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Research article

Interest rate sensitivity of traditional, green, and stable cryptocurrencies: A comparative study across market conditions

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Abstract: *Background*: This study examines the impact of interest rate fluctuations on the returns of traditional, "green", and "stable" cryptocurrencies from April 2019 to April 2023. Bitcoin, Cardano, and Tether represent these categories due to their market significance. *Methods*: Using quantile regression (QR), the study analyzes the impact of interest rate shocks on cryptocurrency returns during bullish and bearish market periods. It also decomposes nominal interest rates into real interest rates and inflation expectations. The sample period is divided into stable and rising interest rate sub-periods for robustness. *Results*: The results show that cryptocurrency returns are more sensitive to interest rate fluctuations in both bullish and bearish periods. The sensitivity varies across cryptocurrency types, with Cardano acting as a hedge against inflation risk during bearish periods. *Conclusions*: The results support the research hypotheses and provide insights into the behavior of cryptocurrencies under different market conditions. These findings help portfolio managers and policymakers to make informed decisions in a digital financial environment. Future research should explore the interactions between cryptocurrencies and other financial markets.

Keywords: interest rates; inflation expectations; cryptocurrency returns; quantile regression; market conditions

JEL Codes: C21, C22, C51, F21, G12, G32, H12

1. Introduction

Over the past decade, cryptocurrencies have experienced an unprecedented boom, becoming a global phenomenon that has captured the attention of investors, enthusiasts, and governments alike. These decentralized digital currencies have revolutionized the way we think about money and financial transactions, challenging traditional models and presenting new opportunities and challenges. Unlike traditional fiat currencies, which are backed by central banks and regulated by monetary policy, cryptocurrencies operate in a decentralized environment and are not controlled by any centralized institution. This aspect, together with their growing adoption and market capitalization, has led to an increase in their importance as an asset class and has attracted the interest of institutional investors.

On the other hand, the growing uncertainty generated at global level by the Russia–Ukraine conflict; the energy crisis, which is partly the result of the conflict; and the shortages not only of energy but also of other products (in some cases, essential goods) have created a context of strong inflationary pressures. To counter this situation and also to alleviate the economic repercussions of the COVID-19 pandemic, the major central banks have begun to raise interest rates sharply at a global level, which has brought this variable back into the spotlight as an international risk factor after a prolonged period of low and stable rates. Therefore, in this current economic context, it is particularly relevant to study how cryptocurrencies are influenced by these fluctuations in interest rates and how these, in turn, may affect the global economy.

Thus, the aim of this paper was to examine how the variability of interest rates can affect the demand and supply of cryptocurrencies, which, in turn, can exert a significant influence on price volatility, liquidity, and investment in this emerging market. Moreover, understanding this relationship can help policymakers to make more informed decisions in an increasingly digitalized and globalized financial environment. Specifically, this paper analyzes three different types of cryptocurrencies, selecting the most relevant cryptocurrencies by market capitalization for each of them. Thus, Bitcoin, Cardano, and Tether represent "traditional", "green", and "stable" cryptocurrencies, respectively. It is highly significant that these three cryptocurrencies dominate 60–75% of the market, especially considering that there are more than 10,000 different cryptocurrencies in circulation. In addition, Bitcoin, Cardano, and Tether are representative and provide the most insight into their respective categories, beyond leading the market capitalization rankings, due to their pioneering roles, market influence, and differentiated contributions. Specifically, Bitcoin is the most representative traditional cryptocurrency, distinguished by its pioneering role in establishing blockchain technology, its recognition as the first decentralized digital currency, its status as the most valuable asset in the crypto market, and its position as a benchmark for other cryptocurrencies, with the highest adoption rate in terms of active users. Cardano stands out as a leading green cryptocurrency, renowned for its energy-efficient Ouroboros proof of stake (PoS) protocol and its commitment to sustainable, scalable blockchain solutions that address environmental and social challenges. Tether, the pioneering stablecoin, remains the most representative in its category, dominating the market through extensive adoption, high liquidity, global acceptance, and a key role in cryptocurrency exchanges, DeFi applications, and digital finance. Moreover, in accordance with previous research, such as Jareño and Navarro (2010) and González and Jareño (2019), among others, this paper proposes decomposing nominal interest rates into real interest rates and inflation expectations, thus estimating two different models. Specifically, the two models proposed in this paper analyze the sensitivity of the returns of the three types of cryptocurrencies –“traditional”, “green”, and “stable” – to fluctuations in the nominal interest rates (Model 1), and real interest rates and inflation expectations (Model 2).

In this research, we apply the quantile regression (QR) method (Koenker & Bassett, 1978) as the basis of our model to know the response of the dependent variables to variations in the explanatory variables across different quantiles (0.04, 0.25, 0.5, 0.75, and 0.96), as the lower quantiles are associated with economic downturns, whereas the higher quantiles are connected to periods of economic growth. The choice of this method is based on its ability to produce more robust and reliable results in comparison with other approaches, such as ordinary least squares (OLS) estimation, allowing for a more detailed examination of the interaction between variables along the entire distribution of returns, beyond the median, in line with previous studies such as Sevillano and Jareño (2018) and Jareño et al. (2020), among others.

It is interesting to note that in this work, we have proposed the estimation of the two models in three different sample periods, with the aim of providing greater robustness to our conclusions. First, we analyze the full sample period from 7 April 2019 to 2 April 2023. This sample period has been split into two sub-periods to examine the robustness of the QR model results. The first sub-period includes the sample before COVID-19, when interest rates were stable, and runs from 7 April 2019 to 14 March 2021; on the other hand, the second sub-period, after COVID-19, when interest rates were no longer stable and suffered growth due to the central banks’ policies to mitigate the rise in inflation, partially due to the Russia–Ukraine conflict and the consequences of COVID-19, runs from 15 March 2021 to 2 April 2023.

In addition, this work was carried out with the aim of completing part of the economic literature that we will describe in detail, since, as we will see, there are hardly any previous works that study the sensitivity of the cryptocurrency market to fluctuations in interest rates, since most of the literature has analyzed the impact of variations in interest rates on the stock market.

In this context, the paper tests two hypotheses. Hypothesis 1 (H1) assumes that the returns of the chosen cryptocurrencies are projected to exhibit greater sensitivity to interest rate changes at the extreme quantiles, reflecting extreme market conditions. Hypothesis 2 (H2) suggests that the returns of these three types of cryptocurrencies are expected to respond differently to changes in interest rates, influenced by their unique intrinsic characteristics, such as mining practices, backing or anchored value, stability, and efficiency.

The main findings of this research indicate that, over the full period, the stablecoin (Tether) exhibits significant sensitivity to nominal and real interest rates, as well as inflation expectations, particularly during economic peaks. Both Tether and the green cryptocurrency (Cardano) show significant sensitivity to nominal interest rates and inflation expectations during bearish crypto market periods, where inflationary shocks appear to boost returns. In the first sub-period, Cardano demonstrates heightened sensitivity to nominal and real interest rates in both bullish and bearish periods. In the second sub-period, Bitcoin (traditional) and Cardano (green) are significantly influenced by nominal interest rates and inflation expectations during bearish periods, and by nominal and real interest rates during bullish periods. These results support the two hypotheses proposed in this study. First, it was observed that the analyzed cryptocurrency returns are more sensitive to variations in explanatory factors during bullish periods (related to high quantiles) as well as during bearish periods (associated with low quantiles) of the cryptocurrency market. This supports Hypothesis H1. Second, we find that the behavior of returns differs significantly between the different cryptocurrencies analyzed. These results suggest that cryptocurrency returns may respond differently to fluctuations in interest rates because of their different intrinsic characteristics, confirming the second hypothesis (H2) of this study. Therefore, it is essential to take the specific characteristics of each virtual currency into account when analyzing and forecasting virtual currency returns.

In addition, the two models proposed in this study exhibit a U-shaped explanatory power across quantiles in all periods, with the highest values during bearish markets (Quantile 0.04), followed by bullish markets (Quantile 0.96). This pattern holds across the sub-periods into which the sample period has been split, confirming the suitability of the QR method for estimation and the robustness of the results. Moreover, the highest R^2 values are observed for Bitcoin, followed by Cardano, during bearish periods of the first sub-period of stable interest rates under Model 2. Furthermore, Model 2 consistently outperforms Model 1 in explanatory power, supporting the decomposition of nominal interest rates into real and expected inflation rates.

This study makes several important contributions to the literature. First, it examines the impact of interest rate shocks on the cryptocurrency market, identifying different patterns of behavior for different types of cryptocurrencies (Esparcia et al., 2024). Second, building on the work of Jareño and Navarro (2010), it decomposes nominal interest rates into real interest rates and inflation expectations. Finally, it contributes by using US market inflation swaps as a proxy for inflation expectations, following Gimeno and Ibáñez (2018).

The rest of the paper is structured as follows. Section 2 reviews economic and financial literature on cryptocurrencies, stock markets, interest rate fluctuations, and their interconnections. Section 3 presents the data and descriptive statistics analysis of the main variables. Section 4 details the methodology, focusing on the QR method. Section 5 analyzes the results across the full sample period, the sub-period of stable interest rates, and the sub-period of rising interest rates. Finally, Section 6 outlines the conclusions, discusses the implications, and suggests future research lines.

2. Literature review

The emergence of cryptocurrencies and their blockchain technology is changing the way we interact with the digital world, with the possibility of making transactions without the need for traditional stock intermediaries, opening new business opportunities (Díaz et al., 2022). Despite this, the fact that cryptocurrencies are decentralized assets with no regulation has led to a great deal of criticism of these assets, as they generate a great deal of distrust due to their financial instability. However, the following branches of previous literature demonstrate the strong interest in cryptocurrencies in academic research.

Exploring the impact of interest rate fluctuations on different types of cryptocurrencies is highly relevant, given the current global economic challenges, such as inflationary pressures driven by the Russia–Ukraine conflict and the energy crisis. The sharp interest rate hikes by central banks, after a long period of stability, have brought interest rates back to the forefront as a key risk factor. Cryptocurrencies, which are becoming increasingly prominent in financial markets, can react to these changes in unique ways, depending on whether they are traditional (e.g., Bitcoin), green (e.g., Cardano) or stable (e.g., Tether). Understanding how interest rates affect their demand, supply, price volatility, and liquidity is critical for both investors and policymakers.

By analyzing these different cryptocurrency types and applying advanced methodologies such as quantile regression, this study aims to provide a detailed understanding of how cryptocurrencies behave under different economic conditions, from recessions to expansions. This research not only enhances the understanding of cryptocurrencies' sensitivity to interest rates, but also provides valuable insights for making well-informed decisions in a financial environment that is becoming increasingly digitalized and globalized. Such an analysis is crucial, as cryptocurrencies continue to play a growing role in financial markets.

2.1. Role of cryptocurrencies in investment portfolios

Numerous studies have examined whether cryptocurrencies serve as safe havens or speculative investments, providing different insights into the complex dynamics of the cryptocurrency landscape. In addition, many of the studies have focused on these roles of cryptocurrencies during the COVID-19 pandemic and even, in some of the more current ones, during the Russia–Ukraine conflict. Mokni et al. (2022) conducted a comprehensive analysis of major cryptocurrencies during periods of global uncertainty, including the COVID-19 pandemic, using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Safe Haven Index (SHI). They found that, except for Tether, most cryptocurrencies exhibited weak safe haven characteristics rather than robust hedges. This suggests that while cryptocurrencies may offer some protection, they cannot be reliably considered as alternative safe havens during severe economic and political turmoil.

Conversely, Wang et al. (2020) studied the diversification, hedging, and safe haven features of stablecoins linked to the US dollar and gold compared with traditional cryptocurrencies, using Autoregressive Moving Average – Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) and Dynamic Conditional Correlation (DCC) models to analyze the correlations between cryptocurrencies. They concluded that stablecoins can act as an effective diversifier under normal conditions and that US dollar-linked stablecoins act as a safe haven better than gold-linked stablecoins during periods of political and economic turbulence, highlighting their role in mitigating significant losses.

González et al. (2020) analyzed the interdependencies between cryptocurrencies using a Non-linear Autoregressive Distributed Lag (NARDL) approach and found significant correlations between Bitcoin and 10 other leading cryptocurrencies. This suggests potential diversification opportunities within cryptocurrency portfolios. In addition, González et al. (2021) explored the role of cryptocurrencies as a diversifier, safe haven, or hedging asset by comparing these assets with gold, which has been considered a pure safe haven. Ren and Lucey (2022) investigated the hedging and safe haven properties of several clean energy indices against "dirty" and "clean" cryptocurrencies and found that clean energy is more likely to be a safe haven for dirty cryptocurrencies than clean cryptocurrencies during market downturns. Li (2023) highlighted the relationship between cryptocurrency market volatility and correlations. Higher volatility led to higher correlations, which affected the effectiveness of diversification strategies. In contrast, Aharon et al. (2021) found that Bitcoin lacked safe haven characteristics during market turbulence, challenging its status as a reliable haven. Umar et al. (2021) examined the performance dynamics of cryptocurrencies and fiat currencies, showing that cryptocurrencies acted as return and volatility transmitters, while fiat currencies acted as receivers during the first two waves of the COVID-19 pandemic.

Finally, among the most recent studies examining the risk and volatility of cryptocurrencies, in the context of the COVID-19 pandemic and the Russian invasion of Ukraine, the following papers are particularly notable. Just and Echaust (2024) analyzed the potential of cryptocurrencies as tools for hedging and as safe havens against stock market risk, concluding that the likelihood of successfully using cryptocurrencies for effective hedging is extremely low, and the probability that cryptocurrencies can act as safe havens for global equities is similarly low. Eldomiaty and Khaled (2024), who examined the relationship between the volatilities of cryptocurrencies and stock market indexes, showed that the higher the investors' interest in trading cryptocurrencies, the lower the volatility of stock market indexes as investors trade stocks less frequently and, in addition, that cryptocurrencies can provide hedge and diversification benefits for investors. Finally, Okorie et al. (2024) investigated the market efficiency of non-fungible tokens (NFTs) in comparison with the market for fungible tokens (FTs), including Bitcoin and Ethereum, in the context of the COVID-19 pandemic and the Russia–Ukraine conflict. Their findings reveal that the impact of COVID-19 varies across both markets, while the effect of the Russian invasion of Ukraine is uniform for NFTs but diverse for FTs.

2.2. Cryptocurrencies' behavior according to their nature

The literature covers various facets of cryptocurrencies' behavior and market dynamics. Lobão (2022) investigated herding behavior in the sustainable cryptocurrency market. By using two herding measures: cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) of returns, the study revealed variable herding dynamics, with a pronounced amplification throughout the COVID-19 pandemic. The authors emphasized the importance of regulatory attention in the green cryptocurrency sector to enhance market efficiency and attract investors.

Conversely, Haq and Bouri (2022) analyzed the hedging potential of traditional (Bitcoin, Ethereum, Tether, and Binance Coin) and green cryptocurrencies (Cardano, Powerledger, Ripple, and Stellar) in times of cryptocurrency uncertainty. Their bivariate wavelet consistency analysis over short-, medium-, and long-term periods revealed short-term hedging utility for green cryptocurrencies, but reduced effectiveness in the medium term. The authors noted that pricing and regulatory uncertainties may negatively impact long-term returns for both categories, highlighting the role of sustainable cryptocurrencies in investment and advocating for broader sustainability efforts.

Examining the impact of cryptocurrencies on portfolios during the COVID-19 crisis, González et al. (2020) selected 10 major cryptocurrencies and observed their risk control potential. Most cryptocurrencies show a consistent risk level of no more than 50 basis points relative to cash portfolios. Bitcoin, Litecoin and Tezos, are less stable, while Ethereum and Bfinance offer portfolios with lower realized risk when combined with cash assets. This highlights the risk-control potential of certain altcoins, such as Bfinance and Tether, for well-diversified cash portfolios.

Urdaneta et al. (2019) approached the cryptocurrency market from the perspective of marginal capital efficiency, focusing on Bitcoin and Ripple. They found that fluctuations in closing prices and cryptocurrency issuance follow diminishing returns, while daily fluctuations in market capitalization are inversely correlated with closing prices. Kamal and Hassan (2022) studied the link between cryptocurrencies and green assets, evaluating the effect of the Cryptocurrency Environment Care Index (ICEA) on clean energy equities and environmentally sustainable bonds. They found positive relationships between the ICEA and the Standard & Poor's 500 Index (SP500), while clean energy and environmentally sustainable bond stocks show less significant relationships.

In addition, Naeem et al. (2022) assessed the non-symmetrical effectiveness of clean and dirty energy markets using asymmetric variance analysis. They concluded that clean energy markets tend to be more efficient, emphasizing their low-risk and sustainability attributes. The authors also highlighted pandemic-related inefficiencies in both the clean and dirty energy markets. Taken together, these studies contribute to a comprehensive understanding of cryptocurrencies' behavior, risk management potential, and sustainability considerations.

2.3. Impact of changes in interest rates on different financial markets

The literature has extensively examined the effect of interest rate variations on the banking sector and has come to different conclusions. Ampudia and Van den Heuvel (2022) used a high-frequency event study methodology to observe banks' vulnerability to interest rate risk and found a shift from positive to negative effects when interest rates reach zero or negative values. They emphasized the role of deposit funding in this reversal, while policy-induced reductions in long-term interest rates have positive effects on banks' capital values. In contrast, Schelling and Towbin (2022) examined the pass-through of interest rates below zero to bank lending. Banks that depend significantly on deposit funding or adjust for deposit funding are more adaptable in adjusting their lending terms and lend more under lower policy rates, suggesting increased risk-taking to preserve profits.

Bats et al. (2023) examined the effect of variations in the interest rate on bank stock returns and found a decline in deposit margins due to a negative yield curve, which differed from the findings of Ampudia and Van den Heuvel (2022). Cao et al. (2023) assessed the influence of low/negative interest rates on bank lending in open small economies. The effect depends on the interest rate in the central economy, with an international credit channel emerging under low interest rates in the central economy. Adão et al. (2022) examined the repercussions of interest rates on banks' risk-taking and found that lending to the real sector and to risky customers increases when interest rates fall. Iwanicz-Drozdowska and Rogowicz (2022) analyzed the influence of a policy of negative interest rates on systemic risk and revealed that monetary policy significantly affects systemic risk and contagion, especially under negative interest rates. In contrast, Caggese and Perez-Orive (2022) studied the impact of low real interest rates on intangible capital and found their limited impact on firms with high intangible capital intensity, aligned with the results of Adão et al. (2022).

Zaremba et al. (2023) examined the interaction between global equity returns and interest rate shocks, suggesting that slow-moving capital and rational inattention explain delayed investor responses. Bullock (2023) assessed the resilience of Australian households to rising interest rates, finding that they are resilient due to prudent lending standards and wealth, but noted potential concerns about debt burdens. Yousaf et al. (2022) examined the quantile connectivity of loan tokens and commercial bank stocks, finding increased sensitivity to extreme shocks.

2.4. Linkages between interest rates and cryptocurrencies of a different nature

Next, it is interesting to look at the literature responsible for analyzing interest rates and the relationships that exist with cryptocurrencies. A relevant study is that carried out by Díaz et al. (2022) on the impact of cryptocurrencies on the financial system by using the Vector Autoregressive (VAR) methodology and the variables Bitcoin, gold, SP500, and Nasdaq. The authors concluded that the evolution of Bitcoin and the development of the cryptocurrency market have shaped a new way of conducting transactions without the need for traditional stock intermediaries, providing new business opportunities and the development of systems to execute such transactions. They emphasize that the process of development of the cryptocurrency market will involve an incursion of products derived from them, which will be built within the legal and stock exchange operating schemes of the organized markets, and that the maturity of the cryptocurrency market will consider the development of the legal schemes established in different countries. Finally, they highlighted that the cryptocurrency market is directly influenced by the international financial market. Complementarily, Xiao and Sun (2020) studied the determinants of cryptocurrency returns using a NARDL methodology. These authors highlighted the responsiveness of cryptocurrencies to fluctuations changes in financial markets such as the New York stock exchange (NYSE) and the SP500, as well as to changes in the price of gold.

On the other hand, Aharon et al. (2021) examined the relationship among the level, slope, and curvature components of the US interest rate curve; the exchange rates and volatility of major safe haven currencies; and Bitcoin returns. It used a static and dynamic cointegrated framework to measure the relationships among the variables. The study found that Bitcoin is unaffected by shocks to the US interest rate curve component and all safe haven currencies. However, it found that during periods of stress, Bitcoin returns are connected to those of other currencies and the elements of the yield curve.

Thus, in this context of the financial literature, this paper aimed to deepen the study of the relationship of interest rates and the returns of different types of cryptocurrencies (traditional, “green”, and “stable”). Specifically, this study contributes to the literature by analyzing the impact of interest rate shocks on the cryptocurrency market in order to identify possible different patterns of behavior, depending on the type of cryptocurrency analyzed. Furthermore, following Jareño and Navarro (2010). and González and Jareño (2019), we propose the decomposition of nominal interest rates into their two components: real interest rates and inflation expectations. Finally, the last contribution of the paper is to use US market inflation swaps as a proxy for inflation expectations, following the work of Gimeno and Ibáñez (2018).

3. Data

To develop the research, three categories of cryptocurrencies were selected – traditional, “green”, and “stable” – choosing the cryptocurrency with the highest market capitalization and relevance in each category. Specifically, Bitcoin was chosen to represent traditional cryptocurrencies, Cardano for green cryptocurrencies, and Tether for stable cryptocurrencies, as these top three collectively dominated between 60% and 75% of the cryptocurrency market during our sample period, highlighting their significance among over 10,000 different cryptocurrencies in circulation. In addition, the SP500 index was chosen as a proxy for the US stock market. To calculate continuously compounded returns for cryptocurrencies and the US stock market, logarithmic returns were calculated by comparing the closing index of the final day of the current week with that of the final day of the preceding week. According to Jareño and Navarro (2010). and González and Jareño (2019), among others, unexpected fluctuations in the nominal interest rate can be approximated by variations in the 10-year US Treasury bond yields. Moreover, to estimate unanticipated shifts in the real interest rate, this research utilized the Fisher approximation (Equation 1) and deducted the expected inflation rate, approximated by US inflation swaps, from the nominal interest rate.

$$i_{realt} \approx i_{nominalt} - E_{inflationt} \tag{1}$$

Returns on selected cryptocurrencies, the SP500 index, and the 10-year US Treasury bond yields were obtained from the Investing.com website. Data on US inflation expectations were obtained from the US Federal Reserve via the website fred.stlouisfed.org. To contribute to previous studies (Jareño and Navarro, 2010), this study follows Gimeno and Ibáñez (2018) by using US market inflation swaps as a proxy for inflation expectations.

The sample period spans from 7 April 2019 to 2 April 2023. After homogenizing the data, we have 209 weekly observations. The reason for choosing this sample period was to have a part of the sample before COVID-19, when interest rates were stable, and another part after the pandemic, when interest rates were no longer stable and had risen due to the central banks' policies to mitigate the rising inflation due to the Russia–Ukraine conflict and the consequences of COVID-19. Therefore, in this current economic context, it is particularly relevant to study how cryptocurrencies are impacted by these fluctuations in interest rates and how these, in turn, may affect the global economy. For this reason, two sub-periods of the same length were distinguished within the full sample period to make a comparison between them for the consequences of the conflict between Russia and Ukraine and the pandemic, while examining the robustness of the results, which will lead to the conclusions of this paper. The first sample sub-period comprises the data until 14 March 2021 (with more stable and declining interest rates), while the second sample sub-period analyzes the rest of the period (with less stable and rising interest rates).

Regarding the individual analysis of the variables, Table 1 shows the descriptive statistics, along with the results of the unit root and stationarity tests for the variables. The mean of the returns is positive, indicating an upward trend in the returns of the variables, except for Tether, which is negative. The standard deviation gives the volatility of the returns of the variables selected for the study, which shows relatively low results, ranging from 0.1% to 14.1%. These relatively low values suggest that the data are clustered around their mean, indicating minimal variability and implying a degree of homogeneity within the data.

Table 1. Descriptive statistics of the sample variables.

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB stat.	ADF stat.	PP stat.	KPSS stat.
Bitcoin	0.008277	0.007265	0.27381	−0.53935	0.10267	−0.907242	7.371821	194.1781***	−13.99271***	−14.00113***	0.225168
Cardano	0.007525	0.00095	0.6219	−0.6374	0.141206	0.293378	7.092612	148.1459***	−12.5706***	−12.72492***	0.231804
Tether	−0.0000182	0.000000	0.006777	−0.011336	0.001661	−1.180285	15.08775	1314.612***	−20.36938***	−31.03084***	0.047507
SP500	0.001658	0.004438	0.114237	−0.162279	0.029903	−0.839908	9.03106	339.6941***	−15.36819***	−15.35181***	0.09124
$\Delta i_{nominal}$	0.0000246	0.00001	0.003	−0.004	0.001237	−0.191534	3.917465	8.566857**	−13.94167***	−14.02311***	0.517074
$\Delta E_{inflation}$	0.0000197	0.0001	0.0034	−0.0045	0.000906	−0.697237	8.157277	247.3646***	−9.045502***	−14.83387***	0.115769
Δi_{real}	0.0000253	0.00042	0.04110	−0.04694	0.00825	−0.37451	12.32282	1210.09***	−15.99842***	−16.00259***	0.482673

Note: The table presents the weekly descriptive statistical parameters of the log returns of cryptocurrencies and the SP500 index and the changes in the first differences of nominal and real interest rates and inflation expectations analyzed over the period from 7 April 2019 to 2 April 2023. It collects data on the mean, median, minimum, maximum, standard deviation, skewness, and kurtosis coefficient. Includes the Jarque–Bera (JB) test, the augmented Dickey–Fuller (ADF), and the Phillips–Perron (PP) unit root tests and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test. *** and ** indicate a significance level of 1% and 5%, respectively.

The skewness is negative for all the variables analyzed, with the highest occurrence for Tether (−1.18), which means that the values tend to be concentrated to the left of the mean. This means that there is a greater amount of data with values less than the mean compared with data with values greater than the mean. The kurtosis coefficient indicates the concentration of the values of a variable according to a distribution zone. In this case, we see that the kurtosis coefficient is high for all cryptocurrencies, indicating leptokurtic distributions. With the Jarque–Bera (JB) test, we tried to check whether our variable has the same skewness and kurtosis characteristics as a normal distribution. As the values are higher than the JB reference value (5.99) with 95% probability, we rejected the null hypothesis and can say that the variables do not conform to a normal distribution.

On the other hand, the Augmented Dickey–Fuller (ADF) test, the Phillips–Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test are all related to testing for unit roots, but they belong to different categories: the ADF and PP tests are unit root tests that assess the null hypothesis of a unit root, indicating non-stationarity, with the PP test adjusting for heteroscedasticity and autocorrelation, while the KPSS test is a stationarity test that evaluates the null hypothesis of stationarity, meaning the absence of a unit root. In cases where we found a unit root or non-stationarity, the data were adjusted using the first-differencing technique to ensure that all variables became stationary. Overall, the results of these tests confirm that the daily log returns of the cryptocurrencies analyzed are stationary. We also obtained the same result for the explanatory variables in first differences, in line with previous literature (Jareño and Navarro, 2010).

Finally, the correlation matrix of the model's explanatory variables (SP500, nominal and real interest rates, and expected inflation rates) was further examined. Table 2 shows that the SP500 index has a positive and statistically significant correlation with inflation expectations of 36%, indicating that when inflation rises, so does the SP500 index. On the other hand, the nominal interest rate has a positive and statistically significant correlation with the real interest rate of 76%, suggesting that when the nominal interest rate rises, so does the real interest rate. However, these variables are separated in the two different study models, so this correlation would not affect our estimates.

Table 2. Matrix of correlations between explanatory variables.

	SP500	$\Delta i_{nominal}$	$\Delta E_{inflation}$	Δi_{real}
SP500	1	0.041799	0.363418***	−0.19554***
$\Delta i_{nominal}$	0.041799	1	0.186579***	0.764216***
$\Delta E_{inflation}$	0.363418***	0.186579***	1	−0.47943***

Note: The table shows the correlations between the explanatory variables of the model. *** indicates a 1% significance level.

The inflation rate shows a negative and statistically significant correlation with the real interest rate of −48%, suggesting that when inflation rises, the real interest rate falls. The nominal interest rate has a low positive and statistically significant correlation with inflation expectations of about 19%. The latter is also unaffected, as the nominal interest rate is decomposed into real interest rates and expected inflation rates, thus separating these variables into two different models. Finally, the real interest rate shows a negative and statistically significant correlation with the SP500 index of 20%, suggesting that when the SP500 index rises, the real interest rate falls.

Overall, the correlation matrix suggests that the explanatory variables are related, indicating that further analysis is needed to understand the complex and dynamic relationships among them. It should also be noted that a high correlation between variables can lead to multicollinearity problems. This can make it difficult to distinguish the effect of one variable from that of another, leading to unstable, imprecise, or even contradictory coefficients. To remove the high correlation between the explanatory variables, an orthogonalization procedure has been applied to the SP500 index and inflation expectations, which consists of regressing the variances of these variables on a model that includes a constant and the rest of the variables with which they are highly correlated, all using OLS regression. The orthogonalized variance is measured as the residual of this regression, which captures the movement that remains after separating out the effects of each factor.

Table 3. Correlation matrix of the orthogonalized explanatory variables.

	SP500	$\Delta i_{nominal}$	$\Delta E_{inflation}$	Δi_{real}
SP500	1	−0.002567	−0.000000	−0.000000
$\Delta i_{nominal}$	−0.002567	1	0.630105***	0.764216***
$\Delta E_{inflation}$	−0.000000	0.630105***	1	−0.000000

Note: The table shows the correlations between the orthogonalized explanatory variables of the model. *** indicates a 1% significance level.

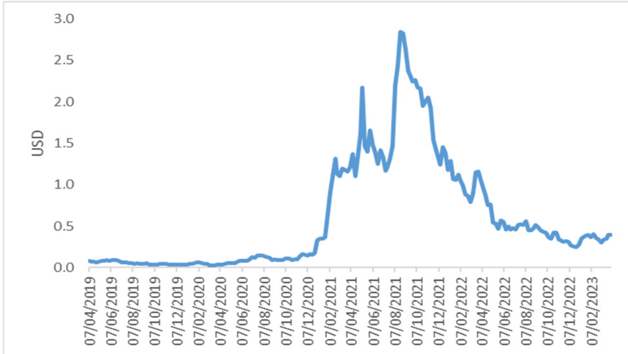
Table 3 shows that once the SP500 index and inflation expectations are orthogonalized, the correlation between them is very low and insignificant. The correlation between the SP500 return and the real interest rate has lost its statistical significance, and the correlation between inflation expectations and the real interest rate also no longer holds statistical significance.

On the other hand, the correlation between variations in the nominal interest rate and expected inflation rates remains positive and highly significant, as does the correlation between the nominal and real interest rates. However, we recall that this does not affect the study carried out because of the proposed decomposition of the nominal interest rate into inflation expectations and the real interest rate, which will be included in the study of the second model.

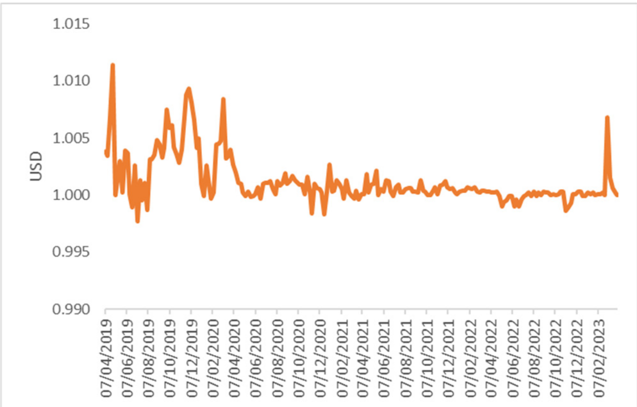
(a)


USD

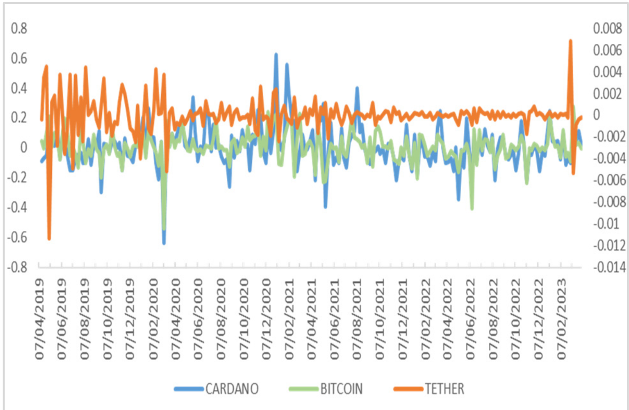
(b)


USD

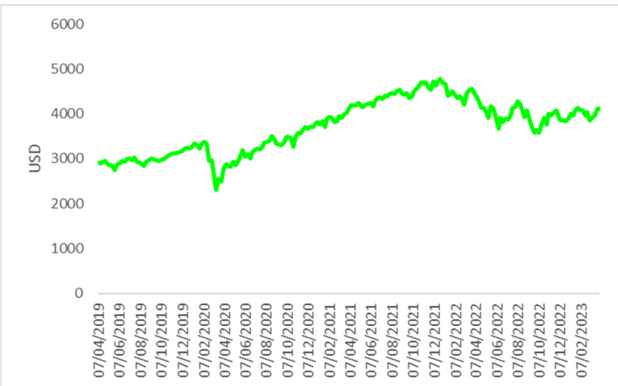
(c)


USD

(d)


CARDANO
BITCOIN
TETHER

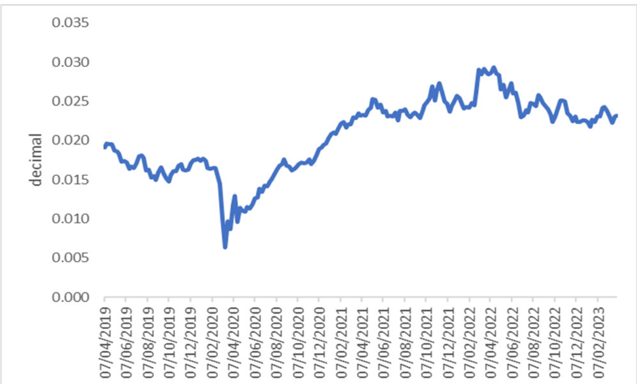
(e)


USD

(f)


decimal

(g)


decimal

(h)


decimal

(i)

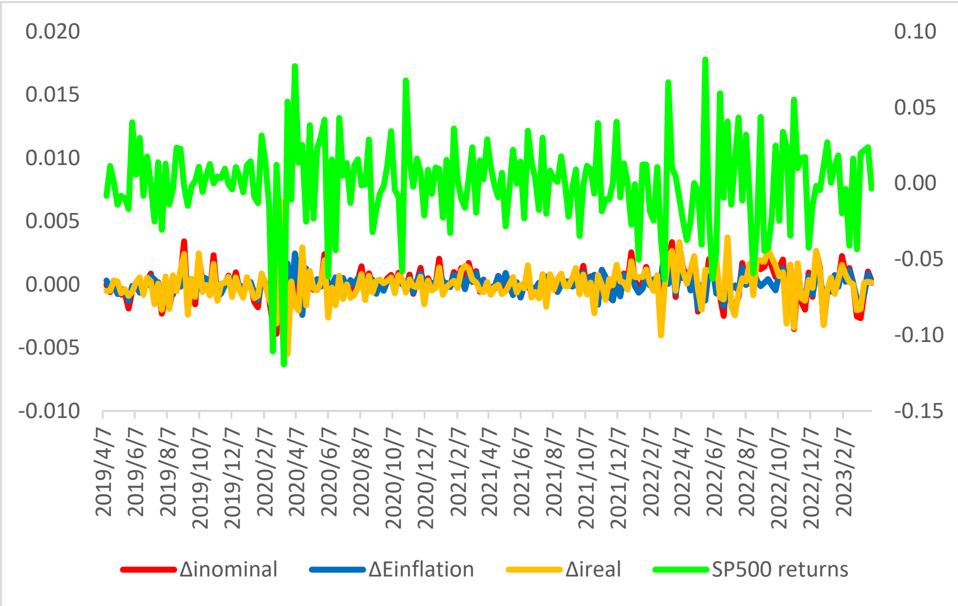


Figure 1. Temporal evolution of the variables included in the analysis: (a) Bitcoin prices; (b) Cardano prices; (c) Tether prices; (d) cryptocurrency returns (Tether on the right axis); (e) SP500 prices; (f) nominal interest rates; (g) inflation expectations; (h) real interest rates; (i) transformed explanatory variables (SP500 returns on the right axis). Source: own elaboration based on Investing and Federal Reserve Economic Data (FRED) dataset.

Figure 1 contains nine panels where the temporal evolution of the variables included in the analysis is displayed. Specifically, Panel A shows the evolution of Bitcoin prices over the period analyzed, highlighting its highest peak in November 2021. Panel B reports Cardano prices over the period analyzed, which reached its maximum price level in August 2021. Panel C illustrates Tether prices over the sample period, showing that this stablecoin does not fluctuate much, as it maintains its value in direct relation to the US dollar. Panel D shows the time evolution of the prices of the cryptocurrencies analyzed together, where it is observed that these variables are stationary after the data transformation process, as they do not follow a trend. Panel E displays the evolution of the SP500 index price and its upward trend from April 2019 to February 2020. Moreover, a period of sharp decline can be observed in March 2020, coinciding with the impact of the COVID-19 pandemic on the financial markets; meanwhile, from mid-2021 onwards, a general upward trend can be observed. Panel F illustrates the temporal evolution of nominal interest rates over the sample period and its noticeable downward trend from April 2019 to February 2020, highlighting a sharp fall in interest rates in March 2020, which coincides with the repercussions of the COVID-19 pandemic. From mid-2021 onwards, an upward trend is found. Similarly, Panel G shows the evolution of inflation expectations and its downward trend from mid-2020 to mid-2021, highlighting its trough around March 2020, which marks the onset of the COVID-19 pandemic, followed by a slight recovery in the second half of 2021. Additionally, Panel H displays the evolution of real interest rates, which show a downward trend in 2019 and remain in negative territory in 2020, indicating that inflation exceeds nominal interest rates. During the first months of the pandemic, we see a further decline in real interest rates, reaching levels close to –1%, which can be attributed to the expansionary monetary policies implemented by central banks to stimulate the economy and mitigate the negative effects of the crisis. From 2021 onwards, an upward trend in real interest rates can be observed. Finally, Panel I shows the evolution of the explanatory variables analyzed together, where it can be seen that after the transformation of the variables, they become stationary, as they do not follow a trend.

4. Methodology

This section presents the methodology used in this study to analyze the sensitivity of the returns of three different types of cryptocurrencies (traditional, “green”, and “stable”) to changes in interest rates, focusing the analysis on three periods: the full period (from 7 April 2019 to 2 April 2023); the first sub-period (from 7 April 2019 to 14 March 2021), characterized by more stable or even declining interest rates; and the second sub-period (from 15 March 2021 to 2 April 2023), characterized by rising interest rates due to central bank policies aimed at containing inflation resulting from the Russian–Ukrainian conflict and the aftermath of the COVID-19.

Specifically, the quantile regression approach (QR) developed by Koenker and Bassett (1978) and Koenker and Hallock (2001) is the estimation method chosen in this research because for our study, we need a method that considers the different quantiles related to periods of economic recession and expansion, such as those during our sample period. The QR method examines the complete distribution of returns and accounts for differences in the response of the dependent variable to changes in the explanatory variables across different quantiles (the lower quantiles are related to periods of economic recession and the higher quantiles are related to periods of economic boom), providing robust estimators even when the conditions are not ideal. This methodology is far superior to the classical and widely used OLS technique, which only considers what happens at the median of the distribution of returns and states that to guarantee the consistency of the model, it is necessary to avoid the presence of perfect multicollinearity, which occurs when there is a high correlation among the explanatory variables. This technique also requires the model errors to be homocedastic, i.e., that the error variance remains constant across all data points and is not affected by the value of the explanatory variables. Thus, this method gives us the minimum variance when the errors have finite variances, assuming that the errors follow a normal distribution. If the distribution of the dependent variable – in this case, cryptocurrency returns – exhibits skewness or kurtosis, indicating non-normal characteristics, it may lead to biased estimates, making the model not efficient.

The use of QR in this study is well justified due to its robustness in analyzing the entire distribution of returns and accounting for different responses across quantiles. However, this methodology also has potential limitations, such as sensitivity to outliers and multicollinearity between independent variables. While QR is generally robust to outliers, significant outliers can still bias the results, requiring robust diagnostic tools. In addition, multicollinearity can inflate the variance of coefficient estimates, making them unstable. Addressing these issues through methods such as robust standard errors, principal component regression, and comprehensive diagnostic tools would improve the reliability of QR estimates. Furthermore, a comparison of QR with OLS highlights the advantages of QR in capturing heterogeneity, although it requires more complex interpretation. Incorporating these considerations provides a more comprehensive understanding of the application and robustness of QR in this context.

Therefore, the QR method outperforms the OLS technique in situations where the distribution of the dependent variable does not meet the assumptions required for linear regression, such as the normality of errors or the homogeneity of variances, and has therefore been chosen in this research to study the sensitivity of traditional, "green", and "stable" cryptocurrency returns to changes in interest rates across different quantiles (0.04, 0.25, 0.5, 0.75, and 0.96). Koenker and Bassett (1978) introduced the use of the minimum absolute deviation in quantile regressions, where for a dependent variable (y_b) and multiple independent variables (x_b), the sum of the squared absolute errors is minimized for each quantile θ, on the basis of the sign of the residuals. This approach yields the corresponding estimates: $\frac{Min}{\beta}\frac{1}{n} = \sum t(y_{bt} - x_{bt}{'}\beta)^2$

$$= \frac{Min}{\beta}\frac{1}{n}\{ \sum_{b\in\{i:yi\geq xb\beta} \theta|y_b - x_{bt}{'}\beta| + \sum_{b\in\{i:yi\geq xb\beta}(1-\theta)|y_b - x_{bt}{'}\beta|\} \quad (2)$$

$$= \frac{Min}{\beta}\frac{1}{n}\sum p\theta\ (y_{bt} - x_{bt}{'}\beta)$$

where $p(\theta)$ is referred to as the verification function, taking values in the interval (0,1), from which we obtain the approximation of the vector β.

Given that $y_b - x_b{'}\beta = u_b$, and that the conditional expectation of u_b given x_b is zero, meaning the error's expected value is zero given the observations, the conditional mean of y_b based on x_b is a linear function of the vector

$$E\ (y_b|\ x_b) = x_b{'}\beta. \quad (3)$$

The resolution of the optimization problem involves taking the inverse of the conditional quantiles

$$F - 1^{\theta} = (y_b|x_b). \quad (4)$$

According to Buchinsky (1998), we assume that

$$y_b = x_b{'}\beta_\theta + u_b\theta. \quad (5)$$

The conditional expected value does not have to be zero, but the θth quantile of the error in relation to the independent variables is as follows:

$$(Q_\theta(u_b|x_b) = 0. \quad (6)$$

The θth quantile of y_b in terms of the explanatory variables would be:

$$Q_\theta(y_b|x_b) = x_b{'}\beta. \quad (7)$$

Hence, the QR linear model is defined as follows:

$$y_b = x_b{'}\beta\ \theta + u_b\theta \quad (8)$$

where:

u_b represents unknown conditional errors;

y_b represents the variable being explained, which, in this study, represents the returns of three distinct types of cryptocurrencies (Bitcoin, Cardano, and Tether);

β_θ is a k × 1 vector of unknown parameters linked to the quantile θ;

$x_b{'}$ is a k × 1 vector of explanatory variables, which could incorporate a constant term.

This QR method is applied to estimate the two models proposed in this study to examine the sensitivity of the returns of these three types of cryptocurrencies to changes in nominal interest rates (Model 1) and to changes in real interest rates and inflation expectations (Model 2). Specifically, the first model (Model 1) analyzes the relationship between the returns of Bitcoin, Cardano, and Tether and two explanatory factors: US stock market returns, proxied by the SP500 index, and unexpected shocks in the nominal interest rates. The expressions of this Model 1 would be as follows:

$$Bitcoin_t = \propto + \beta_{1,t} SP500_t + \beta_{2,t} \mathbf{\Delta inominal}_t + s_t \tag{9}$$

$$Cardano_t = \propto + \beta_{1,t} SP500_t + \beta_{2,t} \mathbf{\Delta inominal}_t + s_t \tag{10}$$

$$Tether_t = \propto + \beta_{1,t} SP500_t + \beta_{2,t} \mathbf{\Delta inominal}_t + s_t \tag{11}$$

The second model (Model 2) studies the relationship between the returns of these traditional, "green", and "stable" cryptocurrencies and three explanatory factors: US stock market returns, unexpected changes in the real interest rates, and changes in the expected inflation rates.[1] In this second model, we have decomposed the nominal interest rates into their constituent parts: real interest rates and expected inflation rates (see González and Jareño, 2019, among others). The equations of the model are as follows:

$$Bitcoin_t = \propto + \beta_{1,t} SP500_t + \beta_{2,t} \mathbf{\Delta ireal}_t + \beta_{3,t} \mathbf{\Delta Einflation}_t + s_t \tag{12}$$

$$Cardano_t = \propto + \beta_{1,t} SP500_t + \beta_{2,t} \mathbf{\Delta ireal}_t + \beta_{3,t} \mathbf{\Delta Einflation}_t + s_t \tag{13}$$

$$Tether_t = \propto + \beta_{1,t} SP500_t + \beta_{2,t} \mathbf{\Delta ireal}_t + \beta_{3,t} \mathbf{\Delta Einflation}_t + s_t \tag{14}$$

where $Bitcoin_t$ shows Bitcoin returns in *t*, $Cardano_t$ denotes Cardano returns in *t*, $Tether_t$ represents Tether returns in *t*, $SP500_t$ is the US stock market return at *t*, $\mathbf{\Delta inominal}_t$ captures unexpected shocks in the nominal interest rates at *t*, $\mathbf{\Delta ireal}_t$ denotes unexpected shocks in the real interest rates at *t*, $\mathbf{\Delta Einflation}_t$ shows shocks in the expected inflation rates at *t*, and s_t represents the random disturbance in cryptocurrency returns.

The proposed models (Models 1 and 2) have been estimated in triplicate, as the analysis involves the returns of three cryptocurrencies (Bitcoin, Cardano, and Tether), which serve as the dependent variables. Furthermore, these two models have been estimated for Quantiles 0.04, 0.25, 0.5, 0.75, and 0.96 of the distribution because the QR methodology allows the analysis of bullish (corresponding to high quantiles) and bearish (associated with low quantiles) phases in the returns of the cryptocurrencies selected for the study. Finally, for robustness, the models have been estimated in three periods (the full period, the first sub-period of stable interest rates, and the second sub-period of rising interest rates) according to the differentiated behavior of interest rates over time.

5. Empirical results and discussion

This section presents the results of the QR method's estimates from the two models proposed in this paper, which analyze the sensitivity of the returns of three types of cryptocurrencies – traditional (Bitcoin),

[1] After we examined the matrix of correlations between the independent variables, it was decided to orthogonalize the variables to remove the excessive correlation between them. This orthogonalization was applied to the SP500 index returns and inflation expectations.

"green" (Cardano), and "stable" (Tether) – to changes in the SP500 index and nominal interest rates (Model 1), and real interest and expected inflation rates (Model 2). The QR method allows us to study the impact of interest rates (nominal interest rates and their decomposition into real interest rates and inflation expectations) on cryptocurrency returns, not only at the center of the distribution (median) but also at the extremes of the distribution of cryptocurrency returns, and to determine whether the impact is statistically significant. Thus, we analyzed these two models in five specific quantiles of the distribution: 0.04, 0.25, 0.5, 0.75, and 0.96, with the aim of studying the behavior of the selected cryptocurrencies' returns at the more extreme quantiles, beyond the median, leveraging one of the key advantages of the QR methodology over OLS (Sevillano and Jareño, 2018).

On the other hand, this paper estimates both models over the period from 7 April 2019 to 2 April 2023, dividing the sample period into two sub-periods of equal length in order to examine the robustness of the results of the QR model and to be able to make a comparison between the full period and the two sub-periods, which will lead to the conclusions of this work. The first sample sub-period runs from 7 April 2019 to 14 March 2021 and includes more stable and even falling interest rates, while the second sample sub-period runs from 15 March 2021 to 2 April 2023 and involves less stable or even rising interest rates.

Thus, this section is divided into three sub-sections, separately analyzing the full sample period, the first sub-period of stable interest rates, and the second sub-period of increasing interest rates.

5.1. Empirical results: Full sample period (7 April 2019 to 2 April 2023)

Table 4 shows the coefficients obtained for the estimation of cryptocurrency returns to fluctuations in nominal interest rates (Model 1) and real interest and inflation expectations returns (Model 2) for the full period (Panel A), the first sub-period of stable interest rates (Panel B), and the second sub-period of increasing interest rates (Panel C) for Quantiles 0.04, 0.25, 0.5, 0.75, and 0.96.

After analyzing the coefficients of cryptocurrency returns to changes in nominal interest rates (Model 1) during the full period (from 7 April 2019 to 2 April 2023), shown in Columns 3 and 4 of Panel A, we observe that for Quantile 0.04, which corresponds to market turbulence, there is a positive and statistically significant relationship, mainly at the 1% significance level, between Bitcoin, Cardano, and Tether returns and changes in the SP500 index. Moreover, there is also a significant positive relation, at the 1% significance level, between Cardano and Tether returns and fluctuations in nominal interest rates. At Quantiles 0.25 and 0.5, Bitcoin and Cardano show a positive and significant relationship, at the 1% significance level, with the SP500 index, and just Tether has a positive and statistically significant relationship, at the 5% significance level, with nominal interest rates at Quantile 0.25. Moreover, for Quantile 0.75, just Cardano has a positive and significant relationship, at the 5% level, with the SP500 index, and just Tether has a negative and significant relationship, also at the 5% level, with nominal interest rates. Finally, at Quantile 0.96, just Tether shows statistically significant and negative coefficients, at the 1% level, indicating a significant inverse relationship between Tether returns and changes in the SP500 index and in the nominal interest rates.

Table 4. Coefficients of cryptocurrency returns to fluctuations in nominal interest rates (Model 1) and real interest rates and inflation expectations (Model 2).

Panel A: Full period (7 April 2019 to 2 April 2023)								
		Model 1			Model 2			
Theta-quantile	Cryptocurrency	SP500	$\Delta i_{nominal}$	R^2	SP500	Δi_{real}	$\Delta E_{inflation}$	R^2
Quantile 0.04	Bitcoin	1.951614**	22.88622	0.121051	0.349089	−13.114	45.46738**	0.149873
	Cardano	1.835719***	30.17767***	0.113636	1.17802*	−6.76023	70.0309***	0.168028
	Tether	0.011398***	0.703262***	0.080799	0.003917	0.152617	0.946962***	0.101106
Quantile 0.25	Bitcoin	0.790634***	−0.39732	0.059448	0.890129**	−10.18854	22.21737	0.06107
	Cardano	1.223365***	−0.768011	0.063727	1.207918***	−9.70307	17.78213	0.065912
	Tether	0.0000156	0.150124**	0.007737	−0.000249	0.025033	0.154074	0.007174
Quantile 0.5	Bitcoin	0.973201***	−1.407299	0.040676	1.011844***	−4.354621	7.816947	0.041403
	Cardano	1.536414***	−0.240626	0.059616	1.513609***	−6.083564	15.96076	0.059903
	Tether	0.000422	−0.040517	0.002721	0.000559	−0.026384	−0.048289	0.003528
Quantile 0.75	Bitcoin	0.525301	−2.100532	0.012083	0.604108	−1.087123	−7.098537	0.016755
	Cardano	1.278816**	−7.052989	0.022979	1.294455**	−12.1772	8.04567	0.023956
	Tether	0.000747	−0.164862**	0.019869	0.000821	−0.065573	−0.224226*	0.023403
Quantile 0.96	Bitcoin	0.245885	−26.71876	0.035701	0.218325	−19.29162	−22.53751	0.029151
	Cardano	0.527722	52.46132**	0.024261	0.365974	28.52143	58.60961**	0.023161
	Tether	−0.022904***	−0.777728***	0.120779	−0.011761	−0.427412***	−1.210354***	0.129027
Panel B: First sub-period (7 April 2019 to 14 March 2021)								
		Model 1			Model 2			
Theta-quantile	Cryptocurrency	SP500	$\Delta i_{nominal}$	R^2	SP500	Δi_{real}	$\Delta E_{inflation}$	R^2
Quantile 0.04	Bitcoin	1.46819***	−13.18473	0.184071	0.210978	−38.7827***	31.33787	0.258748
	Cardano	2.370983***	−41.3358***	0.205734	−0.788618	−30.90649***	101.3713***	0.22242
	Tether	0.024107***	−0.894959**	0.082954	−0.002879	−0.46814	0.445193	0.119666
Quantile 0.25	Bitcoin	0.428976	2.827043	0.026489	0.857603**	−0.828961	−10.39663	0.035142
	Cardano	1.29874***	−1.588599	0.055425	1.640081***	0.566319	−13.18658	0.065974
	Tether	0.006508	−0.136316	0.007952	0.006749	−0.083853	0.195553	0.011106
Quantile 0.5	Bitcoin	0.059902	4.848198	0.002159	0.513293	2.558045	−13.62399	0.024703
	Cardano	1.014535	−4.426298	0.009468	1.10893*	10.38582	−22.35356	0.037641
	Tether	0.001005	−0.121012	0.013454	0.003425	−0.090555	−0.226419	0.013972
Quantile 0.75	Bitcoin	−0.606531**	11.65678	0.02322	−0.416681	8.960723	−3.6583	0.022956
	Cardano	0.035383	11.80129	0.001291	0.240629	13.97816	−5.897879	0.019154
	Tether	−0.001112	−0.390399	0.021244	0.005837	−0.050064	−0.789558**	0.062883
Quantile 0.96	Bitcoin	−0.03524	36.56444***	0.043769	0.402526	23.39139	14.76698	0.054157
	Cardano	0.741957	73.34951***	0.127367	2.459198***	81.48846***	51.27715	0.152036
	Tether	−0.005156	−0.28536	0.036253	−0.001292	−0.250882	−0.713539	0.06036

Continued on next page

Panel C: Second sub-period (15 March 2021 to 2 April 2023)								
		Model 1			Model 2			
Theta-quantile	Cryptocurrency	SP500	$\Delta i_{nominal}$	R^2	SP500	Δi_{real}	$\Delta E_{inflation}$	R^2
Quantile 0.04	Bitcoin	2.893254***	45.49394***	0.184561	2.65331***	24.82306	78.06209**	0.186664
	Cardano	1.798189**	36.27105***	0.116236	1.249515**	3.150267	70.62274***	0.14862
	Tether	0.001191	0.332268***	0.154969	−0.003436	0.293389*	0.400154*	0.154365
Quantile 0.25	Bitcoin	1.907433***	0.058285	0.096655	1.427528***	−14.8249*	40.57228***	0.128468
	Cardano	1.983331***	8.860896	0.06984	1.637225***	−11.96476	35.7902**	0.080549
	Tether	0.001694	0.069606	0.016603	0.000145	0.052512	0.049674	0.017978
Quantile 0.5	Bitcoin	1.353681***	2.142607	0.126176	1.471945***	−8.942745	26.40232**	0.136058
	Cardano	2.296983***	1.168749	0.110703	2.178487***	−13.13173	40.57681**	0.117566
	Tether	0.001162	−0.013696	0.004821	0.001424	−0.011215	−0.023155	0.0058
Quantile 0.75	Bitcoin	1.535168***	6.532834	0.138223	1.525773***	−3.807898	26.42321*	0.140735
	Cardano	1.920754***	−7.619381	0.10751	2.512617***	−18.55184**	76.39846***	0.156556
	Tether	0.002142	−0.074684*	0.04079	0.001748	−0.079163*	−0.031061	0.041301
Quantile 0.96	Bitcoin	1.640497**	−33.4163***	0.202302	2.513754***	−38.73982***	11.76645	0.220225
	Cardano	3.462127***	34.21743***	0.084095	2.571802***	−46.13207***	125.2677***	0.175876
	Tether	−0.006592	−0.476662	0.097652	−0.007393	−0.106443	−0.433992*	0.105821

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
After examining the matrix of correlations among the independent variables, SP500 index returns, and inflation expectations were orthogonalized in Model 2 to remove the excessive correlation between them.

These results of Model 1 for the full period show how, during bearish periods in the cryptocurrency market (at the lowest quantile, 0.04), changes in nominal interest rates do not affect the returns of traditional cryptocurrencies (Bitcoin), while we observe a positive impact of fluctuations in nominal interest rates on the returns of green (Cardano) and stable (Tether) cryptocurrencies. Moreover, at Quantile 0.5 (the median of the distribution) changes in nominal interest rates have no impact on the returns of any cryptocurrency, which confirms the relevance of using the QR method, as opposed to the OLS method, which only focuses on analyzing the median of the distribution. Furthermore, during peak periods of the cryptocurrency market (at the highest quantile, 0.96), interest rate changes do not seem to affect the returns of traditional (Bitcoin) and green (Cardano) cryptocurrencies, while we observe a negative impact of nominal interest rate fluctuations on the stable cryptocurrency (Tether) analyzed in this paper. Thus, it seems that stablecoins such as Tether are more sensitive to changes in nominal interest rates during economic peaks.

Regarding the coefficients of cryptocurrency returns to fluctuations in real interest and expected inflation rates (Model 2) during the full period (7 April 2019 to 2 April 2023) shown in Columns 6, 7, and 8 of Panel A, we find that for Quantile 0.04, just Cardano shows a positive and significant coefficient, at the 10% significance level, for the SP500 index, indicating a significant positive relationship between Cardano returns and fluctuations in the SP500 index. On the other hand, the coefficients for the real interest rate are not significant, indicating that there is no significant relationship between any cryptocurrency returns and shocks in real interest rates. However, the coefficient for inflation expectations is significant at the 1% level and positive for the three cryptocurrencies, indicating a significant positive relationship between Bitcoin, Cardano, and Tether returns and fluctuations in inflation expectations. For the 0.25 and 0.5 quantiles' cases, Bitcoin and Cardano show a statistically significant coefficient (at the 5% and 1% level, respectively) for the SP500 index, indicating a positive and significant relationship between Bitcoin and Cardano returns and changes in the SP500 index for both quantiles. In contrast, we observe a non-significant coefficient for fluctuations in real interest rates and inflation expectations, suggesting that there is no significant relationship between Bitcoin and Cardano returns and changes in real interest rates and inflation expectations. In the case of Tether, none of the coefficients is significant, implying that there is no significant relationship between Tether returns and shocks in the SP500, real interest rates, and inflation expectations. At Quantile 0.75, just Cardano shows a significant and positive coefficient at 5% for the SP500 index, indicating a significant and positive relationship of Cardano returns with fluctuations in the SP500 index. On the other hand, just Tether has a significant and negative coefficient at the 10% level for inflation expectations, suggesting a significant relationship between Tether returns and inflation expectations. In the case of Bitcoin, none of the coefficients (SP500 index, real interest rate, inflation expectations) is statistically significant, indicating that there is no significant relationship of Bitcoin returns with variations in the SP500, real interest rates, and inflation expectations. Finally, at Quantile 0.96, none of the Bitcoin coefficients is significant, indicating that there is no significant relationship of Bitcoin returns with fluctuations in the SP500, real interest rates, and inflation expectations. Moreover, there is a positive and highly significant relationship between Cardano returns and changes in inflation expectations. Furthermore, there is a significant and negative relationship of Tether returns with variations in real interest rates and inflation expectations.

Thus, these results of Model 2 during the full period show that at low quantiles (i.e., at bearish moments in the cryptocurrency market), inflation expectations show positive and statistically significant coefficients, indicating that they have a positive impact on the three types of cryptocurrencies returns. This result would be consistent with previous works such as Sevillano and Jareño (2018) and Escribano et al. (2023), among others. Therefore, an increase in inflation expectations during bearish markets could be interpreted as good news for the market, which would cause cryptocurrency returns to rise. On the other hand, during peak periods of the cryptocurrency market (at high quantiles), the stablecoin Tether confirms the results obtained by estimating Model 1, that is, there is a negative impact of fluctuations in both real interest and expected inflation rates on this stable cryptocurrency, and thus it seems that stablecoins such as Tether are more sensitive to variations in real interest rates and inflation expectations at economic peaks during the period under study.

Finally, Column 5 of Table 4 Panel A shows how the explanatory power (analyzed by the R^2 coefficient) of Model 1 for Quantile 0.04 varies between the 12.1% shown for Bitcoin returns and the

8.07% shown for Tether returns; for Quantiles 0.25, 0.5, and 0.75, the explanatory power moves between 0.27% and 6.4%, and for Quantile 0.96, the explanatory power varies between 2.4% for Cardano returns and 12.1% for Tether returns. On the other hand, Column 9 of Table 4 Panel A shows that the explanatory power of Model 2 for Quantile 0.04 varies between the 10.1% shown for Tether returns and 16.8% for Cardano returns; for Quantiles 0.25, 0.5, and 0.75, it moves between 0.35% and 6.6%; and for Quantile 0.96, this explanatory power varies between 2.3% for Cardano returns and 12.9% for Tether returns.

5.2. Empirical results: First sub-period of stable interest rates (7 April 2019 to 14 March 2021)

The coefficients of cryptocurrency returns to fluctuations in nominal interest rates (Model 1) during the first sub-period of stable and even falling interest rates (from 7 April 2019 to 14 March 2021) shown in Columns 3 and 4 of Table 4 Panel B show that for Quantile 0.04, Bitcoin, Cardano, and Tether have positive and statistically significant coefficients at the 1% level for the SP500 index, indicating a positive and significant relationship between the returns of the three cryptocurrencies and changes in the SP500 index. In contrast, Bitcoin does not have a significant coefficient on the nominal interest rate while Cardano and Tether do, which indicates that there is a negative and significant relationship of Cardano and Tether returns with changes in the nominal interest rates. At Quantile 0.25, there is a significant and positive relationship between Cardano returns and changes in the SP500 index, and there is no significant relationship between the returns of any of the three cryptocurrencies and fluctuations in the nominal interest rates. Furthermore, at Quantile 0.5 (the median of the distribution), there is no significant relationship between Cardano, Bitcoin, and Tether returns and changes in the SP500 index or variations in the nominal interest rates. At Quantile 0.75, there is a significant and negative relationship between Bitcoin returns and changes in the SP500 index, while there is no significant relationship between the returns of any of the three cryptocurrencies and fluctuations in the nominal interest rates. At Quantile 0.96, there is no significant relationship between Bitcoin, Cardano, and Tether returns and variations in the SP500 index. However, there is a positive and highly significant relationship of Bitcoin and Cardano returns with shocks in the nominal interest rates.

These results of Model 1 for the first sub-period of stable interest rates suggest that during bearish periods in the cryptocurrency market (related to the lowest quantile, 0.04), variations in nominal interest rates do not affect the returns of traditional cryptocurrencies (Bitcoin), while we observe a negative impact of nominal interest rate fluctuations on the returns of green (Cardano) and stable (Tether) cryptocurrencies. It is also interesting that changes in the SP500 index have a positive impact on the three selected cryptocurrency markets. On the other hand, during bullish periods in the cryptocurrency market (related to the highest quantile, 0.96), changes in the nominal interest rates do not seem to affect the returns of stable cryptocurrencies (Tether), while we observe a positive and huge impact of fluctuations in nominal interest rates on the traditional (Bitcoin) and the green (Cardano) cryptocurrencies. However, changes in the SP500 index have no impact on any of the three selected cryptocurrency markets. Therefore, it seems that “green” cryptocurrencies such as Cardano appear to be more sensitive to shocks in nominal interest rates both during bearish and bullish periods.

The coefficient of cryptocurrency returns to fluctuations in real interest rates and inflation expectations (Model 2) during this first sub-period of stable interest rates are shown in Columns 6, 7, and 8 of Table 4 Panel B. At Quantile 0.04, there is no significant relationship between the returns of any of the three cryptocurrencies and changes in the SP500 index. Instead, there is a highly significant (at the 1% level) inverse relationship between Bitcoin and Cardano returns and fluctuations in the real interest rates, and a positive and highly significant relationship of Cardano returns with variations in inflation expectations. Moreover, Tether shows no significant relationship with the SP500 index, real interest rates, or inflation expectations. At Quantile 0.25, there is a significant and positive relationship of Bitcoin and Cardano returns with shocks in the SP500 index. However, there is no significant relationship between the returns of these two cryptocurrencies and fluctuations in the real interest rates or in the expected inflation rates. Additionally, Tether shows no significant relationship with the SP500 index, real interest rates, or inflation expectations. At Quantile 0.5, there is a positive and significant relationship between Cardano returns and changes in the SP500 index. Thus, there is no significant relationship of Cardano returns with variations in the real interest rates and inflation expectations, or between Bitcoin and Tether returns and changes in either the SP500 index, the real interest rates, or inflation expectations. At Quantile 0.75, Cardano and Bitcoin do not show a significant relationship with the SP500 index, real interest rates, or inflation expectations. Similarly, Tether also has no significant relationship with the SP500 index and the real interest rates, but there is a significant and negative relationship of Tether returns with fluctuations in inflation expectations. Finally, at Quantile 0.96, we find a positive and statistically significant relationship of Cardano returns with shifts in the SP500 index, as well as with changes in the real interest rates. However, there is no significant relationship between Cardano returns and shocks in the expected inflation rates; moreover, Bitcoin and Tether show no significant relationship with the SP500 index, real interest rates, or inflation expectations.

These results of Model 2 for the first sub-period of stable interest rates indicate that during bearish periods in the cryptocurrency market, changes in real interest rates and inflation expectations do not affect stable (Tether) cryptocurrency returns, while we observe both a negative and high impact of fluctuations in real interest rates on traditional (Bitcoin) and green (Cardano) cryptocurrency returns, and a positive and huge impact of variations in inflation expectations on green (Cardano) cryptocurrency returns. However, during peak periods of the cryptocurrency market, changes in the real interest rates and inflation expectations do not seem to affect the returns of traditional (Bitcoin) and stable (Tether) cryptocurrencies, while we observe a positive and huge impact of fluctuations in real interest rates on the green (Cardano) cryptocurrency analyzed in this paper. Thus, it seems that green cryptocurrencies such as Cardano are more sensitive to changes in inflation expectations in downward periods, and they are also highly sensitive to shocks in real interest rates in bearish as well as in bullish periods during this first sub-period of stable interest rates.

Finally, Column 5 of Table 4 Panel B shows that the explanatory power (analyzed by the R^2 coefficient) of Model 1 for Quantile 0.04 varies between the 8.3% shown for Tether returns and 20.6% for Cardano returns. For Quantiles 0.25, 0.5, and 0.75, the explanatory power decreases, and it is between 0.13% and 5.5%. Meanwhile, at Quantile 0.96, the explanatory power varies between 3.6% for Tether returns and 12.7% for Cardano returns. On the other hand, Column 9 of Table 4 Panel B shows that the explanatory power, R^2, of Model 2 for Quantile 0.04 varies between the 11.97% shown for Tether returns and 25.9% for Bitcoin returns. For Quantiles 0.25, 0.5, and 0.75, the explanatory power is lower and moves between 1.1% and 6.6%, while at the 0.96 quantile, the explanatory power varies between 6.04% for Tether returns and 15.2% for Cardano returns.

5.3. Empirical results: Second sub-period of rising interest rates (15 March 2021 to 2 April 2023)

The coefficients obtained from the estimation of Model 1 during the second sub-period of rising interest rates (from 15 March 2021 to 2 April 2023) are shown in Columns 3 and 4 of Table 4 Panel C.

The most noteworthy point is that Bitcoin and Cardano show positive and statistically significant coefficients, mainly at the 1% significance level, for the SP500 index at all quantiles, indicating a consistently significant positive relationship of Bitcoin and Cardano returns with fluctuations in the SP500 index for all the quantiles. On the other hand, Tether has no significant relationship with the SP500 index at any quantile. In addition, there is a highly significant positive relationship between Bitcoin, Cardano, and Tether returns and shifts in nominal interest rates at Quantile 0.04. However, there is no significant relationship between the returns of any of the three cryptocurrencies and fluctuations in the nominal interest rates at Quantiles 0.25 and 0.5. Moreover, at Quantile 0.75, there is a significant inverse relationship of Tether returns with variations in nominal interest rates, while there is no significant relationship between Bitcoin and Cardano returns and changes in nominal interest rates. Finally, at Quantile 0.96, there is a negative and highly significant relationship between Bitcoin returns and fluctuations in the nominal interest rates, while there is a positive and highly significant relationship of Cardano returns with shocks in nominal interest rates and there is no significant relationship of Tether returns with variations in nominal interest rates.

These results of the first model, during bearish periods in the cryptocurrency market, imply that fluctuations in nominal interest rates have a positive impact on the returns of all cryptocurrencies. Furthermore, it is remarkable that in bearish periods, the returns of the three types of cryptocurrencies are more affected by changes in nominal interest rates in this second sub-period of rising interest rates than in the full period and in the first sub-period of stable interest rates. Additionally, during bullish periods, fluctuations in nominal interest rates do not seem to affect the returns of stable cryptocurrencies (Tether), while we observe a negative and high impact of shifts in nominal interest rates on the traditional cryptocurrency market and a positive and huge impact on the green cryptocurrency market analyzed in this paper. Thus, it seems that traditional (such as Bitcoin) and green cryptocurrencies (such as Cardano) are more sensitive to fluctuations in nominal interest rates in both bearish and bullish periods during this second sub-period of increasing interest rates.

The coefficients obtained from the estimation of Model 2 during this second sub-period of rising interest rates are shown in Columns 6, 7, and 8 of Table 4 Panel C. In line with the results of Model 1, in this Model 2, Bitcoin and Cardano show statistically significant and positive coefficients, mainly at the 1% significance level, for the SP500 index for all quantiles, implying a consistently positive and significant relationship of Bitcoin and Cardano returns with fluctuations in the SP500 index in all quantiles. In addition, Tether has no significant relationship with the SP500 index at any quantile, as was the case in Model 1. Moreover, there is a highly significant positive relationship between the returns of each of the cryptocurrencies and changes in inflation expectations at Quantile 0.04. These highly significant positive relations are consistently maintained at Quantiles 0.25, 0.5, and 0.75 between Bitcoin and Cardano returns and changes in inflation expectations, and at Quantile 0.96 just for Cardano returns. Additionally, there is no significant relationship between the returns of Tether and inflation expectations at Quantiles 0.25, 0.5, and 0.75, although there is a significantly inverse relationship of Tether returns with fluctuations in inflation expectations at Quantile 0.96. Finally, there is a highly significant inverse relationship of Bitcoin returns with shifts in real interest rates at Quantiles 0.25 and 0.96; similarly, there is another highly significant inverse relationship of Cardano returns with variations in real interest rates at Quantiles 0.75 and 0.96, but, on the other hand, there is a low significant positive relationship of Tether returns with fluctuations in real interest rates at Quantile 0.04 and a negative relationship between them at Quantile 0.75.

These results of Model 2 show how in bearish periods of the cryptocurrency market (at the lowest quantile, 0.04), changes in real interest rates do not affect the returns of traditional (Bitcoin) and green (Cardano) cryptocurrencies, while we observe a positive impact of fluctuations in real interest rates on the returns of stable cryptocurrencies (Tether). Nevertheless, the most noteworthy feature is that there is a positive and huge impact of variations in inflation expectations on the returns of the three cryptocurrencies selected for the study. The results are consistent with previous studies, which suggest that increased inflation expectations in bearish market conditions may be perceived as favorable for the market. Consequently, this could lead to a rise in cryptocurrency returns (Sevillano & Jareño, 2018; Escribano et al., 2023). Moreover, throughout bullish periods of the cryptocurrency market (at the highest quantile, 0.96), changes in real interest rates do not seem to affect the returns of stable cryptocurrencies (Tether), while we observe a negative and huge impact of fluctuations in real interest rates on the traditional (Bitcoin) and green (Cardano) cryptocurrencies. Furthermore, variations in inflation expectations do not apparently affect the returns of the traditional cryptocurrency (Bitcoin), while we note a negative impact of these changes on the stable (Tether) cryptocurrency and a really huge impact of changes in inflation expectations on the green (Cardano) cryptocurrency. Thus, it seems that traditional (Bitcoin) and green (Cardano) cryptocurrencies are more sensitive to fluctuations in inflation expectations in bearish periods. Moreover, in bullish periods, Bitcoin and Cardano are also very sensitive to shocks in real interest rates, while Cardano shows the highest sensitivity of the research to changes in inflation expectations at these economic peaks of the second sub-period of rising interest rates.

Furthermore, another outstanding feature of the results of Models 1 and 2 for this second sub-period is that the relationships of Bitcoin and Cardano returns with changes in the SP500 index continue to be consistently significant and maintain the same positive sign across all quantiles, suggesting an interrelationship between conventional and cryptocurrency markets.

Finally, the fifth column of Table 4 Panel C reveals that the explanatory power of Model 1 for the 0.04 quantile varies between the 11.62% shown for Cardano returns and the 18.5% shown for Bitcoin returns. The explanatory power decreases over the 0.25, 0.5, and 0.75 quantiles, varying between 0.48% and 13.82%. Moreover, at the 0.96 quantile, the explanatory power moves between 8.41% for Cardano returns and 20.23% for Bitcoin returns. Regarding Model 2, the ninth column of Table 4 Panel C reports that for the 0.04 quantile, the explanatory power moves between the 14.86% shown for Cardano returns and the 18.67% shown for Bitcoin returns. For the 0.25, 0.5, and 0.75 quantiles, the explanatory power moves between 0.58% and 15.66%. Furthermore, for the 0.96 quantile, the explanatory power varies between 10.58% for Tether returns and 22.02% for Bitcoin returns.

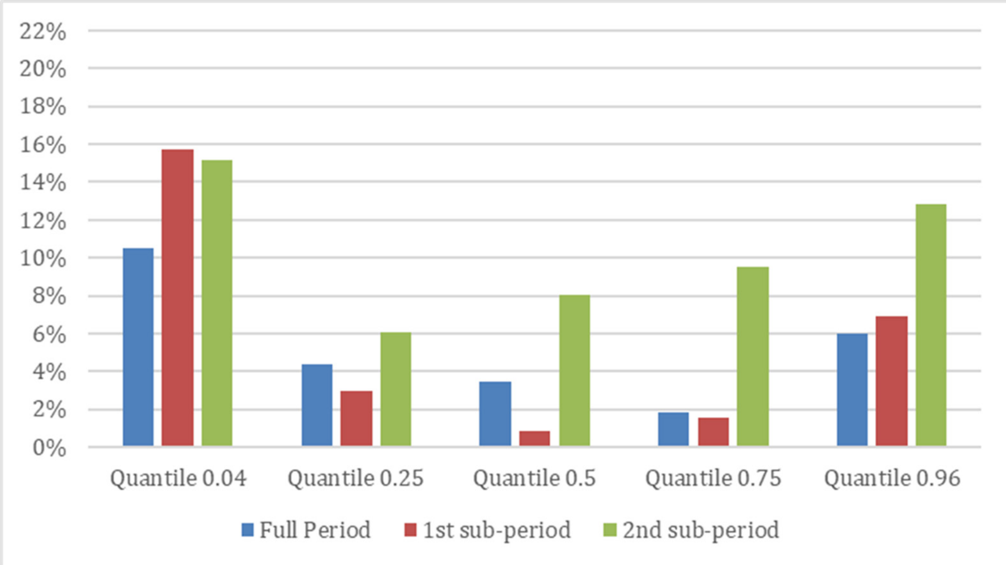


Figure 2. Average explanatory power of the three cryptocurrencies for the full period and the first and second sub-periods in Model 1.

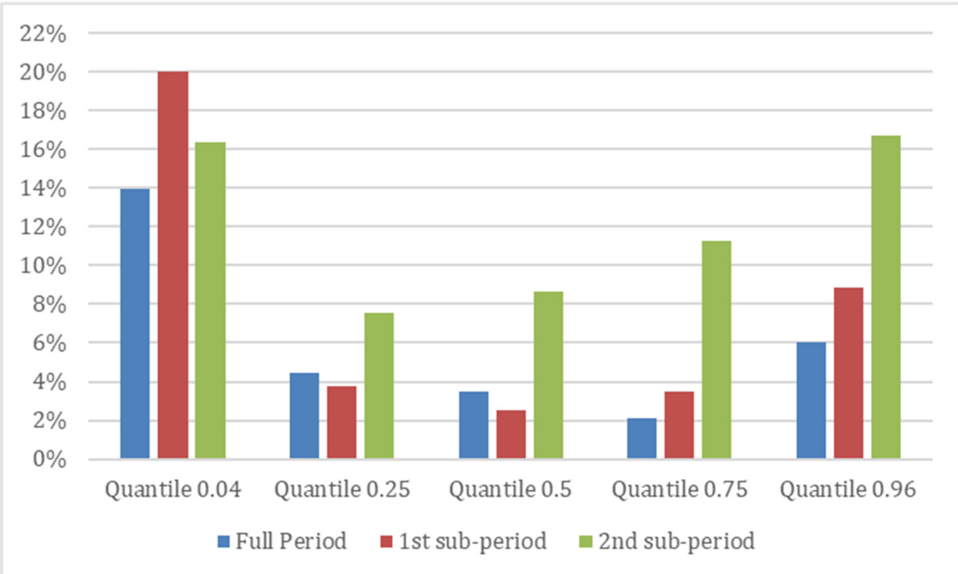


Figure 3. Average explanatory power of the three cryptocurrencies for the full period and the first and second sub-periods in Model 2.

In addition, Figures 2 and 3 show the average R^2 coefficients of the three cryptocurrencies for Models 1 and 2, respectively, at the different quantiles for the full period, the first sub-period of stable interest rates, and the second sub-period of rising interest rates. In both figures, and thus in both models, the maximum values of R^2 are found at Quantile 0.04, followed by Quantile 0.96, suggesting that the estimates are more reliable at these extremes of the distribution of the returns in all periods. It shows the superiority of the QR method compared with OLS because the most relevant results are found at the extremes of the return distribution (Quantiles 0.04 and 0.96) rather than at the median of the distribution (0.5 quantile), corroborating the appropriateness of its choice over classical OLS.

Moreover, a clear U-shaped trend emerges in the average explanatory power of the three cryptocurrencies for both models across the full period and the two sub-periods, confirming greater explanatory power at the extreme quantiles in all periods (in line with González and Jareño (2019) and Jareño et al. (2020), and reinforces the examination of the full sample period, factoring in various sub-periods corresponding to the economic phase. Furthermore, Model 2, which captures real interest rates and inflation expectations, shows higher explanatory power in all quantiles than Model 1, which analyzes nominal interest rates over the full sample period and both sub-periods. It implies that by decomposing nominal interest rates into real interest rates and inflation expectations, a better understanding and prediction of cryptocurrency returns is achieved.

6. Conclusions

The main objective of this research was to analyze how the returns of three different types of cryptocurrencies (traditional, "green", and "stable") respond to changes in nominal interest rates over a sample period from 7 April 2019 to 2 April 2023 in which central banks have had to raise nominal interest rates to alleviate the economic repercussions of the COVID-19 pandemic and to tackle the sharp rise in inflation as a consequence of the Russia–Ukraine conflict. Bitcoin, Cardano, and Tether were chosen to represent traditional, "green", and "stable" cryptocurrencies, respectively, as they are the market capitalization leaders in each category. The study also decomposes nominal interest rates into real interest rates and inflation expectations to analyze the impact of their shocks on the returns of these three types of cryptocurrencies. Thus, this paper proposes two models to analyze the sensitivity of Bitcoin, Cardano, and Tether returns to fluctuations in interest rates. Specifically, the first model (Model 1) examines the sensitivity of the returns of these three types of cryptocurrencies to shocks in the nominal interest rates; meanwhile, the second model (Model 2) examines the sensitivity of the returns of these cryptocurrencies to variations in the real interest rates and the expected inflation rates.

The QR model was used to estimate both models by examining the entire distribution of returns, which provides more comprehensive results than standard methods such as OLS. The QR approach considers distinct effects on the dependent variable by shifts in the explanatory variables across various quantiles (0.04, 0.25, 0.5, 0.75, and 0.96) and provides robust estimates in different economic scenarios. Specifically, lower quantiles are related to bearish periods and higher quantiles are related to bullish periods of the cryptocurrency market. For robustness, the analysis was conducted over three different sample periods: the full period from 7 April 2019 to 2 April 2023; the first sub-period from 7 April 2019 to 14 March 2021, characterized by stable interest rates prior to the COVID-19 pandemic; and a second sub-period from 14 March 2021 to 2 April 2023, marked by rising interest rates due to central banks' policies implemented to reduce the repercussions of the COVID-19 pandemic and the inflationary pressures instigated by the conflict between Russia and Ukraine.

Over the full period, nominal interest rates are observed to affect the "green" cryptocurrency (Cardano) and the stablecoin (Tether) during bearish periods, and just the stablecoin during bullish periods. On the other hand, fluctuations in real interest rates have a negative impact on just the stable cryptocurrency during bullish periods, while fluctuations in expected inflation rates have a positive impact on all three types of cryptocurrencies during bearish periods, as well as both a negative impact on the stablecoin and a positive impact on the "green" cryptocurrency during bullish periods. In the first sub-period, characterized by stable interest rates, we find that shifts in nominal interest rates have a negative impact on the "green" and the "stable" cryptocurrencies during bearish periods and a positive and high impact on the traditional (Bitcoin) and the "green" cryptocurrencies during bullish periods. On the other hand, we observe that changes in real interest rates have a negative impact on the traditional and the "green" cryptocurrencies, while fluctuations in inflation expectations have a positive and really huge impact on the "green" cryptocurrency in bearish periods. Additionally, changes in real interest rates show a positive and huge impact on the "green" cryptocurrency in bullish periods. In the second sub-period, which is characterized by rising interest rates, it is observed that fluctuations in nominal interest rates have a positive impact on all three cryptocurrency returns in bearish periods and both a negative impact on the traditional cryptocurrency and a positive impact on the "green" cryptocurrency in bullish periods. Furthermore, variations in real interest rates have a positive and low impact on the stablecoin during bearish periods, and a negative and high impact on the traditional and the "green" cryptocurrencies during bullish periods. Moreover, changes in expected inflation rates have a positive and huge impact on all three cryptocurrencies during bearish periods, while these changes have both a negative and low impact on the stablecoin and a positive impact, which is the largest in the whole study, on the "green" cryptocurrency during bullish periods.

Therefore, it can be concluded that, first, over the full period, the "stable" cryptocurrency (Tether) shows a statistically significant sensitivity to fluctuations in nominal interest rates, real interest rates, and inflation expectations during economic peaks. In addition, the "green" cryptocurrency (Cardano), together with the stablecoin (Tether), shows a statistically significant sensitivity to variations in the nominal interest rate and the expected inflation rate during bearish periods of the cryptocurrency market, suggesting that in this scenario, inflationary shocks are interpreted as good news, increasing their returns. Second, throughout the first sub-period, the "green" cryptocurrency (Cardano) is highly sensitive to fluctuations in nominal interest rates and real interest rates during bearish as well as bullish periods. Third, during the second sub-period, the "traditional" (Bitcoin) and the "green" (Cardano) cryptocurrencies are highly sensitive to shifts in nominal interest rates and inflation expectations in bearish periods, while they are highly sensitive to fluctuations in nominal interest rates and real interest rates in bullish periods. These results confirm the two hypotheses put forward in the study. On the one hand, they reveal that cryptocurrency returns are more sensitive to fluctuations in interest rates during bullish and bearish market periods, confirming the first hypothesis. On the other hand, they show that the sensitivity of the returns of the three different types of cryptocurrencies to variations in interest rates in different scenarios depends on their unique characteristics, thus corroborating the second hypothesis. Moreover, these intrinsic characteristics of each type of cryptocurrency need to be considered by portfolio managers when investing in cryptocurrencies.

On the other hand, it is noteworthy that there is a significantly positive relationship between the SP500 index and all the cryptocurrencies in bearish periods during the full period and the first sub-period of stable interest rates for Model 1. Furthermore, for the second sub-period of rising interest rates, it is even more remarkable that there is a positive and significant relationship between the SP500 index and traditional and "green" cryptocurrencies, which remains consistently significant and positive for all quantiles and both models. These results suggest an interrelationship between conventional and cryptocurrency markets.

In addition, the explanatory power of the models is observed to be U-shaped across the different quantiles in all the periods analyzed and for both models, confirming the robustness of the results over three different sample periods. Moreover, the maximum values are found in the bearish periods of the cryptocurrency market (at Quantile 0.04), followed by the bullish periods (at Quantile 0.96), mainly in the sub-periods into which the whole sample period has been divided, which confirms the suitability of using the QR approach to estimate the models suggested in this study. In addition, it is remarkable that the maximum value of the explanatory power (measured by the R^2) of the entire study corresponds to Bitcoin in the first place and Cardano in the second place during bearish periods of the first sub-period of stable interest rates for Model 2. It is also noteworthy that Model 2 shows greater explanatory power than Model 1 in all quantiles, justifying the breakdown of nominal interest rates into real interest rates and inflation expectations, as proposed in this research.

In summary, the study provides a detailed analysis of how traditional, "green", and "stable" cryptocurrencies respond to fluctuations in interest rates at different stages of the market, and it contributes to the understanding of the impact of nominal and real interest rates and expected inflation rates in the context of cryptocurrencies. It also enables portfolio managers and policymakers to make more informed decisions in an increasingly digital and global financial world. Thus, the observed sensitivities of Cardano and Tether to inflation expectations can significantly influence investment strategies over different market cycles. During economic expansions, Cardano's potential as an inflation hedge makes it attractive for preserving purchasing power, while Tether's stability may be less appealing to those seeking higher returns. Conversely, during economic recessions, Cardano's volatility may encourage investors to reduce exposure, while Tether's stability provides a safe haven. In inflationary times, Cardano may be in greater demand due to its inflation-resistant characteristics, while Tether offers a reliable store of value. In deflationary times, Cardano may see less demand, making the stability of Tether beneficial for capital preservation. In addition, market sentiment and speculative behavior can amplify Cardano's price movements, requiring risk management strategies, while Tether's stability helps to balance portfolio volatility. Understanding these sensitivities allows investors to tailor their strategies to optimize for both growth and stability under varying economic conditions.

This paper suggests possible future lines of research, such as exploring the interactions between cryptocurrencies and other financial markets, analyzing the impact of government policies on cryptocurrencies, and examining the use of cryptocurrencies in different industries. Thus, future research could explore several key areas to deepen our understanding of the cryptocurrency market. First, examining the impact of emerging government regulations on green cryptocurrencies, such as Cardano, could shed light on how policies promoting sustainability affect market dynamics and investors' behavior. Second, examining stablecoins' responses to interest rate shocks under tighter monetary policy conditions would provide insights into their stability and risk management strategies. In addition, analyzing investors' behavioral responses to interest rate changes and inflation expectations across different types of cryptocurrencies could improve our understanding of market liquidity and trading patterns. Furthermore, the study of technological innovations and adaptation strategies within the cryptocurrency sector could highlight advances that enhance resilience to economic fluctuations. These avenues of research would provide valuable insights for policymakers, investors, and market participants, supporting more informed decision-making in an increasingly digital and global financial environment.

Author contributions

Conceptualization: F.J.; data curation: J.M.A.; formal analysis: F.J., M.O.G., and J.M.A.; funding acquisition: F.J. and M.O.G.; investigation: F.J., M.O.G., and J.M.A.; methodology: F.J., M.O.G., and J.M.A.; project administration: F.J.; software: J.M.A.; resources: F.J., M.O.G., and J.M.A.; supervision:

F.J. and M.O.G.; validation: F.J. and M.O.G.; visualization: F.J., M.O.G., and J.M.A.; writing – original draft: F.J. and J.M.A.; writing – review and editing: F.J. and M.O.G.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

References

Adão LFS, Silveira D, Ely RA, et al. (2022) The impacts of interest rates on banks' loan portfolio risk-taking. *J Econ Dyn Control* 144: 104521. https://doi.org/10.1016/j.jedc.2022.104521

Aharon DY, Umar Z, Vo XV (2021) Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies. *Financial Innovation* 7: 59. https://doi.org/10.1186/s40854-021-00274-w

Ampudia M, Van den Heuvel SJ (2022) Monetary Policy and Bank Equity Values in a Time of Low and Negative Interest Rates. *J Monetary Econ* 130: 49–67. https://doi.org/10.1016/j.jmoneco.2022.05.006

Bats JV, Giuliodori M, Houben ACFJ (2023) Monetary policy effects in times of negative interest rates: What do bank stock prices tell us? *J Financ Intermed* 53: 101003. https://doi.org/10.1016/j.jfi.2022.101003

Buchinsky M (1998) Recent advances in quantile regression models: a practical guideline for empirical research. *J Hum Resour* 33: 88–126. https://doi.org/10.2307/146316

Bullock M (2023) How well placed are households for interest rate increases. *Econ Anal Policy* 77: 222–230. https://doi.org/10.1016/j.eap.2022.11.004

Caggese A, Pérez-Orive A (2022) How stimulative are low real interest rates for intangible capital? *Eur Econ Rev* 142: 103987. https://doi.org/10.1016/j.euroecorev.2021.103987

Cao J, Dinger V, Gómez T, et al. (2023) Monetary policy spillover to small open economies: Is the transmission different under low interest rates? *J Financ Stabil* 65: 101116. https://doi.org/10.1016/j.jfs.2023.101116

Díaz CO, Mayorga RM, Amaya AJ, et al. (2022) The importance of cryptocurrencies and their impact on international financial Markets based on the evolution of bitcoin. *Realidad Empresarial* 14: 10–25. https://doi.org/10.51378/reuca.v1i14.7525

Eldomiaty T, Khaled N (2024) Cryptocurrency volatility and Egyptian stock market indexes: A note. *Modern Financ* 2: 121–130. https://doi.org/10.61351/mf.v2i1.138

Escribano A, Jareño F, Cano JA (2023) Study of the leading European construction companies using risk factor models. *Int J Financ Econ* 28: 3386–3402. https://doi.org/10.1002/ijfe.2598

Esparcia C, Fakhfakh T, Jareño F (2024) The green, the dirty and the stable: Diversifying equity portfolios by adding tokens of different nature. *N Am J Econ Financ* 69: 102020. https://doi.org/10.1016/j.najef.2023.102020

Gimeno R, Ibáñez A (2018) The eurozone (expected) inflation: An option"s eyes view. *J Int Money Financ* 86: 70–92. https://doi.org/10.1016/j.jimonfin.2018.03.018

González MO, Jareño F (2019) Testing extensions of Fama & French models: A quantile regression approach. *Q Rev Econ Financ* 71: 188–204. https://doi.org/10.1016/j.qref.2018.08.004

González MO, Jareño F, Skinner FS (2020) Nonlinear autoregressive distributed lag approach: An application on the connectedness between bitcoin returns and the other ten most relevant cryptocurrency returns. *Mathematics* 8: 810. https://doi.org/10.3390/MATH8050810

González MO, Jareño F, Skinner FS (2021) Asymmetric interdependencies between large capital cryptocurrency and Gold returns during the COVID-19 pandemic crisis. *Int Rev Financ Analy* 76: 101773. https://doi.org/10.1016/j.irfa.2021.101773

Haq IUI, Bouri E (2022) Sustainable versus Conventional Cryptocurrencies in the Face of Cryptocurrency Uncertainty Indices: An Analysis across Time and Scales. *J Risk Financ Manag* 15: 101773. https://doi.org/10.3390/jrfm15100442

Iwanicz-Drozdowska M, Rogowicz K (2022) Does the choice of monetary policy tool matter for systemic risk? The curious case of negative interest rates. *J Int Financ Mark I* 79: 101608. https://doi.org/10.1016/j.intfin.2022.101608

Jareño F, Navarro E (2010) Stock interest rate risk and inflation shocks. *Eur J Oper Res* 201: 337–348. https://doi.org/10.1016/j.ejor.2009.03.025

Jareño F, González MO, Tolentino M, et al. (2020) Bitcoin and gold price returns: A quantile regression and NARDL analysis. *Resour Policy* 67: 101666. https://doi.org/10.1016/j.resourpol.2020.101666

Just M, Echaust K (2024) Cryptocurrencies against stock market risk: New insights into hedging effectiveness. *Res Int Bus Financ* 67: 102134. https://doi.org/10.1016/j.ribaf.2023.102134

Kamal JB, Hassan MK (2022) Asymmetric connectedness between cryptocurrency environment attention index and green assets. *J Econ Asymmetries* 25: e00240. https://doi.org/10.1016/j.jeca.2022.e00240

Koenker R, Bassett G (1978) Regression Quantiles. *Econometrica* 46: 33–50. https://doi.org/10.2307/1913643

Koenker R, Hallock K (2001) Quantile regression. *J Econ Perspect* 15: 143–156. https://doi.org/10.1257/jep.15.4.143

Li L (2023) The risks of trading on cryptocurrencies: A regime-switching approach based on volatility jumps and co-jumping behaviours. *Appl Econ* 56: 779–795. https://doi.org/10.1080/00036846.2023.2170970

Lobão J (2022) Herding Behavior in the Market for Green Cryptocurrencies: Evidence from CSSD and CSAD Approaches. *Sustainability* 14: 12542. https://doi.org/10.3390/su141912542

Mokni K, Youssef M, Ajmi AN (2022) COVID-19 pandemic and economic policy uncertainty: The first test on the hedging and safe haven properties of cryptocurrencies. *Res Int Bus Financ* 60: 101573. https://doi.org/10.1016/j.ribaf.2021.101573

Naeem MA, Karim S, Farid S, et al. (2022) Comparing the asymmetric efficiency of dirty and clean energy markets pre and during COVID-19. *Econ Anal Policy* 75: 548–562. https://doi.org/10.1016/j.eap.2022.06.015

Okorie DI, Bouri E, Mazur M (2024) NFTs versus conventional cryptocurrencies: A comparative analysis of market efficiency around COVID-19 and the Russia-Ukraine conflict. *Q Rev Econ Financ* 95: 126–151. https://doi.org/10.1016/j.qref.2024.03.001

Ren B, Lucey B (2022) A clean, green haven?—Examining the relationship between clean energy, clean and dirty cryptocurrencies. *Energ Econ* 109: 105951. https://doi.org/10.1016/j.eneco.2022.105951

Schelling T, Towbin P (2022) What lies beneath—Negative interest rates and bank lending. *J Financ Intermed* 51: 100969. https://doi.org/10.1016/j.jfi.2022.100969

Sevillano MC, Jareño F (2018) The Impact of International Factors on Spanish Company Returns: A Quantile Regression Approach. *Risk Manage* 20: 51–76. https://doi.org/10.1057/s41283-017-0027-7

Umar Z, Jareño F, González M de la O (2021) The impact of COVID-19-related media coverage on the return and volatility connectedness of cryptocurrencies and fiat currencies. *Technol Forecast Social Change* 172: 121025. https://doi.org/10.1016/j.techfore.2021.121025

Urdaneta AJ, Borgucci EV, Campuzano JA, et al. (2019) Hechos estilizados del mercado de criptomonedas desde el enfoque de la eficiencia marginal del capital. *Visionario Digital* 3: 228–244. https://doi.org/10.33262/visionariodigital.v3i2.421

Wang GJ, Ma X, Wu H (2020) Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests? *Res Int Bus Financ* 54: 101225. https://doi.org/10.1016/j.ribaf.2020.101225

Xiao H, Sun Y (2020) Forecasting the Returns of Cryptocurrency: A Model Averaging Approach. *J Risk Financ Manag* 13: 278. https://doi.org/10.3390/jrfm13110278

Yousaf I, Jareño F, Esparcia C (2022) Tail connectedness between lending/borrowing tokens and commercial bank stocks. *Int Rev Financ Anal* 84: 102417. https://doi.org/10.1016/j.irfa.2022.102417

Zaremba A, Cakici N, Bianchi RJ, et al. (2023) Interest rate changes and the cross-section of global equity returns. *J Econ Dyn Control* 147: 104596. https://doi.org/10.1016/j.jedc.2023.104596