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Impact of Covid-19 On tail risk dynamics for cryptocurrencies and traditional assets

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Abstract

In this paper, we investigate the evolution of tail codependency and risk between the two largest cryptocurrencies (Bitcoin and Ethereum) and two traditional assets (Gold and the S&P500 index) before and after the Covid-19 pediod. Using a quantile regression framework, we compute the conditional tail risk (CoVaR) and $Delta$CovaR measures. Our results suggest that cryptocurrencies show increased shock transmission, systemic vulnerability, and risk spillovers in the post Covid-19 period. We also find that risk spillovers between Gold, the most recognizable safe haven in the literature, and cryptocurrencies, although still small, also increased after the pandemic. We believe that our study provides valuable information to help investors make better informed investment decisions and develop effective trading and diversification strategies.

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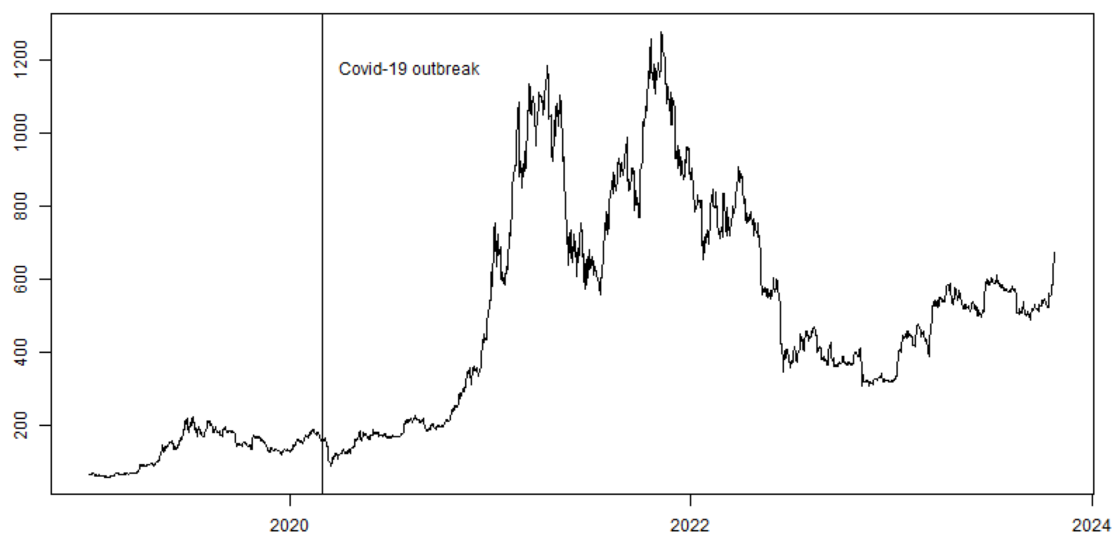
1. Introduction

Since the onset of the pandemic in early 2020, we have observed steady growth in the digital asset markets. As an illustration, Figure 1 shows the market capitalization of Bitcoin from 2019 to 2024, which can be qualitatively taken as the representation of cryptocurrency markets in general. After pronounced peaks in April and November 2021, Bitcoin's market capitalization steadily declined through the end of our sample period in late 2023.

Anecdotal evidence, though mixed, suggests that the bullish period observed in cryptocurrency markets from 2020 to late 2021 was driven by the abundance of direct governmental transfers, such as stimulus checks in developed countries, and by abrupt changes in consumers' spending patterns in response to lockdown policies. Similarly, we observe a steady drop in cryptocurrencies prices from the beginning of 2022 that coincided with interest rate hikes in developed countries in response to rapidly increasing inflationary pressure (see Ren et al., 2020).

Figure 1: Bitcoin Market Capitalization



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

Regardless of the underlying cause, there is evidence that investment conditions in cryptocurrency markets changed with the onset of the Covid-19 pandemic. In addition, there is a considerable body of literature documenting tail codependency between cryptocurrencies and their relationship with more traditional asset markets during the pre- and post-pandemic period (e.g., Borri, 2019; Xu et al., 2021; Lahiani et al., 2021; Sebastião and Godinho, 2020; Goodell and Goutte, 2021; and Lee and Baek, 2022). However, none of these studies analyze structural breaks in tail codependency and systemic risk emission and their effects on both cryptocurrencies and traditional markets.

To examine this issue, we implement the method proposed by Qu (2008) and Oka and Qu (2011), which tests for the presence of structural breaks in quantile regressions with unknown dates. We found out that both cryptocurrencies, Bitcoin and Ethereum, display structural breaks in the 5% quantile dated to early 2020. 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.

Therefore, in this paper, we measure and compare the tail codependency and systemic risk emission among the two main cryptocurrencies, Bitcoin and Ethereum, and traditional assets, Gold and the S&P500 index. We compute CoVaR and ΔCoVaR measures through the quantile regression framework introduced by Adrian and Brunnermeier (2016). CoVaR, or Conditional Value-at-Risk, extends the notion of risk of extreme losses that occurs in the left tails of the distribution of asset returns, know as tail risk, to an conditional framework. CoVaR measures the tail risk of some asset i conditional on asset j displaying extreme losses. On the other hand, ΔCoVaR measures the emission of tail risk between these assets.

Based on the results of the structural break tests, we split our sample into two subsamples: one before the pandemic, covering the period from the end of 2017 to early 2020, and one after, covering 2020 onwards. We believe that market experience during the Covid-19 pandemic, and the subsequent 2022 period, also provide a suitable episode to further investigate the narrative of cryptocurrencies offering safe haven hedging properties against downturns in traditional markets.

Our results show that the measures of CoVaR and ΔCoVaR, on average, became higher (in absolute terms) after the pandemic, indicating greater connectivity in extreme events between these assets. We also find that Gold has similar values of VaR and CoVaR, while also displaying the lowest values of ΔCoVaR in our estimates, which reinforces the notion of Gold as a safe haven asset. When comparing BTC and ETH, the two largest cryptocurrencies in market value, we note that BTC has the lowest ΔCoVaR (on average), meaning that it is less systematically vulnerable than ETH.

2. Related Literature and Methodology

The idea that such assets could display safe haven properties against downturns in conventional markets is a reoccurring theme in the literature. However, empirical evidence is mainly focused on Bitcoin and conclusions are mixed (see, for example Bouri et al., 2017; Selmi et al., 2018; Urquhart and Zhang, 2019; Klein et al., 2018; Smales, 2019; Mariana et al., 2021; Liu and Li, 2022).

A safe haven is defined by Baur and Lucey (2010) as "an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil". This means that while a hedge instrument is an asset whose returns are uncorrelated or negatively correlated with another asset's returns on average market conditions, a safe haven is an asset that displays hedging properties in periods of market stress or turmoil.

In order to provide a suitable measure of the tail codependency and systemic risk, we estimate VaR, CoVaR and also ΔCoVaR for the cryptocurrencies (Bitcoin (BTC) and Ethereum (ETH)) and the traditional assets (Gold and S&P500 Index) via quantile regression[1].

First, the Value-at-Risk (VaR) of an asset i at level q is defined as the q-quantile of its return distribution,

$$\Pr(r^i \leq VaR^i_q) = q, \tag{1}$$

where r^i denotes the log returns of asset i. This means we expect to see returns below VaR^i at $100q$ percent of days. Next, the Conditional Value-at-Risk (CoVaR), introduced by Adrian and Brunnermeier (2016), measures the q-quantile of asset j's return distribution conditional on asset i being at its own VaR distress level, and is calculated as follows:

$$\Pr\left(r^j \leq CoVaR^{j|i}_q \middle| r^i = VaR^i_q\right) = q. \tag{2}$$

We follow Adrian and Brunnermeier (2016) and Borri (2019) and compute both VaR and CoVaR using quantile regressions. The main advantage of this method is its simplicity: VaR can be obtained directly as the predicted value of the quantile regression at level q, and CoVaR measures can then be computed as the predicted value of a second quantile regression with VaR values as regressors. Thus, our time-invariant measures of VaR and CoVaR are the predicted values from the following regressions:

$$VaR^i_q = \alpha^i_q + \epsilon^i_q, \tag{3}$$

$$CoVaR^{j|r^i=VaR^i_q}_q = \hat{\beta}^{j|i}_{0,q} + \hat{\beta}^{j|i}_{1,q} VaR^i_q. \tag{4}$$

In equation (4), $\hat{\beta}1, q^{j|i}$ measures the impact of asset i's stressed state on the contemporaneous left-tail returns of asset j. A safe haven asset should display little codependency with other assets in times of market turmoil, and thus we would expect smaller values of $\hat{\beta}1, q^{j|i}$ if asset j is a safe haven asset.

Adrian and Brunnermeier (2016) define ΔCoVaR$_q$ as the difference between asset j's CoVaR conditional on asset i being at its VaR$_q$ return level, and asset j's CoVaR when asset i is at its median return level. ΔCoVaR$_q$ measures the additional volatility incurred by asset j due to extreme downward movements of asset i's returns.

$$\Delta CoVaR^{j|i}_q = CoVaR^{j|X^i=VaR^i_q}_q - CoVaR^{j|X^i=VaR^i_{50}}_q \tag{5}$$

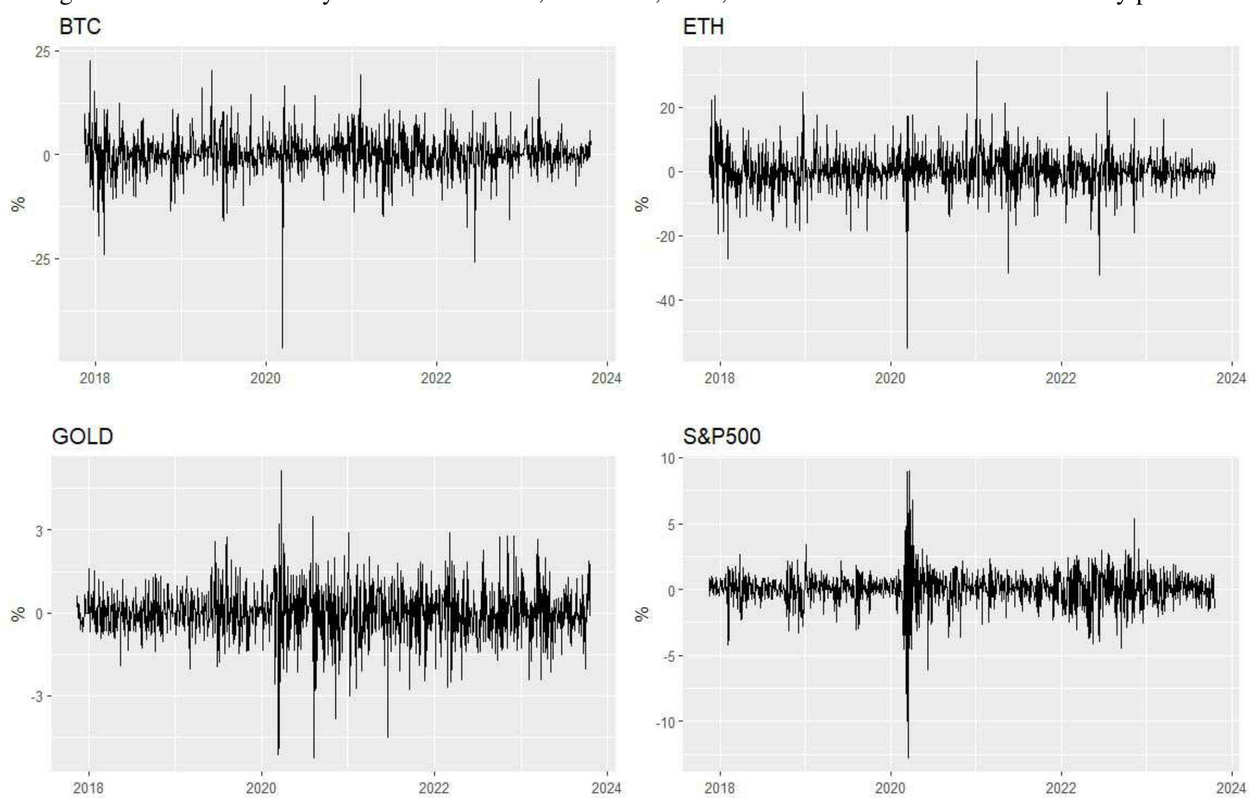
[1]For details on quantile regression methods, we point to Koenker (2005) or Koenker et al. (2017).

The interpretation of the $\Delta CoVaR_q^{j|i}$ measure is as follows: When asset i is at its median level, $VaR_{50\%}^{j|i}$, and moves to its stress level, $VaR_{5\%}^{j|i}$, a percentage variation is expected in asset j. For example, if the value of $\Delta CoVaR_q^{j|i}$ for asset j conditioned on asset i is -10%, this means that when asset i moves from its median to its stress level, asset j is expected to decrease by -10%

3. Data Description

Table 1 reports the results of the structural break tests from Qu (2008), applied to the 5% and 1% percentiles of the return series for Bitcoin, Ethereum, Gold, and the S&P500 index. For the 5% percentile, we find evidence of two structural shifts for Bitcoin and Ethereum, and one break in the return series of Gold. The null hypothesis of no structural break in the 5% percentile is not rejected for the S&P500 returns series. The second break for cryptocurrencies Bitcoin and Ethereum is dated to April 14th and 16th of 2020, respectively, with a 95% confidence interval spanning late December 2019 to July 2020. The period coincides with the outbreak of Covid-19 in early 2020, suggesting a shift in the dynamics of left tail quantiles of cryptocurrencies. Because the dates of the structural breaks are not the same for both cryptocurrencies (at least for the 5% quantile), we follow Goodell and Goutte (2021) and set the cut-off dates based on changes in the volatility dynamics of VIX returns. However, it is important to note that the date of choice, 2020-02-26, is within the 95% confidence interval of the structural break test for both the cryptocurrencies.

Figure 2: Evolution of daily returns for Bitcoin, Ethereum, Gold, and the S&P500 Index over the study period.



We define two sub-samples: a pre-pandemic period (from 2017-11-15 to 2020-02-26) and a post-pandemic period (from 2020-02-27 to 2023-10-20). The database is composed of daily data on asset returns for the following variables: Bitcoin, Ethereum, Gold and the S&P500 index[2]. Tables 2 and 3 summarize the descriptive statistics for the chosen assets. Figure 2 plots the evolution of daily returns of the assets analyzed.

[2]Data on cryptocurrency returns was sourced from `coinmarketcap.com`, while the remaining data was sourced from the Federal Reserve Economic Data, `fred.stlouisfed.org`.

Table 1: Structural Break Test Results for 1% and 5% Quantiles of Bitcoin, Ethereum, Gold, and the S&P500 Index.

Quantiles	0.01	0.05
BTC		
SQ(1|0)	1.327	2.020**
SQ(2|1)	-	1.692**
SQ(3|2)	-	1.258
Number of breaks	0	2
1st Break date	-	2018-01-24
95% C. I.	-	[2017-11-15; 2018-03-06]
2st Break date	-	2020-04-14
95% C. I.	-	[2019-12-29; 2020-06-03]
ETH		
SQ(1|0)	1.001	1.850**
SQ(2|1)	-	1.505**
SQ(3|2)	-	1.181
Number of breaks	0	2
1st Break date	-	2018-06-13
95% C. I.	-	[2017-11-15; 2018-11-05]
2st Break date	-	2020-04-18
95% C. I.	-	[2020-01-09; 2020-06-14]
Gold		
SQ(1|0)	1.465**	2.303**
SQ(2|1)	1.775**	1.207
SQ(3|2)	1.494	-
Number of breaks	2	1
1st Break date	2019-01-11	2018-08-30
95% C. I.	[2018-12-31; 2019-02-15]	[2018-07-25; 2019-03-15]
2st Break date	2019-05-23	-
95% C. I.	[2019-03-28; 2019-07-01]	-
S&P500		
SQ(1|0)	1.334	1.283
SQ(2|1)	-	-
SQ(3|2)	-	-
Number of breaks	0	0
1st Break date	-	-
95% C. I.	-	-
2st Break date	-	-
95% C. I.	-	-

Note: This table reports $SQ(l+1|l)$ tests, where l is the number of structural breaks under the null hypothesis, and the estimated break dates for 1% and 5% quantiles, ** denotes statistical significance at 5% level.

Analyzing the descriptive statistics before and after the pandemic, we see that the mean returns of assets, except Gold, were higher in the post-pandemic period. The median, with the exception of BTC, was higher in the post-pandemic period. Also, it is interesting to note that the 5% quantile for BTC and ETH was lower, in absolut terms, in the post-pandemic period. Meanwhile, the 5% quantile of Gold and S&P500 was higher in the post-pandemic period.

Table 2: Descriptive statistics - pre pandemic period (2017-11-15 to 2020-02-26)

	Bitcoin (BTC)	Ethereum (ETH)	Gold	S&P500
Mean (%)	0.136	0.050	0.020	0.028
Std (%)	4.819	5.993	0.652	0.891
Skew	-0.019	-0.046	0.418	-0.948
Kurt	6.907	5.700	4.547	6.295
Min.	-23.874	-27.163	-2.044	-4.184
Quantile 5%	-7.251	-9.611	-0.967	-1.654
Median	0.139	-0.039	0.000	0.080
Quantile 95%	8.242	9.828	1.204	1.291
Max.	22.512	24.745	2.746	3.376

Note: This table reports mean, standard deviation, skewness, kurtosis, minimum, quantile of 5%, median, quantile of 95% and maximum for the log daily returns on Bitcoin (BTC), Ethereum (ETH), Gold and the S&P500 index for the pre-pandemic period. The sample for pre-pandemic period is composed by 524 observations.

Table 3: Descriptive statistics - post pandemic period (2020-02-27 to 2023-10-20)

	Bitcoin (BTC)	Ethereum (ETH)	Gold	S&P500
Mean (%)	0.137	0.198	0.011	0.037
Std (%)	4.393	5.813	1.019	1.535
Skew	-1.646	-1.187	-0.423	-0.786
Kurt	20.705	16.990	6.528	15.122
Min.	-46.473	-55.073	-5.265	-12.765
Quantile 5%	-6.220	-7.997	-1.604	-2.181
Median	0.137	0.255	0.008	0.085
Quantile 95%	6.923	8.324	1.649	1.972
Max.	19.153	34.352	5.133	8.968

Note: This table reports mean, standard deviation, skewness, kurtosis, minimum, quantile of 5%, median, quantile of 95% and maximum for the log daily returns on Bitcoin (BTC), Ethereum (ETH), Gold and the S&P500 index for the post-pandemic period. The sample for post-pandemic period is composed by 839 observations.

4. Empirical Results

We analyze the results for both the 5% and 1% quantiles, as these significance levels are commonly used in the literature (e.g., Müller et al., 2022; Trucíos, 2019; Ardia et al., 2019; Müller and Righi, 2018).

The results for the time-invariant risk measures are displayed in Tables 4 and 5 for the 5% quantile, while Tables 6 and 7 present the results for the 1% quantile. The absolute VaR estimates for BTC and ETH decreased when Covid-19 began, while the VaR estimates for Gold and the S&P500 increased. This is evidence of a differing impact of Covid-19 on risk-sharing between cryptocurrencies and traditional assets

Parameters $\hat{\beta}_{1,q}^{j|i}$ measure the sensitivity of asset j's returns q-quantile to extreme downturns in conditioning asset i's returns. As a general trend, the point estimates are higher for the post-pandemic sub-sample. These results suggest that Covid-19 fundamentally altered the risk landscape, particularly the interdependence between assets. The increased interconnectedness between BTC, ETH, Gold, and S&P500 post-pandemic indicates a rise in systemic risk.

While our results align with previous studies (Bouri et al., 2021, 2022; Goodell and Goutte, 2021; Xu et al., 2022), it is important to emphasize that cryptocurrencies like BTC and ETH, traditionally considered independent assets, have become more sensitive to traditional assets like Gold and the S&P500 post-pandemic. This points to a shift toward greater market co-movement during times of stress.

The estimates of $\hat{\beta}_{1,q}^{j|i}$ suggest that ETH and BTC left-tail returns show some degree of simultaneity. In the pre-pandemic sample, we observe positive and statistically significant values for both Ethereum's exposure to Bitcoin's tail risk (0.902) and Bitcoin's exposure to Ethereum (0.478). In the post-pandemic period, these values increase to 1.08 for Ethereum's exposure to Bitcoin's tail risk and 0.562 for Bitcoin's exposure to Ethereum. Such a feature is to be expected since the two cryptocurrencies should have similar driving risk factors. Interesting note that in the 1% quantile, the assets have almost the same results for the parameters $\hat{\beta}_{1,q}^{j|i}$ than 5% quantile, in the pre-pandemic period. However, in the post-pandemic period, the assets seems to be more interconnected in the 1% quantile.

The increased exposure of Ethereum to Bitcoin's tail risk, and vice versa, shows that market participants may be viewing these cryptocurrencies as more similar in their risk profiles post-pandemic, which could impact how investors adjust their strategies in times of market turmoil.

Comparing time-invariant CoVaR estimates, we notice less extreme values for BTC after the pandemic, and more extreme values for Gold and S&P500. The exposure of ETH to BTC's tail risk and ETH's exposure to S&P500 index's tail risk decrease after pandemic, however, the degree of ETH's exposure to Gold is higher than the measure obtained before pandemic.

Analyzing $\Delta CoVaR_q^{j|i}$ in the quantile 5%, before the pandemic (Table 4), we note that this measure was positive for S&P500 (0.455%) when conditioning on Gold, which result is also found in Borri (2019), and also positive for Gold (0.082%) when conditioning on S&P500. However, only the parameter $\hat{\beta}_{1,q}^{j|i}$ for S&P500 conditioned on Gold was negative and statistical significantly, this results found may indicate that S&P500, was, at least, a hedge for Gold before the pandemic. In the post pandemic period (Table 5), this effect is lost and no positive value of $\Delta CoVaR_q^{j|i}$ is found.

The $\Delta CoVaR_q^{j|i}$ measure on 1% quantile, for pre-pandemic period, result in positive values for S%P500 index (0.182%) when conditioning on Gold and for Ethereum (3.051%) when conditioning on Gold, but none of this conditional measures has parameter of interconnect, $\hat{\beta}_{1,q}^{j|i}$, statistical significantly. In the post-pandemic period, these positive values were lost.

The disappearance of the hedging effect post-pandemic suggests that these assets may no longer offer the same protection during crises. This indicates that traditional hedging strategies may need re-evaluation or supplementation with newer methods, especially after major market shocks.

Analyzing Gold, the most recognized safe haven asset in the literature (Ciner et al., 2013; Baur and Lucey, 2010; Burdekin and Tao, 2021; Selmi et al., 2018; Klein et al., 2018), we find that it maintains similar values for VaR_q^i and $CoVaR_q^{j|VaR_q^i}$, along with the lowest value of $\Delta CoVaR_q^{j|VaR_q^i}$ for both $q = 5\%$ and $q = 1\%$. However, the risk spillovers between gold and cryptocurrencies, although still small, increased after the pandemic. The $\hat{\beta}_{1,q}^{j|i}$ for Gold conditional on cryptocurrencies are weakly and positively related after pandemic, which means that even with a higher connection, Gold can at least be a hedge for BTC and ETH.

While our results show that Gold still retains its hedge properties, as evidenced by its lower values of $\Delta CoVaR_q^{j|VaR_q^i}$, the increased risk spillovers from Gold to cryptocurrencies post-pandemic suggest a weakening of its isolation as a hedge against financial instability. This change reflects the growing correlation between cryptocurrencies and traditional markets, which may indicate that investors may need to re-evaluate their risk management portfolios.

In summary, our analysis shows that the conditional tail risk and systemic risk measures (i.e., CoVaR and ΔCoVaR) are, on average, higher in the post-pandemic period than in the pre-pandemic period.

5. Conclusion

We analyzed conditional tail risk, using the method proposed by Adrian and Brunnermeier (2016), between the two largest cryptocurrencies, Bitcoin and Ethereum, as well as a proxy for equity markets, the S&P500 index, and Gold. Our results suggest that extreme event co-dependence increased during the pandemic, indicating a rise in shock transmission—even for Gold, traditionally considered a safe haven asset. This increase in shock transmission persists nearly two years after the onset of Covid-19, suggesting a shift in the tail risk structure among the analyzed assets. We note that Bitcoin has the lowest average $\Delta CoVaR_q^{j|VaR^i}$ (in absolute terms), indicating it is less systematically vulnerable than Ethereum.".

In terms of safe haven and hedge properties, the results indicate that both Bitcoin and Ethereum fail to exhibit these characteristics during both periods analyzed. This suggests that achieving effective portfolio diversification in the cryptocurrency markets is challenging, especially during periods of extreme market volatility.

Table 4: Conditional tail-risk - pre pandemic period (2017-11-15 to 2020-02-26) - 5% quantile

j/i	BTC	ETH	Gold	S&P500
VaR^i_q	-7.254	-9.656	-0.969	-1.665
		$\beta^{j\|i}_{1,q}$		
Bitcoin (BTC)	-	0.478***	0.752	1.743
Ethereum (ETH)	0.902***	-	0.108	3.825***
Gold	0.015	0.022**	-	-0.047
S&P500	0.016	0.027	-0.47**	-
		$CoVaR^{j\|VaR^i}_q$		
Bitcoin (BTC)	-	-9.112	-7.969	-10.63
Ethereum (ETH)	-12.029	-	-9.807	-15.914
Gold	-1.141	-1.238	-	-0.899
S&P500	-1.783	-1.868	-1.154	-
		$\Delta CoVaR^{j\|VaR^i}_q$		
Bitcoin (BTC)	-	-4.599	-0.729	-3.036
Ethereum (ETH)	-6.669	-	-0.104	-6.661
Gold	-0.112	-0.214	-	0.082
S&P500	-0.116	-0.258	0.455	-

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 reported in this table were estimated using the quantile q = 5%.

Table 5: Conditional tail-risk - post pandemic period (2020-02-27 to 2023-10-20) - 5% quantile

j/i	BTC	ETH	Gold	S&P500
VaR^i_q	-6.255	-8.063	-1.612	-2.299
		$\beta^{j\|i}_{1,q}$		
Bitcoin (BTC)	-	0.562***	0.829	1.427***
Ethereum (ETH)	1.08***	-	2.065***	1.863***
Gold	0.03	0.032	-	0.128
S&P500	0.169***	0.125***	0.518**	-
		$CoVaR^{j\|VaR^i}_q$		
Bitcoin (BTC)	-	-8.007	-7.646	-8.98
Ethereum (ETH)	-11.342	-	-11.747	-11.968
Gold	-1.828	-1.901	-	-1.932
S&P500	-3.188	-3.112	-3.127	-
		$\Delta CoVaR^{j\|VaR^i}_q$		
Bitcoin (BTC)	-	-4.677	-1.343	-3.403
Ethereum (ETH)	-6.904	-	-3.344	-4.442
Gold	-0.19	-0.266	-	-0.305
S&P500	-1.082	-1.036	-0.839	-

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 are on the table rows (variables j). The results reported in this table were estimated using the quantile q = 5%.

Table 6: Conditional tail-risk - pre pandemic period (2017-11-15 to 2020-02-26) - 1% quantile

j/i	BTC	ETH	Gold	S&P500
VaR_q^i	-13.884	-18.324	-1.464	-3.075
		$\beta_{1,q}^{j\|i}$		
Bitcoin (BTC)	-	0.5***	1.68	2.335
Ethereum (ETH)	0.615***	-	-2.084	2.428***
Gold	0.007	0.04	-	0.206*
S&P500	0.035	0.016	-0.124	-
		$CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-19.315	-16.094	-21.284
Ethereum (ETH)	-21.023	-	-14.769	-24.469
Gold	-1.534	-2.187	-	-2.147
S&P500	-3.627	-3.423	-3.008	-
		$\Delta CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-9.145	-2.46	-7.358
Ethereum (ETH)	-8.619	-	3.051	-7.653
Gold	-0.091	-0.737	-	-0.648
S&P500	-0.486	-0.287	0.182	-

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 reported in this table were estimated using the quantile q = 1%.

Table 7: Conditional tail-risk - post pandemic period (2020-02-27 to 2023-10-20) - 1% quantile

j/i	BTC	ETH	Gold	S&P500
VaR_q^i	-13.601	-16.702	-2.737	-4.433
		$\beta_{1,q}^{j\|i}$		
Bitcoin (BTC)	-	0.532***	2.83	2.014***
Ethereum (ETH)	1.056***	-	3.456	2.546***
Gold	0.066	0.049	-	0.232***
S&P500	0.251***	0.151***	0.992**	-
		$CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-17.392	-20.258	-20.596
Ethereum (ETH)	-21.729	-	-24.388	-25.125
Gold	-3.606	-3.582	-	-3.86
S&P500	-7.778	-7.077	-7.599	-
		$\Delta CoVaR_q^{j\|VaR^i}$		
Bitcoin (BTC)	-	-9.015	-7.768	-9.101
Ethereum (ETH)	-14.508	-	-9.486	-11.504
Gold	-0.904	-0.824	-	-1.05
S&P500	-3.45	-2.554	-2.721	-

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 reported in this table were estimated using the quantile q = 1%.

CoVaR (Conditional Value-at-Risk) has become a key tool for assessing systemic risk in financial markets. Given the rapidly evolving landscape of risk assessments in cryptocurrency markets, our findings offer valuable insights for investors, particularly in terms of portfolio allocation and risk management.

However, it's worth to note that CoVaR focus only on joint risk between pairs of assets or institutions. This structure not fully capture more complex systemic risks arising from interconnectedness across multiple institutions or the broader financial network. Therefore, in future work, it may be interesting to apply complementary tools to capture the full scope of systemic risk.

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