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One crash, too many: Global uncertainty, sentiment factors and cryptocurrency market

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ABSTRACT

Recent studies document that cryptocurrencies offer an alternative store of value, medium of exchange and can be used to hedge against currency and price fluctuations. However, the frequent collapse of the crypto-market undermines its safe-haven characteristics, as investors' fear and anxiety could intensify market volatility and trigger a financial crisis. Motivated by the current global vicissitudes, this study examines the impact of uncertainty and sentiment factors on price behaviour of cryptocurrencies. To estimate our model, we used daily, low, high and closing price data for major crypto projects, from January 2018 to January 2023. We show that economic and political uncertainty factors significantly drive crypto prices. Furthermore, the interaction between sentiment dynamics as expressed by investors on different social platforms has a significant adverse effect on the returns of the cryptocurrency market, and the impact is more pronounced for tokens within the same ecosystem. Using the asymmetric GARCH-MIDAS model and TVP-VAR, we also demonstrate the existence of a significant contagion among tokens within the same ecosystem when bad (or good) news occurs. Considering the massive unprotected losses incurred by crypto investors during crises, our results provide important insights into how portfolio managers can effectively design investment strategies.

1. Introduction

In this paper, we address a cardinal issue in the cryptocurrency market: how do investor sentiment and global uncertainties surrounding current and future government actions shape the price of crypto assets? The frequent loss of significant investment capital makes it imperative to investigate whether behavioural, economic, and political uncertainty factors affect the returns and volatility of crypto assets. One of the recent breakthroughs in the financial technology ecosystem is the invention of cryptocurrencies, whose usage includes facilitating inexpensive and swift decentralised payment systems across global frontiers. These electronically mined assets (cryptocurrencies) have witnessed significant growth in types, usage, and value, from \$1 billion market value in 2010 (IMF, 2013) to roughly \$2.9 trillion in market capitalisation during the last quarter of 2021 (U.S. Dept. of the Treasury, 2022).

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Some arguments in favour of ownership of crypto assets are hedging against economic turbulence (Bouri et al., 2017, 2023), exchange rate fluctuation hedging (Urquhart and Zhang, 2019), and portfolio diversification (Brière et al., 2015; Platanakis and Urquhart 2020). Other benefits include fund transfers with minimal cost, private transaction channels and freedom, and fewer legal or regulatory bureaucracies. Nonetheless, cryptocurrencies exhibit some snags such as excessive price volatility, market bubbles, and eluding supervisory, and regulatory frameworks (Brennan et al., 2019; Giudici et al., 2020; Jalan and Matkovskyy, 2023). Other drawbacks include claims of correlation with fraud metrics, money laundering, and capital flights (Moll and Yigitbasioglu, 2019; Alnasaa et al., 2022). Seemingly, cryptocurrencies create some level of risk together with some opportunities for the financial system, thus providing prospects for academics to explore.

Despite the numerous benefits offered by cryptocurrencies, the frequent collapse of the crypto-market challenges its safe-haven characteristics, as investors' fear and anxiety exacerbate volatility in the market that could trigger a financial crisis. For example, in May 2022, the price of LUNA[1] plunged from an all-time high of $117 to a record low of barely one-thousandth of a cent. Then, in November, FTT[2] crashed from $32 billion in capitalization to nearly half a billion dollars, causing the price of Bitcoin[3] to drop sharply to its 2-year low. Unlike previous crises, the incidence of these tokens sent massive shockwaves across the crypto-market, thus raising concerns about hedging properties of crypto assets, dynamic connectedness, and spill-over transmission effects.

Relatively few studies have explored the association between crypto market and behavioural factors, as well as its relationship with global uncertainties. Empirical contributions include Walther et al. (2019); Yen and Cheng (2021); Lucey et al. (2022), and Raza et al. (2023). Two papers most closely related to our study are Corbet et al. (2020) and Akyildirim et al. (2021) who separately find that economic uncertainty and investor sentiments have significant impact on cryptocurrencies. However, our study differs from these studies and others in the literature in several crucial ways. First, in stark contrast to prior studies, we use a robust array of possible behavioural and uncertainty proxies that might affect the price development of the sampled tokens. For the behavioural factors, we employ the novel Thomson Reuters Market-Psych cryptocurrency indices to capture investor sentiments in the crypto-market. This database offers a more extensive insights than the extant proxies in the literature and allows us to analyse investors' immediate reactions to market information. Next, we construct new sentiment scores using data from Twitter and Reddit. We strongly conjecture that investors express their opinions about trending tokens and market news using these social media platforms. We also follow prior studies by separating global uncertainty into economic and political uncertainties. Economic uncertainty proxies in our study include the global economic policy uncertainty (GEPU), US equity market volatility index (VIX), and monetary policy uncertainty (MPU). For the political uncertainty, we adopt the geo-political risk data from the EPU website. Importantly, we also introduce the ongoing Russia-Ukraine war to proxy political uncertainty, thus making our paper the first to examine the cryptocurrency market from that perspective.

Another salient novelty in our study is the sample selection method. Most studies in the literature primarily focus on Bitcoin and other cryptocurrencies based on market capitalisation (see Demir et al., 2018; Corbet et al., 2020; Akyildirim et al., 2021). Our paper draws its sample from two leading blockchain projects. Before the recent crypto crisis, these projects, also called ecosystems −Terra and FTX- were among the dominant blockchain projects in the cryptocurrency market. We obtain data for six cryptocurrencies native to these two projects. Also, we consider more recent sample period covering daily data from January 2018 – January 2023, thus enriching the findings of prior studies. We use recent methodology developed by Rapach et al. (2016) to estimate returns of the tokens while GARCH-MIDAS model is used to estimate volatility, separating the impact of good news and bad news. We also use the TVP-VAR method to identify dynamic connectedness among the tokens. Interestingly, using these methods give a broader picture of the impact of both uncertainty and sentiment factors on the cryptocurrency market. Similar to Walther et al. (2019), who conducted a mixed-data forecasting analysis for cryptocurrencies, we also adopt six loss-function criteria to assess the predictive stability of our models over time.

Our findings reveal that sentiment factors, economic uncertainty, political uncertainty and market factors are important predictors of cryptocurrency assets. Specifically, we find that the indices of economic and political uncertainties as well as sentiment factors have negative and significant effects on the cryptocurrency market, particularly when there is bad global news. Additionally, we observe that due to information asymmetry and mistrust, the volume of search for tokens rises sharply after major global events as well as policy announcements by crypto exchanges. Such events and announcements shape investors' sentiments, consequently having a drastic and most times, irreversible impact on the price of cryptocurrencies. Moreover, *a falling knife* situation occurs in the absence of a 'circuit breaker' to halt trades on crypto assets. This further magnifies the risk of loss by investors, raises uncertainties, and transmits to other tokens within the market.

Our findings are crucial on at least four grounds. First, given the ongoing crisis in the crypto market, our paper contributes to the behavioural finance strand of literature which shows how returns of crypto assets are shaped by investor sentiments, as expressed on different media platforms. The importance of investor sentiment in pricing financial assets has been documented well in the literature (Baker and Wurgler, 2006; Waggle and Agrawal, 2015; Sakariyahu et al., 2021, Paterson et al., 2023; Chen et al., 2023). Proponents of investor sentiment demonstrate that movements of asset prices within the financial market reflect the psychological processes of investors and their immediate reactions toward the market (Shefrin and Statman, 2000; Sakariyahu et al., 2023). Although financial

[1] LUNA is one of the native tokens on Terra's blockchain. Due to the collapse of the old Terra LUNA, with its ticker redesignated as LUNC, a new LUNA token (2.0) has been airdropped to erstwhile holders of LUNA. Before the collapse, LUNA was one of the world's leading digital currencies.

[2] FTT is the native token of the world's second-largest crypto exchange FTX, founded by a significant donor to the Democratic party in the US-Sam Bankman-Fried.

[3] Bitcoin is the largest cryptocurrency in the world.

markets are structured to prevent consistent abnormal returns, a plethora of studies in the literature reveal that sentiments can be devised as a trading strategy (Renault, 2017; Sakariyahu et al., 2021), thus significantly accounting for the frequent movements in asset prices. For example, the effect of investor sentiments was more pronounced during the GameStop saga in January 2021, where some investors used social media platforms to generate significant bullish herding sentiment towards the stock. Our findings extend these prior studies on the connection between investors' reactions and market performance by showing that behavioural factors significantly drive crypto prices. Thus, our results provide important insights into how portfolio managers can effectively design investment strategies.

Second, our findings also contribute to the growing literature that investigate the impact of uncertainties on the financial market. Since the last global financial crisis, concerns about the influence of global unpredictability on financial assets have intensified. Extensive research finds that economic and political uncertainties, particularly among developed nations, have a significant association with the outcomes of financial markets around the world, and can lead to positive or negative spill-overs among nations (Belo et al., 2013; Brogaard et al., 2020; Chan and Marsh, 2021). For example, the International Monetary Fund (IMF) (2013) reported that economic and monetary uncertainties within the United States contributed to the slow recovery from the last global recession in 2009. Some studies also demonstrate the importance of global politics on asset pricing. For instance, Li and Born (2006), Belo et al. (2013), and Chan and Marsh (2021) provide substantial evidence of the influence of U.S. mid-term and presidential elections on global asset returns, while Liu et al. (2017) attest to the importance of Chinese elections on global investment and financing decisions. More recently, the IMF (2022) observed that the current war between Russia and Ukraine, the U.S.-China trade and political tensions, and the resurgence of the COVID pandemic in China, are likely to worsen global uncertainties and may push the world into another recession. Using economic and political uncertainty indices, we document a negative relationship between these proxies and crypto pricing. Our results thus deviate from prior studies such as Kalyvas et al. (2020) and Colon et al. (2021).

Third, by providing a novel understanding of how dynamic and time-varying factors drive the volatility of crypto assets, our findings resonate the importance of portfolio diversification, particularly for tokens within the same ecosystem. While most research work on cryptocurrencies have focused their samples on market capitalisation (Walther et al., 2019; Corbet et al., 2020; Yen and Cheng, 2021; Raza et al., 2023), our study selects samples from two major cryptocurrency projects that have recently suffered a severe collapse, hence providing practical reasons for the collapse, and offering guidance to forestall future occurrence.

Given the recurring unprotected losses incurred by crypto investors, our findings are vital to relevant stakeholders in academia, industry and government. Our study highlights the imperative for regulators to implement stringent financial controls on the cryptocurrency market. The interdependence of assets in the market, especially those within a shared ecosystem, underscores the importance of formulating regulatory measures aimed at safeguarding the entire financial system from imminent collapse. Our research outcomes provide valuable insights for industry professionals, offering guidance to investors and other market participants regarding risk modelling, hedging, and diversification strategies. The interconnectedness and contagion effects of assets can exacerbate portfolio performance during periods of financial crisis. Therefore, comprehending these mechanisms might assist investors in mitigating potential losses. Finally, our research expands upon the existing scholarly works regarding the impact of global uncertainties and sentiment factors on asset prices. The paper progresses with the following structure: Section 2 shows the literature review, section 3 describes the data and illustrates the estimation strategy, section 4 reports on the empirical analysis and section 5 concludes the study.

2. Literature review and hypothesis development

Although the crypto market is relatively new, its adoption and usage have increased tremendously. Recently, the market has become popular as individuals and institutions invest in crypto assets to hedge and diversify their traditional portfolios. Furthermore, since cryptocurrencies provide speedy, decentralised, and anonymous systems, investors have enormous opportunities to reduce transaction costs and understand their investment environment (Lucey et al., 2022). Considering the numerous benefits and continuous development of the market, research on crypto assets is still evolving. Prior studies have identified various factors associated with the price development of cryptocurrencies; in this study, we explore how global uncertainty, and behavioural factors affect price movements in the market.

2.1. Global uncertainties and asset pricing

Uncertainty is a common economic phenomenon with multifaceted meanings, but concerning the financial landscape, Jurado et al. (2015) and Rossi and Sekhposyan (2015) equate uncertainty to the difficulty in predicting or forecasting economic direction. Literature abounds on the relationship between economic uncertainties and financial assets (see Caldara et al., 2016; Cesa-Bianchi et al., 2020; Elsayed, 2022) with all showing different levels and dimensions of the vulnerabilities of financial system to such phenomenon. If the relationship between assets and uncertainties has been established in the traditional financial system, it would be interesting to know how this concept extends to the crypto market.

On the one hand, uncertainty could drive up prices of crypto assets if government provides a proper fiscal and monetary response to unexpected shocks. Prompt government intervention in times of financial crisis boosts investors' confidence in the financial markets and insulates assets from unprotected losses. On the other hand, happenings worldwide, particularly political uncertainty, are a non-diversifiable risk. Essentially, the crypto market is fully decentralised and not controlled by any government or institution. We opine that the impact of global economic and political events on the crypto market can be severe and depressing as investors' risk aversion may increase due to a lack of coordinated legislation to protect their investments.

Most studies have diffused uncertainties into political and economic uncertainties, with the latter generating much interest on the academic spectrum. For example, Bekaert et al. (2009) examine the significance of changes in risk aversion and time-varying uncertainty in asset pricing and risk premiums. Their results indicate that risk aversion only influences risk premiums, while uncertainty is crucial in driving the volatility of asset returns. Bloom (2009) also proxied economic uncertainty using stock market volatility and shows that it is strongly associated with other measures of uncertainty, with a substantial effect on macroeconomic variability. Also documenting the impact of mis-specified economic and central bank policies on asset volatilities, Ulrich (2012) demonstrates that the *fear of the unknown* accounts for 45 % of variations in implied and interest rate volatilities, thus signifying an inverse relationship between volatility and changes in economic fundamentals. Explaining the implications of economic policy uncertainty (EPU) on asset pricing, Brogaard and Detzel (2015) employ news-based measure and shows the importance of EPU as a risk factor by revealing that excess market returns are positively predicted by measures of economic policy uncertainty. Their findings also reveal that an increase in three-month abnormal returns is associated with an increase in standard deviations. In addition, they constructed portfolios based on size and momentum returns and tested the impact of EPU on the returns of the portfolios. Controlling for realised and implied volatility, they show that portfolios with low coefficients of EPU perform better than those with high coefficients of EPU. Other studies that have applied the economic policy uncertainty (EPU) index as a proxy for uncertainty include Baker et al. (2012); Belke et al. (2018); Zhang et al. (2020) and Batabyal and Killins (2021).

A thread of academic papers has also adopted the volatility index *VIX* to measure economic uncertainty. For instance, Wang et al. (2020) confirm the predictive ability of the VIX index as a more efficient economic uncertainty measure to estimate potential volatility. Aıt-Sahalia et al. (2021) also argue that in the instance where volatility and other proxies of uncertainty are segregated, there is a likelihood that the relationship between the VIX index and asset return will be negative. Their study proves that asset returns react adversely to the VIX index but move in the same direction as with other proxies of uncertainty. From a different perspective, Morikawa (2019) measure economic uncertainty using survey data and showed that output from the survey represents a good predictor of asset price movements. The survey method of measuring uncertainty is done on widely available data and represents the different sectors of the economy with a more all-encompassing result (Girardi and Reuter, 2017). Other studies with similar approaches (such as Altig et al., 2020) applied text analysis to generate uncertainty estimates.

The impact of political uncertainties on the cryptocurrency market has also received considerable attention in the literature. For example, Kalyvas et al. (2020) reveal that the crash risk of Bitcoin prices is not unconnected with political uncertainties. Specifically, they show that when there is high political uncertainty, the risk of a crash of Bitcoin is low, thus suggesting a significant negative association between the price of Bitcoin and indicators of uncertainties. Their findings also indicate that Bitcoin could be a practical hedge against economic uncertainty. Providing evidence of political uncertainty on asset prices, Chan and Marsh (2021); Belo et al. (2013); Pastor and Veronesi (2013), and Liu et al. (2017) all show that global political uncertainty, measured by election cycles, has a crucial impact on stock markets around the world. Their findings depict that an increase in political uncertainties due to upcoming and concluded elections raises investors' risk aversion and exposes the domestic financial market. Other studies include Colon et al. (2021), who adopt political and economic uncertainty; and Raza et al. (2023), who used the GARCH-MIDAS model to investigate the effects of uncertainties on the volatility of cryptocurrencies. Their findings reveal that an increase in uncertainty instigates a decline in returns for the crypto market and spurs excessive volatility. Based on the foregoing, we focus on the predictive power of cryptocurrency returns using both global economic and political uncertainties.

Hypothesis 1 Global economic and political uncertainties can significantly predict behaviour of the cryptocurrency market.

2.2. Investors sentiment and asset pricing

The inability of the efficient market hypothesis (EMH) to account for the extent of anomalies inherent in stock market valuation aided the growth of behavioural finance studies. While EMH provides a foremost model in the estimation and pricing of financial assets, the behavioural school of thought, on the other hand, puts forward an argument that human psychology plays a significant role in shaping investment judgments, depending on specific behavioural biases. Since humans make financial decisions, their actions and thoughts might be influenced by other factors like sociodemographic, sociopsychological, economic, and norms, among others, which thereafter find a way to shape their investment decisions (Sakariyahu et al., 2021; Rathee and Aggarwal, 2022; Dosumu et al., 2023; Sakariyahu et al., 2023). Ángeles et al. (2020) note that behavioural finance represents a universal theoretical set, which houses other behavioural biases regarded as subsets, i.e., prospect theory, loss aversion, and mental accounting.

The persistent crash of the crypto market underscores the importance of behavioural dispositions and how they form the basis for decision-making by investors. In the absence of government regulations in the cryptocurrency market, crypto investors generally rely on information from leading crypto exchanges through media platforms when confronted by the need to make investment choices. Sadly, crypto exchanges, many of whom are institutional holders of primary tokens, are privy to classified information more than retail investors. In trying to avoid public misconceptions and provocations, they often divulge less-sensitive information for public consumption, thus creating information asymmetry. In addition, crypto exchanges usually introduce peculiar measures during crises, with some imposing tight restrictions on fund withdrawals but not on trading. Given the increase in levels of uncertainty and risk, the efficacy of those measures is undermined by mistrust; such scepticism occasioned by information asymmetry limits investors' ability to make rational decisions. In the face of a looming disaster and people's means of livelihood already in danger, massive disposal of crypto assets is often driven by sentiments.

Using direct or survey methods to explain the motives or outlooks of investors, Clarke and Statman (1998) applied the 'Bullish Sentiment Index' to represent an analysis of some numbers of non-brokerage entities. Furthermore, Fisher and Statman (2000) also analyse the exact sentiment of three groups of investors, which consist of strategists, writers, and individual investors, while Brown and Cliff (2004) apply market participant sentiment of both 'American Association of Individual investors' and 'Investors Intelligence'. Although these studies produced mixed findings, the usage of the views and feelings of few investors to represent the whole market view of investors might be biased and subjective.

Another strand of research adopts the indirect method. According to Hu et al. (2021), this method involves building sentiment scores using market-based data. Variables adopted include closed-end fund discount, log difference of the average market-to-book ratios of payers and nonpayers, the share of equity issues in total equity and debt issues, number of IPOs, and average first-day returns on IPOs. For instance, Pan and Poteshman (2006) apply the put-call proportion from options trade size by buyers to prove inherent information about future prices of assets. Chung et al. (2012) apply the famous Baker and Wurgler (2006) indirect sentiment, which was derived using the principal component of different proxies of investors' sentiment. The sentiment indices developed were treated to ensure they were statistically unrelated to numerous macroeconomic variables. Huang et al. (2015) also present a modified version of the investor sentiment index, which was statistically and economically meaningful in forecasting returns with certainty for a risk-return investor. Other studies in line with the indirect sentiment methods include Baker and Yuan (2012); Xu and Zhou (2018), and Sakariyahu et al. (2023).

Apart from both the direct and indirect approaches discussed above, which are viewed to likely have some biases towards chosen methodology or size of the market, other studies in the literature (such as Chen et al., 2014) utilise principal component analysis (PCA) to develop a composite sentiment index that combines macroeconomic variables and market-based variables, and their study shows some high forecast accuracy for stock market changes. Liao et al. (2011) also use the composite sentiment measure to explain herding as a behavioural concept with fund managers. Concerning the sell-side, their study demonstrates that investor sentiment was statistically significant in explaining herding in mutual fund managers. Other studies in line with the composite measure of sentiment include Ho and Hung (2009); Bathia et al. (2016); Rakovska (2021) and Hu et al. (2021).

Alternative to direct, indirect, and composite sentiment measures, studies have also used opinion within the internet to gauge investor sentiment. For example, Shuhidan et al. (2018) pull data from the online version of financial news and applied the Lexicon and Naïve Bayes procedures in machine learning to provide sentiment evaluation. Atzeni et al. (2018) generate data from social media platforms and blogs for sentiment analysis. Bullish and bearish sentiments were estimated from stock by adopting lexical and semantic characteristics from the adopted "fine-grained" methodology. The outcome was efficient compared to other traditional sentiment approaches. Other studies (such as Rao and Srivastava, 2012; Oliveira et al., 2013; Ranco et al., 2015; Zhang et al., 2017) also report mixed outcomes between online/social media sentiments and asset prices. Considering the foregoing, we hypothesise that sentiment factors can significantly predict cryptocurrency returns.

Hypothesis 2 Investor sentiment can significantly predict behaviour of the cryptocurrency market.

3. Data description

To estimate our model, we collect daily, low, high and closing price data of cryptocurrencies from Yahoo! Finance. Our data focus is on native tokens of the Terra ecosystem (LUNC, USTC, ANC, and MIR), FTT and SOLANA for the period 1 January 2018 to 1 January 2023. Our study uses this timeframe given that this period witnessed several episodes of extreme volatility, which may allow us to generate robust estimates. We focus on these tokens given the calamitous events that rocked the crypto market in year 2022. Specifically, in May 2022, Terra ecosystem which had the third largest stable coin (USTC) lost a whopping $500 billion dollar to the market and its flagship coin, LUNA declined from an all-time high of about $106 to nearly 1 cent in 5 days. With the decline of Terra being identified as the first big project to fail, it culminated into a significant setback for other crypto assets. FTX, a prominent crypto exchange with a market valuation of $32 billion had a sudden and unprecedented downfall, leading to the collapse of its native coin FTT and suspension of trading by other notable crypto exchanges (Bouri et al., 2023; Jalan and Matkovskyy, 2023). Additionally, the value of Bitcoin, which serves as a key metric for assessing the overall state of the cryptocurrency market, also experienced a decline from an all-time high of $68,000 to less than $20,000. This significantly sparked liquidity crisis and impacted investor confidence, thus raising serious concerns on the connectedness of crypto assets. The dependent variables in our study are the return and volatility series of the sampled tokens. Following prior studies in the literature, returns R_t are computed as the first-order difference of the natural logarithm of the price index P_t (Colon et al., 2021) and the volatility series are computed by following the approach of Diebold and Yilmaz (2012):

$$R_t = 100^*[\Delta log(P_t)] \tag{1}$$

$$\delta_t^2 = 0.361\left[ln\left(P_t^{High}\right) - ln\left(P_t^{Low}\right)\right]^2 \tag{2}$$

Where δ_t^2, P_t^{High} and P_t^{Low} are an asset's volatility series, highest and lowest prices at day t, respectively.

As explanatory variables capturing factors that may affect the predictability of these tokens, we use four groups of predictors: economic uncertainty, political uncertainty, sentiment factors and specific market factors. To capture economic uncertainties, we use the economic policy uncertainty (EPU), implied volatility index (VIX) and monetary policy uncertainty (MPU) (Baker et al., 2016; Wang et al., 2020). For the political uncertainty, first we use geo-political risk data, then a dummy variable to capture Russia-Ukraine war. For example, a placeholder that takes the value of one (1) for days before the Russian invasion of Ukraine[4] and days after the invasion is zero (0). Data for the economic and political uncertainty are sourced from the economic policy uncertainty website (EPU).

Next, we sourced our main crypto sentiment data from Thomson Reuters Market-Psych Indices (TRMI). Likewise, we collect tweets on the tokens during the time frame, using https://twitter.com/explore and follow the methodological approach of Oliveira et al. (2016) to measure the textual tone of the tweets by calculating the number of negative words minus the number of positive words in a tweet, scaled by the total word count. We further obtain sentiment data on the tokens from https://reddit.com. We opine that internet trends or searches on Reddit gauge the extent of investors' anxieties about a token. Similar to prior studies that have used trading volume (Gagnon and Karolyi, 2009; Chen, 2012; Sakariyahu et al., 2021) to capture market factors, we include the natural logarithm of CEX-Vol and DEX-Vol. These proxies measure how much a token trades in the last 24 h on a centralized (CEX) and decentralised exchange (DEX), thus providing useful insights into investors' immediate response to any good or bad news. Furthermore, we introduce the returns on bitcoin, S&P 500 index, and FTSE-100 index as part of market variables to explain cross-dependence and co-movements. We include these variables since the literature acknowledges that any events around them, particularly Bitcoin, have the potential to transmit to other altcoins (Demir et al., 2018; Kalyvas et al., 2020). The variables, measures and sources are described in Table 1.

3.1. Empirical models

3.1.1. Estimating returns of sampled tokens

We turn attention to the empirical models employed in this study. To give a robust perspective to our results, we deemed it pertinent to estimate the returns of the tokens first, as a time-series component. We adopt this approach given that the events of the two eco-projects happened at separate periods, hence investors' reactions might be divergent. Our empirical strategy starts with the computation of Twitter/Reddit sentiment scores as shown below:

$$TSS = \left[\sum\nolimits_{n=i}^{m} NW - \sum\nolimits_{n=i}^{m} PW\right)]/\sum\nolimits_{n=i}^{m} TW \tag{3}$$

TSS, NW, PW, and TW represent Twitter (or Reddit) sentiment scores, negative words, positive words, and total words in a particular tweet, respectively. If the output of TSS is positive, it suggests that there are more negative words than positive ones.

Considering the distribution of the returns of the tokens, we adopt and specify a predictive regression model proposed by Welch and Goyal (2006), Rapach and Zhou (2013) and further developed by Rapach et al. (2016).

$$Returns_{t,t+h} = \alpha + \beta X_t + \varepsilon_{t,t+h} \tag{4}$$

Where $Returns_{t,t+h}$= (1/h) $(RET_{t+1} + \cdots + RET_{t+h})$ denotes the daily return of the tokens for day t. X_t represents the group of predictors: economic uncertainty proxies, political uncertainty proxies, sentiment factors, and market factors, h is the forecast horizon and β is a metric that quantifies the significance of X_t in forecasting the returns of the tokens. For example, when β equals 0.5, it indicates that a change of one standard deviation in the predictor linked to β would lead to a modification of 50 basis points in the returns of the tokens on the subsequent day. Regarding the h-day time horizons, we adhere to the methodology proposed by Rapach et al. (2016). The authors contend that a monthly in-sample R^2 statistic of around 0.5 % signifies a level of return predictability that is economically feasible.

Our aim is to investigate the importance of β in Equation (4), thus we compute a wild bootstrapped p-value in accordance with Rapach et al. (2016) to test H0: $\beta = 0$ against HA: $\beta > 0$. Moreover, according to Welch and Goyal (2008), the in-sample prediction could exaggerate the β associated with a certain predictor in real time. Thus, we further evaluate the predictability of the tokens' returns in an out-of-sample forecast setting. This is conducted after we find strong in-sample evidence that a predictor is statistically significant. Specifically, we aim to predict the out-of-sample returns of the token on day $(t + 1)$ using individual predictor variables up until day t. In addition, we estimate out-of-sample $R^2{}_{OS}$ statistic to evaluate the predictors' out-of-sample performance. The estimation processes are detailed below.

$$\widehat{RET}_{t,t+h} = \widehat{\alpha}_t + \widehat{\beta}_t x_t, \tag{5}$$

$$\mathrm{R}^2{}_{OS} = 1 - \frac{\sum_{t=m}^{T-h} (RET_{t+h} - \widehat{RET}_{t+h})^2}{\sum_{t=m}^{T-h} (RET_{t+h} - \overline{RET})^2}, \tag{6}$$

[4] Months after deploying its military close to the border with Ukraine, Russia officially launched its attack on Ukraine on 24 February 2022. Several months later, the war is still ongoing and has had a considerable impact on the global economy and financial markets.

Table 1
Definition of variables.

Variables	Measurements	Source
Returns (R_t)	first-order difference of the natural logarithm of the price index P_t	Yahoo! Finance
Economic Uncertainty	(i) Global economic policy uncertainty (GEPU) (ii) VIX (iii) Monetary policy uncertainty	Economic policy uncertainty (EPU) website
Political Uncertainty	(i) Geo-political risk (ii) Russia-Ukraine war (iii) Pandemic	(i) EPU website (ii) a placeholder that takes the value of one (1) for days before the Russian invasion of Ukraine and days after the invasion is zero (0) (iii) a placeholder that takes the value of one (1) for days before the pandemic and days after the pandemic is zero (0)
Sentiment factors	(i) TRMI (ii) Twitter Sentiment Score (TSS) (iii) Reddit Sentiment Score (RSS)	(i) Thomson Reuters Market-Psych Indices (ii) Twitter (iii) Reddit
Control variables	(i) CEX-Vol (ii) DEX-Vol (iii) BTC (iv) S&P (v) FTSE	(i) Coin market cap (ii) Coin market cap (iii) Yahoo! Finance (iv) investing.com (v) investing.com

Notes: This table shows the variables considered in this paper and their sources.
EPU website: http://www.policyuncertainty.com/index.html.
Twitter website: https://twitter.com/explore.
Reddit website: https://reddit.com.
Coin market cap website: Cryptocurrency Prices, Charts And Market Capitalizations | CoinMarketCap.
Yahoo! Finance website: https://finance.yahoo.com/.
Investing.com website: https://uk.Investing.com/.

Table 2
Summary statistics.

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	J-B	ERS	Q (20)
Panel A: Price series of tokens									
FTT	36.63	14.34	0.85	79.87	3.48	7.19	320.11**	−10.19	509.22***
SOL	72.36	62.37	1.80	258.93	3.02	10.11	592.80**	−15.11	410.04***
LUNC	27.34	32.02	0.00	116.41	2.79	13.27	480.02*	−12.18	390.33***
USTC	0.73	0.43	0.007	1.04	3.70	9.19	405.61**	−13.55	532.11***
MIR	2.90	2.59	0.16	12.46	2.84	7.08	601.15*	−9.01	409.22***
ANC	2.34	1.37	0.08	5.91	1.66	7.35	855.23*	−10.11	501.34***
Panel B: Economic uncertainty									
GEPU	138.13	55.90	37.25	198.16	1.08	1.55	451.09**	−21.18	229.80***
VIX	22.62	4.89	15.01	38.50	1.54	2.60	101.19**	−19.70	127.19**
MPU	89.17	6.22	35.10	258.01	1.99	3.18	290.11**	−19.89	155.08**
Panel C: Political uncertainty									
GPR	87.56	44.12	20.19	155.10	1.722	4.409	281.22**	−10.35	180.19**
War	0.45	0.39	0.00	0.98	1.01	3.20	45.30***	−19.26	155.46**
Pandemic	0.29	0.50	0.00	1.00	0.75	4.59	36.18***	−14.54	129.37**
Panel D: Sentiment factors									
TRMI	0.68	0.37	0.12	1.45	1.76	3.39	59.12***	−27.10	200.189*
TSS	0.33	0.55	0.26	1.37	1.25	3.06	65.17***	–23.45	146.09**
RSS	0.51	0.46	0.47	0.78	1.39	3.65	44.21***	−16.04	134.36**
Panel E: Market characteristics									
CEX-Vol	5.24	4.29	2.65	12.19	1.45	3.98	72.55***	−17.88	120.15***
DEX-Vol	6.31	5.55	2.44	17.44	3.08	4.29	87.63***	−21.09	172.34***
BTC	37,888.2	13,769	15,787	67,566.8	2.82	15.66	489.24*	−12.10	490.41**
S&P	4,185.45	303.24	3,577	4,796.56	2.98	18.09	823.15**	−9.76	534.15***
FTSE	7,173.27	283.14	6,407	7,672.4	3.43	22.10	770.12**	−11.89	540.23***

This table shows the descriptive statistics of all variables used in this study. Panels A, B, C, D and E show the price series of the tokens, economic uncertainty indices, political uncertainty indices, sentiment factors, and market characteristics, respectively.

Table 3
In-sample predictive regression estimation results ($h = 1$ *day*).

	LUNC			ANC			USTC			MIR			FTT			SOL			Equally-weighted			Value-weighted		
	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)
Panel A: Economic Uncertainty factors																								
GEPU	0.09	1.19**	0.51	0.16	1.25*	0.11	0.14	0.21*	0.43	0.25	0.41**	0.39	0.08	0.25***	0.16	0.12	0.43**	0.25	0.30	0.17	0.11	0.05	0.29	0.41
VIX	0.21	1.38***	0.44	0.09	0.87*	1.08	0.02	0.30	0.24	0.19	0.37*	0.54	0.13	0.04	0.72	0.09	0.38	0.31	0.12	0.06*	0.22	0.31	0.23**	0.15
MPU	0.16	0.96*	0.29	0.01	0.34	0.35	0.05	0.29***	0.51	0.10	0.28	0.07	0.21	0.17	0.06	0.10	0.15**	0.57	0.02	0.19	0.25	0.04	0.38	0.02
Panel B: Political Uncertainty factors																								
GPR	0.07	1.06	0.31	0.03	0.94	0.12	0.25	0.61*	0.35	0.06	0.17	0.22	0.10	0.02**	0.35	0.07	0.18*	0.35	0.21	0.19	0.28	0.30	0.16	0.09
War	0.13	1.15*	0.42	0.05	0.61**	0.52	0.08	0.13**	0.24	0.18	0.04*	0.15	0.27	0.17***	0.82	0.12	0.40	0.54	0.31	0.28	0.36	0.23	0.01	0.43
Pandemic	0.12	0.82*	0.65	0.22	0.73	0.21	0.21	0.39*	0.12	0.26	0.03	0.50	0.31	0.44	0.09	0.25	0.18*	0.29	0.37	0.05*	0.11	0.09	0.34*	0.20
Panel C: Sentiment factors																								
TRMI	0.09	0.55	0.38	0.13	0.65***	0.26	0.37	0.21	0.18	0.30	0.11**	0.10	0.06	0.53	0.41	0.32	0.18**	0.03	0.25	0.61	0.39	0.46	0.31	0.22
TSS	0.06	0.93*	0.60	0.19	0.93*	0.61	0.09	0.18***	0.24	0.48	0.35	0.64	0.50	0.16*	0.33	0.12	0.27	0.58	0.09	0.53	0.21	0.10	0.37	0.24
RSS	0.07	0.60**	0.52	0.30	0.77	0.33	0.27	0.46*	0.17	0.02	0.18*	0.05	0.16	0.49**	0.58	0.35	0.10*	0.21	0.25	0.09	0.15	0.08	0.30	0.15
Panel D: Market characteristics																								
CEX-Vol	0.14	1.02*	0.64	0.17	0.80**	0.09	0.30	0.18	0.26	0.31	0.22*	0.59	0.37	0.56	0.19	0.23	0.17	0.33	0.26	0.04	0.19	0.22	0.04	0.17
DEX-Vol	0.20	0.99*	0.37	0.03	1.05	0.27	0.18	0.10**	0.19	0.15*	0.07**	0.51	0.29	0.38	0.40	0.27	0.20	0.14	0.28	0.31	0.25	0.09	0.13	0.21
BTC	0.17	1.96***	0.56	0.42	0.73***	0.55	0.41	0.33*	0.13	0.19	0.40	0.52	0.57	1.34***	0.65	0.40	0.78*	0.69	0.09	0.43*	0.33	0.21	0.60*	0.12
S&P	0.08	0.58	0.44	0.09	0.64	0.38	0.26	0.15	0.34	0.30	0.16**	0.11	0.15	0.89*	0.07	0.22	0.37	0.08	0.14	0.10	0.25	0.08	0.17	0.20
FTSE	0.12	1.03	0.35	0.14	0.19	0.26	0.20	0.19**	0.25	0.41	0.09*	0.47	0.20	0.15	0.30	0.29	0.17	0.06	0.21	0.35	0.06	0.11	0.08	0.17

This table reports the ordinary least squares estimate of β and R^2 statistic for the predictive regression model. The outcome variable is the token's excess return. The key explanatory variables are the predictors: economic uncertainty factor, political uncertainty factors, sentiment factors and market characteristics. Definitions of variables and data sources are provided in table 1. *, **, *** stand for levels of significance at 10%, 5% and 1% respectively.

Table 4

In-sample predictive regression estimation results (*h* = *7 days*). This table reports the ordinary least squares estimate of β and R^2 statistic for the predictive regression model. The outcome variable is the token's excess return. The key explanatory variables are the predictors: economic uncertainty factor, political uncertainty factors, sentiment factors and market factors.

	LUNC			ANC			USTC			MIR			FTT			SOL			Equally-weighted			Value-weighted		
	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)	$\hat{\beta}$	t-stat	R^2 (%)
Panel A: Economic Uncertainty factors																								
GEPU	0.13	1.10**	0.23	0.15	0.39**	0.48	0.06	0.38**	0.33	0.26	0.26**	0.43	0.33	0.20*	0.31	0.19	0.37	0.31	0.20	0.04	0.11	0.29	0.36	0.23
VIX	0.26	1.48***	0.18	0.32	0.27*	0.50	0.09	0.26*	0.29	0.19	0.20*	0.29	0.08	0.11	0.50	0.23	0.33	0.25	0.07	0.13***	0.24	0.10	0.24*	0.08
MPU	0.14	0.76	0.09	0.08	0.16	0.12	0.24	0.30	0.72	0.24	0.36	0.50	0.34	0.30**	0.41	0.34	0.29*	0.62	0.11	0.19	0.08	0.24	0.15	0.24
Panel B: Political Uncertainty factors																								
GPR	0.08	1.39*	0.16	0.36	1.31*	0.37	0.18	0.24*	0.79	0.03	0.22**	0.39	0.33	0.10	0.62	0.18	0.40	0.68	0.23	0.19	0.26	0.01	0.18	0.29
War	0.11	1.13**	0.20	0.23	0.73**	0.40	0.27	0.38**	0.34	0.01	0.40*	0.28	0.58	0.12*	0.44	0.13	0.38	0.53	0.15	0.07	0.32	0.14	0.05	0.17
Pandemic	0.05	1.47	0.13	0.19	0.51	0.29	0.15	0.20	0.83	0.14	0.35*	0.44	0.56	0.08	0.35	0.29	0.27*	0.46	0.06	0.14	0.21	0.14	0.30	0.25
Panel C: Sentiment factors																								
TRMI	0.19	1.25*	0.47	0.26	0.33***	0.36	0.19	0.08*	0.43	0.26	0.29*	0.14	0.23	0.29	0.38	0.25	0.10**	0.78	0.30	0.15	0.29	0.10	0.25	0.09
TSS	0.26	1.11	0.29	0.31	0.50	0.49	0.26	0.31	0.28	0.15	0.30	0.42	0.19	0.17*	0.26	0.31	0.22	0.51	0.18	0.13	0.08	0.16	0.21	0.17
RSS	0.10	0.98*	0.16	0.42	0.28**	0.33	0.14	0.27**	0.32	0.21	0.18*	0.50	0.22	0.36	0.40	0.28	0.35*	0.42	0.06	0.22	0.11	0.14	0.05	0.19
Panel D: Market characteristics																								
CEX-Vol	0.19	1.16**	0.39	0.29	0.49*	0.38	0.20	0.12***	0.27	0.03	0.31*	0.29	0.37	0.15**	0.30	0.36	0.29	0.70	0.09	0.15	0.26	0.34	0.07	0.12
DEX-Vol	0.15	1.40**	0.71	0.41	0.30	0.42	0.17	0.36**	0.41	0.21	0.24*	0.35	0.38	0.30*	0.95	0.10	0.17	0.55	0.22	0.19	0.07	0.10	0.25	0.17
BTC	0.05	1.25*	0.58	0.33	0.27**	0.56	0.25	0.48*	0.43	0.24	0.15	0.11	0.26	0.39	0.84	0.25	0.30*	0.83	0.08	0.20	0.06	0.12	0.31	0.25
S&P	0.09	0.71***	0.42	0.52	0.38	0.32	0.24	0.29	0.32	0.16	0.39	0.28	0.22	0.28*	0.60	0.11	0.26	0.42	0.23	0.15	0.34	0.16	0.28	0.17
FTSE	0.17	0.95**	0.60	0.28	0.19***	0.18	0.30	0.12**	0.39	0.30	0.51**	0.42	0.37	0.21	0.81	0.46	0.33*	0.50	0.25	0.36	0.27	0.18	0.05	0.11

Definitions of variables and data sources are provided in table 1. *, **, *** stand for levels of significance at 10%, 5% and 1% respectively.

4. Empirical analysis

Table 2 reports the summary statistics of the price series of the sampled tokens, the economic uncertainty index, the political uncertainty index, behavioural factors, and control variables. The results of the skewness, kurtosis and Jarque-Bera show that all the series, at the 1 % level of significance, are not normally distributed. The results of Fisher and Gallagher's (2012) portmanteau tests (Q) also reject the null hypothesis of no autocorrelation for all the series, thus suggesting evidence of serial correlation within the series. We also test for stationarity using Elliot et al. (1996) (ERS) test and the results show that the series are stationary, at least, at the 1 % level of significance.

The findings obtained from the in-sample test utilising the predictive regression across different tokens are presented in Tables 3 and 4. We ensure the inclusion of predictors with robust in-sample evidence by establishing a baseline based on two criteria. For the predictor(s) to be considered statistically significant, it is necessary for the estimated coefficient to meet this criterion. Furthermore, it is necessary for the in-sample R^2 statistic to exceed 0.5 % since a monthly statistic of 0.5 % signifies a significant level of predictability in terms of returns, as established by previous studies (see Rapach et al., 2016). The LUNC token demonstrates the presence of six predictors that surpass the benchmark, as determined by the specified criteria. They consist of one predictor derived from economic uncertainty, one predictor derived from political uncertainty, two predictors derived from behavioural or sentiment factors, and two predictors derived from market factors. The token's DEX-Vol has the highest estimated $\hat{\beta}$ value (0.20) among the predictors, indicating that a one-standard deviation rise in DEX-Vol results in a 20-basis point increase in the subsequent day's LUNC excess returns. Furthermore, the excess returns of the token exhibit a substantial correlation with variations in nearly all the predictors, except for GPR, TRMI, S&P, and FTSE.

The ANC token also adheres to the benchmark criteria by the inclusion of one predictor pertaining to economic uncertainty factors, one predictor related to political uncertainty elements, one predictor associated with behavioural variables, and one predictor concerning market components. Among the many predictors examined, it is evident that GEPU, VIX, War, TRMI, TSS, CEX-Vol, and BTC exhibit significantly higher levels of predictive capability compared to other predictors. Specifically, their respective estimators are 0.16, 0.09, 0.05, 0.13, 0.19, 0.17, and 0.12. The R^2 statistics provide additional support for our estimation findings. BTC exhibits the highest $\hat{\beta}$ estimate of 0.42 among the predictors, indicating that a one-standard deviation increase in BTC results in a 42-basis point increase in the subsequent day's ANC excess returns. Furthermore, there is a notable correlation between the excess returns of the token and fluctuations in GEPU, VIX, War, TRMI, TSS, CEX-Vol, and BTC.

In relation to the USTC token it is found that only one predictor among the economic uncertainty components satisfies the benchmark criteria of a 0.5 % degree of return predictability. Except for VIX, TRMI, CEX-Vol, and S&P, the remaining predictors exhibit significantly greater predictive efficacy compared to other predictors. The R^2 statistics provide additional support for our estimation findings. The predictor with the highest estimated coefficient, $\hat{\beta}$, is TRMI, which has a value of 0.37. This indicates that a

Table 5
Out-of-sample test results (*h = 1 day*).

	LUNC		ANC		USTC		MIR		FTT		SOL	
	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat
Panel A: Economic Uncertainty factors												
GEPU	0.33	1.49**	0.51	1.23	0.41	1.91	0.42	1.64	0.45	1.31	0.39	1.37**
VIX	0.20	1.35**	0.19	0.98	0.38	1.27**	0.20	0.89**	0.20	0.92*	0.24	2.91*
MPU	0.29	1.08	0.35	1.46*	0.26	1.35	0.11	1.23	0.31	0.85	0.32	1.59
Panel B: Political Uncertainty factors												
GPR	−0.35	−3.07	0.28	1.59	0.29	0.77	0.34	0.84	0.27	1.15	0.35	1.44
War	0.21	1.96	0.51	0.92**	0.35	1.61***	0.26	0.52	0.33	1.48**	0.26	0.82**
Pandemic	0.46	2.20***	0.30	1.51	0.44	1.70	0.31	1.33*	0.19	2.35	0.35	1.40
Panel C: Sentiment factors												
TRMI	0.36	1.23	0.58	1.24***	0.53	1.47	0.24	0.50	0.46	2.30	0.89	1.77
TSS	0.73	2.09*	−0.29	0.37	0.28	1.33	0.10	0.89***	0.14	1.08	0.37	2.43
RSS	0.61	1.98	0.36	1.53	0.50	2.70*	0.67	1.46	0.37	1.20**	0.18	1.30*
Panel D: Market characteristics												
CEX-Vol	0.84	1.67**	0.47	1.40**	0.82	1.08**	0.64	1.55*	0.56	1.17	0.22	1.57
DEX-Vol	−0.37	−1.20	0.35	0.84	0.38	0.91	0.83	0.92	0.44	0.97	0.39	2.11***
BTC	0.51	1.46***	0.26	1.67***	0.21	2.29*	0.45	1.30**	0.26	1.30*	0.30	1.49*
S&P	0.69	2.48	0.45	1.34	0.33	0.96	0.52	1.40	0.32	1.49	0.14	1.38
FTSE	0.30	1.27	0.39	0.78*	0.25	1.80	0.36	0.91	0.29	1.24**	0.21	1.54

This table reports the R^2 statistic and C-W stat for different tokens. Predictive regression forecast of the excess return is based on the predictors: economic uncertainty factor, political uncertainty factors, sentiment factors and market factors. Definitions of variables and data sources are provided in table 1. *, **, *** stand for levels of significance at 10%, 5% and 1% respectively. Statistical significance is based on the Clark and West (2007) statistic.

one-standard deviation rise in TRMI is associated with a 37-basis point increase in the USTC excess returns observed on the following day. The MIR token exhibits predictors that satisfy the specified criteria, encompassing one predictor derived from economic uncertainty factors, one from political uncertainty factors, one from behavioural or sentiment components, and three from market elements. Most of the predictors also exhibit substantial predictive capability. In the case of both FTT and SOL, it is seen that only one predictor from each set of predictors satisfies the benchmark condition of exhibiting a degree of return predictability of at least 0.5 %. BTC has the highest β estimate among the predictors for both tokens, with values of 0.57 and 0.40, respectively. This indicates that a one-standard deviation increase in BTC results in a 57 and 40 basis points increase in the subsequent day's excess returns for the two tokens. The results obtained over the 7-day timeframe, as presented in Table 4, exhibit a resemblance to the findings depicted in Table 3, with no significant disparities seen.

In general, the findings of our study align with those of Demir et al. (2018), suggesting that external uncertainty variables possess a robust predictive capacity. The findings of our study provide additional evidence to bolster the claim that political events, economic events, sentiment indicators, and intrinsic market traits possess substantial predictive capabilities, thus affirming the two hypotheses for this study. The results of our study suggest that policy-related economic uncertainty and financial market uncertainty have a predictive relationship with cryptocurrencies. It is evident that several predictors have been excluded due to either their lack of statistical significance in the estimated coefficient β or their R^2 value being less than 0.5 %. Nevertheless, this discovery aligns with expectations, as Rapach et al. (2016) demonstrate that only a limited number of factors that forecast overall stock returns exhibit significant predictive ability. Nevertheless, the Stambaugh bias may affect in-sample forecasts; hence, evaluating out-of-sample predictability is crucial.

4.1. *Out-of-sample forecasting*

Welch and Goyal (2008) argue that the phenomenon of in-sample predictability may arise due to overfitting, whereas out-of-sample forecasting provides a more rigorous assessment of return predictability. In the next set of analysis, we place greater emphasis on our out-of-sample findings. Tables 5 and 6 display the out-of-sample R^2 (R^2OS) and Clark and West's (2007) MSFE adjusted statistics for the out-of-sample return predictability across the sampled tokens. We choose the predictors that have positive R^2OS values and demonstrate statistical significance according to the Clark and West (2007) test. Our analysis specifically examines predictors that have a positive estimated coefficient (β) and an in-sample R^2 greater than 0.5 %.

In the context of the LUNC token, it is observed that all predictors, except for GPR and DEX-Vol, demonstrate a positive R^2OS. The statistical significance of the Clark and West (2007) test outcomes is also established. Moreover, the predictors for ANC demonstrate positive R^2OS values, and the test findings conducted by Clark and West (2007) are statistically significant. However, the TSS predictor does not match the established threshold. In the case of USTC, MIR, FTT, and SOL, it is observed that all the predictors demonstrate a

Table 6
Out-of-sample test results (*h* = *7 days*).

	LUNC		ANC		USTC		MIR		FTT		SOL	
	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat	R^2 (%)	CW-stat
Panel A: Economic Uncertainty factors												
GEPU	0.31	1.54**	0.22	1.03	0.35	1.08	0.12	0.76	0.23	1.08	0.17	0.84
VIX	0.19	0.74	0.37	1.14*	0.28	1.45**	0.30	1.58	0.17	1.01*	0.13	0.78*
MPU	0.23	1.09	0.06	1.39	0.10	1.96	0.18	0.96	0.34	0.96	0.21	1.03
Panel B: Political Uncertainty factors												
GPR	0.18	1.45	0.34	0.95	0.12	1.80	0.25	1.41**	0.17	0.95	0.14	0.93
War	0.26	0.90*	0.27	1.09**	0.23	1.14	0.33	1.60	0.29	1.07*	0.28	1.01**
Pandemic	0.33	0.76**	0.15	1.37	0.16	1.45*	0.14	2.07	0.24	0.98	0.16	0.79
Panel C: Sentiment factors												
TRMI	0.16	1.20	0.14	0.99	0.29	1.70*	0.26	1.39*	0.31	1.15	0.20	0.89
TSS	0.37	0.77	0.26	1.15**	0.35	0.96**	0.22	1.44	0.34	1.01	0.14	1.04
RSS	0.26	0.94*	0.14	0.96	0.28	1.50	0.10	0.72	0.47	1.22**	0.26	0.93*
Panel D: Market characteristics												
CEX-Vol	0.13	1.42	0.21	1.31	0.13	0.82	0.13	2.15	0.33	0.95	0.09	0.85
DEX-Vol	0.18	0.95	0.10	1.25	0.24	1.27*	0.28	1.29*	0.26	1.19*	0.17	0.92**
BTC	0.40	2.11**	0.14	1.31**	0.30	1.33***	0.13	1.40**	0.14	0.98***	0.13	0.70
S&P	0.35	1.27	0.17	1.42	0.25	1.08	0.18	1.75	0.23	1.00	0.22	1.18***
FTSE	0.16	0.89	0.24	1.39	0.16	1.43*	0.15	0.94	0.16	0.85	0.14	1.43

This table reports the R^2 statistic and C-W stat for different tokens. Predictive regression forecast of the excess return is based on the predictors: economic uncertainty factor, political uncertainty factors, sentiment factors and market factors. Definitions of variables and data sources are provided in Table 1. *, **, *** stand for levels of significance at 10%, 5% and 1% respectively. Statistical significance is based on the Clark and West (2007) statistic.

positive R^2OS, and the statistical significance of the Clark and West (2007) test results is evident. The robust performance exhibited by these predictors aligns with previous research findings, which indicate that returns in the cryptocurrency market exhibit a high degree of volatility (see Detzel et al., 2020). Therefore, it may be argued that significant economic benefits can be attained by considering the potential risks posed by external uncertainty factors.

Moreira and Muir (2017) discover that utility gains are substantial for volatility-managed portfolios, which employ low weights during periods of high volatility and high weights during periods of low volatility. As a result, we scale down our predictors downwards during periods of low volatility and upwards during periods of high volatility, thereby ultimately enhancing the accuracy of predictions. It is worth mentioning that the reduction in the number of predictors aligns with the findings of Rapach, Ringgenberg, and Zhou (2016). There is a contention that the significant reduction in the quantity of predictors may be associated with the spuriously high in-sample return predictability that can be generated by highly persistent predictors. The sentiment predictors, particularly TRMI, exhibit superior performance compared to all other predictors, as evidenced by the highest R^2OS statistic of 0.89 %. Based on these results, it appears that predictive regression forecasts that incorporate this sentiment factor generate a significantly reduced MSFE and surpass the performance of the benchmark.

4.2. Estimating volatility and cross-dependence

To explore the dynamic connectedness and spill-over effects among the tokens, we introduce the GJR GARCH-MIDAS model. This helps in explaining the impact of positive (good news) and negative (bad news) shocks. The GARCH-MIDAS model, which is widely used in financial research, incorporates mixed frequency sampling to effectively separate the overall conditional volatility of assets into distinct short-term and long-term components (Sakariyahu et al., 2023). The model is estimated as follows:

$$g_t = (1-\alpha-\beta-0.5\gamma)+\left(\alpha+1_{(rt-1)}\gamma\right)x\frac{(r_t-\mu)^2}{\gamma_t}+\beta g_{t-1} \tag{7}$$

Table 7
Estimating short- and long-term volatilities & Estimation results for the GJR GARCH-MIDAS model.

	LUNC	UST	ANC	MIR	FTT	SOL
μ	0.044***	0.023**	0.065***	0.045*	0.056**	0.035***
	(0.013)	(0.012)	(0.012)	(0.009)	(0.011)	(0.012)
α	0.513**	0.534*	0.525***	0.553*	0.551**	0.535***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.002)	(0.004)
B	0.420*	0.438***	0.450*	0.422***	0.436*	0.455***
	(0.013)	(0.011)	(0.009)	(0.011)	(0.012)	(0.009)
Ω	2.59***	2.38**	1.57*	1.55***	1.63***	2.35
	(0.480)	(0.299)	(0.172)	(0.138)	(0.156)	(0.221)
M	0.433*	0.398	0.541***	0.250**	0.681***	0.567***
	(0.036)	(0.058)	(0.073)	(0.058)	(0.042)	(0.055)
Θ	0.177**	0.114**	2.35	2.19	0.567***	−0.613
	(0.003)	(0.008)	(0.221)	(0.065)	(0.055)	(0.039)
θ *	0.031***	0.056**	0.205***	0.104*	0.030**	0.125**
	(0.001)	(0.026)	(0.015)	(0.093)	(0.032)	(0.001)
$\theta+$	0.342**	0.411*	0.200**	0.311*	0.142*	0.315**
	(0.000)	(0.003)	(0.000)	(0.000)	(0.002)	(0.004)
$\theta-$	0.255*	0.311**	0.201*	0.221**	0.321*	0.252***
	(0.022)	(0.005)	(0.009)	(0.033)	(0.022)	(0.011)
$\theta+$*	0.152**	0.326**	0.212*	0.321**	0.341**	0.521
	(0.081)	(0.029)	(0.012)	(0.131)	(0.162)	(0.121)
$\theta-$*	0.315*	0.293*	0.421**	0.125**	0.221**	0.361**
	(0.036)	(0.058)	(0.073)	(0.058)	(0.042)	(0.055)
γ	0.121**	0.143**	0.251	0.191	0.367**	0.123
	(0.003)	(0.008)	(0.221)	(0.065)	(0.055)	(0.039)
$\gamma+$	0.139*	0.141*	0.225***	0.223*	0.190*	0.322**
	(0.000)	(0.003)	(0.000)	(0.000)	(0.002)	(0.004)
$\gamma-$	0.250*	0.328***	0.125*	0.220**	0.311*	0.225*
	(0.013)	(0.011)	(0.009)	(0.011)	(0.012)	(0.009)
$\gamma+$*	0.59***	0.230**	0.457	0.155***	0.363***	0.35
	(0.103)	(0.212)	(0.215)	(0.181)	(0.215)	(0.021)
$\gamma-$*	0.133*	0.228	0.133***	0.190**	0.323**	0.352***
	(0.036)	(0.058)	(0.073)	(0.058)	(0.042)	(0.055)

This table shows the output of the GJR GARCH-MIDAS model. We report the coefficients and the standard errors (shown in parentheses). ***, **, * refer to statistical significance level at 1%, 5%, and 10% respectively. Variable coefficients: The constant component in the GARCH model is represented by the symbol (alpha), which represents the impact of past squared returns on current volatility. Using the symbol (beta), we represent the coefficient of the delayed conditional variance, which demonstrates the persistence of volatility shocks through time. The average rate of return is represented by the Greek symbol mu. The conditional variance coefficient is represented by the symbol (omega). The lagged conditional variance coefficient is denoted in the GARCH model by the notation (theta). This coefficient represents the effect of prior volatility on current levels of unpredictability.

$$\gamma_t = m + \theta^- \sum_t^N \varphi_k(\omega) RS_t^- + \theta^+ \sum_t^N \varphi_k(\omega) RS_t^+ \tag{8}$$

Importantly, we also assessed the potency of equations (7) and (8) by examining the out-of-sample forecasting abilities to determine the future predictive power of the models. Precisely, we followed the literature (Pan and Liu, 2018; Wang et al., 2020) to adopt six loss-function criteria as follows:

$$MSE = \frac{1}{M} \sum_{i=1}^{M} \left(\sigma_i^2 - \widehat{\sigma}_i^2\right)^2 \tag{9}$$

$$MAE = \frac{1}{M} \sum_{i=1}^{M} \left| \left(\sigma_i^2 - \widehat{\sigma}_i^2\right)^2 \right| \tag{10}$$

$$HMSE = \frac{1}{M} \sum_{i=1}^{M} \left(1 - \sigma_i^2 / \widehat{\sigma}_i^2\right)^2 \tag{11}$$

$$HMAE = \frac{1}{M} \sum_{i=1}^{M} \left| \left(1 - \sigma_i^2 / \widehat{\sigma}_i^2\right)^2 \right| \tag{12}$$

$$R^2LOG = \frac{1}{M} \sum_{i=1}^{M} \left(\ln\left(\sigma_i^2 / \widehat{\sigma}_i^2\right)\right)^2 \tag{13}$$

$$QLIKE = \frac{1}{M} \sum_{i=1}^{M} \ln\left(\widehat{\sigma}_i^2\right) - \sigma_i^2 / \widehat{\sigma}_i^2 \tag{14}$$

MSE and *MAE* represent the mean squared error and mean absolute error, while *HMSE* and *HMAE* are the non-linear heteroscedasticity-adjusted versions of *MSE* and *MAE*, respectively. R^2LOG represents the regression coefficient of determination, and *QLIKE* denotes the impact of extreme volatility. M in the above equation represents the total number of out-of-sample volatility forecasts; ${\sigma_i}^2$ denotes the actual volatility value, which is calculated as a squared daily return, while $\hat{\sigma_i}^2$ is the forecast value of volatility obtained from equations (6)–(7) above.

We further employ the TVP-VAR methodology developed by Antonakakis et al. (2020), regarding dynamic connectedness of assets. Literature identifies two primary benefits associated with this methodology. First, it addresses the difficulty associated with the arbitrary selection of the most suitable rolling-window size (Sakariyahu et al., 2023). Additionally, this approach effectively addresses the issue of potential loss of valuable observations, rendering it applicable even in cases of limited sample size. By employing this approach, we check for the average and dynamic connectedness among the sampled tokens. The TVP-VAR model is formulated as follows:

$$y_t = C_t v_{t-1} + \mu_t \mu_t | \rho_{t-1} \quad N(0, \tau_t) \tag{15}$$

Table 7 shows the dynamic connectedness and spill-over transmission effects among the sampled tokens for short- and long-term volatilities. In the short-term elements, the parameters of the GJR-MIDAS model are all statistically significant, indicating a solid

Table 8
Out-of-sample results of the Diebold–Mariano test for the tokens.

	LUNC	UST	ANC	MIR	FTT	SOL
MSE	0.906**	0.912*	0.780	0.900**	0.855*	0.723*
	(−1.22)	(−0.98)	(−1.57)	(−3.41)	(−2.09)	(−1.10)
MAE	0.889*	1.074***	1.250	0.857*	0.460**	0.255*
	(−0.887)	(−0.625)	(−1.150)	(−1.213)	(−0.687)	(−0.804)
HMSE	0.945**	0.930*	1.216*	0.830*	0.910	0.718**
	(−0.531)	(−0.722)	(−0.556)	(−0.442)	(−0.610)	(−0.433)
HMAE	0.963*	0.961	1.008*	0.944**	0.922**	0.681
	(−0.713)	(−0.544)	(−0.912)	(−1.300)	(−1.446)	(−0.257)
R^2LOG	0.876**	0.533	0.448*	0.455*	0.813	0.870*
	(−1.233)	(−0.242)	(−1.066)	(−0.412)	(−0.551)	(−0.367)
QLIKE	0.870	0.685*	0.621	0.866**	0.851*	0.670**
	(−0.844)	(−0.751)	(−1.101)	(−1.106)	(−0.883)	(−0.677)

This table reports the forecasting performance of the tokens using the GARCH-MIDAS model. A ratio lower than 1 suggests that the model has better predictive ability than the standard model. We report the t-statistics, and the standard errors are shown in parentheses. ***, **, * refer to statistical significance level at 1%, 5%, and 10%, respectively.

Table 9
Average joint connectedness of variables.

	LUNC	UST	ANC	MIR	FTT	SOL	EU	PU	BF	BTC	S&P	FTSE	FROM
LUNC	42.19	9.02	4.19	6.37	7.24	7.30	7.19	4.22	6.34	0.11	0.08	0.18	49.35
UST	4.18	43.08	5.58	7.06	6.13	6.03	8.21	5.19	7.02	0.93	0.31	0.11	41.12
ANC	5.12	4.33	38.55	6.06	6.13	7.82	6.12	4.23	6.02	0.53	0.14	0.41	45.92
MIR	4.12	7.08	6.01	45.71	8.02	6.09	1.08	6.31	7.33	2.64	2.38	1.15	50.23
FTT	5.09	5.81	5.04	7.19	48.33	7.15	7.03	3.55	6.14	0.62	0.37	0.67	56.44
SOL	5.03	7.30	1.15	4.20	7.87	56.00	3.14	4.19	6.69	0.74	1.40	2.08	45.00
EU	9.61	6.14	3.67	5.38	7.45	8.48	47.67	4.11	7.51	2.61	1.73	8.74	55.01
PU	4.21	3.10	2.22	4.19	5.08	4.77	5.18	49.51	6.22	3.66	5.19	1.84	60.00
BF	6.62	7.38	4.08	1.771	7.12	8.14	1.95	5.19	51.91	1.93	1.32	4.33	45.90
BTC	8.24	6.37	4.74	3.72	8.51	7.73	8.71	6.11	0.16	52.70	1.30	1.40	50.32
S&P	5.51	11.440	1.884	3.28	6.56	8.31	7.89	5.03	3.28	1.93	33.29	2.19	50.66
FTSE	5.03	8.763	11.4	4.35	5.17	6.64	1.14	4.44	5.732	1.55	2.45	48.44	40.23
TO	55.67	49.23	55.12	47.40	46.75	45.99	47.29	40.00	50.43	45.31	65.09	35.90	584.18
NET	6.32	8.11	−0.80	−12.8	−9.69	−19.0	2.29	2.29	14.53	−5.01	14.43	−4.33	TCI = 23.05

The above table is based on a TVP-VAR model with two lags and the values are determined by the Bayesian Information Criterion. TO in the table refers to the extent of volatility transmission from one token to others, excluding its own contribution while FROM explains the extent of volatility spill over a token receives from all other tokens. The difference between TO and FROM is the net volatility transmission indicated with NET. TCI denotes the average of the total connectedness index. EU, PU, BF represent economic uncertainty, political uncertainty, behavioural factors, respectively.

volatility clustering effect for the short-term fluctuations of LUNC, UST, ANC, MIR, FTT, & SOL at 1 %, 5 % and 10 % level of significant. The other short-term components showed mixed results, such as LUNC, UST and FTT, indicating a solid volatility clustering effect for the short-term fluctuations, while ANC, MIR, and SOL tokens are not statistically significant. The result indicates that in the Terra ecosystem, the collapse of old LUNA significantly cascades to the Anchor protocol (ANC), Mirror protocol (MIR), and the stablecoin for the ecosystem (UST). Similarly, we confirm that the impact of the FTX token (FTT) transmits to the Solana (SOL) ecosystem, whose primary holder was FTX. Explicitly, the parameters are all greater than zero and close to 1, indicating that the impact of positive shocks on short-term volatility is minimal. Similarly, the parameters of the short-term price volatility is strongly influenced by prior period volatility, and short-term volatility is highly memorable and persistent. Since the parameters are all positive, it therefore indicates that short-term price volatility has an asymmetric nature of shocks, and adverse shocks have a more significant impact than positive shocks of the same magnitude.

In the long-term component, the parameter of the model is significant. The estimation result confirms a positive relationship between these tokens and other projects within the same ecosystem and that risk from assets in the same environment impacts other assets within the same ecosystem. We can extract the following conclusion from the result. According to the parameters, the leading crypto assets in the terra ecosystem (LUNC & UST) are significantly positive. This indicates that for the sample period under consideration for the study, high uncertainty in the leading asset exacerbates the long-term variation in ANC and MIR within the same environment. Similarly, FTT is significantly positive, with a long-term variation effect on SOL. From a crypto trading and investment perspective, when a token within the same ecosystem is distressed, it spreads to another token with the same environment. Hence, portfolio managers should diversify appropriately because of the spillover from the impact of bad (or good) news on these tokens (Corbet et al., 2020). The consequence of having a portfolio of assets from the same ecosystem is that the fall (or rise) of one token has a corresponding effect on others, hence a contagion.

We further report the outcome of the loss functions using the D-M technique shown in Table 8. The results reveal that the model with extreme long-term volatility produces less statistical accuracy considering that it has a ratio of less than 1 for only four out of six loss criteria. The finding implies that, in the long run, extreme uncertainty factors do not significantly affect volatility forecasts for the cryptocurrency market. Notwithstanding, we can conclude that the model adequately predicts future volatility depending on the choice of the loss function (Wang et al., 2020).

Lastly, for additional checks, we use the time-varying vector autoregression (TVP-VAR) model to further analyse the average connectedness among the variables. The results, shown in Table 9, explain the cross-correlation from one variable to another and their contribution. The columns communicate the impact of each token on other tokens, while the rows explain the contribution of each token to the forecast error variance. Empirically, our results indicate that the average total connectedness index (TCI) is 23.05 %. The result suggests that the uncertainty indices explain 23.05 % of the variation in the cryptocurrency market. We also imply from this result that the unexplained variation, otherwise called idiosyncratic effects, creates about 76 % of the forecast error variance of the FTX system. Hence, a substantial part of the forecast error variance is related to behavioural dispositions.

Furthermore, the contribution from the FTX network to the Terra system is about 51 %. However, that of Terra to FTX is slightly higher at 56 %. Importantly, we also confirm that the interaction of the sentiments from different platforms has significant co-movement with all the tokens, implying that these variables account for a significant part of the tokens' return volatilities. Additionally, the contributions of S&P 500 volatility and FTSE-100 have significantly affected the tokens' volatilities; however, there is a light transmission from the tokens to these indices. Among the Terra ecosystem, LUNC is the net transmitter of shocks to the system with a significant impact on other tokens, thus suggesting little or no diversification gains. Within the FTX system, FTT is the dominant transmitter of shocks. Nevertheless, both systems significantly impact BTC, implying frequent dominance over all tokens in the cryptocurrency market. Our results align with Zhang and Broadstock (2020) and Hernandez et al. (2021) who also show the dynamic relationship between financial assets.

5. Conclusion and policy implications

A number of recent studies have highlighted the importance of cryptocurrencies in facilitating transactions and providing an alternative store of value. Nevertheless, the unique qualities of the crypto-market are compromised by its frequent collapses, sparking criticisms of the viability of digital currencies as hedging mechanisms. More so, investors' fears and anxieties due to persistent crash heighten market volatility. The present global upheavals inspired this research, which looked at how factors like global uncertainty and sentiment affect the market behaviour of cryptocurrencies. Using native tokens of the Terra ecosystem (LUNC, USTC, ANC, and MIR), as well as FTT and SOLANA, we prove that political and economic uncertainties are major factors influencing cryptocurrency values. Additionally, we show that when good (or negative) news happens, there is a substantial contagion among tokens within the same ecosystem using the asymmetric GARCH-MIDAS model and TVP-VAR.

Our findings convey vital information for policymakers, industry practitioners, and academia. For regulators, our study ignites the necessity to provide strict financial regulations to the cryptocurrency market that will insulate investors from heavy losses and protect the entire financial system from an imminent collapse. For industry practitioners, our findings would guide investors and other market participants on risk modelling and portfolio diversification. The joint connectedness and spill-over of crypto assets can worsen portfolios during financial turmoil, hence understanding these mechanisms will help investors minimise potential losses. Given the co-dependence of assets, particularly those within the same ecosystem, our findings also offer vital information for portfolio managers seeking to hedge their portfolio using crypto assets, thus mitigating the enormous uninsured losses suffered during crypto-crash. Lastly, Our study contributes to the growing stream of research on cryptocurrencies and the digital asset market. We add to this expanding body of work by identifying a connection between uncertainty, sentiments and crypto assets. Future research may explore how cryptocurrencies react to changes in financial uncertainty as well as the impact of financial literacy on investors' attitudes towards cryptocurrency adoption.

CRediT authorship contribution statement

Rilwan Sakariyahu: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Rodiat Lawal:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Rasheed Adigun:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Audrey Paterson:** . **Sofia Johan:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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