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CRASH RISK AND SYNCHRONICITY OF CRYPTOCURRENCIES: AN ANALYSIS DURING AND AFTER COVID-19

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ABSTRACT

The advent of cryptocurrencies, beginning with Bitcoin in 2008, introduced an approach to peer-to-peer transactions by eliminating the need for traditional intermediaries. Nowadays the cryptocurrencies market is seen not only as an alternative monetary system but also as an investing opportunity, and events such as the COVID-19 pandemics or the war between Russia and Ukraine, that impacted the world finances, could also affect its behavior. The study aims to analyze the influence of external worldwide events on crash risk of cryptocurrency markets during and after COVID-19, controlling for synchronicity. For the research, it was extracted a minute high-frequency intra-day data for a sample of crypto assets to compute synchronicity and crash risk daily indicators, and also daily data for control variables. The multivariate regression model was used to identify the determinants of crash risk. The findings indicates that the cryptocurrency market, despite facing challenges posed by such events, exhibits resilience and reduced the crash chance. The significance of synchronicity and the negligible impact of external events suggest that decentralized markets might offer protection against the adverse effects when the world is experiencing a crisis.

Keywords: Cryptocurrency, Bitcoin, Ethereum, Cardano, Binance, Crash Risk, Synchronicity, Upside Volatility, COVID, Russian-Ukraine Conflict

RESUMO

O advento das criptomoedas, começando com o Bitcoin em 2008, introduziu uma abordagem de transações peer-to-peer, eliminando a necessidade de intermediários tradicionais. Atualmente, o mercado de criptomoedas é visto não apenas como um sistema monetário alternativo, mas também como uma oportunidade de investimento, e eventos como a pandemia de COVID-19 ou a guerra entre Rússia e Ucrânia, que impactaram as finanças mundiais, também podem afetar seu comportamento. O estudo tem como objetivo analisar a influência de eventos externos globais no risco de queda dos mercados de criptomoedas durante e após a COVID-19, com a sincronicidade como estatística de controle. Para a pesquisa, foi extraído dados intra-diários de alta frequência por minuto para uma amostra de cripto ativos, a fim de calcular indicadores diários de sincronicidade e risco de *crash*, além de dados diários para variáveis de controle. O modelo de regressão multivariada foi utilizado para identificar os determinantes do risco de queda. Os resultados indicam que o mercado de criptomoedas, apesar dos desafios impostos por tais eventos, mostra resiliência e reduz a chance de *crash*. A significância da sincronicidade e o impacto reduzido de eventos externos sugerem que mercados descentralizados podem oferecer proteção contra os efeitos adversos quando o mundo enfrenta uma crise.

Palavras-chave: Criptomoedas, Bitcoin, Ethereum, Cardano, Binance, Risco de Crash, Sincronicidade, Volatilidade Positiva, COVID, Conflito Rússia-Ucrânia

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1. INTRODUCTION

The first appearance of a cryptocurrency was in 2008 when a white paper titled "*Bitcoin: A Peer-to-Peer Electronic Cash System*" was published on a cryptography mailing list (NAKAMOTO, 2008). In January 2009, the world witnessed the first transaction using it as a currency. The base idea for creating the currency was to eliminate third parties involved in transactions. For example, when an interested party uses their credit card to purchase a good in the market, there are actually two transactions involved. The first one occurs between the party and the card company, where a debt charge is issued on their statement. The second transaction takes place when the company pays the value to the business, receiving a spread fee for the transaction. In this case using the definition of peer-to-peer trade, the third party (the company) is eliminated. This could only be possible with the existence of a system called *blockchain*, which will be discussed next.

The *blockchain* consists of an immutable digital ledger that records all transactions in the system in a transparent and decentralized manner. It is directly connected to the internet, which means it requires nodes or computers to create blocks (DI PIERRO, 2017). These blocks contain transaction data, a timestamp, and a unique generated code called a "*hash*", ensuring that any user can verify authenticity. Once a transaction occurs, a block is immediately added to the chain and cannot be altered or removed.

In the following years, the market witnessed the emergence of numerous digital currencies (LI, LUCEY, URQUHART, 2023), commonly referred to as "*altcoins*". There are a few ways to develop a new currency: the first, and most complex way, is to create a decentralized network and subsequently a new blockchain. Secondly, it is possible to partition an existing chain through a process commonly known as a fork, where the native code is used and splits into two separate branches. Lastly, a new token can be launched on an existing network and negotiated in contracts using the main currency as the base for the initial transaction. As these currencies are directly connected to the internet, users have created names to classify and sort the recently spawned currencies. They are referred to as *stablecoins*, which are crypto assets financially backed by regular exchanges; *memecoins*, which are derived from humor or a joke; or simply as regular altcoins. Due to their rapid global growth, cryptocurrencies have drawn the attention of not only researchers but also institutional investors, whose cryptocurrency trading has enhanced the profitability of their portfolios (BIALKOWSKI, 2020).

Hermans et al (2022) in a study from the European Central Bank list diverse risks when investing in cryptos. They are volatility and subjected to continuous financial innovation, and with time passing they are more interconnected with traditional financial sector, increasing the systemic risk. Crypto-assets lack intrinsic economic value or reference assets, and their frequent use as an instrument of speculation, high volatility, and energy consumption make them highly risky instruments. Despite the risks, investor demand for crypto-assets has been increasing, driven by perceived opportunities for quick gains, unique characteristics of crypto-assets compared with conventional asset classes, and benefits perceived by institutional investors with regard to portfolio diversification.

In this study we focus on crash risk. A recently study by Ma and Luan (2022) aims to understand the correlation between Bitcoin ($BTC) and Ethereum ($ETH) and how it affects the risk of a crash. This correlation is referred to as "synchronicity," and crash risk refers to periods when a security experiences a sudden shock, resulting in significant changes in its value, either positive or negative.

This study intents to update the aforementioned study by selecting a model that has demonstrated efficacy in predicting and analyzing stock behavior, as seen in An and Zhang (2013), Jin and Myers (2006), and Bouri (2020). The methodology used in these studies will be applied using additional crypto tokens that have experienced growth in recent years and new data from recent turbulent periods. This analysis is important due to two major events that have significantly impacted global finances: the Covid-19 pandemic (2020-2023) and the ongoing invasion of Ukraine by Russia, which began in March 2022. These events have led to significant changes in European and Asian financial markets, and all over the world.

1.1. RESEARCH PROBLEM

The inclusion of crypto assets in investment portfolios has shown some diversification benefits and the potential to improve risk-adjusted returns (BRIERE, 2015), and considering that Bitcoin has exhibited hedging properties during times of economic uncertainty (BOURI 2017), it is interesting to explore the synchronicity of a certain number of cryptocurrencies and their correlation with crash risk. Left tail risk and the cross-section of expected stock returns has received considerable attention in the recent empirical asset pricing literature (AN and ZHANG, 2013; BOURI et al., 2019; HANG et al. 2021; MA and LUAN, 2022; KALYVAS, 2020; SHABI-YO et al., 2022). In this scenario it is important to analyze de cryptocurrencies crash risk, especially during times of crisis such as the COVID-19 and the ongoing Ukraine and Russia War that started in 2022. Also, one major source of crash risk is the assets' synchronicity and is also necessary to research how it has changed or not during these turbulent times. The cryptocurrencies selected for this research are Binance Coin (BNB), Ethereum (ETH), Bitcoin (BTC), Cardano (CAR), and Solano (SOL).

1.2. OBJECTIVES

1.2.1. GENERAL OBJECTIVE

This research aims to analyze the influence of external worldwide events on crash risk of cryptocurrency markets from 1st of January 2019 to 3rd of October 2023, controlling for synchronicity. The focus will be on understanding how major global events, such as geopolitical conflicts and sanitary crisis, impact the behavior and dynamics of various cryptocurrencies. By examining the correlation between these events and the movements in cryptocurrency markets, this study seeks to provide insights into the interplay between external events and the cryptocurrency ecosystem, and the hedge capacity of this coins in those periods.

1.2.2. SPECIFIC OBJECTIVES

- Analyze the returns of the currencies in situations of geopolitical conflicts and pandemics.
- Analyze synchronicity and crash risk among selected virtual coins: The synchronicity, which measures the level of correlation among the chosen cryptocurrencies, will be estimated and crash risk associated with these coins will be assessed.
- Analyze the effects of the COVID-19 and the ongoing Ukraine and Russia war on crash risk.

1.3. JUSTIFICATION

Firstly, the cryptocurrency market is growing rapidly and becoming increasingly integrated into the global financial system (HERMANS et al., 2022). This integration means that understanding the synchronicity of cryptocurrency prices is essential to grasp the potential impact of crypto market volatility on the wider financial system. Secondly, the decentralized nature of cryptocurrencies and the lack of regulation make the market more susceptible to sudden price fluctuations and crashes, which can have significant economic consequences, for individual investors, institutions and also governments. Therefore, studying the crash risk associated with the selected assets, along with their synchronicity, can help investors, and others manage their risks better and make informed investment decisions, such as portfolio hedging or investing in those coins. Additionally, this research can contribute to understanding the general behavior of markets during global crisis, and determine whether global events do indeed impact decentralized markets such as the cryptocurrency market, thereby demonstrating a potential of impacting the risk of a Bitcoin or Ethereum Market Crash.

1.4. RESEARCH STRUCTURE

The research is structured as follows: This introduction section explores the research problem, objectives, and justification, followed by Section 2 presenting the theoretical background. Section 3 will discuss the methodology used, and after that, the results found will be presented in Section 4. Lastly, Section 5 will present final considerations and future research suggestions.

2. THEORETICAL BACKGROUND

2.1. Cryptocurrency Market

Cryptocurrencies are often classified as decentralized peer-to-peer payment networks, where the users are the main participants, and no entity or central authority sponsors, finances, or regulates the transactions (ZOHURI, NGUYEN & MOGHADDAM, 2022). As a result, two individuals from any part of the world can engage in a transaction by connecting to the internet and using the nodes in the blockchain, while being secured by cryptography. This not only eliminates the problem of double spending that is common in financial market transactions (BRITO, SHADAB & CASTILHO, 2014), but also prevents any government or financial authority from controlling the supply of the currency or acting with protectionist motives.

The blockchain is updated with new information every time a transaction or request is created, affecting all the nodes in the network and making the information accessible to everyone, not just a few. The parties involved, also known as crypto wallets (JØRGENSEN & BECK, 2022), are hidden by hash numbers in the blockchain. A person can have multiple wallets, and even if one hash number is linked to an individual, the others can still be masked, ensuring user privacy and maintaining the decentralized nature of cryptocurrencies. The only information required for validation is the existence of the sender wallet and whether it has enough token value, as well as the existence of the receiver wallet. Then, a request is sent to the blockchain, and the transaction is completed.

One of the first and most influential tokens in the market is "Bitcoin: A Peer-to-Peer Electronic Cash System," a research paper published in 2008 by Satoshi Nakamoto. This name is widely believed to be a pseudonym, but it is unclear whether it refers to a single person or a group of anonymous developers. The paper introduced a system for creating new bitcoins by rewarding users, called miners, who use their computing power to verify transactions according to the protocol. The total number of bitcoins is limited to 21 million, and the reward for miners depends on the existing supply and the difficulty of the verification process (SEGENDORF, 2014). Bitcoins are stored in a wallet and can be transferred to other wallets for further transactions. In this scenario, exchanges emerged to allow users to buy bitcoins with fiat currencies (BORDO, 2021), without having to participate in the mining process. These exchanges receive money from users and credit them with a certain amount of mined bitcoins. Some exchanges also offer their own generated tokens for trading, enabling users to buy them and then exchange them for other cryptocurrencies by placing buy/sell orders based on the current exchange rates between them.

The emergence of Bitcoin as a widely accepted virtual currency in the market sparked the creation of other digital currencies that sought to enhance some features of the Bitcoin protocol. These features include transaction speed, mining/rewarding system, volume availability, or ultimate objective (REED, 2017). The present study has selected some of these currencies for analysis and will discuss them in the following section.

2.2. Altcoin Market

Ethereum is the second most important cryptocurrency in the market. It was introduced in 2014 by Vitalik Buterin, who published a white paper online titled "A next-generation smart contract and decentralized application platform". The native token of the platform is Ether ($ETH), which enables the use of smart contracts. These are pieces of code that can run on the blockchain, making Ethereum the first programmable blockchain (CERNERA, LA MORGIA, MEI and SASSI, 2022). On Ethereum, the user who initiates a transaction pays a fee to the users who verify it. This fee is called gas, and it depends on the complexity of the verification. Moreover, some of the gas is burned, meaning that it is sent to an empty address and removed from circulation. This makes Ether a deflationary asset, as its supply decreases over time while its demand increases. As a result, its value is expected to rise in the long term. This also encourages users to hold on to their Ether, creating a positive feedback loop (PISTUNOV, NIKOLAENKO, 2023).

One of the most prominent centralized exchanges in the cryptocurrency market is Binance, as discussed previously. Binance operates like a functional stock exchange company with owners and boards, unlike decentralized exchanges that are maintained by the users. Binance launched its own currency, Binance Coin ($BNB), in 2020, which stands for Build and Build. The main function of BNB is to facilitate transactions within its own network, initially called Binance Smart Chain and now renamed as BNB Smart Chain. Users can create an account on the Binance exchange and link it to a wallet. They can then buy BNB with fiat currency, which allows them to trade other virtual currencies. BNB is important because its chain is widely used for trading various altcoins, either within the Binance market or through different wallets on decentralized exchanges like Pancake Swap.

Another cryptocurrency that deserves attention is Cardano ($ADA). This coin was launched in 2017, after two years of development, and it is regarded as a third-generation crypto asset. This means that it aims to solve the problems that Ethereum, a second-generation coin, faced when trying to improve upon Bitcoin, the first-generation coin. Cardano's protocol rewards users based on the number of tokens they stake, which means keeping them in their wallets. The initial supply of tokens was fixed, and the only way to obtain more is to purchase the existing ones in the market and hold them.

2.3. Stock Price Synchronicity and Crash Risk

According to Morck, Yeung, and Yu (2000) synchronicity is a concept that refers to how much prices reflect assets specific and market information. The authors used the coefficient of determination (R2) from the market model to measure synchronicity. A lower R2 means that prices are more influenced by company or assets specific information and thus more aligned with their true value. Therefore, lower synchronicity could help to predict prices and assets returns, and higher synchronicity could be positively related to crash risk (MA and LUAN, 2022).

The correlation analysis of various cryptocurrencies is essential for a comprehensive understanding of crash risk. Diversification is a key principle of Markowitz's (1952) Portfolio Theory, which implies that investors should consider how their investments interact with each other when forming a portfolio, i.e., a collection of stocks they own. To construct a portfolio, investors need to assess the risks of the securities, usually measured by the standard deviation of the historical returns, and balance them to optimize the risk-return trade-off. A deeper analysis reveals that assets within the same sector have positive correlation, while assets across different sectors have zero or negative correlation. Therefore, investors can achieve higher returns for the same or lower risk if they diversify their portfolio composition.

To assess the risk of a portfolio, the investor needs to account for not only the individual risk of the stocks that make up the portfolio and their proportion, but also the correlation among them. This approach is based on Markowitz's Theory, which was further developed in Sharpe's (1964) work, where he proposed the Capital Asset Pricing Model (CAPM). He also distinguished two types of risk: systematic risk – the risk that cannot be diversified away – and unsystematic risk – the one captured by the standard deviation of the model's errors. The measure of systematic risk is called beta, and it indicates how much an asset responds to market movements. Therefore, to estimate the expected return of an asset, the investor should multiply beta and the market risk premium, and add the return of a risk-free bond.

Investing in cryptocurrencies involves a high level of market risk, which means that the prices or rates of these assets can fluctuate significantly and unpredictably (HERMANS et al., 2022). A useful tool to quantify and manage this risk is the Value at Risk (VaR), which was introduced by Linsmeier and Pearson (1996) as the maximum potential loss that can occur with a given confidence level over a given time horizon. VaR can be computed using different methods, such as Historical or Monte Carlo Simulation, which rely on historical data and random scenarios, respectively, or the variance-covariance method, which assumes a normal distribution of returns. VaR can also be applied to assess the tail risk, which is the likelihood of extreme events that can activate circuit breakers and lead to a market crash. Circuit breakers are mechanisms that halt trading when the market reaches a certain threshold of volatility or decline.

To understand how crash risk relates to cryptocurrencies, one must first examine the concept of crash risk itself. Hong and Stein (1999) define a crash as a sudden and large drop in price and return that follows certain kinds of news or media events, usually with a negative connotation. This definition is consistent with historical data analysis, especially the analysis of the S&P 500 since 1947, which shows that nine out of the ten biggest crashes resulted in negative returns. This leads to the first element that will be used in this study, which is the negative correlation between returns and volatility, also known as negative skewness.

A thorough analysis of crash events requires observing the market behavior during such periods. The main point to consider is that a crash usually affects only a few stocks that are directly linked to the event that caused the crash, while most of the market remains unaffected. Historical data analysis of stock prices shows a significant increase in their correlation when the market experiences a downturn (DUFFEE, 1995). Therefore, when important information that can trigger a shock is disclosed, the wider market reacts to it, leading to a drop in the value of the most traded indices within that market.

Building on Fama's (1969) research, it is anticipated that the market will exhibit signals of reversals or recovery in the aftermath of a crash, aligning with the concept of efficient markets. During this period, a distinct form of volatility, known as "down-to-up" volatility, is observed, which differs from the volatility witnessed during the preceding descent. This particular volatility (DUVOL), as highlighted by Chen et al. (2001), holds significance in providing insights into the resilience and stability of a security during its recovery phase. The presence of high volatility during this period is often indicative of instability and low confidence, suggesting a potential downturn.

Regarding the cryptocurrency market, Bouri et al. (2019) suggests that shocks or crashes in a single cryptocurrency can trigger a similar trend in other cryptocurrencies, similar to the findings of Hong and Stein's (1999) research on stocks. Additionally, Ji et al. (2019) investigated how cryptocurrencies are interrelated and found that negative returns have a greater impact than positive returns. This finding underscores the significance of negative returns when evaluating crash risk in the cryptocurrency market and supports the idea of a connected market on responding to internal shocks.

Lastly, the tight connection between Bitcoin and Ethereum in the general cryptocurrency market is explained by Ma and Luan (2022). They discuss how the explosivity of one cryptocurrency can affect the other, highlighting their interdependence, particularly in the upper and lower tails of digital currencies. Ma and Luan (2022) stated that in highly speculative instruments, investors' behavior plays an important role in asset pricing. To account for that they propose to estimate the role of synchronicity conditioned on upside volatility of Bitcoin as a proxy for the fear of high Bitcoin prices. They results revealed that when upside volatility is high, Ethereum synchronicity exerts a significant positive influence on Bitcoin crash risk. This research aims to build upon this understanding by examining a variety of assets in the context of two significant global events: the Covid-19 Pandemics and the Russia/Ukraine War.

Gaio et al (2022) aimed to mainly examine the effects of the war between Russia and Ukraine based on the efficiency of stock markets (FAMA, 1969) in different countries. They selected indexes from US, Germany, UK, France, Italy and Spain to construct a data frame. Because of the timeframe selected, they also explored COVID, separating all the data in before and during COVID, before Russia-Ukraine conflict and after. Their results showed that the Efficient Market Hypothesis (EHM) was not supported and that herd behavior and irrationality were prevalent during that period, leading to high instability.

3. DATA AND METHODOLOGY

3.1. Research Type

This is considered a descriptive study, as its main purpose is to establish a relationship between variables and describe the characteristics of a population (GIL, 1999).

Regarding the approach selected to conduct the study, it is defined as a quantitative study, as the data was collected and processed using statistical models (RICHARDSON, PERES, 1999).

3.2. Data and Sample

This research used a minute level high frequency data available on Binance Exchange Data, from 01-Jan-2019 to 3-October-2023. With this intraday data we compute our main variables to be analyzed, the synchronicity and crash risk measures on daily basis.

Regarding the control variables, all the data was extracted from the website Investing.com on a daily frequency and their return was calculated.

The data was processed and modeled using both the statistical software R-Studio and Python library Pandas.

3.3. Dependent Variables

From the minute-level frequency (intra-daily) data, log returns were calculated. Based on those values it was possible to compute our main variables and estimate the models further described.

Regarding crash risk, this research use three measures for analysis: $NCSKEW_t$, $DUVOL_t$ (CHEN, 2001; KALYVAS, 2020) and $CRASH_t$ (MA, LUAN, 2022). The first measure ($NCSKEW_t$) represents the negative coefficient of skewness of intra-daily returns and it's represented by the equation (1):

$$NCSKEW_t = \frac{-\left[n(n-1)^{\frac{3}{2}}\sum r^3\right]}{\left[(n-1)(n-2)(\sum r^2)^{\frac{3}{2}}\right]} \qquad (1)$$

In equation (1), n represent the number (volume) of one-minute returns, and r represents the intra-day one-minute return.

The second measure, CRASHt, is a binary variable that indicates whether the return for day t is below a certain threshold, indicating a crash. The threshold is calculated as the 20-day rolling moving average minus the 20-day rolling standard deviation.

The third measure, DUVOL, which stands for "down-to-up volatility," is less sensitive to extreme returns as it does not consider the third moment:

$$DUVOL_t = \log\left[\frac{(n_u - 1)\sum_{DOWN} r^2}{(n_d - 1)\sum_{UP} r^2}\right] \qquad (2)$$

In equation (2), n_u and n_d represents the volume of positive or negative returns (volume) and r represents the returns within a day. In order to calculate this measure for each day (t), first it is necessary to consider both positive and negative returns. Next, assess whether each minute’s return is above or below the mean for the mean for that day. If that return is above it will contribute to the upper trend; if it is below, it contributes to the downtrend. Finally, calculate the standard deviation for each trend and the log ratio of downtrend volatility divided by uptrend volatility.

3.4. Explanatory Variables and Control Variables

Following the study of Jin and Myers (2006), it’s necessary to build a regression using intra-day returns, in order to understand the synchronicity between chosen assets. Equation (3) shows the first regression model, where $r^b_{t,m}$ denotes the return of Bitcoin and $r^e_{t,m}$ denotes the return of Ethereum, at day (t) and intra-day minute (m). The model also includes lags (m-1) and leads (m+1). The results for this model will be displayed on the appendix. Equation (4) modifies the previous regression by adding not only Bitcoin lags and leads, but also the time series data of other cryptocurrencies, where $r^b_{t,m}$ represents the return of Cardano and $r^n_{t,m}$ represents the return of Binance Coin. The aim is to assess whether the prices of other crypto assets also affect Bitcoin crash risk.

$$r^e_{t,m} = \alpha_i + \beta_{1,t}\, r^b_{t,m-1} + \beta_{2,t}\, r^b_{t,m} + \beta_{3,t}\, r^b_{t,m+1} + \varepsilon_i \quad (3)$$

$$r^b_{t,m} = \alpha_i + \beta_{1,t}\, r^b_{t,m-1} + \beta_{2,t}\, r^b_{t,m+1} + \beta_{3,t}\, r^e_{t,m-1} + \beta_{4,t}\, r^e_{t,m} + \beta_{5,t}\, r^e_{t,m+1} + \beta_{6,t}\, r^n_{t,m-1}$$
$$\beta_{7,t}\, r^n_{t,m} + \beta_{8,t}\, r^n_{t,m+1} + \beta_{9,t}\, r^a_{t,m-1} + \beta_{10,t}\, r^a_{t,m} + \beta_{11,t}\, r^a_{t,m+1} + \varepsilon_i \qquad (4)$$

Once the regression model is estimated, it's R² is evaluated and used to calculated the value of SYNC, the synchronicity of the cryptocurrencies x and y in the day t. Equation (5) demonstrates SYNC formula:

$$\mathrm{SYNCt} = \left(\frac{R_t^2}{1-R_t^2}\right) \qquad (5)$$

The next measure that will compose the final model will be UPSD. Representing the upside volatility of the experimented currency. Equation (6) demonstrates UPSD formula:

$$UPSD_t = \sqrt{\frac{1}{n}\sum(\bar{r}_t - r^U{}_{t,m})^2} \ (6)$$

Following the past formulas, $r^U{}_{t,m}$ represents the positive return on day t, considering $\bar{r}_t$ as the mean of positive returns on that day.

The control variables include the daily returns of gold price (*gold*), wti crude oil (*oil*), MOEX Russia Index (*moex*), NIKKEI 225 (*nikkei*), Stand & Poor Index (sp500), dollar index (*usd*), Shanghai Composite (*ssec*), and Euro 50 Stoxx Index (*stoxx*). These are major indices from around the world that are compared with crypto prices. The variables that describe the world events are represented by two dummy variables – that can assume 1 or 0 – for the presence of the Covid-19 Pandemics and the Russia and Ukraine War.

Lastly, with the variables created by the previous equations it's possible to build the final regression model to be used on this research.

3.5. Analysis Model

$$CrashRiskMeasures_i = \alpha_i + \beta_1\, SYNC_t + \beta_2\, UPSD_t + \beta_3\, SYNC_t \times UPSD_t + \sum controls + \varepsilon_i \qquad (7)$$

The three types of crash risk measures explained earlier will take place of the dependent variable $CrashRiskMeasures_i$ - $NCSKEW_t$, $DUVOL_t$, and $CRASH_t$. $\sum controls$ stand for the combination of control variables described previously.

The equation (7) also present a moderating effect of synchronicity by upside volatility (SYNC X UPSD). According to previous results of Ma and Luan (2022) β_3 is expected to be positive indicating that when upside volatility is high, synchronicity exerts a significant positive influence on crash risk.

3.6. Statistical Tests

The regression model described before requires some additional steps before applying it to the time series data. The data may exhibit heteroscedasticity, autocorrelation, or non-normality, which would violate the assumptions of the regression analysis (HYNDMAN, ATHANASOPOULOS, 2018). Therefore, some modifications are needed to ensure the validity and robustness of the model.

For this research, the final regression model for all variables — $NCSKEW_t$, $DUVOL_t$ and $CRASH_t$ — was subjected to tests to explore its characteristics. The variance inflation factor (VIF) test was used to control for multicollinearity, especially when testing the interaction.

The second test employed is the Breusch-Pagan test, as described by Breusch and Pagan (1979), that aimed at rejecting the null hypothesis of homoscedasticity in the model. This assessment is crucial as the presence of heteroscedasticity can lead to increased inefficiency in parameter estimates and impact the validity of the analysis. The Breusch-Pagan test involves obtaining the residuals of the regression model and regressing their squared values onto another regression. Significantly different coefficients in this second regression suggest the presence of heteroscedasticity in the data. The distribution of this regression will follow a chi-squared pattern.

When assessing autocorrelation, the Ljung-Box test was selected for its capability to discern whether the residuals exhibit a discernible departure from white noise conditions (LJUNG, BOX, 1978). A white noise scenario implies that the residuals are independent and identically distributed, with zero mean and constant variance. This test is applied to scrutinize patterns and correlations across different time periods, and the detection of significance allows for rejecting the null hypothesis of no autocorrelation between the residuals. The equation (8) outlines the test procedure, where n is the sample size, h is the lag test for autocorrelation and ρ the sample autocorrelation:

$$Q(h) = n\,(\mathrm{n}+2) \sum_{\mathrm{k}=1}^{\mathrm{h}} \frac{{\rho_k}^2}{n-k} \qquad (8)$$

The final test to assess the data will be the Shapiro-Wilk test (SHAPIRO, WILK, 1965), conducted with the aim of determining whether the sample data significantly deviates from a normal distribution. The equation (9) demonstrates how the statistic (W) is calculated, where *n* represents the sample size, x_i is the i-th order statistic, $\bar{x}$ is the sample mean, and a_i is a constant that depend on the size obtained from a statistic table:

$$\mathrm{W} = \frac{(\sum_{i=1}^{n} a_i x_i)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \qquad (9)$$

3.7. Regression Types

Following the studies by Newey and West (1986), it is evident that when dealing with time-series data, certain datasets may exhibit heteroscedasticity and autocorrelation, thereby violating the fundamental assumptions of classical regression models. In such instances, these issues can be addressed through the application of a Newey-West regression, which relies on robust standard errors, leading to more accurate parameter estimation. Consequently, the regression model adjusts for serial correlation among the parameter's residuals, incorporating these corrections within the context of time series analysis. If the regression indicates signs of heteroscedasticity or autocorrelation, employing the Newey-West model becomes imperative for refining and enhancing the reliability of the analysis. The equation (10) represents the Newey-West estimator of the covariance matrix, where β is the vector of estimated coefficients, x_i is the vector of regressors for observation I, r_k is the vector of residuals from regressing the product of the residuals and the regressors *k* periods apart, ω_k is the weight assigned to the residuals *k* periods apart:

$$\mathrm{Var}_{\mathrm{NW}}(\beta) = (\textstyle\sum^{n}_{i=1} x_i x'_i)^{-1} (\sum^{m}_{k=-m} \omega_k\, r_k\, r'_k)\, (\sum^{n}_{i=1} x_i x'_i)^{-1} \qquad (10)$$

Also, in the context of time series data, it is common to employ quantile regression as a method for analyzing the relationship between selected variables (KOENKER, BASSETT JR, 1978). This approach becomes particularly crucial in datasets exhibiting the presence of outliers and non-normality, factors that could potentially compromise the reliability of inferences following model completion. Upon estimating quantiles, valuable insights into the relationship among variables across the distribution can be gained. This method is equally significant in predicting or uncovering hidden patterns within the data frames, contributing to a more comprehensive understanding of the underlying dynamics. The equation (11) represents the quantile regression for the τ-th quantile ($0 < \tau < 1$), where *n* is the number of observations, y_i the observed value of the variable for time *i*, x_i the vector of predictor variables at time *i,* and ρ_t is a linear function based in $\tau - I(u<0)$:

$$Q_\tau(\beta) = \textstyle\sum^{n}_{i=1} \rho_t\,(y_i - x'_i\,\beta) \qquad (11)$$

Another regression approach that can be implemented to assess variables in this research is logit regression. Given that the variable CRASHt is a dummy variable, representing categorical data with a binary outcome, it is more suitable to utilize a logit approach (GREENE, 2008). The logarithmic function employed ensures that predictions fall within the range of 0 and 1, making it well-suited for the nature of the chosen variable. Equation (12) represents the logistic regression model, where $P(Y=1|X)$ is the probability of Y being equal to 1, given values of X, e is the base of the natural logarithm, β_0 is the intercept and β_1 *to* β_k the coefficients associated with each predictor variable X_k.

$$P(Y=1|X) = (1+e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k)})^{-1} \qquad (12)$$

4. EMPIRICAL RESULTS

4.1. Descriptive analysis

The table (1) comprehends the values of descriptive statistics of the analyzed series, where $NCSKEW_t$ stand for the negative coefficient of skewness defined by formula (1); $CRASH_t$ is the dummy variable that indicate if Bitcoin has crashed on that day t; $DUVOL_t$ is the down-to-up volatility defined by formula (2), and those three are the main variables that represent the Crash Risk on this research. SYNC*t* is the Bitcoin-Ethereum synchronicity, first regress using formula (3) considering the returns of the other coins and use the R^2 for every day to calculate SYNC*t* by formula (4), and UPSD*t* as the upside volatility defined by formula (5). The control variables return data are gold (GOLD) and wti oil (OIL) commodities daily return and indexes MOEX (MOEX), NIKKEI225 (NIKKEI), Standard & Poor (SP500), STOXX50 (STOXX) and dollar index return (USD). Lastly the two dummy variables COVID (COVID19) and WAR (Russia-Ukraine War).

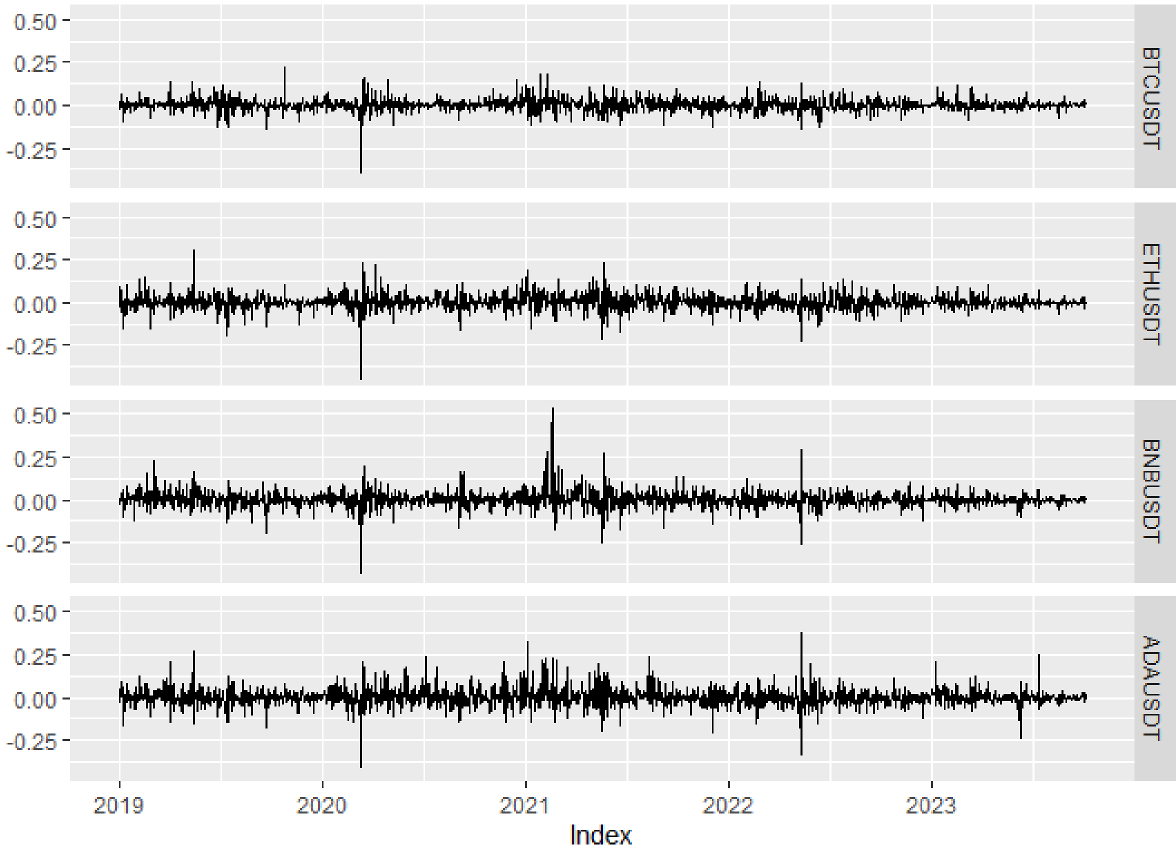
TABLE 1 – DESCRIPTIVE STATISTICS OF RESEARCH VARIABLES BASED ON INTRA DAY DATA

Variables	*N*	*Mean*	*Standard Deviation*	*Min*	*Max*
$NSKEW_t$	1737	0,212	1,964	-17,069	19,128
CRASH	1718	0,126	0,332	0,0000	1,0000
$DUVOL_t$	1737	0,007	0,217	-0,976	1,025
$SYNC_t$	1737	0,957	0,511	-1,460	2,329
$UPSD_t$	1737	0,001	0,0004	0,0001	0,006
OIL	1737	0,001	0,020	-0,225	0,165
GOLD	1737	0,0002	0,007	-0,048	0,058
MOEX	1737	0,0003	0,011	-0,093	0,183
NIKKEI	1737	0,0001	0,008	-0,063	0,077
SP500	1737	0,0003	0,010	-0,101	0,087
SSEC	1737	-0,00002	0,007	-0,051	0,034
STOXX	1737	0,0002	0,010	-0,132	0,088
USD	1737	0,0001	0,003	-0,022	0,021
COVID	1737	0,686	0,464	0,000	1,000
WAR	1737	0,340	0,474	0,000	1,000

Source: Elaborated by the author

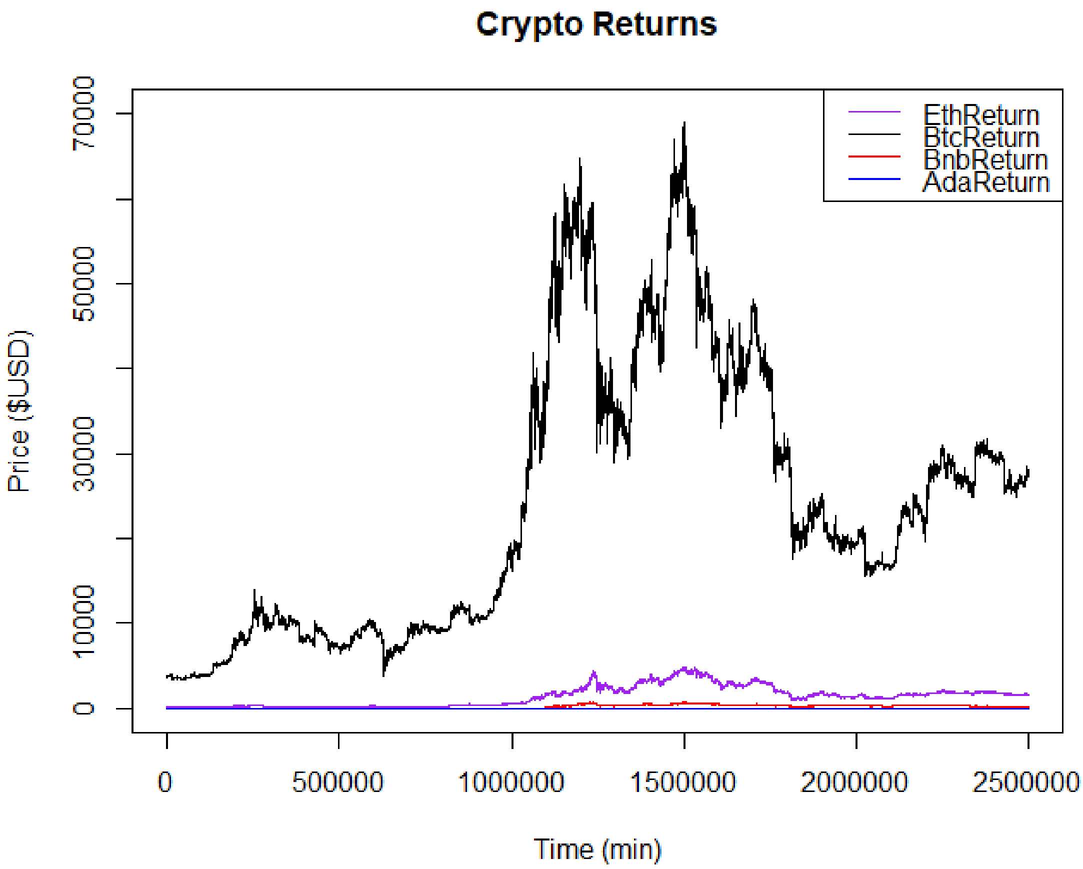
The graph (1) portraited next show how the crypto actives performed during the time frame by every minute interval. It shows increased volatility during the period of 100.000 to 175.000 minutes, that would comprehend the dates between October 2020 and July 2023, with its peak around May 2021. Before analyzing any statistical measures with the model, that might be an indicative that even though the world was facing complications due to the COVID-19 pandemics, the coins managed to achieve peak values, as shown in graph (2).

GRAPH 1 – CRYPTOCURRENCIES LOG RETURN FROM 1/1/2019 TO 3/10/2023



Source: Elaborated by the Author

GRAPH 2 – CRYPTOCOINS PRICE FLUCTUATION MINUTE DATA FROM 1/1/2019 TO 10/03/2023



Source: Elaborated by the Author

The correlation patterns among the variables are presented in Table 2. The measures of crash risk NSKEW and DUVOL have significant negative associations with the global events COVID and WAR, which means that these risk indicators decrease when such events happen. However, this could also imply that the market risk actually increases, since the coefficients are negative values due to that being the negative coefficient of skewness. The variable CRASH does show a significant relationship with both NSKEW and DUVOL, with positive values. Moreover, CRASH has a positive but insignificant correlation with COVID, which could indicate that the market crashes were influenced by the pandemic, increasing the risk. Additionally, the variable SYNC has positive and significant correlations with both COVID and WAR, suggesting that these events raise the synchronicity of stock returns across countries.

TABLE 2 – PEARSON CORRELATION MATRIX OF VARIABLES

	NSKEW	DUVOL	CRASH	SYNC	UPSD	OIL	GOLD	MOEX	NIKKEI	SP500	SSEC	STOXX	USD	COVID	WAR
NSKEW	1,000														
DUVOL	0,872*	1,000													
CRASH	0,318*	0,345*	1,000												
SYNC	0,033	-0,017	0,186*	1,000											
UPSD	-0,109*	-0,16*	0,191*	0,339*	1,000										
OIL	0,031	0,054*	0,005	-0,010	-0,059*	1,000									
GOLD	0,015	0,022	-0,01	-0,031	-0,063*	0,146*	1,000								
MOEX	0,031	0,037	-0,004	0,005	-0,046*	0,256*	0,124*	1,000							
NIKKEI	-0,009	0,005	-0,033	-0,035	-0,093*	0,171*	0,091*	0.16*	1,000						
SP500	0,006	0,005	-0,006	-0,027	-0.113*	0,243*	0.1*	0,272*	0,174*	1,000					
SSEC	-0,011	-0,002	-0,025	-0,044*	-0,040*	0,168*	0,152*	0,122*	0,331*	0,093*	1,000				
STOXX	-0,015	-0,013	-0,009	-0,025	-0,094*	0,368*	0,075*	0,419*	0,316*	0,601*	0,178*	1,000			
USD	-0,029	-0,036	-0,008	0,053*	0,080*	-0,128*	-0,398*	-0,143*	-0,149*	-0,253*	-0,115*	-0,271*	1,000		
COVID	-0,043*	-0,091*	0,023	0,445*	0,15*	0,009	0,003	-0,018	-0,005	-0,009	0,013	-0,012	-0,013	1,000	
WAR	0,013	0,005	-0,001	0,337*	-0,218*	0,004	-0,003	0,009	0,008	-0,017	-0,005	-0,004	0,006	0,079*	1,000

** Denotes the significance of correlation, *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$*

Source: Elaborated by the Author

4.2. Regression results

After regressing the crash risk variables using the model suggested in equation (7), the variance inflation factor (VIF) test was computed, with the purpose of identifying if there is multicollinearity. The results showed that SYNC had a moderate level, while both UPSD and the product between SYNC and UPSD had high VIF values. Because of that, it was made an adjustment on the variables, centralizing values by subtracting their mean (BARANGER et al., 2023). After it, the new regression showed low level of multicollinearity.

The table (3) presents the results of other regression tests after the multicollinearity adjustment. Tests before the adjustment can be found in appendix. Analysis of Breusch-Pagan test shows that all the models of crash risk have enough evidence to reject the null hypothesis of homoscedasticity, meaning that is found evidence of the presence of heteroscedasticity. Regarding the Box-Ljung test, there wasn't strong evidence that leads to rejecting the null hypothesis of no autocorrelation for NSKEW and CRASH, but DUVOL had significance on a 5% value. Finally, assumptions based on the Shapiro-Wilk test strongly suggests that neither of the variables follows a normal distribution.

TABLE 3 – REGRESSION TESTS AFTER MULTICOLLINEARITY ADJUSTMENT

	NSKEW	*p-value*	CRASH	*p-value2*	DUVOL	*p-value3*
Breusch-Pagan	28,333	*0,008*	98,414	*3,37E-15*	53,801	*6,55E-07*
Box-Ljung	0,034	*0,855*	1,523	*0,217*	4,577	*0,032*
Shapiro-Wilk	0,764	*2,20E-16*	0,38857	*2,20E-16*	0,979	*4,62E-15*

Source: Elaborated by the Author

With the results found, the regression model becomes less efficient on dealing with heteroscedasticity and non-normality and therefore a Newey-West adjustment become optimal, alongside with a quantile regression for comparation. For the CRASH variable, the logit model becomes more beneficial. The linear model results are presented on table (4) and the comparison with adjusted Newey-West are on table (5). Table (6) comprehends quantile regression for different τ values.

TABLE 4 – MODEL COEFFICIENTS FOR CRASH RISK REGRESSIONS

Coefficients	NSKEW	DUVOL	CRASH
Intercept	0,49***	0,053***	0,172***
SYNC	0,544***	0,054***	0,118***
UPSD	-820,575***	-109,062***	113,681***
SYNC*UPSD	146,176	6,949	-14,616
OIL	3,343	0,642*	0,296
GOLD	-1,697	-0,252	-0,409
MOEX	6,907	0,527	-0,156
NIKKEI	-2,619	-0,133	-0,711
SP500	0,751	-0,108	0,255
SSEC	-1,258	-0,102	-0,472
STOXX	-12,436*	-1,629*	-0,137
USD	-19,247 .	-2,388	-3,387
COVID	-0,291*	-0,050***	-0,056**
WAR	-0,261*	-0,034**	-0,018
F-statistic	*3,84*	*6,53*	*0,2126*
p-value	*3,92E-06*	*2,77E-12*	*0,9986*

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05,* **.** *for p < 0.1*

Source: Elaborated by the Author

The model allows us to make some preliminary inferences before the adjustments in table (5). The positive and significant values of synchronicity indicate a direct relationship with crash risk, as expected. The upside volatility also has a significant effect on all the variables, but with a negative coefficient. Upon comparing with the results obtained by Ma and Luan (2022), it is possible to observe that it follows the same polarity for NSKEW and DUVOL, but not for significance, being significant in this research. That would imply that higher UPSD values reduces the crash risk, when previous empirical results (LEE, JIANG, INDRO, 2002) have shown that excess returns leads to downward revisions. However, this contradiction is resolved by analyzing the CRASH column, which has a positive value and indicates that UPSD is high on the days when crashes occur. Upon comparing formulas (2) and (6), regarding DUVOL and UPSD, respectively, it makes sense for the relation to have a negative coefficient, since bigger returns would reduce the factor, not meaning that it would indeed lower the crash risk chance.

Among the market control variables, only the STOXX index had a significant negative correlation with the crash risk, implying that higher European stock performance decreased the likelihood of crypto crashes. COVID and WAR variables showed a possible negative tendency, which might contradict the initial beliefs.

TABLE 5 – MODEL COEFFICIENTS FOR NEWEY-WEST REGRESSION

Coefficients	NSKEW	DUVOL
Intercept	0,490*** (0,122)	0,053*** (0,012)
SYNC	0,544*** (0,151)	0,054*** (0,015)
UPSD	-820,575*** (181,957)	-109,062*** (23,358)
SYNC*UPSD	146,176 (222,450)	6,949 (32,447)
OIL	3,343 (2,060)	0,642*** (0,241)
GOLD	-1,697 (5,317)	-0,252 (0,632)
MOEX	6,907** (3,351)	0,812* (0,423)
NIKKEI	-2,619 (5,566)	-0,133 (0,667)
SP500	0,758 (4,829)	-0,108 (0,732)
SSEC	-1,258 (5,832)	-0,102 (0,716)
STOXX50	-12,436*** (4,709)	-1,629*** (0,603)
USD	-19,247 (13,683)	-2,388 (1,809)
COVID	-0,291** (0,143)	-0,050*** (0,014)
WAR	-0,261** (0,109)	-0,034** (0,014)
F-statistic	12,963	12,368
p-value	3,18E-04	4,37E-04

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05, **.** for p < 0.1*

Source: Elaborated by the Author

On table (5), after the Newey-West adjustment, besides changes on significancy, f-statistic and model p-value, there is no major changes on the values for the regression. OIL and MOEX gained substantial importance and appear as positive correlated with the crash risk, suggesting that the MOEX performance is proportional inverted to the crash risk, with less risk for better results. COVID and WAR variables became significant.

TABLE 6 – MODEL COEFFICIENTS FOR QUANTILE REGRESSION

Coefficients	NSKEW (τ = 0.75)	NSKEW (τ = 0.90)	DUVOL (τ = 0.75)	DUVOL (τ = 0.90)
Intercept	0,914*** (0,112)	2,196*** (0,316)	0,121*** (0,024)	0,231*** (0,043)
SYNC	0,244*** (0,074)	0,573** (0,260)	0,056*** (0,019)	0,089** (0,038)
UPSD	-91,942 (118,013)	-32,224 (293,924)	26,900 (41,125)	38,823 (58,235)
SYNC*UPSD	-252,219 (191,999)	-405,335 (418,910)	-54,407** (27,420)	-41,145 (38,665)
OIL	3,035 (1,867)	3,923 (5,720)	0,542* (0,277)	-0,165 (0,624)
GOLD	-3,303 (4,568)	12,719 (13,162)	-0,364 (0,649)	0,351 (1,311)
MOEX	3,998 (3,024)	18,061 (11,335)	0,555 (0,453)	1,166 (0,893)
NIKKEI	1,745 (4,566)	-2,026 (9,841)	0,086 (0,663)	1,191 (1,581)
SP500	3,855 (4,843)	0,193 (13,617)	0,068 (0,729)	1,118 (1,541)
SSEC	-4,761 (5,314)	10,119 (13,596)	-1,073** (0,472)	1,112 (1,421)
STOXX50	-7,093 (5,647)	-19,326 (13,596)	-0,759 (0,780)	-1,644 (1,404)
USD	-5,340 (13,944)	-20,424 (34,061)	-2,647 (1,900)	-2,394 (3,829)
COVID	-0,407*** (0,110)	-0,714** (0,312)	-0,058*** (0,018)	-0,098*** (0,027)
WAR	0,109 (0,106)	0,505** (0,247)	0,013 (0,016)	0,053* (0,028)

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05,* **.** *for p < 0.1*

Source: Elaborated by the Author

Upon observation of the variable’s trough different quantiles on table (6), specifically quadrants τ(0.75) and τ(0.90), because the interest is on the right tail behavior, it is possible to aggregate more conclusions to the results. The variables SYNC and COVID kept the previous regression significance, with close values to it. For DUVOL, SSEC appeared with significance, meaning that partially SSEC might influence risk. The previous hypothesis of variable correlation with crash risk stays sustained for COVID, while WAR showed possible positive coefficients, meaning that the hypothesis might not be correct upon war-based predictions. The next table (7) will comprehend the logit regression with variable CRASH.

TABLE 7 – MODEL COEFFICIENTS FOR LOGIT REGRESSION

Coefficients	CRASH
Intercept	-1,617*** (0,161)
SYNC	1,389*** (0,214)
UPSD	1023,89*** (238,127)
SYNC*UPSD	-799,885*** (299,309)
OIL	2,824 (3,975)
GOLD	-3,411 (11,059)
MOEX	-1,547 (7,693)
NIKKEI	-6,831 (9,191)
SP500	1,452 (8,934)
SSEC	-5,306 (11,899)
STOXX50	-1,470 (10,441)
USD	-32,783 (24,510)
COVID	-0,588*** (0,190)
WAR	-0,232 (0,179)
Log-Likelihood	-598,655

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05,* **.** *for p < 0.1*

Source: Elaborated by the Author

Following the tendency of the other regressions, the logit regression on table (7) confirms the results shown previously. UPSD and SYNC had a significant and positive coefficient and surprisingly for the first time their interaction showed significance with a negative value. That suggests that the stronger the relation between SYNC and UPSD, less is the chance of a crash happening. The same was found by Ma and Luan (2022). Another value that surprised was the coefficient for COVID, and it was the first time that it showed inverse relation with the crash measure. That could imply that in pandemics days, the likelihood of a crash was indeed reduced upon comparison with regular days.

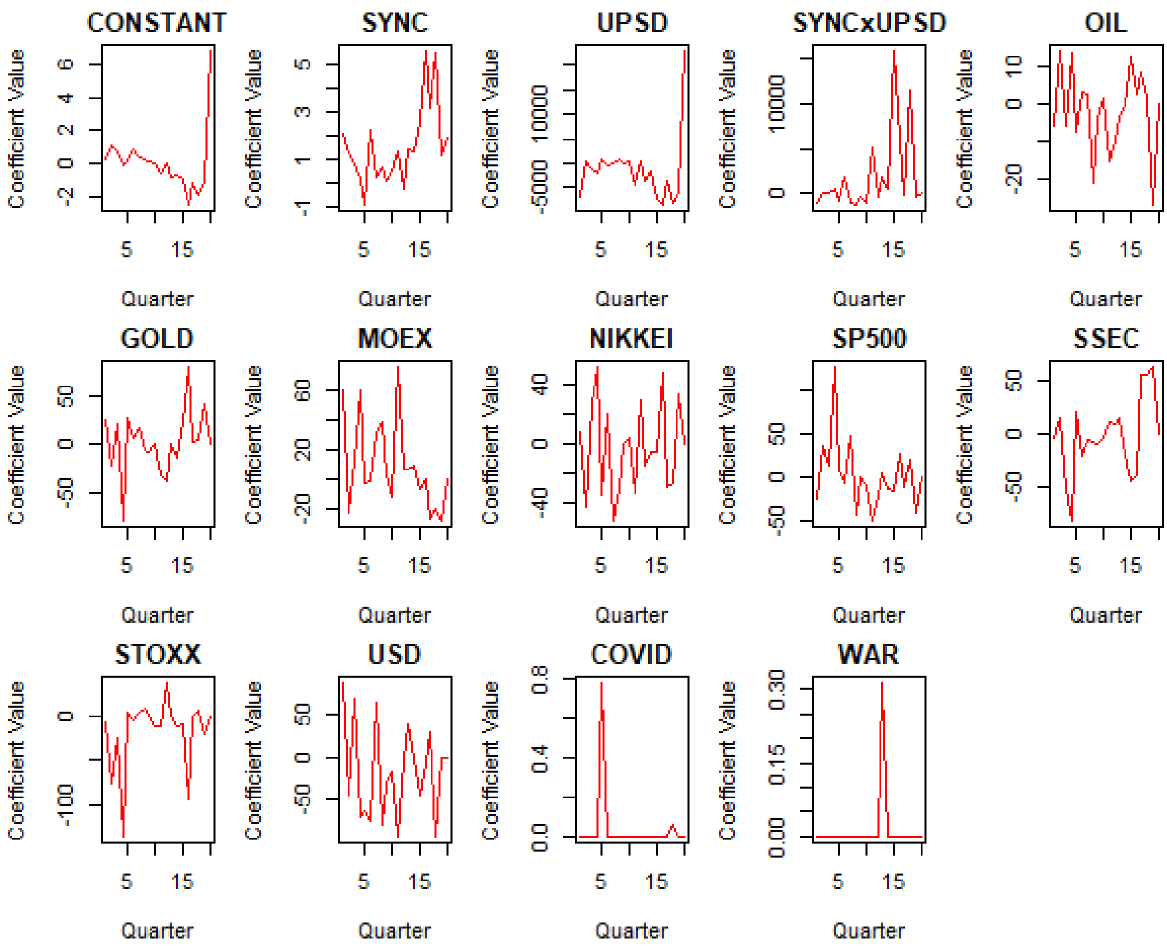
The final comparison of all four models have similarities regarding the behavior of the variables and have shown with significance that the synchronicity (SYNC) is positively associated with most of the variables of crash risk with increased value when multiple currencies are considered, what would reinforce the findings of Bouri et al. (2019); the upside volatility (UPSD) demonstrated to be associated with higher odds of crashes happening, while the negative coefficient value encountered in some of the models reflected the accordance with the negative of the skewness; STOXX also had significant values on most tests, meaning that out of all the selected indexes, Europe sentiment is the one with most importance when assessing crash risk, while Russian stocks good performance demonstrate an increase on that risk. Most of the regressions placed GOLD comoving with Bitcoin and complying with previous studies (KANG, MCIVER, HERNANDEZ, 2019).

The DUVOL crash risk measure proposes an addition to the investigation, demonstrating that the negative coefficient value encountered for both COVID and WAR create two hypotheses: the first is that the variance of positive returns was decreasing in the presence of the events, relative to the variance of negative returns; the second is that the number of positive returns was increasing relative to the number of negative returns. Because of the findings of high price predictability during COVID (Gaio et al, 2022), this indicates association with the low value of DUVOL, in accordance with Chen et al. (2001) findings on low down to up volatility levels.

Upon consideration in parallel with the other measures, the suggestion is that the events influenced crash risk upon increasing negative skewness of the returns, that is, the risk is less concentrated in the lower end of the distribution, meaning that, overall, the chance of extreme crash risks happening is decreased. In addition to that, the study corroborates to the idea that during those events, the variance of positive returns was increasing when in a uptrend and the number or negative returns was increasing when in a down trend. Lastly, the findings regarding synchronicity and upside volatility correspond to those found by Ma and Luan (2022).

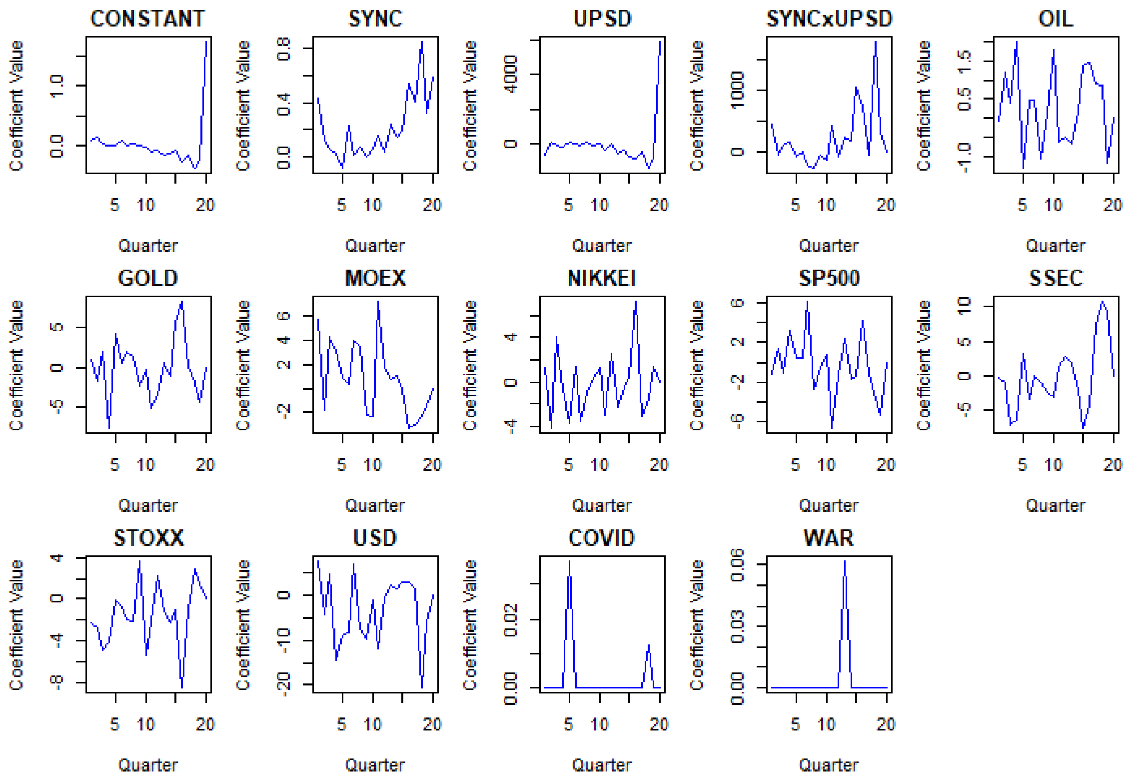
Finally, graphs (6) will contemplate the behavior of the NSKEW coefficient measures quarterly along the time frame, while graphs (7) will contemplate DUVOL measures.

GRAPH 3 – NSKEW COEFFICIENT FLUCTUATION FROM 1/1/2019 TO 10/03/2023



Source: Elaborated by the Author

GRAPH 4 – DUVOL COEFFICIENT FLUCTUATION FROM 1/1/2019 TO 10/03/2023



Source: Elaborated by the Author

The behavior of the variables on quarterly models showed similar tendency when comparing different crash risk measures, mostly having differences on the magnitude of the value and high volatility. Also, it is possible to observe that the majority of individual quarterly values follow the same tendency as the general model considering all time frame. Synchronicity (SYNC) had more positive quarters than negative in both NSKEW and DUVOL analysis, the same shown in table (5) for Newey-West model coefficient, upside volatility (UPSDt) had more negative quarters than positive, also the same from the Newey-West model tendency.

5. FINAL CONSIDERATIONS

This research had the ulterior motive of investigating cryptocurrencies crash risk upon the exposition the large-scale events, such as the COVID-19 pandemics and the Russia-Ukraine War.

The analysis of key variables, including NCSKEW, CRASH, and DUVOL, revealed increased volatility in the market between October 2020 and July 2023, with a notable peak around April 2021. Despite global challenges posed by the pandemics, evident in the low returns of most indexes, cryptocurrencies displayed resilience and achieved their peak values during this period.

The regression analysis unveiled nuanced relationships among variables, with DUVOL emerging as a significant crash risk measure, exhibiting a negative correlation with global events. Control variables, including the STOXX50 index and COVID and WAR dummies, demonstrated negative correlations with crash risk, suggesting that these events did not increase the risk of market crashes.

These findings contribute valuable insights into the factors influencing crash risk in the cryptocurrency market. The significance of synchronicity, control variables, and the limited impact of global events on crash risk strongly suggest that the presence of a decentralized market protects the assets of exposure to those type of events. Next, it’s suggested to observe any specific events that might have happened during this period of time might’ve influenced the endurance and growing of cryptocurrencies, as well of alternative crash risk measures and a comparative analysis with traditional markets.

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7. APPENDIX

GRAPH 5 - CRYPTOCURRENCIES SYNCHRONICITY OVER TIME FROM 1/1/2019 TO 3/10/2023

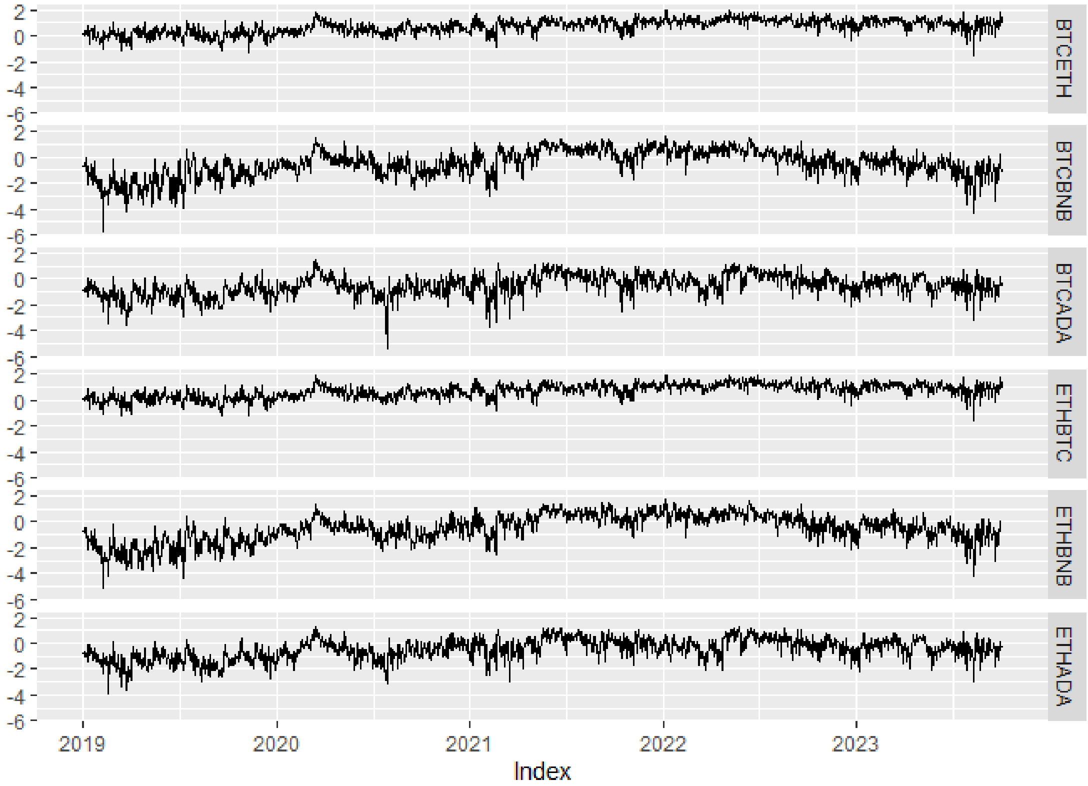

TABLE 8 – DESCRIPTIVE STATISTICS OF RESEARCH VARIABLES BASED ON INTRA DAY DATA (SYNCHRONICITY BTC-ETH)

Variables	*N*	*Mean*	*Standard Deviation*	*Min*	*Max*
$NSKEW_t$	1737	0,212	1,964	-17,069	19,128
CRASH	1718	0,126	0,332	0,0000	1,0000
$DUVOL_t$	1737	0,007	0,217	-0,976	1,025
$SYNC_t$	1737	0,718	0,535	-1,546	1,983
$UPSD_t$	1737	0,001	0,0004	0,0001	0,006
OIL	1737	0,001	0,020	-0,225	0,165
GOLD	1737	0,0002	0,007	-0,048	0,058
MOEX	1737	0,0003	0,011	-0,093	0,183
NIKKEI	1737	0,0001	0,008	-0,063	0,077
SP500	1737	0,0003	0,010	-0,101	0,087
SSEC	1737	-0,00002	0,007	-0,051	0,034
STOXX	1737	0,0002	0,010	-0,132	0,088
USD	1737	0,0001	0,003	-0,022	0,021
COVID	1737	0,686	0,464	0,000	1,000
WAR	1737	0,340	0,474	0,000	1,000

Source: Elaborated by the author

TABLE 9 – PEARSON CORRELATION MATRIX OF VARIABLES (SYNCHRONICITY BTC-ETH)

	NSKEW	SYNC	UPSD	DUVOL	CRASH	OIL	GOLD	MOEX	NIKKEI	SP500	SSEC	STOXX	USD	COVID	WAR
NSKEW	1,000														
SYNC	0,012	1,000													
UPSD	-0,109*	0,263*	1,000												
DUVOL	0,872*	-0,032	-0,16*	1,000											
CRASH	0,318*	0,144*	0,191*	0,345*	1,000										
OIL	0,031	0,005	-0,059*	0,054*	0,005	1,000									
GOLD	0,015	-0,031	-0,063*	0,022	-0,010	0,146*	1,000								
MOEX	0,031	0,007	-0,046*	0,037	-0,004	0,256*	0,124*	1,000							
NIKKEI	-0,009	-0,027	-0,093*	0,005	-0,033	0,171*	0,0907*	0,16*	1,000						
SP500	0,006	-0,015	-0,113*	0,005	-0,006	0,243*	0,1*	0,272*	0,174*	1,000					
SSEC	-0,011	-0,046*	-0,040*	-0,002	-0,025	0,168*	0,152*	0,122*	0,331*	0,093*	1,000				
STOXX	-0,015	-0,015	-0,094*	-0,013	-0,009	0,368*	0,075*	0,419*	0,316*	0,601*	0,178*	1,000			
USD	-0,029	0,040	0,080*	-0,036	-0,008	-0,128*	-0,398*	-0,143*	-0,149*	-0,253*	-0,115*	-0,271*	1,000		
COVID	-0,043*	0,472*	0,15*	-0,091*	0,023	0,009	0,003	-0,018	-0,005	-0,009	0,013	-0,012	-0,013	1,000	
WAR	0,013	0,435*	-0,218*	0,0051	-0,001	0,004	-0,003	0,008	0,008	-0,017	-0,005	-0,004	0,006	0,079*	1,000

TABLE 10 – REGRESSION TESTS AFTER MULTICOLLINEARITY ADJUSTMENT (SYNCHRONICITY BTC-ETH)

	NSKEW	*p-value*	CRASH	*p-value2*	DUVOL	*p-value3*
Breusch-Pagan	22,403	*0,049*	76,438	*5,13E-11*	60,31	*4,62E-08*
Box-Ljung	0,397	*0,5286*	1,260	*0,262*	2,600	*0,1069*
Shapiro-Wilk	0,765	*2,20E-16*	0,38857	*2,20E-16*	0,979	*4,62E-15*

Source: Elaborated by the Author

TABLE 11 – MODEL COEFFICIENTS FOR LINEAR REGRESSION (SYNCHRONICITY BTC-ETH)

Coefficients	NSKEW	DUVOL	CRASH
Interval	0,469***	0,052***	0,166***
SYNC	0,366***	0,038***	0,088***
UPSD	-617.361***	-87,886***	134,726***
SYNC*UPSD	-126,518	-28,936	-29,168
OIL	3,221	0,628*	0,268
GOLD	-1,621	-0,246	-0,344
MOEX	7,225	0,848	-0,099
NIKKEI	-2,846	-0,156	-0,708
SP500	0,387	-0,150	0,274
SSEC	-1,499	-0,124	-0,499
STOXX	-12,434*	-1,630**	-0,129
USD	-17,639	-2,228	-3,068
COVID	-0,252*	-0,047***	-0,049**
WAR	-0,225*	-0,031**	-0,05
F-statistic	*3,022****	*6,013****	*7,072****

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05,* **.** *for p < 0.1*

Source: Elaborated by the Author

TABLE 12 – MODEL COEFFICIENTS FOR NEWEY-WEST REGRESSION (SYNCHRONICITY BTC-ETH)

Coefficients	NSKEW	DUVOL
Intercept	0,469*** (0,128)	0,052*** (0,013)
SYNC	0,366** (0,161)	0,038** (0,016)
UPSD	-617,361*** (187,093)	-87,886*** (24,567)
SYNC*UPSD	-126,518 (250,375)	-28,936 (27,150)
OIL	3,221 (2,116)	0,628** (0,247)
GOLD	-1,621 (5,372)	-0,246 (0,639)
MOEX	7,225** (3,375)	0,848** (0,426)
NIKKEI	-2,846 (5,641)	-0,156 (0,674)
SP500	0,387 (4,940)	-0,150 (0,748)
SSEC	-1,499 (5,822)	-0,124 (0,715)
STOXX50	-12,434*** (4,795)	-1,630*** (0,617)
USD	-17,639 (13,954)	-2,228 (1,831)
COVID	-0,252* (0,151)	-0,047*** (0,014)
WAR	-0,225** (0,114)	-0,031** (0,015)
F-statistic	5,139	5,693
p-value	0,0234	0,0170

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05,* **.** *for p < 0.1*

Source: Elaborated by the Author

TABLE 13 – MODEL COEFFICIENTS FOR QUANTILE REGRESSION (SYNCHRONICITY BTC-ETH)

Coefficients	NSKEW (τ = 0.75)	NSKEW (τ = 0.90)	DUVOL (τ = 0.75)	DUVOL (τ = 0.90)
Intercept	0,898*** (0,116)	2,137*** (0,286)	0,157*** (0,017)	0,319*** (0,021)
SYNC	0,094 (0,094)	0,110 (0,254)	0,005 (0,013)	0,018 (0,026)
UPSD	10,930 (104,391)	102,482 (299,477)	-15,897 (19,257)	32,479* (18,055)
SYNC*UPSD	-557,513*** (181,255)	-960,125 (423,720)	-106,290*** (26,518)	-166,436 (46,681)
OIL	3,037 (2,051)	2,524 (4,821)	0,546* (0,288)	-0,089 (0,623)
GOLD	-1,946 (5,230)	11,058 (14,274)	-0,109 (0,669)	0,327 (1,453)
MOEX	4,283 (5,170)	16,994 (12,566)	0,577 (0,692)	0,882 (0,954)
NIKKEI	3,498 (4,907)	-10,159 (11,103)	0,228 (0,697)	1,122 (1,290)
SP500	1,197 (4,226)	12,315 (10,060)	0,130 (0,587)	1,285 (1,326)
SSEC	-6,611 (5,442)	15,133 (11,841)	-1,16 (0,796)	2,174 (1,474)
STOXX50	-6,594 (5,233)	-30,508** (13,675)	-0,588 (0,797)	-2,869* (1,527)
USD	-10,784 (14,347)	-32,590 (29,959)	-1,952 (2,119)	-1,942 (3,467)
COVID	-0,394*** (0,119)	-0,592* (0,307)	-0,057*** (0,017)	-0,102*** (0,025)
WAR	0,121 (0,105)	0,531** (0,226)	0,016 (0,016)	0,051* (0,028)

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05, . for p < 0.1*

Source: Elaborated by the Author

TABLE 14 – MODEL COEFFICIENTS FOR LOGIT REGRESSION (SYNCHRONICITY BTC-ETH)

Coefficients	CRASH
Intercept	-1,644*** (0,167)
SYNC	1,063*** (0,211)
UPSD	1078,731*** (217,697)
SYNC*UPSD	-845,559** (344,953)
OIL	2,280 (3,967)
GOLD	-2,208 (10,965)
MOEX	-0,665 (7,674)
NIKKEI	-6,296 (9,235)
SP500	2,804 (9,093)
SSEC	-5,064 (11,762)
STOXX50	-1,034 (10,662)
USD	-27,999 (24,504)
COVID	-0,472** (0,190)
WAR	-0,260 (0,191)
Log-Likelihood	-608,059

** Denotes the significance of correlation, *** for p < 0.001 ** for p < 0.01, * for p < 0.05,* **.** *for p < 0.1*

Source: Elaborated by the Author