Understanding the FTX exchange collapse: A dynamic connectedness approach

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Abstract

Employing a TVP-VAR dynamic connectedness analysis, we identify avenues through which the collapse of the FTX exchange manifested contagion effects throughout a number of financial markets. Results indicate that interaction effects become significantly pronounced, coinciding with key milestones during the collapse of FTX and related companies. Specifically, sources of contagion stem from two tokens created by the exchange and related companies, namely FTT Token and Serum. Such results further develop the expanding literature based on the inherent contagion effects of such unregulated products.

Keywords: TVP-VAR; Dynamic Connectedness; GARCH; Fraud; Cryptocurrency; Tokens.

1. Introduction

The November 2022 collapse of major cryptocurrency exchange FTX has received widespread attention, not just due to the magnitude of investor losses, but the audacity of identified breaches of corporate governance and the public trust (not yet having a final legal determination); as well as its broad reliance upon a cryptocurrency bull market. As investor interest in cryptocurrencies has grown, there are reasonable concerns regarding contagion to traditional markets [Goodell and Corbet, 2023]. The collapse of the FTX exchange presents a unique opportunity to examine such contagion channels, directly corresponding to areas of recent finance scholarly interest. Recent research has offered new results regarding contagion effects, both financial and otherwise, that occur following significant detrimental events to particular firms [Corbet and Goodell, 2022, Wang et al., 2022, Goodell et al., 2022, Dai et al., 2022, Yousaf et al., 2022]. Further, recent research has shown great interest in tokens, particularly in whether they have diversification utility for portfolio construction [Corbet et al., 2022, Yousaf et al., 2022].

We investigate pathways in which the recent collapse of the FTX cryptocurrency exchange created spillovers to other assets significantly connected to FTX. These include Bitcoin, GBTC (Grayscale Bitcoin Trust), BITW (Bitwise 10 Crypto Ind), and Robinhood (HOOD). We note a particularly interesting opportunity to expand our knowledge of contagion by considering the connection of FTX to other assets via its associated tokens FTT Token (FTT) and Serum (SRM).[1]

Results suggest significantly elevated connectedness of BTC, as well as dynamic changes in relationships with other assets. EUR, USD, USDT, and ETH are identified to have a negative reaction, indicative of a broad detachment of FTX from traditional assets. Key events are determined to generate persistent influence. Findings are consistent with cryptocurrency traders actively revising valuations based on events relating to FTX. Further, attempts by FTX representatives to artificially underpin asset values and restore confidence resulted in significant contagion effects. Results confirm for practitioners and scholars that the cryptocurrency markets are driven by informed traders reacting sharply to releases of hoarded bad news and that cryptocurrency tokens act idiosyncratically in relation to other assets.

2. Data and methodology

Data related to each of the examined assets is obtained on an hourly basis for the period from midnight on 1 January 2022 through to midnight on 14 November 2022 from Thomson Reuters Eikon, a total of 7,632 observations. In Table 1, key events relating to the decline of the FTX

[1] SRM is the native, utility, token of Serum, a decentralised exchange affiliated with FTX, based on the Solana blockchain.

exchange are presented, where data is collated, along with the exact time and specific source from news wire searches on Bloomberg, Thomson Reuters Eikon, and LexisNexis. The FTX balance sheet dated Thursday, 10 November, is obtained from that reported by the Financial Times. These dates are separated and utilised to test for differentials in dynamic connectedness. Conlon et al. [2022] identified that the asset-price collapse of privately-issued cryptocurrencies, FTT and Serum, manifested directly in the failure of FTX and subsequently led to contagion effects across a range of financial market products. Specifically, the authors also identify several potential avenues through which the FTX collapse can manifest in contagion effects throughout the financial system, focusing on Bitcoin, GBTC (Grayscale Bitcoin Trust), BITW (Bitwise 10 Crypto Ind), and Robinhood (HOOD). Substantial amounts of each asset were held by FTX and related companies; therefore, interaction effects are theoretically plausible. Such interactions can manifest in important information flows throughout the cryptocurrency industry. Interactions with Robinhood are particularly interesting due to the exceptional risk-loving reputation associated with the company and its association with situations such as the market influence generated by the /wallstreetbets Reddit forum [Corbet et al., 2022]. Influential behaviour sourced from FTT upon GBTC or BITW would indicate the existence of connectedness differentials with the broad cryptocurrency industry due to the collapse of FTX. The financial assets are, therefore, of primary interest in the following research. Using the approach of Antonakakis et al. [2020], we estimate the dynamic connectedness measures based on a time-varying parameter vector auto-regression (TVP-VAR). In particular, we employ the following TVP-VAR model:

$$z_t = B_t z_{t-1} + u_t, \qquad u_t, \sim N(0, S_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + v_t, \qquad v_t \sim N(0, R_t) \tag{2}$$

where B_t and S_t are $k \times k$ dimensional matrices and z_t, z_{t-1} and u_t are $k \times 1$ dimensional vectors. $vec(B_t)$ and v_t are $k^2 \times 1$ dimensional vectors whereas R_t is a $k^2 \times k^2$ dimensional matrix.[2]

Furthermore, we compute the H-step ahead (scaled) generalised forecast error variance decomposition (GFEVD) suggested by Koop et al. [1996], which is independent of the variable ordering. Subsequently, we rewrite the TVP-VAR as a vector moving average (VMA) process utilising the following equation: $z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j}$. Considering that cross-variable and own variance shares do not necessarily add up to one, the (unscaled) GFEVD, $\phi^g_{ij,t}(H)$, is normalised so that the (scaled) GFEVD, $\tilde{\phi}^g_{ij,t}(H)$, shows the effect variable j has on variable i concerning its

[2]Using the Bayesian information criterion (BIC), we select one lag length for the TVP-VAR model.

share of forecast error variance. This measure is represented by,

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t}\sum_{t=1}^{H-1}(\iota_i' A_t S_t \iota_j)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}(\iota_i A_t S_t A_t' \iota_i)}, \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k}\phi^g_{ij,t}(H)}, \tag{3}$$

where $\sum_{j=1}^{k}\tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k}\tilde{\phi}^g_{ij,t}(H) = k$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. Then, the total connectedness index (TCI) is computed using the following equations based on the GFEVD:

$$TO_{jt} = \sum_{i=1, i\neq j}^{k}\tilde{\phi}^g_{ij,t}(H), \tag{4}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k}\tilde{\phi}^g_{ji,t}(H), \tag{5}$$

$$NET_{jt} = TO_{jt} - FROM_{jt}, \tag{6}$$

$$TCI_t = k^{-1}\sum_{j=1}^{k}TO_{jt} \equiv k^{-1}\sum_{j=1}^{k}FROM_{jt}, \tag{7}$$

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H), \tag{8}$$

where $\tilde{\phi}^g_{ij,t}(H)$ represents the effect a shock in variable j has on variable i. Eq.(4) illustrates the overall impact of a shock in variable j has on all *other* variables. It is defined as *total directional connectedness to others* whereas Eq.(5) indicates the aggregated influence all *other* variables have on variable j (*total directional connectedness from others*). Eq.(6) subtracts the influence on variable j from others from the influence of variable j on *others*, giving us the *net total directional connectedness*, which provides information to identify whether a variable is a net receiver or a net transmitter of the shocks in the network. Variable j is a net receiver (*transmitter*) of shocks - and hence driven (*driving*) by the network - when the effect of variable j has on others is larger (*smaller*) than the influence all others have on variable j, $NET_{jt} > 0$ ($NET_{jt} < 0$). Eq.(7) represents the TCI_t, that is, the average effect one variable has on all *others*. Higher values of this measure imply that the network becomes more connected, indicating that a shock in one variable will have more impact on others. Finally, Eq.(8) defines *net pairwise directional connectedness* *($NPDC_{ij,t}$)* which indicates whether variable j is driving variable i or vice versa.

In the secondary stage of the analysis, we utilise dummy variables based on critical events associated with the decline of FTX. Within a standard GARCH(1,1) framework [Sensoy et al., 2021, Corbet et al., 2021, Goodell et al., 2022], we specifically test for significant differential dynamic connectedness responses to examine the differential effects that were sourced across each market listed as an asset owned by FTX on 2 November. Dummy variables ranging over the hourly periods [-12,-1], [-6,-1], [0,+6], [0,+12], [-3,+3], and [-12,+12] are examined.[3] In Table 1, as per Conlon et al. [2022], we present an overview of the critical events that occurred during the decline of FTX before the formal announcement of the filing for voluntary Chapter 11 bankruptcy protection in the United States on 11 November. Ten major events are identified as of specific interest to examine market discontinuities. In particular, those surrounding the release of significant phases of negative news attempts to restore confidence in FTX, an attempted takeover and subsequent withdrawal by competitor Binance, followed by both the implementation of asset freezes in the Bahamas and the subsequent formal application for Chapter 11 protection.

3. Results

The results of the TVP-VAR-based dynamic connectedness analyses are presented in Figure 1 and Table 2 respectively. The analysis is separated to represent the periods both before and after 2 November at 14:44 GMT, when CoinDesk published an article revealing key balance-sheet details of Sam Bankman-Fried's Alameda Research trading firm, showing their substantial investment in the FTX exchange's FTT token, presented as D_i representing each key event earlier outlined. This news release acts as the primary catalyst to the subsequent collapse of FTX, dividing the following analyses into periods before and after this date. In Figure 1, we focus on interactions between key FTX-related tokens FTT and Serum, with Bitcoin, cryptocurrency ETFs BITW and GBTX, and, as one channel of contagion through to US stock markets, Robinhood.

Evidence suggests that FTT acted as a significant source of connectedness upon Serum, as would be expected due to the internal creation of both tokens. While Bitcoin significantly influences GBTC, it is interesting to observe meaningful flows sourced from FTT. After the release of the balance sheet positions held by Alameda Research and the subsequent collapse of the FTX exchange, the influence of FTT Token becomes far more acute. In particular, FTT is found to directly influence both examined ETFs, the token Serum, and even the most prominent cryptocurrency in the world, Bitcoin. Further, one of the most significant interactions is between FTT Token and Robinhood. These interactions are further validated in Table 2, where sharp elevations in dynamic connectedness

[3] Extended results and associated robustness testing procedures are omitted for brevity of presentation and are available from the authors upon request. Only results surrounding the periods [0,+6] and [0,+12] are presented hereafter. In our selection, other competitive models included EGARCH, TGARCH, Asymmetric Power ARCH (APARCH), Component GARCH (CGARCH) and the Asymmetric Component GARCH (ACGARCH). The optimal model is chosen according to three information criteria, namely the Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ).

sourced from the FTT token are presented.

In the secondary phase of our analysis, GARCH-estimated differentials of dynamic connectedness based on key events are presented in Table 3. Assets are divided as per FTX-defined liquidity conditions, with dummy variables separated for the periods [0,+6] and [0,+12]. Significant positive outcomes are identified as phases of increased dynamic connectedness. Results indicate several significant changes. When focusing on liquid assets, significantly elevated connectedness is observed for BTC when Mr Bankman-Fried claimed "assets are fine" on social media, followed quickly by the collapse of FTX below the $22 threshold implemented by Ms Ellis, CEO of Alameda Research. Dynamic changes in relationships with other assets such as EUR, USD, USDT, and ETH are identified to be negative, indicative of a broad detachment of FTX from these other assets.

The strong interactions identified between FTX and those assets defined to be 'less liquid' by FTX merits substantial attention, as evidence suggests that the initial phase of significant escalation and elevated probability of corporate collapse manifested in almost immediate response across cryptocurrency markets. Further, considerable relationship discontinuities are also identified during the winding-up announcement of FTX and the subsequent freezing of corporate assets by The Securities Commission of The Bahamas. In addition, FTX-denoted illiquid assets are identified to present evidence of a relatively delayed response to FTX announcements compared to relatively liquid assets. Finally, critical events from 9 November are identified to generate persistent influence upon the assets analysed. Results appear to be broadly indiscriminate concerning the reported assets held by FTX; however, clear, significant market discontinuities are immediately observable throughout most cryptocurrency products examined. This result indicates that not only were cryptocurrency traders actively monitoring and revising their asset valuations based on the events relating to FTX, the attempts of Mr Bankman-Fried and Ms Ellis to underpin asset values and restore confidence artificially resulted in significant contagion effects.

4. Concluding comments

Recent research has offered new results regarding contagion effects, both financial and otherwise, that occur following significant detrimental events to particular firms. We investigate pathways through which the recent collapse of the FTX cryptocurrency exchange created spillovers to other cryptocurrency markets, focusing on assets held in substantial quantity by FTX. These include Bitcoin, GBTC (Grayscale Bitcoin Trust), BITW (Bitwise 10 Crypto Ind), and Robinhood (HOOD).

Developing upon a TVP-VAR dynamic connectedness analysis, we identify paths through which the collapse of the FTX exchange engendered contagion to cryptocurrency markets and other assets. Results indicate that interaction effects became significantly pronounced on critical dates during the failure of FTX, stemming from two tokens created by the exchange and related companies, namely FTT Token and Serum SRM. We investigate pathways in which the recent collapse of the FTX cryptocurrency exchange created spillovers to other assets significantly connected to FTX. These include Bitcoin, Grayscale Bitcoin Trust, Bitwise 10 Crypto Ind., and Robinhood. We note a particularly interesting opportunity to expand our knowledge of contagion by considering the connection of FTX to other assets via its associated tokens, FTT and Serum.

Findings are consistent with cryptocurrency traders actively revising valuations based on events relating to FTX. Further, our results are consistent with the specific times when FTX representatives acted to publicly restore confidence creating or being concurrent with significant contagion effects. Results are also compatible with the notion of cryptocurrency valuations being driven by informed traders that react sharply and negatively to releases of hoarded bad news. Finally, results also suggest that cryptocurrency tokens act idiosyncratically in relation to other assets, especially traditional currencies. Overall, findings further develop the expanding literature based on the inherent contagion effects of such unregulated products and related corporate malpractice.

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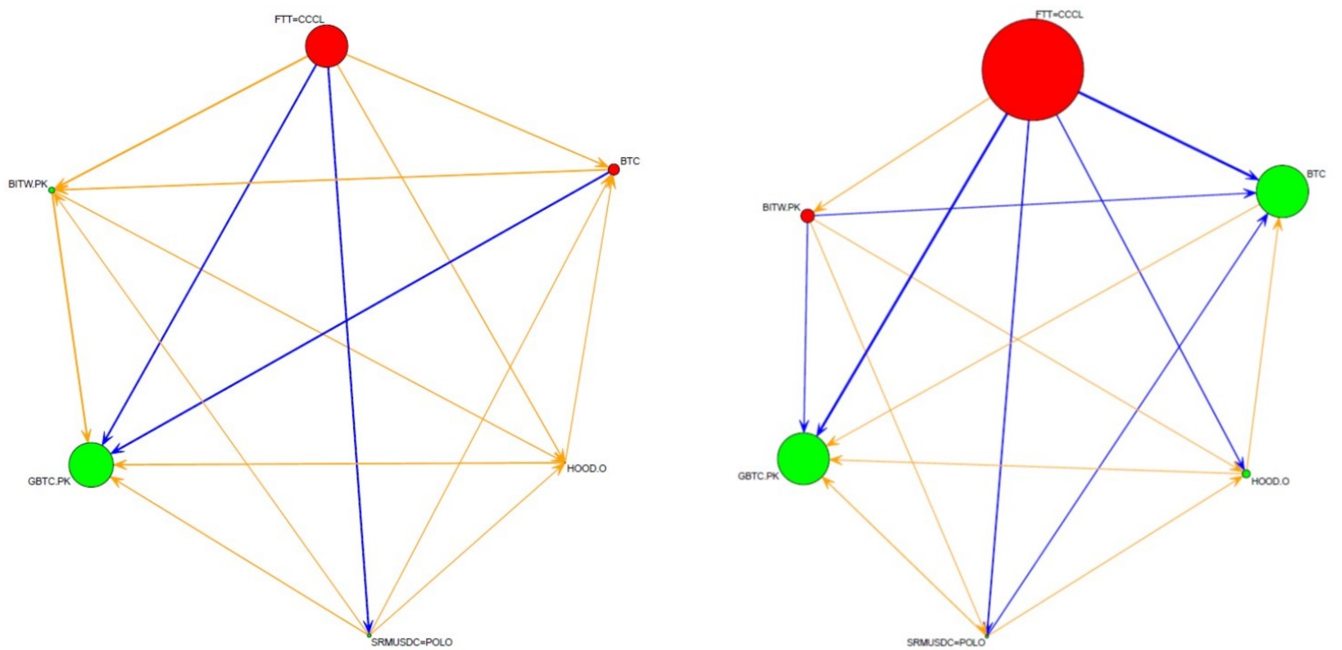
Figure 1: TVP-VAR-Based Dynamic Connectedness, Before and After the FTX Exchange Collapse

i) 1 May 2022 through 1 Nov 2022

ii) 2 Nov 2022 through 15 Nov 2022



Note: In the above figure, results are generated through the use of the approach of Antonakakis et al. [2020], where we estimate the dynamic connectedness measures between the selected variables based on time-varying parameter vector auto-regression (TVP-VAR). Data is obtained from Thomson Reuters Eikon.

Table 1: Key events during the collapse of the FTX exchange

Dummy	Date	Event
D_1	02/11/2022	CoinDesk publishes exclusive revealing key balance-sheet details of Sam Bankman-Fried's Alameda Research trading firm, showing it's heavily invested in the FTX exchange's FTT token. Available here
D_2	06/11/2022	Binance CEO Changpeng "CZ" Zhao says he's selling his remaining holdings of FTT tokens. (Minutes later, Caroline Ellis, CEO of Alameda Research, tweets that Alameda will buy Zhao's FTT tokens for $22 each. Available here
D_3	07/11/2022	Bankman-Fried tweets "A competitor is trying to go after us with false rumors. FTX is fine. Assets are fine." Remains available here
D_4	08/11/2022	The FTT token price falls below $22. This acts as a critical price barrier given the commitments provided by Caroline Ellis, CEO.
D_5	08/11/2022	Binance announces non-binding letter of intent to buy FTX, subject to due diligence, easing the industry panic. Available here
D_6	09/11/2022	Article on CoinDesk released titled: "Binance Is Strongly Leaning Toward Scrapping FTX Rescue Takeover After First Glance at Books: Source" Available here
D_7	09/11/2022	Binance formally walks away from any deal to acquire FTX. Available here
D_8	10/11/2022	Bankman-Fried says Alameda Research is being wound down, stating: "They aren't doing any of the weird things that I see on Twitter–and nothing large at all. And one way or another, soon they won't be trading on FTX anymore." Available here
D_9	10/11/2022	The Securities Commission of The Bahamas froze the assets of FTX Digital Markets and related parties. Available here
D_{10}	11/11/2022	FTX, FTX US, and Alameda formally files for voluntary Chapter 11 bankruptcy protection in US. Available here

Note: All times converted to GMT. Key events collated as per Conlon et al. [2022].

Table 2: TVP-VAR-Based Dynamic Connectedness Results

	FTT Token	Bitcoin	Robinhood	Serum	GBTC	BITW	From
			1st May through 1st November				
FTT Token	72.51	6.24	5.95	10.00	1.13	4.17	4.58
Bitcoin	6.68	83.69	3.91	1.16	1.86	2.70	2.72
Robinhood	6.23	3.74	81.42	1.65	0.70	6.26	3.10
Serum	11.02	1.01	1.52	84.69	0.60	1.17	2.55
GBTC	2.10	2.94	1.26	0.92	91.19	1.58	1.47
BITW	5.06	3.31	5.99	1.29	0.74	83.62	2.73
To	5.18	2.87	3.10	2.50	0.84	2.65	17.15
Net	0.60	0.16	0.01	-0.05	-0.63	-0.08	
			2nd November through 15th November				
FTT Token	81.62	0.42	5.61	3.24	1.00	8.11	3.06
Bitcoin	15.84	67.89	7.21	4.43	0.73	3.91	5.35
Robinhood	10.34	5.95	72.72	2.26	0.42	8.32	4.55
Serum	10.64	0.66	1.46	83.66	1.11	2.47	2.72
GBTC	16.09	1.30	1.51	3.22	73.56	4.32	4.41
BITW	10.19	0.78	8.01	1.84	0.36	78.82	3.53
To	10.52	1.52	3.97	2.50	0.60	4.52	23.62
Net	7.45	-3.83	-0.58	-0.23	-3.80	0.99	

Note: In the above table, results are generated through the use of the approach of Antonakakis et al. [2020], where we estimate the dynamic connectedness measures between the selected variables based on time-varying parameter vector auto-regression (TVP-VAR). All times are converted to GMT.

Table 3: GARCH-estimated connectedness differentials as a result of key FTX events

	6-hour GARCH-estimated connectedness differential						12-hour GARCH-estimated connectedness differential					
	Described as a "Liquid Asset"											
	EUR	BTC	USD	USDT	ETH	JPY	EUR	BTC	USD	USDT	ETH	JPY
d_1	0.001	0.004	0.002	0.000	0.002	0.000	-0.018*	0.001	-0.018*	-0.053***	-0.050***	0.032
d_2	-0.024**	0.004	-0.019*	-0.026**	-0.046***	0.003	0.015	-0.042*	-0.014	0.058***	0.015	0.008
d_3	-0.003	0.141***	0.013	-0.027**	-0.013	0.073*	-0.001	0.049***	0.007	-0.018***	-0.021**	0.039
d_4	-0.005	0.111***	0.012	-0.030***	-0.036***	0.064*	-0.001	0.071***	0.007	-0.025***	-0.024**	0.035
d_5	0.011	0.019	0.015	0.043	0.054***	0.078*	0.073***	0.008	0.117***	0.024**	0.075***	0.016
d_6	-0.003	0.016	0.000	0.009	0.045***	0.010	-0.002	0.013	0.001	0.009	0.021**	0.010
d_7	-0.001	0.019	0.002	0.009	0.013	0.010	0.001	0.009	0.001	0.001	-0.001	0.011
d_8	-0.001	-0.009	-0.003	0.000	-0.014	-0.050	-0.003	-0.017	-0.006	-0.070***	-0.100***	-0.024
d_9	0.000	-0.005	0.000	-0.004	-0.007	-0.072*	0.000	0.000	0.000	-0.003	-0.001	0.005
d_{10}	0.000	0.004	0.000	0.001	0.007	0.010	0.000	0.000	0.000	0.000	0.004	0.008
	Described as a "Less Liquid Asset"											
	HOOD	USDB	DAI	TUSD	EURT	BRZ	HOOD	USDB	DAI	TUSD	EURT	BRZ
d_1	0.000	-0.021	-0.017	-0.028	-0.006	0.000	-0.078**	-0.037	0.047	0.162***	-0.002	0.036
d_2	-0.008	-0.024	-0.009	-0.009	-0.004	0.000	-0.007	-0.026	-0.014	-0.008	-0.005	0.002
d_3	0.199***	0.267***	0.329***	0.251***	0.146***	0.175***	0.158***	0.212***	0.264***	0.200***	0.116***	0.140***
d_4	0.364***	0.500***	0.635***	0.452***	0.263***	0.325***	0.194***	0.261***	0.325***	0.246***	0.143***	0.172***
d_5	-0.055	0.083**	0.090	0.107	0.025	-0.127***	0.020	0.074*	0.070	0.086*	-0.022	0.055*
d_6	0.017	0.025	0.021	0.036	0.013	0.010	0.017	0.029	0.022	0.038	0.013	0.011
d_7	0.017	0.032	0.022	0.038	0.013	0.011	0.017	0.029	0.022	0.039	0.013	0.010
d_8	-0.034	-0.122***	-0.134**	-0.152***	-0.194***	-0.061*	-0.021	-0.092*	-0.072	-0.098*	-0.171***	-0.047
d_9	-0.033	-0.126***	-0.151**	-0.166***	-0.201***	-0.066*	0.012	0.015	0.014	0.021	-0.003	0.006
d_{10}	0.004	0.018	0.015	0.021	-0.001	0.013	0.008	0.017	0.014	0.021	-0.001	0.010
	Described as an "Illiquid Asset"											
	SOL	SRM	MSOL	ASD	BITW	GBTC	SOL	SRM	MSOL	ASD	BITW	GBTC
d_1	-0.002	-0.002	-0.007	0.005	0.000	-0.007	-0.051***	-0.001	-0.039***	-0.002	0.000	-0.016
d_2	-0.014	-0.002	0.005	-0.002	-0.010	-0.027*	0.010	0.026**	0.012	-0.029*	-0.008	-0.022
d_3	-0.028	0.005	0.001	0.014	0.012	-0.001	-0.026*	0.000	-0.015	0.010	0.004	-0.001
d_4	-0.049***	0.002	-0.030*	0.024*	0.009	-0.002	-0.023*	0.000	-0.016	0.015	0.007	0.014
d_5	0.059***	0.097***	0.027*	0.141***	0.027*	-0.009	0.104***	0.014	0.058***	-0.009	0.042***	0.051***
d_6	0.024	0.024*	0.007	-0.066***	0.023	-0.004	-0.008	0.004	-0.008	-0.038***	-0.038***	-0.048***
d_7	-0.064***	-0.017	0.010	-0.053***	-0.100***	-0.110***	-0.022*	-0.004	-0.016*	-0.019*	-0.026**	-0.038***
d_8	-0.018	-0.019	0.002	-0.001	-0.040**	0.013	-0.008	-0.014	0.004	-0.003	-0.027*	-0.004
d_9	-0.002	-0.001	-0.002	-0.003	-0.013	0.034**	0.079***	-0.031**	-0.024*	0.020	-0.024	-0.024*
d_{10}	0.016	0.004	0.007	0.000	0.028*	0.002	0.001	-0.006	0.023**	-0.004	-0.007	-0.006

Note: All times converted to GMT. We utilise dummy variables as listed in Table 1, based on key events associated with the decline of FTX, within a standard GARCH(1,1) framework, specifically testing for significant differential dynamic connectedness response. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Extended results and associated robustness testing procedures are omitted for brevity of presentation and are available from the authors upon request.