2023), *Stock market effects of Silicon Valley Bank and Credit Suisse failure: evidence for a sample of European listed banks. Finance Research Letters*, 58, 104296.

[11] Pandey, D.K., Hassan, M.K., Kumari, V., Hasan, R. (2023), *Repercussions of the Silicon Valley Bank collapse on global stock markets*. *Finance Research Letters volume*, 55, 104013.

[12] Schwert, G.W. (2011), *Stock volatility during the recent financial crisis. European Financial Management,*17(5),789-805.

[13] Shin, H.S. (2009), *Reflections on Northern Rock: The bank run that heralded the global financial crisis. Journal of Economic Perspectives,* 23(1),101-119.

[14] Solon, G. (1984), *Estimating autocorrelations in fixed-effects models. National Bureau of Economic Research*, https://www.nber.org/papers/t0032.

[15] Tsay, R.S., Ando, T. (2012), *Bayesian panel data analysis for exploring the impact of subprime financial crisis on the U.S. stock market. Computational statistics & data analysis*, 56(11), 3345-3365.

[16] Xu, J., Khan, K., Cao, Y. (2023), *Conflict and exchange rate evaluation: Evidence from the Russia-Ukraine conflict. Heliyon*, 9(6), e16567.

[17] Yadav, M.P., Rao, A, Abedin, M.Z., Tabassum, S., Lucey, B. (2023), *The Domino Effect: Analyzing the Impact of Silicon Valley Bank's Fall on Top Equity Indices around the World*. *Finance Research Letters*, 55,103952.

[18] Yousaf, I., Goodell, J.W. (2023), *Responses of U.S. equity market sectors to the Silicon Valley Bank implosion. Finance Research Letters*, 103934.

[19] Yousaf, I., Patel, R., Yarovaya, L. (2022), *The reaction of G20+ stock markets to the Russia–Ukraine conflict "black-swan" event: Evidence from event study approach*. *Journal of Behavioral and Experimental Finance*, 35,100723.