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Financial contagion in cryptocurrency exchanges: Evidence from the FTT collapse

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ABSTRACT

To what extent does the collapse of a digital token spread contagion across cryptocurrency markets? How do markets incorporate information in this turbulent setting? We examine contagion effects across major digital exchanges during the collapse of the FTX exchange and its token, FTT. We find evidence of contagion across crypto exchanges. We also examine the information cascade effects of other crypto assets on FTX when nearly all withdrawals were prohibited. We find abnormal returns for major assets, indicating a flight to safety from less to more authoritative digital assets. The implications for traders, exchanges, and policymakers are discussed.

1. Introduction

The bankruptcy of the Bahamian-based cryptocurrency exchange, FTX,[1] and the collapse of its FTT token in November 2022 appeared to lead to major declines in cryptocurrency prices and billions of dollars in lost or stranded assets. Interestingly, there was a four-day period where trading continued on the FTX, but almost all withdrawals were prohibited (Galati et al., 2024). This study examines that collapse and attempts to answer two research questions. First, did the collapse of FTT spark contagion effects across assets and exchanges? Second, how did the ability to trade stranded assets on the FTX while withdrawals of funds were frozen influence trader behavior and market returns?

Answering these questions is important as the November 2022 collapse of FTT, alongside the resultant volatility in multiple important cryptocurrencies, demonstrated the fragility of centralized exchanges (CEXs) in cryptocurrency markets and the importance of credible collateral for CEXs' tokens. Furthermore, cryptocurrency exchanges are key for understanding the ecosystem from regulatory, industrial, and academic perspectives (Cong et al., 2022). We use high-frequency-trading (HFT) data and a BEKK multivariate generalized-autoregressive-conditional-heteroskedasticity (GARCH) model over a sample period of 12 days surrounding the FTT token crash on the 6th of November 2022 in order to test whether the collapse of an exchange-issued digital token spreads

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[1] FTX.US, a related US-regulated exchange with fewer products, existed for US users and is not the focus of this paper. In this document, FTX refers to the international exchange, and FTX.US refers to the US-regulated exchange. However, some quoted sources may refer to the entire corporate group as FTX.

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contagion across cryptocurrency markets. Indeed, we find evidence of contagion effects across all the cryptocurrency exchanges analyzed and find major information cascade effects in cumulative returns, particularly in assets likely to be perceived as higher in quality.

As cryptocurrencies gain prominence, new research examines how these new markets react to crises. De Blasis et al. (2023) use contagion tests and differential price reactions among stablecoins as a proxy to test market trust in the underlying stablecoin design. Stablecoins with quality reserves, greater transparency, and regulatory certainty outperformed those with greater regulatory and asset uncertainty. The same study also shows evidence of contagion effects across major cryptocurrencies during the collapse of Terra and Luna on and around 12 May 2022. A similar model was applied by Galati and Capalbo (2023) to test whether the bankruptcy of the Silicon Valley Bank (SVB) spread contagion among stablecoins and Bitcoin. In contrast with the literature, they find that the only market that was severely affected by the SVB collapse was the cryptocurrency market.

Several other studies underscore Bitcoin's continued importance and influence on cryptocurrency markets. Bitcoin's key role in volatility spillover effects is shown in research focusing on cryptocurrency only (Nguyen et al., 2019; Moratis, 2021; Ampountolas, 2022), cryptocurrencies and foreign exchange markets (Hsu, 2022), Non-Fungible Token (NFT) markets (Wang, 2022), Bitcoin and Alternative Coins (altcoin) (Nguyen et al., 2019), Bitcoin, gold and the US Dollar (Dyhrberg, 2016), and perpetual futures linked to stablecoins (De Blasis and Webb, 2022). Smales (2021) reports asymmetric spillover effects from Bitcoin to Ethereum, but not from Ethereum to Bitcoin. In contrast with the studies mentioned above, this paper uses a unique proprietary dataset from Refinitiv, similar to Galati and Capalbo (2023) and De Blasis et al. (2023), and exploits an exogenous shock not yet utilized for the purpose of investigating financial contagion. While previous research has examined the volatility spillover across stablecoins caused by the collapse of a commercial bank (Galati and Capalbo, 2023) and that of a stablecoin itself (De Blasis et al., 2023), this paper investigates volatility spillover effects among cryptocurrency exchanges triggered by the collapse of a token, which led to the bankruptcy of a crypto exchange itself.

We contribute to these strands of literature by investigating financial contagion on cryptocurrency exchanges during turbulent periods, such as the FTT collapse alongside the FTX going bankrupt. Additionally, this paper provides implications for cryptocurrency exchanges, trader behavior, and contagion effects in the centralized cryptocurrency exchange crisis, which is useful for academics, practitioners, and policymakers alike interested in potentially destabilizing risks arising from the cryptocurrency ecosystem. Although previous research has examined whether the FTX collapse engendered significant systemic risks in the cryptocurrency system (Jalan and Matkovskyy, 2023), and has gauged the impact of the FTX bankruptcy on financial markets more broadly (Yousaf et al., 2023) and on other cryptocurrency tokens (Yousaf and Goodell, 2023), to the best of our knowledge, a comprehensive investigation of the magnitude and direction of response to market movements as a consequence of an exchange-issued token collapsed is yet to be done. As such, this study fills this gap and extends the work of both Galati and Capalbo (2023) and De Blasis et al. (2023), as well as previous studies on volatility spillover across cryptocurrencies by testing the extent to which the collapse of a digital token spreads contagion across cryptocurrency exchanges. Moreover, this study makes an additional contribution to the literature as it enables us to test the information cascade effects when traders can buy and sell assets on the exchange that issued the token but not withdraw their funds.

2. Method

We employ a methodology similar to that used by Galati and Capalbo (2023) and De Blasis et al. (2023) to test for financial contagion across digital exchanges. Consistent with Galati and Capalbo (2023) and De Blasis et al. (2023), we assume that the logarithmic returns follow a normal distribution with zero means and the variance–covariance matrix H_t, so that we can model the conditional covariances using a BEKK GARCH model 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 in Galati and Capalbo (2023) and De Blasis et al. (2023), we employ a scalar version of (1) and apply the concept of variance targeting to eliminate the term CC' to reduce parameters and therefore difficulties within the estimation process. 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 Galati and Capalbo (2023) and De Blasis et al. (2023), these constraints are imposed to keep the process stationary and to guarantee the positive definiteness of the covariance matrices.

We then perform the contagion test as proposed in Galati and Capalbo (2023) and De Blasis 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 conditional correlations means of the population during the SVB pre-collapse and collapse periods, respectively, with variances σ_{pre} and σ_{post}.

Following Galati (2024), we focus on a 99.999% confidence interval ($\alpha = 0.001$) to identify significant results, avoiding the issue of rejecting virtually all null hypotheses in large, high-frequency datasets.

Table 1
BEKK dynamic conditional correlation matrices. Pre-collapse period is from 31.10.2022 to 06.11.2022. Collapse period is from 06.11.2022 to 12.11.2022.

	CRYPTOCOMPARE	FTX	BINANCE	BITFINEX	HITBTC	KUCOIN	LIQUID	POLONIEX	AAXE
Panel A: pre-collapse period (31 October 2022–6 November 2022)									
CRYPTOCOMPARE	1								
FTX	0.2929	1							
BINANCE	0.5043	0.4282	1						
BITFINEX	0.1444	0.0931	0.1521	1					
HITBTC	0.2452	0.1577	0.2628	0.1152	1				
KUCOIN	0.2726	0.1722	0.3203	0.0871	0.1826	1			
LIQUID	−0.0315	−0.0350	0.0130	−0.0318	0.0046	0.0087	1		
POLONIEX	0.1191	0.1138	0.1612	0.0253	0.1351	0.1194	0.0050	1	
AAXE	0.3923	0.2336	0.4186	0.0759	0.2024	0.2150	−0.0013	0.1392	1
Panel B: collapse period (6 October 2022–12 November 2022)									
CRYPTOCOMPARE	1								
FTX	0.3926	1							
BINANCE	0.6553	0.4807	1						
BITFINEX	0.2000	0.1699	0.2225	1					
HITBTC	0.3776	0.2806	0.3912	0.1845	1				
KUCOIN	0.4241	0.2810	0.4537	0.1575	0.3269	1			
LIQUID	0.0406	0.0221	0.0492	0.0236	0.0451	0.0551	1		
POLONIEX	0.1845	0.1643	0.2079	0.0820	0.1932	0.1871	0.0308	1	
AAXE	0.5461	0.3277	0.5767	0.1254	0.3131	0.3709	0.0251	0.1994	1

3. Data

This study uses proprietary minute-by-minute price transaction data for the most liquid cryptocurrencies, Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), and Litecoin (LTC), and the most liquid stablecoins available to trade on the FTX exchange, namely: Tether (USDT) and Dao Coin (DAI).[2] In addition, the dataset also includes the FTX token (FTT) and the Binance token (BNB) for comparison across the two major cryptocurrency tokens. We collect data from the FTX exchange, the current world-leader cryptocurrency exchange Binance, the data provider CryptoCompare for comparison, and all the other cryptocurrency exchanges available from the database, supplied by Refinitiv. Data are sourced from the Refinitiv Tick History (RTH) database, and the final dataset consists of 40 days, extending from October 3, 2022, to November 12, 2022, and 57,600 price observations of the digital assets mentioned above. For the purpose of the volatility spillover analysis, we use price series data for FTT traded across FTX, Binance, Bitfinex, HiTBTC, Kucoin, Liquid, Polonex, AAXE[3] and CryptoCompare. The sample used for the BEKK GARCH model spans 12 days, extending from October 31, 2022, to November 12, 2022,[4] and covers a symmetrical pre- and post-period of almost one week around the FTX exchange collapse starting November 6, 2022.

We compute cryptocurrency and stablecoin returns as $ln(P_t/P_{t-1})$ where P_t is the price of the digital asset at time t. To divide the sample, we consider the first media-based announcement of the potential insolvency of FTX.[5] Therefore, we use 5:59 AM (UTC time) on the 6th of November as the starting point of the collapse period. Finally, we also calculate cumulative returns for the purpose of the second analysis, accounting for a wider pre-event window.

4. Results

Fig. 1 shows the stationary returns of FTT against USDT on the following exchanges: FTX; Binance; Bitfinex; HTBTC; Liquid; Polonex; AAXE. As is readily apparent, there is a substantial deviation from zero in the stationary returns for all exchanges during the collapse of FTT, namely the period that the FTX is open for trading, but withdrawals of funds are frozen. Fig. 1 also shows the stationary return of FTT against USDT using the Cryptocompare index of the average price of USDT across multiple cryptocurrency exchanges. Interestingly, deviations from zero for FTT against USDT emerge around November 6th for most of the exchanges studied. Polonex is an exception, as significant deviations from zero are apparent from October 31st. Table 1, instead, presents the dynamic conditional correlation matrices between the returns of FTT on all cryptocurrency exchanges analyzed during both the pre-collapse (Panel A) and collapse (Panel B) periods.

Table 2 presents the dynamic conditional covariance estimates of the BEKK-GARCH model and the relative t-test statistics on the existence of contagion. Evidence shows that the allegation that FTX was insolvent precipitated a series of spillover effects across all the major cryptocurrency exchanges analyzed. All tests are statistically significant at the 1% per cent level, supporting the existence of contagion effects between all exchanges and CryptoCompare — a measure of average cryptocurrency prices across exchanges.

[2] These data are from the study of Galati et al. (2024). While they analyze slippage in prices, selling-pressure, and turnover activity, we focus on the information cascade effects in cumulative abnormal returns.

[3] We used the Reuters identification code (RIC) for AAXE as we were not able to identify the name of the exchange from the database.

[4] This is the last active day of trading on FTX and, therefore, where data availability terminates.

[5] See news at https://twitter.com/du09btc/status/1589135270103773184?lang=en.

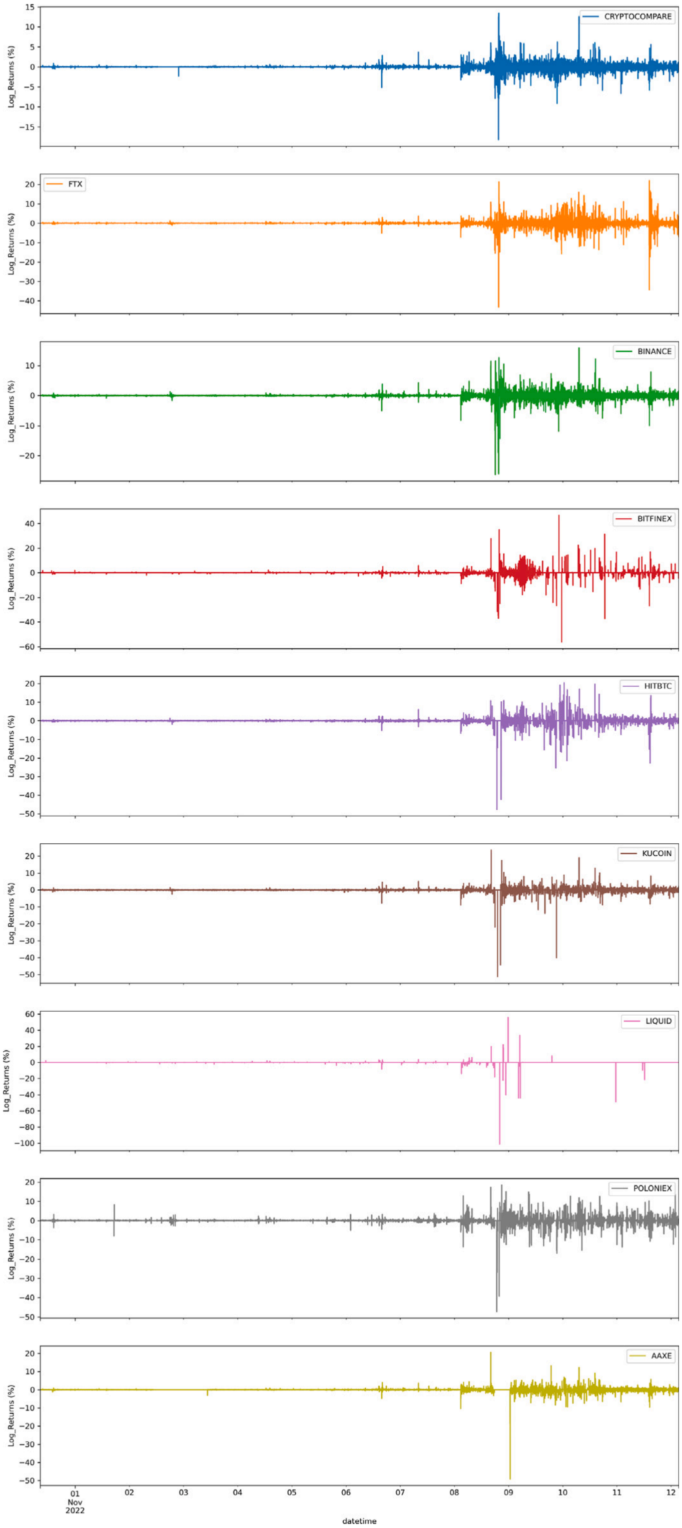


Fig. 1. Stationary returns of FTT traded on different exchanges.

Table 2
BEKK dynamic conditional covariance coefficients and contagion effect tests. Pre-collapse period is from 31.10.2022 to 06.11.2022. Collapse period is from 06.11.2022 to 12.11.2022.

	Mean	Variance	T-statistic
Pre-collapse BEKK-covariances FTX_CryptoCompare	0.2929	0.0020	−44.11***
Collapse BEKK-covariances FTX_CryptoCompare	0.3926	0.0414	
Pre-collapse BEKK-covariances FTX_Binance	0.4282	0.0016	−19.05***
Collapse BEKK-covariances FTX_Binance	0.4807	0.0629	
Pre-collapse BEKK-covariances FTX_Bitfinex	0.0931	0.0003	−41.34***
Collapse BEKK-covariances FTX_Bitfinex	0.1699	0.0290	
Pre-collapse BEKK-covariances FTX_HiTBTC	0.1577	0.0026	−47.27***
Collapse BEKK-covariances FTX_HiTBTC	0.2806	0.0525	
Pre-collapse BEKK-covariances FTX_Kucoin	0.1722	0.0027	−42.83***
Collapse BEKK-covariances FTX_Kucoin	0.2811	0.0525	
Pre-collapse BEKK-covariances FTX_Liquid	−0.0350	0.0003	−42.74***
Collapse BEKK-covariances FTX_Liquid	0.0221	0.0149	
Pre-collapse BEKK-covariances FTX_Poloniex	0.1138	0.0017	−25.32***
Collapse BEKK-covariances FTX_Poloniex	0.1643	0.0321	
Pre-collapse BEKK-covariances FTX_AAXE	0.2336	0.0019	−40.66***
Collapse BEKK-covariances FTX_AAXE	0.3277	0.0435	

*** Indicates the significance level at 0.01%.

This suggests that the collapse of the FTT was responsible for broader dislocation and contagion in the cryptocurrency markets in November 2022. Fig. 2 shows the dynamic conditional covariances of FTT against USDT on the following exchanges: FTX; Binance; Bitfinex; HiTBTC; Liquid; Polonex; AAXE. It also shows the covariance between FTT and Cryptocompare, an index of the average prices of the USDT. As is readily apparent, the right-hand side of all graphs presents an evident movement in stationary covariances, meaning that after the collapse of the FTT token, all exchanges experienced significant price movements caused by a spillover effect in the period after 6th of November 2022. CryptoCompare demonstrates that this was consistent even on average across all other cryptocurrency exchanges not analyzed.

Furthermore, Stablecoins should have an expected return of zero, but around the halt of trading at FTX we see major disruptions in the cumulative returns of both DAI and Tether. As the withdrawal halt at FTX continues, the cumulative returns of Tether skyrocket for periods, before generally falling back to around 0. This suggests illiquid demand for Tether, possibly by traders wanting to cut their losses or seek a ‘stable’ asset. On cryptocurrency exchanges, assets can be priced in US dollars, stablecoins like Tether, or against other cryptocurrencies. Figs. 3(a) and 3(b) clearly shows those abnormal movements also in other major cryptocurrencies and BNB due to the crash of FTT: interestingly, all major cryptocurrencies analyzed started to gain approximately 12 days before the collapse of FTT, and then followed the information cascade together with the stablecoins and tokens analyzed. We leave the question of whether there was insider trading for future research.

While returns for stablecoin like DAI experienced a fall, the positive returns for Theter suggest a flight to safety from less to more authoritative assets. BNB, a cryptocurrency created by Binance which is in some ways analogous to FTT, saw major gains as trading at FTX continued to be allowed while withdrawals were frozen, in contrast with the collapse of the FTX token FTT. This provides further evidence of flight to safety and suggests that crypto investors are mainly the retail type of investors that do not behave similarly to equity investors. They rarely trade safer assets such as cash or treasury bonds to protect their portfolios against systemic risks intrinsic in the crypto ecosystem but rather prefer to move their funds and savings to other digital assets considered safer by the majority of market participants.

Thus, we find contagion effects across exchanges, showing the interrelated nature of cryptocurrency prices across exchanges as well as the fallout from the collapse of FTT and the bankruptcy of its issuer FTX. The cascade effects in cumulative returns, however, support information inefficiency across crypto markets.

5. Conclusion

The collapse of FTT and the crisis of its issuer FTX, had a major impact on cryptocurrency markets. We find evidence of contagion in FTT across exchanges during the time of the FTT price turmoil. This contagion is widespread and found across all exchanges in our sample.

We contribute to several new strands of research. First, we examine the contagion effects resulting from the crash of the token FTT. We track this contagion across major cryptocurrency exchanges, providing new insights about market reactions to the failure of exchange-issued cryptocurrencies. This sheds further light on the market behavior of cryptocurrencies in periods of crisis and adds to the literature on financial contagion in cryptocurrency markets. Second, we analyze trader behaviors during the period when FTX allowed the trading of cryptocurrencies but generally prohibited their withdrawal from the exchange. Last, our results have important implications for traders, cryptocurrency exchanges, and policymakers as per the demonstrated fragility of CEXs and the importance of credible collateral for CEXs’ tokens. Drops in returns and the resultant volatility in cryptocurrencies should be prevented by stricter regulations within the market in order to avoid deteriorating market quality and, in turn, negatively affecting investors.

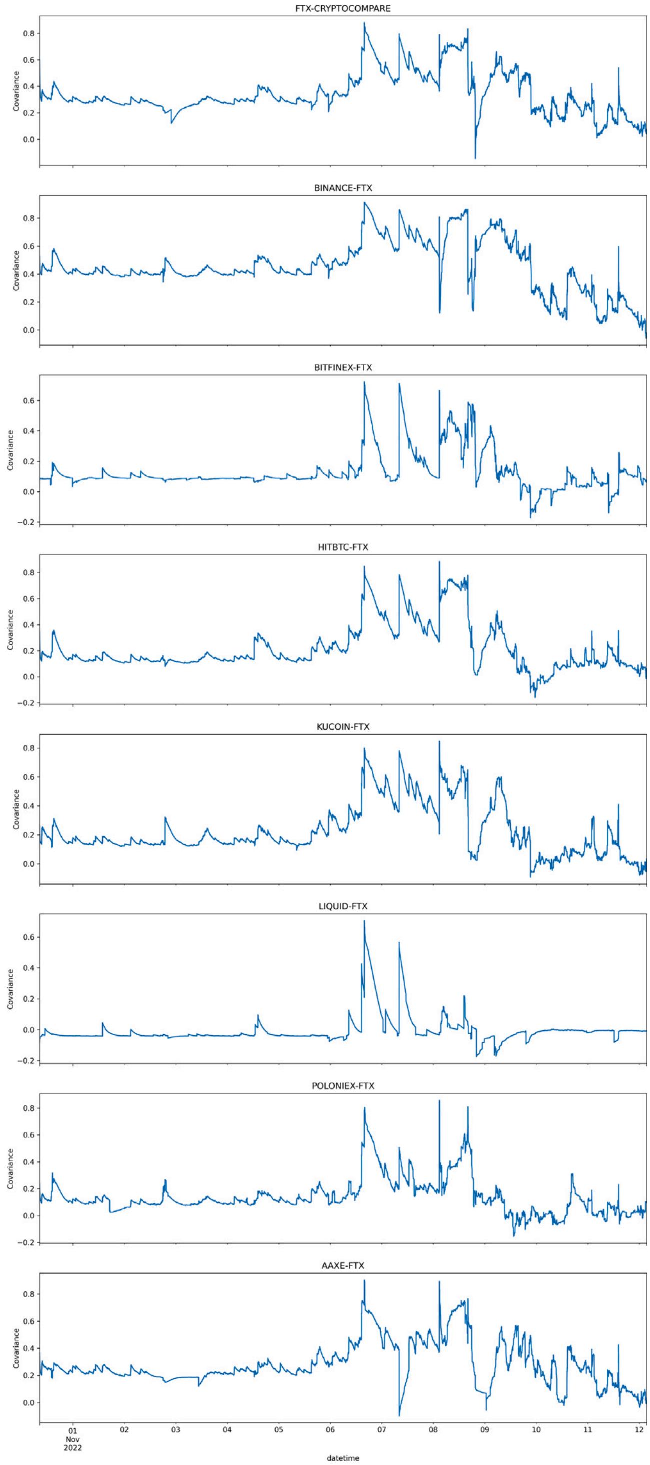
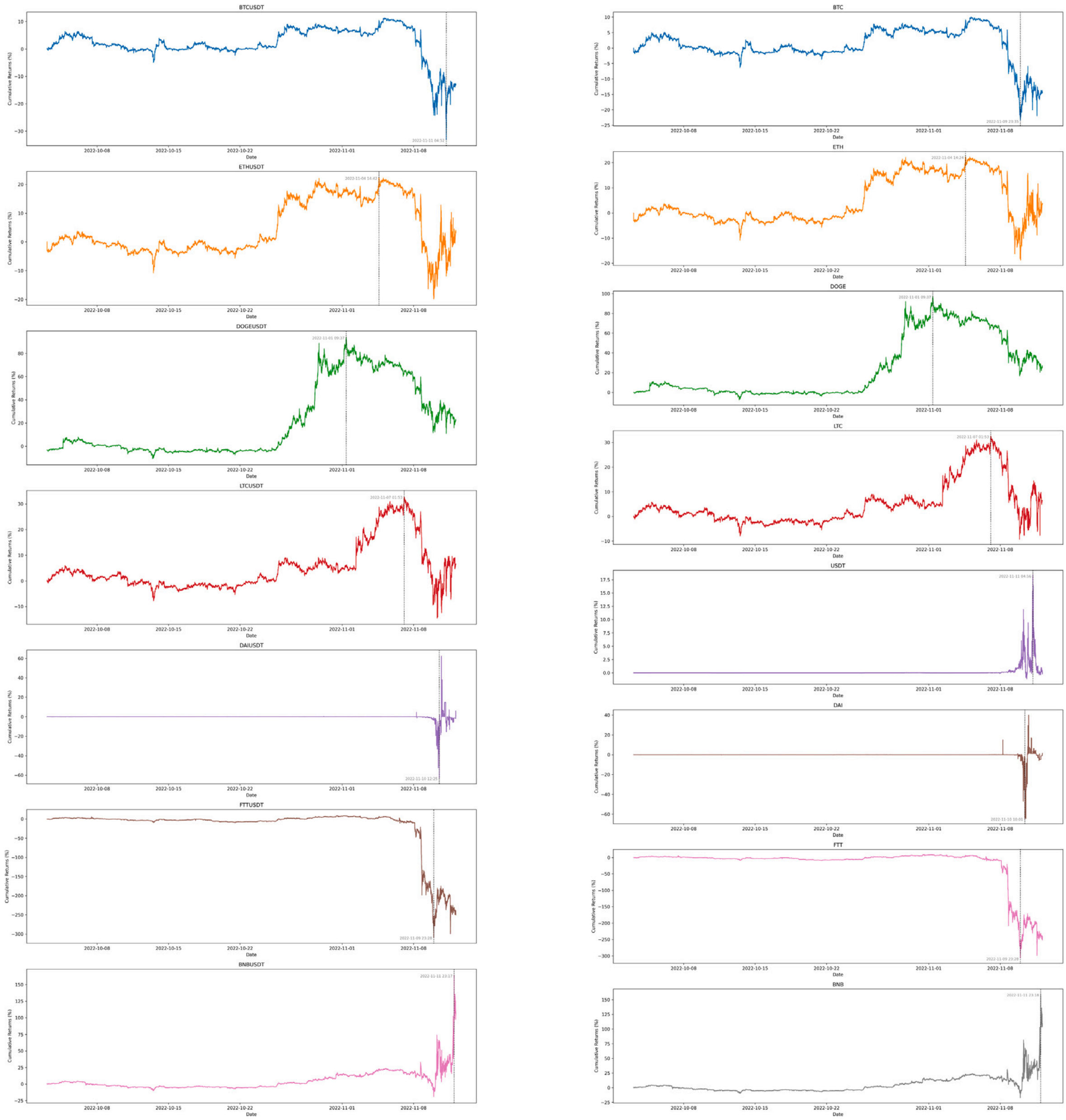


Fig. 2. BEKK covariances of FTT token traded on different exchanges.



(a) Pairs against Tether (USDT) (b) Pairs against US Dollar

Fig. 3. Cumulative returns for major cryptocurrencies.

Future studies may continue the analysis of stranded assets on FTX, particularly given that some traders or hackers may have been able to get some assets off the exchange. A limitation of this study is that it cannot export its findings to wider and normal periods of more tranquil markets. Further research may, therefore, look at the price behavior of every cryptocurrency asset traded by FTX and its long-term performance, to ascertain whether the assets traders paid above market prices outperformed the cryptocurrency market as a whole. Future research may also look at the value of using public on-chain transaction records to inform traders. During the crisis, the movement of $500 million in FTT by Binance was almost instantly reported on Twitter. Implications for traders and market efficiency in cryptocurrency markets could be explored by also looking at potential informed trading activities around the leakage of information preceding the market crash.

Table 3
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.

	CRYPTOCOMPARE	FTX	BINANCE	BITFINEX	HITBTC	KUCOIN	LIQUID	POLONIEX	AAXE
Panel A: pre-collapse period (31 October 2022–6 November 2022)									
Mean	0.0001	0.0011	−0.001	0.0652	−0.001	0.0009	0.2619	−0.0123	−0.0052
Median	0.0016	0.0013	0.0	−0.0433	0.0	0.0	0.0707	−0.0015	−0.0134
Max	0.8463	1.3049	1.3267	2.1743	1.3629	1.4864	2.4405	8.3301	0.9903
Min	−2.3326	−1.1576	−1.6087	−2.6408	−1.8744	−2.5237	−3.5982	−8.0132	−3.1223
Std. Dev.	0.063	0.1039	0.0868	0.523	0.0836	0.1188	1.1511	0.366	0.0804
Skewness	−5.8547	0.4718	0.6292	0.6305	−0.5955	−1.2461	0.3152	−12.1409	−6.3874
Excess Kurtosis	233.5447	18.0317	46.2639	5.0847	49.233	41.0083	0.8645	336.4233	283.7602
Jarque–Bera	19 343 141.0***	115 334.0***	757 709.0***	9708.0***	857 951.0***	597 091.0***	405.0***	40 246 235.0***	28 541 631.0***
ADF	−39.7***	−18.1***	−14.8***	−6.7***	−25.8***	−15.8***	−4.2**	−20.1***	−13.8***
ARCH(1)	2.0	2349.6***	1387.6***	8126.1***	52.0***	75.1***	8346.2***	6777.7***	4.2*
ARCH(6)	3.3	2475.2***	1485.9***	8132.3***	99.8***	97.9***	8341.3***	6789.4***	6.2
ARCH(12)	3.6	2483.3***	1496.5***	8126.6***	141.5***	106.4***	8335.4***	6834.5***	7.4
Q(6)	863.7***	1665.3***	503.7***	44 532.3***	112.2***	1408.8***	49 276.4***	7189.2***	182.3***
Q(12)	884.5***	1688.2***	512.8***	81 262.2***	137.0***	1456.6***	96 003.9***	7525.2***	215.9***
$Q^2(6)$	3.4	3883.3***	2214.1***	44 264.3***	120.5***	112.9***	48 904.5***	25 025.5***	6.1
$Q^2(12)$	3.8	4165.7***	2306.5***	79 358.6***	202.3***	128.0***	94 461.2***	28 106.8***	7.6
Panel B: collapse period (6 October 2022–12 November 2022)									
Mean	−0.0269	−0.081	−0.1115	0.2992	−0.1483	−0.7403	−3.9188	−0.1364	−0.1384
Median	−0.0125	−0.0026	−0.0151	−0.02	−0.0118	−0.0089	−0.0255	−0.0061	−0.0342
Max	13.4563	22.0353	15.9036	46.683	20.5057	23.6105	55.9116	18.5697	20.6306
Min	−18.2648	−43.3569	−26.3323	−56.2513	−47.6953	−51.375	−101.6307	−47.2953	−49.2013
Std. Dev.	0.9935	2.3686	1.8154	7.3327	3.0648	5.7002	10.0753	2.8938	1.6445
Skewness	−0.2195	−2.7506	−5.0471	1.8033	−0.7701	−7.2766	−3.3316	−3.3552	−0.3979
Excess Kurtosis	34.6831	63.2071	70.3895	17.2637	24.7479	59.834	25.7585	50.4839	146.3553
Jarque–Bera	425 600.0***	1 423 983.0***	1 788 761.0***	110 032.0***	217 497.0***	1 341 386.0***	250 420.0***	917 506.0***	7 577 500.0***
ADF	−14.0***	−15.5***	−11.2***	−9.1***	−13.6***	−6.6***	−6.7***	−20.3***	−19.2***
ARCH(1)	374.4***	3960.9***	6166.5***	7959.7***	2142.1***	8262.6***	7716.6***	4428.6***	946.3***
ARCH(6)	1942.9***	4201.9***	6262.0***	7965.5***	3002.5***	8264.1***	7714.2***	4609.1***	1845.5***
ARCH(12)	2223.7***	4285.5***	6312.4***	7960.9***	3023.3***	8260.3***	7711.0***	4665.9***	1850.8***
Q(6)	821.0***	2052.5***	10 497.7***	32 432.0***	14 642.8***	42 870.6***	42 395.6***	10 467.1***	11 590.8***
Q(12)	856.8***	2107.9***	12 204.2***	51 632.6***	17 283.0***	80 474.6***	74 037.6***	11 308.8***	14 718.1***
$Q^2(6)$	3706.7***	6289.6***	24 640.3***	42 914.1***	9360.9***	47 569.4***	37 517.4***	12 385.3***	4216.4***
$Q^2(12)$	6665.2***	7478.5***	32 792.5***	75 618.6***	14 060.8***	90 086.9***	57 707.2***	12 680.3***	4994.7***
Panel C: entire period (31 October 2022–12 November 2022)									
Mean	−0.0134	−0.04	−0.0563	0.1822	−0.0746	−0.3697	−1.8285	−0.0743	−0.0718
Median	0.0	0.0	−0.0005	−0.0228	−0.0013	0.0	−0.0255	−0.0028	−0.0181
Max	13.4563	22.0353	15.9036	46.683	20.5057	23.6105	55.9116	18.5697	20.6306
Min	−18.2648	−43.3569	−26.3323	−56.2513	−47.6953	−51.375	−101.6307	−47.2953	−49.2013
Std. Dev.	0.704	1.677	1.2863	5.1995	2.1692	4.0486	7.4692	2.0635	1.1661
Skewness	−0.3673	−3.9483	−7.2215	2.5961	−1.1876	−10.4271	−4.842	−4.7482	−0.729
Excess Kurtosis	71.7417	129.1315	143.8016	37.3088	52.4401	124.2318	49.6272	101.1638	292.5029
Jarque–Bera	3 641 798.0***	11 841 647.0***	14 777 897.0***	1 003 872.0***	1 949 588.0***	11 226 924.0***	1 808 823.0***	7 304 438.0***	60 533 759.0***
ADF	−17.4***	−15.7***	−14.5***	−12.2***	−16.0***	−8.8***	−8.7***	−15.0***	−15.5***
ARCH(1)	826.3***	7980.2***	12 373.4***	15 956.9***	4421.0***	16 532.8***	15 506.8***	8929.6***	1886.8***
ARCH(6)	4041.4***	8461.6***	12 566.2***	15 971.8***	6176.1***	16 540.7***	15 505.3***	9291.7***	3695.6***
ARCH(12)	4607.9***	8632.9***	12 671.2***	15 968.1***	6223.5***	16 538.9***	15 504.0***	9409.6***	3707.0***
Q(6)	1645.7***	4116.4***	20 994.5***	64 981.3***	29 291.5***	85 780.4***	86 173.6***	20 856.4***	23 235.6***
Q(12)	1717.2***	4226.2***	24 446.2***	103 551.2***	34 601.3***	161 080.6***	152 382.8***	22 527.8***	29 581.6***
$Q^2(6)$	7926.6***	12 834.0***	49 547.3***	86 182.3***	19 632.8***	95 161.1***	75 469.3***	25 201.9***	8568.8***
$Q^2(12)$	14 322.9***	15 407.6***	66 171.4***	152 357.5***	29 830.5***	180 267.5***	116 709.5***	25 928.7***	10 196.7***

* Indicate the rejection of the null hypothesis at the 5% significance level.

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

*** Indicate the rejection of the null hypothesis at the 0.01% significance level.

CRediT authorship contribution statement

Luca Galati: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Alexander Webb:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Robert I. Webb:** Supervision, Writing – original draft, 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.

Data availability

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.

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Appendix. Descriptive statistics and assumption tests

Table 3 illustrates the descriptive statistics of the returns of the FTT token throughout both periods analyzed (i.e. pre-collapse in Panel A and collapse of FTT in Panel B) and for the entire sample (panel C). In order to run the analysis, we test whether the returns (and squared returns) are normally distributed with the Jarque–Bera test, whether the null hypothesis that a unit root is present in the returns time series sample through the augmented Dickey–Fuller test, if there is heteroskedasticity in sample distribution with the ARCH model, and finally we use Ljung–Box test for autocorrelations within our data. All statistical tests are consistently significant at the 0.01% level in the sample period, except for the *ARCH* and Q^2 tests in CryptoCompare and AAXE during the pre-collapse period. Table 3 also clearly shows that the assumption made in the methodology section is valid, as all returns (except for FTT traded on Liquid which may be affected by scarce liquidity and therefore a low number of observations) have approximately zero means. Another noteworthy statistic is the fact that the median is 0 in all the return distributions. As in Celık (2012), all the distributions of returns are leptokurtic, a common characteristic of financial markets data.

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