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João Pedro Malim Franco

Revisiting Volatility Spillover and Tail-Risk Dependency in Cryptocurrency Markets

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JOÃO PEDRO MALIM FRANCO

Revisiting Volatility Spillover and Tail-Risk Dependency in Cryptocurrency Markets

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Orientador: Dr. Pedro Luiz Paolino Chaim

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João Pedro Malim Franco

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Prof. Dr. João Frois Caldeira
Universidade Federal de Santa Catarina

Prof. Dr. Lucas Argentieri Mariani
University of Milano-Bicocca

Prof. Dr. Márcio Poletti Laurini
Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto - USP

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Prof. Dr. Pedro Luiz Paolino Chaim(Orientador)
Universidade Federal de Santa Catarina

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Resumo

Neste trabalho, estimamos o risco de cauda condicional nos mercados de criptomoedas (Bitcoin, Ethereum, Ripple, Binance Coin e Litecoin) e também dos ativos tradicionais (Ouro e S&P500) antes e depois do período pandêmico. Os resultados apontaram que a dependência de risco de cauda aumenta durante o período pandêmico, apontando assim para a maior transmissão de choques. Os *spillovers* de risco entre o Ouro, o *safe haven* (porto seguro) mais reconhecido na literatura, e as criptomoedas, também aumentaram após a pandemia, embora ainda sejam relativamente pequenos. As variáveis de estado macroeconômico, com exceção da taxa de câmbio USD/EUR (DEXUSEU), prevêem um risco de cauda futuro para os ativos analisados em horizontes de tempo mais longos (21 dias).

Palavras-chaves: Bitcoin; Criptomoedas; Risco de cauda; Safe Haven; CoVaR

Resumo expandido

Introdução

De acordo com Akhtaruzzaman et al. (2022), as criptomoedas receberam maior atenção por parte dos investidores, reguladores e formuladores de políticas nos últimos anos devido ao aumento em sua capitalização do mercado, que atingiu US$ 2,23 trilhões em 01/05/2022. Desde o início do período pandêmico, no início de 2020 em diante, observamos um crescimento constante dos mercados digitais. Como ilustração, a Figura (1.1) mostra a capitalização do mercado de Bitcoin de 2019 a 2020, que pode ser tomada qualitativamente como representação dos mercados de criptomoedas em geral. Depois de chegar ao seu maior valor em abril e novembro de 2021, a capitalização de mercado de Bitcoin tem diminuído de forma constante desde então. As evidências, embora mistas, poderiam ser interpretadas de tal forma que o período de alta observado nos mercados de criptomoedas de 2020 até o final de 2021 é atribuído à abundância de transferências governamentais diretas como estímulo nos países desenvolvidos, e devido a mudanças abruptas nos padrões de gastos dos consumidores, como resposta a políticas de *lockdown*. Uma queda constante nos preços das criptomoedas pode ser observada a partir do início de 2022, coincidindo com aumentos das taxas de juros nos países desenvolvidos como resposta ao rápido aumento da pressão inflacionária ((Ren, Althof e Härdle (2020))). Embora exista uma literatura considerável documentando a codependência de cauda entre as criptomoedas e sua relação com os mercados de ativos mais tradicionais ((Borri (2019); Xu, Zhang e Zhang (2021); Lahiani, Jlassi et al. (2021); Sebastião e Godinho (2020); Goodell e Goutte (2021) Nguyen et al. (2019))), há razões para acreditar que o ambiente de investimento nos mercados digitais passou por mudanças suficientes para justificar uma renovação em suas evidências empíricas.

Objetivos

As mudanças estruturais no mercado de criptomoedas nos motivam a renovar as evidências empíricas a respeito da codependência de cauda e do risco sistêmico, tanto dentro da classe de ativos digitais quanto entre as criptomoedas e os ativos tradicionais, como o patrimônio líquido e o ouro. Acreditamos que a experiência do mercado durante a pandemia de Covid-19 e o período subseqüente de 2022 também proporciona um episódio adequado para investigar melhor a narrativa de tais ativos oferecer propriedades de *safe-haven* contra queda nos mercados tradicionais.

Metodologia

Medimos a codependência de cauda e a emissão de risco sistêmico entre os ativos digitais e tradicionais através da estrutura de regressão quantílica introduzida por Adrian e Brunnermeier (2011). O condicionamento de estado e a variação temporal são capturadas pelo condicionamento das medidas de VaR e CoVaR sobre um conjunto de variáveis de estado defasadas selecionadas para retratar as condições macroeconômicas e financeiras gerais. Também analisamos uma medida *forward* de risco sistêmico em um horizonte de 7, 14 e 21 dias, a fim de orientar decisões de portfólio, política macroeconômica e monitoramento da estabilidade financeira. A base de dados é composta de dados diários, começando em 13-11-2017 e terminando em 30-09-2022 de preços de abertura, preços de fechamento, preços máximos e mínimos, volume de transações e números de comércio para as seguintes variáveis: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Binance Coin (BNB), Ripple (XRP), Ouro e pelo Índice S&P500. A tabela (4.1) resume as estatísticas descritivas para as moedas criptográficas escolhidas. A base de dados das criptomoedas é do site `coinmarketcap.com`. Enquanto as variáveis macroeconômicas escolhidas, para o mesmo período, são: Preços do Petróleo Brent - Europa (DCOILBRENTEU), Índice de Volatilidade CBOE (VIX), Taxa de Expectativa de Inflação a Termo de 5 Anos (T5YIFR), Índice de Títulos Corporativos (CORP), taxa de câmbio USD/EUR (DEXUSEU), Índice Nominal do Dólar Americano Amplo (DTWEXBGS) e Índice de commodities S&P (SPGSCI). A tabela (4.4) resume as estatísticas descritivas para estas variáveis. As definições das variáveis e fontes estão listadas no Apêndice 1. O banco de dados é sincronizado excluindo os fins de semana como em Klein, Thu e Walther (2018). Seguindo os autores Goodell e Goutte (2021), dividimos os dados diários no período Pré - pandêmico (13-11-2017 a 26-02-2020) e Pós - pandêmico (27-02-2020 a 30-09-2022) a fim de analisar as criptomoedas em diferentes situações econômicas e financeiras. Goodell e Goutte (2021) escolheram esta data influenciados pela volatilidade dos retornos da VIX que, de acordo com a Figura (4.1), aumentou após 26-02-2020.

Resultados e Discussão

Os resultados apontam que, enquanto o valor de VaR_q^i de algumas criptomoedas (Bitcoin, Ethereum, Litecoin e Ripple), em valor absoluto, se tornaram menores, os valores de $\beta_{1,q}^{j|i}$, $CoVaR_q^{j|r^i}$ e $\Delta CoVaR_q^{j|i}$, em média, tornaram-se mais altos (em termos absolutos) após a pandemia. Descobrimos também que o ouro, o mais reconhecido *safe-haven* da literatura, apresenta valores similares de VaR_q^i e $CoVaR_q^{j|VaR_q^i}$ e, também, possui o valor mais baixo de $\Delta CoVaR_q^{j|VaR_q^i}$ quando q = 5%. No entanto, o *spillover* de risco entre o ouro e as criptomoedas, embora ainda pequeno, aumentou após a pandemia. A dependência de risco de cauda aumenta durante o período pandêmico, apontando assim para a maior transmissão de choques. Comparando as duas maiores criptomoedas em valor de mercado (Bitcoin e Ethereum), observamos que Bitcoin possui os menores valores, em termos absolutos, do $\Delta CoVaR_q^{j|VaR^i}$ (em média), ou seja, ele é menos sistematicamente vulnerável do que o Ethereum. A medida $\Delta CoVaR_q^{j|VaR^i}$ condicional a variáveis macroeconômicas de estado atinge seu pico (em termos absolutos) no início de março de 2020, quando o valor da medida é de cerca de 35,77% para o Bitcoin condicional ao índice SP500 e 35,26% para o Ethereum condicional ao Bitcoin. Os baixos retornos passados do índice de commodities S&P (SPGSCI) e do Índice de Títulos Corporativos (CORP) prevêem grandes valores negativos futuros de $CoVaR_q^{j|VaR^i}$ e $\Delta CoVaR_q^{j|VaR^i}$. No entanto, altos valores passados do Brent - Europa (DCOILBRENTEU), taxa de expectativa de inflação a termo de 5 anos (T5YIFR), taxa de câmbio USD/EUR (DEXUSEU), Índice Nominal do Dólar Americano Amplo (DTWEXBGS), Índice de Volatilidade CBOE (VIX) e da volatilidade do Bitcoin prevêem um risco de cauda negativo. Também descobrimos que todas as macro variáveis de estado, com exceção da taxa de câmbio USD/EUR (DEXUSEU), prevêem o risco de cauda futuro para ativos em horizontes mais longos (h = 21 dias).

Considerações Finais

A recente pandemia é uma oportunidade para investigar a estrutura de risco de cauda de alguns ativos durante um período de turbulência. Portanto, neste estudo, analisamos o risco de cauda condicional nos mercados para algumas criptomoedas como Bitcoin, Ethererum, Ripple, Binance Coin, Litecoin e também para o ouro e o Índice S&P500 antes (13-11-2017 a 26-02-2020) e depois (27-02-2020 a 30-09-2022) do período pandêmico. Estes resultados são úteis para a literatura sobre gestão de risco e decisões de portfólio. Alguns autores (Su et al. (2021) e outros), apontam que as medidas de risco condicional podem se mostrar pouco informativas ou mesmo não especificadas quando os riscos mudam drasticamente, o que ocorre em períodos de turbulência ou estresse no mercado. Portanto, em estudos futuros, sugere-se o uso de outra freqüência de tempo ou mesmo outros métodos de risco de cauda a serem comparados e analisados.

Palavras-chaves: Bitcoin; Criptomoedas; Risco de cauda; Safe Haven; CoVaR

Abstract

In this paper we estimate the conditional tail-risk in the markets for cryptocurrencies (Bitcoin, Ethereum, Ripple, Binance Coin and Litecoin) and also for traditional assets (Gold and S&P500) before and after the pandemic period. We find that the tail risk dependence increases during the pandemic period, thus pointing out the higher transmission of shocks. The risk spillovers between Gold, the most recognizable safe-haven in the literature, and cryptocurrencies, although still small, also increased after the pandemic. The macro state variables, with exception of USD/EUR exchange rate (DEXUSEU), predict future tail-risk for assets at longer horizons (21 days).

Keywords: Bitcoin; Cryptocurrencies; Tail-Risk; Safe Haven; CoVaR

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1 Introduction

According to Akhtaruzzaman et al. (2022), cryptocurrencies have received higher attention from investors, regulators, and policymakers over the recent years due to the rise of the market capitalization, which reached USD 2.23 trillion on 2022/01/05. In this paper we investigate tail-risk codependency dynamics among major cryptocurrencies and traditional assets (Gold and S&P500).

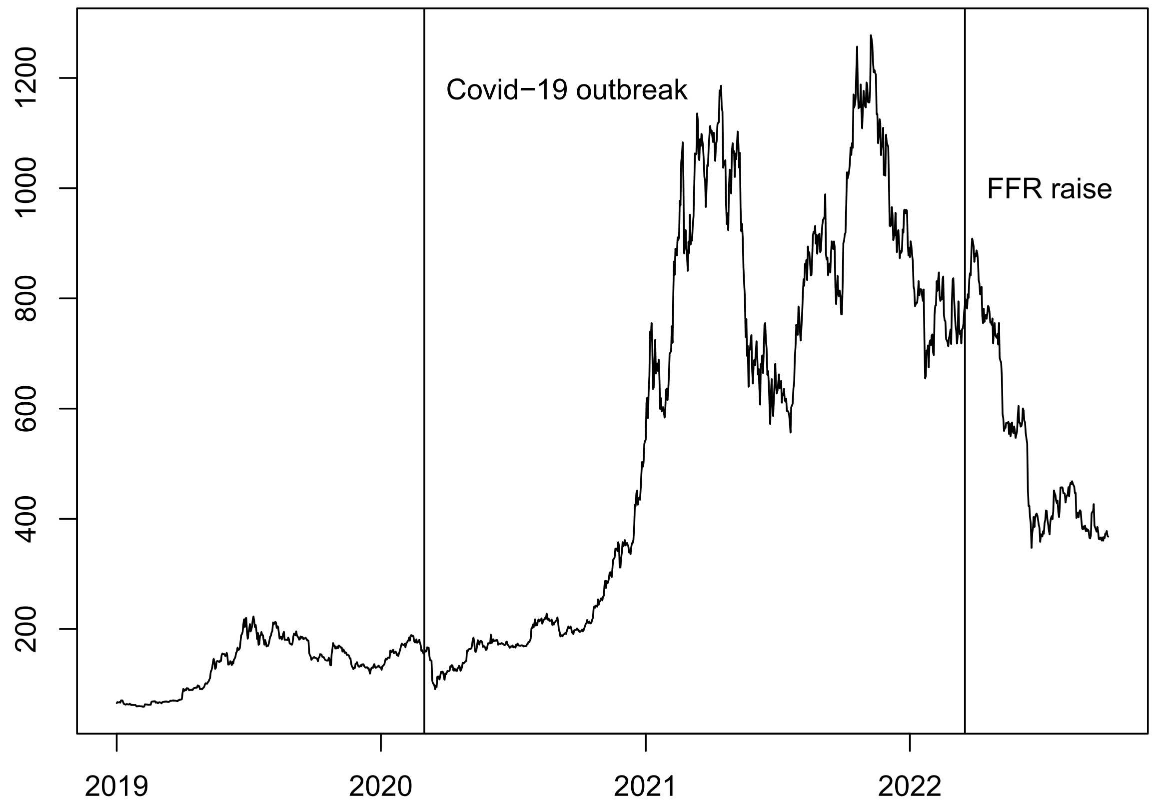
Although there is a considerable body of literature documenting tail codependency among cryptocurrencies and their relationship with more traditional asset markets (Borri (2019); Xu, Zhang and Zhang (2021); Lahiani, Jlassi et al. (2021); Sebastião and Godinho (2020); Goodell and Goutte (2021); Nguyen et al. (2019)), 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 markets. As illustration, Figure (1.1) 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 (Ren, Althof and Härdle (2020)).

Whatever the underlying cause, it is clear investment conditions pertaining cryptocurrency 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 safe-haven properties against downturns in conventional markets is a recurring theme in the literature. Taking the usual 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 et al. (2017); Selmi et al. (2018); Urquhart and Zhang (2019); Klein, Thu and Walther (2018); Smales (2019); Mariana, Ekaputra and Husodo (2021)). We believe market experience during the Covid-19 pandemic and the sub-

Figure 1.1 – Bitcoin Market Capitalization



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

sequent 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 digital and traditional assets through the quantile regression framework introduced by Adrian and Brunnermeier (2011). State contingency and time variation are captured by conditioning VaR and CoVaR measures on a set of lagged state variables selected to portray general macroeconomic and financial conditions. We also analyze a forward systemic risk measure on a horizon of 7, 14 and 21 days in order to guide portfolio decisions, macroeconomic policy and monitoring financial stability.

This article relates to the literature on the extreme risks of cryptocurrencies. In related literature, for example, Borri (2019) uses the CoVaR measure proposed by Adrian and Brunnermeier (2011) to estimate the conditional tail-risk in the markets for some cryptocurrencies such as Bitcoin, Ether, Ripple, and Litecoin. The author finds that cryptocurrencies are highly exposed to tail-risk within cryptomarkets, however they are not exposed to tail-risk with the other global assets, like the U.S. equity market or gold. Borri (2019) shows that idiosyncratic risk can be reduced and that portfolios of cryptocurrencies offer better risk-adjusted and conditional returns than an individual cryptocurrency. The results also indicate that cryptocurrency specific and macro variables can predict future conditional tail-risk.

Härdle, Wang and Yu (2016) propose a semi-parametric measure to estimate systemic interconnectedness across financial institutions and this measure is based on tail-driven spillover effects in a high dimensional framework. The model has been called Tail Event driven Network technique (TENET). Using this model, they ranked the Systemic Risk Receivers and Systemic Risk Emitters in the U.S. financial market. They found out that the depositories sector received and transmitted more risk among other groups and the insurers sector were less affected by the financial crisis.

Xu, Zhang and Zhang (2021) utilize TENET approach for analyzing the tail - risk interdependence among 23 cryptocurrencies. The authors found that the risk spillover effects exist and the degree of the total connectedness of all the sampled cryptocurrencies increases over time. They also find that Bitcoin is the largest systemic risk receiver and Ethereum is the largest systemic risk emitter.

Lahiani, Jlassi et al. (2021) analyse the tail dependence between cryptocurrency and stock market returns of BRICS and Developed countries using a new nonparametric cumulative measure that is model free and permits measuring tail risk before and after the introduction of Bitcoin futures. The results point out that the S&P500, Nasdaq and DAX 30 predict BRICS and developed countries' stock market returns while in BRICS countries, the BVSP predicts stock market returns. Lahiani, Jlassi et al. (2021) also points out that Bitcoin and Ethereum have the leading role in predicting cryptocurrencies. The analysis of the subsamples of the Bitcoin futures contracts shows that there is a reshaping of the mean and tail dependence between cryptocurrency and stock market returns.

Sebastião and Godinho (2020) investigate the hedging properties of CBOE Bitcoin futures during the initial months of trading. The authors point out that futures contracts of Bitcoin make an effective hedging instrument not only for Bitcoin, but also for other major cryptocurrencies. Sebastião and Godinho (2020) also say that futures contracts can deal with Bitcoin tail risk but they may leverage the existence of extreme losses for other currencies.

Our results point out that the measures of $CoVaR_q^{j|r^i}$ and $\Delta CoVaR_q^{j|i}$, on average, became higher (in absolute terms) after the pandemic. We also find 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. Comparing Bitcoin and Ethereum, the two biggest cryptocurrencies in market value, we note that Bitcoin have the lowest $\Delta CoVaR_q^{j|VaR^i}$ (on average), i.e is less systematically vulnerable. We also find that all macro state variables, with excetion of USD/EUR exchange rate (DEXUSEU), predict future tail-risk for assets at longer horizons (21 days).

This paper is structured as follows. Section 2 discuss the Tail - Risk in cryptocurrencies. Section 3 presents the methodology to be estimated, Section 4 describes the data, Section 5 presents and discusses our main results. Section 6 analyzes the forward conditional tail-risk. Section 7 concludes.

2 Tail-Risk in Cryptocurrencies

Kelly and Jiang (2014) point out that tail risk is an extreme event risk in asset markets. For Harris, Nguyen and Stoja (2019) a tail risk measure should capture the performance of asset returns conditional on a market tail event. For Lahiani, Jlassi et al. (2021), portfolio managers and policy makers uses tail dependence analyses to investigate the contagion effect during crisis times in order to adopt strategies to portfolio diversification and absorbing the economic shocks, therefore Lahiani, Jlassi et al. (2021) point the necessity to measuring the tail dependence with accuracy in order to provide information to investment and policy decisions.

According to Lahiani, Jlassi et al. (2021), the tail risk gained a lot of interest in the literature due to the recent global financial crisis (Subprime crisis and COVID19). For Jiang, Xu and Zhang (2022), the recent crisis showed how the codependency between institutions can pose systemic risk to the entire financial system and break the functioning of the whole economy.

Xu, Zhang and Zhang (2021) and Ren, Althof and Härdle (2020) point out that analyzing the tail-risk spillovers of the cryptocurrencies are of great significance for forming portfolios once the primary use of the cryptocurrencies is investment. For Ren, Althof and Härdle (2020), the importance of analyzing the behavior of cryptocurrencies during economic stress is due to the capacity of cryptocurrencies to provide some alternative hedging against devaluation of fiat currencies.

The authors Feng, Wang and Zhang (2018) studies the tail risks of the innovations rather than the price movement caused by dynamic variance of seven cryptocurrencies: Bitcoin, Ethereum, Ripple, Litecoin, Dash, NEM and Monero. They fit the Pareto distribution to the innovation in the ARMA-GARCH model. The analysis of the results for the bivariate correlations point out that the cryptocurrencies are more correlated in the left tail than the right tails and, also that the tail correlations increase over the time. Feng, Wang and Zhang (2018) also find that the Bitcoin has the highest correlations with other cryptocurrencies.

Before the pandemic, there were some studies with monetary variables (Nguyen et al. (2019); Li and Wang (2017)) and they already pointed out that inflation, interest and money supply affect cryptocurrencies returns. After the pandemic, the interest rate increase in developed countries as response to rapidly increasing inflationary pressure caused a drop in cryptocurrencies prices from the beginning of 2022.

Marmora (2022) show that monetary policy announcements of Central Banks increase local Bitcoin trade volume. Ma et al. (2022) analyze the impact of US monetary policy shocks on Bitcoin prices. They found out that an unexpected monetary tightening by 1 basis point of two-year Treasury yield is associated with a 0.25% drop in the price of Bitcoin and also found through a quantile regression that Bitcoin is more sensitive to monetary policy surprises during a market boom.

2.1 Safe Haven and Hedge

According to Baur and Lucey (2010) an asset is called a hedge when is uncorrelated or negatively correlated with another asset or portfolio on average. Differently to hedge, an asset that presents safe haven properties presents uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil. Bouri et al. (2017) point out that a strong (weak) hedge is an asset that is negatively correlated (uncorrelated) with another asset and a strong (weak) safe haven is an asset that is negatively correlated (uncorrelated) with another asset during times of stress.

Bitcoin is becoming an alternative to currencies and in case that investors lose their trust to mainstream currencies or to the entire economy, they might resort to this cryptocurrency. For Perron and Qu (2010), this is the main reason why Bitcoin has been called digital gold or new gold.

Bouri et al. (2017) use a dynamic conditional correlation (DCC) model to analyze whether Bitcoin can act as a hedge and safe haven for major world stock indices, bonds, oil, gold, the general commodity index and the US dollar index. They found out that Bitcoin can serve as an effective diversifier but is a poor hedge for most of the cases.

The authors Corbet et al. (2020) analyze the relationships between some of the largest cryptocurrencies before and during the COVID-19. They found out, controlling through the polarity and subjectivity of social media, indications that cryptocurrencies acted not only providing diversification benefits for investors but that they have the similar properties of precious metals during historic crises or financial market stress.

Urquhart and Zhang (2019) analyze Bitcoin in an intraday perspective. The results indicate that cryptocurrency can be considered a hedge and diversifier for the CAD, CHF and GBP currencies. Results also pointed out that Bitcoin does have a relationship with other financial assets. In contrast, the authors Klein, Thu and Walther (2018) show that Bitcoin are positively correlated with downward markets. They also analyzed Bitcoin as a portfolio component and found no evidence of hedge properties.

Selmi et al. (2018) seek to analyze the role of Bitcoin as a hedge, a safe haven and/or a diversifier against extreme oil price changes utilizing a quantile-on-quantile regression approach to capture the dependence structure between the considered market returns under different Bitcoin market conditions. Selmi et al. (2018) found out that the Bitcoin would serve the roles of a hedge, a safe haven and a diversifier for oil price movements. They also utilize the Conditional

Value-at-Risk (CoVaR) approach for providing robust evidence for those results.

3 Methodology

3.1 Quantile Regression

Following Koenker (2005), the quantile τth of a random variable X can be characterized by its inverse probability function.

$$F(x) = P(X \leq x), \tag{3.1}$$
$$F^{-1}(\tau) = \inf \{x : F(x) \geq \tau\}, \tag{3.2}$$

where $0 < \tau < 1$ and the median is represented for $F^{-1}(1/2)$. As an extension of the linear regression, Koenker (2005) consider a simple bivariate regression model (Equation (3.3)) in order to exemplify the quantile regression.

$$y_i = \beta_0 + x_i\beta_1 + u_i, \tag{3.3}$$
$$\mathbb{Q}_y(\tau|x) = \beta_0 + x\beta_1 + F_u^{-1}(\tau), \tag{3.4}$$

where F_u is the distribution function of the errors. Equation (3.4) denotes the conditional quantile function and $\hat{\beta}(\tau)$ is solve as

$$\min_{\beta \in \mathbb{R}^p} \sum_{\mathrm{i}=1}^{\mathrm{n}} \rho_\tau(\mathrm{y_i} - \mathrm{x_i}^\top \beta), \tag{3.5}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$. According to Koenker (2005), the quantile regression offers much more interesting and more focused results of the applications than conditional mean models. The authors also point out that quantile regression is used when conditions of linear regression (independence or homoscedasticity for example) are unknown. For further details on quantile regression methods, see, for example Koenker (2005) or Koenker et al. (2017).

3.2 Value at Risk

According to Linsmeier and Pearson (2000), the Value at Risk (VaR) is a measure of the losses from the normal market movements and losses greater than the VaR are suffered only with a specified small probability, in other words, VaR measure its a simply manner to describe the magnitude of likely losses in a portfolio. There are three basic methods of calculating VAR.

The first method is called Historical Simulation and consists of using historical changes in market rates and prices to construct a distribution of potential future portfolio profits and losses.

The second one depends on the assumption that the underlying market factors have a multivariate normal distribution and is called the Delta-Normal Approach. According to Linsmeier and Pearson (2000) this assumption is important because through that can determine the distribution of mark-to-market portfolio profits and losses, which is also assumed to be normal. Once the distribution of possible portfolio profits and losses has been obtained, one can determine the VaR.

The last approach use Monte Carlo Simulation which consists in choosing a statistical distribution that is believed to approximate the changes in the market factors. Then, a pseudo random number generator is used to generate thousands of hypothetical changes in the market factors and these hypothetical changes are used to construct thousands of hypothetical portfolio profits and losses on the current portfolio and the distribution of possible portfolio profit or loss. The VAR is determined from this distribution. According to Adrian and Brunnermeier (2011), VaR_q^i is implicitly defined as the q% quantile where X^i is the return loss of institution i.

$$\mathrm{Pr}(\mathrm{X}^i \leq \mathrm{VaR}_q^i) = \mathrm{q}\%. \tag{3.6}$$

Civan, Simsek and Akay (2020) compute the unconditional VaR value of an institution i for the q-quantile using the predicted value of the following quantile regression

$$VaR_q^i = \alpha_q^i + \epsilon_q^i. \tag{3.7}$$

3.3 Conditional Value at Risk

According to Adrian and Brunnermeier (2011), the most popular measure of risk in the financial market, Value at risk (VaR), focus only in the risk of an individual institution, leaving aside your connection to overall systemic risk. A systemic risk is, generally, build in times of low asset price volatility and come out during economic crises. Adrian and Brunnermeier (2011) say that 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. Borri (2019) use the ΔCoVaR as a measure of vulnerability of individual assets to tail risk in another assets.

First, according to Borri (2019), CoVaR allow us estimated a exposure of any asset to tail-risk of a second asset, or more formally, CoVaR is a risk measure of conditional upon an adverse shock where risk is the Value at Risk (VaR) measure. Adrian and Brunnermeier (2011) 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 measure proposed by the authors Adrian and Brunnermeier (2011) is a statistical tail dependency measure and can measures the component of systemic risk that comoves with the distress of a particular institution.

Denoting $CoVaR_q^{j|\mathbb{C}(X^i)}$ as the VaR of the financial system conditional on some event $\mathbb{C}(X^i)$ of institution i, where $CoVaR_q^{j|\mathbb{C}(X^i)}$ is defined by the following q%-quantile of the conditional probability distribution.

$$\Pr\left(X^j|\mathbb{C}(X^i) \leq CoVaR_q^{j|\mathbb{C}(X^i)}\right) = q\% \tag{3.8}$$

Following Borri (2019), the conditional value at risk can be estimated using the quantile regression as follows

$$CoVaR_q^{j|r^i=VaR_q^i} = \hat{\beta}_{0,q}^{j|i} + \hat{\beta}_{1,q}^{j|i} VaR_q^i, \tag{3.9}$$

where $\hat{\beta}^{j|i}$ 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 the CoVaR measure varying over the time, the authors Härdle, Wang and Yu (2016) use 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.

$$VaR_{i,t,q} = \hat{\alpha}_i + \hat{\gamma}_i M_{t-1}, \tag{3.10}$$

$$CoVaR_{j|i,t,q} = \hat{\alpha_{j|i}} + \hat{\gamma_{j|i}} M_{t-1} + \hat{\beta}_{j|i} VaR_{i,t,q}. \tag{3.11}$$

Assuming $F_{\epsilon_{i,t}}^{-1}(q|M_{t-1}) = 0$ and $F_{\epsilon_{j|i,t}}^{-1}(q|M_{t-1}, X_{i,t}) = 0$. The variable M_{t-1} is a vector of macro state variables lagged, reflecting the state of the economy.

In order to estimate ΔCoVaR measures, Adrian and Brunnermeier (2011) employ quantile regressions due to its simplicity but the authors says that GARCH models can be used too as in Girardi and Ergün (2013) and Trabelsi and Naifar (2017). The part of j's systemic risk that can be attributed to i is denoted as follows

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_{50}^{j|X^i=VaR_{50}^i} \tag{3.12}$$

Adrian and Brunnermeier (2011) argue that the ΔCoVaR approach helps to measure the directional tail dependence of pairs of assets and allows one to map links across the whole network of financial assets. Borri (2019) point out that the larger the ΔCoVaR in absolute value, the higher will be vulnerability of asset j to shocks from tail risk events of asset i.

Zhang (2015) change the definition of ΔCoVaR for the percentage change of the CoVaR standardized by absolute value of benchmark state CoVaR in order to capture both positive and negative dependence. The new measure is defined as follows

$$\Delta CoVaR_{\alpha,\beta,t}^{j|i} = \frac{CoVaR_{\alpha,\beta,t}^{j|i} - CoVaR_{\alpha=0.5,\beta,t}^{j|i}}{|CoVaR_{\alpha=0.5,\beta,t}^{j|i}|} \cdot 100 \tag{3.13}$$

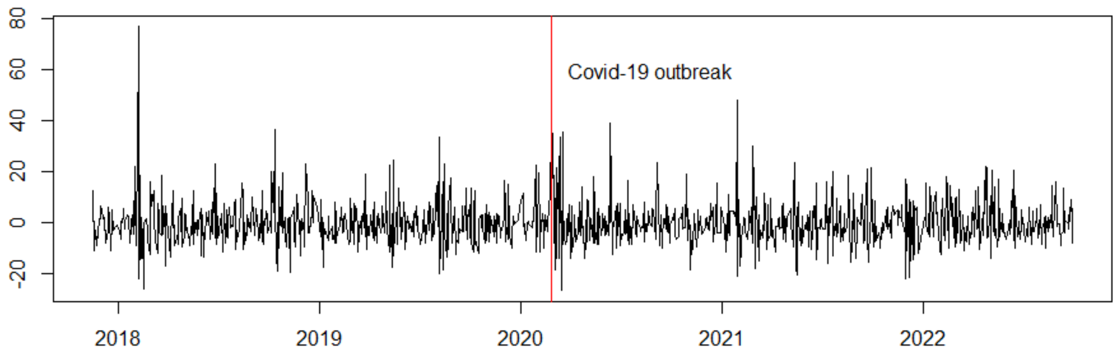
4 Data Description

As in Goodell and Goutte (2021), we divide the daily data in Pre - pandemic period (2017-11-13 to 2020-02-26) and Post - pandemic period (2020-02-26 to 2022-09-30) in order to analyze cryptocurrencies in different economic and financial situations. Goodell and Goutte (2021) chose this date influenced by the volatility of VIX returns which, according to the Figure (4.1), increased after 2020-02-26.

The database is composed of daily data starting on 2017-11-13 and ending on 2022-09-30 of opening prices, closing prices, maximum and minimum prices, transaction volume and trade numbers for the following variables: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Binance Coin (BNB), Ripple (XRP), Gold and S&P500 Index (GSPC). Table (4.1) summarize the descriptive statistics for the chosen cryptocurrencies. The database of cryptocurrencies are from `coinmarketcap.com`.

While the chosen macroeconomics state variables for the same period are Oil Prices Brent - Europe (DCOILBRENTEU), CBOE Volatility Index (VIX), 5-Year Forward Inflation Expectation Rate (T5YIFR), Corporate Bond Index (CORP), USD/EUR exchange rate (DEXUSEU), Nominal Broad U.S. Dollar Index (DTWEXBGS) and S&P commodity index (SPGSCI). Table (4.4) summarizes the descriptive statistics for these variables. The definitions of the variables and sources are listed in Appendix 1. The database are synchronized excluding the weekends as in Klein, Thu and Walther (2018).

Figure 4.1 – 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 (2020-02-26 to 2022-09-30)

Table 4.1 – Descriptive Statistics

	BTC	LTC	BNB	ETH	XRP	Gold	S&P500
Min. (%)	-46.473	-44.906	-54.308	-55.073	-55.050	-5.265	-12.765
Mean (%)	0.143	0.022	0.437	0.074	0.074	0.021	0.029
Median (%)	0.158	0.126	0.206	0.088	-0.039	0.034	0.111
Max. (%)	22.512	53.984	52.922	24.706	62.674	5.133	8.968
Std. (%)	4.821	6.478	6.865	6.023	7.349	0.904	1.382
Skew	-0.885	0.143	0.200	-1.030	0.939	-0.466	-0.989
Kurt	13.481	13.541	14.843	11.754	18.715	7.713	17.416
Quantile 5%	-7.145	-9.444	-8.906	-9.154	-10.171	-1.374	-2.124
Quantile 95%	7.614	9.174	10.030	9.178	9.931	1.490	1.726
ADF	-9.282***	-9.562***	-8.683***	-8.914***	-10.122***	-11.444***	-9.333***
KPSS	0.137	0.083	0.144	0.147	0.054	0.128	0.120

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 entire sample. The entire sample is composed by 1115 observations. The p-values are represented for $^{***}p < 0.01$ $^{**}p < 0.05$ and $^{*}p < 0.10$.

Table 4.2 – Descriptive Statistics - 2017-11-13 to 2020-02-26 (Pre - pandemic period)

	BTC	LTC	BNB	ETH	XRP	Gold	S&P500
Min. (%)	-23.874	-18.028	-36.434	-27.163	-24.605	-2.044	-4.184
Mean (%)	0.076	0.060	0.463	-0.102	0.062	0.040	0.044
Median (%)	0.107	-0.257	0.122	-0.145	-0.309	0.018	0.101
Max. (%)	22.512	53.984	48.179	23.474	60.689	2.746	3.376
Std. (%)	4.791	6.617	6.745	5.734	7.240	0.652	0.913
Skew	0.126	1.840	0.872	-0.237	2.050	0.450	-1.014
Kurt	6.728	14.695	10.734	5.290	17.261	4.505	6.231
Quantile 5%	-7.741	-9.476	-9.246	-9.402	-10.150	-0.936	-1.744
Quantile 95%	8.128	10.104	11.493	9.399	10.155	1.210	1.296
ADF	-6.841***	-7.089***	-6.515***	-6.658***	-6.675***	-8.069***	-7.209***
KPSS	0.088	0.116	0.308	0.113	0.127	0.500**	0.034

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

Table 4.3 – Descriptive Statistics - 2020-02-26 to 2022-09-30 (Post - pandemic period)

	BTC	LTC	BNB	ETH	XRP	Gold	S&P500
Min. (%)	-46.473	-44.906	-54.308	-55.073	-55.050	-5.265	-12.765
Mean (%)	0.201	-0.011	0.414	0.227	0.083	0.005	0.016
Median (%)	0.245	0.305	0.355	0.474	0.151	0.046	0.127
Max. (%)	19.153	23.695	52.922	24.706	62.674	5.133	8.968
Std. (%)	4.850	6.359	6.973	6.263	7.449	1.077	1.687
Skew	-1.731	-1.517	-0.328	-1.567	0.052	-0.573	-0.860
Kurt	19.145	12.253	17.920	15.706	19.823	6.608	14.181
Quantile 5%	-6.765	-9.379	-7.631	-8.454	-10.290	-1.711	-2.605
Quantile 95%	7.433	8.798	9.455	8.981	9.660	1.717	2.109
ADF	-7.796***	-8.283***	-7.003***	-7.458***	-7.631***	-8.307***	-7.499***
KPSS	0.520**	0.189	0.251	0.384*	0.100	0.084	0.236

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

Table 4.4 – Descriptive Statistics for state variables

	VIX	SPGSCI	CORP	DCOILBRENTEU	T5YIFR	DEXUSEU	DTWEXBGS
Min. (%)	-0.768	-0.125	-0.051	-0.644	-0.246	-0.018	-0.019
Mean (%)	0.001	0.001	-0.000	0.001	-0.000	-0.000	0.000
Median (%)	0.011	0.002	0.000	0.002	0.000	-0.000	-0.000
Max.	0.266	0.077	0.068	0.412	0.325	0.017	0.019
Std.	0.086	0.016	0.005	0.040	0.024	0.004	0.003
Skew	-1.534	-1.208	-0.027	-3.111	0.455	-0.167	0.356
Kurt	11.349	13.380	49.493	83.503	51.542	4.487	6.415
ADF	-11.210***	-9.647***	-10.797***	-9.406***	-10.828***	-12.041***	-10.947***
KPSS	0.025	0.213	0.228	0.114	0.057	0.272	0.125

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

5 Empirical Results

This section reports and discusses the results of the tail codependency between some macroeconomic state variables and cryptocurrencies during the daily period 2017-2022. A sub-sample analysis is also conducted (Table 5.2 and Table 5.3) in order to examine the effect of the pandemic on the tail dependence structure.

5.1 Unconditional CoVaR

In Table 5.1 the results of the VaR, $\hat{\beta}_{1,q}^{j|i}$, CoVaR and $\Delta CoVaR_q^{j|i}$ for the whole sample. The Table 5.1 is organized in which way that the right-hand variables are on the table columns (variables i), and the left-hand conditioning variables on the table rows (variables j).

First, we analyze the VaR_q^i values with q = 5%, which means that, on 95% of the days, we should have a return greater than the calculated value of the $VaR_{5\%}$. For Borri (2019), the $VaR_{5\%}$ value corresponds to the maximum return in a situation of stress for the analyzed asset. The results point out Binance Coin (BNB) has the lowest $VaR_{5\%}$ value (-10.18%) among the cryptocurrencies while Bitcoin (BTC) has the highest value (-7.23%). The $VaR_{5\%}$ value of the macroeconomic variables, gold and S&P500, are, respectively, -1.37% and -2.14%.

The coefficient $\beta_{1,q}^{j|i}$ represents the sensitivity of log return of an institution j to changes in tail event log return of an institution i and the results point out that it is positive for all the conditionings except for the gold with Binance Coin (BNB). These results indicate that when asset prices experience large drops in value, the value of other assets tends to fall. For Civan, Simsek and Akay (2020), the positive coefficient estimation seems to provide strong evidence of spillover effects between the institutions. The results also point out that tail-events for cryptocurrencies do not have a significant effect in gold but they have a significant effect on equity (S&P500).

The CoVaR measure gives the maximum loss incurred by an asset when another asset return is at $\text{VaR}_{5\%}$ level. The found results point out that the unconditional $CoVaR_q^{j|VaR^i}$ are highly correlated and they are in the left tail of the distribution, i.e, they have negative values. Our results are in accordance with Borri (2019), which concludes that when the price of one cryptocurrency drops significantly, the price of another cryptocurrency also tends to drop significantly. However, the $CoVaR_q^{j|VaR^i}$ values when we condition for equity (S&P500) are higher, in absolute terms, than when we condition for another cryptocurrency or gold.

As define Adrian and Brunnermeier (2011), $\Delta CoVaR_q^{j|VaR^i}$ is the difference in the VaR_q with respect to its value in the median state ($\text{VaR}_{0.50}$) and measures the vulnerability of asset j to tail-risk in asset i. The higher $\Delta CoVaR_q^{j|VaR^i}$, in absolute value, the greater the contribution to the systemic risk. For the cryptocurrencies, the results point out that Ethereum, Litecoin and Ripple have the highest $\Delta CoVaR_q^{j|VaR^i}$ and are the most vulnerable to tail-risk in the market for Bitcoin, while Bitcoin appears to have the lowest $\Delta CoVaR_q^{j|VaR^i}$, in absolute terms, of the cryptocurrencies to shocks to the other cryptocurrencies and the equity (S&P500).

Analyzing the Table (5.1), we can conclude that if Bitcoin is at its VaR_q, when q = 0.05, a -7.45% drop in Ethereum returns is expected with respect to the case when Bitcoin is at median state ($VaR_{0.5}$). The gold, when Bitcoin is at its $VaR_{0.05}$, has no expected loss compared to the case when Bitcoin is at median state, however, when Binance Coin is at its $VaR_{0.05}$, there is a expected gain about 0.09% compared to the median state.

We note that the $CoVaR_q^{j|VaR^i}$ and $\Delta CoVaR_q^{j|VaR^i}$ values of the cryptocurrencies based on other cryptocurrencies are larger than those of the values with respect to gold and equity (S&P500). This finding indicates that the cryptocurrencies have a major impact on the contagion effect of the other cryptocurrencies than macroeconomic variables (gold and equity).

5.1.1 Subsample analysis

Since assets become more correlated during economic downturns (Borri (2019)), the pandemic is an opportunity to investigate the behavior in the tail risk structure of the cryptocurrencies of the highest market capitalization during economic stress.

Comparing the before and after pandemic periods (Table (5.2) and Table (5.3)), we note that the VaR_q^i value of the Bitcoin, Ethereum, Litecoin and Ripple fell (in absolute value) during the post pandemic period, while the VaR_q^i value of the Binance Coin, gold and equity (S&P500) become higher (in absolute value).

However, while the VaR_q^i value of some cryptocurrencies (Bitcoin, Ethereum, Litecoin and Ripple), in absolute value, fall down, the values of $\beta_{1,q}^{j|i}$, $CoVaR_q^{j|r^i}$ and $\Delta CoVaR_q^{j|i}$, on average, became higher (in absolute terms). These results are 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, in the Table (5.2), the $\Delta CoVaR_q^{j|i}$ measure was positive for Bitcoin (0.15%), Ethereum (0.94%), Ripple (0.18%) 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. In the post - pandemic period (Table (5.3)), the only positive value of $\Delta CoVaR_q^{j|i}$ occurs when gold is conditioning on Binance Coin.

We can note that gold gained this propriety after the pandemic, according Table (5.2) (Pre-Pandemic sample), if Binance Coin is at $VaR_{0.05}$, a -0.08% drop in gold returns is expected with respect to the median state ($VaR_{0.5}$) in Binance Coin. Gold and equity are the assets that

Table 5.1 – Conditional Tail-Risk

j/i	BTC	ETH	LTC	XRP	BNB	Gold	S&P500
VaR_q^i	-7.23	-9.45	-9.23	-8.93	-10.18	-1.37	-2.14
				$\beta_{1,q}^{j\|i}$			
Bitcoin (BTC)	-	0.50***	0.60***	0.42***	0.32***	1.14	1.45***
Ethereum (ETH)	1.01***	-	0.83***	0.60***	0.50***	0.63	1.94***
Litecoin (LTC)	0.95***	0.72***	-	0.53***	0.46***	1.85***	1.92***
Ripple (XRP)	0.88***	0.67***	0.73***	-	0.44***	1.18	2.40***
Binance Coin (BNB)	0.81***	0.65***	0.72***	0.46***	-	0.99	2.25***
Gold	0.00	0.02	0.02	0.03	-0.01	-	0.12
S&P500	0.12***	0.08***	0.11***	0.07***	0.06***	0.45	-
				$CoVaR_q^{j\|VaR^i}$			
Bitcoin (BTC)	-	-8.66	-9.42	-8.87	-8.94	-8.92	-10.26
Ethereum (ETH)	-12.88	-	-12.61	-12.39	-11.99	-10.75	-13.37
Litecoin (LTC)	-12.16	-11.80	-	-11.50	-11.61	-12.02	-12.73
Ripple (XRP)	-12.53	-11.95	-12.55	-	-11.26	-10.60	-14.31
Binance Coin (BNB)	-12.48	-12.23	-12.83	-12.06	-	-11.93	-14.95
Gold	-1.37	-1.64	-1.59	-1.68	-1.29	-	-1.69
S&P500	-2.94	-2.78	-3.14	-2.71	-2.68	-2.83	-
				$\Delta CoVaR_q^{j\|VaR^i}$			
Bitcoin (BTC)	-	-4.83	-5.56	-3.88	-3.23	-1.60	-3.26
Ethereum (ETH)	-7.45	-	-7.72	-5.48	-5.08	-0.89	-4.36
Litecoin (LTC)	-7.06	-6.89	-	-4.83	-4.71	-2.60	-4.31
Ripple (XRP)	-6.50	-6.45	-6.80	-	-4.46	-1.67	-5.38
Binance Coin (BNB)	-6.02	-6.21	-6.72	-4.17	-	-1.39	-5.05
Gold	-0.00	-0.21	-0.18	-0.26	0.09	-	-0.27
S&P500	-0.90	-0.75	-1.04	-0.61	-0.58	-0.63	-

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%.

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

have the least systemic risk among the analyzed either before and after the pandemic.

The results found in Table (5.2) may indicate that Bitcoin, Ethereum, Ripple and S&P500, was, at least, a hedge for Gold before the pandemic. However, in the post pandemic period (Table (5.3)), this effect is lost and the only positive value of $\Delta CoVaR_q^{j|VaR^i}$ occurs when Gold is conditional on Binance Coin.

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, Thu and Walther (2018)) we note, through the Table (5.2) and Table (5.3), 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.

5.2 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 (5.1), Figure (5.2) and Figure (5.3).

The set of state variables are: Oil Prices Brent - Europe (DCOILBRENTEU), CBOE Volatility Index (VIX), 5-Year Forward Inflation Expectation Rate (T5YIFR), Corporate Bond Index (CORP), USD/EUR exchange rate (DEXUSEU), Nominal Broad U.S. Dollar Index (DTWEXBGS) and S&P commodity index (SPGSCI). Table (5.4) shows the significance of the coefficients for the macro state variables for Bitcoin, Ethereum, Gold and S&P500 conditioning in Bitcoin and S&P500.

Borri (2019) point out that conditional tail-risk rise during global economic downturns or periods of distress in global markets, in other words tail events tend to spill across markets. Also, for Adrian and Brunnermeier (2011), this spillovers are preceded by a moment in which risk rise up.

Analyzing the significance of the macro state variables coefficients based on Table (5.4), we note that, different from Borri (2019), Bitcoin volatility is not always significantly, however, is negatively associated with other assets. The expected inflation rate (T5YIFR) 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

Table 5.2 – Conditional Tail-Risk - 2017-11-13 to 2020-02-26 (Pre - pandemic period)

j/i	BTC	ETH	LTC	XRP	BNB	Gold	S&P500
VaR^i_q	-7.85	-9.60	-9.66	-9.29	-10.17	-0.94	-1.75
				$\beta^{j\|i}_{1,q}$			
Bitcoin (BTC)	-	0.44***	0.54***	0.38***	0.25***	-0.16	0.69
Ethereum (ETH)	0.81***	-	0.70***	0.50***	0.37***	-0.98	0.41
Litecoin (LTC)	0.85***	0.60***	-	0.53***	0.44***	1.04	2.60**
Ripple (XRP)	0.63***	0.55***	0.59***	-	0.34***	-0.19	2.43**
Binance Coin (BNB)	0.73***	0.54***	0.71***	0.37***	-	0.02	2.10*
Gold	0.01	0.01*	0.01	0.02**	0.01	-	-0.05
S&P500	0.01	0.03	0.04	0.03	0.02	-0.50**	-
				$CoVaR^{j\|VaR^i}_q$			
Bitcoin (BTC)	-	-8.57	-9.51	-8.89	-8.76	-7.63	-8.95
Ethereum (ETH)	-12.13	-	-11.85	-11.79	-11.56	-8.51	-10.30
Litecoin (LTC)	-12.31	-11.95	-	-11.98	-11.69	-10.42	-14.54
Ripple (XRP)	-12.05	-10.89	-11.81	-	-11.30	-8.97	-13.89
Binance Coin (BNB)	-12.86	-11.98	-12.20	-11.73	-	-10.19	-14.19
Gold	-1.05	-1.13	-1.09	-1.15	-1.06	-	-0.87
S&P500	-1.82	-2.00	-2.04	-2.04	-1.93	-1.17	-
				$\Delta CoVaR^{j\|VaR^i}_q$			
Bitcoin (BTC)	-	-4.14	-5.10	-3.59	-2.48	0.15	-1.26
Ethereum (ETH)	-6.44	-	-6.64	-4.66	-3.66	0.94	-0.76
Litecoin (LTC)	-6.78	-5.62	-	-4.96	-4.35	-0.99	-4.80
Ripple (XRP)	-5.03	-5.14	-5.66	-	-3.36	0.18	-4.49
Binance Coin (BNB)	-5.83	-5.06	-6.74	-3.49	-	-0.02	-3.87
Gold	-0.09	-0.12	-0.11	-0.22	-0.08	-	0.09
S&P500	-0.10	-0.26	-0.34	-0.33	-0.21	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%.

$$VaR^i_q = \alpha^i_q + \epsilon^i_q,$$

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

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

Table 5.3 – Conditional Tail-Risk - 2020-02-27 to 2022-09-09 (Post - pandemic period)

j/i	BTC	ETH	LTC	XRP	BNB	Gold	S&P500
VaR_q^i	-6.77	-9.41	-8.68	-7.72	-10.72	-1.73	-2.62
				$\beta_{1,q}^{j\|i}$			
Bitcoin (BTC)	-	0.62***	0.63***	0.43***	0.33***	0.93	1.44***
Ethereum (ETH)	1.20***	-	0.92***	0.64***	0.57***	1.37***	1.93***
Litecoin (LTC)	1.06***	0.81***	-	0.57***	0.48***	1.92**	1.91***
Ripple (XRP)	1.03***	0.77***	0.88***	-	0.57***	1.39	2.27***
Binance Coin (BNB)	1.02***	0.76***	0.81***	0.52***	-	1.66	2.25***
Gold	0.07*	0.07**	0.06**	0.04**	-0.00	-	0.14
S&P500	0.19***	0.17***	0.15***	0.11***	0.08**	0.65*	-
				$CoVaR_q^{j\|VaR^i}$			
Bitcoin (BTC)	-	-9.79	-9.23	-8.33	-9.07	-8.39	-10.11
Ethereum (ETH)	-13.53	-	-12.84	-11.78	-12.79	-11.76	-14.16
Litecoin (LTC)	-12.29	-12.63	-	-10.31	-11.80	-12.44	-13.34
Ripple (XRP)	-13.06	-12.37	-13.48	-	-12.08	-10.32	-13.99
Binance Coin (BNB)	-13.66	-12.93	-13.51	-11.80	-	-13.05	-15.65
Gold	-2.32	-2.56	-2.37	-2.09	-1.68	-	-2.12
S&P500	-3.58	-4.05	-3.68	-3.44	-3.46	-3.63	-
				$\Delta CoVaR_q^{j\|VaR^i}$			
Bitcoin (BTC)	-	-6.02	-5.77	-3.46	-3.58	-1.64	-3.96
Ethereum (ETH)	-8.40	-	-8.41	-5.16	-6.22	-2.43	-5.29
Litecoin (LTC)	-7.43	-7.88	-	-4.60	-5.21	-3.40	-5.25
Ripple (XRP)	-7.21	-7.45	-8.05	-	-6.20	-2.46	-6.23
Binance Coin (BNB)	-7.12	-7.38	-7.41	-4.19	-	-2.95	-6.19
Gold	-0.50	-0.67	-0.55	-0.34	0.03	-	-0.39
S&P500	-1.34	-1.63	-1.37	-0.91	-0.92	-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 5.4 – State Variable Exposures

	VIX	SPGSCI	CORP	DCOILBRENTEU	T5YIFR	DEXUSEU	DTWEXBGS	BTC VOL
BTC|S&P500	0.103	-0.454	0.017	0.117	0.408**	-0.239	2.278	-1.157***
S&P500|BTC	-0.007	-0.198	0.273	0.082	-0.046	-0.488	-0.558	-0.199*
ETH|S&P500	0.139*	-0.801*	-1.136	0.143	0.396*	-1.096	-0.491	-0.470
ETH|BTC	-0.034	0.240	0.006	-0.171	0.179	-1.044	-0.176	-0.367**
GOLD|S&P500	-0.016	-0.015	0.163	0.014	0.079**	-0.333	-0.765	-0.035
GOLD|BTC	-0.010	-0.073	0.264	0.032	0.042	-0.312	-0.691	-0.028

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

association between cryptocurrencies and forward inflation rates on the onset period of the COVID19. The authors also find that outside of the COVID19 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 present in Table 5.5. These results shows that the averages of the $CoVaR_q^{j|VaR^i}$ are very similar to those obtained in the constant estimates. However, the averages of the $\Delta CoVaR_q^{j|VaR^i}$ don't even come close, in fact, the averages are way higher than the constant estimates. The highest values of $\Delta CoVaR_q^{j|VaR^i}$ occurs when we condition Bitcoin on equity (S&P500) and Ethereum on equity (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 these two conditional variables (S&P500 and Bitcoin).

The $\Delta CoVaR_q^{j|VaR^i}$ measure reaches your peak (in absolute terms) on onset March 2020, when the value of the measure is about 35.77% for Bitcoin conditional on S&P500 and 35.26% for Ethereum conditional on Bitcoin (Figure 5.1).

Analyzing the Figures (5.1), (5.2) and (5.3) of the time-varying $\Delta CoVaR_q^{j|VaR^i}$, we can conclude, as in Akhtaruzzaman et al. (2022), the tail risk dependence increase during the pandemic period, thus pointing out the higher transmission of shocks. 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 (5.1), Figure (5.2) and Figure (5.3), the conditional measures in the analyze cryptocurrencies are below the respective VaR, this result reflects the positive dependencies between the assets. This result is also found by Waltz, Singh and Okhrin (2022), which also points out that the conditional measures are driven by similar dynamics as the univariate VaR.

Table 5.5 – Time-varying Conditional Tail Risk

	Min. (%)	Mean (%)	Median (%)	Max. (%)	Std (%)	Skew	Kurt
				$CoVaR_q^{j\|VaR^i}$			
BTC|S&P500	-32.890	-10.786	-10.352	-2.761	2.848	-1.516	8.968
S&P500|BTC	-7.640	-2.958	-2.855	-0.381	0.610	-1.710	10.831
ETH|S&P500	-30.452	-14.306	-14.002	-2.903	2.420	-1.392	9.818
ETH|BTC	-34.859	-12.137	-11.734	-0.616	2.685	-1.318	9.384
GOLD|S&P500	-5.466	-1.802	-1.787	0.724	0.327	-1.977	26.777
GOLD|BTC	-5.661	-1.780	-1.764	0.674	0.295	-2.741	40.761
				$\Delta CoVaR_q^{j\|VaR^i}$			
BTC|S&P500	-35.774	-10.923	-10.476	-3.630	2.954	-1.573	9.686
S&P500|BTC	-8.147	-3.067	-2.956	-0.252	0.653	-1.774	11.137
ETH|S&P500	-32.791	-14.431	-14.100	-2.867	2.525	-1.433	9.309
ETH|BTC	-35.262	-12.228	-11.787	-4.876	2.781	-1.435	9.021
GOLD|S&P500	-4.594	-1.843	-1.830	-0.306	0.274	-1.448	18.565
GOLD|BTC	-4.091	-1.820	-1.811	-0.050	0.241	-1.416	22.154

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 entire sample.

Table 5.6 – 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

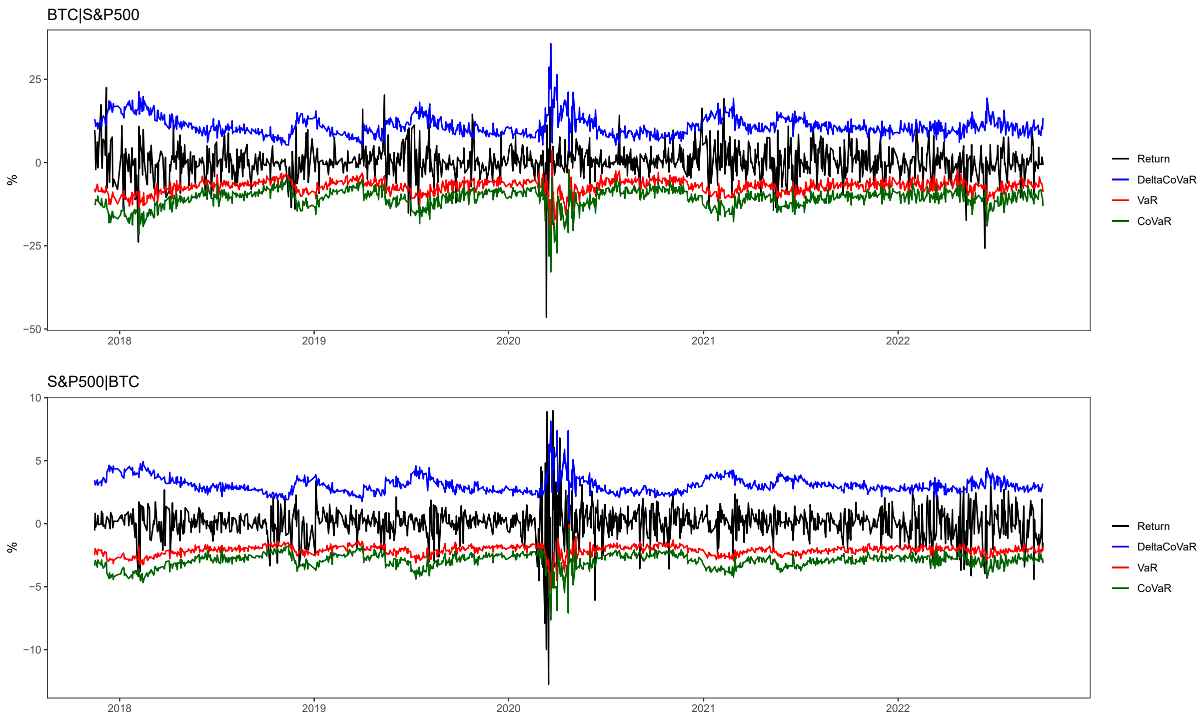
Note: The table shows the descriptive statistics for the estimates of the time-varying CoVaR and ΔCoVaR for BTC, ETH, Gold and S&P500 given BTC and S&P500 for the Pre - Pandemic period.

Table 5.7 – 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

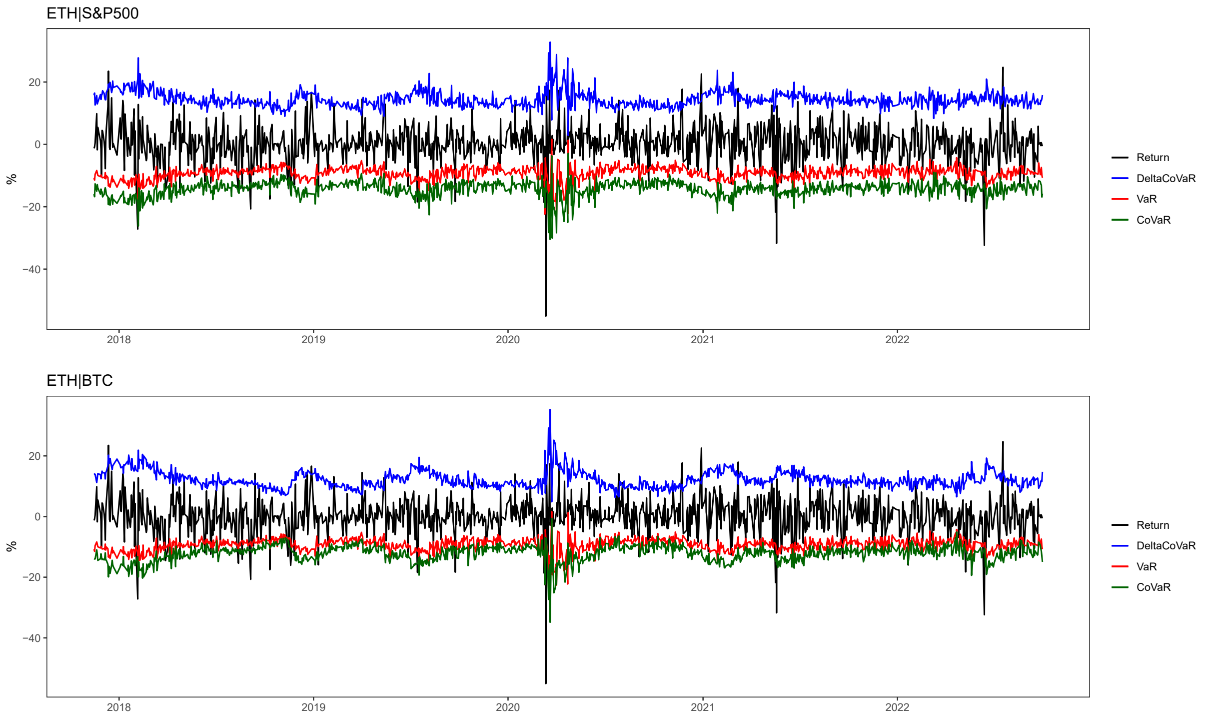
Note: The table shows the descriptive statistics for the estimates of the time-varying CoVaR and ΔCoVaR for BTC, ETH, Gold and S&P500 given BTC and S&P500 for the Post - Pandemic period.

Figure 5.1 – CoVaR and ΔCoVaR of Bitcoin and S&P500 Conditional on, respectively, S&P500 and Bitcoin



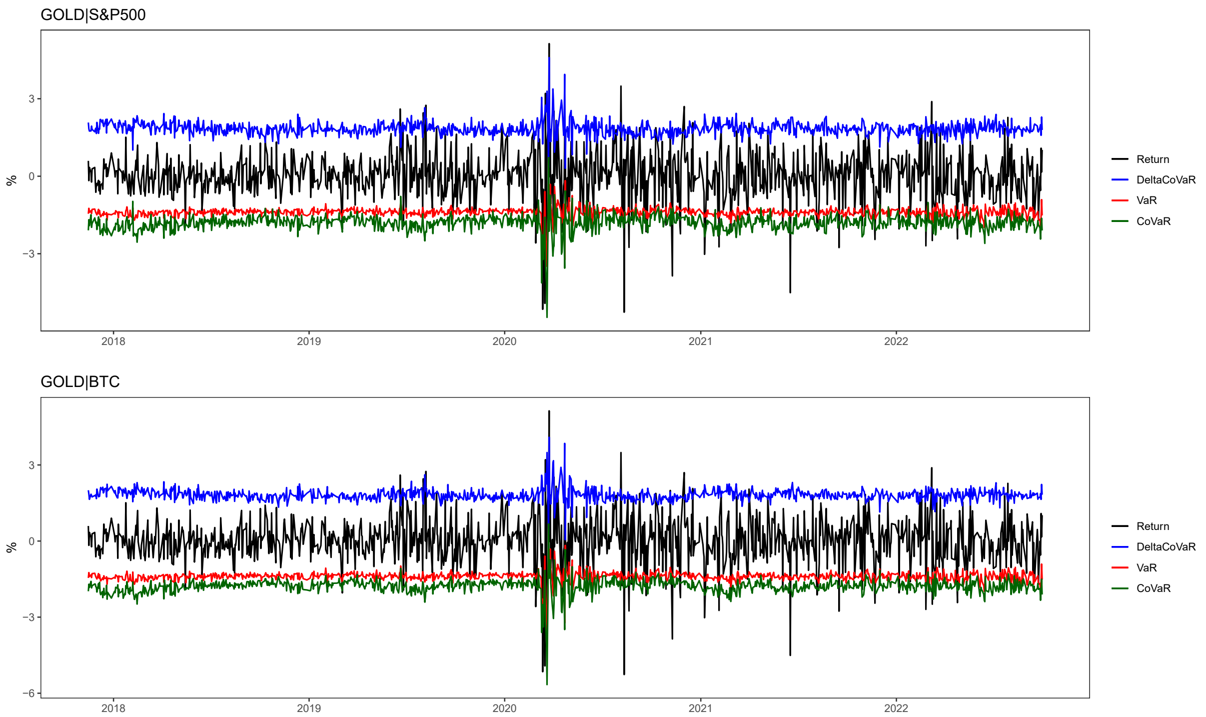
Note: This figure shows the CoVaR (green), ΔCoVaR (blue), the $\text{VaR}^i_{95,t}$ (red), and the returns (black) for the entire sample.

Figure 5.2 – 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 5.3 – 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.

6 CoVaR and ΔCoVaR Forecasts

Following Adrian and Brunnermeier (2011) and Borri (2019), we calculate a forward systemic risk measure in order to guide portfolio decisions, macroeconomic policy and monitoring financial stability. For forecasting, we estimate $CoVaR^{j|i}_{q,t}$ and $\Delta CoVaR^{j|i}_{q,t}$ on a horizon h equal to 7, 14 and 21 days as follows

$$CoVaR^{j|i}_{q,t} = a + cM_{t-h} + bX^{j}_{t-h} + \eta^{j}_{t}, \tag{6.1}$$

$$\Delta CoVaR^{j|i}_{q,t} = a + cM_{t-h} + bX^{j}_{t-h} + \eta^{j}_{t}, \tag{6.2}$$

where j, i = Bitcoin, Ethereum, Litecoin, Ripple, Binance Coin, Gold, S&P500, j $\neq$ i, M_{t-h} is the vector of macro state variables lagged h days and X^{j}_{t-h} is the vector of asset j-specific which is composed with lagged value-at-risk (VaR) and returns. The macro state variables are the lagged returns on Oil Prices Brent - Europe (DCOILBRENTEU), CBOE Volatility Index (VIX), 5-Year Forward Inflation Expectation Rate (T5YIFR), Corporate Bond Index (CORP), USD/EUR exchange rate (DEXUSEU), Nominal Broad U.S. Dollar Index (DTWEXBGS), S&P commodity index (SPGSCI) and Bitcoin Volatility.

As in Borri (2019), we include a fixed effect in the regressions. The results are present in Table (6.1). Analysing first the j-specific variables (VaR and returns), we note that high (in absolute terms) value-at-risk (VaR) and low returns forecast large future negative CoVaR and ΔCoVaR values for 14 days and 21 days forecasts, however the predictability of the j-specific variables declines with the horizon as found in Borri (2019).

Considering the macro state variables that are common to the assets analysed, we can conclude that past low returns of S&P commodity index (SPGSCI) and Corporate Bond Index (CORP) forecast large future negative $CoVaR^{j|VaR^i}_{q}$ and $\Delta CoVaR^{j|VaR^i}_{q}$ values. However, past high values of Oil Prices Brent - Europe (DCOILBRENTEU), 5-Year Forward Inflation Expectation Rate (T5YIFR), USD/EUR exchange rate (DEXUSEU), Nominal Broad U.S. Dollar Index (DTWEXBGS), CBOE Volatility Index (VIX) and Bitcoin Volatility forecast negatively tail-risk measures. We also find that all macro state variables, with excetion of USD/EUR exchange rate (DEXUSEU), predict future tail-risk for assets at longer horizons, i.e., h = 21 days. This results are in according to Borri (2019), which also point out that commodities are a complementary asset to cryptocurrencies.

Table 6.1 – CoVaR and ΔCoVaR Forecasts

	h = 7 days		h = 14 days		h = 21 days	
	$CoVaR_{q,t}^{j\|i}$	$\Delta CoVaR_{q,t}^{j\|i}$	$CoVaR_{q,t}^{j\|i}$	$\Delta CoVaR_{q,t}^{j\|i}$	$CoVaR_{q,t}^{j\|i}$	$\Delta CoVaR_{q,t}^{j\|i}$
VaR	0.313^{***}	0.333^{***}	0.253^{***}	0.270^{***}	0.164^{***}	0.173^{***}
	(0.014)	(0.014)	(0.012)	(0.013)	(0.013)	(0.014)
Ret	-0.003	0.000	0.019^{***}	0.018^{***}	0.012^{**}	0.011^{**}
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
VIX	-0.012^{***}	-0.013^{***}	0.002	0.002	-0.007^{*}	-0.008^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
SPGSCI	0.109^{***}	0.111^{***}	0.128^{***}	0.127^{***}	0.113^{***}	0.115^{***}
	(0.025)	(0.025)	(0.021)	(0.021)	(0.019)	(0.020)
CORP	0.536^{***}	0.530^{***}	0.279^{***}	0.310^{***}	0.272^{***}	0.274^{***}
	(0.054)	(0.051)	(0.058)	(0.058)	(0.068)	(0.070)
DCOILBRENTEU	-0.023^{*}	-0.027^{**}	-0.049^{***}	-0.052^{***}	-0.034^{***}	-0.034^{***}
	(0.009)	(0.009)	(0.007)	(0.007)	(0.005)	(0.005)
T5YIFR	-0.137^{***}	-0.135^{***}	-0.087^{***}	-0.090^{***}	-0.069^{***}	-0.071^{***}
	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
DEXUSEU	-0.510^{***}	-0.582^{***}	-0.462^{***}	-0.530^{***}	-0.108	-0.131
	(0.062)	(0.065)	(0.079)	(0.078)	(0.077)	(0.077)
DTWEXBGS	-0.697^{***}	-0.788^{***}	-0.364^{**}	-0.410^{***}	-0.262^{**}	-0.320^{**}
	(0.097)	(0.099)	(0.118)	(0.118)	(0.100)	(0.100)
BTC.VOL	-0.523^{***}	-0.541^{***}	-0.360^{***}	-0.374^{***}	-0.274^{***}	-0.285^{***}
	(0.015)	(0.016)	(0.013)	(0.013)	(0.011)	(0.011)
R^2	0.303	0.314	0.161	0.171	0.085	0.089
Adj. R^2	0.302	0.314	0.161	0.170	0.084	0.088
Num. obs.	46536	46536	46242	46242	45948	45948

Note: The p-values are calculated with standard errors computed by Newey–West estimator and are represented for $^{***}p < 0.001$, $^{**}p < 0.01$ and $^{*}p < 0.05$.

7 Conclusion

The recent pandemic is an opportunity to investigate the tail risk structure of some assets during a turmoil period. Therefore, in this study, we analyze conditional tail-risk in the markets for some cryptocurrencies such as Bitcoin, Ethererum, Ripple, Binance Coin, Litecoin and also for Gold and S&P500 before (2017-11-13 to 2020-02-26) and after (2020-02-27 to 2022-09-09) the pandemic period.

The results point out that, while the VaR_q^i value of some cryptocurrencies (Bitcoin, Ethereum, Litecoin and Ripple), in absolute value, fall down, the values of $\beta_{1,q}^{j|i}$, $CoVaR_q^{j|r^i}$ and $\Delta CoVaR_q^{j|i}$, on average, became higher (in absolute terms) after the pandemic. We also find that gold, the most recognizable safe-haven in the literature, 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 tail risk dependence increase during the pandemic period, thus pointing out the higher transmission of shocks. Comparing the two biggest cryptocurrencies in market value (Bitcoin and Ethereum), we note that Bitcoin have the lowest $\Delta CoVaR_q^{j|VaR^i}$ (on average), i.e., is less systematically vulnerable. The $\Delta CoVaR_q^{j|VaR^i}$ measure conditional on state macroeconomic variables reaches your peak (in absolute terms) on onset March 2020, when the value of the measure is about 35.77% for Bitcoin conditional on S&P500 and 35.26% for Ethereum conditional on Bitcoin.

The past low returns of S&P commodity index (SPGSCI) and Corporate Bond Index (CORP) forecast large future negative $CoVaR_q^{j|VaR^i}$ and $\Delta CoVaR_q^{j|VaR^i}$ values. However, past high values of Oil Prices Brent - Europe (DCOILBRENTEU), 5-Year Forward Inflation Expectation Rate (T5YIFR), USD/EUR exchange rate (DEXUSEU), Nominal Broad U.S. Dollar Index (DTWEXBGS), CBOE Volatility Index (VIX) and Bitcoin Volatility forecast negatively tail-risk measures. We also find that all macro state variables, with excetion of USD/EUR exchange rate (DEXUSEU), predict future tail-risk for assets at longer horizons (h = 21 days).

These results are useful for the literature on risk management and portfolio decisions. Some authors (Su et al. (2021) and others), point out that measures of conditional risk, may prove uninformative or even unspecified when risks 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.

Bibliography

ADRIAN, T.; BRUNNERMEIER, M. K. *CoVaR*. [S.l.], 2011.

AKHTARUZZAMAN, M. et al. Systemic risk-sharing framework of cryptocurrencies in the covid–19 crisis. *Finance research letters*, Elsevier, p. 102787, 2022.

BAUR, D. G.; LUCEY, B. M. Is gold a hedge or a safe haven? an analysis of stocks, bonds and gold. *Financial review*, Wiley Online Library, v. 45, n. 2, p. 217–229, 2010.

BORRI, N. Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance*, Elsevier, v. 50, p. 1–19, 2019.

BOURI, E. et al. On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, Elsevier, v. 20, p. 192–198, 2017.

BURDEKIN, R. C.; TAO, R. The golden hedge: From global financial crisis to global pandemic. *Economic Modelling*, Elsevier, v. 95, p. 170–180, 2021.

CINER, C.; GURDGIEV, C.; LUCEY, B. M. Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis*, Elsevier, v. 29, p. 202–211, 2013.

CIVAN, Z.; SIMSEK, G. G.; AKAY, E. C. Identifying the systemically important banks of turkey with the covar method. *Heliyon*, Elsevier, v. 6, n. 9, p. e04790, 2020.

CONLON, T.; CORBET, S.; MCGEE, R. J. Inflation and cryptocurrencies revisited: A time-scale analysis. *Economics Letters*, Elsevier, v. 206, p. 109996, 2021.

CORBET, S. et al. Any port in a storm: Cryptocurrency safe-havens during the covid-19 pandemic. *Economics Letters*, Elsevier, v. 194, p. 109377, 2020.

FENG, W.; WANG, Y.; ZHANG, Z. Can cryptocurrencies be a safe haven: a tail risk perspective analysis. *Applied Economics*, Taylor & Francis, v. 50, n. 44, p. 4745–4762, 2018.

GIRARDI, G.; ERGÜN, A. T. Systemic risk measurement: Multivariate garch estimation of covar. *Journal of Banking & Finance*, Elsevier, v. 37, n. 8, p. 3169–3180, 2013.

GOODELL, J. W.; GOUTTE, S. Diversifying equity with cryptocurrencies during covid-19. *International Review of Financial Analysis*, Elsevier, v. 76, p. 101781, 2021.

HÄRDLE, W. K.; WANG, W.; YU, L. Tenet: Tail-event driven network risk. *Journal of Econometrics*, Elsevier, v. 192, n. 2, p. 499–513, 2016.

HARRIS, R. D.; NGUYEN, L. H.; STOJA, E. Systematic extreme downside risk. *Journal of International Financial Markets, Institutions and Money*, Elsevier, v. 61, p. 128–142, 2019.

JIANG, W.; XU, Q.; ZHANG, R. Tail-event driven network of cryptocurrencies and conventional assets. *Finance Research Letters*, Elsevier, v. 46, p. 102424, 2022.

KELLY, B.; JIANG, H. Tail risk and asset prices. *The Review of Financial Studies*, Oxford University Press, v. 27, n. 10, p. 2841–2871, 2014.

KLEIN, T.; THU, H. P.; WALTHER, T. Bitcoin is not the new gold–a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, Elsevier, v. 59, p. 105–116, 2018.

KOENKER, R. Quantile regression. *Econometric society monographs*, Cambridge university press Cambridge, 2005.

KOENKER, R. et al. Handbook of quantile regression. CRC press, 2017.

LAHIANI, A.; JLASSI, N. B. et al. Nonlinear tail dependence in cryptocurrency-stock market returns: The role of bitcoin futures. *Research in International Business and Finance*, Elsevier, v. 56, p. 101351, 2021.

LI, X.; WANG, C. A. The technology and economic determinants of cryptocurrency exchange rates: The case of bitcoin. *Decision support systems*, Elsevier, v. 95, p. 49–60, 2017.

LINSMEIER, T. J.; PEARSON, N. D. Value at risk. *Financial Analysts Journal*, Taylor & Francis, v. 56, n. 2, p. 47–67, 2000.

MA, C. et al. Monetary policy shocks and bitcoin prices. *Research in International Business and Finance*, Elsevier, v. 62, p. 101711, 2022.

MARIANA, C. D.; EKAPUTRA, I. A.; HUSODO, Z. A. Are bitcoin and ethereum safe-havens for stocks during the covid-19 pandemic? *Finance research letters*, Elsevier, v. 38, p. 101798, 2021.

MARMORA, P. Does monetary policy fuel bitcoin demand? event-study evidence from emerging markets. *Journal of International Financial Markets, Institutions and Money*, Elsevier, v. 77, p. 101489, 2022.

NGUYEN, T. V. H. et al. Asymmetric monetary policy effects on cryptocurrency markets. *Research in International Business and Finance*, Elsevier, v. 48, p. 335–339, 2019.

PERRON, P.; QU, Z. Long-memory and level shifts in the volatility of stock market return indices. *Journal of Business & Economic Statistics*, Taylor & Francis, v. 28, n. 2, p. 275–290, 2010.

REN, R.; ALTHOF, M.; HÄRDLE, W. K. Tail risk network effects in the cryptocurrency market during the covid-19 crisis. *Available at SSRN 3753421*, 2020.

SEBASTIÃO, H.; GODINHO, P. Bitcoin futures: An effective tool for hedging cryptocurrencies. *Finance Research Letters*, Elsevier, v. 33, p. 101230, 2020.

SELMI, R. et al. Is bitcoin a hedge, a safe haven or a diversifier for oil price movements? a comparison with gold. *Energy Economics*, Elsevier, v. 74, p. 787–801, 2018.

SMALES, L. A. Bitcoin as a safe haven: Is it even worth considering? *Finance Research Letters*, Elsevier, v. 30, p. 385–393, 2019.

SU, Q. et al. Efficiently backtesting conditional value-at-risk and conditional expected shortfall. *Journal of the American Statistical Association*, Taylor & Francis, v. 116, n. 536, p. 2041–2052, 2021.

TRABELSI, N.; NAIFAR, N. Are islamic stock indexes exposed to systemic risk? multivariate garch estimation of covar. *Research in International Business and Finance*, Elsevier, v. 42, p. 727–744, 2017.

URQUHART, A.; ZHANG, H. Is bitcoin a hedge or safe haven for currencies? an intraday analysis. *International Review of Financial Analysis*, Elsevier, v. 63, p. 49–57, 2019.

WALTZ, M.; SINGH, A. K.; OKHRIN, O. Vulnerability-covar: investigating the crypto-market. *Quantitative Finance*, Taylor & Francis, v. 22, n. 9, p. 1731–1745, 2022.

XU, Q.; ZHANG, Y.; ZHANG, Z. Tail-risk spillovers in cryptocurrency markets. *Finance Research Letters*, Elsevier, v. 38, p. 101453, 2021.

YU, J.; SHANG, Y.; LI, X. Dependence and risk spillover among hedging assets: Evidence from bitcoin, gold, and usd. *Discrete Dynamics in Nature and Society*, Hindawi, v. 2021, 2021.

ZHANG, J. *Systemic risk measure*. Dissertação (Mestrado) — Humboldt-Universität zu Berlin, Wirtschaftswissenschaftliche Fakultät, 2015.

.1 Appendix: State Variables Description

Table .1 – Descriptive Summary of State Variables

Variable	**Definition**	**Transformation**	**Source**
VIX	It is one of the most recognized measures of volatility – widely reported by financial media and closely followed by a variety of market participants as a daily market indicator	Rate of Change	Yahoo Finance
DCOILBRENTEU	Oil Prices Brent - Europe	Rate of Change	FRED - St. Louis Fed
T5YIFR	Measures the expected inflation rate (on average) over the five-year period that begins five years from today	Rate of Change	FRED - St. Louis Fed
CORP	Corporate Bond Index ETH, is used as a proxy for the bond market	Rate of Change	Yahoo Finance
DEXUSEU	USD/EUR exchange rate	Rate of Change	FRED - St. Louis Fed
DTWEXBGS	Nominal Broad U.S. Dollar Index - tracks the performance of the US dollar against a basket of major foreign currencies, is used as a proxy for the currency market	Rate of Change	FRED - St. Louis Fed
SPGSCI	S&P commodity index	Rate of Change	Yahoo Finance

Note: This table reports the definition, transformation and source of the used macro state variables.