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Is my bank the same? heterogeneity in market reactions to the silicon valley bank and signature bank failures

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ABSTRACT

This paper examines stock market reactions to the Silicon Valley Bank (SVB) and Signature Bank (SB) failures in March 2023. Using an event study of U.S. bank holding companies, we document significant negative abnormal returns surrounding the failures, with losses emerging prior to the SVB closure and intensifying on the event dates. We further analyze cross-sectional heterogeneity in market reactions based on banks' common exposures to SVB and SB. Banks with similar balance sheet characteristics—particularly large holdings of held-to-maturity and available-for-sale securities, sizable unrealized losses, concentrated lending portfolios, and high uninsured deposits—experienced significantly more adverse stock price responses. These findings are consistent with an indirect contagion channel in which investors react to common unfavorable signals rather than direct interbank linkages. Overall, the results inform ongoing policy debates regarding accounting measurement, disclosure, and banking sector stability during periods of systemic stress.

1. Introduction

In 2023, the U.S. was shocked by the major bank failures of Silicon Valley Bank (SVB) and Signature Bank (SB), which were closed by regulators on March 10th and 12th, respectively.[1] Together, these two failures accounted for 43% of the total assets of all failed banks in the U.S. since 2001 (Young and Doolittle, 2023). Both banks were characterized by having large held-to-maturity (HTM) and available-for-sale (AFS) securities portfolios, and large concentrated loan portfolios and uninsured deposit bases. These made both banks vulnerable to fair-value losses and a loss of depositor and investor confidence following negative signals about their banks' balance sheets.[2] Once doubts about the solvency of SVB and SB emerged, uninsured depositors had strong incentives to withdraw quickly, and digital banking channels and social media uniquely accelerated outflows and panic (Banque de France, 2024).

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[1] The significance of these failures prompted the U.S. Federal Reserve to introduce the Bank Term Funding Program ("Program") as an additional borrowing facility to help banks to meet the withdrawal requests of depositors without having to sell high quality securities quickly to meet obligations (see: Federal Reserve Board, 2024).

[2] For example, a loss of confidence led to an outflow in excess of 25 percent of SVB's total deposits on March 9th, 2023 (Federal Reserve Board, 2023a). This figure is very close to the 20 percent of deposits reported by Blickle et al. (2022) who study how depositors behaved in the absence of deposit insurance during the German Crisis of 1931.

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Not only were the SVB and SB bank failures and the panic of 2023 unique compared to prior bank failure episodes,[3] but they also highlighted significant weaknesses in the wider banking sector (Jiang et al., 2024; Metrick, 2024). Consistent with this, recent evidence infers that overall stock market reactions to SVB and SB were negative for U.S. banks; for instance, Martins (2025) finds that U.S. bank stock prices responded negatively to the SVB failure. Yet the fact that only SVB and SB failed despite sharp interest rate hikes between early 2022 and 2023 that devalued banks' long-term securities could potentially imply that investors and depositors may have differing responses with respect to the failures. Therefore, from one perspective, market participants may have viewed these events as evidence of the broader sector's resilience (DeMarzo et al., 2025; Kelly and Rose, 2025). Thus, some investors may have reacted positively to the news. Conversely, since significant bank failures represent information shocks or "common signals", investors may have reacted by withdrawing funds from banks they believe have common exposures to asset classes or interlocking exposures (Iori et al., 2006; Allen et al., 2012; Beatty and Liao, 2014). As theorized by Iori et al. (2006), the effects of such signals are, therefore, likely ambiguous in a heterogeneous banking sector and can result in indirect contagion even in the presence of government intervention. Therefore, the SVB and SB failures raise specific questions, which have yet to be addressed in the literature, as to how investors of other banks react to their failures, especially in the case of banks with common exposures.

In this paper, we address the implications of the SVB and SB shocks on U.S. bank holding company (BHC)[4] stock returns by employing a classic event study approach, which facilitates granular analysis that explores how common exposures to these institutions condition market reactions. In doing so, our focus is on a potential indirect channel of contagion, whereby major bank shocks can induce "criticality" in the banking system (Iori et al., 2006) as investors react to a common unfavorable signal. We conjecture that if banks with common exposures to SVB and SB suffer more adverse market reactions than peers, this is more consistent with the response of investors to a common signal. Underpinning this conjecture is the notion that indirect linkages between banks can be as important as direct ones. Such connections often emerge when banks hold similar or correlated assets, which exposes them to common risk factors. In periods of market stress, rapid asset liquidation can depress prices, thereby adversely affecting other institutions with common exposures (e.g., Adrian and Shin, 2010; Shleifer and Vishny, 2011; Greenwood et al., 2015; Duarte and Eisenbach, 2021).

By way of preview, we document several findings. First, we find that SVB and SB failures resulted in BHC shares suffering significant losses on average. Our event study evidence suggests that the average return over the seven trading days surrounding the SVB shock was −13.1%. Second, based on conditional analyses that facilitate analysis of the extent of common exposures to SVB and SB, we show that banks with common exposures were worst affected, which we interpret as more consistent with the response of investors to a common unfavorable signal than a pure contagion effect (Iori et al., 2006). Specifically, we find that the key common exposures are the relative size of HTM and AFS securities, unrealized gains and losses on these securities, as well as lending portfolios, asset growth, and uninsured deposits. Moreover, the most negative market reactions were realized by banks that had worse positions for these characteristics relative to SVB and SB. Additionally, we find that more general bank-specific structural weaknesses in terms of quality of bank capital and assets, and more general deposit portfolio and lending structure, explain market reactions for specific banks.

We make two main contributions. First, we add to recent literature on the SVB failure (e.g., Martins, 2023; 2025; Yousaf and Goodell, 2023; Perdichizzi and Reghezza, 2023). This literature finds that the banking sector (e.g., Martins, 2023, 2025; Perdichizzi and Reghezza, 2023), as well as other industries (e.g., Yousaf and Goodell, 2023), reacted negatively overall to the SVB shock. However, the literature has yet to examine whether stock price reactions are more salient for banks with common exposures to SVB and SB. We address this gap by demonstrating that banks with common exposures to the failed institutions suffered the most adverse market reactions.

In doing so, we also contribute more broadly to the classic literature on bank fragility, bank runs and contagion. From this literature, we know that bank failures can cause real economic harm (Diamond and Dybvig, 1983; Iori et al., 2006; Allen and Carletti, 2013; Beatty and Liao, 2014; Hodder and Hopkins, 2014; Molyneux and Wilson, 2017; Dicks and Fulghieri, 2019; Bischof et al., 2021). For example, Dicks and Fulghieri (2019) argue that bank runs can promulgate stock market crashes and flights to quality, which in turn can promote contagion and undermine the fragility of the entire financial system, making it more fragile and prone to crises. Moreover, if investors and depositors are uncertain of the quality and accuracy of banks' disclosures, this can promote indirect contagion and reach a critical point that threatens the stability of the banking system, as emphasized by the GFC (Bischof et al., 2021). Iori et al. (2006) argue that major shocks, such as those caused by significant bank failures, can exacerbate informational asymmetries, thereby making it harder for depositors and investors to monitor banks and resulting in indirect contagion as market participants react to common unfavorable signals.

We add to this literature by demonstrating the potential for transmission of shocks from recent key bank failures to other banking institutions and that the degree of distress is contingent on common exposures. Our findings are generally consistent with an indirect contagion effect, whereby investors and depositors react to a common unfavorable signal rather than through direct contagion (Iori

[3] For example, the bank failures of 2023 differ fundamentally from those of the global financial crisis (GFC) of 2007–2009. The primary causes of the 2023 bank failures include interest-rate risk associated with long-duration securities. SVB and similar institutions accumulated large portfolios of fixed-income securities financed by volatile deposits. Rapid monetary tightening beginning in 2022, accompanied by the sharp increase in the fed fund rate, led to a decline in the value of these assets and substantial unrealized mark-to-market losses, transforming previously assumed safe assets into sources of balance sheet stress when liquidity was needed to meet withdrawals. The GFC, by contrast, originated in the credit and housing markets and was characterized by excessive leverage, deteriorating mortgage credit quality, and fragilities in short-term funding markets. The prevailing excessive use of securitization and opaque derivatives further helped transmit credit risk throughout the financial system. Therefore, interest-rate risk, not credit risk during GFC, was pivotal in 2023.

[4] We empirically focus on BHCs in this paper but use the terms "BHC" and "bank" interchangeably.

et al., 2006). Importantly, our findings support the notion that although investors of U.S. banks reacted negatively on average, reactions differed based on the degree to which other banks had common exposures to SVB or SB prior to their collapse. From a regulatory and supervisory perspective, knowing which bank characteristics are deemed riskier by the market can assist in identifying fragilities and weaknesses early and help facilitate timely responses to bank failure shocks (Burton and Seale, 2005).

2. Relevant literature and hypothesis development

2.1. Systemic risk, contagion, and investor reactions to common signals

Since the GFC there has been increased attention by regulators and policymakers on systemic risk based on interactions between banking institutions and financial markets (Allen and Carletti, 2013; Beatty and Liao, 2014; Molyneux and Wilson, 2017; Berger et al., 2020; Jiang et al., 2024). This macroprudential perspective contrasts with the traditional approach to measuring risk, based on the summation of individual risk within the banking and financial sector, which did not capture systemic risk (Allen et al., 2012; Allen and Carletti, 2013; Beatty and Liao, 2014). According to Allen and Carletti (2013), systemic risk can be classified according to one of four categories: banking panics that arise from multiple equilibria, banking crises attributable to falls in asset prices, mismatches of foreign exchange rates within the banking system, and contagion – the focus, alongside *investor reactions to common signals*, of this section.

The relative importance of banks within economic systems, combined with the strength of direct and indirect linkages and exposures between individual banks, financial markets, and the real economy, means that contagion is a key characteristic of the banking sector, and one reason banks are considered special. From the perspective of traditional banking theory, and even in the presence of government intervention in the form of bank bailouts and deposit insurance, an always present concern is of a potential "contagious" effect whereby a loss of public confidence may incite panic, and bank runs even in healthy institutions. Major bank failures can incite contagion and potentially lead to 'systemic failure' through these channels or via a classic 'bank run', a self-fulfilling panic where depositors and investors rush to withdraw money, leading to runs on multiple banks (Diamond and Dybvig, 1983).

Although firm failures are not unique to the banking sector, the threat of contagion uniquely influences bank incentives (Dell'Ariccia and Ratnovski, 2019; Vives, 2014); one core idea to emerge from traditional banking and economic theory is that the failure of significant banks can lead to widespread contagion, which emphasizes a need for effective risk management and crisis response mechanisms. Similarly, another outcome from major bank failures, though not mutually exclusive, is that they can result in large losses of value and threaten bank stability – especially for banks that investors believe have similar exposures to asset classes or interlocking exposures, as investors react to unfavorable market signals (Iori et al., 2006).

Yet, since Bagehot (1873), it has often been argued that government interventions, in the form of bailouts and guarantees, can exacerbate long-term moral hazard problems and result in increases in systemic risk within the banking sector (Gale and Vives, 2002; Iori et al., 2006; Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012; Dam and Koetter, 2012; Chari and Kehoe, 2016; Altinoglu and Stiglitz, 2023). Moreover, especially pertinent to the cases of SVB and SB, existing literature highlights that government intervention in the banking sector, or the expectation of intervention, can distort incentives, particularly when banks come to expect bailouts in times of distress. Notably, they can incentivize banks to engage in excessive risk-taking and hence invest in similar risky assets, which results in ex-ante common exposures. In other words, when the downside of failure is implicitly covered by the state, banks may respond by aligning their portfolios toward similar high-risk assets, essentially becoming more systemically important and therefore more bailout-worthy. The failures of SVB and SB serve to highlight such concerns in the case of large banking institutions and lead to questions regarding safety net design and the methods for planning and carrying out the resolution of banks (Gruenberg, 2023).

Acharya and Yorulmazer (2007) develop a model showing that banks have a strategic incentive to herd into correlated exposures, not out of informational efficiency, but to increase the likelihood of joint failure, which strengthens their bargaining position in a crisis. In different words, common exposures are not necessarily accidental or exogenous. Instead, they may be the result of rational, forward-looking behavior in a world where the state cannot credibly commit not to intervene. Farhi and Tirole (2012) build on this idea and demonstrate that when the costs of letting banks fail are too high, governments are effectively forced to intervene, which in turn encourages financial institutions to mimic one another's risk-taking ex ante. More recently, Altinoglu and Stiglitz (2023) show how expectations of government bailouts during financial crises incentivize banks to become excessively interconnected and risk-taking, with negative implications for systemic risk. The authors' model infers that even smaller banks mimic the behaviour of large banks, leading to widespread exposure to similar risky assets.

Empirical research echoes these theoretical insights. For instance, a comprehensive survey of the post-2008 financial crisis literature by the Financial Stability Board (2021) concludes that expectations of government support historically encouraged excess risk-taking. Representative of these studies, Duchin and Sosyura (2014) find that banks that received federal funds capital during the 2008 financial crisis were more likely to issue riskier loans and increase capital allocations towards more complex and risky securities. This led to an increase in the probability of default of recipient banks as well as a significant increase in systemic risk.

2.2. Stock market reactions to banking crises and bank failures

There is a growing literature that employs the classic event study methodology to assess the impact of a wide range of banking crises and bank failures. Existing studies typically focus on abnormal stock returns around crisis-related announcements, capturing both direct and spillover effects. In doing so, studies capture not just the immediate impact on affected banks, but also broader market sentiment and contagion effects.

First, one stream of this research uses the event study methodology to examine how financial markets respond to banking crises (e.

g., Bowen and Khan, 2014; Correa et al., 2014; Duchin and Sosyura, 2014; Fahlenbrach et al., 2012). For instance, Fahlenbrach et al. (2012) find that banks with high reliance on short-term funding, as well as those with higher leverage and growth, experienced significantly more negative abnormal returns during the 2007–2009 financial crisis, suggesting that market participants viewed certain funding structures as particularly vulnerable. Iannotta et al. (2013) conduct a similar event study across European banks and show that announcements of bank losses or failures triggered sharp negative reactions not only for the affected institutions but also for others in the same region, reflecting fears of contagion. Their results point to a breakdown of differentiation during crises, with the market treating banks as interconnected rather than isolated entities.

Subsequent studies refined this approach by analyzing specific policy interventions and how investors interpret government actions. Duchin and Sosyura (2014) perform an event study around the announcement of Troubled Asset Relief Program (TARP) capital injections and find that banks receiving assistance saw abnormal returns that were either positive or negative depending on pre-existing market expectations. The authors suggest that investors distinguish between healthy banks receiving precautionary support and weaker institutions viewed as being rescued. Using data on 37 countries, Correa et al. (2014) examine announcements of public support for national banks in response to sovereign rating shocks, which signal changes in the financial conditions of governments, and find that these events often resulted in abnormal losses for both banks and their sovereigns, highlighting concerns over fiscal risk and the credibility of bailouts. Finally, Miyajima and Yafeh (2007) investigate the impact of key events during the Japanese banking crisis of 1995 to 2000 on the market value of Japanese non-financial companies and find heterogeneity in firms' exposures. Specifically, they find that smaller, more leveraged, poorly rated, as well as firms with low market-to-book ratios and low-tech firms were the most adversely affected. Taken together, this first stream of the banking event study literature underscores the continued relevance of event study methods in capturing how investors interpret signals during banking crises and also highlights the role of both firm characteristics and institutional context in shaping market responses.

A second major stream of this literature uses the event study method and examines how specific firms respond to bank failures. Several studies look at the impacts of specific bank failures on the market value of other firms. Goldsmith-Pinkham and Yorulmazer (2010) analyze spillover effects around the 2008 failure and government bailout of Northern Rock in the UK. The authors show that both the initial run on the bank and the subsequent bailout announcement negatively impacted banks that shared a similar liability side of the balance sheet. Zhou (2023) investigates the market reactions of losing and winning banks participating in auctions of failed banks by the Federal Deposit Insurance Corporation (FDIC) between 2007 and 2013. He finds that losing (winning) banks realize significant negative (positive) abnormal stock returns. Schiereck et al. (2016) examine the stock market and CDS spreads reactions of banks to both the failure of Lehman Brothers in September 2008, as well as to the results of the June 2016 Brexit referendum in the UK. The authors show that while the Brexit result had a more severe negative effect on banks – especially those from the EU, the increase in CDS spreads was larger following the Lehman Brothers bankruptcy filing. Goldsmith-Pinkham and Yorulmazer (2010) analyze the spillover effects from the Northern Rock episode in the UK. Their findings support the notion that the event had a negative impact on the stock returns of banks that similarly relied heavily on funding from wholesale markets, which is consistent with investors reacting to an unfavorable signal.

Finally, a very recent focus of this second literature stream is on the SVB and SB bank failures. Martins (2025) examines the impact of the SVB and Credit Suisse failures on the stock of the 100 largest U.S. banks and find that bank stock prices respond negatively to both events. The author shows that banks with preexisting higher liquidity, interest margin, risk aversion, operational efficiency, and lower institutional ownership realize less adverse market reactions to both shocks.

Although SVB was a U.S. bank failure, several recent studies examine bank equity market reactions in countries other than the U.S. For example, Perdichizzi and Reghezza (2023) consider its impact on euro-area banks — arguing that spillover effects could extend beyond the U.S. banking sector. Consistent with this, they find that European banks suffered adverse market reactions to the shock, with bank CARs decreasing about 10% in response to news of the SVB failure. However, they observe no differences in market reactions based on salient bank characteristics and business models, as was found by Goldsmith-Pinkham and Yorulmazer (2010) in the case of UK bank market reactions to the 2008 Northern Rock failure. Similarly, Martins (2023) examines the stock market reactions of the 100 largest European listed banks in response to the failures of SVB and Credit Suisse. In the case of both failures, the author observes significant negative stock market reactions at and around the failure announcements. Consistent with the Credit Suisse shock being more relevant to European banks, the negative market reactions are stronger to this event. Similar to Martins (2025), the author further demonstrates that the magnitude of abnormal return declines is moderated by preexisting bank characteristics, including liquidity, capitalization, profitability, and institutional ownership. In the spirit of these papers, Ali et al. (2024) examine cross-regional effects from the SVB collapse. They find that U.S. and European banks experience significant negative responses to SVB's failure, whilst Chinese banks were relatively unaffected. Their findings infer differing regional sensitivities to the SVB shock. Finally, like Perdichizzi and Reghezza (2023), Ali et al. (2024) and Martins (2023), Yousaf and Goodell (2023) study the impact of the SVB shock. However, the focus of Yousaf and Goodell (2023) is on the impact of the event on 11 different U.S. industries. They find that only firms operating in specific sectors (financial, materials, and real estate) realized negative market reactions around the event.

In summary, the SVB literature establishes that stock prices of financial firms (e.g., Perdichizzi and Reghezza 2023; Yousaf and Goodell 2023) and banks specifically (e.g., Martins, 2023, 2025) reacted negatively to the SVB failure. Moreover, such stock price reactions exhibit significant bank-specific heterogeneity based on bank business model (Martins, 2023; 2025). However, the existing literature has yet to explore whether the extent of common exposures to SVB and SB condition the response of investors to these shocks, which is an important question from a bank regulatory and supervisory perspective. We address this gap.

2.3. Hypotheses development

In this subsection, we outline two hypotheses regarding the impact of the SVB and SB failures on other banks. As the previous discussions imply, the collapse of SVB and SB raised immediate concerns amongst investors across the banking sector. These reactions were not just about direct exposure or financial contagion, but rather they reflected deeper anxieties about systemic risk and the possibility that other banks might share similar vulnerabilities (i.e., common exposures). For example, the literature on financial contagion emphasizes how the collapse of a single institution can shift investors' perceptions of risk across the system (Allen and Gale, 2000; Kodres and Pritsker, 2002).

As Allen and Carletti (2013) argue, systemic risk arises not simply from individual failures but from the interconnectedness of institutions and the signals those failures send. SVB's collapse highlighted how quickly investor sentiment can shift when a bank's business model appears fragile in the face of rising interest rates and concentrated depositor bases. More specifically, SVB's reliance on a concentrated depositor base and its heavy exposure to interest rate risk underscored how quickly investor confidence can erode when doubts about a bank's financial stability emerge. This appears consistent with the extant banking literature, which suggests that investors are highly sensitive to common exposures and shared risk structures when a significant bank fails (e.g., Greenwood et al., 2015). In this sense, investor reactions to the SVB and SB failures were unlikely to be just about direct exposures but rather about the recognition of shared vulnerabilities. As classic models of bank fragility suggest, even the fear of weaknesses can spark broader sell-offs (Diamond and Dybvig, 1983; Iyer and Peydró, 2011).

Martins (2025) shows that banks with weaker liquidity and higher institutional ownership experienced sharper stock price declines following SVB's failure. This aligns with findings from Iannotta et al. (2013), who observed that during crises, markets tend to treat banks as interconnected rather than isolated entities. Investors may not have full visibility into each bank's balance sheet, but they do respond to signals that suggest broader sectoral weaknesses. In the case of SVB, the widespread use of HTM and AFS securities portfolios meant that many banks were sitting on unrealized losses. Even if those losses weren't immediately threatening, the failure of SVB made them harder to ignore.

Expectations of government intervention also play a complicated role. On the one hand, interventions can stabilize markets in the short term. On the other hand, they can distort incentives and encourage banks to take on similar risks, knowing that bailouts are likely in times of distress. Acharya and Yorulmazer (2007) argue that banks may even herd into correlated exposures to increase the likelihood of joint rescue. This behavior, driven by moral hazard, makes the system more fragile. Investors, aware of these dynamics, may interpret SVB's failure as a symptom of deeper structural problems, rather than an isolated event.

At the same time, there is a counterpoint worth considering. The fact that only several banks failed despite the fact that the Federal Reserve's rapid interest rate increases around this period (between the second quarter of 2022 and the 1st quarter of 2023) significantly devalued long-term securities held by banks, including those classified as HTM and AFS (DeMarzo et al., 2025; Kelly and Rose, 2025), might potentially signal to other banks' investors that their banks are resilient. The SVB and SB shocks could be seen by market participants and depositors as a positive signal of the resilience and ability of their banks to withstand shocks. In some cases, the failures of SVB and SB may have even reinforced confidence in better-managed banks. Consistent with these ideas, Martins (2025) finds that although abnormal returns were negative for many banks immediately following the SVB collapse, market reactions were moderated by bank-specific characteristics such as liquidity and capitalization. A separate reason why investors of peer banks may have reacted positively to the SVB and SB episodes relates to the swiftness and depth of regulatory intervention, including the systemic risk exception and full deposit guarantees (Metrick, 2024; Martins, 2025). As emphasized by the Financial Stability Board (2024), the swift and wide-reaching interventions helped reassure investors about the safety of the broader banking system, thereby restoring market confidence and preventing broader contagion.

Still, the balance of evidence leans toward a more cautious interpretation. Information asymmetries make it difficult for investors to know which banks are truly resilient. The existing literature consistently shows that during banking crises negative reactions are more widespread and severe than any positive reassurances. In such environments, fear tends to dominate, and market reactions are expected to emphasize increased systemic risk, reduced confidence in the banking sector, and heightened liquidity concerns.

Based on this discussion, we therefore hypothesize an overall negative stock market reaction from U.S. peer banks to the SVB and SB failures:

Hypothesis 1. *All else equal, there is an adverse market reaction to the stocks of other banks following the failure of SVB and SB.*

Although the overall stock market reaction to the SVB and SB shocks is expected to be negative, there is good reason to conjecture that stock market reactions will vary in the cross-section. Based on our earlier discussions, one important reason why there would be cross-sectional variation relates to banks' common exposures. The underlying notion is that common exposures may trigger negative spillover effects or "correlated losses" (Stiroh and Rumble, 2006). *In the remainder of this section, we therefore develop a second hypothesis that considers that stock price reactions should be more adverse for banks with common exposures to SVB or SB.*

First, the failures of SVB and SB were directly related to their exposure to long duration bonds classified as HTM and available-for-sale (AFS) securities. For example, in the years prior to failure, SVB has invested a large portion of client deposits in long-dated HTM, government, or agency-issued mortgage-backed securities (agency MBS) (Federal Reserve, 2023b). Moreover, the relative size of both banks' HTM and AFS securities was far higher than that of the average bank, which played a significant role in their failures (Federal Reserve, 2023b). This was especially true in the case of SVB, since they obscured the bank's exposure to interest-rate risk and its deteriorating capital position (Chen et al., 2024), which happened in response to changes in the rate environment (Federal Reserve, 2023b). This meant that when problems emerged, both banks were forced into recognizing huge unrealized losses in their books in relation to HTM and AFS securities. Therefore, two key commonalities relate to the relative size of HTM and AFS securities as well as the magnitude of unrealized losses on these securities.

Second, a further area of common exposure is bank lending. Both SVB and SB had significantly lower *loans to total asset* ratios compared to peers. As shown by the Federal Reserve (2023b) as of year-end 2022 SVB had a ratio of *loans to total assets* of 35%, in contrast to an average of 58% for large banking organizations (those with total assets in excess of $100 billion). SB bank also differed but in the other direction with a ratio of 67.3%, which was higher than typical. The low ratio of SVB compared to peers reflects its business strategy of holding large securities portfolios, while the business strategy of SB was much more focused on lending. While SVB and SB differed in terms of *loans to total assets* compared to peer banks, albeit in different directions, what was interesting about both SVB and SB is that both also had highly concentrated loan portfolios compared to peers. The highly concentrated loan portfolios of both banks were commented on by the regulator. For example, in the case of SB the FDIC stated that the bank's "*loan and deposit portfolio was highly concentrated in commercial real estate and commercial & industrial loans, including significant exposure to a limited number of high-value business clients. This concentration increased the bank's vulnerability to market shocks and rapid deposit outflows*." SVB had very high proportions of customers from venture capital-backed technology and life sciences companies, which would fall within commercial and industrial (C&I) loans in Call Report data, while similarly, SB had a high concentration of C&I loans relative to a typical bank.[5]

Third, another relevant factor is asset growth. The banking literature emphasizes that rapid asset growth can significantly increase a bank's risk of failure, particularly when growth is concentrated in a few sectors or financed by unstable deposits. For example, empirical studies show that banks growing faster than their peers face higher probabilities of distress, especially when asset growth occurs in nontraditional areas or concentrated sectors (e.g., Schaeck, 2008). Both SB and SVB were characterized by aggressive growth in the years prior to their failure compared to peers. From 2019 to 2021, the total assets of SVB and SB increased by 198% and 134% percent, respectively, compared to a 33% growth in the median total assets group of 19 peer banks (U.S. Government Accountability Office, 2023). Their experiences reflect the literature's warning that fast, concentrated growth, combined with funding and liquidity vulnerabilities, can sharply increase default risk.

Fourth, another source of commonality relates to uninsured deposits.[6] Both SVB and SB were characterized by having extremely high concentrations of uninsured deposits above FDIC insurance limits, which were used to fund aggressive asset growth in the years prior to their demise. Linking asset growth with uninsured deposits, the FDIC commented that in the case of SVB, 94% of deposits exceeded the maximum compensation as of year-end 2022, compared to the banking sector average for large banking organizations (Federal Reserve, 2023b).

Together, these characteristics associated with SVB and SB facilitate analysis of stock market reactions for non-failed banks based on the degree to which they exhibit commonalities to these identifiable characteristics: 1) *the size of HTM and AFS securities holdings*, 2) *the size of unrealized losses on HTM and AFS securities*, 3) *loans relative to total assets*, 4) *lending portfolio concentration*, 5) *asset growth*, and 6) *the size of uninsured deposits*. In other words, the extent of non-failed banks' common exposures to SVB and SB. As previously mentioned, a key gap in the existing literature on the SVB failure is a granular examination as to whether the degree of common exposures to SVB (and SB) induces heterogeneity in bank stock price reactions. This is an important gap, given the uniqueness of these bank failures. In all cases, our *a priori* expectation is that banks with greater (lower) common exposures in key areas should experience more (less) negative market reactions to the SVB and SB shocks.

To address this question empirically and examine banks' stock price reactions conditioned on bank characteristics that reflect common exposures to SVB or SB, we formulate the following hypothesis:

Hypothesis 2. *All else equal, the adverse stock price reaction is more salient for banks with common exposures to SVB and SB in terms of*: 1) *the size of HTM and AFS securities holdings*, 2) *the size of unrealized losses on HTM and AFS securities*, 3) *loans relative to total assets*, 4) *lending portfolio concentration*, 5) *asset growth, and* 6) *the size of uninsured deposits*.

3. Data and methodology

We collect financial statement data for all U.S. banks as of March 2023 from the Compustat Bank Fundamentals database. Stock price data for these institutions are obtained from the CRSP database. We supplement these data with granular information on loans, deposits, and securities holdings from the FR Y-9C regulatory reports. We use the Federal Reserve Bank of New York CRSP–FRB Link, accessed through the WRDS Bank Regulatory database, to merge CRSP and Compustat data with the FR Y-9C regulatory filings. We further restrict our sample to institutions classified as bank holding companies (BHCs) in this CRSP-FRB Link Dataset. The final sample, therefore, consists of BHCs for which both financial statement data and stock price information are available. For the sample banks, we

[5] It is not possible to obtain individual bank lending data broken down by industry for our sample because bank call reports only report loan data aggregated to the following four categories: *Commercial & Industrial (C&I) loans*, *Real estate loans (commercial, construction, residential)*, *Agricultural loans*, and *Loans to individuals*. While more granular (and normally confidential) data is available for stress tested bank holding companies through the FR Y-14Q schedules this only applies to a very small number of institutions (32 currently). Given this data restriction we therefore focus on aggregated lending data.

[6] From the banking literature, we know that a high proportion of uninsured deposits relative to total deposits exposes banks to heightened liquidity risk because uninsured depositors are more prone to rapid withdrawals in response to adverse news, thereby amplifying the likelihood of destabilizing bank runs (e.g., Diamond and Dybvig, 1983). These points are summarized by the FDIC (2023, p5) who state that "*uninsured deposits are considered higher risk as they are more prone to rapid runoff during reputational or financial stress than insured deposits*." In support, recent evidence by Chen et al. (2024) finds that U.S. banks with larger shares of uninsured deposits and lower capital ratios are generally more exposed to HTM securities when the Fed funds rate increases.

construct uninsured deposits at the BHC level by aggregating estimated uninsured deposits across subsidiary banks. Estimates of uninsured deposits are obtained from FFIEC reports where parent–subsidiary relationships are identified using the Bank Relationships database. Both databases are accessed via the WRDS Bank Regulatory database. Our accounting data sample consists of 263 publicly traded U.S. BHCs with financial data available as of the end of 2022 (i.e., the closest to the SVB and SB failures). Of these, two BHCs are excluded from the event study analysis due to insufficient stock price history to satisfy the 250-day estimation window, resulting in a final study sample of 261 BHCs.

3.1. Descriptive statistics

Table 1 displays descriptive statistics for the full accounting sample based on 263 publicly traded BHCs, excluding SVB and SB, since these are the reference banks. It includes all variables used in the paper, which are defined in Appendix A. We find, in all cases, that the reported values for our sample are very close to the equivalent values reported for BHCs in 2022 in the "BHCPR Peer Group Average Reports" (see Federal Financial Institutions Examination Council, 2025).

Regarding *asset size and quality*, banks in our sample have average total assets of 58 billion U.S. dollars with an average annual asset growth of 5.42%. We also find that non-performing assets are 0.46% on average for a typical bank, and that banks have loan loss provisions to total assets of 0.17% of total assets on average. Regarding risk, a typical BHC has a risk-weighted assets to total assets ratio of 77.73%. With respect to *profitability and income diversification indicators*, average profitability, measured as the return on assets, stands at 1.11%, with 18.62% of income coming from non-interest sources. Under *loans*, we find that a typical BHC has 68% of loans to total assets. In terms of the distribution of bank lending, a typical BHC has about 67% of total loans in real estate, 5.5% in consumer loans, and 18% in industrial loans.[7]

Examining *investments*, the average BHC invests 19.71% of total assets in securities and holds 10% in U.S. Treasury securities, 7% in U.S. government agency and sponsored agency obligations, 16% in securities issued by U.S. states and political subdivisions, 58% in mortgage-backed securities (MBS), and in 6% asset-backed securities and structured financial products. In U.S. dollar terms, the HTM security holding is about 10.6 billion in HTM and 7.9 billion in AFS securities. By the end of 2022, our sample BHCs had incurred average unrealized losses, measured as the difference between securities' amortized cost and fair value, of $1.3 billion for HTM securities and $685 million for AFS securities. With respect to *deposits*, the average BHC funds 82.5% of its total assets with deposits. Among these deposits, savings deposits account for 41.8% on average, followed by demand deposits at 16.7% and time deposits at 12.5%. The remaining 29% of deposits, approximately $17.2 billion, are non-interest-bearing. On average, about $12.9 billion of deposits are uninsured. Finally, in terms of *funding* structure, BHCs have Tier 1 capital of 12.5%, on average, with a leverage ratio (total shareholders' equity to total assets) of 9.46%. Approximately 7% of funding is supported by non-deposit short-term sources.

3.2. Methodology

To calculate the average Cumulative Abnormal Return (CAR) for our sample firm over the seven-day event window spanning from three days before to three days after the event, we start by estimating the following market model for each bank stock in our sample:

$$R_{i,t} = \widehat{\alpha}_i + \widehat{\beta}_i R_{m,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the logarithmic daily returns of bank i on day t, and $R_{m,t}$ is the market return on day t. We use the CRSP value-weighted index to represent the market index and use OLS regression to estimate the parameters (i.e., $\widehat{\alpha}_i$ and $\widehat{\beta}_i$) of the model. Following Ahmed et al. (2022), we use the market model regression with a 250-day estimation window that ends 25 days before the event day to calculate the daily Abnormal Return (AR) and CAR for each sample bank. Using the estimated parameters from equation (1), the daily abnormal return is calculated using the following equation:

$$AR_{i,t} = R_{i,t} - \left(\widehat{\alpha}_i + \widehat{\beta}_i R_{m,t}\right) \tag{2}$$

here, $AR_{i,t}$, is the daily abnormal return for bank i on day t. The cumulative abnormal return CAR_i for bank i is then calculated by summing the daily abnormal returns $AR_{i,t}$ over the event period $[\tau_1, \tau_2]$.

$$CAR_i = \sum_{t=\tau1}^{\tau2} AR_{i,t} \tag{3}$$

Throughout our analyses, we report Kolari and Pynnönen's (2010) cross-sectional correlation adjusted *t*-statistics (henceforth, KP test) for the standardized cross-sectional test statistic of Boehmer et al. (1991) (known as the BMP test statistic in the literature). Following Campbell et al. (1997), we use the estimation period standard deviation corrected for the sampling error to calculate the BMP test statistic. The assumption of the cross-sectional independence among sample firms' abnormal returns, specifically for events simultaneously affecting all firms, can lead to underestimating the standard errors and a severe over-rejection of the null hypothesis

[7] As we only use loans secured by real estate (real estate loans), commercial and industrial loans (industrial loans) and loans to individuals for household, family, and other personal expenditures (consumer loans) leaving other loan types reported in the FR Y–9C reports, the aggregate of these three loan shares does not add up to 100%.

Table 1
Descriptive statistics.

Variable	Mean	Median	SD	1st tercile	2nd tercile	Obs
Asset size and quality						
TA (in $ millions)	58,144	5,681	321,516	3,214	9,930	263
GA (%)	5.42	3.69	12.44	0.02	7.39	262
NPL (%)	0.46	0.36	0.41	0.22	0.50	262
LLP (%)	0.17	0.13	0.34	0.08	0.19	263
RWA (%)	77.73	79.15	11.60	75.56	81.90	180
Profitability and income diversification indicators						
ROA (%)	1.11	1.14	0.68	1.01	1.25	263
NII (%)	18.62	16.78	13.36	13.31	20.93	263
Loan portfolio composition:						
L2A (%)	68.03	71.17	13.36	64.82	75.20	263
RL2L (%)	68.63	71.76	17.29	65.21	78.03	184
CL2L (%)	5.51	1.74	7.82	0.86	4.16	184
IL2L (%)	18.80	16.33	11.27	12.59	21.83	184
Securities holdings						
I2A (%)	19.71	18.13	10.54	13.96	23.29	263
T2I (%)	9.90	3.34	15.88	0.25	8.91	184
F2I (%)	6.93	3.51	9.50	1.45	6.88	184
M2I (%)	16.18	11.08	16.43	5.62	20.30	184
MBS2I (%)	55.79	57.80	21.66	45.05	68.15	184
ABS2I (%)	5.99	0.76	10.56	0.02	4.50	184
HTM (in $ millions)	10,600	417	60,900	12	919	184
HTMUGL (in $ millions)	−1,370	−40	9,010	−96	0	184
AFS (in $ millions)	7,880	1310	26,000	776	2,483	184
AFSUGL (in $ millions)	−685	−163	1,710	−306	−99	184
Deposits structure						
D2A (%)	82.49	82.98	5.44	80.47	85.03	263
DD2D (%)	16.74	15.55	11.82	9.91	22.55	184
SD2D (%)	41.82	38.49	16.51	32.78	46.35	184
TD2D (%)	12.48	10.40	9.10	7.53	13.21	184
ND (in $ millions)	17,200	2,100	75,900	1,256	4,093	184
UID (in $ millions)	12,900	1,610	71,700	942	3,346	253
Funding sources						
LEV (%)	9.46	9.20	2.25	8.39	10.19	263
NDF (%)	6.98	5.98	5.17	4.29	8.12	263
TIER1 (%)	12.50	12.18	3.53	11.12	12.88	251

This table presents the mean, median, standard deviation (*SD*), 1st and 2nd tercile values, and the number of observations (*Obs*) of the variables for the sample bank holding companies (BHCs). The variables include total assets (TA), asset growth (GA), non-performing loans (NPL), loan loss provisions (LLP), risk-weighted assets (RWA), return on assets (ROA), non-interest income (NII), loans to assets (L2A), industrial loans to total loans (IL2L), consumer loans to total loans (CL2L), real estate loans to loans (RL2L), total investments to total assets (I2A), treasury securities to total investments (T2I), federal agency securities to total investments (F2I), state and municipal securities to total investments (M2I), mortgage-backed securities to total investments (MBS2I), asset-backed securities to total investments (ABS2I), held-to-maturity securities (HTM), unrealized gains and losses in HTM (HTMUGL), available-for-sale debt securities (AFS), unrealized gains and losses in AFS (AFSUGL), total deposits to total assets (D2A), saving deposits to total deposits (SD2D), demand deposits to total deposits (DD2DD), time deposits to total deposits (TD2D), non-interest deposits (ND), uninsured deposits (UID), leverage (LEV), non-deposit funding (NDF), tier 1 capital (TIER 1). The variables are defined in Appendix A.

(Kolari and Pynnönen, 2010). Following best practice in the literature, we report the KP test to mitigate the effect of cross-sectional correlation (e.g., Cellier et al., 2016).

In Section 4.1 to measure ex-ante identifiable potential common exposures, we determine the tercile to which SVB and SB would belong under a simple tercile split. Our focus is on 1) *the size of HTM and AFS securities holdings*, 2) *the size of unrealized losses on HTM and AFS securities*, 3) *loans relative to total assets*, 4) *lending portfolio concentration*, 5) *asset growth*, and 6) *the size of uninsured deposits*. This approach allows us to assess CAR relative to their peers for relevant bank common exposure variables and to compare outcomes across BHCs in lower and higher terciles, thereby shedding light on how responses vary with stronger or weaker performance along a given dimension. Furthermore, we also conduct additional analyses based on other, more general bank-specific characteristics, further consider whether they also represent common exposure factors, structural indicators of bank performance and condition, or are simply not perceived as important.

In Section 4.2, we expand the approach used in Section 4.1. and explicitly condition market reactions for each bank characteristic (i.e., ex-ante identifiable potential common exposures and other bank variables) based on the extent of a bank's similarity to SVB.[8] Specifically, we examine CARs for tercile portfolios formed on each variable (ex-ante common exposure factors and other variables) for our sample BHCs over different event windows. For each variable, BHCs are sorted into terciles based on their Euclidean distance from SVB, measured as the absolute difference between each BHCs' characteristics and those of SVB. Because Euclidean distances are strictly

[8] In unreported analyses available upon request, we do the same for SB.

non-negative and BHCs whose characteristics most closely resemble those of SVB have distances close to zero, sorting BHCs into Euclidean distance–based terciles assigns the most similar BHCs to the bottom tercile and the most dissimilar BHCs to the top tercile. We report test statistics based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns.

4. Empirical results

4.1. Overall market reactions to SVB and SB failure

We begin by examining how investors reacted to the failures of SVB and SB. Our expectation, as hypothesized in H1, is that the shock of these failures led to a significant decline in the share price values of BHCs on average within the U.S. banking sector. Consistent with this hypothesis, in Fig. 1, we observe significant negative abnormal returns around the main event day (SVB failure). Moreover, Table 2 reveals a statistically significant CAR of −13.11% for the full window [-3, 3]. Interestingly, the day before SVB's collapse, bank stocks generated statistically significant average abnormal returns of −3.58%, while on the event day, market returns were also negative yet not statistically significant. Yet, on March 13, the next trading day and date of the Signature Bank (SB) failure, was the highest single-day negative AR of −7.67%. Overall, while negative CARs are present in both pre- and post-event periods, losses are heavily concentrated in the post-event period [1, 3]. Taken together, our evidence in this section supports hypothesis H1.

The negative market reactions we observe are broadly comparable to those reported for other significant banking shocks. For example, Demirguc-Kunt et al. (2013) shows that the mean quarterly stock return of 0.4% during the period of Q1 2006 to Q2 2007. During the GFC from Q3 2007 to Q1 2009, the average quarterly stock return was −3.5% that reached −5.3% in the post-Lehman period of Q3 2008 to Q1 2009. Studying a sample of financial institutions with total assets exceeding $10 billion in 2006, Beltratti and Stulz (2012) report that the average stock return was −54.43% from July 2007 to December 2008. For banks in the worst-performing quartile, the average loss reached 87.44%, while those in the best-performing quartile lost substantially less, with an average loss of 16.58%.

4.2. Market reactions based on common exposures

Having found support for H1, in this section onwards, we begin to test H2. To do so, we split BHCs into tercile portfolios based on first the six key characteristics we identified for SVB and SB ((i.e., (1) *the size of HTM and AFS securities holdings*, 2) *the size of unrealized losses on HTM and AFS securities*, 3) *loans relative to total assets*, 4) *lending portfolio concentration*, 5) *asset growth*, and 6) *the size of uninsured deposits*)), and later on, other common financial variables are understood to affect bank performance (e.g., Adhikari and Agrawal, 2016). We then examine how these relate to CAR over [-3, 3], [-3, 1], and [1, 3] windows. In the results tables, we highlight to which tercile SVB and SB belong to facilitate comparisons. For the sake of brevity, we focus our discussions on results for the [-3, 3] window throughout. In all the tables and subsections discussed in this section (i.e., 4.2), the tercile to which SVB would belong is shaded in dark grey, while light grey shading denotes the tercile corresponding to SB when it differs from SVB's tercile and data for SB are available.

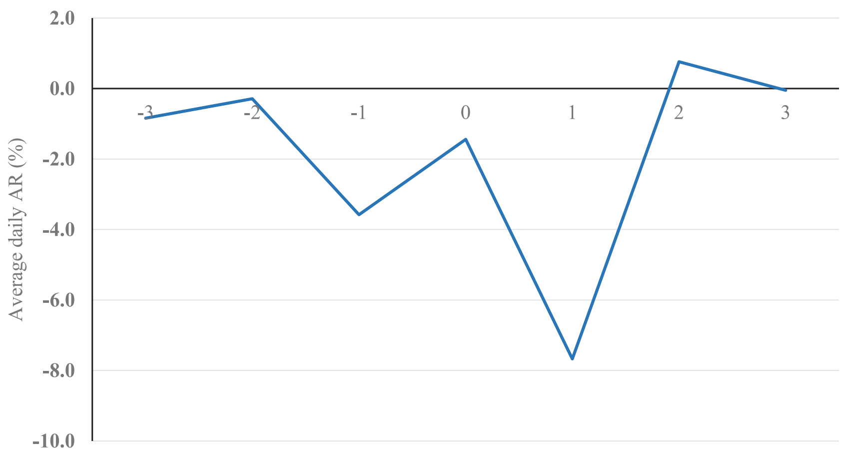

Fig. 1. Average daily abnormal return.

Table 2
Market reactions to the SVB and SB failures.

Window	CAR	KP	Obs
[-3,3]	−13.11	−3.06***	261
[-3,-1]	−4.71	−2.8***	261
[1,3]	−6.96	−2.19**	261

This table presents the average cumulative abnormal return (CAR) (measured in percentage), over different event windows for our sample BHCs. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3
Market reactions based on securities holdings.

Panel A	[-3,3]	[-3,-1]	[1,3]	Obs.
HTM				
Top	−16.59*	−6.74***	−8.93	61
Middle	−13.13**	−5.22***	−6.53*	60
Bottom	−11.94**	−5.38**	−5.21	61
HTMUGL				
Top	−11.89***	−5.44**	−4.99	61
Middle	−12.79**	−5.06***	−6.54	60
Bottom	−16.98*	−6.83***	−9.14	61
AFS				
Top	−19.06*	−7.71***	−10.17	61
Middle	−10.84**	−5.26***	−5.14	60
Bottom	−11.73***	−4.36**	−5.34*	61
AFSUGL				
Top	−11.85***	−4.49**	−5.44*	61
Middle	−12.06***	−6.04***	−5.13	60
Bottom	−17.74*	−6.82***	−10.08	61
Panel B	[-3,3]	[-3,-1]	[1,3]	Obs.
I2A				
Top	−13.47***	−5.14**	−7.33**	87
Middle	−11.97***	−4.35***	−6.30**	87
Bottom	−13.90***	−4.65***	−7.23**	87
T2I				
Top	−13.43**	−6.02***	−6.85	61
Middle	−14.49**	−5.89**	−7.24	60
Bottom	−13.76*	−5.44***	−6.59	61
F2I				
Top	−12.86***	−5.78**	−5.89	61
Middle	−14.15**	−5.55***	−7.33	60
Bottom	−14.67*	−6.02***	−7.46	61
M2I				
Top	−11.97*	−5.10**	−5.39	61
Middle	−12.90**	−5.53***	−6.62	60
Bottom	−16.78**	−6.71***	−8.66	61
MBS2I				
Top	−17.01**	−6.77***	−8.81	61
Middle	−13.24***	−5.82***	−6.33	60
Bottom	−11.42*	−4.76**	−5.53	61
ABS2I				
Top	−15.22*	−5.87**	−8.04	61
Middle	−14.88***	−6.73***	−6.97	60
Bottom	−11.59**	−4.76**	−5.68	61

This table presents the average cumulative abnormal return (CAR), in percent, of tercile portfolios formed on various investment types for our sample BHCs over different event windows. The investment measures include held-to-maturity securities (HTM, in $ millions), unrealized gains and losses in HTM (HTMUGL, in $ millions), available-for-sale debt securities (AFS, in $ millions), unrealized gains and losses in AFS (AFSUGL, in $ millions), total investments to total assets (I2A, in %), treasury securities to total investments (T2I, in %), federal agency securities to total investments (F2I, in %), state and municipal securities to total investments (M2I, in %), mortgage-backed securities to total investments (MBS2I, in %), asset-backed securities to total investments (ABS2I, in %). Variables are defined in Appendix A. Rows shaded in dark grey indicate the tercile to which SVB would belong, while light grey shading for variable I2A, HTM, HTMUGL, denotes the tercile corresponding to SB when it differs from SVB's tercile. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

4.2.1. Securities holdings

First, in Table 3, we consider market reactions based on securities holdings. In Panel A, we focus on the accounting classification of securities: Available for Sale (*AFS*) and Held-to-Maturity (*HTM*), as well as unrealized gains or losses arising from their accounting classification. For unrealized gains and losses in AFS and HTM, we construct two variables, *AFSUGL* and *HTMUGL*, by taking the difference between the fair value and the amortized cost of the respective components of the securities. As previously discussed, SVB and SB were characterized by having large HTM and AFS securities portfolios, which also meant that many banks were sitting on unrealized losses.

We find that common exposures to all these variables (*AFS*, *HTM*, *AFSUGL,* and *HTMUGL*) are very important. BHCs with large holdings of AFS and HTM (i.e., those in the same terciles of SVB and SB) were most adversely affected. Similarly, BHCs with greater unrealized losses on AFS and HTM securities (i.e., those sharing the bottom tercile with SVB and SB), were also the worst affected. Together, these results infer that banks with the highest degree of common exposures to both SVB and SB have realized the most negative market returns, with the difference between banks in the terciles further away from SVB and SB having losses between 4.65% (*HTM*) and 7.33% (*AFS*) less than those in the same tercile for each variable as SVB and SB. Interestingly, in the case of *AFS,* we also see some tentative evidence of a potential non-linearity with banks in the middle tercile having slightly less negative returns (−10.84%) than those in the bottom tercile (−11.73). It would therefore appear that while common exposure, in terms of *AFS*, was the most important driver of negative stock returns, investors also consider having very low *AFS* as a structural weakness. Consistent with this interpretation, existing literature highlights that low holdings of AFS securities can be detrimental for banks because they reduce readily marketable liquidity and balance-sheet flexibility, thereby increasing banks' vulnerability to funding and interest-rate shocks (e.g., Anani and Elwasify, 2024).

In summary, our main findings based on Panel A support our second hypothesis that BHCs with common exposures to SVB and SB in terms of both the size of HTM and AFS securities holdings, and the size of unrealized losses on HTM and AFS securities, should be most negatively impacted by the SVB shock.

Next, in Panel B, we look more granularly into the different categories of securities, and focus on Total Investments to Total Assets (*I2A*) and its components: Treasury Securities to Total Investments (*T2I*), Federal Agency Securities to Total Investments (*F2I*), State and Municipal Securities to Total Investments (*M2I*), Mortgage-backed Securities to Total Investments (*MBS2I*), and Asset-backed securities to total investments (*ABS2I*).

Market reactions for *I2A* are non-linear with banks in the same tercile as SVB and SB as well as those further away realizing the most negative market reactions. Again, we interpret this as evidence that both common exposure and having a potential structural weakness (i.e., a low proportion of total investments to total assets) matter. In this case, a low ratio of total investments to total assets may be detrimental because it indicates limited holdings of liquid, marketable securities, reducing a bank's ability to absorb funding shocks, manage interest-rate risk, and adjust its balance sheet without disrupting lending (Kashyap et al, 2002).

A substantial proportion of SVB's assets were treasury bonds and securities, which are typically considered as being high-quality and relatively liquid. Recent evidence suggests that such higher-quality and liquid securities can help banks better survive a banking sector crisis period (e.g., Blickle et al., 2022; Mahieux, 2024). The results for both *T2I* and *ABS2I* seem to support this assertion, with banks in the middle tercile (in the case of *T2I*), or upper terciles (in the case of *ABS2I*), rather than those in the terciles to which SVB and SB belong, releasing more negative returns. The results for these variables suggest that they were less important as common exposures but rather as structural indicators. However, banks closest to SVB and SB in terms of *F2I* and *MBS2I* had worse returns, which points towards common exposure being most important for investors with respect to these two variables.

4.2.2. Lending

One notable characteristic shared by both SVB and SB was the high concentrations of total lending within the commercial and industrial (C&I) loans category. Given this, in Table 4 we consider bank lending in terms of both the proportion of lending relative to total assets, as well as lending within the three main lending areas most relevant to SVB and SB. Specifically, we examine portfolios formed on the basis of Loans to Total Assets (*L2A*), Industrial Loans to Total Loans (*IL2L*), Consumer Loans to Total Loans (*CL2L*), and Real Estate Loans to Total Loans (*RL2L*).

From the table, we see that banks in the same bottom tercile as SVB for *L2A* experienced the most negative returns, as did those in the top tercile. Interestingly, banks in the middle tercile, shared by SB, fared better. It is important to note that SB was at the upper threshold of this middle tercile, however. In this case, it seems having a low ratio of loans to total assets, like SVB, was most important to investors. However, given the results for the middle and top terciles, it is difficult to conclude whether investors are reacting to a common exposure or a structural weakness in the case of *L2A*. We also observe a similar picture in the case of *CL2L*, albeit since we observe clearly more negative returns for the bottom tercile (−14.96%), to which SVB and SB belong, and for the upper tercile (−14.50%), compared to the middle tercile (−12.18%) in appears that investors see this deviation from the average BHC as a sign of potential weakness. It should also be noted that consumer lending was not a particularly important lending category for SVB or SB.

We see much clearer evidence in support of investors' reactions to common exposures in the case of both *RL2L* and *IL2L*, with banks in the same categories as SVB and SB experienced much larger negative returns compared to peers in other terciles. For example, BHCs in the bottom tercile for *IL2L* experienced an average loss of −10.71% compared to banks in the top and same tercile as SVB and SB, who had an average loss of −17.27%. While we observe tentative evidence of a potential non-linearity for *RL2L*, we consider that the linear, and, much more pronounced, result for *IL2L* is consistent with bank investors internalising the importance of this lending category in the case of SVB and SB and reacting to this common exposure. In other words, our findings are consistent with investors reacting more negatively to the shock in the case of banks with more similar lending portfolios to SVB, which were mainly focused on industrial and commercial lending, than to SB, which lent more to commercial real estate. Furthermore, considering the magnitudes of

Table 4
Market reactions based on loan portfolios.

	[-3,3]	[-3,-1]	[1,3]	Obs.
L2A				
Top	−13.88***	−4.48***	−7.24**	87
Middle	−11.31***	−4.15**	−6.01**	87
Bottom	−14.15***	−5.51***	−7.63*	87
RL2L				
Top	−12.12**	−5.02**	−5.66	61
Middle	−11.38***	−5.26***	−5.09	60
Bottom	−18.14*	−7.06***	−9.90	61
CL2L				
Top	−14.50**	−5.64***	−8.13	61
Middle	−12.18**	−5.57***	−5.81	60
Bottom	−14.96**	−6.14**	−6.72	61
IL2L				
Top	−17.27*	−6.95***	−8.92	61
Middle	−13.69***	−5.49***	−7.05**	60
Bottom	−10.71**	−4.90**	−4.72	61

This table presents the average cumulative abnormal return (CAR) (measured in percentage) of tercile portfolios formed by bank loan-to-assets ratios and loan types for our sample BHCs across different event windows. The loan measures include loans to assets (L2A, in %), real estate loans to loans (RL2L, in %), consumer loans to total loans (CL2L, in %), and industrial loans to total loans (IL2L, in %). Variables are defined in Appendix A. Rows shaded in dark grey indicate the tercile to which SVB would belong, while light grey shading denotes the tercile corresponding to SB when it differs from SVB's tercile. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

high industrial loans and low real estate loan shares, our findings further support the idea that the market perceived industrial loans as riskier than real estate loans.

4.2.3. Assets

Next, we examine market reactions based on asset growth, given that SVB and SB were categorized by having extremely high asset growth in the years prior to their failures. In addition, we also consider a wider set of indicators pertaining to asset size and quality. Table 5 presents the results.

From Table 5, we see that market reactions based on asset growth (*GA*) are most negative for banks in the top tercile, to which SVB

Table 5
Market reactions based on asset size and quality.

	[-3,3]	[-3,-1]	[1,3]	Obs.
GA				
Top	−13.92***	−5.25***	−6.84**	87
Middle	−13.05***	−4.22**	−7.30**	86
Bottom	−12.50***	−4.68**	−6.84**	87
TA				
Top	−17.17*	−7.13***	−9.05	87
Middle	−11.02***	−4.91***	−4.80*	87
Bottom	−11.15***	−2.10***	−7.03***	87
NPL				
Top	−12.41***	−4.70***	−6.47**	87
Middle	−12.68***	−4.97***	−6.57*	86
Bottom	−14.23***	−4.47***	−7.81**	87
LLP				
Top	−13.72***	−5.22***	−7.21**	87
Middle	−12.91**	−4.67***	−6.75*	87
Bottom	−12.71***	−4.24***	−6.91***	87
RWA				
Top	−13.07**	−5.58***	−6.49	59
Middle	−14.69*	−5.38**	−7.86	60
Bottom	−14.25**	−6.66***	−6.49	59

This table presents the average cumulative abnormal return (CAR) (measured in percentage) of tercile portfolios formed using bank size and asset quality indicators for our sample of BHCs across different event windows. The variables include asset growth (GA, in %), total assets (TA, in $ millions), non-performing loans (NPL, in %), loan loss provisions (LLP, in %), and risk-weighted assets (RWA, in %). Variables are defined in Appendix A. Rows shaded in dark grey indicate the tercile to which SVB would belong, while light grey shading denotes the tercile corresponding to SB when it differs from SVB's tercile. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

and SB (−13.92%) belong, and that banks in the bottom tercile (i.e., furthest from the failed institutions) have the least negative market reactions (−12.50%). This effect exists for the whole event window ([-3,3]) and the pre-event window of [-3, −1] but not for the post-event three-day window ([1, 3]), where the reactions of banks in the top and bottom terciles are identical, yet banks in the middle tercile had larger losses of −7.30%. Considered together, the results based on the whole event window ([-3,3]) and the pre-event window of [-3, −1] suggest, consistent with H2, tentatively infers that investors may be reacting to common exposure to asset growth. However, after the event, investors become more concerned about banks in the middle tercile for asset growth, which could be reflective of this being a structural indicator of "strategic inertia" outside of the most important event dates. More specifically, following the SVB shock average (rather than low or high) asset growth may be detrimental because it reflects strategic inertia; that is, banks neither contract to preserve liquidity nor expand to capture flight-to-quality inflows. Consequently, they fail to optimally reallocate balance sheets in response to heightened risk and funding uncertainty (Vives, 2014). Based on this discussion, we therefore cannot conclude whether *GA* represents a common exposure or a structural indicator.

Regarding the other indicators, asset size and quality, we find clear evidence that total assets (*TA*) are viewed more as a structural indicator than a common exposure by investors. The most negative market reactions are found for the larger tercile of banks (−17.17%), which are approximately 6% larger compared to banks in the middle (to which SVB belongs) or bottom (to which SB belongs) terciles. In contrast, there is some suggestive evidence that investors view non-performing loans relative to total assets as a common exposure. This is evident for the [-3,3] and [1,3] event windows with banks in the same tercile as SVB performing worse than banks in other terciles. There is also some evidence that investors perceive loan loss provisions (*LLP*) as a common factor, with banks in the same tercile group as SVB realizing the largest losses and those in the bottom tercile the least. This result is interesting in the sense that it provides early feedback to policymakers regarding the potential systemic risk implications of the change towards replacement of incurred loss recognition models, which occurred in response to the GFC, at a time of the most significant banking crisis since the GFC (Fleer, 2025). Finally, there is no clear pattern to the results for risk-weighted assets (*RWA*), with banks in the bottom two terciles experiencing marginally worse returns than those in the top tercile.

4.2.4. *Deposits*

It is important to note that both SVB and SB were also quite unusual in that nearly all their deposit bases were uninsured by the government safety net. In Table 6, we therefore focus on market reactions based on total uninsured deposits (*UID*) as a potentially important common exposure. Moreover, we also examine the importance of wider deposit structure using the following additional variables: total deposits to total assets (*D2A*), savings demand deposits to total deposits (*DD2D*), deposits to total deposits (*SD2D*), time deposits to total deposits (*TD2D*), and non-interest deposits to total deposits (*ND*).

In support of H2, we find strong evidence that the magnitude of uninsured deposits represents an important common exposure to BHC investors. Market reactions are over 6% more negative for banks in the top tercile to which SVB and SB belong compared to banks in the middle and bottom terciles. Regarding wider deposit structure, we see a pattern for *D2A* over the whole event window [-3,3] and the pre-event window of [-3, −1], which suggests that deposits to total assets are also seen as a common exposure factor by investors, although the difference in negative returns between terciles is much less compared to *UID* at 2.79%. For *DD2D* we find evidence that this also represents a common exposure to SVB for BHC investors, with banks in the bottom tercile (to which SVB belongs) suffering market returns 2.58% greater than banks in the top tercile. There is no clear evidence for *SD2D*, with results varying across event windows. The mixed results indicate that this factor is viewed neither as a structural indicator nor as a common exposure by investors. However, *TD2D* appears to represent a common exposure, with banks in the bottom tercile, including SVB and SB, realizing more negative returns than those in the other two terciles. Finally, the results for *ND* strongly support this being a further common exposure factor since banks in the top tercile to which SVB and SB belong, which also have the highest ratios of non interest deposits to total deposits, realize returns approximately 6% more negative than peers located in the bottom tercile. These last two results underscore the importance of having stable funding structures, as highlighted by the failures of SVB and SB and the broader literature on bank liquidity and funding risk (e.g., Egan et al., 2022).

4.3. *Euclidean distance-based market reactions based on common exposures*

Thus far, our findings provide support for both H1 and H2. For instance, in section 4.2. We provided confirmatory evidence in support of H2 that all the common exposures to SVB and SB hypothesized ((i.e., 1) the size of HTM and AFS securities holdings, 2) the size of unrealized losses on HTM and AFS securities, 3) loans relative to total assets, 4) lending portfolio concentration, 5) asset growth, and 6) the size of uninsured deposits)) are seen as common exposure factors by BHC investors. Moreover, additional factors that are not readily identifiable as potential common factors based on existing documentation of the SVB and SB failures are examined in the Internet Appendix.

However, one potential concern with the approach used in section 4.2 is that while we formed portfolios based on each key variable and assigned each BHC to one of three terciles, we do not directly capture the "distance" of each variable from SVB.[9] In other words, we may fail to fully capture the reaction of investors to potential common exposures or structural indicators of bank performance and condition. To address this concern, in this section, we provide more direct tests of H2. Specifically, we adopt an alternative sorting procedure by grouping BHCs with characteristics similar to those of SVB into the same portfolio. We sort banks into terciles based on

[9] In the interests of brevity, in this section we focus on SVB since this was the most important failure shock. However, we also produced the same analyses using SB instead. These results are available upon request.

Table 6
Market reactions based on deposit structure.

	[-3,3]	[-3,-1]	[1,3]	Obs.
UID				
Top	−17.12*	−7.06***	−9.07	84
Middle	−11.04***	−4.78***	−4.83*	83
Bottom	−11.10***	−2.27***	−6.87***	84
D2A				
Top	−12.14***	−3.48***	−7.11***	87
Middle	−12.27***	−4.48**	−6.60**	87
Bottom	−14.93**	−6.19***	−7.17	87
DD2D				
Top	−12.96**	−5.80***	−6.13	61
Middle	−13.17	−5.37***	−6.78	60
Bottom	−15.54***	−6.18**	−7.77*	61
SD2D				
Top	−13.90***	−5.04**	−7.27**	61
Middle	−14.35	−6.02***	−7.22	60
Bottom	−13.44**	−6.29***	−6.19	61
TD2D				
Top	−13.71***	−6.04***	−5.93	61
Middle	−13.35	−5.20**	−7.20	60
Bottom	−14.61**	−6.10***	−7.56	61
ND				
Top	−17.43*	−6.75***	−9.99	61
Middle	−12.46**	−6.32***	−5.17	60
Bottom	−11.76***	−4.29**	−5.50*	61

This table presents the average cumulative abnormal return (CAR) (measured in percentage) of tercile portfolios formed on bank deposits for our sample BHCs over different event windows. The variables include uninsured deposits (UID, in $ millions), total deposits to total assets (D2A, in %), demand deposits to total deposits (DD2DD, in %), saving deposits to total deposits (SD2D, in %), time deposits to total deposits (TD2D, in %), and non-interest deposits (ND, in $ millions). Variables are defined in Appendix A. Rows shaded in dark grey indicate the tercile to which SVB would belong, while light grey shading denotes the tercile corresponding to SB when it differs from SVB's tercile. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

their Euclidean distance from SVB, measured as the absolute difference between each bank's characteristics and those of SVB. Because this distance measure is strictly nonnegative, banks with characteristics most similar to SVB have distances close to zero, while larger values indicate greater dissimilarity in attributes between a BHC and SVB. Accordingly, BHCs most similar to SVB are assigned to the bottom tercile when sorted into terciles based on Euclidean distance, and the most dissimilar in the top tercile. The order of presentation of analyses follows that of the previous section.

4.3.1. Securities holdings

We begin by considering market reactions based on securities holdings. The results are presented in Table 7. In Panel A, we focus on the size of HTM and AFS securities holdings and the size of unrealized losses on HTM and AFS securities. Across all event windows, we find that BHCs closest to SVB in terms of *AFS*, *HTM,* and *AFSUGL* and *HTMUGL* experienced negative market returns between 3.62% (*AFSUGL*) and 5.74% (*HTMUGL*), larger than banks further from SVB. The results are fully consistent, and in fact even stronger than our earlier results in subsection 4.2.1. They support H2 and confirm the importance of these variables as common exposure characteristics that matter to bank investors. More granularly, the slightly more pronounced difference between the bottom tercile groups for *AFSUGL* and *HTMUGL* compared to *AFS*, *HTM* is suggestive that the size of unrealized losses on HTM and AFS securities mattered more as a common exposure to investors than the size of HTM and AFS securities holdings.

Panel B considers the different categories of bank securities. Again, we find results largely consistent with subsection 4.2.1. Market reactions for *I2A* are marginally more negative for banks closest to SVB over the [-3,-1] and [1,3] event windows, but interestingly slightly less negative for banks closest to SVB over the full event window. This is consistent with our previous unclear conclusion as to whether this variable is perceived as a common factor or a structural indicator. The finding that returns based on *F2I* are most negative for banks closest to SVB is also consistent with our prior finding and with this factor representing a further common exposure factor. Similarly, the result for *M2I* is consistent with our earlier analysis in suggesting that this is seen as a structural indicator by investors. The results for *MBS2I* and *ABS2I* are similarly aligned with our earlier results. We again find evidence in support of *MBS2I* being an additional common exposure factor, and *ABS2I* representing a structural indicator. However, the result for *T2I* differs from our earlier conclusion. Whilst we previously found inconclusive evidence, here we find evidence consistent with a common exposure factor interpretation, with banks closest to SVB realizing negative returns 2.77% greater than those furthest away.

Table 7
Market reactions of BHCs with similar securities holdings to SVB.

Panel A	[-3,3]	[-3,-1]	[1,3]	Obs.
HTM				
Top	−11.88***	−5.50**	−5.25	61
Middle	−12.42***	−5.06***	−6.18	60
Bottom	−17.36*	−6.78***	−9.23	61
HTMUGL				
Top	−11.87***	−5.44**	−5.24	61
Middle	−12.17***	−5.05***	−5.88	60
Bottom	−17.61*	−6.84***	−9.54	61
AFS				
Top	−12.27***	−4.63**	−5.76*	61
Middle	−11.15**	−5.17***	−5.31	60
Bottom	−18.21*	−7.54***	−9.58	61
AFSUGL				
Top	−12.78**	−4.72**	−6.30	61
Middle	−12.47***	−5.93***	−5.40*	60
Bottom	−16.40*	−6.70***	−8.96	61
Panel B	[-3,3]	[-3,-1]	[1,3]	Obs.
I2A				
Top	−13.90***	−4.65***	−7.23**	87
Middle	−11.97***	−4.35***	−6.30**	87
Bottom	−13.47***	−5.14**	−7.33**	87
T2I				
Top	−11.71**	−4.99**	−6.38**	22
Middle	−14.02**	−5.55**	−6.79	99
Bottom	−14.48**	−6.45***	−7.24	61
F2I				
Top	−12.86***	−5.78**	−5.89	61
Middle	−14.15**	−5.55***	−7.33	60
Bottom	−14.67*	−6.02***	−7.46	61
M2I				
Top	−11.97*	−5.10**	−5.39	61
Middle	−15.04**	−6.54***	−7.25	60
Bottom	−14.68**	−5.72***	−8.05	61
MBS2I				
Top	−11.42*	−4.76**	−5.53	61
Middle	−13.29**	−5.71***	−6.38	60
Bottom	−16.96**	−6.88***	−8.76	61
ABS2I				
Top	−15.22*	−5.87**	−8.04	61
Middle	−14.88***	−6.73***	−6.97	60
Bottom	−11.59**	−4.76**	−5.68	61

This table presents the average cumulative abnormal return (CAR) (measured in percentage) of tercile portfolios formed on various investment types for our sample BHCs over different event windows. For each variable, BHCs are sorted into terciles based on their Euclidean distance from SVB, measured as the absolute difference between each BHCs' characteristics and those of SVB. Because Euclidean distances are strictly non-negative and BHCs whose characteristics most closely resemble those of SVB have distances close to zero, sorting BHCs into Euclidean distance–based terciles assigns the most similar BHCs to the bottom tercile and the most dissimilar BHCs to the top tercile. The investment measures include held-to-maturity securities (HTM, in $ millions), unrealized gains and losses in HTM (HTMUGL, in $ millions), available-for-sale debt securities (AFS, in $ millions), unrealized gains and losses in AFS (AFSUGL, in $ millions), total investments to total assets (I2A, in %), treasury securities to total investments (T2I, in %), federal agency securities to total investments (F2I, in %), state and municipal securities to total investments (M2I, in %), mortgage-backed securities to total investments (MBS2I, in %), and asset-backed securities to total investments (ABS2I, in %). Variables are defined in Appendix A. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

4.3.2. Lending

Table 8 examines market reactions of BHCs with similar loan portfolios to SVB. Consistent with our earlier results and with H2, we find that banks closest to SVB in terms of *RL2L* and *IL2L* realized more negative losses. The results for both *L2A* and *CL2L* also mirror our earlier findings for these variables, whereby we identified non-linearities, and we noted that it was difficult to conclude whether investors are reacting to a common exposure or a structural weakness. Here, we do find slightly more negative returns for BHCs closest to SVB, but only marginally fewer negative returns for banks in the top terciles and more significantly less for banks in the medium tercile (i.e., closer to the bottom tercile). Therefore, we argue that while investors do consider these as common exposure factors to SVB to some extent, it seems these are generally more regarded as being structural indicators.

Table 8
Market reactions of BHCs with similar loan portfolios to SVB.

	[-3,3]	[-3,-1]	[1,3]	Obs.
L2A				
Top	−13.88***	−4.48***	−7.24**	87
Middle	−11.82***	−4.65**	−5.94**	87
Bottom	−13.64***	−5.01***	−7.69*	87
RL2L				
Top	−12.12**	−5.02**	−5.66	61
Middle	−11.38***	−5.26***	−5.09	60
Bottom	−18.14*	−7.06***	−9.90	61
CL2L				
Top	−14.50**	−5.64***	−8.13	61
Middle	−14.81*	−6.57***	−6.64	60
Bottom	−12.37**	−5.15**	−5.91	61
IL2L				
Top	−12.70**	−5.76**	−5.86	61
Middle	−13.41**	−5.59***	−6.88	60
Bottom	−15.56**	−6.00***	−7.93	61

This table presents the average cumulative abnormal return (CAR) (measured in percentage) of tercile portfolios formed on bank loans to assets ratios and loan types for our sample BHCs over different event windows. For each variable, BHCs are sorted into terciles based on their Euclidean distance from SVB, measured as the absolute difference between each BHCs' characteristics and those of SVB. Because Euclidean distances are strictly non-negative and BHCs whose characteristics most closely resemble those of SVB have distances close to zero, sorting BHCs into Euclidean distance–based terciles assigns the most similar BHCs to the bottom tercile and the most dissimilar BHCs to the top tercile. The loan measures include loans to assets (L2A, in %), real estate loans to loans (RL2L, in %), consumer loans to total loans (CL2L, in %), and industrial loans to total loans (IL2L, in %). Variables are defined in Appendix A. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

4.3.3. Assets

In Table 9 we consider market reactions for BHCs with similar asset size and quality to SVB. We hypothesized in H2 that asset growth was an important common exposure. Previously, our findings led us to surmise that it was unclear whether *GA* represents a common exposure or a structural indicator. However, the result in Table 9 suggests that banks further away from SVB for asset growth actually experienced more negative returns. Therefore, this result more conclusively points towards *GA* representing a structural

Table 9
Market reactions for BHCs with similar asset size and quality to SVB.

	[-3,3]	[-3,-1]	[1,3]	Obs.
GA				
Top	−14.96***	−5.89***	−7.27*	87
Middle	−12.81***	−4.29**	−6.69**	86
Bottom	−11.69***	−3.97**	−7.01**	87
TA				
Top	−11.64***	−2.35***	−7.51***	87
Middle	−11.08***	−4.81***	−4.71*	87
Bottom	−16.62*	−6.97***	−8.65	87
NPL				
Top	−12.41***	−4.70***	−6.47**	87
Middle	−12.97***	−4.70***	−6.88*	86
Bottom	−13.94**	−4.74***	−7.49**	87
LLP				
Top	−13.14***	−4.30***	−7.13***	87
Middle	−12.63**	−4.51**	−6.63*	87
Bottom	−13.57***	−5.32***	−7.11*	87
RWA				
Top	−13.85**	−6.39***	−6.38	59
Middle	−14.92*	−5.37**	−8.04	60
Bottom	−13.24**	−5.86***	−6.41	59

This table presents the average cumulative abnormal return (CAR) (measured in percentage) of tercile portfolios formed using bank size and asset quality indicators for our sample BHCs across different event windows. For each variable, BHCs are sorted into terciles based on their Euclidean distance from SVB, measured as the absolute difference between each BHCs' characteristics and those of SVB. Because Euclidean distances are strictly non-negative and BHCs whose characteristics most closely resemble those of SVB have distances close to zero, sorting BHCs into Euclidean distance–based terciles assigns the most similar BHCs to the bottom tercile and the most dissimilar BHCs to the top tercile. The variables include asset growth (GA, in %), total assets (TA, in $ millions), non-performing loans (NPL, in %), loan loss provisions (LLP, in %), and risk-weighted assets (RWA, in %). Variables are defined in Appendix A. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

indicator rather than a common exposure factor and is therefore inconsistent with H2.[10]

Regarding other factors, the results for *NPL* and *LLP*, which highlight that banks closest to SVB have more adverse market returns, are consistent with our earlier conclusions that these are additional common exposure factors. Similarly, we again find no clear pattern to the results for risk-weighted assets (*RWA*). Yet we find that the result for *TA* differs from our earlier findings, whereby we found that the largest tercile banks (rather than the tercile to which SVB or SB belonged) had the most negative returns. We therefore interpreted this as evidence that *TA* is likely considered as a structural indicator by BHC investors. In contrast, Table 8 presents compelling evidence that *TA* is in fact a common factor, since banks closest to SVB (i.e. the bottom tercile) have returns 5% points more negative than those in either the middle or top tercile.

4.3.4. Deposits

In Table 10, we assess market reactions for BHCs based on the similarity of deposit structure to SVB. Our main variable of interest as a potential common exposure is total uninsured deposits (*UID*). The result shows that banks closest to SVB realized negative market returns approximately 6% larger than those in the middle and top terciles, with also little variation (0.05%) between those terciles. Thus, consistent with H2 and our earlier finding, this is strong evidence that uninsured deposits are seen by bank investors as a common exposure factor.

Examining wider deposit structures variables, we find more negative market reactions for BHCs closest to SVB in terms of *D2A*, *DD2D,* and *TD2D*. These results are also consistent with our earlier findings and support the notion that investors considered these as further common exposure factors of interest. Furthermore, the evidence for *SD2D* remains unclear, with market reactions slightly more negative for banks in the further tercile from SVB, followed by the SVB tercile, and then the middle tercile. We therefore continue to conclude that this variable is not considered as either a structural indicator or common exposure by investors. Finally, the table shows that bank reactions based on *ND* were actually less negative for banks in the middle tercile, while banks in the top tercile (and therefore further from SVB) suffered the most negative returns. This is in stark contrast to our earlier finding and underlines the importance of conditioning market responses based on the similarity of characteristics to SVB.

4.4. Robustness checks

A concern is that CARs may be sensitive to the choice of estimation model or estimation window used. To mitigate these concerns, we first estimate abnormal returns using alternative asset-pricing models. The results are presented in Table IA2 of the Internet Appendix. Specifically, we employ the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, and we also employ the Fama–French five-factor model augmented with momentum (Carhart, 1997). These models augment the standard market model with factors for size (SMB), value (HML), operating profitability (RMW), investment intensity (CMA), and momentum (UMD), providing a more comprehensive benchmark for expected returns and mitigating concerns that estimated abnormal returns reflect omitted risk factors. Unreported results indicate that the magnitude of the estimated CARs declines under the alternative model, while our main conclusions remain unchanged.

After checking the robustness of our results using alternative models, in Internet Appendix Table IA3, we probe the sensitivity of our findings to alternative estimation-window specifications. Following Ahmed et al. (2022), our baseline specification uses a 250-trading-day estimation window ending 25 trading days prior to the event date. As alternatives, we consider a 250-trading day estimation window ending 41 trading days prior to the event and a shorter 120 trading day estimation window ending 25 trading days before the event. The results show that while the magnitude of the estimated CARs varies marginally across specifications, our baseline results remain unchanged across alternative estimation window choices.

5. Conclusions

This paper examines the stock market reactions of U.S. BHCs to the SVB and SB failures, taking the SVB failure as the primary shock. We begin by examining the reaction of banks to the shock and find, consistent with H1, that the overall market reaction was negative and statistically significant. This result provides support for recent findings that U.S. banks reacted negatively to the SVB shock (Martins, 2025). We then proceed to test our second hypothesis. Our evidence is mostly consistent with the SVB and SB failures representing significant information shocks, whereby investors react more (negatively) to unfavorable market signals in banks that they believe share common exposures to SVB and SB. In support of Hypothesis 2, the size of HTM and AFS securities holdings, the size of unrealized losses on HTM and AFS securities, as well as the size of uninsured deposits, most likely represent common exposure factors from the perspective of investors, with banks closest to SVB realizing more negative market returns following the SVB and SB shocks. Similarly, regarding lending portfolio concentration, we find evidence consistent with H2, that banks closest to SVB in terms of industrial loans to total loans (*IL2L*) and real estate loans to loans (RL2L) realized the most negative market returns. However, we find mixed evidence for the loans to total asset ratio and for other loan categories, which point more towards these factors representing structural indicators rather than common exposure to investors. Furthermore, the results for asset growth are in fact more consistent with bank investors reacting to a structural indicator rather than an important common exposure factor.

Our main findings contribute novel empirical evidence to the classic literature on bank fragility, bank runs, and contagion (e.g.,

[10] As a caveat, however, it should be noted that while SVB has extremely high growth for several years prior to its failure its growth rate from 2021 to 2022 was low compared to many peers.

Table 10
Market reactions of BHCs with a similar deposit structure to SVB.

	[-3,3]	[-3,-1]	[1,3]	Obs.
UID				
Top	−11.13***	−2.28***	−6.94***	84
Middle	−11.08***	−4.79***	−4.83*	83
Bottom	−17.05*	−7.04***	−8.99	84
D2A				
Top	−12.60***	−4.12***	−6.96***	87
Middle	−12.25***	−4.43**	−6.56**	87
Bottom	−14.49**	−5.59***	−7.36	87
DD2D				
Top	−12.96**	−5.80***	−6.13	61
Middle	−13.17	−5.37***	−6.78	60
Bottom	−15.54***	−6.18**	−7.77*	61
SD2D				
Top	−13.44**	−6.29***	−6.19	61
Middle	−14.35	−6.02***	−7.22	60
Bottom	−13.90***	−5.04**	−7.27**	61
TD2D				
Top	−13.71***	−6.04***	−5.93	61
Middle	−13.35	−5.20**	−7.20	60
Bottom	−14.61**	−6.10***	−7.56	61
ND				
Top	−17.45**	−5.94***	−9.58*	61
Middle	−10.49***	−4.61**	−4.60	60
Bottom	−13.68*	−6.78***	−6.46	61

This table presents the average cumulative abnormal return (CAR) (measured in percentage) of tercile portfolios formed on bank deposits for our sample BHCs over different event windows. For each variable, BHCs are sorted into terciles based on their Euclidean distance from SVB, measured as the absolute difference between each BHCs' characteristics and those of SVB. Because Euclidean distances are strictly non-negative and BHCs whose characteristics most closely resemble those of SVB have distances close to zero, sorting BHCs into Euclidean distance–based terciles assigns the most similar BHCs to the bottom tercile and the most dissimilar BHCs to the top tercile. The variables include uninsured deposits (UID, in $ millions), total deposits to total assets (D2A, in %), demand deposits to total deposits (DD2DD, in %), saving deposits to total deposits (SD2D, in %), time deposits to total deposits (TD2D, in %), and non-interest deposits (ND, in $ millions). Variables are defined in Appendix A. The test statistics are based on cross-sectional correlation-adjusted BMP test statistics proposed by Kolari and Pynnönen (2010), where the BMP test statistics are the standardized cross-sectional test of Boehmer et al. (1991) obtained using standardized cumulative abnormal returns. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Molyneux and Wilson, 2017; Dicks and Fulghieri, 2019; Bischof et al., 2021) and add to the recent literature on the impact of the SVB bank failure (e.g., Martins, 2023, 2025; Perdichizzi and Reghezza, 2023). Specifically, we demonstrate that both common exposures and structural weaknesses explain the heterogeneous responses of bank investors to significant bank failures. To the best of our knowledge, prior research has yet to focus on common exposure factors, yet our findings suggest that they are very important for understanding the dynamics of investor behavior in the context of adverse industry shocks.

Taken together, our results serve to ignite the debate regarding the wider impacts of significant bank failures. From the perspective of public policy, the heterogeneous reactions of BHCs to SVB and SB serve to reignite the debate regarding the implications of large banking institutions for financial stability (Gruenberg, 2023) and contribute to nascent understanding regarding how investors respond to informational shocks from significant bank failures. In evaluating how investors perceive different bank attributes during a significant bank failure shock, our findings have important implications for banking sector regulators and supervisors looking to promptly identify both structural weaknesses in individual institutions, as well as potential fragilities in the cross-section of banks stemming from common exposures. In particular, our results suggest that investors were most concerned with their bank being closely related to SVB and SB in several common exposure dimensions. Moreover, they also highlight other bank characteristics that appear to be perceived by investors as important structural indicators of a banks condition such as the Tier 1 capital adequacy ratio, asset growth, the loans to total assets ratio, asset-backed securities to total investments, as well as return on assets, non-interest income, leverage, and non-deposit funding (the latter four of which are examined in detail in the Internet Appendix). In this respect, and to the extent our findings can be generalized, our findings provide guidance with respect to what policy makers and accounting standard setters may wish to focus more attention on going forward.

Finally, our paper is not without limitations, which also present opportunities for future research. Notably we focus on one significant period of market stress following the failures of SVB and SB. The common exposure and structural indicator factors we identify as being important to investors may therefore be distinct to this failure episode. Future researchers may therefore wish to apply our approach to new settings in the banking sector and beyond to see which firm characteristics are important to investors in a time of crisis. Future research could focus attention of the individual and collaborative roles played by state and federal regulators in addressing different bank failures, given that even the failure of state-chartered banks such as SVB and SB can invoke systemic risk concerns. Finally, although beyond the scope of the present paper, future research may also wish to focus more explicitly on the impact of sudden writedowns in asset values in key failing institutions on banking sector stability using higher frequency market data.

Declarations and Compliance with Ethical Standards
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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Variable definitions

Symbol	Variables	Definition
Asset and asset quality:		
TA	Total assets	Total bank assets in million U.S. dollars.
GA	Asset growth	Annual growth in total assets.
NPL	Non-performing loans	Non-performing assets as the percentage of total loans.
LLP	Loan loss provisions	Provision for credit losses as the percentage of the total loans
RWA	Risk-weighted Assets	The aggregate of each asset class multiplied by their associated risk weights assigned by the bank regulators divided by the total assets.
Profitability and income diversification indicators:		
ROA	Return on assets	Return on assets in percentage.
NII	Non-interest income	Non-interest income as the percentage of aggregate of non-interest and interest income.
Loans:		
L2A	Loans to assets	Total loans as the percentage of total assets
IL2L	Industrial Loans to total loans	The ratio of commercial and industrial loans a bank makes to the businesses and industry to its total loans.
CL2L	Consumer loans to total loans	Loans to individuals for household, family, and other personal expenditures (i.e., consumer loans) to the total loans.
RL2L	Real estate loans to loans	Loans secured by real estate to total loans.
Investments and securities:		
I2A	Total investments to total assets	The ratio of total investments to total assets. Securities considered under the investment assets include U.S. treasury securities, federal agency securities, state and municipal securities, federal funds sold, trading accounts securities, securities purchased under resale agreements, mortgage-backed securities, federal funds, other securities and investments, and total securities available for sale.
T2I	Treasury securities to total investments	Treasury Securities to total investments. The purchase of treasury securities creates a direct loan made by the bank to the government. Such securities include treasury bills, notes, bonds, and treasury securities available for sale.
F2I	Federal agency securities to total investments	Federal agency securities to total investments where federal agency securities include U.S. government agency and sponsored agency obligations.
M2I	State and municipal securities to total investments	State and municipal securities to total investments. These securities are issued by states and political subdivisions in the U.S.
MBS2I	Mortgage-backed securities to total investments	Mortgage-backed securities to total investments. Mortgage-backed securities are backed by a pool of mortgage or trust deeds.
ABS2I	Asset-backed securities to total investments	Asset-backed securities and structured financial products to total investments.
HTM	Held-to-maturity securities	Held-to-maturity securities in million U.S. dollars.
HTMUGL	Unrealized gains and losses in HTM	The difference between the fair value and amortized cost of HTM securities
AFS	Available-for-sale debt securities	Available-for-sale debt securities in million U.S. dollars.
AFSUGL	Unrealized gains and losses in AFS	The difference between the fair value and amortized cost of AFS securities
Deposits:		
D2A	Total deposits to total assets	Ratio of total deposits to total assets.
SD2D	Saving Deposits to total deposits	Interest-bearing saving deposits as a percentage of the total deposits.
DD2D	Demand deposits to total deposits	Demand deposits as a percentage of the total deposits.
TD2D	Time deposits to total deposits	Time deposits as a percentage of the total deposits.
ND	Non interest deposits	Sum of Noninterest-bearing demand, time, and savings deposits.
UID	Uninsured deposits	The aggregate subsidiary-level uninsured deposits of a BHC, estimated for domestic offices and insured branches in Puerto Rico and U.S. territories and possessions.
Funding:		
LEV	Leverage	Total stockholders' equity to total assets.

(*continued on next page*)

(*continued*)

Symbol	Variables	Definition
NDF	Non-deposit Funding	Non-deposit Funding (NDF) ratio is computed as Short-term Funding (STF) divided by the total assets in excess of total capital. STF is calculated as the total assets in excess of total capital, long-term debt, and total deposits.
TIER 1	Tier 1 capital	Tier 1 capital adequacy ratio is the ratio of Tier 1 capital to total risk-weighted assets, calculated in accordance with banking regulations and expressed as a percentage.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jaccpubpol.2026.107432.

Data availability

The authors do not have permission to share data.

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