Revisiting Volatility Tail Codependency in Cryptocurrency Markets

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ABSTRACT
In this paper we investigate how tail codependency and systemic risk between the two major cryptocurrencies (Bitcoin and Ethereum) and two traditional assets (the S&P500 index and Gold) evolved before and after the Covid-19 pandemic. Using a quantile regression framework and a selected set of macroeconomic state variables we compute CoVaR and ΔCoVaR measures. Our results suggest cryptocurrencies display increased shock transmission and systemic vulnerability in the post Covid-19 period.

KEYWORDS
Bitcoin; Cryptocurrencies; Tail-Risk; Safe Haven; CoVaR

1. Introduction

Although there is a considerable body of literature documenting tail codependency among cryptocurrencies and their relationship with more traditional asset markets (e.g., Borri, 2019; Xu, Zhang, and Zhang, 2021; Lahiani, Jlassi, et al., 2021; Sebastião and Godinho, 2020; Goodell and Goutte, 2021; and Lee and Baek, 2022), there are reasons to believe the investment environment in digital markets has undergone enough change to warrant renewed empirical evidence.

From the beginning of the pandemic periods in early 2020 onward, we observed a steady growth of digital assets' markets. As illustration, Figure 1 plots Bitcoin market capitalization from 2019 to 2020, which can be qualitatively taken as representation of cryptocurrency markets in general. After pronounced peaks in April and November 2021, Bitcoin market capitalization has steadily declined ever since. Anecdotal evidence, although mixed, could be interpreted such that the bullish period observed in cryptocurrency markets from 2020 to late 2021 is attributed to the abundance of direct governmental transfers as stimulus checks in developed countries, and due to abrupt changes of consumers' spending patterns due as response to lockdown policies. In similar anecdotal manner, we observe a steady drop in cryptocurrencies prices from the beginning of 2022 coinciding with interest rate hikes in developed countries as response to rapidly increasing inflationary pressure (see Ren, Althof, and Härdle, 2020).

Whatever the underlying cause, it is clear investment conditions pertaining cryp-

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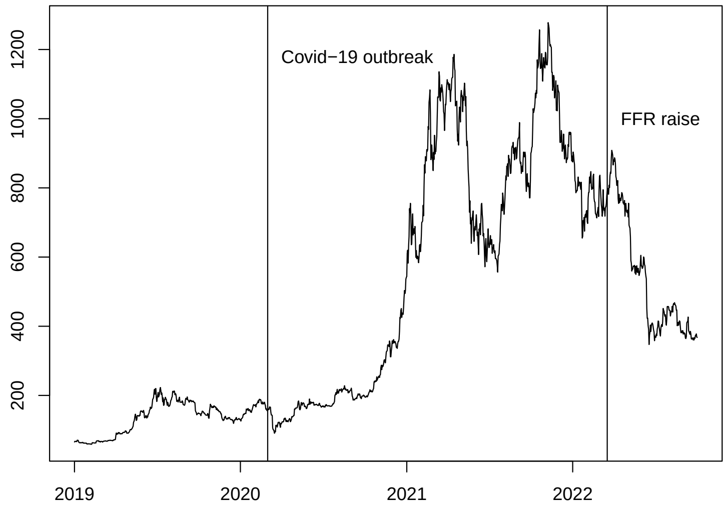
Figure 1. Bitcoin Market Capitalization



Note: Bitcoin market capitalization as the total USD value of bitcoin supply in circulation, as calculated by the daily average market price across major exchanges.

tocurrency markets underwent changes from the beginning of the Covid-19 pandemic to present days. Such structural shifts motivate us to renew empirical evidence regarding tail codependency and systemic risk, both within the class of digital assets and between cryptocurrencies and traditional assets such as equity and gold.

The idea that digital assets could display save haven properties against downturns in conventional markets is a reoccurring theme in the literature. Taking the usually applied definition by Baur and Lucey (2010), "a safe haven is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil". Empirical evidence is mainly focused on Bitcoin and conclusions are mixed (Bouri, Molnár, Azzi, Roubaud, and Hagfors, 2017; Selmi, Mensi, Hammoudeh, and Bouoiyour, 2018; Urquhart and Zhang, 2019; Klein, Thu, and Walther, 2018; Smales, 2019; Mariana, Ekaputra, and Husodo, 2021; Liu and Li, 2022). We believe market experience during the Covid-19 pandemic and the subsequent 2022 period provide a suitable episode to further investigate the narrative of such assets offering safe-haven hedging properties against downturns in traditional markets.

We measure tail codependency and systemic risk emission among the two main cryptocurrencies, Bitcoin and Ethereum, and traditional assets (Gold and the S&P500 index) by computing CoVaR and ΔCoVaR measures through the quantile regression framework introduced by Adrian and Brunnermeier, 2011. State contingency and time variation are captured by conditioning CoVaR measures on a selected set of lagged state variables selected to portray general macroeconomic and financial conditions. Our sample is split in two subsamples: the first one covering a pre-pandemic period from late 2017 to early 2020, and a second which covers 2020 onward representing post-pandemic conditions.

Our results point out that the measures of CoVaR and ΔCoVaR, on average, became higher (in absolute terms) after the pandemic, indicating higher connectivity in extreme events between those assets. We also find that gold has similar values of VaR and CoVaR, while also displaying the lowest values of ΔCoVaR in our estimates — this reinforces the notion of gold as a safe haven asset. Comparing Bitcoin and Ethereum, the two biggest cryptocurrencies in market value, we note that Bitcoin have the lowest ΔCoVaR (on average), meaning it is less systematically vulnerable than Ethereum.

2. Methodology

The Value at Risk (VaR) of asset i at some level q is implicitly defined as the q-quantile of its return distribution at period t. That is,

$$\Pr(r_t^i \le VaR_{q,t}^i) = q, \tag{1}$$

where r^i denotes the log returns of asset i at period t. This means we expect to see returns below VaR^i at $100q$ percent of days.

Adrian and Brunnermeier (2011) introduce a measure of tail codependency between two assets i and j, Conditional Value at Risk (CoVaR), which is defined as the q-quantile of asset i's return distribution, conditional on asset j being at its own VaR distress level.

$$\Pr\left(r^i \le CoVaR_q^{i|j} \middle| r^j = VaR_q^j\right) = q$$

We follow Adrian and Brunnermeier (2011) and Borri (2019) and compute both VaR and CoVaR quantities through quantile regressions. The main allure of such method is its simplicity, since $VaR_{q,t}$ can be obtained directly as predicted values of the quantile regression at level q. Thus our measures of unconditional, time invariant, VaRs are the predicted values of regression

$$VaR_q^i = \alpha_q^i + \epsilon_q^i. \tag{2}$$

For details on quantile regression methods we point to Koenker (2005) or Koenker, Chernozhukov, He, and Peng (2017).

CoVaR measures then can be computed as the predicted value of a second quantile regression with VaR values as regressors.

$$CoVaR_q^{j|r^i=VaR_q^i} = \hat{\beta}_{0,q}^{j|i} + \hat{\beta}_{1,q}^{j|i} VaR_q^i. \tag{3}$$

Here $\hat{\beta}^{j|i}$ determines the sensitivity of log return of an asset j to changes in tail event log return of an asset i, i.e., the degree of interconnectedness between the assets.

In order to estimate CoVaR measure varying over time, Härdle, Wang, and Yu (2016) employ two steps of linear quantile regression. Firstly, should be determined VaR of an asset i by applying quantile regression of log return of asset i on macro state variables. The second step would be to calculate the CoVaR measurement itself.

$$VaR_{i,t,q} = \hat{\alpha}_i + \hat{\gamma}_i M_{t-1}, \tag{4}$$

$$CoVaR_{j|i,t,q} = \hat{\alpha_{j|i}} + \hat{\gamma_{j|i}} M_{t-1} + \hat{\beta}_{j|i} VaR_{i,t,q}, \tag{5}$$

where M_{t-1} represents a vector of lagged financial and macroeconomic variables, reflecting the overall state of the economy.

Adrian and Brunnermeier (2011) argue systemic risk is, generally, built up in times of low asset price volatility and realized during economic crises. They point out a good systemic risk measure should capture this build-up, so they proposed the ΔCoVaR measure that captures the tail dependency between the financial system and a individual institution.

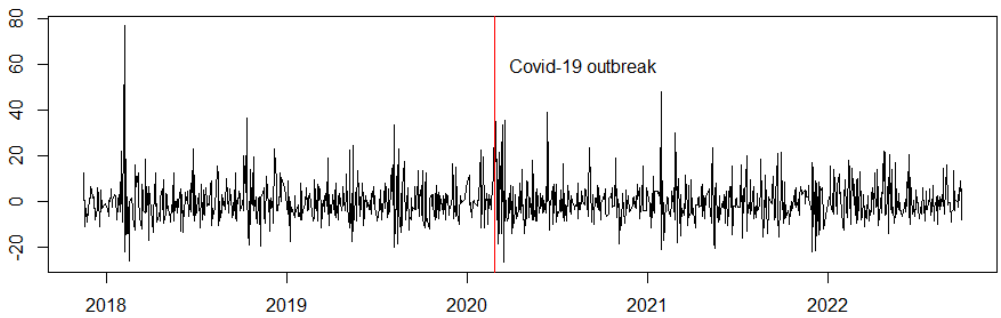
The authors define ΔCoVaR measure as the difference between CoVaR conditional on the distress of an institution and your CoVaR conditional on the median state of that same institution. The part of j's systemic risk that can be attributed to i is denoted as follows

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_{50}^{j|X^i=VaR_{50}^i}. \tag{6}$$

3. Data Description

We define two subsamples dividing our daily data in a pre-pandemic period (from 2017-11-13 to 2022-02-26) and a post-pandemic period (from 2022-02-17 to 2022-09-30). Cutoff dates were motivated by Goodell and Goutte (2021), who recognize changes in the dynamics of volatility of VIX returns, suggesting a structural shift in overall market conditions.

Figure 2. VIX Returns



Note: This figure represent the volatility of VIX returns divide in pre-pandemic period (2017-11-13 to 2020-02-26) and post-pandemic period (2020-02-27 to 2022-09-30)

The database is composed of daily data on asset returns starting on 2017-11-13 and ending on 2022-09-30, for the following variables: Bitcoin, Ethereum, Gold and the S&P500 index[1]. Table 1 and Table 2 summarize the descriptive statistics for the chosen cryptocurrencies.

While the chosen macroeconomics state variables for the same period are Oil Prices Brent - Europe, CBOE Volatility Index, 5-Year Forward Inflation Expectation Rate,

[1]Data on cryptocurrency returns was sourced from coinmarketcap.com, while the remaining data was sourced from the Federal Reserve Economic Data.

Corporate Bond Index, USD/EUR exchange rate, Nominal Broad U.S. Dollar Index and S&P commodity index.

Table 1. Descriptive Statistics - 2017-11-13 to 2020-02-26 (pre-pandemic period)

	Bitcoin (BTC)	Ethereum (ETH)	Gold	S&P500
Min. (%)	-23.874	-27.163	-2.044	-4.184
Mean (%)	0.076	-0.102	0.040	0.044
Median (%)	0.107	-0.145	0.018	0.101
Max. (%)	22.512	23.474	2.746	3.376
Std. (%)	4.791	5.734	0.652	0.913
Skew	0.126	-0.237	0.450	-1.014
Kurt	6.728	5.290	4.505	6.231
Quantile 5%	-7.741	-9.402	-0.936	-1.744
Quantile 95%	8.128	9.399	1.210	1.296

Note: This table reports minimum, mean, median, maximum, standard deviation, skewness, kurtosis and quantile of 5% and 95% for the log daily returns on Bitcoin, Binance Coin, Ethereum, Ripple, Litecoin, Gold and the S&P500 index for the pre-pandemic period. The sample for pre-pandemic period is composed by 518 observations.

Table 2. Descriptive Statistics - 2020-02-26 to 2022-09-30 (post-pandemic period)

	Bitcoin (BTC)	Ethereum (ETH)	Gold	S&P500
Min. (%)	-46.473	-55.073	-5.265	-12.765
Mean (%)	0.201	0.227	0.005	0.016
Median (%)	0.245	0.474	0.046	0.127
Max (%)	19.153	24.706	5.133	8.968
Std (%)	4.850	6.263	1.077	1.687
Skew	-1.731	-1.567	-0.573	-0.860
Kurt	19.145	15.706	6.608	14.181
Quantile 5%	-6.765	-8.454	-1.711	-2.605
Quantile 95%	7.433	8.981	1.717	2.109

Note: This table reports minimum, mean, median, maximum, standard deviation, skewness, kurtosis and quantile of 5% and 95% for the log daily returns on Bitcoin, Binance Coin, Ethereum, Ripple, Litecoin, Gold and the S&P500 index for the post-pandemic period. The sample for post-pandemic period is composed by 597 observations.

Table 3. Descriptive Statistics for state variables

	Min. (%)	Mean (%)	Median (%)	Max.	Std.	Skew	Kurt
VIX	-0.768	0.001	0.011	0.266	0.086	-1.534	11.349
S&P Commodity Index	-0.125	0.001	0.002	0.077	0.016	-1.208	13.380
Corporate Bond Index	-0.051	-0.000	0.000	0.068	0.005	-0.027	49.493
Oil Prices Brent	-0.644	0.001	0.002	0.412	0.040	-3.111	83.503
Inflation Expectation Rate	-0.246	-0.000	0.000	0.325	0.024	0.455	51.542
USD/EUR Exchange Rate	-0.018	-0.000	-0.000	0.017	0.004	-0.167	4.487
Dollar Index	-0.019	0.000	-0.000	0.019	0.003	0.356	6.415

Note: This table reports minimum, mean, median, maximum, standard deviation, skewness and kurtosis for the entire sample. The returns of VIX index are multiplied by -1 so that negative returns correspond to an increase in the value of the index and, thus, to turmoil moments in the economy. The sample for macro state variables is composed by 1115 observations.

4. Empirical Results

We define two subsamples dividing our daily data in a pre-pandemic period (from 2017-11-13 to 2022-02-26) and a post-pandemic pediod (from 2022-02-17 to 2022-09-30). Cutoff dates were motivated by Goodell and Goutte (2021), who recognize changes in the dynamics of volatility of VIX returns, sugesting a structural shift in overall market conditions.

Tables 4 and 5 report our time invariant VaR and CoVaR measures for pre-pandemic and post-pandemic subsamples, respectively. We note the VaR estimates for Bitcoin and Ethereum fell (in absolute value) with the onset of Covid-19, while VaR estimates for Gold and S&P500 became higher (also in absolute values). This is some evidence of a different impact of Covid-19 on cryptocurrencies VaR when compared to more traditional assets.

Our estimates time invariant measures of tail codependency $\beta_{1,q}^{j|i}$, $CoVaR_q^{j|r^i}$, and $\Delta CoVaR_q^{j|i}$ became higher in absolute terms. These results suggest increased amout of systemic risk between those markets in the post-pandemic pediod. This is in accordance with Goodell and Goutte (2021), which point out that the co-movements between cryptocurrencies and equity indices increased as COVID19 progressed.

Before the pandemic (Table 4), the $\Delta CoVaR_q^{j|i}$ measure was positive for Bitcoin (0.15%), Ethereum (0.94%) and S&P500 (0.47%) when this assets was conditional for Gold. Borri (2019) also find a positive value for Ripple and equity but not for the cryptocurrencies. The results found in Table 4 may indicate that Bitcoin, Ethereum and S&P500, was, at least, a hedge for Gold before the pandemic. However, in the post pandemic period (Table 5), this effect is lost and no positive value of $\Delta CoVaR_q^{j|i}$ is found.

Analyzing Gold, the most recognizable safe-haven in the literature (Ciner, Gurdgiev, and Lucey, 2013; Baur and Lucey, 2010; Burdekin and Tao, 2021; Selmi et al., 2018; Klein et al., 2018) we note, through the Table 4 and Table 5, that Gold have similar values of VaR_q^i and $CoVaR_q^{j|VaR_q^i}$ and, also have the lowest value of $\Delta CoVaR_q^{j|VaR_q^i}$ when q = 5%. However, the risk spillovers between Gold and cryptocurrencies, although still small, increased after the pandemic. The $\beta_{1,q}^{j|i}$ for Gold conditional on cryptocurrencies are weakly and positively related, these results are also found in Yu, Shang, and Li (2021), the authors also point that the risk spillover between Gold and Bitcoin are not stable.

4.1. CoVaR Conditional on Macroeconomic Variables

In this section, the time-varying estimation results of the VaR_q^i, $CoVaR_q^{j|r^i}$ and $\Delta CoVaR_q^{j|i}$ of Bitcoin, Ethereum, Gold and S&P500 are present using either Bitcoin and S&P500 as conditioning variables. The inclusion of the state variables is important, according Borri (2019), to differentiate the sensibility of each asset j with respect to tail-risk in asset i from the to macroeconomic factors. The results of the time-varying conditional tail risk are represented by Figure 3, Figure 4, and Figure 5. Table 6 shows the significance of the coefficients for the macro state variables for Bitcoin, Ethereum, Gold and S&P500 conditioning in Bitcoin and S&P500.

Analyzing the significance of the macro state variables coefficients based on Table (6), we note that, different from Borri (2019), Bitcoin volatility is not always significantly, however, is negatively associated with other assets. The expected inflation rate

Table 4. Conditional Tail-Risk - 2017-11-13 to 2020-02-26 (Pre - pandemic period)

j/i	BTC	ETH	Gold	S&P500
VaR_q^i	-7.85	-9.60	-0.94	-1.75
		$\beta_{1,q}^{j\|i}$		
Bitcoin (BTC)	-	0.44***	-0.16	0.69
Ethereum (ETH)	0.81***	-	-0.98	0.41
Gold	0.01	0.01*	-	-0.05
S&P500	0.01	0.03	-0.50**	-
		$CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-8.57	-7.63	-8.95
Ethereum (ETH)	-12.13	-	-8.51	-10.30
Gold	-1.05	-1.13	-	-0.87
S&P500	-1.82	-2.00	-1.17	-
		$\Delta CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-4.14	0.15	-1.26
Ethereum (ETH)	-6.44	-	0.94	-0.76
Gold	-0.09	-0.12	-	0.09
S&P500	-0.10	-0.26	0.47	-

Note: The p-values are calculated with standard errors computed by bootstrap and are represented for $^{***}p < 0.01$ $^{**}p < 0.05$ and $^{*}p < 0.10$. The right-hand variables are on the table columns (variables i), and the left-hand conditioning variables on the table rows (variables j). The results that are reports in this table was estimated using the following equations with level q = 5%.

$$VaR_q^i = \alpha_q^i + \epsilon_q^i,$$

$$CoVaR_q^{j|r^i=VaR_q^i} = \hat{\beta}_{0,q}^{j|i} + \hat{\beta}_{1,q}^{j|i} VaR_q^i,$$

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_{50}^{j|X^i=VaR_{50}^i}.$$

Table 5. Conditional Tail-Risk - 2020-02-27 to 2022-09-09 (Post - pandemic period)

j/i	BTC	ETH	Gold	S&P500
VaR_q^i	-6.77	-9.41	-1.73	-2.62
		$\beta_{1,q}^{j\|i}$		
Bitcoin (BTC)	-	0.62***	0.93	1.44***
Ethereum (ETH)	1.20***	-	1.37***	1.93***
Gold	0.07*	0.07**	-	0.14
S&P500	0.19***	0.17***	0.65*	-
		$CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-9.79	-8.39	-10.11
Ethereum (ETH)	-13.53	-	-11.76	-14.16
Gold	-2.32	-2.56	-	-2.12
S&P500	-3.58	-4.05	-3.63	-
		$\Delta CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-6.02	-1.64	-3.96
Ethereum (ETH)	-8.40	-	-2.43	-5.29
Gold	-0.50	-0.67	-	-0.39
S&P500	-1.34	-1.63	-1.15	-

Note: The p-values are calculated with standard errors computed by bootstrap and are represented for $^{***}p < 0.01$ $^{**}p < 0.05$ and $^{*}p < 0.10$. The right-hand variables are on the table columns (variables i), and the left-hand conditioning variables on the table rows (variables j). The results that are reports in this table was estimated using the following equations with level q = 5%.

$$VaR_q^i = \alpha_q^i + \epsilon_q^i,$$
$$CoVaR_q^{j|r^i=VaR_q^i} = \hat{\beta}_{0,q}^{j|i} + \hat{\beta}_{1,q}^{j|i} VaR_q^i,$$
$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_{50}^{j|X^i=VaR_{50}^i}.$$

Table 6. State Variable Exposures

	BTC|S&P500	S&P500|BTC	ETH|S&P500	ETH|BTC	Gold|S&P500	Gold|BTC
VIX	0.103*	-0.007	0.139	-0.034	-0.016	-0.010
Comm.Index	-0.454	-0.198	-0.801*	0.240	-0.015	-0.073
Bond Index	0.017	0.273	-1.136	0.006	0.163	0.264
Oil Prices Brent	0.117	0.082	0.143	-0.171	0.014	0.032
Inf. Exp. Rate	0.408**	-0.046	0.396*	0.179	0.079**	0.042
USD/EUR	-0.239	-0.488	-1.096	-1.044	-0.333	-0.312
Dollar Index	2.278	-0.558	-0.491	-0.176	-0.765	-0.691
BTC Vol	-1.157***	-0.199*	-0.470	-0.367**	-0.035	-0.028

Note: The p-values are represented for $^{***}p < 0.01$ $^{**}p < 0.05$ and $^{*}p < 0.10$.

have a positive sign and is significant statistically for BTC|S&P500 , Gold|S&P500 and ETH|S&P500. These results are in accordance with Conlon, Corbet, and McGee (2021), which also found a positive association between cryptocurrencies and forward inflation rates on the onset period of the COVID19. The authors also find that outside of the pandemic period, there is no evidence of any inflation hedging capacity of the cryptocurrencies during moments of increasing forward inflation expectations.

The averages of the $CoVaR_q^{j|VaR^i}$ and $\Delta CoVaR_q^{j|VaR^i}$ are presented in Table 7 and Table 8. The highest values of $\Delta CoVaR_q^{j|VaR^i}$ occurs when we condition Bitcoin on S&P500 and Ethereum on S&P500 and Bitcoin. This results implies that the largest tail risk effects to the cryptocurrencies, in other words, the largest $CoVaR_q^{j|VaR^i}$ values, appear to come from S&P500 and Bitcoin.

Trajectories of time-varying $\Delta CoVaR_q^{j|VaR^i}$ in Figures 3, 4, and 5, suggest, echoing Akhtaruzzaman, Boubaker, Nguyen, and Rahman (2022), that tail risk dependence increased during the pandemic period, therefore pointing to higher transmission of shocks within the system. Comparing Bitcoin and Ethereum, the two biggest cryptocurrencies in market value (coinmarketcap.com, as of November 2022), we note that Bitcoin have the lowest $\Delta CoVaR_q^{j|VaR^i}$ in absolute values (on average), i.e, is less systematically vulnerable.

According to Figure 3, Figure 4 and Figure 5, conditional measures of analyzed cryptocurrencies are below the respective VaR levels; this result reflects the positive dependencies between such assets. This result is also found by Waltz, Kumar Singh, and Okhrin (2022) which also point out that the conditional measures are driven by similar dynamics as the univariate VaR.

Table 7. Time-varying Conditional Tail Risk - Pre Pandemic Period

	Min. (%)	Mean (%)	Median (%)	Max. (%)	Std (%)	Skew	Kurt
			$CoVaR_q^{j\|VaR^i}$				
BTC|S&P500	-26.051	-9.733	-9.292	-2.603	2.867	-0.720	4.717
S&P500|BTC	-3.142	-1.565	-1.550	0.170	0.433	-0.179	3.523
ETH|S&P500	-31.433	-12.524	-12.262	-6.101	2.472	-1.183	9.487
ETH|BTC	-26.056	-11.471	-11.023	-4.804	2.802	-0.748	4.081
Gold|S&P500	-1.349	-0.901	-0.912	-0.271	0.168	0.381	3.274
Gold|BTC	-1.567	-1.094	-1.100	-0.560	0.145	0.173	3.367
			$\Delta CoVaR_q^{j\|VaR^i}$				
BTC|S&P500	-26.733	-9.946	-9.492	-2.588	2.958	-0.701	4.612
S&P500|BTC	-3.235	-1.673	-1.649	-0.088	0.399	-0.207	3.534
ETH|S&P500	-30.704	-12.413	-12.134	-6.135	2.425	-1.120	9.286
ETH|BTC	-27.169	-11.262	-10.828	-4.245	2.922	-0.793	4.345
Gold|S&P500	-1.406	-0.900	-0.912	-0.312	0.158	0.317	3.386
Gold|BTC	-1.532	-1.104	-1.107	-0.606	0.124	0.119	3.588

Note: The table shows the descriptive statistics for the estimates of the time-varying CoVaR and ΔCoVaR for BTC, ETH, Gold and S&P500 given BTC and S&P500 for the Pre - Pandemic period.

5. Conclusion

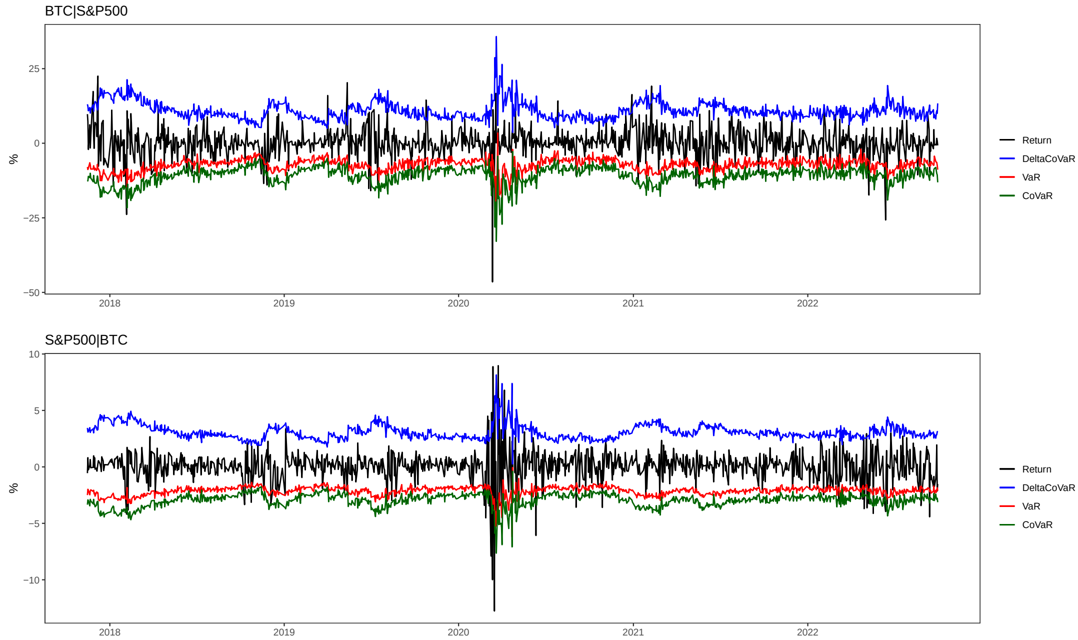
We analyzed conditional tail risk between the two largest cryptocurrencies, Bitcoin and Ethereum, as well as a proxy for equity markets, the S&P500 index, and Gold — a tra-

Table 8. Time-varying Conditional Tail Risk - Post Pandemic Period

	Min. (%)	Mean (%)	Median (%)	Max. (%)	Std (%)	Skew	Kurt
				$CoVaR_q^{j\|VaR^i}$			
BTC|S&P500	-33.007	-11.639	-11.301	-5.774	2.503	-2.411	15.882
S&P500|BTC	-9.101	-3.647	-3.502	-1.356	0.903	-2.270	12.335
ETH|S&P500	-38.695	-14.372	-14.095	-0.861	2.579	-2.093	19.499
ETH|BTC	-41.546	-12.548	-12.161	-1.033	3.137	-2.391	18.809
Gold|S&P500	-6.156	-2.458	-2.446	0.415	0.430	-1.429	21.164
Gold|BTC	-5.165	-2.266	-2.243	-0.428	0.405	-1.867	14.588
				$\Delta CoVaR_q^{j\|VaR^i}$			
BTC|S&P500	-34.462	-11.787	-11.353	-6.584	2.662	-2.479	16.403
S&P500|BTC	-9.447	-3.705	-3.563	-0.999	0.953	-2.310	13.148
ETH|S&P500	-40.504	-14.764	-14.490	-6.106	2.602	-2.585	21.500
ETH|BTC	-40.604	-12.885	-12.402	-6.570	3.127	-2.624	18.738
Gold|S&P500	-3.657	-2.528	-2.533	-0.630	0.294	0.636	8.318
Gold|BTC	-5.988	-2.317	-2.300	-1.099	0.367	-1.833	19.760

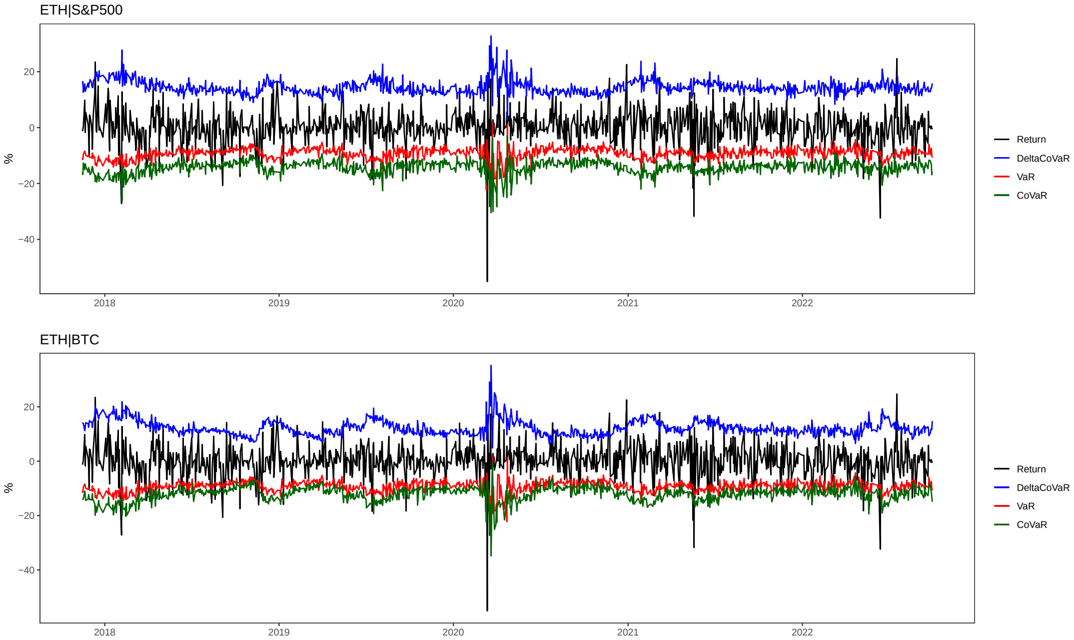
Note: The table shows the descriptive statistics for the estimates of the time-varying CoVaR and ΔCoVaR for BTC, ETH, Gold and S&P500 given BTC and S&P500 for the Post - Pandemic period.

Figure 3. CoVaR and ΔCoVaR of Bitcoin and S&P500 Conditional on, respectively, S&P500 and Bitcoin



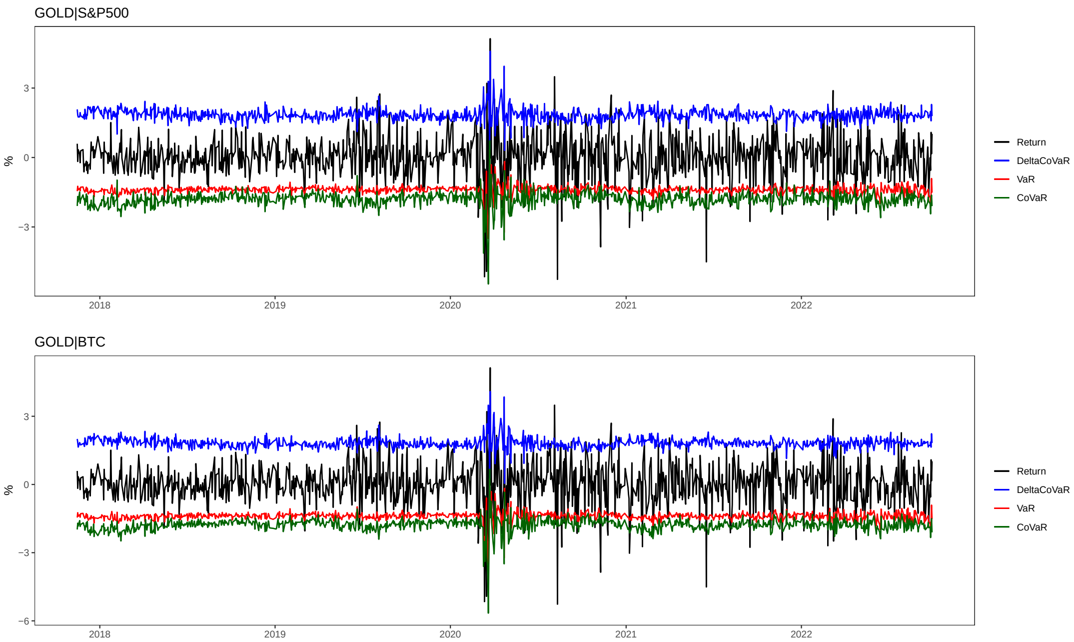
Note: This figure shows the CoVaR (green), ΔCoVaR (blue), the $\text{VaR}^i_{95,t}$ (red), and the returns (black) for the entire sample.

Figure 4. CoVaR and ΔCoVaR of Ethereum Conditional on S&P500 and Bitcoin



Note: This figure shows the CoVaR (green), ΔCoVaR (blue), the $\text{VaR}^i_{95,t}$ (red), and the returns (black) for the entire sample.

Figure 5. CoVaR and ΔCoVaR of Gold Conditional on S&P500 and Bitcoin



Note: This figure shows the CoVaR (green), ΔCoVaR (blue), the $\text{VaR}^i_{95,t}$ (red), and the returns (black) for the entire sample.

ditional safe haven asset. Our results suggest extreme event codependency increased suring the pandemic period, thus pointing towards increased shock transmission. Comparing Bitcoin and Ethereum, we note that Bitcoin have the lowest $\Delta CoVaR_q^{j|VaR^i}$ on average (in absolute terms) i.e., is less systematically vulnerable.

Some authors (Su, Qin, Peng, and Qin (2021) and others), point out that measures of conditional risk may prove uninformative or even unspecified when risk factors change dramatically, which occurs in periods of market turbulence or stress. Therefore, in future studies, it is suggested the use of another frequency of time or even other tail risk methods be compared and analyzed.

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