

How do AI-based tokens react to interest rate shocks? Evidence from quantile regression

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Abstract

Purpose – This study aims to investigate how artificial intelligence (AI)-based tokens respond to changes in nominal and real interest rates, particularly in different market conditions, and to evaluate their potential role in portfolio diversification.

Design/methodology/approach – This study uses quantile regression to analyse the effect of changes in the nominal interest rate on the returns of five AI-based tokens. Two models are used to evaluate the performance of the tokens in relation to the S&P 500 and interest rates, taking into account inflation expectations and sub-period analysis.

Findings – AI-based tokens are sensitive to shocks in the US stock market, particularly during periods of market decline. Negative changes in the real interest rate affect tokens negatively in bear markets, while changes in the nominal rate are more harmful during market peaks. The behaviour of tokens varies across sub-periods.

Originality/value – This research provides valuable insights into the dynamics of AI-based token markets and how they interact with macroeconomic variables. It offers guidance for investors and portfolio managers.

Keywords Interest rates, Tokens, Quantile regression, Market conditions

Paper type Research paper

1. Introduction

In today's globalised and highly digitised financial landscape, asset prices are increasingly affected by macroeconomic shocks that transcend national borders. In recent years, we have witnessed a succession of disruptive events, from the global pandemic to the war in Ukraine, that have reshaped economic expectations and triggered significant volatility in financial markets. One of the most pressing macroeconomic challenges currently facing developed economies, particularly in Europe and the USA, is the resurgence of inflation. In response, central banks have implemented restrictive monetary policies, notably by raising interest rates repeatedly in an attempt to temper inflationary pressures.

These monetary interventions have profound implications for asset valuation and investor behaviour. While the impact of changes in interest rates on traditional financial assets is well documented, the emergence of digital assets – especially those linked to artificial intelligence

JEL classification – C21, C22, C51, F21, G12, G32, H12

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(AI) – raises new questions about how these novel instruments respond to macroeconomic shocks (Díaz *et al.*, 2023). Due to their unique technological foundations and market dynamics, AI-based tokens may be sensitive to interest rate changes in ways that differ from those of conventional asset classes.

This paper explores the relationship between changes in the interest rate and returns on AI-based digital assets, focusing particularly on recent cycles of monetary tightening. The central research question is whether these tokens react differently to interest rate shocks due to their innovative nature and speculative appeal, compared to traditional financial instruments. In this sense, implementing traditional frameworks to digital assets introduces new theoretical challenges. Unlike stocks or bonds, tokens generally lack intrinsic cash flows, and their valuation typically primarily reflects market conditions. This raises a fundamental question in asset pricing theory: are monetary shocks transmitted through classical mechanisms? Addressing this question extends conventional sensitivity models. Furthermore, it is investigated whether such reactions vary across different market regimes, for which a quantile regression (QR) methodology is applied to differentiate these market states. Moreover, by decomposing nominal interest rates into real interest rates and inflation expectations, this study provides a more nuanced understanding of how monetary policy affects the performance of digital assets.

This research builds on the pioneering work of Jareño (2006, 2008) and Jareño and Navarro (2010), who proposed decomposing nominal rates to more accurately capture asset sensitivities. In terms of methodology, the study adopts the approach proposed by Gimeno and Ibáñez (2018), which involves using US inflation-linked swaps as a proxy for inflation expectations. This enables a market-based estimation of expected inflation, thereby enhancing the precision of the analysis. Recently, this methodology has been applied in the context of the European electricity sector (Esparcia *et al.*, 2025). Furthermore, QR is used to examine asset behaviour under different market conditions, such as bullish and bearish ones, thus capturing asymmetric responses to interest rate shocks.

While previous studies have primarily focused on major cryptocurrencies or broad digital asset classes, this research fills a significant gap by examining the behaviour of AI-linked tokens, an emerging and under-explored segment. Benigno (2023) offers a theoretical perspective on the interplay between monetary policy and cryptocurrency adoption, arguing that the proliferation of digital assets constrains central banks' ability to set interest rates to maintain price stability. Elsayed and Sousa (2024) investigate the dynamic spillovers between international monetary policies in the Eurozone, Japan, the UK and the USA, and three cryptocurrencies (Bitcoin, Litecoin and Ripple). The results show that cryptocurrency returns and monetary policy spillovers were particularly significant when policy rates turned negative and sharpened again as cryptocurrency buoyancy returned. More recently, Buthelezi (2025) explores the effect of US monetary policy shocks on cryptocurrency prices and volatility using Markov switching and GARCH models. The study concludes that interest rate increases are associated with reduced cryptocurrency prices and volatility, particularly in higher price states. Jareño *et al.* (2025) use QR to analyse interest rate sensitivity across traditional, green and stable cryptocurrencies. Their results reveal that cryptocurrencies are highly responsive to interest rate shocks, with Cardano acting as an inflation hedge during bearish market conditions. Similarly, Tosun and Ugurlu (2025) investigate the long-term impact of US Federal Reserve monetary policy on Bitcoin, Ethereum and Tether using an ARDL bounds testing approach. Their findings indicate that Bitcoin and Ethereum exhibit positive long-term responses to monetary policy changes, whereas Tether demonstrates a negative relationship, suggesting heterogeneous sensitivity among crypto assets.

Collectively, these studies underscore the significant role of interest rate variations in shaping cryptocurrency market dynamics and focus primarily on major cryptocurrencies such as Bitcoin and Ethereum or broad digital asset classes, leaving AI-based tokens largely unexplored. Thus, to the best of our knowledge, this study makes three contributions to the literature on digital financial assets and monetary policy. Firstly, whereas previous research has focused almost exclusively on major cryptocurrencies (e.g. Bitcoin and Ethereum) or broad digital asset classes, this paper is the first to examine the response of AI-based tokens to variations in nominal and real interest rates, as well as inflation expectations, across different market regimes. This addresses a significant knowledge gap regarding an emerging and under-explored segment of the crypto ecosystem. Secondly, based on the methodology of [Jareño and Navarro \(2010\)](#), we decompose changes in nominal interest rates into two components: fluctuations in inflation expectations and shifts in real interest rates. This decomposition enables us to identify the specific macro-financial linkages that influence AI-token performance, providing a more detailed perspective than previous studies. Thirdly, in line with [Esparcia et al. \(2025\)](#), we use US inflation-linked swap rates as a proxy for inflation expectations. This ensures that we are using a market-based and forward-looking measure, rather than relying on survey data or backward-looking indicators. This methodological choice makes our findings more robust and relevant for investors and policymakers. By combining three innovations – a novel focus on asset classes, a refined decomposition of interest rate dynamics and a sophisticated measure of inflation expectations – our study provides actionable insights into the behaviour of AI-linked tokens under different monetary policy environments. Our findings indicate that these tokens exhibit sensitivity to different regimes and could provide diversification benefits under specific macroeconomic conditions, which is highly relevant for portfolio management and policy design.

The remainder of the paper is organised as follows: Section 2 provides a review of the relevant literature on interest rate sensitivity and the behaviour of digital assets. Section 3 describes the data sources, variables and methodological framework. Section 4 presents the empirical results and discusses their implications. Section 5 concludes with a summary of the key findings, their practical applications and directions for future research.

2. Literature review

The emergence of blockchain technology has catalysed a paradigm shift in financial markets, giving rise to a diverse ecosystem of digital financial assets, including cryptocurrencies, non-fungible tokens (NFTs), decentralised finance (DeFi) instruments and, more recently, AI-based tokens. These assets challenge traditional financial theories by introducing instruments that are decentralised and algorithmically governed, and which often lack intrinsic value yet exhibit high volatility and speculative appeal. Their behaviour in response to macroeconomic stressors, particularly interest rate shocks, is not well understood, predominantly compared to conventional assets such as equities or bonds.

The theoretical basis for analysing how assets are sensitive to changes in interest rates is rooted in the concept of “duration”, which was initially applied to fixed-income securities and later extended to equities ([Stone, 1974](#); [Flannery and James, 1984](#)). According to this framework, asset returns are influenced by changes in nominal interest rates, which are composed of real interest rates and inflation expectations. Decomposing these components enables a more precise understanding of the mechanisms through which monetary policy is transmitted. Although this approach has been widely applied to traditional sectors ([Jareño, 2006](#); [Jareño and Navarro, 2010](#); [Esparcia et al., 2025](#)), its application to digital assets, particularly AI-based tokens, remains largely unexplored.

Recent empirical studies have begun to examine how digital assets behave under macroeconomic shocks. For example, [Corbet et al. \(2018\)](#) and [Jiang et al. \(2021\)](#) have emphasised the benefits of diversifying into cryptocurrencies during periods of market turbulence, indicating that these assets could act as a hedge or a safe haven. Introducing a QR approach, [Ma et al. \(2022\)](#) show that the sensitivity of Bitcoin to monetary surprises is higher during bullish phases of the market, suggesting that investor reactions to policy shocks are asymmetric and more intense in periods of optimism. However, these findings often focus on major cryptocurrencies such as Bitcoin and Ethereum, leaving a gap in our understanding of the behaviour of more specialised tokens, such as those linked to AI technologies.

Moreover, the literature provides conflicting evidence regarding the sensitivity of digital assets to changes in interest rates. [Jareño et al. \(2025\)](#) use QR to analyse the impact of interest rate fluctuations on the returns of Bitcoin, Cardano and Tether from 2019 to 2023, distinguishing between real rates and inflation expectations. The study finds that sensitivity varies by cryptocurrency type and market condition, meanwhile [Aharon et al. \(2021\)](#) suggested that Bitcoin was largely unaffected by shocks to the US yield curve. [Lin et al. \(2025\)](#) find that Treasury yields influence cryptocurrency returns asymmetrically across the distribution: the effect is negative in lower quantiles (bearish market conditions) and turns positive in upper quantiles (bullish regimes), indicating a state-dependent sensitivity of Bitcoin to interest rate changes. These results challenge conventional asset pricing models and raise questions about the applicability of traditional duration-based frameworks to digital assets. However, they also highlight the need for a more nuanced approach that considers the heterogeneity of digital tokens and their varying exposure to macroeconomic variables. Lastly, [Esparcia et al. \(2025\)](#) use QR to analyse how changes in nominal and real interest rates – especially those driven by inflation expectations – affect Eurozone electricity sector portfolios from 2019 to 2022. The analysis reveals that changes in the real interest rate have a stronger impact on electricity stock returns, particularly during periods of market volatility and for companies with higher debt levels. Taken together, empirical evidence remains mixed regarding how digital assets respond to monetary dynamics. This heterogeneity suggests that conventional mean-based models may conceal important asymmetries in market reactions. The QR framework is therefore particularly suited to uncover how interest rate shocks propagate across the distribution of returns and to clarify the mechanisms through which macroeconomic policy affects digital asset performance.

In this context, AI-based tokens are a new type of digital asset whose value may be affected by market conditions, technological adoption and macroeconomic fundamentals. Their speculative nature, coupled with their association with emerging technologies, makes them particularly susceptible to changes in investor expectations, particularly in a changing interest rate environment. However, the literature has yet to systematically investigate how these tokens respond to changes in the real interest rate versus inflation expectations, or whether these responses vary across market conditions.

This study closes the existing gap in the literature by applying a QR framework to analyse the sensitivity of AI-based token returns to decomposed interest rate components. By distinguishing between real interest rates and inflation expectations and examining behaviour across bullish and bearish market regimes, the research advances the empirical and theoretical understanding of digital asset dynamics. Building on the theoretical foundation of interest rate exposure, it extends this to a new class of financial instruments, thereby advancing the ongoing debate on the impact of monetary policy on decentralised, technology-driven markets.

3. Data and methodology

3.1 Data

This study examines the effect of interest rate fluctuations, particularly the recent rises intended to curb inflation, on the performance of digital financial assets, with a particular focus on AI-based tokens. Due to the large number of AI-related tokens listed on platforms such as CoinMarketCap, a rigorous selection process was necessary to ensure analytical tractability and relevance. Therefore, five AI-based tokens were selected based on three key criteria ([Jareño and Yousaf, 2023](#)):

- (1) market capitalisation;
- (2) liquidity (as measured by trading volume); and
- (3) representativeness within the AI token ecosystem.

The selected tokens – AGIX (SingularityNET), CTXC (Cortex), FET (Fetch.ai), NMR (Numeraire) and OCEAN (Ocean Protocol) – are among the most highly capitalised and actively traded AI-related tokens. Each is linked to a different AI application, such as decentralised machine learning, data marketplaces and predictive modelling. This selection ensures diverse representation of the AI token landscape while maintaining analytical coherence.

To evaluate the impact of macroeconomic factors on these tokens, the study incorporates three independent variables: the S&P 500 index, nominal interest rates and inflation expectations. The S&P 500 index was selected as the adjusted variable to capture systemic risk in the US financial market, which remains a dominant force in global asset pricing. This variable helps to control for broader equity market movements that could distort the relationship between interest rates and token returns.

Nominal interest rates are represented by the yield on ten-year US Treasury bonds, which is a widely accepted benchmark for long-term interest rate expectations. To separate the effects of real interest rates and inflation expectations, the nominal rates are analysed using the methodology proposed by [Jareño and Navarro \(2010\)](#). Inflation expectations are proxied using US inflation-linked swap rates, in line with the methodologies of [Gimeno and Ibáñez \(2018\)](#) and [Esparcia et al. \(2025\)](#). These methodologies offer market-based estimates of future inflation and are favoured over survey-based measures due to their greater frequency and responsiveness to market conditions. Real interest rates are then derived by subtracting inflation expectations from nominal rates.

The analysis covers 207 weekly [1] observations from 7 April 2019 to 2 April 2023. This period encompasses two distinct macroeconomic regimes:

- (1) a period of relative monetary stability and falling interest rates before the onset of the pandemic; and
- (2) a period of monetary tightening and rising interest rates after the pandemic and the outbreak of the Russia–Ukraine conflict.

To capture the structural shift in monetary policy and its potential differential impact on asset behaviour, the sample has been divided into two subperiods. The first subperiod, which ends on 14 March 2021, reflects a low-interest-rate environment, while the second captures the transition to a high-interest-rate regime. This segmentation enables a more detailed analysis of how AI-based tokens respond to interest rate shocks in different economic conditions.

All financial data were sourced from reputable databases: macroeconomic variables were obtained from the Federal Reserve Economic Data (FRED), while asset prices were obtained from CoinMarketCap. This ensures consistency and reliability in the empirical analysis [2].

3.2 Methodology

This study uses the QR methodology, originally introduced by [Koenker and Bassett \(1978\)](#) and widely applied in financial econometrics ([Koenker and Hallock, 2001](#); [Sevillano and Jareño, 2018](#); [Umar et al., 2018](#); [Jareño et al., 2023](#); [Esparcia et al., 2025](#)), to investigate the sensitivity of AI-based digital asset returns to interest rate dynamics. Unlike ordinary least squares (OLS) regression, which estimates the conditional mean of the dependent variable, QR enables the estimation of conditional quantiles. This captures the heterogeneous effects of explanatory variables across the entire distribution of asset returns.

This approach is particularly well-suited to analysing digital assets, which are characterised by non-normal return distributions, high volatility and asymmetric responses to macroeconomic shocks. Furthermore, QR allows us to study how assets behave in different market conditions, specifically bullish (upper quantiles) and bearish (lower quantiles), which is crucial for understanding how AI-based tokens react to interest rate changes during periods of optimism and stress.

From a theoretical standpoint, the use of QR is further justified by risk aversion theory ([Jareño and Navarro, 2010](#)). Investors tend to be more sensitive to macroeconomic signals, such as interest rate hikes, when asset prices are high (upper quantiles), as they anticipate potential reversals. Conversely, in calmer market conditions (central quantiles), reactions may be more muted. This behavioural asymmetry highlights the importance of modelling return sensitivities across the distribution, rather than relying solely on average effects.

To operationalise this framework, the study estimates two risk factor models across the following quantiles: $\theta = 0.1, 0.25, 0.5, 0.75$ and 0.9 . These models provide a balanced view of both extreme and central market conditions.

Model 1 captures the relationship between returns on AI-based tokens and changes in the nominal interest rate, while controlling for general market performance via the S&P 500 index:

$$Token_{it} = \alpha + \beta_{1,\theta} SP500_t + \beta_{2,\theta} \Delta \mathbf{inominal}_t + s_t, t = 1, 2 \quad (1)$$

Model 2 decomposes nominal interest rates into their two fundamental components – real interest rates and inflation expectations – while controlling for the S&P 500 index:

$$Token_{it} = \alpha + \beta_{1,\theta} SP500_t + \beta_{2,\theta} \Delta \mathbf{Einflation}_t + \beta_{3,\theta} \Delta \mathbf{ireal}_t + s_t, t = 1, 2 \quad (2)$$

where $Token_{it}$ denotes the weekly returns of each token i in t ; $SP500_t$ is the performance of the 500 largest US listed companies at t ; $\Delta \mathbf{inominal}_t$ captures changes in nominal interest rates at t ; $\Delta \mathbf{Einflation}_t$ is the change in inflation expectations at t ; $\Delta \mathbf{ireal}_t$ denotes the change in real interest rates at t ; s_t represents the random disturbance in cryptocurrency returns [3].

The decomposition of nominal interest rates follows the methodology proposed by [Gimeno and Ibáñez \(2018\)](#), which was recently applied by [Esparcia et al. \(2025\)](#). This methodology uses market-based instruments to estimate inflation expectations, thereby avoiding the limitations of survey-based or model-implied measures.

By applying QR across multiple quantiles, the study captures the differential impact of interest rate shocks on AI-based tokens in different market conditions. This enables a robust evaluation of whether these digital assets demonstrate asymmetric sensitivities and diverge in behaviour from traditional financial instruments, particularly in response to changes in the real interest rate versus inflation expectations.

4. Sensitivity of the artificial intelligence-based token returns to variations in interest rates

This section presents the results of QR estimations applied to five AI-based tokens. These estimations examine the tokens' sensitivity to interest rate changes and broader market movements across different market regimes. Analysing five quantiles ($\theta = 0.1, 0.25, 0.5, 0.75$ and 0.9) enables us to capture investor behaviour during bearish, neutral and bullish conditions. This provides insight into how monetary policy shocks propagate through the digital asset space.

4.1 Model 1: effects of nominal interest rates

Table 1 shows the estimated coefficients from Model 1, which uses a regression analysis to examine the relationship between token returns and changes in the S&P 500 index and nominal interest rates.

Table 1. Estimates for Model 1: nominal interest rates

Theta-quantile 0.10	SP500	$\Delta i_{\text{nominal}}$	R ²
AGIX	1.114793***	-4.222466	0.05862
CTXC	1.340408**	20.39299	0.028919
FET	1.884192***	12.56132	0.074456
NMR	1.337476***	17.4022	0.044114
OCEAN	1.842587**	23.53791	0.047402
<i>Theta-quantile 0.25</i>			
AGIX	1.796769***	5.176724	0.05722
CTXC	1.198854***	-6.666385	0.037749
FET	1.458923***	0.282034	0.049161
NMR	1.007935***	-7.731125	0.028058
OCEAN	1.821209***	-1.920705	0.039966
<i>Theta-quantile 0.5</i>			
AGIX	1.220995*	2.969406	0.025616
CTXC	0.996551**	-5.845152	0.026414
FET	1.450740***	13.56907	0.038324
NMR	1.109753**	-7.104876	0.035405
OCEAN	1.487075**	-6.956461	0.024703
<i>Theta-quantile 0.75</i>			
AGIX	1.378098*	-7.959625	0.029027
CTXC	1.012937	-18.89564**	0.022147
FET	1.146002	5.961479	0.010803
NMR	0.973282**	-7.357178	0.020622
OCEAN	0.537016	-2.126416	0.005803
<i>Theta-quantile 0.90</i>			
AGIX	1.80541*	18.46797	0.046578
CTXC	1.669433***	-45.74476***	0.042313
FET	1.312647	6.25731	0.026931
NMR	-0.360613	-40.32157*	0.018878
OCEAN	0.362567	-18.41787	0.016765

Note(s): This table shows the estimation results of the proposed Model 1 using the quantile regression methodology. In particular, it shows the sensitivity of the returns of the selected AI-based tokens (AGIX, CTXC, FET, NMR and OCEAN) to variations in US stock market returns and changes in nominal interest rates. The sample period is from 7 April 2019 to 2 April 2023. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

The results reveal clear asymmetries in token sensitivity across quantiles. During bearish market conditions ($\theta = 0.1$ and 0.25), all tokens exhibit a strong, positive and statistically significant correlation with the S&P 500 index. This suggests that AI-based tokens behave procyclically, aligning with broader equity market trends during periods of low market activity. However, changes in the nominal interest rate show no significant impact in these lower quantiles, suggesting that, during market downturns, investors may shift their focus away from macroeconomic fundamentals towards liquidity and market conditions.

At the median quantile ($\theta = 0.5$), the correlation with the S&P 500 weakens and nominal interest rates become insignificant. This reflects a transitional regime in which performance is less influenced by market stress or exuberance, which is consistent with lower levels of investor risk aversion.

In bullish conditions ($\theta = 0.75$ and 0.9), the relationship with the S&P 500 remains, but is more selective. Notably, CTXC and NMR exhibit statistically significant negative sensitivity to changes in the nominal interest rate (Esparcia *et al.*, 2025). This finding is consistent with risk aversion theory, which suggests that investors become more cautious at market peaks in anticipation of reversals. In such conditions, even modest interest rate increases may prompt investors to reallocate funds away from speculative assets such as AI-based tokens, thereby amplifying their downside risk.

Figure 1 illustrates the explanatory power (R^2) across quantiles, revealing a U-shaped pattern. The model performs best in extreme market conditions, indicating that AI-based tokens are more predictable during periods of stress or exuberance than in stable environments (Jareño and Yousaf, 2023).

4.2 Model 2: decomposing nominal interest rates into real interest rates and inflation expectations

Table 2 shows the results of Model 2, in which nominal interest rates are replaced by their two components, real interest rates and inflation expectations.

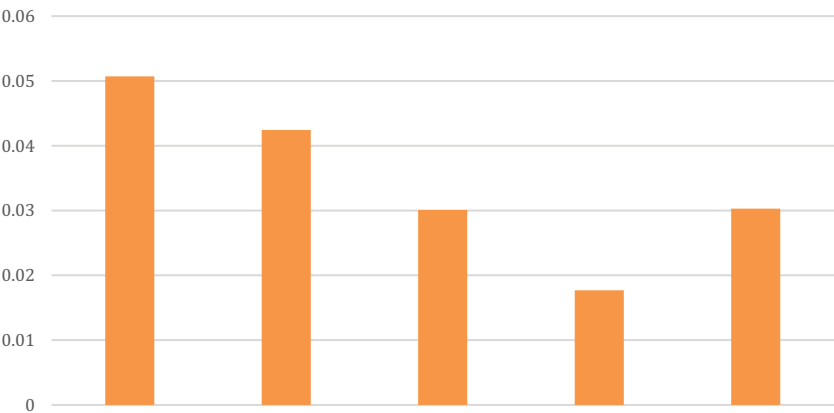


Figure 1. Analysis of the average explanatory power for Model 1 across quantiles
Note(s): The figure shows the average explanatory power of Model 1 (US stock market returns and nominal interest rate changes) on AI-based token returns for the different quantiles examined. The full sample period is from 7 April 2019 to 2 April 2023

Table 2. Estimates for model 2: real interest rates and inflation expectations

Theta-quantile 0.10	SP500	Δi_{real}	$\Delta E_{\text{inflation}}$	R^2
AGIX	0.989489**	$\sim 17.01909^*$	34.36372**	0.078636
CTXC	0.490191	$\sim 34.29925^{***}$	25.41134	0.047983
FET	1.522491***	~ 19.82449	55.37030***	0.098583
NMR	0.496403	~ 13.86742	47.22331***	0.06959
OCEAN	0.594807	~ 14.14649	74.53155***	0.078187
<i>Theta-quantile 0.25</i>				
AGIX	1.866800***	~ 6.004875	30.77427*	0.056954
CTXC	1.449683***	$\sim 25.00147^{**}$	36.57462	0.047392
FET	1.157968***	~ 21.49451	56.31409***	0.072886
NMR	0.841338**	$\sim 15.71389^{**}$	14.66639	0.039295
OCEAN	1.613733***	$\sim 33.99275^{***}$	51.78663	0.068556
<i>Theta-quantile 0.5</i>				
AGIX	1.217611**	~ 3.479335	17.31974	0.025536
CTXC	0.944187*	~ 9.920711	8.165164	0.027646
FET	1.500938***	~ 3.046560	40.61846**	0.042344
NMR	1.218472**	~ 12.51239	9.383165	0.037915
OCEAN	1.404216**	$\sim 21.00132^*$	37.41488	0.034306
<i>Theta-quantile 0.75</i>				
AGIX	1.168511***	~ 6.610962	1.275492	0.029795
CTXC	0.896999	$\sim 15.80658^*$	~ 16.95370	0.026646
FET	1.051117	6.737332	9.611904	0.01303
NMR	0.848747**	~ 12.97766	17.07525	0.024217
OCEAN	0.655457	~ 18.33022	35.1042	0.013108
<i>Theta-quantile 0.90</i>				
AGIX	2.600080***	14.70683	9.845586	0.052004
CTXC	1.791114***	$\sim 35.04032^{***}$	$\sim 36.15552^{**}$	0.049052
FET	1.890992	5.057158	3.990657	0.027037
NMR	~ 0.052178	~ 24.7399	~ 51.99055	0.02446
OCEAN	0.566421	~ 13.99770	~ 22.05520	0.016425

Note(s): This table shows the estimation results of the proposed Model 2 using the quantile regression methodology. In particular, it shows the sensitivity of the returns of the selected AI-based tokens (AGIX, CTXC, FET, NMR and OCEAN) to variations in US stock market returns and changes in real interest rates and inflation expectations. The sample period is from 7 April 2019 to 2 April 2023. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

This model provides deeper insights into the economic mechanisms driving token returns. At the lowest quantile ($\theta = 0.1$), AGIX and FET exhibit a positive and significant correlation with the S&P 500, whereas CTXC and AGIX demonstrate negative sensitivity to changes in the real interest rate. This suggests that, during economic downturns, rising real interest rates – often associated with tighter monetary policy – exert downward pressure on speculative assets, particularly those with weaker fundamentals or lower liquidity.

Interestingly, inflation expectations have a positive and significant impact on AGIX, FET, NMR and OCEAN during periods of market decline. This may reflect investor anticipation that higher inflation could lead to a more relaxed monetary policy in future, thereby supporting riskier assets (Jareño and Navarro, 2010). Alternatively, it could indicate a belief that AI-based tokens possess some inflation-hedging properties, though this effect appears to be token-specific. In this sense, a positive response of token returns to rising inflation

expectations implies that these assets may partially preserve their value when traditional financial instruments, such as bonds or equities, tend to underperform due to higher discount rates. However, such hedging capacity appears to be token-specific rather than systematic across the entire AI-linked asset class.

At the midpoint ($\theta = 0.5$), the impact of real interest rates and inflation expectations weakens, reflecting reduced investor sensitivity in neutral market conditions. However, only the FET continues to benefit from inflation expectations, which suggests that investors have different beliefs about the utility or resilience of tokens.

In bullish regimes ($\theta = 0.75$ and 0.9), CTXC once again exhibits negative sensitivity to changes in the real interest rate, and at $\theta = 0.9$, it is also adversely impacted by inflation expectations. This dual vulnerability suggests that CTXC may be particularly susceptible to macroeconomic tightening, rendering it less appealing during periods of monetary contraction. AGIX and CTXC both have positive correlations with the S&P 500, which reinforces their procyclical nature (Sevillano and Jareño, 2018; Umar *et al.*, 2018).

Figure 2 illustrates the explanatory power of the Model 2 estimates for various tokens across different quantiles. The explanatory power is greatest in the first and last quantiles, suggesting greater reliability in both low- and high-market conditions. This asymmetric U-shaped pattern is consistent with previous research and, in line with Jareño and Yousaf (2023) and Esparcia *et al.* (2025), supports the notion of increased sensitivity to the tails of the distribution.

4.3 Comparative insights between Model 1 and Model 2 and economic implications

A comparison of the two models reveals that decomposing nominal interest rates significantly enhances their explanatory power and economic interpretability (González and Jareño, 2019). While Model 1 primarily identifies nominal rate sensitivity in bullish conditions, Model 2 shows that real interest rates exert downward pressure in bear markets. Furthermore, inflation expectations can have both supportive and adverse effects, depending on the token and market regime. These results are partly consistent with those of Esparcia *et al.* (2025).

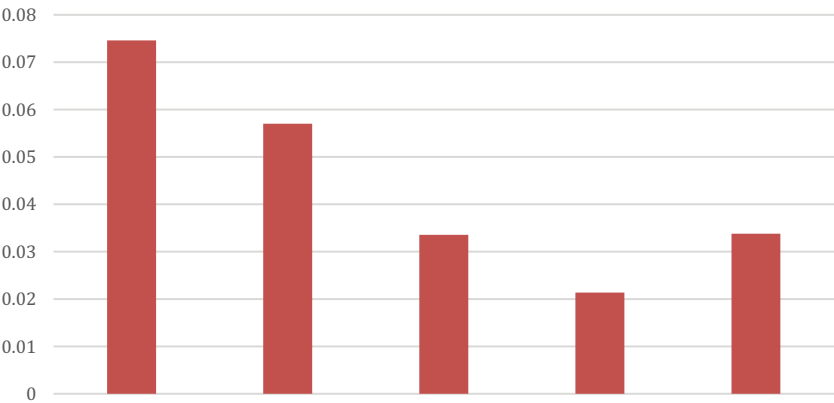


Figure 2. Analysis of the average explanatory power for Model 2 across quantiles
Note(s): The figure shows the average explanatory power of Model 2 (US stock market returns, and changes in real interest rates and inflation expectations) on AI-based token returns for the different quantiles examined. The full sample period is from 7 April 2019 to 2 April 2023

These findings suggest that investors in AI-based tokens respond differently to monetary policy measures. Increases in the real interest rate – often interpreted as a signal of tighter financial conditions – are consistently associated with negative token performance, particularly during economic downturns. Inflation expectations, on the other hand, may be perceived as either a threat or an opportunity depending on the utility, narrative or speculative appeal of the token in question.

The results highlight the importance of risk management that is dependent on the market regime in digital asset portfolios. AI-based tokens do not respond uniformly to interest rate shocks; their behaviour varies across quantiles and depends on whether the shock originates from real rates or inflation expectations. For investors, this means that shifts in monetary policy should be interpreted in light of market conditions and the specific characteristics of each token.

For policymakers, the findings emphasise the increasing interdependence between conventional monetary instruments and emerging digital markets. As AI-based tokens become more popular, they may influence broader financial stability due to their sensitivity to interest rate dynamics, particularly during periods of rapid monetary tightening or inflationary stress.

5. Robustness analysis: interest rate regimes and market sensitivity

To evaluate the reliability of the QR results and examine how AI-based token sensitivities change in response to various macroeconomic conditions, the sample period has been divided into two distinct subperiods.

Subperiod 1 (7 April 2019 to 14 March 2021): Characterised by stable or declining interest rates reflecting an accommodative monetary policy and subdued inflation expectations.

Subperiod 2 (15 March 2021 to 2 April 2023): This period was marked by rising and volatile interest rates, driven by inflationary pressures and central bank tightening.

This segmentation enables a dynamic analysis of the influence of monetary regimes on investor behaviour and asset pricing in the digital token space.

5.1 Subperiod 1: stable or declining interest rates

In the first subperiod, Model 1 (Table 3) shows that returns on AI-based tokens are positively and significantly correlated with S&P 500 performance, especially in the lower quantiles ($\theta = 0.1$). This suggests that AI-based tokens are closely linked to broader equity trends in a bear market, reflecting their procyclical nature.

Interestingly, changes in the nominal interest rate have a negative and statistically significant impact on token returns across most quantiles, except at $\theta = 0.9$, where AGIX, CTXC and FET demonstrate positive sensitivity. This divergence at the upper tail may reflect speculative dynamics: when token prices are at their peak, investors may interpret rising nominal rates as a sign of economic strength or inflationary momentum, which temporarily boosts demand. Conversely, it could suggest that, during periods of market euphoria, traditional macroeconomic signals are overshadowed by momentum-driven trading.

Model 2 (Table 4) provides deeper insights. Changes in the real interest rate are negatively associated with token returns across most quantiles, which reinforces the idea that tighter monetary conditions reduce the performance of speculative assets (Jareño *et al.*, 2025). However, at $\theta = 0.9$, AGIX and OCEAN show a positive response to real rates, which may reflect investor expectations regarding long-term viability or technological adoption that outweigh short-term rate pressures.

Table 3. Estimates for Model 1: nominal interest rates, first subperiod

Theta-quantile 0.10	SP500	$\Delta i_{\text{nominal}}$	R^2
AGIX	1.797344***	-23.24086	0.118842
CTXC	2.406595***	-54.6636**	0.106307
FET	1.995252***	-28.95898	0.081472
NMR	1.873568***	-17.86035	0.044855
OCEAN	3.353147***	-95.90573***	0.125162
<i>Theta-quantile 0.25</i>			
AGIX	1.065879	-8.420493	0.032280
CTXC	1.283032*	-16.79205	0.032095
FET	1.416634**	5.228035	0.054384
NMR	1.022135	-9.364335	0.018097
OCEAN	2.426395**	-37.59387	0.044639
<i>Theta-quantile 0.5</i>			
AGIX	0.0510268	-17.98781	0.028222
CTXC	1.014787	-15.17771	0.016086
FET	1.469335*	31.53370*	0.051858
NMR	0.201208	3.340398	0.009253
OCEAN	0.554384	-20.50507	0.008012
<i>Theta-quantile 0.75</i>			
AGIX	1.000461*	-26.31373	0.025802
CTXC	0.289278	-12.79745	0.013229
FET	0.212786	38.32774**	0.035772
NMR	-0.457201	12.65656	0.003700
OCEAN	0.069066	-40.09829	0.015099
<i>Theta-quantile 0.90</i>			
AGIX	1.432537**	29.40688	0.091523
CTXC	1.213741**	-28.03537	0.053510
FET	1.049592	64.71944**	0.082749
NMR	0.080228	-3.199233	0.000811
OCEAN	0.902273	25.17237	0.020973

Note(s): This table shows the estimation results of the proposed Model 1 using the quantile regression methodology. In particular, it shows the sensitivity of the returns of the selected AI-based tokens (AGIX, CTXC, FET, NMR and OCEAN) to variations in US stock market returns and changes in nominal interest rates. The sample period is from 7 April 2019 to 14 March 2021. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

The effects of inflation expectations are positive and significant at $\theta = 0.25$ and $\theta = 0.9$ for several tokens (Jareño and Navarro, 2010). This suggests that some AI-based tokens may be perceived as assets that can withstand inflation, particularly during periods of rising expectations. Their decentralised nature and independence from fiat currencies could position them as alternative stores of value – a hypothesis that aligns with emerging narratives in the cryptocurrency market.

5.2 Subperiod 2: rising and volatile interest rates

During the second subperiod, which was characterised by aggressive interest rate increases and inflationary uncertainty, Model 1 (Table 5) revealed that the majority of tokens exhibited a positive and substantial correlation with S&P 500 returns within the lower half of the distribution ($\theta = 0.1, 0.25, 0.5$). This confirms their continued alignment with market conditions during periods of decline.

Table 4. Estimates for Model 2: real interest rates and inflation expectations, first subperiod

Theta-quantile 0.10	SP500	Δi_{real}	$\Delta E_{\text{inflation}}$	R^2
AGIX	1.443084**	-29.46074*	6.021224	0.131741
CTXC	0.878359	-46.49924***	10.06325	0.111845
FET	0.970100	-20.59079	44.73726	0.101935
NMR	0.053724	-15.69924	45.88734	0.069553
OCEAN	1.605971	-65.47845***	12.17420	0.161371
<i>Theta-quantile 0.25</i>				
AGIX	0.328785	-12.46022	24.91070	0.042488
CTXC	1.240035*	-40.19347***	64.74371**	0.044718
FET	0.651993	-5.613176	65.17380*	0.063527
NMR	0.770074	-19.64342	3.747738	0.024077
OCEAN	1.626242	-45.22765**	52.13543	0.059471
<i>Theta-quantile 0.5</i>				
AGIX	0.899095	-10.91371	-23.40337	0.032227
CTXC	0.895880	-21.39827	15.72405	0.020094
FET	1.546665*	13.75112	42.88561	0.055037
NMR	0.024124	-10.41134	26.69068	0.015434
OCEAN	0.864792	-32.92292	11.32928	0.012147
<i>Theta-quantile 0.75</i>				
AGIX	1.327159***	-18.37728	-26.09160*	0.031305
CTXC	0.481116	-21.74873	-1.105800	0.016695
FET	0.298576	22.47639*	32.95558	0.037586
NMR	0.151182	-4.142263	52.85801*	0.012509
OCEAN	-0.779316	-36.14159	-10.81196	0.022633
<i>Theta-quantile 0.90</i>				
AGIX	1.021160	8.027169	57.04404	0.093075
CTXC	0.911076	-39.46557*	-1.761961	0.061141
FET	0.663017	32.19357	80.65905**	0.076509
NMR	-4.252211*	-10.98549	82.94273*	0.019403
OCEAN	0.580281	6.303353	41.18498	0.026661

Note(s): This table shows the estimation results of the proposed Model 2 using the quantile regression methodology. In particular, it shows the sensitivity of the returns of the selected AI-based tokens (AGIX, CTXC, FET, NMR and OCEAN) to variations in US stock market returns and changes in real interest rates and inflation expectations. The sample period is from 7 April 2019 to 14 March 2021. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

However, changes in the nominal interest rate now have a positive and significant effect on most tokens, suggesting a change in how investors interpret them. During a tightening cycle, rising rates may be viewed as a sign of the credibility of the central bank or the resilience of the economy, which can temporarily support risk assets. CTXC is the exception, showing negative sensitivity at $\theta = 0.75$, possibly due to its lower correlation with the S&P 500 and weaker investor confidence in tightening conditions.

Model 2 (Table 6) once again highlights the nuanced effects of decomposed rates. Changes in the real interest rate are negatively and significantly associated with token returns across most quantiles, reaffirming their role as a suppressive force on speculative assets. AGIX stands out due to its positive sensitivity at $\theta = 0.9$, which may reflect its stronger alignment with equity market dynamics or investor belief in its long-term utility.

Table 5. Estimates for Model 1: nominal interest rates, second subperiod

Theta-quantile 0.10	SP500	$\Delta i_{\text{nominal}}$	R^2
AGIX	0.936571	11.23065	0.038620
CTXC	-0.192925	26.92707	0.016230
FET	1.982391***	25.69016	0.084934
NMR	1.338577**	19.98565	0.064479
OCEAN	1.562003*	29.46093	0.026683
<i>Theta-quantile 0.25</i>			
AGIX	1.901270**	11.72213	0.063157
CTXC	1.947323***	-1.355107	0.059941
FET	1.521454**	12.81622	0.053360
NMR	1.394290***	-9.578134	0.047655
OCEAN	1.634755**	13.54496	0.050248
<i>Theta-quantile 0.5</i>			
AGIX	2.682606***	21.44459	0.058095
CTXC	1.310852**	-3.027699	0.042156
FET	2.380797**	1.335030	0.037380
NMR	1.527890***	-6.240656	0.088322
OCEAN	2.128075***	9.995483	0.079272
<i>Theta-quantile 0.75</i>			
AGIX	2.340352**	22.31669	0.058092
CTXC	1.262914	-18.90428*	0.036080
FET	1.871980	4.847112	0.033549
NMR	1.575318*	-6.560734	0.064174
OCEAN	1.007435	12.77243	0.029932
<i>Theta-quantile 0.90</i>			
AGIX	4.520352	21.94236	0.059818
CTXC	1.505848	-48.80067*	0.046795
FET	5.203574**	-15.84541	0.086420
NMR	1.182109	-23.18837	0.052903
OCEAN	1.063882	11.34749	0.027259

Note(s): This table shows the estimation results of the proposed Model 1 using the quantile regression methodology. In particular, it shows the sensitivity of the returns of the selected AI-based tokens (AGIX, CTXC, FET, NMR and OCEAN) to variations in US stock market returns and changes in nominal interest rates. The sample period is from 15 March 2021 to 2 April 2023. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

Inflation expectations continue to demonstrate positive and significant effects at $\theta=0.1$, 0.25 and 0.5. This lends weight to the idea that certain AI-based tokens are considered inflation hedges, particularly in contexts where the purchasing power of fiat currencies is deemed to be declining (Jareño *et al.*, 2025). These tokens may play an enhanced role in diversified portfolios under such conditions, particularly for investors seeking exposure to non-traditional inflation-protected assets.

5.3 Economic interpretation and portfolio implications

Robustness analysis confirms that AI-based tokens exhibit sensitivities to interest rate dynamics that depend on the economic environment. In stable environments, real interest rates have a dominant suppressive effect, while inflation expectations may

Table 6. Estimates for Model 2: real interest rates and inflation expectations, second subperiod

Theta-quantile 0.10	SP500	Δi_{real}	$\Delta E_{\text{inflation}}$	R^2
AGIX	1.137492	0.679726	31.31052	0.037416
CTXC	-0.611479	6.704775	61.93258**	0.017878
FET	1.991483***	-24.01062	68.86061***	0.114978
NMR	2.121955***	-26.57777***	78.68403***	0.115081
OCEAN	1.936283***	-22.96833	103.4352***	0.064187
<i>Theta-quantile 0.25</i>				
AGIX	2.093057***	-6.427696	45.65760**	0.063644
CTXC	1.665422***	-19.88236	25.08999	0.063698
FET	1.921143***	-38.70109**	70.36555***	0.111104
NMR	1.714877***	-18.83695**	44.19718**	0.077291
OCEAN	1.353239**	-2499476**	55.92209**	0.093836
<i>Theta-quantile 0.5</i>				
AGIX	2.888693***	-3.662389	61.67546**	0.059648
CTXC	0.831056	-4.913466	-3.925387	0.044892
FET	1.860112**	-31.18966*	61.65250**	0.062425
NMR	1.515369***	-1200200	13.27823	0.091927
OCEAN	2.465441***	-12.48121	68.33506***	0.099965
<i>Theta-quantile 0.75</i>				
AGIX	2.494401**	-4.189630	47.91476	0.060454
CTXC	0.937637	-15.79825	-16.69116	0.044135
FET	2.265676*	-21.24678	60.42570*	0.046162
NMR	1.795993**	-15.12121	21.43126	0.066952
OCEAN	1.114371	-5.933332	44.31389	0.035555
<i>Theta-quantile 0.90</i>				
AGIX	4.697181	0.764675	52.61513	0.062578
CTXC	2.121828	-37.37241*	-31.46429	0.057404
FET	5.515157**	-24.67011	33.36546	0.089732
NMR	1.644160	-14.09015	-21.16983	0.061461
OCEAN	0.747387	-33.27478**	51.22834	0.068875

Note(s): This table shows the estimation results of the proposed Model 2 using the quantile regression methodology. In particular, it shows the sensitivity of the returns of the selected AI-based tokens (AGIX, CTXC, FET, NMR and OCEAN) to variations in US stock market returns and changes in real interest rates and inflation expectations. The sample period is from 15 March 2021 to 2 April 2023. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

support token valuations. In volatile regimes, however, nominal rates gain explanatory power and investor behaviour becomes more differentiated across tokens and quantiles.

In addition, these findings have important implications. For investors, it is crucial to understand the asymmetric response of tokens across market states to time entry and exit strategies effectively. For portfolio managers, the inflation sensitivity of certain tokens suggests their potential usefulness in hedging strategies, particularly when traditional inflation-linked instruments underperform. For policymakers, the growing responsiveness of digital assets to interest rate signals highlights their increasing integration into broader financial ecosystems and therefore warrants closer monitoring during monetary transitions.

6. Conclusions

This study contributes to the growing body of literature on digital financial assets by examining how AI-based tokens respond to changes in interest rates – an area that remains largely unexplored. While previous research has focused on major cryptocurrencies or generalised digital assets, this paper addresses a critical gap in the literature by analysing the response of AI-linked tokens to changes in nominal and real interest rates and inflation expectations across different market regimes.

The study's key contribution lies in its application of a QR framework to capture asymmetric responses across the distribution of token returns. By breaking down nominal interest rates into their fundamental components, the study offers a more detailed insight into the impact of monetary policy on digital assets. The findings show that increases in the real interest rate tend to reduce token returns during bearish market conditions, whereas nominal interest rate shocks have a greater influence during bullish phases. Furthermore, the sensitivity of certain tokens to inflation expectations suggests potential hedging properties that could be valuable for portfolio diversification.

To ensure robustness, the analysis was extended by dividing the full sample into two subperiods: one characterised by stable interest rates, and the other by rising and volatile rates. This temporal segmentation confirmed that token sensitivities are regime-dependent; while most tokens reacted negatively to interest rate changes during the stable period, several showed positive sensitivity in the volatile phase. Additionally, tokens' behaviour with respect to inflation expectations varied, with some acting procyclically, and others countercyclically, depending on the subperiod.

From a practical standpoint, these insights are relevant to investors, portfolio managers and policymakers. The results suggest that AI-based tokens do not behave uniformly in response to macroeconomic stress, and that they may offer diversification benefits, depending on the prevailing interest rate regime and market conditions. For portfolio managers, grasping these dynamics is crucial for devising robust investment strategies in volatile markets.

Despite its contributions, the study has several limitations. Firstly, the relatively short historical window of AI-based token data restricts the generalisability of the findings. Secondly, the analysis focuses on a limited set of tokens, which may not accurately represent the wider AI-linked asset class. Thirdly, the models do not consider other potentially influential factors, such as technological developments specific to tokens, regulatory changes or indicators of investor sentiment.

Future research could address these limitations by expanding the data set to include a broader range of AI-related tokens, as well as extending the time horizon to capture additional macroeconomic cycles. Incorporating alternative modelling approaches, such as wavelet coherence analysis or non-linear autoregressive models, could further enhance understanding of the dynamic relationships between interest rates and digital asset returns. Additionally, investigating the impact of investor behaviour, network effects and token utility on sensitivity to macroeconomic variables would offer valuable theoretical and empirical insights.

In summary, this paper takes a foundational step towards understanding the complex interplay between monetary policy and AI-based digital assets. It contributes to both academic discourse and practical financial decision-making in an evolving digital economy.

Notes

- [1.] In line with [Esparcia et al. \(2025\)](#), the selection of weekly data was not arbitrary. It was chosen to strike a balance between capturing short-term market dynamics and avoiding excessive noise.

The paper also notes that inflation expectations were measured using weekly inflation-linked swap data, which is inherently high-frequency and market-based. This further validates the choice of weekly intervals.

Furthermore, quantile regression enhances robustness by capturing effects across different market conditions (e.g. bullish vs bearish), rather than relying on average effects. This approach is particularly well-suited to weekly data, as it can reflect rapid shifts in sentiment and macroeconomic shocks.

- [2.] Classical unit root and stationarity tests confirm that the series are stationary. The results are available upon request.
- [3.] After examining the matrix of correlations between the independent variables, it was decided to orthogonalise the variables to remove the excessive correlation between them. This orthogonalisation was applied to S&P 500 index returns and inflation expectations.

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