Bio-Bust: Investigating Biotech Stock Factors Contributing to Abnormal Returns in the Wake of Silicon Valley Bank’s Failure

Spencer Kent

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Bio-Bust: Investigating Biotech Stock Factors

Contributing to Abnormal Returns

in the Wake of Silicon Valley Bank's Failure

Submitted to

Professor Eric Hughson

by

Spencer Kent

for

Senior Thesis

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December 4, 2023
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Abstract

Following the unprecedented collapse of Silicon Valley Bank (SVB) in March 2023, this study explores abnormal stock price reactions within the biotechnology sector. As the chosen financial institution for countless Silicon Valley-type technology and healthcare firms, SVB’s failure had a profound impact on small to mid-sized biotech companies. Analyzing a dataset of 180 biotech firms during a two-day event window over SVB’s collapse, I investigate whether exposure to SVB, or other factors, was the primary contributor to negative abnormal stock price reactions, considering variables such as the percentage of cash held at SVB, whether a firm maintained an active SVB relationship, lead drug asset maturity, and market capitalization. Using event study methodology with univariate and multivariate regressions, my findings reveal that firms with active SVB relationships, especially smaller and early-stage entities, experienced more pronounced negative abnormal returns. These results not only emphasize the vulnerabilities of biotech companies tied to financial institutions like SVB but also offer insight on the interplay between market dynamics and institutional failures.
Table of Contents

I. Introduction ......................................................................................................................................... 6

II. Literature review ................................................................................................................................. 9

III. Hypotheses ....................................................................................................................................... 12

IV. Data .................................................................................................................................................. 15

V. Methodology ...................................................................................................................................... 17

VI. Descriptive statistics ......................................................................................................................... 20

VII. Results ............................................................................................................................................ 23

VIII. Conclusion .................................................................................................................................... 32

IX. Bibliography ................................................................................................................................... 34
I. Introduction

In March 2023, global financial markets experienced a shock unlike anything seen in decades. Silicon Valley Bank, one of the largest banks in the US, suffered a complete collapse and bank run after announcing a significant decline in value on held-to-maturity bonds and attempting to raise additional capital. SVB, which at the time of its collapse was the 16th largest bank in the US with over $230 billion in total assets, was the chosen financial institution of countless small to mid-sized healthcare, biotech, and information technology companies. Based in the San Francisco Bay Area, SVB had developed a reputation as the premier financial institution for early and mid-stage Silicon Valley-type companies.¹

Many of these early-stage tech and healthcare companies, while extremely innovative and internationally recognizable, operate with a significant amount of risk. In many cases, high research and development expenses combined with limited or zero revenue lead to significant cash burn and highly volatile stock prices. These types of companies relied heavily on Silicon Valley Bank's strategic expertise, deposit accounts, credit lines, and investment opportunities to fuel their research, development, commercialization, and expansion efforts. However, the COVID-19 pandemic and the years following led to unexpected developments in the global economy that ultimately culminated in this failure.

Before and during the COVID-19 pandemic, federal funds rates reached record lows as the US Federal Reserve attempted to revive the economy, making borrowing extremely inexpensive. However, as the global economy began to reopen in late 2020, consumer spending began to rapidly increase as Americans started spending the large cash balances they accrued during the lockdown.

Inflation began to rapidly increase with economic growth reaching year-over-year rates of close to 10%. The Federal Reserve, which targets a long-term annual rate of inflation of 2%, began hiking interest rates in response. Raising rates increased the cost of borrowing, theoretically incentivizing consumers to slow their spending and thus, slow inflation. However, there is a significant trade-off with raising interest rates—disincentivizing investment in equities, leading to an inability of many of these companies to raise additional capital. As interest rates rose and biotech capital markets declined, SVB’s deposits began to decrease as companies drew on their cash reserves to the point that SVB needed to liquidate some of its bonds at a loss to keep up with withdrawal requests. While SVB assured depositors that the bank was financially solvent and even announced a plan to raise additional equity capital, investors and depositors were spooked.

Fearing that their deposits were at risk, biotech executives and prominent venture capital investors began quickly withdrawing cash which spiraled into a fatal run on the bank. The Federal Deposit Insurance Corporation (FDIC) insures up to $250,000 per depositor per financial institution, however, many of these Silicon Valley depositors held millions of dollars at SVB, meaning the vast majority of the $200+ billion on deposit at SVB was uninsured.

On March 10, 2023, the state of California seized Silicon Valley Bank and placed it under the receivership of the FDIC. Many questions loomed about how much money the various

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healthcare and tech companies would be able to recover. In the days leading up to and immediately following the failure, biotech stocks across the industry suffered a massive crash in valuations as it was unclear which companies had uninsured deposits, the value of these deposits, how much would be returned, and the timeline on the recovery process.

While SVB maintained relationships with companies of all sizes and across industries, biotechnology composed one of the major subcategories of companies impacted by the SVB failure, primarily made up of preclinical and clinical-stage drug developers.

Biotech valuations, on average, fell close to 8% with the S&P Biotechnology Select Industry Index (^XBI) falling about 7 points on the day of the failure. However, taking a closer look at individual biotech stocks, there was a wide range in observed performance. Performance across the industry ranged from close to 30% reduction in stock price to, albeit rare, even increases in stock price. The goal of this paper is to determine whether exposure to SVB was the primary contributor to stock price reactions in response to the bank failure. Exposure to SVB is measured in two ways—as a percentage of a firm’s total cash on hand held at SVB and a binary dummy variable indicating whether a firm had any relationship with SVB. There are a wide variety of alternative factors that could play a role in this equation, three of which this paper primarily focuses on: (1) the size/maturity of the company, (2) the maturity of the company’s most advanced drug asset, and (3) a wider fear of contagion and systemic failure.

This investigation finds that firms exposed to Silicon Valley Bank with an active SVB relationship at the time of the failure were subject to worse abnormal returns compared to those firms that did not bank with SVB. Moreover, smaller firms and firms with less mature drug assets were associated with lower abnormal returns. The results indicate that the impact of being a small

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5 S&P Capital IQ data
firm or being an early-stage firm is generally stronger than the impact of being exposed to SVB, leading to the conclusion that investors feared a wider contagion effect on other financial institutions.

II. Literature review

In the months since the fallout of the SVB collapse, there have been several research papers published that have analyzed the impact of the bank failure. These studies have looked at a variety of specific impacts including on global financial market reactions, bank stocks, US equity sectors, specific countries, and asset classes. At the time of this paper, there has not been any dedicated research into the impact on biotech stocks specifically, a major representative sector of SVB depositors. Starting broadly, Aharon et al. (2023) investigated the impact on the global financial system. Aharon and his team tracked daily data of major equity indices of countries and used event study methodology to determine if there was a ripple-on effect of a large financial institution failure. This study found a negative cumulative average abnormal return of -3.69% at \( t+6 \) across the entire global data set. The authors concluded that this statistically significant result indicates that there was a strong, widespread market reaction to the default of SVB. The methodology also included looking at the days leading up to the failure, resulting in statistically insignificant findings which the authors conclude supports the strong form of market efficiency. The authors also separated the data into individual country market reactions to determine how different countries were affected. Their findings align with previous research completed by Yousaf and Goodell (2023b), Yadav et al. (2023), and Pandey et al. (2023). Similar to the previous studies, Aharon et

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al. find that the SVB collapse did not affect countries uniformly. Financial markets in developed markets showed a more pronounced negative effect due to their level of interdependence with the global economy. Aharon et al. draws attention to the finding that the impact on the overall US market was either statistically significantly positive or insignificant in the days following the crash. They hypothesize that this may be due to the quick reaction by the US government to seize the bank’s assets.\(^7\)

Another study conducted recently in response to the SVB failure is Azmi et al. (2023) which looked at how major global asset classes responded to the SVB failure. Azmi et al. find that most asset classes did not exhibit any significant reaction on the event day except for gold and US Treasury Bills. Interestingly, they found a positive and significant reaction for Gold, indicating that investors moved to Gold as a safe haven. They also found that US Treasury Bills showed a negative reaction to the event, indicating that investors anticipated the Fed slowing or halting interest rate hikes. Azmi et al. identified this as a surprising result as US government securities are typically a safe haven during financial turmoil. It could indicate that investors anticipate interest rates rising further. The third key result from the Azmi study was that the cumulative abnormal returns did not show any reaction to the entire period \(t-1\) to \(t+5\) except for specific negative impacts on Bitcoin in the \(t-1\) period and oil later in the period. The conclusion by Azmi is that diversified indexes are generally protected from crisis periods.\(^8\)

The third study recently conducted regarding the impact of the Silicon Valley Bank failure, and referenced in both of the previously mentioned papers, is Yousaf and Goodell (2023) which investigated the responses of US equity market sectors. Yousaf and Goodell use the event study

\(^7\) Ibid.
methodology to break down the US equity market reaction into specific industry sectors. This paper looks at 11 sectors over the period from December 18, 2022 to March 17, 2023. Their results find that all sectors saw negative returns on the event day, however, most of these negative returns were statistically insignificant. The only sectors that experienced significant negative reactions in these results were financial services, materials, and real estate sectors. As my paper looks primarily at biotech stocks, it is pertinent to look at Yousaf and Goodell’s findings on the Health Care and Information Technology sectors. They find a -1.020% abnormal return in Health Care stocks on the event day and a -1.510% abnormal return in Information Technology stocks on the event day, but neither result is statistically significant. This is somewhat surprising given that most of SVB’s clients fell into these two sectors and many of these companies are smaller and more volatile, however, both of these sectors, the way Yousaf and Goodell organized them, comprise very broad and diversified indices of companies. Both the Health Care and Information Technology sectors are anchored by mega-cap technology and big pharma companies that are very stable and likely immune to a bank failure such as SVB, reducing the overall magnitude and significance of the abnormal returns in these sectors.  

At this time, not only has there been no research into the impact on an isolated sample of biotechnology firms, but none of the prior papers investigate specific firm characteristics that contributed to individual abnormal returns. This paper accomplishes both of these goals to make a conclusion on which characteristics create the most exposure to external financial turmoil.

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III. Hypotheses

There are a wide variety of factors and characteristics that may have contributed to the abnormal stock price reactions in biotech stocks in response to the failure of SVB. In this paper, I analyze a selection of these factors thought to be most likely to contribute to abnormal returns to determine whether exposure to SVB, or other firm characteristics, more accurately explain the magnitude and significance of abnormal returns.

First, I hypothesize that value of SVB deposits as a percentage of total cash contributes to a negative abnormal return. On the event day and in the days following, it was unclear whether depositors would be able to recover any of their funds beyond the generally negligible $250,000 insured by the FDIC. It is logical, therefore, that companies with a greater portion of their cash and cash equivalents held at SVB would be subject to a larger negative valuation impact as investors feared that significant portions of the cash needed to operate in the immediate term would be lost. Cash reserves are of the utmost importance to most clinical stage biotech companies as these firms generate little to no revenue to support the extremely high R&D costs involved in bringing drug assets to market.

Second, I hypothesize that firms that had any kind of active relationship with SVB at the time of the failure would be subject to negative abnormal returns. SVB maintained many different types of relationships with clients that included deposit accounts, credit lines, investment management, and advisory. While some firms directly held cash at SVB, many firms were borrowers or relied on the bank for other services. In addition to the hypothesis that firms with larger percentages of cash held at SVB would experience negative abnormal returns, I expect that firms with any type of relationship or reliance on SVB would be subject to some level of additional scrutiny by the market given the uncertainty around the institution’s future.
Third, I hypothesize that the increasing maturity of a company’s lead drug asset would have a positive impact on abnormal stock price returns. US drug candidates go through three phases as a part of the FDA approval process: Phase I, II, and III.\(^\text{10}\) The vast majority of drug candidates never reach FDA approval/marketing and fail in one of the three phases of clinical trials (and never generate any revenue for the business).\(^\text{11}\) As the asset progresses through the three phases, it becomes increasingly likely to reach approval and eventually generate cash flow for the company. Therefore, when valuing a pre-revenue biotech company, it is critical to discount the future cash flows estimated to be generated by the in-development asset using a probability of success (PoS) measure. For several reasons, I would predict that a company with a less mature lead asset would be subject to a larger negative reaction. There is no certainty that the asset will ever come to market and generate any revenue for the firm, making the firm more reliant on its cash reserves rather than stable cash flows generated by the business. Also, the cost of required clinical trials become significantly more expensive as the asset progresses through the phases, so an earlier stage company has significant costs ahead that further along companies have already passed.\(^\text{12}\)

Finally, I hypothesize that the increasing market capitalization of a firm is associated with more positive abnormal returns. Larger companies naturally provide a greater level of stability to investors. As a company grows, it likely has more substantial cash reserves, improved risk


management practices, greater ability to raise equity or debt capital, and typically has larger, more stable, and/or sooner expected cash flows. While many of these companies still fall into the smaller market cap categories from a broad lens, it is common to see significant market cap increases as developers advance their drug candidates toward approval, so it is important to analyze the impact of a larger market capitalization on the SVB-related reactions.

\[ H_1 = \text{Larger proportions of cash held with SVB are associated with negative abnormal returns} \]
\[ H_0 = \text{Larger proportions of cash held with SVB are not associated with negative abnormal returns} \]

\[ H_2 = \text{Firms with active relationships with SVB are associated with negative abnormal returns} \]
\[ H_0 = \text{Firms with active relationships with SVB are not associated with negative abnormal returns} \]

\[ H_3 = \text{Companies with less advanced lead assets are associated with negative abnormal returns} \]
\[ H_0 = \text{Companies with less advanced lead assets are not associated with negative abnormal returns} \]

\[ H_4 = \text{Smaller firms are associated with negative abnormal returns, relative to large firms} \]
\[ H_0 = \text{Smaller firms are not associated with negative abnormal returns, relative to large firms} \]
IV. Data

The primary dataset utilized in this analysis is built from an initial list of 79 biotechnology companies that issued 8-K filings regarding their relationship with SVB in the wake of the failure. The 8-K filing is required when a significant event occurs and, in this case, dozens of companies filed similar 8-Ks disclosing details of their SVB relationship, so this paper assumes that companies that did not file an 8-K with the SEC did not have an ongoing relationship with SVB. Each 8-K filing contained detailed information about how much money was held at the failed bank, as well as any other active financial product such as debt agreements.\(^\text{13}\)

In addition to the companies that issued 8-K filings disclosing a relationship with Silicon Valley Bank, I added all firms held in the XBI index on the event date to broaden the sample to include similar companies that did not have any relationship with SVB, removing duplicates for any firms that were included in both selections. I added these firms to create a subset of the sample that was not directly exposed to SVB through a banking relationship. The XBI index included a total of approximately 145 firms, 117 of which were not in the previous sample of SVB-banked firms. While many privately-held biotech companies also held money at SVB, this sample only includes publicly-traded firms listed at the time of the bank failure.

This initial full combined sample of firms included a variety of companies classified as “biotechnology” which includes, in addition to traditional drug developers, medical technology, medical devices, surgical tools, and more. In order to maintain consistency among the studied firms, I decided to limit the sample to include only drug developers that have previously or are currently progressing an asset through the FDA drug development clinical trial process for use in

humans. Other biotechnology subcategories such as medical device manufacturers similarly have FDA approval risk, but go through a different evaluation process and inherently cannot be evaluated from the same FDA phase perspective.

After removing all firms that did not satisfy the above conditions, the final sample set contains a total of 180 firms, 113 of which did not have an active relationship with SVB and 67 of which did have an active relationship of some kind with the failed bank.

For each firm, the dataset includes market capitalization, total cash on hand, total debt outstanding, LTM revenue, LTM operating expenditures, total value of deposits held at SVB at the time, a calculated percentage of total cash on hand that was held at SVB, the FDA phase of the company’s most advanced asset, and a dummy variable for whether a company had a relationship with SVB. Unaffected market capitalization is organized using a categorical variable that separates the 180 firms into nano-cap ($0-50M), micro-cap ($50-250M), small-cap ($250M-2B), mid-cap ($2-10B), and large-cap ($10B+). The FDA phase data is a categorical variable ranging from 0 to 4 where 0 represents pre-clinical, 1-3 represent their respective phase, and 4 represents an approved and marketed product in the United States. Financial data is retrieved from the financial statements released most recently prior to the event date filed with the SEC which were, in most cases, released with fourth-quarter 2022 earnings. The FDA phase data for each company was retrieved from the most recently issued press released near the event date, again in most cases the fourth-quarter earnings release. Stock price data (at market close) was collected for each sample firm for \( t-2 \) (March 8) to \( t \) (March 10) from S&P Capital IQ.
V. Methodology

In order to determine the factors that influence the stock price reactions to the failure of Silicon Valley Bank, I analyze the dataset discussed previously, composed of 180 drug-developing firms in the biotech industry, using an event study methodology.

This analysis is conducted as an event study with a two-day compounding event window that begins at market close on March 8, 2023 \((t-2)\) and ends at market close on March 10, 2023 \((t)\), the day the FDIC was appointed receiver. I use these dates as the event window based on XBI returns throughout the SVB saga observing that the initial decline in valuations began on March 8 and reached its lowest point upon seizure of the bank by the state of California. The empirical econometric method of this study is to regress each firm’s cumulative abnormal return (dependent variable) over the event window on the selection of explanatory characteristics (independent variables) previously discussed.

Expected returns are calculated using the Capital Asset Pricing Model (CAPM), assuming that the risk-free rate of return over the event window is negligible. The S&P 500 return over the event window is used as the return on the market. Firm-specific betas are calculated with five-year betas being used wherever possible and one-year betas used for companies without five years of trading data as some of the sample firms are young or newly listed. Abnormal returns \((AR_{i,t})\) are calculated by subtracting the expected CAPM return from the observed stock price reaction. Then, cumulative abnormal returns \((CAR_{i})\) are calculated by adding together the abnormal returns over the two day event window for each firm.
Abnormal return

\[ AR_{i,t} = r_{i,t} - \hat{\beta}_i r_{mt} \]

Cumulative Abnormal Return

\[ CAR_i = \sum_t AR_{i,t} \]

To determine an initial relationship between abnormal returns and each factor, I perform univariate cross-sectional regressions for each of the four independent variables. The univariate regression for the percentage of cash held with SVB covariate limits the sample set to only firms with some level of cash at SVB, and excludes firms without a relationship with SVB.

\[ CAR_i = \beta_0 + \beta_1 (\text{Relationship}_i) + \epsilon \]

\[ CAR_i = \beta_0 + \beta_1 (\% \text{ of Cash Held with SVB}_{\text{firms with SVB cash,}})_i + \epsilon \]

\[ CAR_i = \beta_0 + \beta_1 (\text{Market Capitalization Category}_i) + \epsilon \]

\[ CAR_i = \beta_0 + \beta_1 (\text{Lead Asset Phase Category}_i) + \epsilon \]

After using these initial regressions to determine whether the relationship between abnormal return and the covariates generally align with my hypotheses, I perform two additional regressions to investigate how the results change when regressing multiple covariates together. Because the relationship variable is correlated with the market capitalization and lead asset phase variables, I use interaction terms to resolve the collinearity concern and analyze each potential combination of characteristics separately. The first regression of these two investigates the effect of relationship and market capitalization on abnormal returns. For this analysis, I use ten interactive dummy variables that cross the relationship covariate with each market capitalization category. I exclude the covariate for percentage of cash held at SVB due to its statistical insignificance determined through its univariate regression (see Table 7) and its similarity to the
relationship covariate. The covariate (NoRelationship x LargeCap) is omitted and its result is derived from the regression constant.

\[ CAR = \beta_0 + \beta_1 (\text{Relationship} \times \text{NanoCap}) + \beta_2 (\text{Relationship} \times \text{MicroCap}) \\
+ \beta_3 (\text{Relationship} \times \text{SmallCap}) + \beta_4 (\text{Relationship} \times \text{MidCap}) \\
+ \beta_5 (\text{Relationship} \times \text{LargeCap}) + \beta_6 (\text{NoRelationship} \times \text{NanoCap}) \\
+ \beta_7 (\text{NoRelationship} \times \text{MicroCap}) + \beta_8 (\text{NoRelationship} \times \text{SmallCap}) \\
+ \beta_9 (\text{NoRelationship} \times \text{MidCap}) + \epsilon \]

Next, I similarly investigate the effect of relationship and a company’s lead asset phase on abnormal returns. Again, I create ten interactive dummy variables crossing relationship with each FDA phase category. The (NoRelationship x Marketed) covariate is omitted and its result is derived from the regression constant. The specification of this second regression is outlined below.

\[ CAR = \beta_0 + \beta_1 (\text{Relationship} \times \text{Preclinical}) + \beta_2 (\text{Relationship} \times \text{Phase1}) \\
+ \beta_3 (\text{Relationship} \times \text{Phase2}) + \beta_4 (\text{Relationship} \times \text{Phase 3}) \\
+ \beta_5 (\text{Relationship} \times \text{Marketed}) + \beta_6 (\text{NoRelationship} \times \text{Preclinical}) \\
+ \beta_7 (\text{NoRelationship} \times \text{Phase1}) + \beta_8 (\text{NoRelationship} \times \text{Phase2}) \\
+ \beta_9 (\text{NoRelationship} \times \text{Phase3}) + \epsilon \]

Using the results generated from the full multi-variable regression, I determine whether the results are satisfactory to reject any of the four hypotheses using a 95% confidence interval.
VI. Descriptive statistics

A summary of sample firm market capitalizations is presented in Table 1. Across the 180 firms, 8 are nano-cap, 24 are micro-cap, 98 are small-cap, 36 are mid-cap, and 14 are large-cap. Small-cap firms comprise over 54% of the sample dataset and small-cap or smaller firms represent 72%, which is appropriate for the biotech industry as the vast majority of firms fall into this category and are subject to the associated volatility in stock price. Market capitalizations for the sample firms are fairly evenly dispersed across the five categories and are not excessively concentrated in a specific category.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Capitalization:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nano ($0-50M)</td>
<td>8</td>
<td>4.44%</td>
</tr>
<tr>
<td>Micro ($50-250M)</td>
<td>24</td>
<td>13.33%</td>
</tr>
<tr>
<td>Small ($250M-2B)</td>
<td>98</td>
<td>54.44%</td>
</tr>
<tr>
<td>Mid ($2-10B)</td>
<td>36</td>
<td>20.00%</td>
</tr>
<tr>
<td>Large ($10B+)</td>
<td>14</td>
<td>7.78%</td>
</tr>
<tr>
<td>Total</td>
<td>180</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

The breakdown of sample firms by their drug asset maturity is presented in Table 2. 8 firms have only preclinical assets, 15 are in Phase 1 trials, 45 are in Phase 2, 50 are in Phase 3, and 62 have marketed medicines in the United States actively generating product revenue. Again, the phase data is dispersed across the categories with three of the five categories representing at least a quarter of the data.

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Table 3 summarizes the binary relationship dummy variable that indicates whether a firm had an active relationship with SVB at the time of the failure, including deposits or outstanding debt in the US or UK branches of SVB. 113 (62.8%) of the sample firms had no relationship with the failed bank while 67 (37.2%) firms had some relationship with SVB.

Table 4 summarizes the percentage of cash held at SVB variable. Across the entire dataset, the average percentage of total cash on hand that was held at SVB at the time of the collapse was 1.4%. The t-statistic of 3.75 for this mean indicates statistical significance at the 95% confidence level across the full sample. Isolating the set of sample firms that had an active relationship with SVB (see Table 5), the average percentage of cash held at SVB was around 3.9%. This mean is
also statistically significant with a t-statistic of 4.03. The largest proportion of cash held at SVB across any sample firm is only about 50%. No sample firm held a majority of their cash reserves with the failed bank.

<table>
<thead>
<tr>
<th>TABLE 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Percentage of Total Cash On Hand Held at SVB (all firms):</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Percentage of Total Cash On Hand Held at SVB (firms with SVB cash):</td>
</tr>
</tbody>
</table>

Finally, Table 6 summarizes the abnormal returns across the dataset. Sample firms observed, on average, a 4.9% negative abnormal return over the event window with a standard deviation of 5.5%, statistically significant with a t-statistic of 11.9. Abnormal returns ranged from -30.3% to 12.5%. The juxtaposition of seemingly extreme abnormal returns with the relatively small average percentage of cash held at SVB is interesting, potentially pointing toward other factors as the primary contributors.

<table>
<thead>
<tr>
<th>TABLE 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Cumulative Abnormal Returns (CAR):</td>
</tr>
</tbody>
</table>
VII. Results

To determine any initial relationship between abnormal returns and each independent characteristic, I run univariate regressions for each variable, the results of which are presented in Table 7. The coefficients of the univariate regressions indicate the sign of a general relationship that exists between the dependent variable and the independent variable in question. Because these covariates may have some level of collinearity, the subsequent two interactive regressions show a more accurate result. However, these initial regressions help predict a relationship and whether it aligns with the proposed hypotheses.

The coefficient for the relationship dummy variable univariate regression asserts that firms with a relationship with SVB were associated with a statistically significant -1.8% abnormal return. Based on the sample data, a one standard deviation move in relationship of 0.485 is associated with a -0.8% change in abnormal return. This indicates, logically and in line with my hypothesis H₂, that firms generally performed worse if they had an active relationship with SVB.

The regression evaluating percentage of cash held with SVB interestingly results in a positive coefficient. Limiting the sample to firms holding cash at SVB helps to isolate the effect of deposit levels on abnormal returns. This result theoretically asserts that firms holding more of their cash with SVB observed a more positive CAR, however, the univariate result was statistically insignificant. According to this result, the average firm with deposits at SVB (holding the average 3.87% of total cash at SVB) is associated with a 0.75% increase in abnormal return. This finding goes against the logical idea behind hypothesis H₁ that firms with more cash held at SVB would be subject to worse abnormal returns. The intercept of -6.8% in this regression likely implies that the abnormal returns are caused by another factor. Because the result is insignificant and the percentage of cash covariate is very similar in nature to the generalized relationship dummy
variable, I exclude it from future regressions to focus the measure of exposure to SVB on the relationship covariate only.

The market capitalization regression looked at the various categories of firm size relative to large-cap firms. All categories smaller than large-cap firms observed a negative and significant abnormal return coefficient relative to large-cap firms meaning that mid-cap and smaller firms were subject to worse abnormal returns than the mature large-cap businesses, aligning with my hypothesis H4.

The univariate regression for abnormal return against lead asset phase evaluates how Phase 3 or earlier firms performed relative to companies with marketed products. All of these coefficients are negative and the results for Phases 1-3 are significant, predicting that firms without a product generating revenue are subject to worse abnormal returns, in line with hypothesis H3. These coefficients suggest that, relative to firms with marketed drugs, Phase 1 and 2 companies are associated with a -4.8% and -5.0% change in abnormal return, respectively.

Overall, these initial univariate regressions offer a lens into the general relationships that exists between the various firm characteristics and abnormal returns over the event window. Based on these univariate regressions, three of my four hypotheses seem to be directionally supported by this initial testing.
Next, I combine the covariates into two regressions analyzing the interaction between relationship and the other two covariates—market capitalization and lead asset phase. The results of the first regression crossing relationship and each market cap category are outlined in Table 8. Three of the covariates did not contain any firms—(Relationship x LargeCap), (NoRelationship x NanoCap), and (NoRelationship x MicroCap). The results for these three categories are marked as N/A.

### Table 7 (Univariate Regression Results)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Intercept</th>
<th>s.e.</th>
<th>P-value</th>
<th>R²</th>
<th>[95% Confidence Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relationship</td>
<td>-0.018</td>
<td>-0.042</td>
<td>0.008</td>
<td>0.033</td>
<td>0.025</td>
<td>-0.034, -0.001</td>
</tr>
<tr>
<td>% of Cash Held at SVB (firms with SVB cash)</td>
<td>0.196</td>
<td>-0.068</td>
<td>0.104</td>
<td>0.063</td>
<td>0.052</td>
<td>-0.011, 0.403</td>
</tr>
<tr>
<td>Market Cap:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nano</td>
<td>-0.053</td>
<td></td>
<td>0.233</td>
<td>0.023</td>
<td></td>
<td>-0.996, -0.007</td>
</tr>
<tr>
<td>Micro</td>
<td>-0.078</td>
<td>0.004</td>
<td>0.018</td>
<td>0.000</td>
<td>0.105</td>
<td>-0.113, -0.043</td>
</tr>
<tr>
<td>Small</td>
<td>-0.056</td>
<td></td>
<td>0.015</td>
<td>0.000</td>
<td></td>
<td>-0.085, -0.026</td>
</tr>
<tr>
<td>Mid</td>
<td>-0.046</td>
<td></td>
<td>0.017</td>
<td>0.006</td>
<td></td>
<td>-0.079, -0.013</td>
</tr>
<tr>
<td>Lead Asset Phase:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preclinical</td>
<td>0.000</td>
<td>-0.026</td>
<td>0.193</td>
<td>0.995</td>
<td></td>
<td>-0.038, 0.038</td>
</tr>
<tr>
<td>Phase 1</td>
<td>-0.048</td>
<td></td>
<td>0.015</td>
<td>0.001</td>
<td>0.146</td>
<td>-0.078, -0.019</td>
</tr>
<tr>
<td>Phase 2</td>
<td>-0.050</td>
<td></td>
<td>0.010</td>
<td>0.000</td>
<td></td>
<td>-0.070, -0.030</td>
</tr>
<tr>
<td>Phase 3</td>
<td>-0.022</td>
<td></td>
<td>0.010</td>
<td>0.024</td>
<td></td>
<td>-0.042, -0.003</td>
</tr>
</tbody>
</table>
The results of this regression indicate that smaller firms with an active relationship with SVB were subject to worse abnormal returns over the event window. Beginning with the covariates corresponding to firms that maintained a relationship with SVB, as market cap increased the abnormal return tends to become less negative. The worst abnormal return coefficient observed in these results comes from the (Relationship x MicroCap) covariate. This result indicates that micro-cap firms with an active SVB relationship were associated with a statistically significant -7.8% abnormal return on the day of the bank failure. As market capitalization increases within firms that
bank with SVB, the impact becomes softer with small-cap firms observing a statistically significant -6.1% abnormal return and mid-cap firms seeing a -2.3% abnormal return. Nano-cap firms with an SVB relationship also observed a statistically significant -5.3% abnormal return which is slightly better than the micro-cap firms, straying from the strict pattern, however, there are only eight firms in this category so limited observations may skew these results.

Next, it is interesting to compare these results to the estimations for firms that did not maintain a relationship with SVB. A similar pattern indicating a softening of negative abnormal returns as size of a firm increases exists here too. Small-cap firms were associated with a statistically significant -5.3% abnormal return, mid-cap firms observed a statistically significant -5.0% abnormal return, and large-cap firms were even associated with a slightly positive abnormal return of 0.4%. Comparing the two results for small-cap firms (with and without an SVB relationship), the largest market cap category in the sample representing over 54% of sample firms, there is a noticeable improvement when firms did not bank with SVB (-6.1% vs. -5.3%).

The results of this regression interacting relationship and market capitalization reveal that the most negatively impacted firms were those that were both micro/small-cap and had a relationship with SVB. In the same vein, the most positive abnormal return estimation came from the exact opposite type of firm, large-cap firms that did not bank with SVB. These results are strong enough to reject the nulls of hypotheses H2 and H4 at a 95% confidence level, proving that firms with SVB relationships are associated with lower abnormal returns and smaller firms are similarly associated with lower abnormal returns.

Comparing these results to the univariate relationship regression also highlights the relatively stronger effect that market capitalization has on abnormal returns. The coefficient for
the univariate relationship regression asserts that firms were generally subject to a -1.8% abnormal return if they banked with SVB. However, micro- and small-cap firms were subject to significantly larger negative returns even when they did not bank with SVB, reiterating that small-cap firms without an SVB relationship were associated with a -5.3% abnormal return, more than three percentage points worse than the univariate relationship result. These findings may point to the risk and fear of contagion surrounding the failure of SVB. Investors were likely concerned that this instability could lead to other financial institutions failing as well, giving rise to a more business risk-focused analysis rather than a strict focus on SVB-specific deposits. These results are indicative of the commonly agreed upon notion of being “too big to fail.” Companies considered too big to fail provide strong support to the broader economy and their potential failure may threaten the stability of the US economy. Firms such as General Motors, AIG, and Chrysler were the recipients of government funding in the wake of the 2008 financial crisis because their failure could have a powerful contagion effect to other firms. This concept and political philosophy has been widely debated, but these results as well as other prior research support the idea that the markets believe in the concept of “too big to fail.” In the case of the SVB crisis, investors flocked to larger, more mature companies as a safe haven, subjecting smaller firms to large negative stock price reactions.

Next, I perform the regression interacting the relationship variable with each lead asset phase. The results of this analysis are outlined in Table 9.

Similar to the results in the prior analysis, the results of this regression indicate that earlier stage firms with an active SVB relationship were subject to worse abnormal returns over the event window. The first five covariates examine how the effect on abnormal return changes for firms that bank with SVB as their assets progress into more advanced FDA phases. The worst abnormal return result comes from Phase 1 SVB clients which are associated with a -6.8% abnormal return, followed by Phase 2 SVB clients slightly better at -6.2%, Phase 3 SVB clients improving significantly at -2.1%, and SVB clients with an approved and marketed product observing a positive 0.6% abnormal return. The results for the Phase 1 and Phase 2 covariates are statistically

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>s.e.</th>
<th>p-value</th>
<th>( R^2 )</th>
<th>[95% Confidence Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relationship x Preclinical</td>
<td>0.017</td>
<td>0.022</td>
<td>0.445</td>
<td></td>
<td>-0.027 - 0.060</td>
</tr>
<tr>
<td>Relationship x Phase 1</td>
<td>-0.068</td>
<td>0.021</td>
<td>0.001</td>
<td></td>
<td>-0.109 - 0.028</td>
</tr>
<tr>
<td>Relationship x Phase 2</td>
<td>-0.062</td>
<td>0.013</td>
<td>0.000</td>
<td></td>
<td>-0.088 - 0.037</td>
</tr>
<tr>
<td>Relationship x Phase 3</td>
<td>-0.021</td>
<td>0.013</td>
<td>0.102</td>
<td></td>
<td>-0.047 - 0.004</td>
</tr>
<tr>
<td>Relationship x Marketed</td>
<td>0.006</td>
<td>0.018</td>
<td>0.748</td>
<td>0.185</td>
<td>-0.030 - 0.042</td>
</tr>
<tr>
<td>No Relationship x Preclinical</td>
<td>-0.046</td>
<td>0.037</td>
<td>0.208</td>
<td></td>
<td>-0.119 - 0.026</td>
</tr>
<tr>
<td>No Relationship x Phase 1</td>
<td>-0.030</td>
<td>0.019</td>
<td>0.125</td>
<td></td>
<td>-0.068 - 0.008</td>
</tr>
<tr>
<td>No Relationship x Phase 2</td>
<td>-0.036</td>
<td>0.013</td>
<td>0.006</td>
<td></td>
<td>-0.061 - 0.010</td>
</tr>
<tr>
<td>No Relationship x Phase 3</td>
<td>-0.021</td>
<td>0.012</td>
<td>0.074</td>
<td></td>
<td>-0.045 - 0.002</td>
</tr>
<tr>
<td>No Relationship x Marketed</td>
<td>-0.027</td>
<td>0.007</td>
<td>0.000</td>
<td></td>
<td>-0.041 - 0.013</td>
</tr>
</tbody>
</table>
significant. These results make sense and follow the logic of hypothesis H₃ predicting that firms with less advanced assets would be subject to worse abnormal returns. Similar to the statistically insignificant (Relationship x NanoCap) result that did not follow the pattern in the previous regression, the (Relationship x Preclinical) covariate resulted in a positive coefficient which does not follow the observed pattern. Theoretically, preclinical firms that bank with SVB should be associated with the worst abnormal returns. This surprising positive coefficient, however, is also statistically insignificant and is only built on eight observations.

Again, comparing the results of the SVB-banked firms to firms without any SVB relationship follows the logic that an SVB relationship is detrimental to stock price reactions. This trend observed in the prior regression largely continued in the phase-based analysis. Within the firms without SVB relationships, abnormal returns improve as drug assets advance. For firms that did not bank with SVB, preclinical firms were subject to a -4.6% abnormal return, Phase 1 firms were associated with a -3.0% abnormal return, Phase 2 firms were associated with -3.6%, Phase 3 firms were associated with -2.1%, and approved/marketed firms were associated with a -2.7% abnormal return. Similar to the SVB depositors, the worst abnormal returns were associated with the earlier stage firms. Comparing firms that banked with SVB against firms that did not bank with SVB, the abnormal returns for firms with SVB relationships are significantly worse with coefficients approaching -7%. The lowest coefficient result for firms without direct exposure to SVB was only -4.6%, a meaningful separation from the SVB-banked firms.

The regression interacting relationship with lead asset phase reveals interesting results indicating earlier stage firms with SVB relationships experienced the worst abnormal returns. These results provide the necessary data to reject the nulls for hypotheses H₂ and H₃, proving that less advanced assets and SVB-banked firms were associated with worse abnormal returns.
Similar to the findings in the previous regression involving market capitalization, these results point to a stronger effect from asset maturity than the relationship variable. Again, comparing to the -1.8% abnormal return from the univariate relationship regression, early phase firms without relationships experienced negative abnormal returns more than twice as large, and early phase firms with relationships experienced negative abnormal returns almost four times as large. These findings align with the general principles around the “too big to fail” philosophy with investors showing a preference for maturity and stability in the face of economic turbulence.
VIII. Conclusion

In the aftermath of Silicon Valley Bank's collapse in March 2023, this study explores the intricate relationships shaping abnormal returns in the biotechnology sector. Using a dataset built on firms that were either held in the XBI index or maintained an active relationship with SVB, the analysis focuses on the interplay between exposure to SVB, firm size, and drug asset maturity. My initial hypotheses predicted that holding a greater proportion of total cash at SVB, utilizing any SVB services, having a lower market capitalization, and having less mature drug assets would all contribute to worse abnormal returns.

Univariate regressions reveal an interesting finding of positive and insignificant coefficient for the percentage of cash held with SVB on abnormal returns. This suggests that the binary relationship variable, which resulted in a negative and significant coefficient as expected, might encapsulate exposure more comprehensively than specific cash percentages. Meanwhile, consistent with expectations, smaller firms and those in earlier drug development stages experienced more pronounced negative abnormal returns.

Subsequent multivariate regressions introducing interaction terms validated hypotheses H2, H3, and H4. Firms with active SVB relationships faced negative abnormal returns, highlighting the adverse impact of direct exposure to SVB. Interaction analysis with market capitalization confirmed that smaller SVB-affiliated firms suffered more substantial abnormal returns, emphasizing their vulnerability to economic instability and uncertainty. Similarly, exploring the interrelation between relationship status and lead asset phase emphasized the vulnerability of earlier-stage biotech firms with SVB ties. SVB clients in Phase 2 or earlier experienced notably negative abnormal returns, emphasizing the important role of drug development maturity.
In conclusion, this study offers valuable insights into the nuanced factors influencing abnormal returns during the fall of Silicon Valley Bank. Firms with active SVB relationships, especially those in early drug development and smaller market capitalization categories, faced the most substantial negative impacts. Contrary to my initial expectation, the amount of cash a specific firm held at SVB at the time of the failure does not seem to be of concern to investors. These results assert that investors preferred stocks without SVB relationships, however, the stronger effect came from the size and maturity of the business itself, pointing to a general fear surrounding economic instability and contagion worries. As the biotech industry navigates uncertainties, these findings provide stakeholders with a deeper understanding of dynamics contributing to resilience or vulnerability in times of financial uncertainty.
IX. Bibliography


