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Analysis of Stock Indices during the SVB Bank Run in March 2023 based on Sentiment Analysis

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Abstract

This paper examines the Silicon Valley Bank (SVB) bank run event on March 9, 2023, and seeks to contribute to the understanding of market dynamics during this crisis. The bank run was unique and chilling because of two factors: first, the event was amplified by widespread panic on Twitter following a message by Peter Thiel, a renowned technology entrepreneur; and second, the speed of withdrawals was unprecedented because of the power of social media and the technology that allowed quick reactions. In this paper, we start by examining the market volatility and the impact of the SVB crisis on key indices in the United States and Europe. Then, we analyse the Twitter activity and the corresponding sentiment that emerged throughout the event. Our data indicates that Twitter sentiment accurately mirrored the market's fluctuation and volatility. Moreover, employing readily available Large Language Models (LLMs) for sentiment analysis can potentially serve as an early indicator of market shifts and provide a cautionary signal in the event of a similar occurrence in the future.

Keywords: Bank Run, Stock Indices, GARCH Volatility, Artificial Intelligence, Sentiment Analysis, Social Media Influence.

JEL Classification: G15.

1. Introduction

In this paper, we refer to the holding company Silicon Valley Bank Financial Group as "SVBFG". We refer to the Silicon Valley Bank as "SVB". SVBFG filed for bankruptcy on March 17, after the failure of SVB.

On Wednesday, March 8, 2023, Silicon Valley Bank (SVB) announced a plan to restructure their balance sheet. According to the Federal Reserve analysis (The Fed, 2023) and the SVBFG reporting (Silicon Valley Bank, 2023), SVBFG had sold $21

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billion in available-for-sale (AFS) securities, booked a $1.8 billion after-tax loss, and it was planning to increase term borrowings by $15 billion to $30 billion and was seeking to raise $2.25 billion in capital (Silicon Valley Bank, 2023; Becker, 2023). This announcement worried investors. Founders Fund, a venture capital (VC) firm headed by Peter Thiel, one of the co-founders of PayPal, began to remove their cash from the bank. Furthermore, they recommended that their investors follow suit, instigating widespread panic. By Thursday, the rate of withdrawal for deposits not covered by insurance had increased significantly, reaching a total of US$42 billion. According to the Federal Reserve report (The Fed, 2023), there were other underlying concerns regarding the bank, which seemed to have been triggered by various interconnected factors: increased uncertainty and shifting mood towards the technology sector, as well as the possibility of adverse actions by credit rating agencies. Nevertheless, the decisive factor was the extensive network of venture capital investors and technology enterprises spearheaded by the Founders Fund's warning. These entities, driven by the influence of social media, systematically withdrew uninsured deposits at an unparalleled speed (Lang & Lang, 2023). On March 10, 2023, the California Department of Financial Protection and Innovation (DFPI) seized SVB and placed it under the receivership of the FDIC.

The bank run unfolded on March 9, 2023, a Thursday. By Thursday morning, VC companies had started withdrawing funds (Basel Committee on Banking Supervision, 2023). Our analysis below shows the shift in market indices, as well as the increased volatility of the markets as the crisis happened. There was also panic online, and rumours started to fly about an imminent collapse of the entire tech sector in Silicon Valley, and of many other banks. At noon, the CEO of SVB posted a tweet telling everyone to "Stay Calm", which angered the investors and accelerated the withdrawals. It was not until March 17, several days after the bank collapsed, that the President of the USA made a statement that all those affected will receive their deposits back as guaranteed by the Federal Reserve. A simple analysis of sentiment on Twitter that day reveals the panic and fear that took hold. The analysis was done using publicly available Large Language Models (LLMs) that are easy and cheap to use. On purpose, no advanced programming techniques were used. We show that even with a simple prompt, the signals of panic and negativity can be picked up by LLMs.

2. Problem Statement

Social media is the main source of information for all categories of people, and this has led to the way information is spread. As indicated in the existing literature, social media's significance for stock markets is on the rise (Bales et al., 2023; Bianchi et al., 2023). Since Twitter serves as a primary source of information for so many investors around the world today, tweets have the potential to exert powerful influences on people's individual trading behaviours. On the other hand, Twitter also represents an excellent platform through which people are able to transmit their sentiments and fears at incredible speeds, thus posing great risks. For instance, the GameStop saga presents one major event in which retail investors were able to push stock prices very high, therefore shaving massive losses for short-selling hedge funds (Umar et al., 2021). With Twitter reaching every nook and corner of the world, it can be of crucial importance to financial stability, although the potential effects of social media in causing bank runs are still relatively unexplored (Yousaf & Goodell, 2023). SVB was one of the biggest banks in the United States that focused on meeting the banking needs of tech startups and venture debt.

With over 50% of all US venture-backed companies and many VC firms as its customers, SVB gave banking facilities to many of the then-up-and-coming tech firms like Cisco Systems and Bay Networks (Sharma et al., 2023). The bank collapsed because of its overexposure to the risk-laden startups and the consequent panic amongst the investors and depositors after it disclosed its plans to raise funds to fill the gaps in its balance sheet. The sudden collapse of SVB stranded billions of dollars, hurting companies, investors, depositors, shaking the startup industry, and rocking banking sector stocks. Event studies have become highly diffused in recent times for evaluating the effects of key global events, such as the COVID-19 pandemic (Alabbad & Schertler, 2022; Guadalupe et al., 2023; Pandey & Kumari, 2021; Yarovaya et al., 2021, 2022) and the Russian-Ukrainian war (Boubaker et al., 2022; Martins & Gresse von Wangenheim, 2023; Arfaoui & Yousaf, 2022).

Lately, generative AI models have received much interest from the AI research community and the wider public because of their ability to answer a wide array of complex language-based problems.

These advances in the capability of the LLMs have been conditioned by several factors, including the increased number of model parameters, increased volume of training data, and better training settings. Advanced LLMs, such as Claude, Llama, and GPT-4, have a wide range of applications including translation, classification, creative writing, and code generation (Lee, 2024). In sentiment analysis, the LLMs have proven acceptably capable, specifically in few-shots scenarios (Zhang et al., 2023).

In this paper, we set to use LLMs to identify sentiment analysis in the market at the time of a market crisis and map the sentiment to the market volatility experienced across all global markets.

3. Aim of the Research

The purpose of this paper is to add to the analysis of the bank run crisis for SVB in March 2023. We trace the market volatility of the SVB stock throughout the day, as well as the impact on the national and international market indices. We then study the social media reactions to the crisis, and identify the sentiment changes and fluctuations, in order to visualise how they relate to the market instability.

4. Research Methods

For market volatility analysis, the main method used was multivariate GARCH model, called DCC GARCH (Dynamic Conditional Correlation). They are multivariate GARCH models designed to take into account interrelationships among a set of variables; in particular, volatilities. In the DCC-GARCH model, it investigates time-varying correlations. It combines the flexibility of univariate GARCH models with efficient parametric modeling of correlations and allows investigating dynamic correlations.

The BEKK-GARCH and DCC-GARCH models are both used for modeling conditional variances and correlations in financial data. The difference between them is basically in the way they estimate and update the conditional correlations. Whereas the BEKK-GARCH model directly estimates conditional correlation with the help of realised covariances, the DCC-GARCH model does it in an indirect way by first estimating conditional variances and then updating the correlations according to these variances. The DCC-GARCH model is of more flexible nature and allows for time-varying correlations; however, the BEKK-GARCH model assumes constant correlations over time. The conditional variances and correlations of these models have appeared in empirical research for purposes of inference and forecasting. Of the two, DCC-GARCH generally outperforms BEKK-GARCH in terms of forecasting performance.

First, estimation of the generalized VAR model is required in order to construct the DCC-GARCH model. Subsequently, the residuals are standardised using a univariate GARCH model. This process not only addresses asymmetries in volatility and shock transmission but also accounts for time-varying cross-correlations among the variables.

VAR (1) : $X1,t = \alpha1+\beta11,1X1t-1+\beta12,1X2,t-1+\varepsilon t$

$\varepsilon t \approx \text{Dist}\ (0,Ht)$

$Ht = DtPtDt$

$Dt = \text{diag}\{\ \sqrt{}\ h2t$

- Ht is the conditional variance matrix of the DCC model,

- Dt is the diagonal matrix of ht of univariate GARCH models

- Pt is the correlation matrix that contains expressions from univariate GARCH models

$Pt = Qt^{*}\text{-}1\ Qt\ Qt^{*}\text{-}1$

$Qt = (1\text{-}\ \alpha DCC - \beta DCC)\ Qt^{*})+ \alpha DCC\ \varphi\ t-1 + \beta DCC\ Qt\text{-}1$

- Qt is the conditional covariance matrix,

- Qt* is the unconditioned covariance matrix

- $\varphi t - 1$ is the matrix of standardised residues.

- αDCC and βDCC involve the persistence of shocks. Their amount, which measures the persistence of volatility, must be less than 1.

The second part of the paper is based on sentiment analysis methods. The tweets data set was downloaded from Kaggle (Kaggle, 2023), a platform where data scientists share data and models. The data set structure is shown in Table 1.

Table 1. Tweet data set structure

	date	id	tweet	username	likecount	retweetcount
0	2023-04-03 23:57:12+00:00	1.64E+18	The Biden administration, placing blame on Trump-era rollbacks, called on federal banking regulators to reinstate safeguards for regional banks after the record-setting collapse of Silicon Valley Bank and Signature Bank of New York earlier this month. https://t.co/KqLxvOlFPW	TiffinOhioNews	0	0
1	2023-04-03 23:56:59+00:00	1.64E+18	@1Nicdar With a quick call to his Washington democrats, the Nuiscense saved his millions locked up in the Silicon Valley Bank. But only democrats can do this.	DennisDhg2	0	0

Source: Kaggle.

There were originally 279804 tweets, covering from March 1, 2023 to April 1, 2023.

We cleaned up the data set with the following operations:

- Deleted tweets that were not in English, or had illegible characters
- Only kept the tweets for March 9, 2023 (total 1,291 tweets)
- Deleted the columns for username, retweets, and likes.

We used two LLMs (Claude 3 Sonnet and Copilot/ChatGPT4.5) and we asked them to perform a sentiment analysis on a data set of tweets from the day of the crisis. The clean data file was uploaded to ChatGPT first (Microsoft Copilot in Bing, www.bing.com) and to Claude (claude.ai).

Both LLMs used their own scale to rate sentiment, without any prompting or direction from us. ChatGPT/Copilot created a Neutral category as well, however, when manually reviewing the tweets these were mostly retweets of the big news, so we made the decision to count them as Negative (second sheet in the Excel file, we have both tables with Neutral category and without).

We focused on the day of the crisis, March 9, 2023, only during market open hours (9 am to 4 pm EST). The resulting graphs are in the appendix.

Possible biases in our methodology:

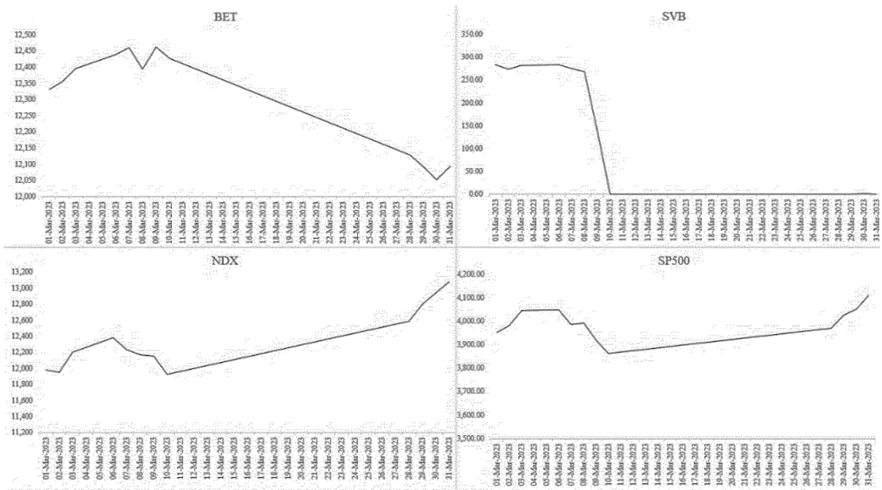
1) The Kaggle data set is manually provided by a Kaggle user, so it could be missing data. However, from our empirical observations, it accurately reflected the number of tweets and the sentiment of the market that day.
2) The number of tweets analysed (1,291) is statistically small, but it still provided enough information. On March 1, there were 10 tweets about SVB. On March 2, there were only 5. Having 1,291 tweets in a day is significant in this situation and it does reflect the flurry of activity and the negative sentiment that was present during the crisis.
3) LLMs are generating answers each time with variations, so reproducibility of the exact conversations is not possible. However, we ran the same queries several times and the results were extremely similar. We chose a representative query and results for each LLM.
3) Both LLMs, ChatGPT and Claude, used their own scale to score sentiment without our guidance or prompting. We wanted to prove that it is useful to use the LLMs in this manner, and it will still capture the sentiment accurately. We wanted to show that even out-of-the-box, simple prompt LLMs can provide some level of warning and can be used by analysts without any technical complexity to possibly identify and prevent another bank run.

5. Findings

The SVB stock SVB lost 87% of its stock market value between March 8 and March 10 (in pre-market trade). The stock closed down 60% on March 9, and continued to plunge another 65% in premarket trade before trade in the shares was halted, according to the Wall Street Journal (WSJ, 2023).

For the market volatility analysis, we used the market data sets publicly available. The historical prices of the variables are presented in Figure 1.

Figure 1. Historical values for market indices



Source: authors' own research.

Notably, all four variables recorded a substantial decline between March 8 and March 10, 2023. A correlation between these variables becomes apparent. Particularly, the highest impact is highlighted in the SVB index series, evidenced by a precipitous 48.09% decrease on March 9 from its value the day before, and subsequently reaching a value of 0.00 on the following day. This significant impact cascaded to other indices, precipitating notable decreases in their respective values as well.

The Table 2 represents the estimation of DCC-GARCH parameters.

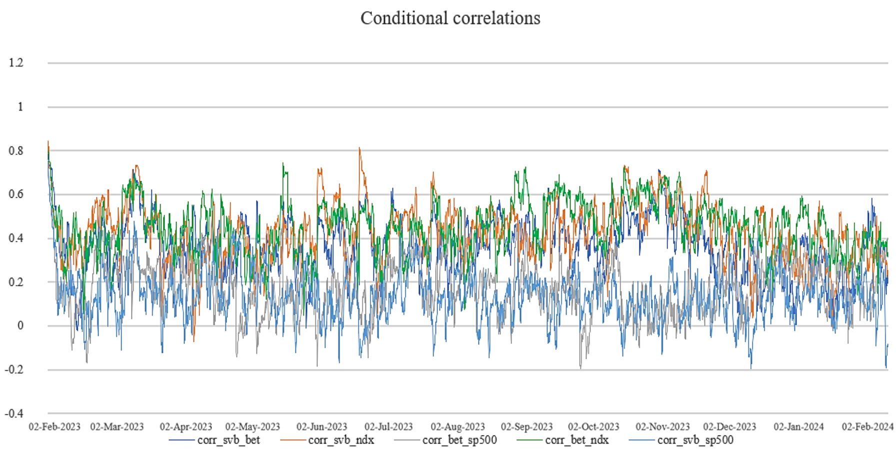
Table 2. DCC-GARCH Parameters

	ω	α1	β1	γ	Skew
BET	0.0000	0.1326	0.0000	1.0000	1.2257
SVB	0.0000	0.7239	0.4206	0.4156	1.2076
NDX	0.0000	0.1245	0.2095	0.9701	0.9656
S&P500	0.0000	0.0521	0.8092	1.0000	0.8856
αDCC	0.215082				
βDCC	0.78445				

Source: authors' own research.

All ARCH and GARCH coefficients, denoted as α and β respectively, exhibit statistical significance, involving the fact that when the market moves, volatility reacts strongly and it takes a while for things to settle down. High values of the β coefficient for all variables suggest that volatility tends to stick around for a while between these variables. The γ term is also significant across the board, hinting at how good or bad news affects volatility differently. With γ being negative, it means that bad news tends to shake things up more than good news. Moreover, the skew coefficient for residue distribution is also significant, and it can claim that the Skew t-Student distribution fits our leftover data best.

Figure 2. Conditional correlations



Source: authors' own research.

The graphical evidence presented in Figure 2 shows that the correlations between indices are not constant but are intensified during major events, especially during the SVB bank run of March 2023. In addition, the graph shows periods of positive and negative correlations.

One important aspect that should be mentioned is that all pairs they seem to move in the same way between March 8 and March 10, the difference being the intensity of the movement which underlines the connection between the variables.

Analysing the pairs correlations, it can be stated that of all the pairs, the correlation of the pair SVB and NDX is the strongest. This is explained by the geographical position, but more importantly, by the close trade relationship between the two entities.

5.1 Twitter Sentiment Analysis

For the Twitter analysis, we used the SVB Crisis Tweets dataset from Kaggle (Kaggle, 2023). The data was cleaned up to only keep tweets in English, and to ignore usernames and numbers, or likes and retweets. The dataset used for our sentiment analysis has the following format: message ID, date and time stamp, tweet text.

Only tweets from March 8 to March 10, 2023, were analysed. There were a total of 19 tweets about SVB on March 8, 2023. There was a total of 1,341 tweets about SVB on March 9, 2023. There was a total of 25,647 tweets about SVB on March 10th, 2023. The sentiment analysis was performed on the tweets from March 9 only, when the crisis unfolded. A total of 1,291 tweets were used for the sentiment analysis, after removing non-English tweets. There is no identifiable business contact information in the dataset, so it is not possible to determine how many of those who used the social media website were SVB customers or stakeholders.

A word cloud for the March 9 tweets reflects the most discussed terms and clearly shows worry and negative sentiment (Figure 3).

Figure 3. Word cloud for March 9th SVB tweets

Source: authors' own research.

Method 1. We used Microsoft Copilot (ChatGPT Large Language Model) for the sentiment analysis. We uploaded the comma-delimited file with tweets.

Results

ChatGPT did not detect the fear, panic, or overall negativity that was spreading through Twitter. Retweets of the negative news items are just marked as Neutral.

Table 3. Copilot Results

Date	Hour	Negative	Positive
09/03/2023	09:00	4	0
09/03/2023	10:00	6	1
09/03/2023	11:00	4	0
09/03/2023	12:00	4	1
09/03/2023	13:00	7	2
09/03/2023	14:00	8	2
09/03/2023	15:00	14	4
09/03/2023	16:00	9	7

Source: author's own research.

Method 2. Large Language Model: Claude 3 Sonnet

Results

Claude's analysis is much better, more detailed, more in-depth, and captures the exact sentiment of the market at that time. Copilot has marked retweets of the news stories as "Neutral", if there were no other words added. To compare the two methods, we consolidated the Neutral and Negative tweets.

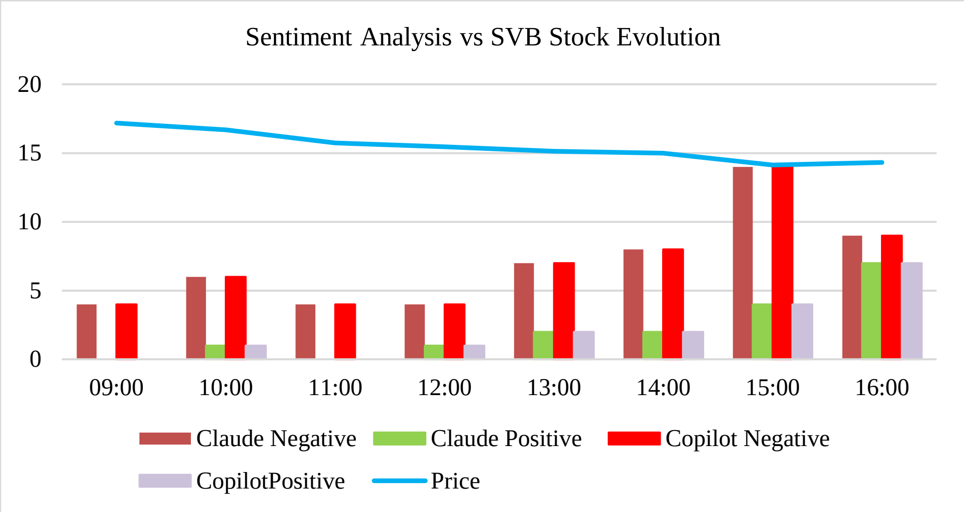
Table 4. Claude Results

Date	Hour	Negative	Positive
09/03/2023	09:00	11	0
09/03/2023	10:00	8	0
09/03/2023	11:00	6	0
09/03/2023	12:00	10	0
09/03/2023	13:00	3	0
09/03/2023	14:00	5	0
09/03/2023	15:00	4	0
09/03/2023	16:00	5	0

Source: authors' own research.

The resulting chart is shown in Figure 5. As we can see, both the sentiment analysis with each method correlates tightly with the stock price tendency and generally with the market indices across US and Europe and paint a clear picture of a crisis in development.

Figure 4. Combined Sentiment Analysis



Source: authors' own research.

Given that the prompts were kept as simple as possible, both models returned valid analyses. The negative sentiment is shown throughout the day. Even if ChatGPT is more inclined to see likes and retweets as positive or neutral, it still captures the negative values and the overall crisis as the volume of tweets increases drastically.

6. Conclusion

We posed the question if we could use an LLM's native sentiment analysis capabilities to identify signals in the market that could possibly indicate an upcoming crisis such as a bank run. We showed that it is possible, and the LLMs correctly picked up as the crisis unfolded.

Panic set in immediately and spread fast. SVB was seen as the bank supporting all tech start-ups in Silicon Valley. Wild theories and rumours started to appear: Etsy buyers worried they will have no cash payments available (Archive 2023); companies such as Facebook or Apple could run out of funds; partner banks of SVB could stop working (Archive 2023); crypto currency would become worthless if crypto startups remain without funds; regional banks would be overwhelmed trying to support the firms and would collapse as well. A list of possible banks in the US that were "ready to collapse" circulated on Twitter in the next days, with most US banks on the list. By March 15, 2023, Credit Suisse in Europe was rumoured to also collapse because of SVB, even though the two banks were not connected in any way:

“Credit Suisse has been a slowing-moving car crash for years,” wrote Peter Boockvar, chief investment officer of Bleakley Financial Group. “But now today’s news of course is happening in the vortex of SVB” (Morrow, 2023).

The speed of the withdrawals was unprecedented and a reflection of the ease of doing so using technology. “The fact that people can communicate so much more quickly ... (has) changed the dynamic of bank runs and perhaps changed the way we have to think about liquidity risk management”, said Todd Baker, a senior fellow at Columbia University's Richmond Centre (Lang 2023). While the bank run could have happened as well without Twitter, the social media site contributed to the panic and negative sentiment about the bank and to the speed of withdrawals.

Since most people receive their news online and follow the same important influencers that disperse information, it makes sense that the regulatory agencies should also monitor social media with great attention. “In theory, a robust system of internal controls at individual banks would include constant social media monitoring for depositor rumours and panic as well”, Patricia McCoy, professor at Boston College Law, told Regulatory Intelligence. “This is particularly important for larger banks that pose the risk of contagion to the larger financial system...Recent events tell us that regional banks can spark systemic risk, just as megabanks” (Lang 2023).

Using LLMs to constantly process social media-selected posts for financial stocks and categorise for sentiment can offer an early view into any rumours or stories that could affect the markets. In our paper, Claude LLM performed a better analysis with a simple prompt, however, with advanced prompting or Retrieval Augmented Generation (RAG) methods, better sentiment analysis results are possible with Claude and other LLMs. We wanted to show that even out-of-the-box, simple prompt LLMs can provide some level of warning, and can be used by analysts without any technical complexity.

If the Federal Reserve had seen the trend in sentiment on Twitter that day, they could have stepped in and made an official announcement about the investors having their money safe. If SVB would have read the sentiment on Twitter correctly, they could have devised a much more effective message than a condescending “Stay Calm”. Both of these actions could have stopped the spread of panic and negativity and maybe avoided the bank run altogether.

The LLMs currently available will evolve and get even better. Because they are pre-trained, anyone can use them for a low price. Companies must take advantage of the new technology and use it to monitor spikes of negativity, so they are hopefully able to step in and avert the next bank run.

Bibliography

[1] Archive, V.A., Twitter, F. on and feed, G. author R. (2023). Nearly 200 banks could fail the same way SVB did: study. [online] Available at: https://nypost.com/2023/03/18/nearly-200-banks-could-fail-the-same-way-svb-did-study/ [Accessed 28 May 2024].

[2] Arfaoui, N., Yousaf, I. (2022). Impact of COVID-19 on volatility spillovers across international markets: evidence from VAR asymmetric BEKK GARCH model. Annals of Financial Economics, 17(01), 2250004.

[3] Bianchi, F., Kung, H., Tirskikh, M. (2023). The origins and effects of macroeconomic uncertainty. Quantitative Economics, 14(3), 855-896.

[4] Basel Committee on Banking Supervision (2023). Report on the 2023 banking turmoil. Retrieved from https://www.bis.org/bcbs/publ/d555.pdf.

[5] Becker, G. (2023). Message to Stakeholders Regarding Recent Strategic Actions Taken by SVB. [online] Available at: https://s201.q4cdn.com/589201576/files/doc_downloads/2023/03/r/Q1-2023-Investor-Letter.FINAL-030823.pdf.

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

[7] Guadalupe, A., Castillo, R., Serna, G.J., Arocutipa, J.P., Berrios, H.Q., Antonio, M., Rodriguez, M., Yanowsky, G., Lopez, H.R., Marina, R., Teves, V., Victor, H., Rivera, H., Arias-Gonzáles, J.L. (2023). Effect of Chat GPT on the digitized learning process of university students. Journal of Namibian Studies : History Politics Culture.

[8] Kaggle (2023). SVB Crisis Tweets dataset, https://www.kaggle.com/datasets/xreyas/svb-crisis-tweets?resource=download , accessed 21st April 2024.

[9] Lee, J., Stevens, N., Han, S. C., Song, M. (2024). A Survey of Large Language Models in Finance (FinLLMs). ArXiv (Cornell University). https://doi.org/10.48550/arxiv.2402.02315.

[10] Morrow, A. (2023, March 15). Analysis: Why banking fears just came roaring back | CNN Business. CNN. https://edition.cnn.com/2023/03/15/business/bank-fears-svb-credit-suisse#:~:text=The%20result%20is%20a%20lot%20of%20fretting%20about.

[11] Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., Sutskever, I. (2019). Language Models are Unsupervised Multitask Learners. [online] Available at: https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf.

[12] Silicon Valley Bank (2023). SVB Financial Group Announces Proposed Offerings of Common Stock and Mandatory Convertible Preferred Stock. [online] ir.svb.com. Available at: https://ir.svb.com/news-and-research/news/news-details/2023/SVB-Financial-Group-Announces-Proposed-Offerings-of-Common-Stock-and-Mandatory-Convertible-Preferred-Stock/default.aspx.

[13] SVB Crisis Tweets dataset, Kaggle, https://www.kaggle.com/datasets/xreyas/svb-crisis-tweets?resource=download, accessed 21st April 2024.

[14] The Fed (2023). Executive Summary, Review of the Federal Reserve's Supervision and Regulation of Silicon Valley Bank. Retrieved from https://www.federalreserve.gov/publications/files/svb-review-20230428.pdf.

[15] Lang, H. and Lang, H. (2023). Analysis: Social media-driven bank runs burden regulators with a bigger problem. Reuters. [online] 21 Mar. Available at: https://www.reuters.com/business/finance/social-media-driven-bank-runs-burden-regulators-with-bigger-problem-2023-03-21/.

[16] Alabbad, A., Schertler, A. (2022). COVID-19 and bank performance in dual-banking countries: an empirical analysis. COVID-19 and bank performance in dual-banking countries: an empirical analysis. Journal of Business Economics, 92, 1511-1557.

[17] Pandey, D.K., Kumari, V. (2021). Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak. International Review of Economics & Finance, 71(C), 467-483.

[18] Yarovaya, L., Brzeszczyński, J., Goodell, J.W., Lucey, B., Lau, C.K.M. (2021, 2022). Rethinking financial contagion: Information transmission mechanism during the COVID-19 pandemic. Journal of International Financial Markets, Institutions and Money, 79, 101589.

[19] Martins, R.M., Gresse von Wangenheim, C. (2023) - Findings on Teaching Machine Learning in High School: A Ten-Year Systematic Literature Review. Informatics in Education, 22(3), 421-440.

[20] Bales, A. (2023). Will AI Avoid Exploitation?. Retrieved from https://globalpriorities institute.org/wp-content/uploads/Adam-Bales-Will-AI-Avoid-Exploitation.pdf.

[21] Yousaf, I., Goodell, J.W. (2023). Responses of US equity market sectors to the Silicon Valley Bank implosion. Finance Research Letters, 55, 103934.

[22] Sharma, S., Aggarwal, V., Dixit, N., Yadav, M. (2023). Time and Frequency Connectedness Among Emerging Markets and QGREEN, FinTech and Artificial Intelligence-Based Index: Lessons from the Outbreak of COVID-19. Vision, 1-11.

[23] Umar, Z., Aziz, S., Tawil, D. (2021). The impact of COVID-19 induced panic on the return and volatility of precious metals. Journal of Behavioral and Experimental Finance, 31, 100525.

[24] WSJ: Stock Halted After Sharp Selloff; Bank Exploring Possible Sale. (n.d.). WSJ. Retrieved May 28, 2024, from https://www.wsj.com/livecoverage/stock-market-news-today-03-10-2023/card/svb-stock-price-slides-another-29-premarket-gdGa9ANN0vNES UUorGqm?mod=hp_lead_pos1.

[25] WSJ (2023). Stock Halted After Sharp Selloff; Bank Exploring Possible Sale. (n.d.). WSJ. Retrieved May 28, 2024, from https://www.wsj.com/livecoverage/stock-market-news-today-03-10-2023/card/svb-stock-price-slides-another-29-premarket-gdGa9ANN0vNES UUorGqm?mod=hp_lead_pos1.

[26] Zhang, W., Deng, Y., Liu, B., Pan, S.J., Bing, L. (2023, May 24). Sentiment Analysis in the Era of Large Language Models: A Reality Check. ArXiv.org. https://doi.org/ 10.48550/arXiv.2305.15005.