THE IMPACT OF THE SVB COLLAPSE ON BANKING INDUSTRY

by

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Abstract

This study investigates the repercussions of SVB collapse on individual banks worldwide. Our investigation employs a multifaceted approach integrating event study methodology and the Capital-Asset-Management-Earnings-Liquidity assessments using a sample of 646 banks across 58 countries. Our findings reveal that the resilience of banks during the SVB collapse is intricately linked to their capital adequacy and liquidity. Specifically, banks exhibiting higher capital adequacy and better liquidity mitigate losses during the SVB collapse. Our research controls for alternative bank-level and country-level and shows that the main results persist. Our findings are also robust to the potential endogeneity concerns. This study offers a further understanding of how specific financial proxies, particularly capital adequacy and liquidity, are crucial in shaping bank's resilience following SVB collapse. Our paper contributes not only to the academic understanding of the SVB collapse's impact on individual banks but also holds practical implications for policymakers striving to understand what makes banks more resilient against external shocks.

Search Terms: Bank; Event Study Methodology (ESM); CAMEL Assessments

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Chapter 1. Introduction

In March 2023, the banking industry experienced terrible challenges and instability. Three large banks in the United States, Silicon Valley Bank (SVB), Signature Bank, and Silvergate Bank, failed due to rapid depositor withdrawal.[1] This marked the first failure of a global systemically important bank since the 2008 financial crisis (Yousaf and Goodell, 2023). The loss of market confidence had compelled these unexpected risks. U.S. Bank indies experienced a loss of approximately 11% weekly, representing the most significant drop since the global lockdown in March 2020.[2] These recent events remind us of the challenges posed by tighter monetary policy and vulnerabilities boosted since the global financial crisis. After years of low interest rates, tighter monetary policy has posed challenges to banks' risk management, particularly in securities portfolios; higher interest rates let security prices go down and loan exposures (Le and Vo, 2023). The tightening monetary is driven by controlling soaring inflation, which further complicates and deteriorates the financial environment for poorly managed banks.

While similarities happened with the previous financial crisis triggered by monetary tightening in 2008 (Guan-Seng, 2023), the current crisis episode is different in meaningful ways. Unlike the 2008 financial crisis, which quickly spread beyond banks to nonbanks, the current turmoil primarily affects the banking system. Additionally, the 2008 crisis stemmed from credit losses due to housing market declines, whereas the current situation involves unrealized losses in portfolios of safe but discounting-in-value securities. Based on the background, we are interested in determining the impact of SVB collapse on the banking industry. Meanwhile, we explore the contagion impact of SVB on other banks. In the immediate aftermath of SVB's collapse, the bank stock prices of other banks could experience a sharp decline. The extent of the decline would likely be proportional to the exposure of each bank.

The increases in interest rates may lead to further impacts of financial instability (Gomez et al., 2021). Riskier segments of capital markets, such as

[1] https://www.cnbc.com/2023/03/13/signature-bank-third-biggest-bank-failure-in-us-history.html

[2] https://www.reuters.com/business/finance/us-bank-stocks-add-losses-regulators-shutter-svb-financial-2023-03-10/

leveraged loans and private credit markets, have experienced a slowdown. Concerns about the commercial real estate market heavily reliant on smaller banks have also arisen. Financial asset allocation decisions, and word of deposit withdrawals spread globally at lightning speed, signaling that future banking stress may propagate faster and be less predictable (Dosumu et al., 2023).

So far, SVB's failure has reverberated throughout the global market, shedding light on the risks associated with the bank's healthiness. This collapse served as a wake-up call, reminding market participants of the potential consequence of such events on the broader financial system (Cetorelli and Goldberg, 2011; Shanshan, 2022; Li et al., 2023; Akhtaruzzaman et al., 2023). Globally, the financial system also suffers terrible short-term and medium-term risks as high debt levels spread significant challenges across many countries. The widening of sovereign and corporate hard-currency spreads indicates the market's sensitivity to global developments, affecting various asset classes within the global market (Mateti et al., 2013). Distressed debt cases in the past have demonstrated the potential for substantial spillovers from debt issues to the real economy, disproportionately affecting banks (Goldsmith-Pinkham & Yorulmazer, 2010). The major markets have contained contagion within their banking system, reflecting their sensitivity during this period of global monetary tightening (Dosumu et al., 2023). However, vulnerabilities remain, particularly for frontier economies and emerging markets with lower credit ratings. Banks in emerging markets have experienced a shock.

SVB, in recent times, has sent shockwaves throughout the financial industry; formerly recognized as the largest U.S. bank failure since 2008, it gained significant attention for its tumultuous collapse.[3] Before its widely publicized downfall, SVB was a high-tech commercial bank based in Santa Clara, California, United States. SVB was a specialized commercial bank that serves the banking and financial needs of the technology, life sciences, and venture capital sectors. SVB actively engages with startups and early-stage companies, providing them with resources, mentorship, and access to its vast network. SVB held a prominent reputation within the tech community, benefiting from the substantial-tech industry.

[3] https://www.bloomberg.com/news/articles/2023-03-16/svb-collapse-reveals-silicon-valley-s-point-of-failure#:~:text=SVB%20was%20a%20regional%20bank,US%20bank%20failure%20since%202008.

Whereas, as venture capital funding dried up in 2022, SVB faced a significant decline in its deposit base, leading to a series of events that ultimately resulted in its collapse. In an attempt to raise fresh capital on March 8th, SVB disclosed a staggering $1.8 billion loss from selling Treasury securities to meet large deposit withdrawals. Unfortunately, the bank's capital-raising efforts failed, sparking concerns among depositors and investors about SVB's liquidity position and solvency. These concerns were primarily derived from several factors, including substantial investment in long-term securities with a low-interest rate, inadequate reliance on equity capital, and a concentrated depositor base that significantly impacted its financial performance (Vo & Le, 2023). During the COVID-19 pandemic, the U.S. Federal Reserve cut interest rates close to zero and purchased lots of Treasury securities to maintain long-term interests at a low level.

Nevertheless, the fiscal relief program rapidly increases inflation, and the Consumer Price Index (CPI) increased from 1.84 percent in October 2020 to 8.46 percent in August 2022. U.S. Federal Reserve's action rose eight times by a sum of 4.25 percentage points, reaching 4.75 percent on February 1st, 2023. Even the Fed also stated that more rate increases are coming.[4] Subsequently, SVB's exposure to unrealized losses of approximately $18 billion stemmed from the impact of higher interest rates on its substantial holdings of fixed-income securities. Moreover, negative sentiments about SVB surged on social media, which caused SVB's stock to experience a precipitous sell-off. On March 9th, the deposit withdrawal requests reached $42 billion, equivalent to over one-fourth of the bank's deposit base.[5] SVB was placed under the receivership of the Federal Deposit Insurance Corporation (FDIC) on March 10th.

Generally, banks, a critical component of the financial system, encounter operational risks that can primarily affect their stability, performance, and reputation. One prominent risk arises from interest rate fluctuations from the maturity mismatch between the assets and liabilities. Secondly, liquidity risk appears when a bank may need more cash or liquid assets to meet its obligations. It arises from a mismatch between the timing of cash inflows and outflows. A bank's ability to manage

[4] https://theconversation.com/why-the-fed-raised-interest-rates-by-the-smallest-amount-since-it-began-its-epic-inflation-fight-199057

[5] https://www.bloomberg.com/news/articles/2023-03-11/svb-depositors-investors-tried-to-pull-42-billion-on-thursday#xj4y7vzkg

liquidity is crucial for maintaining stability and meeting the demands of depositors and other creditors. In times of financial distrust or stress, liquidity risk can become more apparent. Banks should maintain a high liquidity position to meet unexpected withdrawals. of Thirdly, the operation risk consists of a wide range of risks arising from inadequate or failed internal processes, systems, human error, or external events, which includes risks related to governance, compliance, technology, fraud, and reputational damage. Effective management of operational risks requires solid internal controls, robust risk management frameworks, and continuous monitoring and evaluation of processes and systems. Fourthly, the market risk or system risk is a bank's potential losses due to adverse movements in market prices, such as interest rates, foreign exchange rates, equity prices, or commodity prices. Market risk can arise from factors such as changes in interest rates, economic indicators, geopolitical events, or investor sentiment.

SVB has experienced fast development over ten years. However, along with the opportunity and growth, SVB also faced several risks that led SVB to go bankrupt. When interest rate fluctuates widely, banks and depositors respond negatively to it. SVB primarily relies on short-term deposits as a source of borrowing and utilizes these funds to provide long-term loans to their customers (Le & Vo, 2023). Additionally, the rapid escalation of interest rates in 2022 and 2023 resulted in a significant decline in the value of these securities because bonds and similar securities exhibit a characteristic where their prices tend to decrease when yields or interest rates rise.

Consequently, clients, including startups reliant on private fundraising, started withdrawing their funds from the bank. In order to meet these withdrawals, SVB was compelled to sell off assets, including bonds that had suffered losses due to the increase in interest rates. As a result, SVB incurred significant losses estimated at approximately $1.8 billion.[6] Allen and Gale (2004) stated that banks face liquidity risk when they cannot meet their short-term obligations. If depositors lose confidence in the bank's capacity to meet these obligations, they may rush to withdraw their funds, causing a bank run. If a bank cannot meet these withdrawal requests, it may become insolvent and fail. As a result, SVB declared bankruptcy on

[6] https://www.businesstoday.in/latest/in-focus/story/heres-how-silicon-valley-bank-lost-more-than-80-billion-in-24-hours-373020-2023-03-11

March 10, 2023. Previous research investigated the failure reasons based on SVB's financial information. It concluded that significantly low equity capital level, extremely high debt securities, and narrowly focused depositor base directly led SVB to bankruptcy (Guan-Seng, 2023; Pandey et al., 2023).

Moreover, the banking sector is a sensitive component of the global economy, and any significant bank failure can lead to long-term consequences (Beutler et al., 2020). The collapse of SVB triggered a widespread decline in bank stocks. However, different-size banks have different reactions to the collapse. The largest bank, JPMorgan Chase, has only decreased by 1.8%; Bank of America decreased by 5.8 %.[7] Furthermore, even smaller- and mid-sized banks suffered a significant drop. PacWest Bancorp fell by more than 40%, Western Alliance Bancorp declined by 60%, and Zions Bancorp dropped by 12.6%.[8] The KBW Bank Index's overall stock performance decreased by 7%.[9] Particularly, the collapse had broader implication for other banks with similar funding profiles. For example, Signature Bank of New York (SBNY), a $110 billion bank catering to similar clients, faces intense pressure as 20% of its deposit outflows.[10] SBNY's stock delinked by almost 40%, ultimately leading to its failures on March 12.

The collapse of SVB serves as a stark reminder of the risks associated with concentrated exposures and the potential reminder of the risks associated with the consequences of liquidity and solvency concerns in a volatile market environment (Vo et al., 2023). How can we measure the potential bank risks? Bank risk rating systems play an essential role in assessing financial health and predicting the potential bankruptcy of various banks. In 1979, the Uniform Financial Institutions Rating System (UFIRS) was first used in Capital-Asset-Management-Earning-Liquidity (CAMEL). These ratings hold significant importance for depositors as they build trust in banks and safeguard their wealth. By objectively evaluating these critical aspects, the CAMEL rating system offers transparency and assurance to depositors, ensuring their confidence in the soundness of the banks they entrust with

[7] https://www.cbsnews.com/news/bank-stocks-down-us-bank-failure-svb-signature-2023-03-13/
[8] https://www.reuters.com/markets/us/pacwest-western-alliance-hit-us-banking-concerns-widen-2023-05-04/
[9] https://www.cbsnews.com/news/stocks-down-first-republic-debt-ceiling-janet-yellen-2023-05-02/
[10] https://www.bloomberg.com/news/articles/2023-03-14/signature-was-seized-after-leaders-caused-crisis-of-confidence#xj4y7vzkg

their funds.

This research findings reveal a significant relationship between the healthiness of banks, as indicated by their CAMEL ratings, and the magnitude of stock price fluctuations following the SVB bankruptcy. Technically, banks with higher capital adequacy and liquidity levels, reflecting more robust financial performance and soundness, experienced relatively minor declines in their stock prices compared to banks with lower capital adequacy and liquidity levels. The entire market reaction suggests that market participants perceive banks with better financial health as more resilient and better equipped to withstand the impact of a large bank failure or financial crisis, resulting in relatively less severe stock price reactions.

This research contributes to the existing literature in two ways. 1). Explaining the impact of bank collapse (SVB collapse) on the global banking industry and individual bank performance. 2). emphasizing the relevance of the CAMEL rating system in understating the link between the healthiness of banks and stock price fluctuations following SVB's bankruptcy. It underscores the value of using comprehensive financial performance metrics (CAMEL) to evaluate banks' overall health and stability. By considering capital adequacy, asset quality, and earnings, regulators, investors, and market participants can consider banks' vulnerability and make informed decisions regarding risk exposure and investment strategies.

Chapter 2. Literature Review

2.1 SVB Collapse and Bank Crisis

Previous research determined the impact of SVB collapse on the financial systems (Khoo G.S., 2023; Baron Et al., 2022; Akhtaruzzaman et al., 2023; Dosumu et al., 2023). Khoo (2023) addressed SVB as a particular kind of bank in which capital and business structures differ from traditional banks, and Khoo (2023) stated that terrible managemnt caused the collapse. Meanwhile, Baron Et al. (2023), Akhtaruzzaman et al. (2023) and Dosumu et al. (2023) determined the significant negative impact of SVB collapse widespread for the global markets. However, no existing research explores the impact of SVB collapse on the banking industry and specifies individual bank performance after SVB collapse.

2.1.1 Risk Exposures and Risk Causality

The profitability of banks is sensitive to changes in interest rates. Banks with significant interest-bearing deposits suffer a decrease in their earnings (Gomez et al., 2021). The income gap of a bank is determined by the disparity in interest rate sensitivities between its assets and liabilities. This gap is a standard gauge for assessing the extent to which a bank's income is exposed to fluctuations in interest rates (Flannery, 1983). Specifically, banks' interest-earning assets, such as loans or investments, are more sensitive to interest rate fluctuations than interest-bearing liabilities, such as deposits or borrowings. Previous literature (Flannery, 1983; Gomez et al., 2021) on interest rate risk often emphasizes the impact on the asset side of a bank's balance sheet. Banks usually hold long-term fixed-rate securities, which face the risk of capital losses when interest rates rise, which we also call the capital losses price risks. A rising interest rate can lead to a reduction in the market value of securities held by banks. Meanwhile, maturity risks also damage the bank's profitability. Maturity risk occurs when there is a mismatch between the maturity of assets and liabilities. If short-term interest rates increase, banks may face challenges in meeting their interest payment obligations on short-term liabilities with the lower interest income generated from long-term assets. This can result in decreased profitability.

Shui (2023) explains that during the global financial crisis, banks experienced a rise in non-performing loans (NPLs) and tended to shorten their

average loan maturity. Moreover, Black and Rosen (2018), analyzing U.S. short-term business lending data, stated that an increase in the federal funds rate constrains credit supply by shortening loan maturities. Therefore, when commercial banks have a substantial imbalance between the maturity of their assets and liabilities, they become more vulnerable to interest rate fluctuations. Suppose short-term interest rates change rapidly or unpredictably. In that case, commercial banks with significant maturity may face difficulties meeting their obligations, which can erode depositor confidence and trigger bank runs (Deng et al., 2023). The potential withdrawal of funds from wholesale deposits and the loss of other short-term financing sources primarily drives the liquidity risk for banks (Diamond & Dybvig, 1983). Additionally, Gatev et al. (2009), and Cornett et al. (2011) confirmed that banks can hedge the liquidity risk significantly with enough transaction deposits and insured deposits. Here, we are motivated to consider whether banks' conditions or soundness affect market confidence during financial crises or specific events.

Markets and authorities are seriously concerned about the spillover effect when one bank experiences difficulties, as these issues can spread to the overall financial system. An individual bank faces losses, and other challenges influence the broader system. Goldsmith-Pinkham and Yorulmazer (2010) concluded three spillover types:

- Direct exposures through interbank linages, where one bank's financial health can influence other banks' stability.
- Information spillover, whereby difficulties faced by one bank can be interpreted as a negative sign of other banks.
- The interplay of illiquidity and asset price spillover

Goldsmith-Pinkham and Yorulmazer's study (2010) uses an event study methodology to analyze the Northern Rock bankruptcy and the spillover effect on the other U.K. banks. It is worth knowing why systematic risks cause individual bank bankruptcy.

SVB's collapse was not an ordinary occurrence in the banking industry. This was primarily due to the unique nature of SVB as a financial institution. SVB differed from typical banks in two main aspects: its distinctive liability portfolio and the concentrated nature of its assets, mainly comprising long-term fixed-rate government bonds. The continuous interest rate increase, the drop in securities value,

the vulnerability of risk management, and the unrealized loss on the securities are the main factors that promote SVB collapse. Because SVB specializes in financing numerous startup companies, venture debt has been a significant component of its loan activities. A narrow range of funding resources, including startups, venture capital firms, and tech founders, hold amounts exceeding $250,000, more than the FDIC insurance. Moreover, only 12% of its deposit base fell below the FDIC's limit of $250,000. Banks with fewer insured or transaction deposits are likelier to suffer liquidity risks. On March 10, SVB announced bankruptcy.

During the banking troubles of 2022-2023, many banks encountered difficulties in retaining deposits as individuals became increasingly concerned about the growing uncertainty of banks. The existing research has demonstrated that the bankruptcy of banks has a spillover effect on other banks (Liu, 2020; Goldsmith-Pinkham & Yorulmazer, 2010). Meanwhile, Dosumu et al. (2023) stated that the SVB failure has a strong contagion effect in U.S. and European markets, which motivates us to analyze the impact of the collapse of SVB on the global banking industry. The collapse of a large bank like SVB should have significant and long-term consequences for the financial system and lead to spillover effects spreading throughout other banks. Additionally, some empirical evidence suggests that bank failures significantly and negatively impact the stock markets, with the effect being different for the bank's conditions. Simultaneously, A few studies have primarily examined the relationship between bank healthiness and stock prices, such as healthiness check-ups in Nepal banks (Baral, 2005); CAMEL and S&P ratings (Derviz & Podpiera, 2008); analysis of the soundness of the commercial banks in Romania (Roman & Sargu, 2013); and CAMEL rating disclosure and operation (Gopalan, 2022). Ricci's paper (2015) suggests that banks with healthy financial conditions may experience relatively minor stock price declines than banks with terrible financial conditions. These findings indicate that market participants perceive banks with more robust financial health, as reflected in healthier financial statements, as more resilient and better positioned to handle the impact of a large bank failure. SVB was the 16th largest bank in the U.S., which has spillover effects on the overall financial system. Another bank that experienced significant stress from the SVB collapse was Signature Bank. Meanwhile, the collapse had an international spillover effect, as evidenced by a 24% decline in Credit Suisse Bank's

share price on March 15, 2023. We are motivated to understand why different banks reacted differently to the SVB collapse.

This study represents the first attempt to analyze the effects of the SVB's collapse on the global banking industry using an event study methodology (ESM). It explores the determinants of the magnitude of the reaction of each bank to the SVB collapse. Different from previous research that has primarily focused on the impact of specific events on the overall market, including the global market (Dosumu et al., 2023), global equity market (Pandey et al., 2023), and global financial market (Yousaf et al., 2023). This study investigates the repercussions of a large bank's collapse to other banks worldwide. Following Yousaf et al. (2023) paper, we examine the impact of the SVB collapse on the global banking industry. By adopting this comprehensive approach, our study contributes to a deeper understanding of whether the consequences of the SVB collapse on an individual bank's stock price are based on an individual bank's soundness and healthiness.

2.2 CAMEL Assessments

CAMEL, an acronym for Capital Adequacy(C), Asset Quality(A), Management Efficiency (M), Earnings(E), and Liquidity(L), provides a comprehensive framework for assessing the overall strength and healthiness of banks (Rahman & Islam, 2018; Barr et al., 2002). CAMEL rating categories banks into three groups based on their financial health: sound banks (rate 1 or 2), early warning banks (rate 3 or 4), and problem banks (rate 5), which primarily evaluate the soundness of financial institutions by closely examining their balance sheets and income statements.

The CAMEL rating assessments, which have been widely accepted by bank examinations, have a long-term history of measuring banks' financial healthiness and soundness. Several studies have been conducted to measure the healthiness of banks in different countries by using the CAMEL rating assessments (AL-Najjar & Assous, 2021; Baral, 2005; Barr et al., 2002; Derviz & Podpiera, 2008; Maude & Dogarawa, 2016). Most studies have indicated that the CAMEL rating assessment provides a more comprehensive understanding of bank performance than alternative rating systems. However, it is important to note that the findings regarding the impact of CAMEL on banks' healthiness and soundness have needed to be more consistent and controversial. This variation is attributed to differences in the direction of the studies,

the scope of their coverage, and the specific measurement of CAMEL components utilized. Furthermore, these disparities are observed not only across different studies but also among various countries, emphasizing the inconclusiveness of the finding regarding the influence of CAMEL on bank performance. White and Rebel (2012) find that the CAMEL ratings as a proxy to analyze why commercial banks failed in the financial crisis and stated that the CAMEL ratings clearly assessed the healthiness and soundness of commercial banks both in the 2009-2010 crisis and the earlier 1984-1992 crisis. Moreover, White and Rebel (2012) prove that unforeseeable black swan events cause bank crises because banks heavily invest their capital in commercial real estate loans, exposing themselves to risks not adequately captured by existing capital requirements. Meanwhile, the empirical research focused on the survival or failure of banks heavily on the utilization of CAMEL assessments, which have become a prominent tool in analyzing and understanding the outcomes of banks in various studies (Avkiran & Cai, 2012; Cole et al., 2012). The CAMEL rating system represents one of the most widely used frameworks for assessing a bank's performance and healthiness (Derviz & Podpiera, 2008).

A robust and stable banking sector guarantees depositors and stakeholders a healthy and secure economic environment. Especially the evaluation of commercial bank healthiness is the duty of monetary authorities (Roman, 2013). Banks' conditions depend on individual banks' health as a function of several factors, such as quality of assets, liquidity position, capital condition, management efficiency, market size, and earnings. Several previous research stated that the CAMELS rating system could identify and predict financial crises, including Derviz & Podpiera (2008), Mannasoo & Mayes (2009), Avkiran & Cai (2012) and Wanke et al. (2016).

The following discussion provides an overview of each component within the CAMEL framework, highlighting their CAMEL measurement and fundamental parameters.

2.2.1 Capital Adequacy (C)

Capital adequacy is a critical component of bank regulation and supervision that primarily focuses on ensuring that a bank has an adequate amount of capital to safeguard the interests of depositors and withstand potential losses (Baral, 2005). It serves as a protective buffer, assuring depositors that their funds are protected even

in the event of adverse shock or financial distress experienced by banks. Schaeck (2008) employed the ratio of total capital to total assets as a proxy for capital adequacy. Roman and Sargu (2013) use the capital ratio, which is commonly employed as a critical measure. This ratio calculates a bank's total capital by its assets.

Moreover, capital adequacy can be evaluated using other vital ratios, such as total equity to total assets, equity to net loans, or equity to debts. In Baral's (2005) context, capital adequacy measurement involves dividing total capital into Tier I and II. Tier I and Tier II are the most important financial risk part. A bank's capital adequacy is also measured by the ratio of core capital's book value to the book value of its assets, which is the leverage ratio for banks—a higher ratio indicator of a higher capital adequacy level (Saunders & Cornett, 2004). Capital adequacy can also be evaluated using other essential ratios, such as total equity to total assets, equity to net loans, or equity to debt (Roman, 2013). These alternative ratios provide additional insights into the sufficiency of a bank's capital to its assets, equity, loans, and debt. By considering multiple ratios, this research will select some ratios which are available data to compute.

2.2.2 Asset Quality (A)

The level of credit risk is correlated to the asset quality. For banks, loan quality is a significant variable extensively represented in asset quality in empirical studies. Several studies utilize various indicators to assess the asset quality of commercial banks. These indicators include the composition of assets, the Non-Performing Loan (NPL) to total loan ratio, and the NPL to net loan ratios. These measures are employed due to most banks' high-risk nature of loans. Empirical findings have consistently shown that the Loan Losses for Provision (LLP) varies significantly between problem and non-problem banks, indicating the importance of asset quality in financial distress (Sinkey, 1975; AL-Najjar & Assous, 2021).

Meanwhile, some studies suggest that the quality of loans, measured by ratios such as Loan Loss Reserves (LLR) to total assets and LLP to total assets, is associated with bank distress (Calabrese & Giudici, 2015). Failed banks tend to have higher ratios of LLR to total loans. According to the NRB article, commercial banks make specific provisions for different categories of loans. These provisions are

determined based on the classification of loans as pass/performing, substandard, doubtful, or bad loans. Significantly, banks must allocate 1% provision for pass/performing loans, 25% for substantial loans, 50% for doubtful loans, and 100% for bad loans. Another important metric for evaluating asset quality is the ratio of total loans to total assets. Loans generally represent a substantial portion of a bank's assets, and a higher ratio can indicate a greater sensitivity to loan losses (Roman, 2013).

These findings highlight the importance of loan quality as a significant indicator in assessing the bank's condition by incorporating measures such as NPL, LLR, and LLP. We can gain insights into the relationship between asset quality and bank performance in financial distress.

2.2.3 Management Efficiency (M)

The management component determines the performance of banks, which holds significant importance in ensuring bank operations. Numerous indicators have been employed to evaluate management performance and effectiveness. Studies evaluating bank performance have recognized the significance of management quality. Indicators such as expense ratio, earnings per employee, cost per loan, average loan size, and cost per unit of money lent have been used as proxies for management quality (Baral, 2005; Rahman & Islam, 2018); however, some indicators are difficult to find the data, such as earning per employee and cost per unit of money. Empirical studies use other indicators to evaluate management quality such as operating expenses as a percentage of total assets and deposit interest expense as a percentage of total deposits (Roman, 2013); non-interest expense relative to the sum of net interest income and non-interest income and the cost-to-income ratio have all been employed as management efficiency and performance measures (Derviz & Podpiera, 2008).

The evaluation of management efficiency involves assessing the quality of monitoring and support provided by the board and management team in overseeing a bank's activities and their ability to comprehend and address associated risks (Baral, 2005; Barr et al., 2002; Doumpo & Zopounidis, 2010). These factors collectively contribute to the rating of management efficiency and reflect the effectiveness of banks' leadership and responsible operations.

2.2.4 Earnings (E)

Earnings serve as essential performance indicators for banks, describing their profitability. Among the ratios used to assess profitability, earnings spread and return on equity (ROE) are widely recognized as vital indicators (Derviz & Podpiera, 2008; Barr et al., 2002; Doumpo & Zopounidis, 2010). These ratios reflect the ability of banks to generate profits relative to their total assets and equity, respectively. In addition, the earnings ratios include net income margin (NIM), net interest income to total assets, other operating revenue to total assets, and non-interest income to interest income (Doumpo & Zopounidis, 2010). Those studies also proved that higher earnings ratios indicate strong profitability.

These earnings ratios provide valuable assessments of the financial performance of banks, enabling stakeholders to evaluate their profitability and compare their performance to peers. By monitoring and analyzing these ratios, banks can assess their earnings generation capabilities and make decisions to enhance their profitability and overall financial well-being.

2.2.5 Liquidity (L)

Banks typically profit by accepting short-term deposits at lower interest rates and lending funds in the long term at higher rates. However, if a bank encounters a liquidity crisis, there is a significant risk of a bank run occurring. Therefore, maintaining an appropriate level of liquidity is paramount for banks. Liquidity is one of the most important criteria for banks as it determines their ability to meet their short-term obligations and cope with unexpected deposit withdrawals (Le & Vo, 2023; Gertler & Kiyotaki, 2015). The liquidity risk of a commercial bank can be measured by analyzing funding sources and uses of liquidity. Both liability-side liquidity risk and asset-side liquidity risk have adverse effects on the financial health of commercial banks (Schaeck, 2008). However, some papers also stated that maintaining a high liquidity position to minimize these risks can negatively impact profitability. Various liquidity exposure ratios are employed to evaluate the liquidity position of commercial banks, such as the ratio of borrowed funds to total assets, core deposits to total assets, loans to deposits, and commitments to lend to total assets (Baral, 2005; Barr et al., 2002; Mannasoo & Mayes,2009; Schaeck, 2008). Several studies utilize ratios such as total loan to total deposit ratio, cash and

equivalents to total assets ratio, and cash and equivalents to total deposit ratios (Roman, 2013; Shaddady & Moore, 2019). Moreover, Doumpos and Zopounidis (2010) employed different ratios: the cash-to-assets ratio, total loan minus LLP divided by Total deposits, and real funding from credit institutions to total assets ratio. Various indicators are utilized to measure liquidity, with the most commonly employed ratios including the ratio of liquid assets to total deposits (TD) and short-term funding, the ratio of liquid assets to total assets, the ratio of net loans to total deposits and short-term funding, and the ratio of loans to depositors.

2.2.6 Review of Empirical Studies on CAMEL Assessments

Numerous studies have examined that the CAMEL rating system is a helpful tool to measure banks' healthiness and soundness, outputting varied and inconclusive findings. Many papers conducted comparative studies on the financial performance of the banking sector. Baral (2005) analyzed 17 Nepal commercial banks from 2001 to 2004, providing a theoretical framework that clearly defined the CAMEL components. This paper uses Baral's CAMEL definition to choose the components seriously. Yusof & Aliyu (2017) utilize a distinct standard selection of financial indicators as proxies for the CAMEL components, which are often accompanied by other bank-specific variables such as bank size, country, and economic condition. This literature primarily selected to world diversified investment banks demonstrates that these standard financial indicators are crucial in measuring bank conditions. Therefore, we will consider whether the CAMELS components are all available for selected banks.

Previous empirical research has been conducted in the United States, with studies examining various CAMEL components and bank failure probability (Derviz & Podpiera, 2008; Gopalan, 2022; Schaeck, 2008; Barr et al., 2002; Cole et al., 2012; Wang et al., 2019; and Samad et al., 2022). CAMEL rating system research also covered other developed markets, such as the European Union (Calabrese & Giudici, 2015; Shaddady & Moore, 2019; and Doumpo & Zopounidis, 2010). On the other hand, the CAMEL rating system is also available in emerging markets. Much research has been done on many regions' CAMEL rating system analysis. Saudi (AL-Najjar D, Assous HF, 2021), Romania (Roman, 2013), Czech Republic (Derviz & Podpiera, 2008), Nepal (Baral, 2005), *Nigeria* (Maude & Dogarawa, 2016) and

China (Wang et al., 2019). As mentioned earlier, the studies highlight the significance of financial conditions and performance indicators represented by CAMEL. However, several limitations are associated with measuring and evaluating factors such as earnings per employee and cost per loan. The availability and quality of data can pose limitations when measuring various indicators. Internal data points may not be available from published financial statements. And the above studies do not measure whether the CAMEL rating system is used for specific events.

2.3 Event Study Methodology

The Event study methodology (ESM) is a commonly used research methodology in finance to examine the effects of various announcements, regulatory changes, or macroeconomic shocks on stock prices. Ghoul et al. (2020) extend the application of event studies to cross-country financial event studies, including the Covid-19 pandemic, Brexit, and the Paris and Trans-Pacific Partnership agreements.

ESM measures abnormal changes in stock prices or returns that occur in conjunction with specific events (Dyckman et al., 1984). Empirical event studies are based on one assumption: event study methodology relies on the semi-strong version of the efficient market hypothesis, indicating that stock prices fully reflect all publicly available information (Boubaker et al., 2022; Eden et al., 2022; Liu, 2020). Consequently, analyzing the stock price impacts of an event can provide insights into how prices react to specific events related to specific firms, industries, or markets. As mentioned above, a large bank bankruptcy has an information spillover effect on other banks, supporting the event study assumptions indicating that the market can immediately reflect the unexpected information (Goldsmith-Pinkham & Yorulmazer, 2010).

Additionally, Ghoul et al. paper (2020) explores that ESM has several advantages to help address specific events. Firstly, ESM can assess the causality by isolating the single factor and the following effects. Secondly, ESM offers the advantage of timeliness. Unlike most annual or quarterly datasets, ESM utilizes high-frequency stock market data (daily stock price), which allows for the quick analysis of events. For example, ESM has already been employed to assess the recent specific events of COVID-19 (Baker et al., 2020 & Li et al., 2023) and the Ukrian-Russian War (Boubaker et al., 2022; Yousaf et al., 2022) ,highlighting the ability of ESM to provide timely insights into specific events. Thirdly, ESM can

identify and track these effects over time. This accumulation of data allows for studying both the short-term and long-term impacts, and ESM is well-suited for studying events that simultaneously impact multiple firms or countries. For example, Yousaf et al. (2022) examine the impact of the breakout of the conflict between Russia and Ukraine on G20 and other stock markets; Boubaker et al. (2022) examine the impact of the 2022 Russian invasion of Ukraine on the global stock market indices; Fiordelisi et al. (2020) investigate that stock market reactions of policy announcements. And Yousaf et al. (2022) examine the impact of the SVB collapse on global financial markets.

In ESM, abnormal returns (ARs) reflect the unexpected impact on the firm's value. Analyzing periods beyond a single day, known as event windows, the daily abnormal returns are aggregated to form cumulative abnormal returns (CARs). ESM allows for a comprehensive assessment of the cumulative impact of the event on the firm's stock returns over a specific period (Eden et al., 2022).

In this paper, we use the daily data from global bank stock prices from March 10th, 2023, to March 14th, 2023. Empirical evidence also supports that ESM allows researchers to discern causality (Eden et al., 2022). Moreover, EMS enables the isolation of banks' shocks, effectively assigning banks impacted by the SVB collapse events.

Additionally, ESM is a timely way that utilizes high-frequency stock market data. Event studies in international finance (Ghoul et al., 2022) provide practical recommendations to measure cross-country finance event studies. The new event study methodology can analyze the impact of increasing global events, such as COVID-19, the Russian-Ukraine military conflict, Brexit, and supply chain disruption (Baker et al., 2020; Yousaf et al., 2022; Ghoul et al., 2022). While previous studies have explored the impact of SVB's failures on the general market, not focusing on the bank industry (Dosumu et al., 2023; Pandey et al., 2023; Yousaf et al., 2023; Yadav et al., 2023; Akhtaruzzaman et al., 2023); however, a large bank's failure should have the most negative impact on the industry. This paper considers a more direct measurement approach, such as using stock price data at the individual bank level and relating it, especially to the CAMEL rating, which would provide a more granular understanding of how fluctuation in bank healthiness and soundness, as assessed by the CAMEL rating system, directly impacts the stock

price of other banks.

The study aims to investigate and provide insights into the research question: What is the relationship between CAMEL ratings and stock price reactions in the aftermath of the SVB collapse? Nevertheless, the existing research lacks direct measurement of individual bank stock price reactions after a big bank bankruptcy. Banks' conditions depend on individual banks' health as a function of several factors, such as quality of assets, liquidity position, capital condition, management efficiency, market size, and earnings. Therefore, regular financial health check-ups of banks are essential to address the adverse effects of various risks on their well-being.

Chapter 3. Data and Methodology

3.1 Data

In this research, we collected 646 global public bank information. We covered 58 countries from the Refinitiv Eikon and Refinitiv DataStream, including RIC code, country, exchange, CAMEL variables, and daily and monthly stock price. The list of sample information covers the CAMEL rating assessments.

To calculate the abnormal returns, we set the benchmark index to determine the relationship between the individual bank stock's daily return and the benchmark index. We collected two benchmark indices: local and global indices (MSCI global). Refinitiv Eikon provides the bank local indices' data covering 100 unique local indices.

The MSCI World Index is a prominent global equity benchmark encompassing 23 developed market countries. Comprising 1,510 constituents, it delivers extensive coverage of large and mid-cap companies across these nations. This index presents around 85% of each country's free float-adjusted market capitalization, offering a worldwide view of market equities. MSCI World Index is a valuable benchmark for assessing global equity market performance. The MSCI World Index is a good benchmark for all banks. On the other hand, the MSCI World Index as a substitute for local bank benchmark is a practical solution when corresponding local bank index data is unavailable. We extracted daily and monthly stock prices from Refinitiv DataStream.

To determine banking country-level variables, The World Bank provides the Global Financial Development Database, a comprehensive dataset encompassing financial system characteristics for 214 countries. It comprises 108 indicators, offering insights into financial institutions and markets. These indicators cover financial systems' depth, access, efficiency, and stability for financial institutions and financial markets. We chose some indicators to represent the country-level variables in the following part.

3.2 Event Study

We use the daily data of bank stock price and benchmark and set up the date March 10, 2023, as the event date since SVB collapsed that day. The event window

ranges from t (March 10th, 2023) to t+3 (March 14th, 2023). And we collect the daily and monthly prices from January 1st, 2020, to May 31st, 2023.

To assess the impact of the SVB run on global bank industries, this paper employs the conventional event study methodology introduced by Eden et al. (2022). This approach estimates abnormal returns by subtracting expected returns from the actual returns observed during the event period. Specifically, we calculate the daily return ($R_{i,t}$) as follows:

$$R_{it} = \left(\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}\right) \quad (1)$$

In the given equation, we extract the daily price from Refinitiv DataStream. Daily price is adjusted for dividends and stock slips.

In addition, to figure out the expected return $E(\mathrm{R_{i,t}})$, the Eden et al. (2022) event study method (ESM) is applied to calculate the expected return $R^*_{i,t}$. In Eq. (2): this study employs the market model to calculate the expected return by the following equation:

$$R^*_{i,t} = \beta * R_{m,t} \quad (2)$$

Where, R^*_{it} is expected return of individual bank, R_{mt} is market return by using the benchmark index, on day t. β is a measure of stocks' sensitivity in relation to the market return. We extract bank stock's beta from Refinitiv Eikon for the year 2022.

As a robustness test and to create consistency of our results, we also estimate the beta for each of our banks by regressing the bank's monthly return on MSCI global monthly return.

$$\beta = \frac{Cov((R_i, R_{m,t})}{VAR(R_{m,t})} \quad (3)$$

Where, $Cov((R_i, R_{m,t})$ is the covariance between the daily return of banks and markets. $VAR(R_{m,t})$ is the variance of the individual bank stock price performance.

Next, the abnormal return is the difference between the actual return and the expected return, as in Eq. (4):

$$AR_{i,t} = R_{i,t} - R^*_{i,t} \quad (4)$$

Where,

$R^*_{i,t}$ *represents the expected returns for individual stock i.* AR_{it} is the abnormal return of the individual bank i on day t; $R_{i,t}$ represents the actual return of individual stock on day t; R_{mt} represents the daily return of the global bank index on day t.

Finally, we calculate sufficient cumulative abnormal return $CAR_{i,t}$ over the event window [2,3,4,5] using the following equation:

$$CAR_{i,t} = \sum_{i=0}^{j} AR_{i,t} \quad (5)$$

Here, in this study, t represents the March 10th, 2023; j represents the event windows.

3.3 Bank-level Variables: CAMEL

In our rigorous analysis, we meticulously control for both bank-level and country-level variables, ensuring a comprehensive exploration of factors influencing cumulative abnormal returns. Including alternative CAMEL variables in our regression models further enhances the robustness of our study. Appendix B Panel B serves as a valuable resource for detailed insights into each CAMEL variable's definition and data sources, facilitating transparency and reproducibility in our methodology.

3.3.1 Capital Adequacy (C)

The components of CAMEL are as follows: Capital adequacy (C) plays a critical role in determining the financial well-being of the banking sector. It ensures that banks have sufficient capital to absorb potential losses arising from various risks. Several ratios are commonly used to measure capital adequacy in empirical studies. One widely used ratio is the total capital ratio, which represents the proportion of total capital to total risk-weighted assets. This ratio indicates the bank's ability to absorb losses and is a buffer against potential risks.

Additionally, we employ another variable as a capital adequacy proxy, the Tier 1 ratio, which focuses on the bank's Tier 1 capital to its risk-weighted assets. The Tier 1 ratio represents a bank's core capital, which consists of the bank's highest-quality capital elements that are fully available to absorb losses without the bank being required to cease operations. Moreover, Risk-Weighted Assets (RWA)

are the bank's assets adjusted for risk, where different types of assets are assigned, and specific risk is weighted based on their perceived riskiness. This adjustment reflects the potential losses the bank may face due to the credit, market, and operational risks associated with its assets.

Two ratios collectively contribute to assessing a bank's capital adequacy and ability to withstand financial shocks. Banks can enhance their resilience and protect depositors' funds by maintaining adequate capital levels.

3.3.2 Asset Quality (A)

Asset quality (A) is primarily determined by the quality of loans, given their significant presence on a bank's balance sheet. Evaluating loan quality commonly relies on three ratios: 1) The Non-Performing Loan (NPL) ratio measures the proportion of non-performing loans to total loans in a bank's loan portfolio. Non-performing loans refer to loans that are in default or have a high probability of default. A higher NPL ratio indicates a more significant portion of problem loans with the bank's loan portfolio, which may expose risks. 2) The Loan Loss Provision (LLP) Ratio reflects the provisions banks make to cover potential loan losses about their total loans. LLP are funds set aside by the bank to cover anticipated losses from non-performing loans. A higher LLP ratio suggests that the bank has allocated more of its income toward building reserves to absorb potential losses.

3.3.3 Management Efficiency (M)

Management efficiency assesses the operation of banks. However, qualifying management quality can be challenging due to its data availability. This paper utilizes four ratios for determining a bank's operations. These ratios include: 1) the Salary Expense to Total Asset Ratio: This ratio measures the efficiency of cost management by assessing the salary expenses incurred by the bank as a percentage of its total assets. A lower ratio indicates better cost control and operational efficiency 2) The income-to-total assets ratio reflects how effectively a bank utilizes its assets to generate income. It considers both interest-bearing revenue and non-interest income, offering a holistic view of the bank's revenue capacity. Management decisions influence various income streams, and this ratio captures the overview efficiency in harnessing these diverse sources to maximize returns.

3.3.4 Earnings (E)

In the CAMEL rating system, earnings evaluate a bank's profitability and financial performance. Various indicators are considered to assess the earnings in the CAMEL framework. We will employ these ratios: 1) Net Income Margin (NIM): The NIM is a profitability ratio that measures the percentage of net income a bank generates to its total revenue. It indicates how efficiently the bank converts its revenue into profit after all expenses. A higher NIM means better profitability. 2) the efficiency ratio indicates the non-interest expense over the total revenue. This ratio is powerful for assessing how efficiently a bank manages its costs regarding the revenue. A lower efficiency ratio generally indicates a more efficient operation, as it suggests that non-interest expenses consume a smaller percentage of revenue. Banks closely monitor efficiency ratios to assess their competitiveness and sustainability.

3.3.5 Liquidity (L)

The liquidity position is a critical component of a bank's financial stability, with a significant impact on its overall soundness, which assesses a bank's operational performance by looking at its ability to meet short-term obligations and handle unexpected deposit withdrawals. Liquidity indicators are essential in evaluating a bank's resilience to cash flow shocks.

This paper uses liquidity indicators, including 1) The ratio of Liquid Assets to Total Assets calculates the proportion of liquid assets a bank holds to its total assets. Liquid assets include cash, government securities, and other highly marketable and readily convertible assets. A higher ratio indicates a larger proportion of easily accessible funds, indicating a stronger liquidity position. 2) The ratio of non-interest-bearing deposits to total assets (NDEP). Depositors can withdraw the NDEP at any time; however, it is essential to note that the NDEP can potentially contribute to a bank run if depositors panic and rush to withdraw their funds. In this paper, the NDEP can be a good indicator since the SVB caused the systematic confidence loss.

To offer more exhaustive insights into our analysis, we have provided detailed information about the CAMEL variables used in this study in Appendix B. Appendix B Panel B presents a detailed breakdown of the CAMEL variables employed in our study. These variables are fundamental to our assessment of banks'

performance. Understanding their definitions and significance is crucial for comprehending the metrics we use to evaluate banks.

3.3.6 Bank Size

Several previous research have examined the impact of bank size on the financial crisis, with differing viewpoints. Some scholars argue that larger banks suffer more crisis loss (Elyasiani and Jia, 2019; Laeven et al., 2016; Baron et al., 2022). Laeven et al. (2016) indicate that systemic risks are closely tied to bank sizes and suggest that better-capitalized banks tend to exhibit lower levels of systemic risk, particularly pronounced for large banks. Another Laeven et al. (2014) explain that large banks potentially take more risky activities and suffer more loss in crisis. In this paper, measuring the bank size is essential for our analysis. We employ the natural logarithm of total assets, denoted as LN_TA. To standardize the bank size, we extract the total assets with U.S. dollars from Refinitiv Eikon.

3.3.7 Country Level Variables:

In this study, our primary objective is not to determine the causal relationships but to control the influence of country-level variables. Similar to Benbouzid et al.'s paper (2017), we determine the country-level variables from depth, efficiency, and stability. We control country-level variables because we aim to determine whether country-level variables generate multicollinearity issues.

We have access to a comprehensive bank database that provides detailed information about various banks. It encompasses the bank's specific characteristics and includes data on the country banks operate in and the exchange they are listed on. We have diligently considered country-level variables to understand the performance and factors influencing the cumulative abnormal return. These indicators provide critical insights into the broader economic landscape that banks navigate. The data for these indicators has been sourced from the World Bank. To explore these selected country-level indicators and their role in shaping our analysis, we use a set of critical financial indicators to measure country-level variables. Here is a brief introduction to these indicators: 1) Financial system deposits to GDP (FinSD), 2) Bank net interest margin (BankNIM), 3) Bank nonperforming loans to gross loans (BankNPL), 4) Bank capital to total assets (BankCTA), 5) Liquid assets to deposits

and short-term fundings (LAtoDep). In Appendix B, Panel C, we provide each indicator's codes and short definitions.

Chapter 4. Empirical Results

4.1 ARs and CARs Calculations

In this research paper, we employed six ways to calculate ARs to determine the appropriate AR. Through AR1 to AR4, we extract and calculate the daily return for each bank with the local currency and dollar and the corresponding index return with the local currency and dollar. According to Eq. (3), we estimated the beta for each bank by using monthly return data from Definitive DataStream, explicitly considering the beginning and ending monthly returns. Then, the estimated betas are used in AR5 and AR6. Table 1 exhibits six calculations of abnormal returns, which offer substantial ways to determine abnormal returns after SVB collapse.

Table 1: Calculations of Abnormal Returns (ARs).

This table defines the formulas for abnormal returns used in the main regressions. The label AR1 and AR6 stand for two formulas, the label RET_Local, RET_Local_Index, RET_$, Estimated_beta_Beg, and MSCI_RET stand for daily stock returns of local currency, daily index returns of local currency, daily stock return of dollar, calculated beta in beginning month returns, and daily MSCI returns. Appendix A provides the definitions and data sources.

ARs	Formula
AR1	RET_Local -RET_Local_Index
AR2	RET_Local -(beta_2022)*(RET_Local_Index)
AR3	RET_$- RET_$_Index
AR4	RET_$- (beta_2022)*(RET_$_Index)
AR5	RET_$ -(Estimated_beta_End)*MSCI_RET)
AR6	RET_$ -(Estimated_beta_Beg)*MSCI_RET)

To calculate the cumulative abnormal returns (CARs), we set March 10, 2023, as the event date. We calculate the CARs for the following days and sign the names CARs_1DAY, CARs_2DAYs, and CARs_3DAYs. March 10, 2023, is Friday. That is, CARs_1DAY represents only March 10, 2023; CARs_2DAYS represents CARs with March 10, 2023, and March 13, 2023; CARs_3DAYS represents only Table 2 shows cumulative abnormal returns (CARs) calculations from t to t+3, which represent the dependent variable in the main regressions.

Table 2: Calculations of Cumulative Abnormal Returns (CARs).

This table defines the formula for cumulative abnormal returns used in the main regression. The labels CARs_1DAY, CARs_2DAYS, and CARs_3DAYS represent cumulative abnormal returns on March 10th 2023, cumulative abnormal returns of March 10th and March 13th 2023, and cumulative abnormal returns of March 10th, 13th, and 14th 2023.

CARs	Start Date	End Date
CARs_1DAY	March 10th 2023	March 10th 2023

CARs_2DAYS	March 10th 2023	March 13th 2023
CARs_3DAYS	March 10th 2023	March 14th 2023

4.2 Main Results

We plot the percentile distributions of 2-day CARs. Figure 1 reports embarks on a detailed exploration of our cumulative abnormal returns in 2 days, spotlighting key percentile results that illuminate the relative positioning of each data point.

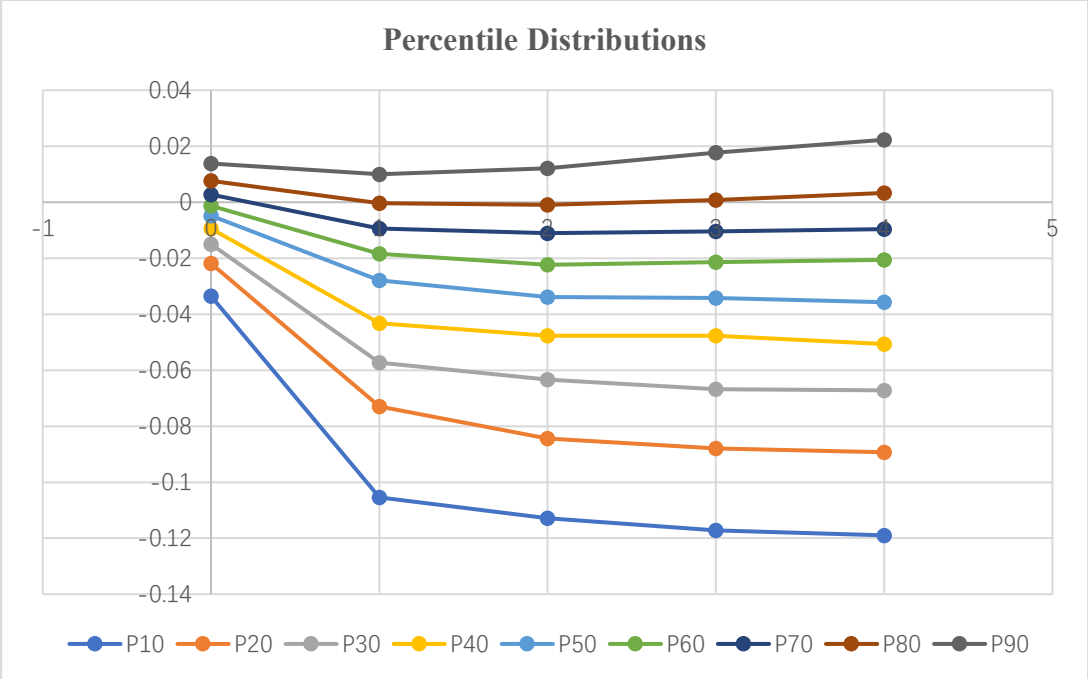

Figure 1: Percentile Distributions of 2-day CARs

The relationship between CARs and CAMEL component is expressed as follows:

$$CARs=f(CAMEL, Bank\ Size) \quad (6)$$

We construct our main regression model, including independent variables, CAMEL proxies, and bank size. We select alternative CAMEL variables as our additional regression model, which provides robustness to our conclusion. Ultimately, we control country-level variables to determine whether country-level variables can impact our main regression.

The magnitude of CARs is an essential aspect of our analysis, ensuring that the impacts of SVB are significant in the observation period. We summarize critical statistical measures related to CARs within two and three days. Table 3 summarizes Cumulative Abnormal Returns, labeled as CAR_XDAYS_ARY, where X represents

the number of days, and Y represents which specific abnormal returns are employed. Table 3 displays Mean, p25, p50, p75, SD, Min, Max, and N stand for the mean, the 25th percentile, the median, the 75th percentile, the standard deviation, and the number of observations.

Table 3 Panel A presents the descriptive statistics of the variables, average (Mean) and median (50th), used in the main regression. In Table 3, average values exhibit consistent negative values, ranging from -0.05 to -0.045 across the different calculation methods, suggesting an overall propensity towards negative abnormal returns over AR1 to AR6. The 25th percentile (p25) reveals that a quarter of the observations had even lower CARs with a value of approximately -0.079. On the other hand, the median (p50) stands at all negative values from -0.029 to -0.026, indicating that half of the observations had CARs below zero. Notably, the range between the maximum and minimum CAR values is large, with the lowest recorded value at -0.756; the maximum value is 0.507, which shows wide ranges in the observations. The maximum observations (N) for 2-day CARs are 646, indicating we have 646 commercial banks for the following analysis.

Meanwhile, Table 3 Panel B provides an analogous analysis for the three days. The 'CARs' value within this framework exhibits a similar consistent negative trend. The average value is approximately -0.048; the minimum value is -0.637, reflecting substantial fluctuations in three days. The comparison between the two sets of Table 3 demonstrates a similar result: both CAR values consistently reveal a negative value. The findings from both sets of Table 3 Panel A and Panel B collectively emphasize the significance of scrutinizing the magnitude of CARs. The observed fluctuations in abnormal returns are substantial and consistent across various calculation methodologies (AR1 through AR6). However, the minimum value does not change compared to CAR in two days. We assumed that the SVB collapse impact was gone. In the following regression, we limit the CARs to three days to measure the relationship between CARs and dependent variables.

Table 3: Summary Statistics of Cumulative Abnormal Returns (CARs).

The table reports the descriptive statistics for CARs used in the main regressions. The labels Mean, p25, p50, p75, SD, Min, Max, and N stand for the mean, the 25th percentile, the median, the 75th percentile, the standard deviation, the minimum value, the maximum value, and the number of observations.

Panel A: Summary statistics of CARs in 2 days

CARs	Mean	p25	p50	p75	SD	Min	Max	N

CAR_2DAYS_AR1	-0.0486	-0.0729	-0.0278	-0.0066	0.0706	-0.6634	0.1430	544
CAR_2DAYS_AR2	-0.0500	-0.0774	-0.0296	-0.0067	0.0703	-0.6576	0.1429	541
CAR_2DAYS_AR3	-0.0494	-0.0774	-0.0276	-0.0023	0.0761	-0.6634	0.1692	540
CAR_2DAYS_AR4	-0.0506	-0.0792	-0.0283	-0.0033	0.0759	-0.6576	0.1692	537
CAR_2DAYS_AR5	-0.0455	-0.0713	-0.0262	-0.0021	0.0812	-0.7550	0.5069	646
CAR_2DAYS_AR6	-0.0457	-0.0711	-0.0261	-0.0019	0.0813	-0.7549	0.5047	646

Panel B: Summary statistics of CARs in 3 days

CARs	Mean	p25	p50	p75	SD	Min	Max	N
CAR_3DAYS_AR1	-0.0484	-0.0754	-0.0339	-0.0073	0.0624	-0.5363	0.1380	544
CAR_3DAYS_AR2	-0.0481	-0.0750	-0.0333	-0.0085	0.0617	-0.5365	0.1379	541
CAR_3DAYS_AR3	-0.0483	-0.0774	-0.0325	-0.0046	0.0683	-0.5363	0.1742	540
CAR_3DAYS_AR4	-0.0478	-0.0772	-0.0323	-0.0040	0.0675	-0.5365	0.1743	537
CAR_3DAYS_AR5	-0.0481	-0.0733	-0.0338	-0.0039	0.0727	-0.6363	0.5024	646
CAR_3DAYS_AR6	-0.0482	-0.0729	-0.0340	-0.0039	0.0727	-0.6366	0.5016	646

Table 4 summarizes descriptive statistics of cumulative abnormal returns (CARs) in countries and areas**.** Each row corresponds to a specific country or area, and the column 'Mean' provides one key statistical measure of average value. These metrics serve as vital indicators for assessing the performance and volatility of bank stock within each respective nation. The value overviews the average cumulative abnormal returns across countries. Countries like Chile, Netherlands, Spain, and the United States exhibit significantly negative mean returns. Table 4 presents a comprehensive overview of cumulative abnormal returns across various countries, which is used in the main regressions in Table 7 to explore the relationship among CARs, CAMEL variables, and country-level variables. Table 4 results support Dosumu et al.'s (2023) findings: SVB failure has a strong contagion effect in U.S. and European markets. Moreover, the empirical results confirmed Goldsmith-

Pinkham and Yorulmazer's (2010) statement that individual bank experiences difficulties that can spread to the overall financial system. In Table 4, the descriptive statistics vary across different countries or areas, which motivates us to explore the relationship between CARs and country-level variables.

Table 4: Summary Statistics of Cumulative Abnormal Returns (CARs) in Countries

This table represents descriptive statistics for median value of cumulative abnormal returns (CARs). The label Countries &Areas and p50 represent countries or areas and median value, respectively.

Panel A: Descriptive statistics for Median value by Country and area in 2 days

	AR1		AR2		AR3		AR4		AR5		AR6	
Country	p50	N	p50	N	p50	N	p50	N	p50	N	p50	N
Austria	-0.038	4	-0.025	4	-0.039	4	-0.031	4	-0.040	4	-0.041	4
Bahrain	0.001	2	0.001	2	-0.002	2	-0.003	2	-0.001	2	-0.001	2
Botswana									-0.001	1	-0.001	1
Brazil	-0.017	5	-0.016	5	-0.017	5	-0.011	5	-0.022	7	-0.022	7
Chile	-0.018	1	-0.019	1	-0.185	1	-0.187	1	-0.191	1	-0.190	1
China	-0.014	39	-0.014	39	-0.014	39	-0.014	39	0.000	39	0.001	39
Colombia									-0.033	4	-0.033	4
Czech Republic	0.019	1	0.022	1	0.020	1	0.023	1	0.005	1	0.005	1
Denmark	-0.069	7	-0.080	7	-0.070	7	-0.076	7	-0.074	7	-0.075	7
Egypt									-0.042	6	-0.042	6
Estonia	-0.019	1	0.000	1	-0.019	1	-0.009	1	-0.024	1	-0.025	1
France	0.013	11	0.001	11	0.013	11	0.006	11	-0.004	11	-0.003	11
Greece	-0.007	3	0.029	3	-0.011	3	0.008	3	0.001	3	-0.001	3
Hong Kong, China	-0.017	6	-0.019	6	-0.016	6	-0.019	6	-0.002	19	-0.001	19
Hungary	-0.011	1	-0.003	1	-0.010	1	0.004	1	-0.037	1	-0.038	1
Indonesia	-0.012	33	-0.011	33	-0.002	30	-0.003	30	0.011	29	0.012	29
Ireland	-0.036	3	-0.026	3	-0.037	3	-0.026	3	-0.037	3	-0.035	3
Israel	-0.013	6	-0.009	6	-0.013	6	-0.009	6	-0.056	6	-0.056	6
Italy	-0.029	1	-0.047	1	-0.030	1	-0.042	1	-0.064	1	-0.061	1
Jordan	0.007	10	-0.002	10	0.005	10	-0.004	10	-0.011	13	-0.011	13
Kazakhstan	0.004	1	0.003	1	0.001	1	-0.004	1	-0.010	2	-0.013	2
Kenya									0.006	4	0.006	4
Korea; Republic	-0.022	6	-0.023	6	-0.021	6	-0.019	6	-0.004	7	-0.002	7
Kuwait									0.000	5	0.000	5
Lebanon									0.007	3	0.008	3
Malaysia	-0.010	5	-0.008	5	-0.011	5	-0.006	5	-0.012	5	-0.012	5
Mauritius									0.007	1	0.007	1
Mexico	-0.055	1	-0.052	1	-0.053	1	-0.036	1	-0.080	1	-0.080	1
Morocco									-0.015	1	-0.016	1
Netherlands	-0.054	2	-0.037	2	-0.055	2	-0.045	2	-0.052	2	-0.052	2
Nigeria	-0.020	9	-0.020	9	0.001	8	0.001	8	0.007	8	0.007	8
Norway	0.014	2	-0.001	2	0.014	2	0.003	2	-0.004	2	-0.004	2
Oman	-0.009	6	-0.011	6	-0.009	6	-0.009	6	0.003	7	0.002	7
Pakistan	0.003	13	0.003	13	0.003	13	0.003	13	0.007	16	0.008	16

Palestine									-0.002	4	-0.003	4
Peru									-0.007	2	-0.006	2
Philippines	-0.001	15	-0.003	15	-0.001	15	-0.001	15	0.005	15	0.004	15
Poland	-0.016	7	0.003	7	-0.017	7	0.000	7	-0.017	7	-0.015	7
Portugal	-0.079	1	-0.058	1	-0.079	1	-0.070	1	-0.065	1	-0.063	1
Qatar	0.003	4	-0.001	4	0.002	4	-0.001	4	-0.023	5	-0.024	5
Romania	0.002	2	0.008	2	0.002	2	0.003	2	0.009	2	0.009	2
Rwanda									-0.001	1	0.000	1
Saudi Arabia	-0.020	9	-0.015	9	-0.020	9	-0.015	9	-0.026	9	-0.023	9
Singapore	-0.005	3	-0.001	3	-0.005	3	-0.002	3	-0.018	3	-0.018	3
Slovak Republic									0.018	1	0.019	1
South Africa	-0.046	2	-0.046	2	-0.047	2	-0.047	2	-0.020	3	-0.019	3
Spain	-0.099	2	-0.085	2	-0.099	2	-0.090	2	-0.116	2	-0.115	2
Sri Lanka	-0.015	2	-0.019	2	-0.009	2	-0.016	2	-0.039	2	-0.040	2
Sweden	-0.018	1	0.000	1	-0.017	1	-0.006	1	-0.029	1	-0.029	1
Switzerland	0.005	3	-0.011	3	0.005	3	0.004	3	0.009	3	0.008	3
Taiwan, China	-0.004	14	-0.010	14	0.003	14	0.000	14	0.003	15	0.003	15
Tanzania									0.004	1	0.003	1
Thailand	-0.002	10	-0.003	10	-0.003	10	-0.002	10	-0.005	10	-0.004	10
Turkey	-0.026	6	-0.018	6	-0.028	6	-0.019	6	-0.036	7	-0.037	7
United Arab Emirates	0.010	12	0.007	12	0.010	12	0.006	12	0.001	14	0.002	14
United Kingdom	-0.070	2	-0.050	2	-0.071	2	-0.060	2	-0.072	3	-0.073	3
United States of America	-0.068	270	-0.071	267	-0.068	270	-0.071	267	-0.066	311	-0.066	311
Venezuela									0.083	1	0.083	1
Total		544		541		540		537		646		646

Panel B: Descriptive statistics for Median value by Country and area in 3 days

	AR1		AR2		AR3		AR4		AR5		AR6	
Country	p50	N	p50	N	p50	N	p50	N	p50	N	p50	N
Austria	-0.032	4	-0.024	4	-0.032	4	-0.029	4	-0.035	4	-0.035	4
Bahrain	0.003	2	0.002	2	-0.001	2	-0.002	2	-0.003	2	-0.003	2
Botswana									0.000	1	0.000	1
Brazil	-0.023	5	-0.020	5	-0.018	5	-0.012	5	-0.044	7	-0.044	7
Chile	-0.006	1	-0.008	1	-0.170	1	-0.173	1	-0.197	1	-0.197	1
China	-0.019	39	-0.020	39	-0.017	39	-0.016	39	-0.011	39	-0.010	39
Colombia									-0.031	4	-0.031	4
Czech Republic	0.011	1	0.013	1	0.011	1	0.013	1	-0.010	1	-0.010	1
Denmark	-0.058	7	-0.065	7	-0.058	7	-0.061	7	-0.063	7	-0.063	7
Egypt									-0.065	6	-0.065	6
Estonia	-0.011	1	-0.001	1	-0.011	1	-0.011	1	-0.008	1	-0.008	1
France	-0.011	11	-0.020	11	-0.011	11	-0.016	11	-0.018	11	-0.018	11
Greece	0.011	3	0.019	3	0.009	3	0.003	3	0.027	3	0.026	3
Hong Kong, China	-0.025	6	-0.034	6	-0.025	6	-0.033	6	-0.013	19	-0.013	19

Hungary	0.009	1	0.017	1	0.010	1	0.023	1	-0.023	1	-0.024	1
Indonesia	-0.019	33	-0.007	33	0.020	30	0.022	30	0.004	29	0.004	29
Ireland	-0.011	3	-0.003	3	-0.011	3	-0.005	3	-0.009	3	-0.009	3
Israel	-0.014	6	-0.011	6	-0.014	6	-0.008	6	-0.054	6	-0.054	6
Italy	-0.041	1	-0.051	1	-0.041	1	-0.046	1	-0.056	1	-0.055	1
Jordan	0.007	10	-0.002	10	0.005	10	-0.004	10	-0.014	13	-0.014	13
Kazakhstan	0.013	1	0.012	1	0.020	1	0.013	1	-0.015	2	-0.016	2
Kenya									0.002	4	0.002	4
Korea; Republic	-0.044	6	-0.051	6	-0.042	6	-0.047	6	-0.070	7	-0.070	7
Kuwait									-0.033	5	-0.033	5
Lebanon									0.002	3	0.003	3
Malaysia	-0.005	5	0.000	5	-0.006	5	-0.005	5	-0.033	5	-0.033	5
Mauritius									0.002	1	0.002	1
Mexico	-0.071	1	-0.066	1	-0.069	1	-0.051	1	-0.113	1	-0.113	1
Morocco									0.017	1	0.016	1
Netherlands	-0.051	2	-0.041	2	-0.052	2	-0.048	2	-0.050	2	-0.050	2
Nigeria	-0.007	9	-0.007	9	0.002	8	0.002	8	0.002	8	0.001	8
Norway	-0.013	2	-0.023	2	-0.013	2	-0.020	2	-0.025	2	-0.025	2
Oman	-0.016	6	-0.020	6	-0.016	6	-0.015	6	0.002	7	0.002	7
Pakistan	-0.001	13	-0.001	13	0.007	13	0.008	13	0.002	16	0.003	16
Palestine									-0.005	4	-0.005	4
Peru									0.001	2	0.001	2
Philippines	0.011	15	-0.008	15	0.011	15	-0.006	15	-0.019	15	-0.019	15
Poland	-0.013	7	0.005	7	-0.011	7	0.001	7	-0.036	7	-0.035	7
Portugal	-0.061	1	-0.051	1	-0.061	1	-0.062	1	-0.050	1	-0.049	1
Qatar	0.005	4	-0.004	4	0.003	4	-0.006	4	-0.041	5	-0.040	5
Romania	0.008	2	0.009	2	0.008	2	0.005	2	0.019	2	0.019	2
Rwanda									0.000	1	0.000	1
Saudi Arabia	-0.030	9	-0.026	9	-0.029	9	-0.025	9	-0.051	9	-0.051	9
Singapore	-0.011	3	-0.008	3	-0.011	3	-0.008	3	-0.030	3	-0.030	3
Slovak Republic									0.016	1	0.016	1
South Africa	-0.036	2	-0.036	2	-0.037	2	-0.037	2	-0.031	3	-0.030	3
Spain	-0.084	2	-0.077	2	-0.085	2	-0.081	2	-0.092	2	-0.092	2
Sri Lanka	-0.034	2	-0.036	2	0.007	2	-0.002	2	-0.043	2	-0.043	2
Sweden	-0.031	1	-0.021	1	-0.031	1	-0.031	1	-0.026	1	-0.026	1
Switzerland	0.003	3	-0.008	3	0.003	3	0.005	3	0.009	3	0.009	3
Taiwan, China	-0.003	14	-0.015	14	-0.004	14	-0.014	14	-0.021	15	-0.021	15
Tanzania									0.001	1	0.001	1
Thailand	-0.008	10	0.010	10	0.003	10	0.011	10	-0.035	10	-0.034	10
Turkey	-0.019	6	-0.003	6	-0.019	6	-0.007	6	-0.058	7	-0.058	7
United Arab Emirates	0.010	12	0.003	12	0.007	12	0.002	12	-0.009	14	-0.009	14
United Kingdom	-0.047	2	-0.032	2	-0.047	2	-0.042	2	-0.026	3	-0.026	3
United States of	-0.069	270	-0.069	267	-0.069	270	-0.069	267	-0.057	311	-0.057	311

America								
Venezuela					0.083	1	0.083	1
Total	544	541	540	537		646		646

4.3 Correlation Matrix

Table 5 provides a correlation matrix of independent variables, reporting correlation coefficients, robust t-values in parentheses, and significance levels denoted by asterisks (*, **, ***) for 10%, 5%, and 1%, respectively. Table 5 panel A and B report the correlation matrix with AR1 and AR6 in 2 days, respectively. The matrix encompasses variables: CARs, CAP, NPL, SRL, NIM, CASHD, and LN_TA. The main variables used in the regression are CARs (cumulative abnormal returns), CAP (Capital Adequacy Ratio), NPL (Non-Performing Loans divided by Total Assets), SRL (Salary Expense divided by Total Assets), NIM (Net Interest Margin), CASHD (Cash and Due from Bank divided by Total Assets), and LN_TA (Natural Logarithm of Total Assets). Appendix B provides definitions and data sources for all variables. Table 5 panel A demonstrates the correlation coefficients between the dependent variable value and other independent variables. The CARs are positively correlated with CAP (0.2023***), NPL (0.0967*), CASHD (0.3395***), and LN_TA (0.1148**). It exhibits a negative correlation with SRL (-0.2020***). Nevertheless, NIM is correlated with CARs at an insignificant level. In Table 5, Panel B, CAP, SRL, and CASHD are still significant (***).

Table 5 panel A and B reveal significant correlations between the independent variables. For example, CAP shows strong positive correlations with NPL (0.0919*), NIM (0.2080***), and CASHD (0.3672***); while SRL exhibits a negative correlation with NIM (-0.0849*) in panel A. In panel B, the correlation among CAMEL variables remains significant. CASHD is correlated to other CAMEL variables at statistically significant level (***). These correlations can provide insights into the multicollinearity issue among the CAMEL variables used in the regression. Therefore, to further enhance the robustness of the regression analysis, this study controls for country-level variables.

Table 5 evidence supports several previous research findings: in capital adequacy, our result is consistent with Baral (2005), Saunders and Cornett (2004);

and Schaeck's (2008) findings: higher total capital ratio assures depositors, ensuring the security of their funds, even in cases of unexpected financial challenges or distress faced by financial institutions.

Table 5: Correlation Matrix of Independent Variables.

This table reports Pearson's correlation coefficients for the main variables used in the regression. The labels value, CAP, NPL, SRL, NIM, CASHD, LN_TA, and N represent total capital ratio, non-performing loan divided by total assets, salary expense divided by total assets, net interest margin, cash and due from bank divided by total assets, natural logarithm of its total assets, and the number of observations. Robust T-values are in parentheses. *, **, *** denote significance level at the 10%, 5%, and 1%, respectively. Appendix. B provides definitions and data sources for all the variables.

Table 5, Panel A: Correlation matrix for the 2-day CARs

	CARs	CAP	NPL	SRL	NIM	CASHD	LN_TA
CARs	1						
CAP	0.2023**	1					
NPL	0.0967*	0.0919*	1				
SRL	-0.2020**	0.0225	-0.0849*	1			
NIM	-0.0188	0.2080**	0.0943*	0.3767**	1		
CASHD	0.3395**	0.3672**	0.1265**	-0.3185**	0.0763	1	
LN_TA	0.1148**	-0.1912**	0.0425	-0.5066**	-0.3118**	0.2299**	1
N	544						

Table 5, Panel B: Correlation matrix for the 3-day CARs

	CARs	CAP	NPL	SRL	NIM	CASHD	LN_TA
CARs	1						
CAP	0.1968***	1					
NPL	0.1095**	0.0461	1				
SRL	-0.1518***	0.0247	-0.0476	1			
NIM	0.02	0.2238**	0.1687***	0.4198***	1		
CAS	0.3169***	0.3560*	0.1460	-0.2239***	0.2156**	1	

HD		**	***		*		
LN_TA	0.0793*	-0.1724**	0.0229	-0.5191***	-0.2714**	0.2105***	1
N	646						

4.4 Expected Signs of Variables

We employed CAP, NPL, SRL, NIM, and CASHD. CAP is the ratio of total regulatory capital to total risk-weighted assets, known as the Capital Adequacy Ratio. It indicates the bank's capacity to withstand losses in market stress. A higher ratio signifies better financial stability, providing confidence to investors. In turn, this increased stability is expected to impact CARs positively. The NPL represents the Non-Performing Loan ratio, calculated by non-performing loans over total loans, which assesses the bank's loan portfolio quality. It quantifies the proportion of loans that have stopped generating interest income or are at risk of default. A high NPL ratio suggests increased credit risk and potential financial instability, while a lower ratio indicates a healthier loan book. We expect NPL to be negatively related to CARs. The SRL, the labor-related expense over total assets, provides insights into the efficiency of a company's labor utilization to its total assets. A lower ratio indicates efficient labor utilization, which can positively impact profitability.

Conversely, a higher ratio suggests a potential need for cost management or a significant labor burden on the bank's asset base. We expect SRL to be negatively related to CARs. The NIM represents the Net Interest Margin. A higher NIM indicates more efficient management of these assets and liabilities, resulting in greater profitability. We suggest that NIM is positively related to CARs. The CASHD, Cash and Due from banks over Total asset, represents its cash holdings and amounts due from other banks. This ratio is a crucial indicator of a bank's liquidity to meet short-term financial obligations. A higher CASHD suggests that a bank is held in a higher liquid form, which can be beneficial for managing day-to-day operations and covering unexpected withdrawals. We expected CASHD to be positively related to CARs. Meanwhile, we employed the natural logarithm of total assets (LN_TA) to address whether a bank's scale is negatively related to CARs. Baron et al.'s paper (2023) states that larger banks are often more vulnerable to

substantial losses in unforeseen circumstances or financial shocks. We expect LN_TA to be negatively related to the CARs. We provide Table 6 representing our expected signs.

Table 6: Expected Sign of Independent Variables.

This table shows the expected sign of independent variables in the main regression: $CARs=\alpha+\beta_1(CAP)+\beta_2(NPL)+\beta_3(SRL)+\beta_4(NIM)+\beta_5(CASHD)+\beta_6(LN\_TA)+\varepsilon$. The Label CAP, NPL, SRL, NIM, CASHD, LN_TA stand for total capital ratio, non-performing loans divided by total loans, salary expenses divided by total assets, net interest margin, cash & due from bank divided by total assets, and natural logarithm of total assets.

Name	Acronym	Expected Sign
CAP	Capital Adequacy Ratio	+
NPL	Non-Performing Loan ratio	-
SRL	The labor-related Expense over Total Assets	-
NIM	Net Interest Margin	+
CASHD	Cash and Due from banks over Total assets	+
LN_TA	Natural Logarithm of Total Assets	-

4.5 Empirical Results

Table 7 presents the main regression results for the relationship between CARs and CAMEL proxies. The model is specified as follows:

$$CARs = \alpha + \beta_1(CAP) + \beta_2(NPL) + \beta_3(SRL) + \beta_4(NIM) + \beta_5(CASHD) + \beta6(LN\_TA) + \varepsilon \quad (7)$$

The labels CAP, NPL, SRL, NIM, CASHD, and LN_TA represent total capital ratio, non-performing loans divided by total loans, salary expenses divided by total assets, net interest margin, cash from bank divided by total assets, and the natural logarithm of total assets. Mitigating the potential outliers or heteroscedasticity in our data, we employ the robust regression model to represent our regression results. Meanwhile, we consider correlated errors since many bank observations are from the same country. For example, the United States of America has 311 observations in AR6. Clustering data by country can make our regression results more robust to outliers within individual countries and reduce the impact of extreme observations on the results.

Table 7 reports coefficients for different CARs scenarios (AR1 through AR6) in two periods: 2 days (Panel A) and 3 days (Panel B). Robust t-statistics are provided beneath each coefficient, with significance levels denoted by *, **, and *** for 10%, 5%, and 1% significance levels, respectively.

In Table 7 Panel A, the coefficient estimates of CAP in six scenarios for CARs are statistically significant with a p-value of 0.001(***), suggesting that changes in the total capital ratio (CAP) have a strong positive association with CARs when measured over a 2-day window. For AR5 and AR6, the coefficient estimates for NPL are statistically significant (**), indicating that the non-performing loans ratio has a meaningful impact on CARs in 2 days. However, for AR1 to AR4, the coefficient for NPL is not statistically significant. This suggests that the significance of the coefficient for NPL in AR5 and AR6 takes on even more importance. The CASHD coefficient has a significant positive impact on CARs in all scenarios (**), indicating that a more significant proportion of cash from banks relative to total assets positively influences CARs for 2 days. The SRL, NIM, and LN_TA coefficient estimates are not statistically significant for all scenarios during the 2-day window.

In Table 7 Panel B, the same CAMEL proxies are employed in the regression models for 3 days. Once again, the coefficient estimate of CAP remains a positive and statistically significant relationship with AR1 (**), AR2 (***), AR3 (*), and AR4 (**). This suggests a strong positive relationship between the total capital ratio (CAP) and CARs when measured over the three days. The NPL coefficient, while not statistically significant, indicates a positive association with CARs over the three days. SRL continues to exhibit a highly significant negative impact on CARs (***) with AR2 and AR4. This implies that high salary expenses relative to total assets adversely affect CARs over the three days. Like Panel A, the coefficients of NIM are not statistically significant in any scenario; employing that Net Interest Margin may not consistently impact CARs over 3 days. The CASHD coefficient is highly significant (***), indicating a positive effect on CARs during the 3-day window. LN_TA is not statistically significant in any of the scenarios, indicating that the natural logarithm of total assets may not consistently impact CARs over 3days.

In summary, the regression results in Table 7 provide valuable insights into the relationship between CAMEL proxies and CARs over 2 and 3 days. The finding highlights the significance of specific financial indicators, such as CAP, SRL, and CASHD, in influencing CARs. Notably, the 2-day regression results are more pronounced and statistically significant than the 3-day regression, suggesting

CAMEL proxies may exert a more immediate influence on CARs over a shorter timeframe. Additionally, within the same assessment period, different calculation methods produce varying results, highlighting the importance of employing multiple calculation scenarios to provide a comprehensive result. We must highlight two noteworthy variables from our analysis results: CAP and CASHD, exhibiting consistently positive impact on CARs in all scenarios over 2 and 3 days. Therefore, our main regression results emphasize the critical roles of capital adequacy and liquidity in influencing CARs.

Moreover, we determine the potential multicollinearity issue by employing the Variance Inflation Factor (VIF) test. The VIF for CAP is 1.29, suggesting a low level of multicollinearity. The reciprocal (1/VIF) is 0.775, indicating that about 77.5% of the variance in CAP is independent of its correlation with other variables. The VIF for NPL is 1.03 and the reciprocal (1/FIV) is 0.996, indicating approximately 99.6% of the variance in NPL is independent of its correlation with other variables. The VIF for SRL is 1.6 and the reciprocal of the VIF (1/VIF) is 0.625, suggesting that approximately 62.5% of the variance in SRL can be attributed to factors. The VIF for NIM is 1.29, indicating relatively low levels of multicollinearity issue, the reciprocal values (1/VIF) for both variables are 0.772, implying that about 77.2% of the variance is independent of their correlation with other variables. The VIF for CASHD is 1.41 and the reciprocal (1/VIF) is 0.707, suggesting that approximately 70.7% of the variance is independent of its correlation. Based on the VIF values, the overall multicollinearity in the main regression model is not a major concern.

Table 7: The Relationship between CARs and CAMEL Proxies.

This table reports main regression results of the following model: $CARs=\alpha+\beta_1(CAP)+\beta_2(NPL)+\beta_3(SRL)+\beta_4(NIM)+\beta_5(CASHD)+\beta_6(LN\_TA)+\varepsilon$. And the table shows the coefficients in 2 days (Panel A) and 3days (Panel B). The dependent variable CARs as calculated in six ways from AR1 to AR6. The labels CAP, NPL, SRL, NIM, CASHD, and LN_TA stand for total capital ratio, non-performing loan divided by total loans, salary expenses divided by total assets, net interest margin, cash & due from bank divided by total assets and Natural logarithm of total assets. Panel A reports the coefficient estimate for CAMEL proxies for 2-day CARs. Panel B reports the coefficient estimate for CAMEL proxies for 3-day CARs. Beneath each coefficient is the robust t-statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: 2-day CARs-CAMEL regressions

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.091**	0.089***	0.085*	0.081**	0.095***	0.097***
	(2.443)	(2.774)	(2.013)	(2.193)	(3.128)	(3.297)
NPL	0.041	0.041	0.039	0.037	0.059**	0.058**
	(1.592)	(1.526)	(1.509)	(1.443)	(2.502)	(2.477)

SRL	-1.351	-1.346	-1.782	-1.861	-1.082	-1.089
	(-1.099)	(-1.156)	(-1.138)	(-1.198)	(-0.939)	(-0.941)
NIM	-0.094	0.041	-0.098	0.014	-0.167	-0.156
	(-0.570)	(0.261)	(-0.536)	(0.078)	(-0.922)	(-0.851)
CASHD	0.224**	0.234**	0.226**	0.233**	0.235**	0.235**
	(2.210)	(2.369)	(2.192)	(2.295)	(2.297)	(2.266)
LN_TA	0.001	0.002	-0.000	0.001	-0.001	-0.000
	(0.316)	(1.504)	(-0.209)	(0.982)	(-0.269)	(-0.193)
Constant	-0.075**	-0.125***	-0.048	-0.094**	-0.047	-0.052
	(-2.140)	(-4.090)	(-1.224)	(-2.397)	(-1.210)	(-1.330)
Observations	544	541	540	537	646	646
R-squared	0.138	0.160	0.125	0.143	0.121	0.123

Panel B: 3-day CARs-CAMEL regressions						
	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.094**	0.098***	0.091*	0.095**	0.044	0.045
	(2.679)	(2.901)	(1.942)	(2.144)	(1.191)	(1.226)
NPL	0.044	0.044	0.043	0.041	0.041	0.041
	(1.468)	(1.429)	(1.377)	(1.356)	(1.607)	(1.603)
SRL	-1.531	-1.313*	-1.964	-1.803*	-0.533	-0.536
	(-1.627)	(-1.713)	(-1.620)	(-1.774)	(-0.711)	(-0.713)
NIM	-0.047	0.075	0.001	0.086	-0.254**	-0.250**
	(-0.317)	(0.473)	(0.009)	(0.558)	(-2.250)	(-2.200)
CASHD	0.237***	0.238***	0.232**	0.230**	0.237***	0.237***
	(2.723)	(2.805)	(2.377)	(2.352)	(3.273)	(3.252)
LN_TA	0.001	0.002	0.000	0.001	-0.002	-0.002
	(0.975)	(1.272)	(0.223)	(0.584)	(-0.895)	(-0.867)
Constant	-0.097**	-0.119***	-0.068	-0.087*	-0.016	-0.018
	(-2.607)	(-3.645)	(-1.264)	(-1.892)	(-0.381)	(-0.420)
Observations	544	541	540	537	646	646
R-squared	0.171	0.176	0.147	0.149	0.095	0.095

4.6 Alternative CAMEL Proxies and Regression Results

In addition to our main regression model, which investigates the relationship between CARs and main CAMEL variables, we extend our analysis to explore the influence of alternative CAMEL proxies on CARs. The alternative CAMEL regression model aims to discern whether different CAMEL proxies have similar significance in determining CARs.

We consider the following variables by integrating these alternative proxies

into our regression. The Tier 1 ratio (TEIR1) provides critical insights into a bank's capital adequacy, indicating its ability to absorb potential losses (Rahman & Islam, 2018; Barr et al., 2002). Meanwhile, Provision for Loan Losses (LLP) offers a focused evaluation of credit risk management, enabling us to gauge the bank's risk management. The total bank revenue to total asset ratio (REV) introduces an earnings perspective, focusing on the bank's revenue capacity to its size. The Efficiency ratio (EFF) addresses resource management efficiency by assessing operating expenses against revenue. Moreover, the No-Interest-Bearing Deposits divided by the Total Assets Ratio (NDEP) are crucial in assessing banks' liquidity. Diamond & Dybivg (1983) state that demand deposit can have a downside in the form of a potential bank run if confidence is lost and panic sets in among depositors. This paper employs NDEP as a substitute for demand deposits. The NDEP refers to accounts where the depositor receives no interest on their balance. These deposits are often used for transactional purposes and are subject to withdrawal on demand, such as demand deposits and checking accounts. And then, we build the alternative regression model:

$$CARs = \alpha + \beta_1(TIER1) + \beta_2(LLP) + \beta_3(REV) + \beta_4(EFF) + \beta_5(NDEP) + \beta6(LN\_TA) + \varepsilon \quad (8)$$

Table 8 Panel A and B present the regression results for CARs and alternative CAMEL proxies over 2 and 3 days, respectively. Two panels offer a detailed breakdown of coefficient estimates by running a robust regression model. The findings in Panel A highlight the vital role of TIER1 in influencing CARs. The positive and statistically significant coefficient estimates across all scenarios within 2 days. Furthermore, noninterest deposit over total assets (NDEP) exhibits a negative and statistically significant impact on CARs. However, the coefficient estimates for REV are not statistically significant in any of the scenarios over 2 days, suggesting total bank revenue may not be a strong determinant of cumulative abnormal returns in our regression. Meanwhile, the EFF is not statistically significant in all scenarios, indicating that the efficiency ratio on CARs is insignificant.

Table 8 Panel B extends the analysis for 3 days. The results continue to highlight the influential role of TIER1 in determining CARs. Once again, all scenarios (AR1 through AR6) show positive and statistically significant coefficients, reaffirming the robust association of our main regression. On the other hand,

coefficient estimates of noninterest deposits over total assets (NDEP) become insignificant for all scenarios.

The regression results remain consistent with Panel B, emphasizing the enduring influence of TIER1 on CARs. However, coefficient estimates in Table 8 Panel B tend to be insignificant compared to Panel A, which covers 2 days. This comparison aligns with the findings presented in Table 7, where the 3-day regression appears to moderate the significance between CARs and CAMEL proxies. Interestingly, the capital adequacy and liquidity proxies continue to exhibit pronounced effects in both Panel A and Panel B of the alternative regression; this reinforces the robustness of CAMEL proxies in influencing CARs.

Table 8: The Relationship between CARs and Alternative CAMEL Proxies.

This table reports main regression results of the following model: $CARs=\alpha+\beta_1(TIER1)+\beta_2(LLP)+\beta_3(BTR)+\beta_4(ER)+\beta_5(IBD)+\beta_6(LN\_TA)+\varepsilon$. And the table shows the coefficients in 2 days (Panel A) and 3 days (Panel B). We show two AR1 and AR6 regression results. The labels CARs, TIER1, LLP, BTR, ER, IBD, and LN_TA represent cumulative abnormal returns, Tier 1 ratio, Provision for loan losses divided by total loans, total bank revenue divided by total assets, efficiency ratio, interest bearing deposits divided by total assets, and natural logarithm of total assets. Panel A reports six scenarios (AR1 through AR6) coefficient estimate for CAMEL proxies in 2 days. Panel B reports the coefficient estimate for CAMEL proxies in 3 days. Beneath each coefficient is the robust t-statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CARs and Alternative CAMEL regression in 2 days

VARIABLES	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
TIER1	0.223***	0.220***	0.230***	0.231***	0.217***	0.215***
	(3.453)	(4.310)	(3.943)	(4.642)	(6.966)	(6.827)
LLP	0.003	0.005	-0.000	0.000	0.005	0.005
	(0.646)	(0.863)	(-0.028)	(0.040)	(0.640)	(0.621)
REV	0.241	0.347	0.178	0.266	0.086	0.100
	(0.573)	(0.882)	(0.418)	(0.649)	(0.241)	(0.282)
EFF	-0.007	-0.008	-0.002	-0.005	0.021	0.022
	(-0.370)	(-0.406)	(-0.103)	(-0.208)	(1.228)	(1.252)
NDEP	-0.047**	-0.041	-0.047*	-0.041	-0.054***	-0.054***
	(-2.095)	(-1.511)	(-1.918)	(-1.528)	(-2.843)	(-2.777)
LN_TA	0.004	0.006	0.004	0.006	0.003	0.003
	(1.049)	(1.595)	(1.081)	(1.611)	(0.687)	(0.722)
Constant	-0.175**	-0.234***	-0.183**	-0.238***	-0.147**	-0.152**
	(-2.699)	(-3.315)	(-2.620)	(-3.297)	(-2.243)	(-2.289)
Observations	411	409	411	409	487	487
R-squared	0.078	0.093	0.065	0.076	0.073	0.073

Panel B: CARs and Alternative CAMEL regression in 3 days

VARIABLES	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
TIER1	0.215***	0.220***	0.226***	0.233***	0.167***	0.167***
	(3.438)	(4.366)	(4.434)	(5.448)	(4.143)	(4.115)
LLP	0.006	0.008	0.004	0.005	0.003	0.003
	(1.124)	(1.659)	(0.522)	(0.772)	(0.523)	(0.516)
REV	0.125	0.271	-0.027	0.099	-0.045	-0.040
	(0.356)	(0.940)	(-0.067)	(0.278)	(-0.146)	(-0.131)
EFF	-0.039**	-0.035*	-0.032	-0.029	0.008	0.008
	(-2.186)	(-1.990)	(-1.463)	(-1.329)	(0.414)	(0.426)
NDEP	-0.011	-0.007	-0.014	-0.011	-0.005	-0.005
	(-0.445)	(-0.249)	(-0.474)	(-0.338)	(-0.283)	(-0.276)
LN_TA	0.005	0.005	0.005	0.005	0.001	0.001
	(1.510)	(1.455)	(1.516)	(1.471)	(0.219)	(0.236)
Constant	-0.182***	-0.202***	-0.178***	-0.195***	-0.097*	-0.098*
	(-3.520)	(-3.094)	(-3.443)	(-3.137)	(-1.810)	(-1.832)
Observations	411	409	411	409	487	487
R-squared	0.087	0.105	0.073	0.084	0.035	0.035

4.7 Quantile Regression Results

Quartile regression handles the heteroscedasticity issue, where dependent variables differ across independent variable levels. Therefore, quartile regression provides estimates that are less affected by these outliers. This makes it particularly valuable when extreme observations may significantly impact the overall analysis.

In the output in Table 9, we report the results of quantile regression analysis conducted at the median (q50) percentiles in 2 and 3 days, respectively. This analysis enables us to explore how the main CAMEL variables impact CARs at different distribution points.

In Table 9, Panels A and B, we observe the positive and statistically significant coefficient estimates of CAP at the median level. This suggests that the effect of CAP is pronounced in the upper percentiles of CARs. Conversely, the relationship between the Non-Performing Loan Ratio (NPL) and CARs is insignificant at the 50th quantile for 2 and 3 days.

At the 50^{th} percentile, Salary expense divided by total asset (SRL) exhibits a negative association with CARs, indicating that an increase in SRL corresponds to a decrease in CARs. The relationship between SRL and CARs may be significant for banks experiencing a median level of CARs. However, in Panel B, SRL exhibits a

different result. SRL has all coefficients to be statistically insignificant at the 50th percentile. These results suggest that the relationship between SRL and CARs may become less discernible over time.

At the 50th percentile, the coefficient estimate of NIM is generally weak, suggesting that NIM may not exert a consistently robust impact on CARs. It indicates that the higher percentile of NIM is more potent to estimate CARs.

The CASHD variable shows a strong positive relationship with the CARs, and this relationship is consistent with the 50th quantile. The coefficients are positive and highly significant (***), suggesting that higher values of CASHD have a strong positive impact on the dependent variable.

The variable LN_TA, representing the natural logarithm of total assets, demonstrates varying impacts on CARs through 2 and 3 days. Both Panel A and B show that LN_TA variables are statistically significant and have a positive relationship with CARs in both the 2-day and 3-day windows, suggesting that, in the 50th percentile, an increase in the logarithm of total assets is associated with higher cumulative abnormal returns.

The consistency in the direction and significance of selected CAMEL variables across different quantiles and the inclusion of AR terms further validate the relevance of these CAMEL factors in explaining the cumulative abnormal return dynamics. The influence of AR terms highlights the persistence of effects, emphasizing the importance of temporal dependencies in the modeling. Table 9 enhances our understanding of how these CAMEL variables interact with the temporal dynamics.

Table 9: The Output of Quantile Regression in The 50th Percentile.

This table represents the results of a quantile regression analysis at the 50th percentile for CAMEL variables. Panels A and B report the 50th quantile regression, respectively. The label CAP, NPL, SRL, NIM, CASHD, and LN_TA stand for total capital ratio, non-performing loan divided by total assets, salary expenses divided by total assets, net interest margin, cash and due from bank divided by the total assets, and natural logarithm.

Panel A: The 50th Quartile Regression in 2DAYS

	CARs_AR1 q50	CARs_AR2 q50	CARs_AR3 q50	CARs_AR4 q50	CARs_AR5 q50	CARs_AR6 q50
CAP	0.102***	0.122***	0.133***	0.138***	0.146***	0.137**
	(2.609)	(3.314)	(3.249)	(2.884)	(2.712)	(2.557)
NPL	0.137	0.253	0.173	0.191	0.078	0.079
	(0.732)	(1.294)	(0.885)	(1.013)	(0.679)	(0.641)
SRL	-1.771**	-1.885***	-1.610*	-1.705**	-1.185*	-1.336*
	(-2.337)	(-3.164)	(-1.728)	(-2.097)	(-1.726)	(-1.691)

NIM	0.032	0.100	-0.040	0.040	-0.214	-0.184
	(0.199)	(0.585)	(-0.211)	(0.235)	(-1.320)	(-1.126)
CASHD	0.130***	0.118***	0.152***	0.166***	0.173***	0.171***
	(3.385)	(3.507)	(3.590)	(4.140)	(3.466)	(3.861)
LN_TA	0.004***	0.005***	0.003**	0.005***	0.002	0.002
	(3.202)	(4.017)	(2.007)	(3.284)	(1.177)	(1.336)
Constant	-0.148***	-0.181***	-0.133***	-0.179***	-0.097**	-0.099**
	(-3.668)	(-4.855)	(-2.668)	(-3.954)	(-1.983)	(-2.052)
Observations	544	541	540	537	646	646

Panel B: The 50th Quartile Regression in 3DAYS

	CARs_AR1 q50	CARs_AR2 q50	CARs_AR3 q50	CARs_AR4 q50	CARs_AR5 q50	CARs_AR6 q50
CAP	0.137***	0.116***	0.153***	0.128**	0.065	0.066*
	(2.657)	(4.236)	(2.794)	(2.277)	(1.444)	(1.683)
NPL	0.139	0.131	0.113	0.051	0.061	0.062
	(0.749)	(0.745)	(0.542)	(0.274)	(0.912)	(0.805)
SRL	-0.631	-0.819	-0.999	-0.819	-0.080	-0.172
	(-0.824)	(-1.068)	(-0.964)	(-0.883)	(-0.117)	(-0.276)
NIM	-0.076	0.218	0.074	0.178	-0.278**	-0.295*
	(-0.481)	(1.088)	(0.436)	(0.996)	(-2.028)	(-1.937)
CASHD	0.134***	0.135***	0.142***	0.156***	0.179***	0.186***
	(3.792)	(3.796)	(3.588)	(3.729)	(5.522)	(5.465)
LN_TA	0.004***	0.005***	0.004**	0.004**	-0.001	-0.001
	(3.387)	(3.483)	(1.987)	(2.419)	(-0.679)	(-0.781)
Constant	-0.166***	-0.179***	-0.153***	-0.169***	-0.020	-0.019
	(-4.250)	(-4.470)	(-2.723)	(-3.147)	(-0.392)	(-0.420)
Observations	544	541	540	537	646	646

4.8 Accounting for Country Level Variables

In this section, we control the effect of country-level variables with Cumulative Abnormal Returns (CARs). It is crucial to consider the potential alternative issue, which occurs when other variables influence the relationship between CARs and CAMEL proxies. This country-level variables are empirically relevant to our main regression. Therefore, we separate country-level variables from CAMEL variables in our main regression.

Table 10 presents the results of the regression of bank-level and country-level variables. We employ CAMEL variables with the same as our main regression and

determine additional country-level variables in three factors: depth, efficiency, and stability (Benbouzid et al., 2017). The Financial system deposits divided by GDP (FinSD) represents the depth factor, reflecting the magnitude of financial resources channeled through the banking system relative to the overall economic output; the Bank net interest margin (BankNIM) represents the efficiency, offering valuable information on the banking industry's ability to generate revenue from its interest-earning assets; the Bank non-performing loans to gross loans (BankNPL), the Bank capital to total assets (BankCTA), and the Liquid assets to deposits and short-term funding (LAtoDep) represent for the stability, addressing the banking industry's ability to meet short-term obligations and unexpected funding demands.

In Table 10, Panel A, we examine the relationship between CARs and CAMEL variables by controlling financial system deposits to GDP (FinSD) in 2 days. CAP and CASHD exhibit statistically significant positive relationships with CARs. In Panel B, we examine the relationship between CARs and CAMEL variables by controlling Bank net interest margin (BankNIM) in 2 days. CAP and CASHD exhibit statistically significant positive relationships with CARs. In Panel C, we continue to explore the association between CARs and the same CAMEL variables by controlling bank nonperforming loans to gross loans (BankNPL). We observe a statistically significant positive relationship (***) between CARs and both CAP and CASHD. Meantime, we control bank capital to total assets and liquid assets to deposits and short term fundings variables and generate Panels D and E in Table 10. Panels D and E show CAP and CASHD still significant and positive (**) through all scenarios. Finally, we introduce and discuss the results together. CAP and CASHD display a statistically significant positive relationship (***) with CARs in all six scenarios (AR1 through AR6).

After controlling for several country-level variables, the regression analysis suggests the robustness of our main CAMEL variables, CAP and CASHD. Both variables exhibit a statistically significant positive relationship with CARs, suggesting the impact of CAP and CASHD on CARs is independent of the broader country-level context. In summary, the alternative variable issue is not a noteworthy concern in our analysis, allowing us to interpret the individual effects of the CAMEL variables with significant confidence.

Table 10: The Relationship among CARs, CAMEL Proxies and Country Level Variables

This table reports main independent variables and country level variable regression results of the following model: $CARs=\alpha+\beta_1(CAP)+\beta_2(NPL)+\beta_3(SRL)+\beta_4(NIM)+\beta_5(CASHD)+\beta_6(LN\_TA)+$ Country level variables$+\varepsilon$. And the table shows the coefficients in 2 days (Panel A) and 3 days (Panel B). The dependent variable CARs are calculated in six ways from AR1 to AR6. The country-level variables have FinSD, BankNIM, BankNPL, BankCTA, and LAtoDep stand for financial system deposit to GDP,' 'Bank net interest margin,' 'Bank nonperforming loans to gross loans,' 'Bank capital to total assets,' 'and Liquid assets to deposits and short-term funding.' The setoff the control variables are FinSD, BankNIM, BankNPL, BankCTA, and LAtoDep. To reserve space, Table 10 report Panel A, B, C, D, E to report the country-level separately. Panel A reports the coefficient estimate for CAMEL proxies with FinSD in 2 days. Panel B reports the coefficient estimate for CAMEL proxies with BankNIM variables in 2 days. Panel C reports the coefficient estimate for CAMEL proxies with BankNPL in 2 days. Panel D reports the coefficient estimate for CAMEL proxies with BankCTA in 2 days. Panel E reports the coefficient estimate for CAMEL proxies with LAtoDep in 2 days. Beneath each coefficient is the robust t-statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CARs and Country-level variable regressions in 2 days

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.087**	0.085**	0.079*	0.076*	0.089***	0.091***
	(2.176)	(2.462)	(1.843)	(2.009)	(2.804)	(2.946)
NPL	0.042	0.042	0.035	0.034	0.053*	0.053*
	(1.411)	(1.359)	(1.280)	(1.242)	(1.993)	(1.978)
SRL	-0.871	-0.862	-1.337	-1.420	-0.764	-0.765
	(-0.705)	(-0.738)	(-0.816)	(-0.870)	(-0.574)	(-0.572)
NIM	-0.039	0.073	-0.006	0.096	-0.045	-0.033
	(-0.243)	(0.475)	(-0.034)	(0.569)	(-0.255)	(-0.186)
CASHD	0.237**	0.248**	0.244**	0.249**	0.254**	0.254**
	(2.211)	(2.398)	(2.234)	(2.313)	(2.255)	(2.229)
LN_TA	0.001	0.003	0.000	0.002	-0.000	-0.000
	(0.446)	(1.373)	(0.064)	(1.024)	(-0.166)	(-0.110)
FinSD	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(-0.317)	(-0.379)	(-0.110)	(-0.224)	(0.443)	(0.447)
Constant	-0.091**	-0.139***	-0.068*	-0.113***	-0.064	-0.069
	(-2.450)	(-3.969)	(-1.734)	(-2.848)	(-1.502)	(-1.609)
Observations	506	503	502	499	596	596
R-squared	0.138	0.162	0.124	0.142	0.115	0.116

Panel B: CARs and Country-level variable regressions in 2 days

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.092**	0.090**	0.085*	0.082**	0.091***	0.094***
	(2.377)	(2.607)	(2.010)	(2.149)	(2.895)	(3.054)
NPL	0.041	0.041	0.038	0.037	0.057**	0.057**
	(1.585)	(1.528)	(1.503)	(1.435)	(2.472)	(2.447)
SRL	-1.297	-1.316	-1.726	-1.819	-1.075	-1.081
	(-1.044)	(-1.109)	(-1.096)	(-1.159)	(-0.879)	(-0.880)
NIM	-0.000	0.084	0.028	0.109	-0.217**	-0.202*
	(-0.005)	(0.645)	(0.305)	(1.095)	(-2.069)	(-1.902)
CASHD	0.233**	0.239**	0.235**	0.240**	0.255**	0.254**
	(2.392)	(2.479)	(2.386)	(2.448)	(2.431)	(2.392)

LN_TA	0.000	0.002	-0.001	0.001	-0.001	-0.001
	(0.217)	(1.297)	(-0.307)	(0.832)	(-0.290)	(-0.221)
BankNIM	-0.003	-0.001	-0.004	-0.003	0.001	0.001
	(-0.472)	(-0.224)	(-0.615)	(-0.470)	(0.162)	(0.143)
Constant	-0.067*	-0.122***	-0.039	-0.087**	-0.046	-0.051
	(-1.687)	(-3.299)	(-0.988)	(-2.277)	(-1.033)	(-1.128)
Observations	541	538	537	534	639	639
R-squared	0.142	0.160	0.129	0.144	0.125	0.126

Panel C: CARs and Country-level variable regressions in 2 days

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.092**	0.089***	0.084**	0.080**	0.098***	0.101***
	(2.574)	(2.983)	(2.114)	(2.325)	(3.402)	(3.555)
NPL	0.020	0.017	0.018	0.015	0.032**	0.031**
	(0.992)	(0.873)	(0.911)	(0.804)	(2.349)	(2.290)
SRL	-0.482	-0.446	-0.929	-1.008	-0.559	-0.563
	(-0.387)	(-0.381)	(-0.577)	(-0.627)	(-0.413)	(-0.414)
NIM	-0.077	0.034	-0.069	0.033	-0.249	-0.237
	(-0.486)	(0.238)	(-0.402)	(0.203)	(-1.207)	(-1.136)
CASHD	0.188**	0.192**	0.193**	0.199**	0.192**	0.191**
	(2.316)	(2.467)	(2.311)	(2.425)	(2.055)	(2.019)
LN_TA	0.001	0.003	0.000	0.002	-0.001	-0.000
	(0.441)	(1.281)	(0.080)	(0.934)	(-0.212)	(-0.149)
BankNPL	0.004*	0.005**	0.004	0.004*	0.004**	0.004**
	(1.702)	(2.241)	(1.628)	(1.848)	(2.544)	(2.533)
Constant	-0.105***	-0.154***	-0.079**	-0.123***	-0.059	-0.064
	(-2.900)	(-4.639)	(-2.097)	(-3.287)	(-1.309)	(-1.415)
Observations	505	502	501	498	584	584
R-squared	0.157	0.190	0.138	0.159	0.140	0.142

Panel D: CARs and Country-level variable regressions in 2 days

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.110**	0.103**	0.099*	0.093*	0.090**	0.093**
	(2.202)	(2.306)	(1.862)	(1.935)	(2.173)	(2.289)
NPL	0.023	0.024	0.019	0.018	0.045**	0.045**
	(1.090)	(1.077)	(1.011)	(0.962)	(2.297)	(2.260)
SRL	-0.634	-0.715	-1.086	-1.233	-0.701	-0.705
	(-0.507)	(-0.588)	(-0.663)	(-0.742)	(-0.492)	(-0.493)
NIM	0.119	0.231*	0.121	0.219*	0.016	0.028
	(1.016)	(1.860)	(1.059)	(1.919)	(0.121)	(0.210)
CASHD	0.203**	0.219***	0.208**	0.220***	0.247**	0.246**
	(2.554)	(2.834)	(2.574)	(2.761)	(2.623)	(2.584)
LN_TA	0.001	0.003	0.000	0.002	-0.000	-0.000
	(0.493)	(1.334)	(0.173)	(1.012)	(-0.167)	(-0.102)

BankCTA	-0.003	-0.002	-0.002	-0.002	-0.001	-0.001
	(-0.857)	(-0.649)	(-0.768)	(-0.652)	(-0.345)	(-0.336)
Constant	-0.083	-0.137**	-0.061	-0.108**	-0.054	-0.059
	(-1.437)	(-2.477)	(-1.226)	(-2.237)	(-0.898)	(-0.977)
Observations	490	487	486	483	564	564
R-squared	0.133	0.156	0.117	0.136	0.112	0.113

Panel E: CARs and Country-level variable regressions in 2 days

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.077**	0.081***	0.070*	0.070**	0.085***	0.088***
	(2.478)	(2.755)	(1.976)	(2.184)	(2.785)	(2.927)
NPL	0.037	0.037	0.035	0.033	0.057**	0.056**
	(1.372)	(1.310)	(1.287)	(1.222)	(2.265)	(2.247)
SRL	-1.170	-1.164	-1.621	-1.713	-0.902	-0.910
	(-0.966)	(-1.019)	(-1.009)	(-1.072)	(-0.774)	(-0.775)
NIM	-0.092	-0.007	-0.092	-0.005	-0.243	-0.232
	(-0.503)	(-0.039)	(-0.442)	(-0.024)	(-1.111)	(-1.051)
CASHD	0.249**	0.262**	0.251**	0.257**	0.288**	0.288**
	(2.386)	(2.592)	(2.273)	(2.361)	(2.617)	(2.583)
LN_TA	0.001	0.003	-0.000	0.002	-0.001	-0.000
	(0.448)	(1.471)	(-0.026)	(1.066)	(-0.215)	(-0.145)
LAtoDep	0.009	0.005	0.012	0.009	-0.008	-0.009
	(0.186)	(0.102)	(0.231)	(0.176)	(-0.171)	(-0.179)
Constant	-0.086**	-0.131***	-0.059	-0.103**	-0.047	-0.052
	(-2.369)	(-4.029)	(-1.530)	(-2.638)	(-1.183)	(-1.297)
Observations	522	519	518	515	620	620
R-squared	0.130	0.153	0.117	0.135	0.122	0.124

4.9 Endogeneity

Endogeneity is a critical concern in regression analysis, as it can lead to biased and inconsistent coefficient estimates, ultimately affecting the validity of causal inferences. Endogeneity arises when an independent variable is correlated with the error term in a regression model. Our study investigates the potential presence of endogeneity in the context of the main regression model between CARs and CAMEL variables. This paper incorporates the average value of the past three years for the main regression variables to determine whether the main independent variables have consistent effects on CARs. This step aims to mitigate the short-term impact by providing a more stable representation of CAMEL variables.

Table 11 Panel A reports the regression results in 2 days. The CAP shows positive and statistically significant (**) for six scenarios (AR1 through AR6). The CASHD variable shows positive and significant effects on CARs in 2 days for all scenarios. In Table 11 Panel B, the CAP variable has a positive and statistically significant effect on CARs with a significance level of 5% (**) or 1% (***). The CASHD variable has consistent positive and significant effects on CARs in 3 days for all scenarios (AR1 through AR6).

In summary, the CAP and CASHD variables consistently show positive and significant effects on CARs in both panels. Panel B generally shows more significant effects for both CAP and CASHD variables, which produce similar results as Table 7. Therefore, endogeneity is not a primary issue in this study.

Table 11: The relationship between CARs and Average CAMEL variables:

The table reports the regression results for the relationship between Cumulative Abnormal Returns (CARs) and average CAMEL variables in two different panels: Panel A for CARs in 2 days and Panel B for CARs in 3 days. The table includes regression coefficients, robust t-statistics, and indicates the significance level of the coefficients. Beneath each coefficient is the robust t-statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Endogeneity of CAR in 2days

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.182*	0.188**	0.196*	0.195**	0.144*	0.141*
	(1.820)	(2.046)	(1.993)	(2.084)	(1.936)	(1.903)
NPL	0.048	0.055	0.052	0.055	0.061	0.061
	(1.325)	(1.384)	(1.351)	(1.372)	(1.394)	(1.400)
SRL	-0.475	-0.363	-0.167	-0.120	0.009	-0.014
	(-0.382)	(-0.306)	(-0.150)	(-0.110)	(0.012)	(-0.017)
NIM	-0.242	-0.060	-0.373	-0.237	-0.182	-0.170
	(-0.712)	(-0.188)	(-1.088)	(-0.720)	(-0.676)	(-0.621)
CASHD	0.221*	0.228*	0.213*	0.224*	0.256**	0.263**
	(1.858)	(1.967)	(1.744)	(1.873)	(2.019)	(2.085)
LN_TA	0.001	0.003**	0.001	0.003*	0.001	0.001
	(0.673)	(2.403)	(0.636)	(1.879)	(0.452)	(0.367)
Constant	-0.105**	-0.167***	-0.109**	-0.163***	-0.099**	-0.094**
	(-2.064)	(-3.572)	(-2.020)	(-3.192)	(-2.259)	(-2.252)
Observations	364	364	362	362	438	438
R-squared	0.144	0.166	0.126	0.145	0.126	0.130

Panel B: Endogeneity of CAR in 3days

	CARs_AR1	CARs_AR2	CARs_AR3	CARs_AR4	CARs_AR5	CARs_AR6
CAP	0.265**	0.296***	0.248**	0.271**	0.124	0.120
	(2.700)	(3.216)	(2.306)	(2.644)	(1.308)	(1.264)

NPL	0.043	0.046	0.054	0.053	0.039	0.040
	(1.310)	(1.302)	(1.350)	(1.313)	(0.985)	(0.991)
SRL	-0.870	-0.651	-0.540	-0.352	0.441	0.410
	(-1.019)	(-0.910)	(-0.715)	(-0.533)	(0.727)	(0.689)
NIM	-0.019	0.189	-0.273	-0.121	-0.250	-0.242
	(-0.057)	(0.553)	(-0.667)	(-0.288)	(-0.911)	(-0.877)
CASHD	0.197*	0.183*	0.183	0.175	0.213**	0.219**
	(1.881)	(1.775)	(1.583)	(1.517)	(2.187)	(2.291)
LN_TA	0.001	0.002	0.000	0.001	-0.001	-0.001
	(0.344)	(1.000)	(0.063)	(0.610)	(-0.266)	(-0.415)
Constant	-0.109**	-0.154***	-0.087	-0.125**	-0.062	-0.055
	(-2.032)	(-3.245)	(-1.515)	(-2.369)	(-1.185)	(-1.099)
Observations	364	364	362	362	438	438
R-squared	0.173	0.179	0.131	0.135	0.082	0.086

Chapter 5. Conclusion

Our research amalgamates two distinct streams of literature. First, we merge the realms of CAMEL assessments and the Event Study Methodology to assess the repercussions of the SVB collapse on the global banking sector. This study employs a dataset comprising information from 646 publicly traded global commercial banks, making it the first of its kind to explore the ramifications of the SVB collapse on other publicly commercial banks across the globe.

Our findings provide robust evidence that a bank's financial health is positively correlated with its stock performance, which underscores the predictive power of CAMEL assessments in evaluating bank performance, with a specific focus on the pivotal roles played by capital adequacy and liquidity. These results offer valuable insights for investors, financial institutions, and regulators seeking a deeper understanding of the interplay between a bank's CAMEL assessment and stock performance.

Additionally, our findings remain consistent even after controlling for various country-level characteristics. We can investigate whether these factors influence cumulative abnormal returns by incorporating country-level variables in our analysis. Our study reveals that country-level variables significantly contribute to explaining the cumulative abnormal returns, highlighting their importance in shaping the impact of the SVB collapse on global banks.

Appendices

Appendix A. Abnormal return formulas and source

ARs	Formula	Source
AR1	RET_Local -RET_Local_Index	Authors' calculation based on DataStream.
AR2	RET_Local -(beta_2022)*(RET_Local_Index)	Authors' calculation based on DataStream.
AR3	RET_$- RET_$_Index	Authors' calculation based on DataStream.
AR4	RET_$- (beta_2022)*(RET_$_Index)	Authors' calculation based on DataStream.
AR5	RET_$ -(Estimated_beta_End)*MSCI_RET)	Authors' calculation based on DataStream.
AR6	RET_$ -(Estimated_beta_Beg)*MSCI_RET)	Authors' calculation based on DataStream.

Appendix B. Definitions and Sources

Panel A: Definitions and data sources of bank Size variable

Variables	Definitions	Sources
LN_TA	the natural logarithm of total assets	Authors' calculation based on Refinitiv Eikon

Panel B: All bank-level variable definitions and sources

	Variables	Definitions	Sources
C	CAP	The ratio of total regulatory capital as a percentage of total risk-weighted assets.	Refinitiv Eikon
	TIER1	Represents the ratio of Tier 1 capital as a percentage of total risk-weighted assets.	Refinitiv Eikon
P	NPL	The ratio of loans that are in default or close to being in default as a percentage of total loans	Authors' calculation based on Refinitiv Eikon
	LLP	This is the ratio of Provision for loan losses for the fiscal period as a proportion of total loans for the same period and is expressed as percentage.	Authors' calculation based on Refinitiv Eikon
M	SRL	The ratio of consists of expenses paid to employees of a company in the form of salaries, wages, fees, benefits or any other form of compensation as a percentage of total assets	Authors' calculation based on Refinitiv Eikon
	REV	The ratio of the sum of: Interest income, Bank and Non-interest Income as a percentage of total assets	Refinitiv Eikon
E	NIM	This value represents Net Interest Income for the fiscal year divided by the average of the Interest Earning Assets for the same period, expressed as a percent.	Refinitiv Eikon
	EFF	This is the ratio of non-interest expense for the fiscal period to Total Revenue less interest expense for the same period and is expressed as percentage.	Authors' calculation based on Refinitiv Eikon
L	CASHD	The ratio of cash on hand and due from banks as a percentage of total assets	Authors' calculation based on Refinitiv Eikon
	NDEP	This ratio of deposits with no interest accrual or with minimal interest earning to total assets as percentage	Authors' calculation based on Refinitiv Eikon

Panel C: Definitions and data sources of country-level variables

Variables	Definitions	Sources
FinSD	Demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP.	International Financial Statistics (IFS), International Monetary Fund (IMF)
BankNIM	Accounting value of bank's net interest revenue as a share of its average interest-bearing (total earning) assets.	International Financial Statistics (IFS), International Monetary Fund (IMF)
BankNPL	Ratio of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio). The loan amount recorded as nonperforming includes the gross value of the loan as recorded on the balance	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)

	sheet, not just the amount that is overdue.	
BankCTA	Ratio of bank capital and reserves to total assets. Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions, and valuation adjustments. Capital includes tier 1 capital (paid-up shares and common stock), which is a common feature in all countries' banking systems, and total regulatory capital.	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)
LAtoDep	The ratio of the value of liquid assets (easily converted to cash) to short-term funding plus total deposits. Liquid assets include cash and due from banks, trading securities and at fair value through income, loans and advances to banks, reverse repos and cash collaterals.	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)

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