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Silicon Valley Bank bankruptcy and Stablecoins stability

Luca Galati [a,b,c,*], Francesco Capalbo [c]

[a] Rozetta Institute (formerly CMCRC-SIRCA), 1 Macquarie Street, Sydney, 2000, NSW, Australia
[b] School of Business, University of Wollongong, Northfields Ave, Wollongong, 2522, NSW, Australia
[c] Department of Economics, University of Molise, Via Francesco De Sanctis, Campobasso, 86100, CB, Italy

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ABSTRACT

To what extent does the collapse of a commercial bank spread contagion across cryptocurrency markets? How do markets behave around bankruptcy if digital assets remain stuck within the bank and cannot be withdrawn? We use a BEKK model to examine contagion effects across major digital assets during the Silicon Valley Bank (SVB) collapse period in early March 2023. We find evidence of contagion across major stablecoins and Bitcoin. We also examine the price action when nearly all withdrawals at SVB were prohibited. We find substantial abnormal movements in stablecoin cumulative returns and traded volumes, indicating a "flight to safety" from less to more authoritative and trusted stablecoins. The implications for practitioners and policymakers are discussed.

1. Introduction

Cryptocurrencies are gradually gaining traction in trading and becoming a notable segment of the financial landscape, providing new investment avenues. However, their inherent volatility continues to hinder their broader acceptance. Among cryptocurrencies, a subset known as stablecoins, which is intended to maintain a "stable" peg to a reference currency, is crucial to the market as it allows traders to work around the volatility issue and keep money in a form equal to US dollars (De Blasis et al., 2023). Access to those digital assets is typically given by new financial technologies (also called Fintech) such as digital wallets or Centralized cryptocurrency Exchanges (CEXs), with the aim of decentralizing finance through innovative offers of financial services. However, due to the high costs associated with the trading of cryptocurrencies in US dollars, the impossibility of using US dollars on cryptocurrency exchanges,[1] and the simplicity and speed of transferring those virtual assets between exchanges, stablecoins occasionally trade at a premium[2] to the underlying asset they imitate (De Blasis et al., 2023). The recent bankruptcy of Silicon Valley Bank (SVB), the largest commercial bank for nearly half of all venture-backed tech startups in Silicon Valley,[3] in March 2023 tied up \$3.3 out of \$40 billions of stablecoins in its financial statement, making this exogenous shock a significant event to study.

Thus, the aim of this research is to examine the impact of bank failure on the stability of stablecoin markets. Specifically, we examine the question of whether halting access to digital assets through the bankruptcy procedure of a traditional finance institution spills over contagion effects across those innovative instruments. Answering this question is important as the March 2023 collapse of SVB, together with the ensuing instability in a number of major stablecoins, demonstrated the importance of the interlinks between traditional and digital financial systems. The results of this research are therefore relevant to policymakers in both the traditional and modern financial systems interested in avoiding the risk of financial contagion, as well as investors willing to defend their savings and balance their portfolios against market uncertainty.

In this study, we use proprietary intraday data and a BEKK-GARCH multivariate model over a sample period of 14 days surrounding the SVB failure in March 2023 to test financial contagion across digital assets. We find evidence of volatility spillover effects across major stablecoins and Bitcoin during the collapse period. We also examine the price and volume actions when all withdrawals at SVB were

* Corresponding author at: School of Business, University of Wollongong, Northfields Ave, Wollongong, 2522, NSW, Australia.
E-mail address: luca.galati@rozettainstitute.com (L. Galati).

[1] For example, Binance, the world-largest cryptocurrency CEX, does not allow investors to trade against the US dollar, but rather promote trading of cryptocurrency pairs against its own token, BNB, or stablecoin, the Binance dollar (BUSD).

[2] See, e.g., Frino et al. (2022) for a better understanding of premiums and discounts as well as their market impact.

[3] Source: The Guardian (https://www.theguardian.com/technology/2023/mar/15/silicon-valley-bank-failure-industries-investors-rattled).

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prohibited. We find substantial deviations from the $1 peg, indicating a "flight to safety" from less to more authoritative and trusted stablecoins. In addition, trading volumes skyrocketed after fear of losing billions of reserves exposed in SVB, with USDC reaching an all-time high.[4] While catastrophic scenarios of market crashes have been seen to be circumscribed to the cryptocurrency ecosystem,[5] negative reactions to the collapse of traditional financial institutions can still spread across digital markets, which in turn have serious implications for regulators, investors, and researchers alike.

This study contributes to the body of knowledge about financial market contagion in periods of crises and volatility spillover effects in cryptocurrency markets. The former topic has been looked at by a large number of studies focusing on the Global Financial Crisis (*e.g.*, Baur, 2012; Fry-McKibbin et al., 2014; Kenourgios & Dimitriou, 2015), some of which have focused on emerging markets (Boubaker et al., 2016; Celık, 2012), Asian markets (Yiu et al., 2010), European markets (Syllignakis & Kouretas, 2011), or foreign exchange markets (Diebold & Yilmaz, 2012; Ding & Vo, 2012). The Covid-19 Pandemic is another example of a crisis that has also been investigated by a large body of research (Akhtaruzzaman et al., 2021; Nguyen et al., 2022; Samitas, Kampouris et al., 2022; Samitas, Papathanasiou et al., 2022; Uddin et al., 2022). The literature mentioned above finds that financial markets respond by dispersing the impacts of volatility across various markets and nations during times of market unrest or economic shocks. The current study provides new evidence of financial contagion in the innovative cryptocurrency ecosystem during tumultuous times, such as the SVB collapse.

The second area of research has also been the subject of numerous more recent studies, which discover that changes in the price of Bitcoin drive the connections between other digital assets. These include works that focus solely on cryptocurrencies (Ampountolas, 2022; Moratis, 2021), on cryptocurrencies and foreign exchange markets (Hsu, 2022; Wang, 2022), on markets for non-fungible tokens (NFTs), on alternative coins (altcoins) (Nguyen et al., 2019), on Bitcoin, gold, and the US dollar (Dyhrberg, 2016), and on stablecoins (De Blasis & Webb, 2022). In particular, De Blasis et al. (2023) similarly analyze the issue of contagion effects in stablecoin markets, albeit it looks at a stablecoin (UST) crash within the market itself. Galati et al. (2023), on the other hand, investigate financial contagion across cryptocurrency exchanges, but do so with regards to blockchain technology (FTX) collapse. As such, this study extends both De Blasis et al. (2023) and Galati et al. (2023) as it enables us to test whether a new dimension of failure (that of a commercial bank) has an impact on cryptocurrency markets.

Recent studies have also looked at the impact of the SVB collapse more broadly. By using a model similar to ours on financial markets, banks, and financial and non-financial firms, Akhtaruzzaman et al. (2023) investigate whether the latter catalyzed financial contagion across major countries, finding short-lived evidence consistent with their claim in global banks. Perdichizzi and Reghezza (2023) analyze the spillover effects to the euro area banking sector from the SVB fallout. They discover an average 10% decline in European banks' cumulative returns, although investors displayed limited response to the shared vulnerabilities among euro area banks but were concerned about the potential adverse effects on banks' balance sheets. Yousaf and Goodell (2023) examine the responses of U.S. equity market sectors to the SVB implosion through an event study and show that not surprisingly the financial sector is almost the only negatively impacted. Pandey et al. (2023) look at the SVB bankruptcy effect on global financial markets through, again, an event study, and find that it triggered panic and uncertainty leading to negative returns worldwide, although not uniformly across countries with different levels of bank solidity and market development. Similarly, Yousaf et al. (2023) examine the same impact of SVB bankruptcy on global financial markets, Bitcoin included, and show insignificant returns for most fiat currencies, metals, and energy markets. They conclude that the SVB event had a narrow effect on the global financial system, affecting a small number of markets, despite highlighting possible contagion points. Our research extends these prior works by looking at the impact of SVB bankruptcy on the stability of stablecoins, a market that was instead significantly affected by large abnormal movements and inefficiency driven by traders' behavior.

To the best of our knowledge, this is the first study attempting to examine whether halting access to digital assets through the bankruptcy procedure of a traditional finance institution spills over contagion effects across those innovative instruments. This has implications for academics, practitioners, and policymakers who are concerned about the interlinks between centralized and decentralized finance. The study's uniqueness is twofold: it uses proprietary minute-by-minute data of major crypto assets and it analyzes a singular exogenous event — the biggest bank failure after the 2007–2008 financial crisis,[6] which permits a clean setting to test for our hypothesis.

The rest of the paper proceeds as follows. Section 2 provides some background details. Section 3 overviews the empirical approach used to test financial contagion. Section 4 describes the data, while Section 5 discusses the findings. The final Section 6 concludes.

2. Background

As shown in Akhtaruzzaman et al. (2023), the actions around the collapse of SVB arguably represented a global bank run, with contagion spreading from mid-market US banks to international players like Credit Suisse. On March 8th, 2023, Silvergate Capital, a bank with a focus on cryptocurrencies, experienced a bank crisis and announced that it would cease operations. On March 10th, SVB failed and was taken over by US regulators.[7] On March 12th, Signature Bank, which also faced a bank run, was seized by regulators. On the same day, the Federal Deposit Insurance Corporation (FDIC) announced a "systemic risk exception" that allows depositors with sums in excess of the federally insured limit of $250,000 to be paid back in full. Perhaps most notably, the game company Roblox had a reported $150 million in deposits, and had stood to potentially lose that money had this exception not been made. On March 19th, after a volatile period of trading and speculation, it was announced that UBS would take over Credit Suisse, which had suffered an extensive series of withdrawals and swirling questions over its viability.

At approximately 3 o'clock in the morning of March 11th, Circle Internet Financial Ltd., the company that created and operates the USD Coin (USDC) - the second largest stablecoin,[8] tweeted that 8% of their USDC reserves remained stuck at SVB after the stop of processing balances removal from the bank.[9] Instant reactions dragged USDC down to less than 87 cents,[10] starting a de-pegging process that stabilized only after days when US authorities announced plans to limit the fallout.[11] Other major virtual currencies experienced a similar

[4] See news on Kaiko Research at https://blog.kaiko.com/the-aftermath-what-happened-to-usdc-581289be30ff.

[5] See, e.g., the Terra sister token (LUNA) crash or the FTX cryptocurrency exchange bankruptcy.

[6] See news article on CNBC at https://www.cnbc.com/2023/03/10/silicon-valley-bank-is-shut-down-by-regulators-fdic-to-protect-insured-deposits.html.

[7] See news article on Bloomberg at https://news.bloomberglaw.com/bankruptcy-law/silicon-valley-bank-fails-as-fdic-takes-over-appoints-receiver.

[8] As of March 2023, USDC is also the fifth largest cryptocurrency in terms of market capitalization. Source: CoinMarketCap (https://coinmarketcap.com/).

[9] See news at https://twitter.com/circle/status/1634391505988206592.

[10] See news article on The Wall Street Journal at https://www.wsj.com/articles/crypto-investors-cash-out-2-billion-in-usd-coin-after-bank-collapse-1338a80f, or on CNBC at https://www.cnbc.com/2023/03/11/stablecoin-usdc-breaks-dollar-peg-after-firm-reveals-it-has-3point3-billion-in-svb-exposure.html.

[11] See news article on Reuters at https://www.reuters.com/technology/bitcoin-usdc-stablecoin-rally-after-us-intervenes-svb-2023-03-13/.

Table 1
Descriptive statistics of Stablecoins returns. The table shows the descriptive statistics for pre-collapse, collapse, and the entire period. *Jarque–Bera* represents the test statistics from the normality test (expressed in $\times 10^6$). *ADF* represents the augmented Dickey–Fuller test. $ARCH(6)$ and $ARCH(12)$ correspond to the test statistics from the ARCH test with 6 and 12 lags respectively. $Q(6)$, $Q(12)$ and $Q^2(6)$, $Q^2(12)$ represent the test statistics from the Ljung–Box test for serial correlation in returns and squared returns with 6 and 12 lags respectively.

	BTC	USDT	BUSD	DAI	TUSD	USDC
Panel A: pre-collapse period (04 March 2023–10 March 2023)						
Mean	−0.0008	0.0001	0.0000	0.0000	0.0000	−0.0001
Median	−0.0004	0.0000	0.0000	0.0000	0.0000	0.0000
Max	0.9679	0.5147	0.5248	4.4031	1.8497	1.6939
Min	−1.3052	−0.702	−0.7222	−3.8063	−1.788	−1.7974
Std. Dev.	0.0596	0.0247	0.0257	0.1593	0.0779	0.0691
Skewness	−1.0801	−1.2571	−0.6057	2.7631	0.7437	−0.1871
Excess Kurtosis	50.9695	143.7236	137.2059	232.0868	146.2333	150.4288
Jarque–Bera	1.0931***	8.6784***	7.9073***	22.6358***	8.9823***	9.5042***
ADF	−16.1***	−11.1***	−22.0***	−25.1***	−27.2***	−24.0***
ARCH(1)	1387.8***	1450.4***	1133.3***	1146.2***	19.7***	2350.6***
ARCH(6)	2116.1***	1594.1***	1308.1***	1381.1***	1480.5***	2760.4***
ARCH(12)	2136.4***	2145.3***	1879.9***	1425.3***	1509.0***	2905.9***
Q(6)	95.8***	1549.3***	1399.1***	1680.2***	1069.0***	1891.8***
Q(12)	98.1***	1750.4***	1542.1***	1799.4***	1074.5***	1951.0***
$Q^2(6)$	3044.6***	2449.5***	1985.2***	2072.4***	1289.6***	2544.1***
$Q^2(12)$	3180.8***	4527.7***	3814.7***	2333.4***	1290.2***	2939.1***
Panel B: collapse period (11 March 2023–18 March 2023)						
Mean	0.0025	−0.0001	0.0000	0.0000	0.0000	0.0001
Median	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000
Max	2.4084	1.677	1.667	5.299	3.9666	40.4417
Min	−2.3581	−1.7045	−1.7245	−5.8086	−3.9666	−42.5359
Std. Dev.	0.1842	0.0694	0.0976	0.4167	0.1404	0.8132
Skewness	0.4252	−0.205	−0.1781	−0.0236	−3.2186	−1.6607
Excess Kurtosis	38.4966	132.8432	34.0716	43.5506	438.079	1193.9417
Jarque–Bera	0.7117***	8.4708***	0.5573***	0.9104***	92.1382***	684.2437***
ADF	−17.4***	−23.2***	−21.2***	−17.1***	−20.4***	−21.5***
ARCH(1)	2019.3***	988.0***	1070.6***	1846.7***	0.0000	2852.5***
ARCH(6)	2284.9***	1472.9***	1622.4***	1996.6***	279.3***	4764.4***
ARCH(12)	2373.5***	1746.8***	1912.3***	2084.4***	457.1***	5014.2***
Q(6)	735.0***	1750.3***	18 594.5***	2037.3***	236.9***	2511.6***
Q(12)	746.9***	1765.5***	34 641.6***	2081.5***	384.3***	2531.0***
$Q^2(6)$	2914.9***	1710.0***	2094.7***	3178.2***	274.2***	2853.6***
$Q^2(12)$	3389.2***	1876.6***	2421.0***	3994.5***	529.6***	2853.8***
Panel C: entire period (04 March 2023–18 March 2023)						
Mean	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	2.4084	1.677	1.667	5.299	3.9666	40.4417
Min	−2.3581	−1.7045	−1.7245	−5.8086	−3.9666	−42.5359
Std. Dev.	0.1406	0.0534	0.0734	0.3232	0.1155	0.5958
Skewness	0.4991	−0.3005	−0.2361	0.1275	−2.9733	−2.2525
Excess Kurtosis	63.1117	206.4942	59.7653	72.0902	524.3701	2213.1534
Jarque–Bera	3.5857***	38.3762***	3.2149***	4.6774***	247.4994***	4408.2616***
ADF	−21.2***	−23.8***	−25.1***	−22.6***	−25.6***	−25.6***
ARCH(1)	3867.7***	1892.3***	2115.0***	3443.8***	0.0000	5352.9***
ARCH(6)	4381.3***	2790.6***	3160.3***	3723.9***	517.1***	8937.6***
ARCH(12)	4554.1***	3290.7***	3694.1***	3904.7***	832.1***	9408.4***
Q(6)	1092.3***	3265.9***	31 603.7***	3779.0***	659.5***	4703.9***
Q(12)	1110.6***	3287.4***	58 540.1***	3873.8***	838.6***	4740.5***
$Q^2(6)$	5774.2***	3291.1***	4268.8***	6062.0***	509.3***	5354.0***
$Q^2(12)$	6834.8***	3638.9***	5069.2***	7673.8***	967.0***	5354.7***

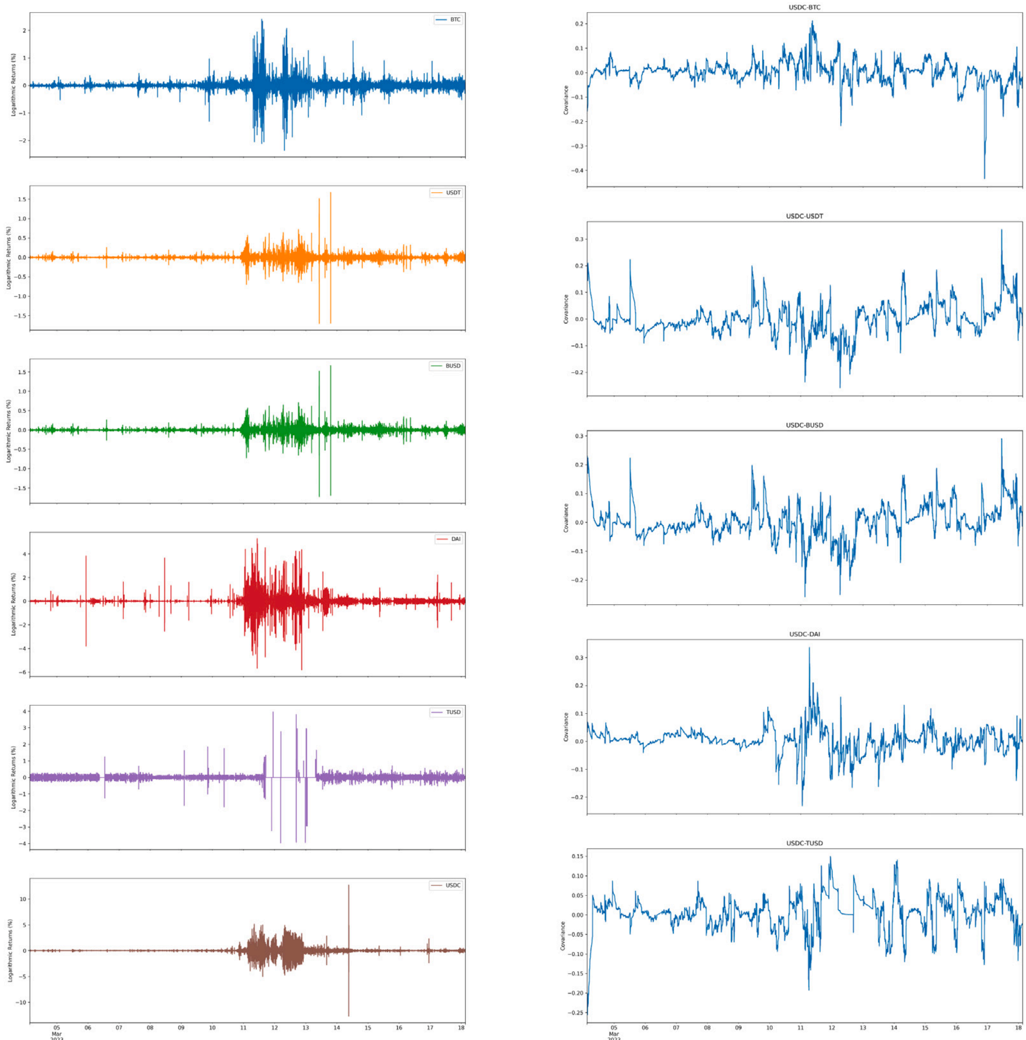
*** Indicates the rejection of the null hypothesis at the 1% significance level.

drop, such as the Marke Dao coin (DAI), while Tether (USDT), the third largest cryptocurrency by market capitalization and the biggest in terms of volume,[12] surged. Although stablecoins seek to maintain a constant peg of 1:1 against the US dollar, their price behavior during the SVB collapse was very diverse, with some trading at a premium and others at a discount, as in the crash analyzed by De Blasis et al. (2023). Since paying \$1.01 or 87 cents for a \$1 asset is uneconomic for investors balancing their portfolios and savings, suggesting also major concerns about the stability and potentially even the survival of stablecoins (De Blasis et al., 2023), it is thus important to shed light on the impact of bank failures on the stability of stablecoin markets.

[12] Source: CoinMarketCap (https://coinmarketcap.com/).

3. Statistical method

We employ a methodology similar to that used by De Blasis et al. (2023) and Galati et al. (2023), who use a BEKK-GARCH model to find evidence of contagion effects between stablecoins during the Terra token crash (De Blasis et al., 2023) and cryptocurrencies during the FTX collapse (Galati et al., 2023), to test for financial contagion across digital assets. Developed by Engle and Kroner (1995), the BEKK model belongs to the family of multivariate GARCH models used to assess conditional covariances and correlations, thus the interaction between time series, and is preferred over the similar DCC-GARCH model (Caporin & McAleer, 2012). Consistent with De Blasis et al. (2023) and Galati et al. (2023), we assume that the logarithmic returns follow a normal distribution with zero means and the variance–covariance matrix H_t,



(a) Stablecoins stationary returns (b) Stablecoins BEKK covariances

Fig. 1. Returns and covariances of major digital assets around the SVB bankruptcy. These figures show the stationary returns for the stablecoins and cryptocurrencies analyzed (in panel a) and the covariances between USDC, the affected stablecoin, and the other digital assets analyzed (in panel b). Logarithmic returns are computed as $ln(P_t/P_{t-1})$, where P_t is the price of the digital asset at time t. The period of investigation is from March 4, 2023, to March 18, 2023.

so that we can model the conditional covariances as

$$H_t = CC' + A\left(e_{t-1}e'_{t-1}\right)A' + BH_{t-1}B' \tag{1}$$

where C, A and B are parameters matrices with C being lower triangular.

As highlighted by De Blasis et al. (2023) and Galati et al. (2023), given the large number of parameters involved when examining numerous time series, the BEKK representation in (1) presents some challenges in the estimation process. To address this, the previous studies mentioned above employ a scalar version of (1) by applying the variance targeting concept to get rid of the term CC' and therefore reduce the parameters. Thus, the model becomes

$$H_t = (1-a-b)\bar{H} + a\left(e_{t-1}e'_{t-1}\right) + bH_{t-1},$$

where $\bar{H} = \sum_{t=1}^{T} e_{t-1}e'_{t-1}$ is the unconditional covariance matrix estimated from the full sample. In this scalar version, the parameters are only a and b, subject to a, $b > 0$ and $a + b < 1$. According to De Blasis et al. (2023) and Galati et al. (2023), these constraints are imposed to keep the process stationary and to guarantee the positive definiteness of the covariance matrices.

Once we obtain the conditional covariances, and thus the conditional correlations, we can perform the contagion test as proposed in De Blasis et al. (2023) and Galati et al. (2023). The hypothesis is as follows.

$$H_0 : \mu_{\text{pre}} = \mu_{\text{post}},$$

where μ_{pre} and μ_{post} are the matrices of the means of conditional correlations of the population during the SVB pre-collapse and collapse periods, respectively, with variances σ_{pre} and σ_{post}. Taking into account two samples with sizes n_{pre} and n_{post} and the matrices of the means of the conditional correlations computed from the BEKK model, $\bar{\rho}_{\text{pre}}$ and $\bar{\rho}_{\text{pre}}$ with variances $s^2_{\text{pre}} = \frac{1}{n_{\text{pre}}-1}\sum_{t=1}^{n_{\text{pre}}}\left(\rho_{\text{pre}} - \bar{\rho}_{\text{pre}}\right)^2$ and $s^2_{\text{post}} = \frac{1}{n_{\text{post}}-1}\sum_{t=1}^{n_{\text{post}}}\left(\rho_{\text{post}} - \bar{\rho}_{\text{post}}\right)^2$, we can compute the t-statistics as

$$t = \frac{\left(\bar{\rho}_{\text{post}} - \bar{\rho}_{\text{pre}}\right) - \left(\mu_{\text{post}} - \mu_{\text{pre}}\right)}{\sqrt{\frac{s^2_{\text{post}}}{n_{\text{post}}} + \frac{s^2_{\text{pre}}}{n_{\text{pre}}}}},$$

with degrees of freedom

$$v = \frac{\left(\frac{s^2_{\text{post}}}{n_{\text{post}}} + \frac{s^2_{\text{pre}}}{n_{\text{pre}}}\right)^2}{\frac{\left(\frac{s^2\text{post}}{n_{\text{post}}}\right)^2}{n_{\text{post}}-1} + \frac{\left(\frac{s^2\text{pre}}{n_{\text{pre}}}\right)^2}{n_{\text{pre}}-1}}.$$

Table 2
BEKK dynamic conditional correlation matrices. Pre-collapse period is from 2023.03.04 to 2023.03.10. Collapse period is from 2023.03.11 to 2023.03.18.

	BTC	USDT	BUSD	DAI	TUSD	USDC
Panel A: pre-collapse period (04 March 2023–10 March 2023)						
BTC	1	0.0088	0.0079	0.0008	0.0357	0.0159
USDT	0.0088	1	0.9596	0.0716	−0.0069	−0.0235
BUSD	0.0079	0.9596	1	0.0813	−0.0098	−0.0353
DAI	0.0008	0.0716	0.0813	1	0.0013	−0.0218
TUSD	0.0357	−0.0069	−0.0098	0.0013	1	0.0021
USDC	0.0159	−0.0235	−0.0353	−0.0218	0.0021	1
Panel B: collapse period (11 March 2023–18 March 2023)						
BTC	1	0.0177	0.0195	−0.0081	0.0149	0.0179
USDT	0.0177	1	0.9913	−0.0338	0.0030	−0.0295
BUSD	0.0195	0.9913	1	−0.0352	0.0027	−0.0271
DAI	−0.0081	−0.0338	−0.0352	1	0.0050	0.0121
TUSD	0.0149	0.0030	0.0027	0.0050	1	0.0271
USDC	0.0179	−0.0295	−0.0271	0.0121	0.0271	1

Table 3
BEKK dynamic conditional covariance coefficients and contagion effect tests. Pre-collapse period is from 2023.03.04 to 2023.03.10. Collapse period is from 2023.03.11 to 2023.03.18.

	Mean	Variance	T-statistic
Pre-collapse BEKK-covariances USDC_BTC	0.0081	0.0009	15.61***
Collapse BEKK-covariances USDC_BTC	−0.0022	0.0034	
Pre-collapse BEKK-covariances USDC_USDT	−0.0028	0.0023	−11.85***
Collapse BEKK-covariances USDC_USDT	0.0071	0.0047	
Pre-collapse BEKK-covariances USDC_BUSD	0.0002	0.0023	−10.54***
Collapse BEKK-covariances USDC_BUSD	0.0088	0.0043	
Pre-collapse BEKK-covariances USDC_DAI	0.0069	0.0011	11.71***
Collapse BEKK-covariances USDC_DAI	−0.0001	0.0025	
Pre-collapse BEKK-covariances USDC_TUSD	−0.0013	0.0013	−17.12***
Collapse BEKK-covariances USDC_TUSD	0.0093	0.0026	

*** Indicates the significance level at 1%.

As in De Blasis et al. (2023) and Galati et al. (2023), the null hypothesis is rejected if the t-statistic is significantly higher than the critical value, indicating the presence of a contagion effect.

4. Data

Consistent with De Blasis et al. (2023), this study uses proprietary minute-by-minute price transactions data for the most liquid cryptocurrency, Bitcoin (BTC), and the five most liquid stablecoins, namely: Tether (USDT); Binance Coin (BUSD); US Dollar Coin (USDC); Dao Coin (DAI); TrueUSD (TUSD).[13] Similarly to Galati et al. (2023), the sample spans a 14-day period extending from March 4, 2023, to March 18, 2023, and covering a symmetric pre- and post-period of one week around the Silicon Valley Bank (SVB) bankruptcy on the 11th of March 2023. We collect data from Kaiko (for BTC, USDT, USDC, DAI, and TUSD), and Binance (for BUSD),[14] all supplied by Refinitiv (formerly Thomson Reuters), a London Stock Exchange Group (LSEG) business, and sourced from the Refinitiv Tick History (RTH) database. The final dataset consists of 20,160 price observations of the 6 digital assets.

The question of which price series to select for analysis naturally emerges given the fragmented nature of the cryptocurrency market and the abundance of alternative trading platforms. Because it is a weighted average of the prices reported on different exchanges, we use price information from Refinitiv, which is consistent with De Blasis et al. (2023). Since the price data are basically smoothed by averaging, this choice lowers the observed volatility and size of the price moves in reaction to the news. Smoothed data, on the other hand, avoid giving undue weight to transactions on smaller trading platforms, and thus provide a more accurate snapshot of where the price was at any given point in time, so that this disadvantage is outweighed (De Blasis et al., 2023).

We compute cryptocurrency and stablecoin returns, consistently with De Blasis et al. (2023), as $ln(P_t/P_{t-1})$ where P_t is the price of the digital asset at time t. To divide the sample into two symmetric periods and test for financial contagion, we use the first tweet by Circle at 3:11 a.m. (UTC time) on 11th of March 2023 as the starting point of the collapse period. Finally, we also calculate cumulative returns for robustness purposes.

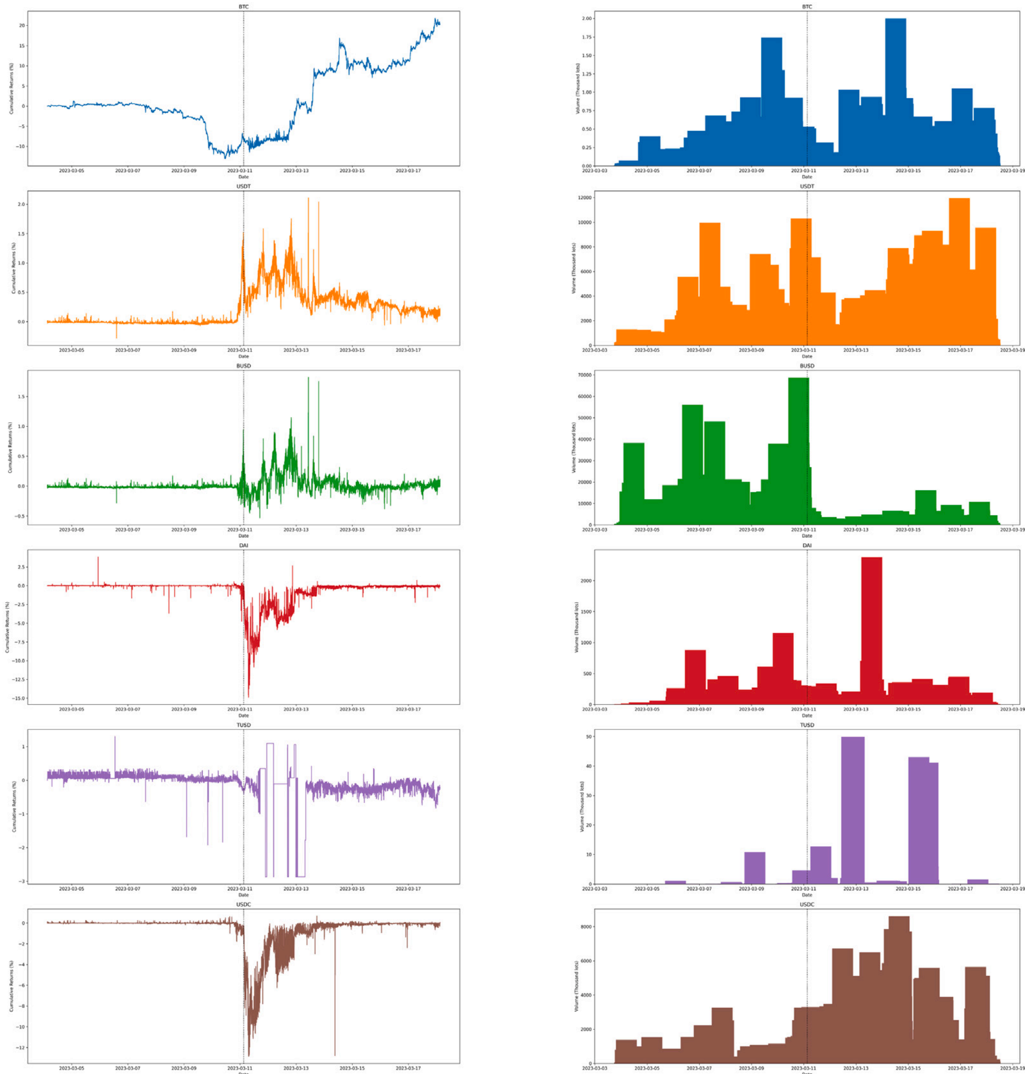
5. Results

5.1. Descriptive statistics

We report in Table 1 the descriptive statistics of the digital assets returns. We use the Jarque–Bera test to determine whether the returns (and squared returns) are normally distributed, the augmented Dickey–Fuller test to determine whether the returns time series sample contains a unit root, the ARCH model to determine whether the sample distribution is heteroscedastic, and the Ljung–Box test to determine whether autocorrelations are present in the data. With the exception of the ARCH test in TUSD during the collapse period, all statistical tests are consistently significant at the 1% level throughout the sample period. Additionally, all returns have roughly zero means, supporting the validity of the assumption made in the method section. Another noteworthy statistic is the fact that the median is 0 in all the return distributions, except for Bitcoin in the pre-collapse period. As in De Blasis et al. (2023) and Galati et al. (2023), all of the return distributions are leptokurtic, which is a common feature of data from the financial markets.

[13] The reliability of our proprietary data allows us to overcome the limitation highlighted in Alexander and Dakos (2020).

[14] Given that Binance does not allow investors to use US dollars on their platform, we converted the BUSD against Tether into the pair against the USD in order to analyze all currency pairs in dollars.



(a) Stablecoins cumulative returns

(b) Stablecoins volumes

Fig. 2. Cumulative returns and traded volumes of major digital assets around the SVB bankruptcy. These figures show the cumulative abnormal returns (in panel a) and the traded volumes (in panel b) for the stablecoins and cryptocurrencies analyzed. Cumulative returns are the sum of the logarithmic returns computed as $ln(P_t/P_{t-1})$, where P_t is the price of the digital asset at time t. The vertical dotted line symmetrically divide the pre-collapse from the collapse period. The period of investigation is from March 4, 2023, to March 18, 2023.

5.2. Volatility spillover and market cascade effects

Fig. 1(a) shows the stationary returns of Bitcoin and the stablecoins analyzed in this study. It is clear that as soon as the tweet on the $43.3 billion of USDC reserves exposed in SVB came out, which corresponds to nearly the middle of all charts, there were widespread market reactions across all those assets. Spikes in abnormal returns are evident during the collapse period, suggesting simultaneous movements after the event. Conspicuous are also the movements in the covariances of Fig. 1(b), implying that volatility spilled over across stablecoin markets during that period of turmoil. We also present the BEKK dynamic conditional correlation matrices in Table 2 for reference to the magnitude of the correlation in volatility spillover effects between digital assets already shown in Fig. 1(b).

Table 3, instead, illustrates the BEKK-GARCH model's dynamic conditional covariance values and relative t-test statistics for the presence of financial contagion. According to the results reported, the claim that SVB failed, and consequently that USDC coins remained stuck within the bank, caused a number of spillover effects to affect all the main virtual currencies examined. One of the reasons behind the observed spillover is the presence of contagion effects between those coins, which is supported by statistical significance at the 1% level. This indicates that, in March 2023, the cryptocurrency markets experienced widespread disruption and contagion as a result of the collapse of the SVB.

Further to the contagion analysis, we present cumulative abnormal returns series in Fig. 2(a) and the distribution of traded volumes in Fig. 2(b), over the sample period. Stablecoins should have an expected return of zero, but around the halt of withdrawals at SVB we see major disruptions in the cumulative returns of all the virtual coins. USDC and DAI experienced a similar drop, with TUSD losing nearly 3%, while BUSD and USDT traded at a premium. This evidence of information cascades in cumulative returns reinforces the reasons behind the observed spillover effects. Despite the adjustment in price after a few days, investors remained skeptical about the future of stablecoins, which can be seen by the fact that USDT was still trading at a premium till the end of the wider sample period.[15] Furthermore, traded volumes clearly skyrocketed for USDC, DAI, and TUSD in the period of market turmoil, with BTC and USDT trading as previously due to their known higher liquidity. This signaled panic within the stablecoin markets as investors feared not being able to withdraw their digital funds. Noteworthy is also the abrupt decline in BUSD volumes in contrast to all the other stablecoins analyzed, indicating a clear investors' preference for higher quality virtual currency.[16]

To conclude, investors seemed to have anticipated the announcement by Circle on the USDC exposure and started to move to "more stable" assets, such as USDT, hours before the news release, while selling less authoritative stablecoin like DAI throughout the uncertain period. This evidence is consistent with the "flight to safety" preposition and attests to the interconnection between traditional and decentralized finance as the main reason behind volatility spillover effects and market reaction cascades in cryptocurrency markets.

6. Conclusion

This study examined the extent to which the collapse of a commercial bank spread contagion across cryptocurrency markets and how those markets behave around the failure when asset withdrawals are halted. We use a BEKK-GARCH multivariate model to test for financial contagion around the Silicon Valley Bank collapse across multiple digital assets. Arguably, this is the second-largest bank run after the global financial crises experienced in history. We find evidence of volatility spillover effects across major stablecoins and Bitcoin, with a "flight to safety" from less to more stable virtual currencies.

Hence, this study provides important evidence of the ways the traditional and cryptocurrency financial systems are interlinked. Arguably, it links centralized and decentralized finance, showing the ways in which spillovers can occur between what seem to be separate realms of finance. Academics, practitioners, and policymakers alike interested in destabilizing risk in the digital finance ecosystem should pay attention to the connections with traditional finance and thus to the results of this research. A limitation of this study is that it focuses on the most liquid stablecoins and cryptocurrencies. Future studies may, therefore, further explore the links between centralized and decentralized finance, including stablecoins and other means of digital value exchange.

CRediT authorship contribution statement

Luca Galati: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Validation, Project administration, Funding acquisition. **Francesco Capalbo:** Supervision, Validation, Funding Acquisition, Writing – review & editing.

Declaration of competing interest

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

Availability of data and materials

The data that support the findings of this study are available from Refinitiv but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of Refinitiv and Rozetta.

[15] See also news article on Yahoo Finance at https://finance.yahoo.com/news/circle-usdc-rebounds-pegging-stablecoin-004023180.html.

[16] Some already argued for the end of the Binance dollar when the New York Department of Financial Services had ordered Paxos to stop issuing BUSD (see news at https://blog.kaiko.com/the-end-of-binance-usd-afc841cc82a).

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Luca Galati is a PhD Candidate in Finance and Accounting at the University of Wollongong (Australia) and at the University of Molise (Italy). He is also an Industrial PhD Researcher in Market Microstructure at the Derivatives Markets Research Centre of the Rozetta Institute (Australia), a Foreign Exchange Benchmark Surveillance Specialist at Refinitiv, an LSEG (London Stock Exchange Group) business (UK), and the Co-founder of 110 Laude, a University of Molise Fintech spin-off. His research interests include Digital Finance, Empirical Financial Markets Microstructure, Financial Economics, Accounting information in capital markets, and Digital and Forensic Accounting. He holds a Bachelor of Commerce Honors and Master's degrees in Business Economics from the University of Molise (Italy), with special mentions of Honor. He was a Visiting Research Fellow at Florida Polytechnic University (USA) in early 2023 and a Visiting Student at Hogeschool Gent (University College Ghent in Belgium) and the University of Wollongong (Australia). His research publications appear in finance, accounting, and applied mathematics journals, such as the Journal of Futures Markets, International Review of Financial Analysis, Financial Innovation, and Chaos, Solitons & Fractals. He has presented at numerous international conferences and reviewed articles for academic journals, such as the Pacific-Basin Finance Journal, International Review of Financial Analysis, Finance Research Letters, Public Budgeting, Accounting & Financial Management, and Pacific Accounting Review.

Francesco Capalbo is Professor of Accounting at the University of Molise (Italy). He is currently a member of the Italian Accounting Standards Board (OIC) and a member of the Scientific Committee of the Internal Training Board of the Italian Supreme Audit Institution (Corte dei Conti). International Public Sector Accounting Standards Board (IPSASB) member from 2016 to 2019, he is currently on the Academic Advisory Board of the IPSASB. He has authored several publications in leading journals on financial accounting issues and has held visiting academic positions at several universities including the University of Gent (Belgium), the University of Birmingham (UK), the University of Sydney (Australia), and the Macquarie Graduate Management School of Sydney (Australia). His current areas of research include public accountability and financial statements quality of public sector entities and State-owned entities. He holds a PhD in International Accounting from the University of Naples "Federico II".