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THE IMPACT OF SILICON VALLEY BANK BANKRUPTCY ON STARTUP FUNDING

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Abstract

This research explores how the collapse of Silicon Valley Bank (SVB) influenced startup funding trends in the United States. Using panel data comprising 23,061 startup funding rounds sourced from S&P Capital IQ, the study evaluates shifts in investment behavior before and after the collapse through Ordinary Least Squares (OLS), Difference in Differences (DiD), and subsample regression methods. The results show varied impacts depending on the funding stage. Early-stage startups saw a notable 9% rise in funding after the SVB incident, whereas later-stage startups experienced an equivalent 9% decline. Syndicated investments were linked to higher funding amounts at all stages, with more pronounced effects in early-stage rounds. In addition, established tech companies secured significantly less funding compared to non-tech firms in the post-collapse period, highlighting a broader reassessment of valuations within the tech industry. Overall, the findings indicate that the SVB failure led to a reallocation of capital rather than a universal funding downturn, with investors shifting toward more cautious, targeted investments, particularly favoring smaller, early-stage ventures amid heightened systemic uncertainty.

Keywords: Venture Capital, Silicon Valley Bank, Financial Shock, Startup Funding, Early-Stage Investment

INTRODUCTION

The evolution of the venture capital industry in the United States illustrates how global crises and unexpected financial disruptions can profoundly impact investor behavior and capital distribution. The Global Financial Crisis of 2008 exemplifies the negative consequences of economic turmoil on startup financing. According to Block and Sandner (2009), the crisis characterized by the collapse of Lehman Brothers and liquidity challenges at major institutions like American International Group (AIG) ed to a deep global recession. Consequently, venture capital investment in later-stage startups fell by around 20%, largely due to the decline of the IPO market, which had been a key exit strategy for investors. This scenario underscores the susceptibility of startups to broader economic shifts and the essential function of venture capital in supporting innovation and the sustainability of new ventures.

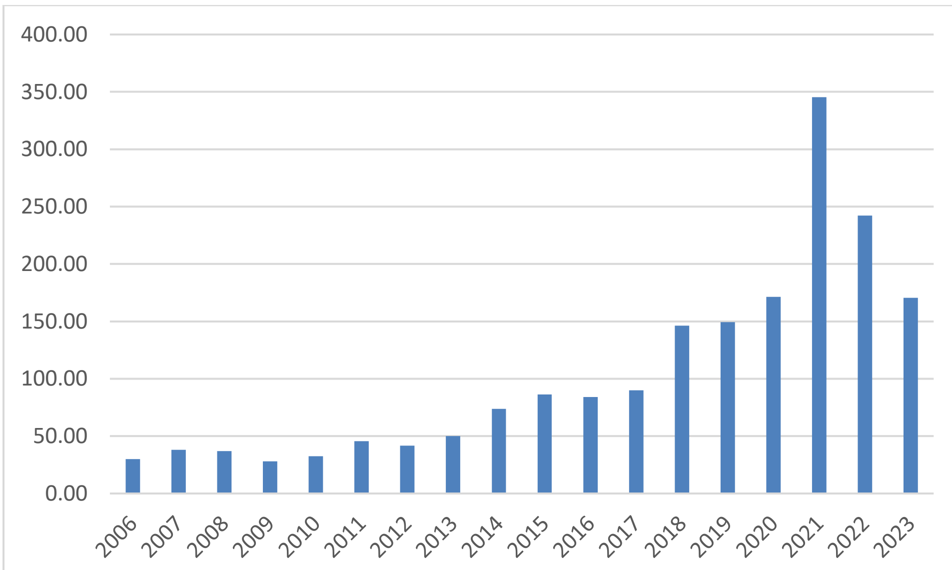

Chart 1.
U.S. Venture Capital Investment Value from 2006 to 2023 (Statista)

In contrast, the COVID-19 pandemic during 2019–2020 brought a different investment trend. Venture capital activity experienced a notable surge, especially in the Health Information Technology (HIT) sector, where global investments rose by over 40% between 2019 and 2020 (Richter, 2019). This upward momentum culminated in 2021, when venture capital investment in the U.S. hit an all time high of USD 345 billion, spread across more than 19,000 deals. However, this rapid growth proved unsustainable. By 2023, venture capital investment had dropped significantly nearly 50% from its 2021 peak reaching only around USD 170.6 billion (Statista, 2024). This steep decline was attributed not only to broader macroeconomic challenges such as inflation and increasing interest rates but also to the sudden collapse of Silicon Valley Bank (SVB) in March 2023, which intensified the downturn.

SVB played a pivotal role in the U.S. startup financing landscape, particularly in supplying venture capital and debt to technology and life sciences companies. Its unexpected failure on March 10, 2023, due to a liquidity crisis, resulted in a widespread loss of investor trust. This triggered significant fund withdrawals, further destabilizing the market (Bruni et al., 2023). Holding accounts for roughly 50% of venture-backed tech startups, SVB's downfall had far-reaching effects, especially within the technology and healthcare sectors (Hamlin, 2024).

Despite general acknowledgment of the broader consequences of SVB's bankruptcy, few studies have directly examined its specific impact on declining startup investment. This indicates a research gap in understanding the structural implications of SVB's collapse on startup financing, providing a strong rationale for this investigation. Given this context, the main research question explored in this study is: *Did the collapse of Silicon Valley Bank (SVB) significantly affect the decline in startup funding in the United States?* This research seeks to empirically evaluate and quantify the effects of SVB's collapse on the amount of capital raised by startups, focusing on a comparative analysis of the pre and post collapse periods.

REVIEW OF LITERATURE

Venture Capital and Funding Mechanisms

Venture capital (VC) represents an equity-based financing model that is essential in fueling the expansion of startups characterized by high growth potential and elevated risk (Ramsinghani, 2021). The VC ecosystem operates through a partnership between general partners (GPs), who manage the funds, and limited partners (LPs), who supply the capital. GPs are responsible for formulating investment strategies, managing startup portfolios, and driving value creation, while LPs commit their funds for approximately ten years, compensated through management fees and a share of the profits, known as carried interest (Ramsinghani, 2021). The venture capital investment cycle typically comprises five stages: (1) defining the investment thesis, (2) raising capital from LPs, (3) constructing the portfolio, (4) actively supporting startups to enhance value, and (5) achieving returns via exit strategies such as acquisitions or public listings (Ramsinghani, 2021). However, this process is often marked by significant information asymmetry especially in the early stages posing risks of agency conflicts between funders and founders (Gill et al., 2024; Sahlman, 1990; Hsu & Kaplan, 2004).

To manage these risks, Gompers et al. (2020) observe that many VC firms adopt specialization strategies, focusing their investments by stage, sector, or region. Specifically, around 62% specialize by investment stage, 61% by industry, and 50% by geography. The size of a fund also plays a critical role in determining its capacity to manage risk and generate returns. Ramsinghani (2021) argues that fund size should align with the investment thesis, target ownership levels, market conditions, and return expectations not the lifestyle preferences of fund managers. Investment staging is another vital risk management tool. Corea et al. (2021) stress the importance of distinguishing between early stage and later stage investments, a view supported by Jeng & Wells (2000). In practical terms, staging means that capital is released in phases based on the startup's progress, thereby reducing exposure to uncertainty (Gompers, 1995; Bernanke & Gertler, 1990).

Regarding financing instruments, the two most commonly used structures are convertible debt and preferred equity (Ramsinghani, 2021). Convertible debt is popular in early-stage deals due to its flexibility and the ability to convert into equity during later funding rounds. In contrast, preferred equity is favored in more mature investments, offering protections like liquidation preferences, anti-dilution clauses, and voting advantages.

Valuation in venture capital is inherently speculative and often based on projected exit values rather than conventional financial metrics (Ramsinghani, 2021). As such, investors typically assess performance using indicators like the cash on cash multiple and internal rate of return (IRR). Exit strategies are a cornerstone of the venture capital model. Ramsinghani (2021) identifies mergers and acquisitions (M&A) and initial public offerings (IPOs) as the two primary exit pathways. Roughly 43% of VC exits occur via M&A, while IPOs account for about 13%. However, M&A outcomes are mixed, with many deals yielding disappointing or negative returns. Alongside these traditional routes, secondary markets and private trading platforms have emerged, offering investors alternative paths to liquidity ahead of public market exits (Ramsinghani, 2021).

Financial Shock and the Consequences of the Silicon Valley Bank Collapse

Silicon Valley Bank (SVB), a key player in funding technology-focused startups, collapsed abruptly in March 2023 due to a severe liquidity crunch (Dong, 2024). In the span of only three days, depositors withdrew USD 42 billion, prompting the bank to incur realized losses of USD 1.8 billion from the forced sale of securities (Dong, 2024). This event triggered a financial shock that quickly reverberated through global markets. According to Aharon et al. (2023), the collapse led to negative abnormal returns in stock markets worldwide, with the most pronounced declines seen in Europe, Latin America, the Middle East, and Africa. However, Yousaf & Goodell (2023) note that the sectoral impact varied: while financials, real estate, and materials experienced steep declines, the technology sector showed comparatively stronger resilience. Pandey et al. (2023) highlight that advanced economies with highly integrated financial systems were more susceptible to the shock than emerging markets. Although some Asian financial markets showed partial recovery, overall global volatility spiked in the aftermath of SVB's collapse. Nonetheless, the stability of domestic banking systems played a role in containing the broader systemic risks (Pandey et al., 2023).

On a macroeconomic scale, Giglio et al. (2020) argue that financial shocks like SVB's collapse significantly influence investor sentiment regarding short term economic growth, thereby shaping decisions on capital allocation especially for high risk assets like startups. As a result, the post-collapse environment has been marked by increased investor sensitivity to economic indicators and market confidence. Past financial crises have shown similar patterns. For instance, Block & Sandner (2009) report that the 2008 global financial crisis led to a roughly 20% drop in funding for later-stage startups, which typically depend on external capital. Similarly, Lingelbach (2019) found that the 1997–1998 Asian Financial Crisis dampened startup investment in Indonesia as local investors became more risk-averse. Supporting this, Conti et al. (2019) found that in post crisis environments, investors tend to become more selective, reallocating funds toward safer, core industries while pulling back from early-stage ventures. Additionally, Gompers et al. (2020) note that during periods of increased uncertainty, capital often shifts toward more defensive sectors like healthcare and consumer staples. This behavior was also evident following the SVB collapse, where investor caution led to a pullback from high-growth technology startups (Block & Sandner, 2009).

RESEARCH METHOD

This research utilizes secondary data sourced from multiple databases that track startup and venture capital funding activities, with the primary source being S&P Capital IQ PRO. The dataset encompasses funding transactions across various development stages, ranging from seed to mature phases and spans a wide array of industry sectors. The analysis period is divided into two distinct intervals: the pre-collapse phase from March 10, 2021, to March 10, 2023, and the post-collapse phase from March 11, 2023, to March 10, 2025.

Building on prior empirical studies (Block & Sandner, 2009; Conti et al., 2019; Gompers, 1995; Corea et al., 2021), the following hypotheses are proposed:

- **Null Hypothesis (H_0):** The collapse of Silicon Valley Bank has no significant effect on startup funding levels ($\beta_1 = 0$).
- **Alternative Hypothesis (H_1):** The collapse of Silicon Valley Bank leads to a significant decline in startup funding ($\beta_1 < 0$).

These hypotheses rest on the premise that SVB functioned as a key systemic player within the startup financing landscape. Its sudden failure is treated as an exogenous financial shock, analogous to historical disruptions such as the 2008 financial crisis and the COVID-19 pandemic. To examine the variation in impact across different firm types, the study incorporates distinctions based on startup stage (early-stage vs. later-stage) and investor syndication (multi-party investment rounds as a measure of risk-sharing). Additionally, control variables such as industry classification are included, recognizing that broader macroeconomic trends also influence investment decisions (Giglio et al., 2020). The empirical analysis is based on a log-linear regression framework, with the natural logarithm of total funds raised serving as the dependent variable. The baseline model is constructed as follows:

$$Ln(RaisedAmount) = \beta_0 + \beta_1 SVB + \beta_2 Stage + \beta_4\, Consortium + + \beta_5 Industry$$

Whereas:

Table 1
Variable

Variable	Label/Description
LnRaisedAmount	Natural logarithm of the amount of funding received by a startup (dependent variable)
SVB	Dummy variable = 1 if the observation falls in the post-SVB collapse period; 0 otherwise
Stage	Dummy variable = 1 if the startup is at a later stage (e.g., growth/mature); 0 if early stage
Consortium	Dummy variable = 1 if the funding round involved two or more investors; 0 otherwise
Industry dummies	Set of dummy variables to control for industry sectors: Financials, Real Estate, Energy, Materials, Healthcare, Industrials, Consumer = 0 and Technology = 1

The data analysis is performed using STATA version 18, employing several estimation techniques:

- **Ordinary Least Squares (OLS):** This serves as the main estimation method to evaluate the effect of the SVB collapse on startup funding, while accounting for factors such as industry classification, investment syndication, and macroeconomic conditions.
- **Difference-in-Differences (DiD):** This method is used to capture varying impacts between early-stage and later-stage startups by introducing interaction terms between the SVB indicator and startup development stage.
- **Subsample Regressions:** To explore differences in treatment effects across funding stages, separate regressions are conducted for early-stage and later stage startup groups.

To verify the reliability of the model, the analysis includes multicollinearity checks using Variance Inflation Factors (VIF). Additionally, descriptive statistics and correlation matrices are presented to support the appropriateness of the model specifications.

RESULTS AND DISCUSSION

Descriptive Statistics

Descriptive analysis serves to provide a straightforward summary of the key characteristics of a dataset. Rather than aiming to draw inferences, test hypotheses, or predict outcomes, its primary purpose is to offer a clear and accessible overview of the data's fundamental patterns and distributions.

Table 2.
Descriptive Statistics (STATA18)

Variable	N	Mean	Std. Dev.	Min	Max	Description
RaisedAmount	23,061	43,080.07	191,989.50	1	10,000,000	Total startup funding raised
SVB	23,061	0.3658	0.4817	0	1	Dummy variable: 1 = Post-SVB collapse
Stage	23,061	0.5853	0.4927	0	1	Dummy: 1 = Later-stage startup
Consortium	23,061	0.6942	0.4607	0	1	Dummy: 1 = ≥2 investors involved
Industry	23,061	0.5408	0.4983	0	1	Industry dummy: Technology = 1

Descriptive Analysis and Classical Assumption Testing

The descriptive evaluation of 23,061 startup funding rounds highlights several important developments following the collapse of Silicon Valley Bank (SVB). While the average amount of funding rose slightly from USD 42.8 million to USD 43.5 million after the event, the modest increase is relatively insignificant given the high standard deviation (approximately USD 192 million), which points to a heavily skewed distribution with notable outliers. To address this, the funding variable was log-transformed (LnRaisedAmount) to reduce the impact of extreme values and stabilize variance for regression analysis.

Notably, the share of later-stage funding dropped from around 60% prior to the collapse to 55% afterward, implying a shift in investor focus toward early-stage startups in the wake of the crisis. In contrast, the proportion of syndicated funding remained stable at approximately 69%, suggesting that collaborative investment strategies persisted as a risk-sharing mechanism during market uncertainty. In terms of industry distribution, the technology sector continued to dominate, with a slight increase in its post-collapse share possibly reflecting investor perception of technology as a relatively resilient sector amid financial instability.

Classical Assumption Tests

To validate the reliability of the regression analysis, standard classical assumption tests were conducted. These tests are essential to confirm that the model meets fundamental econometric assumptions such as normal distribution of residuals, homoskedasticity (constant variance of errors), no multicollinearity among explanatory variables, and error term independence. Failing to meet these assumptions can lead to biased or inefficient estimators and undermine the credibility of statistical inferences. Therefore, these diagnostic checks are a critical step to ensure the robustness and validity of the regression results.

Table 3.
Classical Assumption Tests

Assumption	Test	Statistic (Value)	p-value
Normality (Dependent Variable)	Shapiro Wilk	W = 0.9855	< 0.0001
	Skewness Kurtosis Joint Test	$\chi^2(2) = 623.94$	< 0.0001
Normality (Residuals)	Shapiro Wilk	W = 0.9808	< 0.0001
	Skewness Kurtosis Joint Test	$\chi^2(2) \approx 642$	< 0.0001
Multicollinearity	Variance Inflation Factor (VIF)	$VIF_{max} = 1.04$; $\overline{VIF} = 1.02$	—
Heteroskedasticity	Breusch Pagan Test (constant var(ε))	$\chi^2(1) = 13.44$	0.0002
	White Test (unspecified var(ε))	$\chi^2(10) = 1500.41$	< 0.0001

(Data processed from original Stata output)

Before proceeding with the interpretation of regression outcomes, a series of classical diagnostic tests were conducted to validate the model's assumptions. Normality checks on both the dependent variable and regression residuals revealed significant deviations from a normal distribution (Shapiro-Wilk $W < 0.99$; $p < 0.0001$). However, given the large sample size ($N = 23{,}061$), the central limit theorem justifies the use of asymptotic inference, allowing regression estimates to remain valid. To assess multicollinearity, Variance Inflation Factors

(VIF) were calculated, indicating minimal concern. Both the maximum VIF (1.04) and the mean VIF (1.02) were well below standard thresholds, suggesting no problematic correlations among explanatory variables. Heteroskedasticity was tested using the Breusch Pagan ($\chi^2 = 13.44$; $p = 0.0002$) and White ($\chi^2 = 1500.41$; $p < 0.0001$) procedures, both of which indicated the presence of non-constant error variance. As a result, all regression models in this study were estimated using robust (Huber–White) standard errors to ensure the reliability of statistical inference.

F-Test and Model Goodness-of-Fit

The F-test and measures of model fit are employed to assess the overall explanatory capacity of the regression model. Specifically, the F-test evaluates whether the independent variables collectively contribute significantly to explaining variation in the dependent variable by testing the joint null hypothesis that all slope coefficients are equal to zero. A statistically significant F-statistic suggests that the model outperforms a baseline model without any predictors.

In parallel, the R-squared statistic provides a quantitative measure of goodness-of-fit, indicating the proportion of variance in the dependent variable accounted for by the independent variables included in the model. Higher R-squared values reflect greater explanatory strength, although their interpretation should also take into account model complexity and characteristics of the underlying dataset.

Table 4.
F-Test and Model Goodness-of-Fit

No.	Model & Sample	df num	df denom	F-statistic	Prob > F	R-squared
1	Model 1 (full sample)	4	23,056	5,275.57	0.0000	0.4751
2	Model 2 (full, DiD)	5	23,055	4,230.10	0.0000	0.4758

(Data reprocessed from original Stata output)

Model 1, the initial OLS regression without interaction terms, accounts for roughly 47.5% of the variation in the dependent variable, LnRaisedAmount ($R^2 = 0.4751$). The corresponding F-statistic of 5,275.57 ($p < 0.001$) strongly rejects the null hypothesis that all explanatory coefficients are jointly zero, confirming that the model significantly explains variation in startup funding amounts. Model 2, which introduces an interaction term between *SVBCollapsed* and *Stage*, yields a slight improvement in model fit with an R^2 of 0.4758. The F-statistic for this specification is 4,230.10 ($p < 0.001$), indicating continued overall model significance. Although the increase in explanatory power is marginal, the inclusion of the interaction term offers valuable additional insight by capturing variation in effects across funding stages.

Main Regression Significance Test

The primary significance test in regression evaluates whether each independent variable individually contributes to explaining the dependent variable. This is typically performed using *t*-statistics, where each coefficient is tested against the null hypothesis that it equals zero. A p-value below conventional significance levels (e.g., < 0.05) indicates that the variable has a statistically meaningful impact on the outcome variable. These tests help identify the most influential predictors in the model and distinguish them from variables with limited explanatory relevance.

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Table 5.
Main Regression Significance Test

Variable	Model 1	Model 2: DiD
SVBCollapsed (After = 1)	0.006 (0.745)	0.127 (<0.001)
Stage (later = 1)	2.316 (<0.001)	2.395 (<0.001)
Interaction Term	–	–0.211 (<0.001)
Stage × SVBCollapsed	–	–0.211 (<0.001)
Consortium (≥2 investors)	1.232 (<0.001)	1.227 (<0.001)
Industry (Technology = 1)	–0.125 (<0.001)	–0.127 (<0.001)
Intercept	6.909 (<0.001)	6.866 (<0.001)

(Data reprocessed from original Stata output)

In Model 1, the SVBCollapsed dummy variable (which captures the difference between pre- and post-collapse periods) is statistically insignificant ($\beta = 0.006$; $p = 0.745$), indicating that the SVB collapse had no notable effect on average startup funding when startup stages are not considered. In contrast, the Stage variable shows a strong and highly significant effect ($\beta = 2.316$; $p < 0.001$), suggesting that later-stage startups raise nearly 10 times more capital than early-stage ones, a finding consistent with typical capital scaling patterns in venture financing. The Consortium dummy (indicating syndicated investments) is also highly significant ($\beta = 1.232$; $p < 0.001$), implying that deals involving multiple investors raise about 243% more capital. This underscores the importance of syndication in facilitating risk-sharing and pooling investment resources. Interestingly, the Technology sector dummy shows a significant negative effect ($\beta = -0.125$; $p < 0.001$), suggesting that, on average, technology startups raise smaller amounts compared to more capital-intensive sectors like biotechnology or infrastructure.

In the interaction model (Model 2), the results reveal more granular dynamics. Early-stage startups experienced a significant funding increase post-collapse ($\beta = 0.127$; $p < 0.001$), representing approximately a 13.6% rise. In contrast, later-stage startups saw a decline of about 8% (interaction term $\beta = -0.211$; $p < 0.001$). This pattern points to a “flight to smaller tickets” behavior, in which investors redirect capital toward earlier-stage, lower-risk ventures in response to heightened financial uncertainty.

Subsample Regression Significance

The subsample regression significance test explores whether the influence of independent variables varies across distinct groups within the data. By conducting separate regressions for specific subgroups, such as early-stage versus later-stage startups, the analysis captures potential differences in how predictors affect outcomes. Within each subgroup, the significance of individual coefficients is assessed using t-tests. This method allows researchers to determine whether the relationships observed in the full sample hold consistently across segments or whether unique dynamics are at play, thus providing a deeper understanding of how startup characteristics influence funding outcomes.

Table 6.
Subsample Regression Significance

Variable	**Early-stage (Stage = 0)**	**Later-stage (Stage = 1)**
SVBCollapsed (After = 1)	0.087 *(p = 0.001)*	–0.097 *(p < 0.001)*
Consortium (≥2 investors = 1)	1.797 *(p < 0.001)*	0.762 *(p < 0.001)*
Industry (Technology = 1)	0.027 *(p = 0.313)*	–0.203 *(p < 0.001)*
Intercept	6.417 *(p < 0.001)*	9.642 *(p < 0.001)*

(Data reprocessed from original Stata output)

The subsample regression results reinforce the presence of heterogeneous effects across startup stages. For early-stage startups (Stage = 0), funding increased by approximately 9% following the SVB collapse (β = 0.087; $p = 0.001$), highlighting sustained investor appetite for seed and Series A rounds. Conversely, later-stage startups (Stage = 1) saw funding decline by nearly 9% (β = –0.097; $p < 0.001$), signaling increased investor hesitation toward committing large sums amid heightened systemic uncertainty. Syndication continues to have a positive influence across both groups, though with differing intensity. For early-stage rounds, the presence of multiple investors is associated with nearly a sixfold increase in funding (β = 1.797; $p < 0.001$), whereas for later-stage rounds, the effect is approximately twofold (β = 0.762; $p < 0.001$). This indicates that while syndication is broadly beneficial, its amplifying impact is particularly pronounced in earlier stages of venture financing.

Sectoral effects reveal further variation. The Technology sector dummy is statistically insignificant in the early-stage model (β = 0.027; $p = 0.313$), suggesting no meaningful funding differential relative to non-technology startups. However, it is significantly negative for later-stage startups (β = –0.203; $p < 0.001$), indicating that mature technology ventures raised about 18% less capital than their non-tech counterparts. This aligns with broader declines in technology valuations observed during 2023–2024. Together, these findings suggest that the impact of the SVB collapse was not uniformly contractionary. Rather, it catalyzed a structural reallocation of venture capital, with investors reducing exposure to large, late-stage deals while maintaining or even expanding participation in early-stage opportunities, particularly through syndication strategies and sectoral recalibrations.

CONCLUSION

This study offers empirical insights indicating that the 2023 collapse of Silicon Valley Bank (SVB) did not result in a uniform contraction in startup financing. Instead, it led to a structural redistribution of capital across funding stages and sectors. Early-stage startups benefited from a noticeable uptick in investor interest, as funding preferences shifted toward smaller, more agile rounds. In contrast, later-stage startups experienced significant reductions in funding due to increased uncertainty and heightened investor risk aversion linked to larger funding commitments. Syndicated investments remained a key mechanism for expanding deal sizes, especially in early-stage rounds where co-investment structures were most effective in mitigating risk. Additionally, technology-sector startups particularly those in later development stages, faced a disproportionately negative impact, reflecting widespread valuation corrections within the tech industry during 2023–2024.

Limitations of the Study

Several constraints should be considered when interpreting the findings of this study:

1. **Data Coverage**: The research is based on secondary data, primarily sourced from S&P Capital IQ and similar startup funding databases. While more comprehensive than many alternative sources, the dataset may still omit smaller, undisclosed, or very early-stage deals, leading to potential sample incompleteness—especially among non-venture-backed startups.
2. **Control Variables**: Key firm-level controls such as company age, founder background, historical fundraising patterns, and past performance were not available in the dataset. The absence of these variables may limit the model's capacity to fully explain variations in funding outcomes.
3. **Geographic Scope**: The study is limited to startups headquartered in the United States. As such, the findings may not be directly applicable to international contexts, especially emerging economies, where market dynamics and investor behaviors differ.

Implications and Recommendations for Future Research

To address the above limitations, future studies are encouraged to pursue the following directions:

1. **Broaden Data Sources**: Researchers should consider integrating data from multiple platforms, such as PitchBook, Crunchbase Pro, or expanded Capital IQ datasets, to enhance data coverage, increase sample size, and reduce the risk of selection bias.
2. **Include Richer Control Variables**: Future analyses should incorporate additional startup-level attributes such as firm age, founder expertise, product-market fit, and prior funding milestones to better capture the determinants of capital allocation and more accurately estimate the effects of systemic events.
3. **Explore International Comparisons**: To assess the global implications of financial shocks, cross-country analyses, particularly including emerging markets like Indonesia, should be conducted. This would help evaluate differences in financial resilience and investor behavior across diverse economic systems and regulatory environments.

REFERENCES

Aharon, D. Y., Ali, S., & Naved, M. (2023). Too big to fail: The aftermath of Silicon Valley Bank (SVB) collapse and its impact on financial markets. *Research in International Business and Finance, 66*, 102036. https://doi.org/10.1016/j.ribaf.2023.102036

Bernanke, B., & Gertler, M. (1990). Financial fragility and economic performance. *The Quarterly Journal of Economics, 105*(1), 87–114.

Block, J., & Sandner, P. (2009). What is the effect of the financial crisis on venture capital financing? Empirical evidence from US Internet start-ups. *Venture Capital, 11*(4), 295–309. https://doi.org/10.1080/13691060903184803

Conti, A., Dass, N., Di Lorenzo, F., & Graham, S. J. H. (2019). Venture capital investment strategies under financing constraints: Evidence from the 2008 financial crisis. *Research Policy, 48*(3), 799–812. https://doi.org/10.1016/j.respol.2018.11.009

Corea, F., Bertinetti, G., & Cervellati, E. M. (2021). Hacking the venture industry: An early-stage startups investment framework for data-driven investors. *Machine Learning with Applications, 5*, 100062. https://doi.org/10.1016/j.mlwa.2021.100062

Dong, J. (2024). Silicon Valley Bank bankruptcy—Liquidity risk analysis based on financial statements. *SHS Web of Conferences, 208*, 04009. https://doi.org/10.1051/shsconf/202420804009

Gill, A., Heller, D., & Michel, N. A. (2024). Enabling or accelerating? The timing of innovation and the different roles of venture capitalists. *Research Policy, 53*(8), 105060. https://doi.org/10.1016/j.respol.2024.105060

Gompers, P. A. (1995). Optimal investment, monitoring, and the staging of venture capital. *The Journal of Finance, 50*(5), 1461–1489. https://doi.org/10.1111/j.1540-6261.1995.tb05185.x

Gompers, P. A., Gornall, W., Kaplan, S. N., & Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics, 135*(1), 169–190. https://doi.org/10.1016/j.jfineco.2019.06.011

Hsu, D. H., & Kaplan, S. (2004). What do entrepreneurs pay for venture capital affiliation? *The Journal of Finance, 59*(4), 1805–1844. https://doi.org/10.1111/j.1540-6261.2004.00679.x

Jeng, L. A., & Wells, P. C. (2000). The determinants of venture capital funding: Evidence across countries. *Journal of Corporate Finance, 6*(3), 241–289. https://doi.org/10.1016/S0929-1199(00)00003-1

Lingelbach, D. (2019). Financial crises and venture capital development: Evidence from Indonesia. *Asia Pacific Business Review, 25*(1), 61–80. https://doi.org/10.1080/13602381.2018.1519173

Pandey, D. K., Hassan, M. K., Kumari, V., & Hasan, R. (2023). Repercussions of the Silicon Valley Bank collapse on global stock markets. *Finance Research Letters, 55*, 104013. https://doi.org/10.1016/j.frl.2023.104013

Sahlman, W. A. (1990). The structure and governance of venture-capital organizations. *Journal of Financial Economics, 27*(2), 473–521. https://doi.org/10.1016/0304-405X(90)90065-8

Yousaf, I., & Goodell, J. W. (2023). Responses of US equity market sectors to the Silicon Valley Bank implosion. *Finance Research Letters, 55*, 103934. https://doi.org/10.1016/j.frl.2023.103934

Buku

Feld, B., & Mendelson, J. (2016). *Venture deals: Be smarter than your lawyer and venture capitalist* (3rd ed.). John Wiley & Sons.

http://ebookcentral.proquest.com/lib/indonesiau-ebooks/detail.action?docID=4753455

Ramsinghani, M. (2021). *The business of venture capital* (3rd ed.). Wiley.

Sumber Web / Non-Jurnal

Bruni, M., Karthaus, T., & Holton, M. (2023, April 20). The collapse of SVB: Implications for start-ups and the banking industry. *Newton Investment Management*. https://www.newtonim.com/us-institutional/insights/blog/the-collapse-of-svb-implications-for-start-ups-and-the-banking-industry/

Hamlin, J. (2024). One year after SVB, the throne sits empty. *PitchBook*. https://pitchbook.com/news/articles/one-year-after-svb-the-throne-sits-empty

Richter, F. (2019, July 17). U.S. venture capital funding reaches dot-com era level. *Statista*. https://www.statista.com/chart/18769/venture-capital-investment-in-the-us/

Statista Research Department. (2024, June 21). Value of venture capital investment in the United States from 2006 to 2023. *Statista*.
https://www.statista.com/statistics/277501/value-of-venture-capital-investments-in-the-united-states-since-1995/