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# Cryptocurrency Crises: The Role of Sentiment, Financial Stress, and Economic Policy Uncertainty

**Sirine Ben Yaala*, Jamel Eddine Henchiri****

**Abstract:** This paper investigates the economic and behavioral determinants of crises in three major cryptocurrencies: Bitcoin, Ethereum, and Ripple. It focuses on the impact of key factors such as returns, volatility, investor sentiment, the Financial Stress Index (FSI), and Economic Policy Uncertainty (EPU). Crises are identified using the CMAX method, while their determinants are analyzed using both probit and logit models. The analysis identifies three major crises for Bitcoin – linked to the European sovereign debt crisis, the collapse of Mt. Gox, and the COVID-19 pandemic – along with a prolonged crisis in Ethereum from January 2018 to January 2021, and a persistent crisis in Ripple with no observed recovery. Results show that higher returns significantly reduce the likelihood of crises across all three cryptocurrencies, while increased volatility consistently raises crisis probability, reflecting heightened market uncertainty and risk aversion. Investor sentiment, measured through Google Trends, shows asset-specific effects: both optimistic and pessimistic sentiment increase crisis risk for Bitcoin and Ripple, while only pessimistic sentiment significantly affects Ethereum. Additionally, both FSI and EPU are positively and significantly associated with crisis occurrence, underscoring the influence of macro-financial stress and policy uncertainty on cryptocurrency stability.

**Keywords:** cryptocurrency crises; Bitcoin; Ethereum; Ripple; Google Trends; Financial Stress Index; Economic Policy Uncertainty.

**JEL classification:** G01; G11; G41; E44; C25.

* RED Laboratory, Higher Institute of Management, University of Gabes, Tunisia; e-mail: *sirine17@live.fr* (corresponding author).
** RED Laboratory, Higher Institute of Management, University of Gabes, Tunisia; e-mail: *jamel.henchiri@gmail.com*.

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## 1. INTRODUCTION

Cryptocurrencies have revolutionized the financial landscape by providing a decentralized and secure digital medium for exchange. Since Bitcoin's emergence in 2009, many other cryptocurrencies such as Ethereum, Ripple, and Litecoin have gained popularity, driven by interest in blockchain technology, which ensures transaction security and transparency.

Cryptocurrencies differ from traditional government-issued currencies by relying on cryptography to secure transactions, control new unit creation, and verify asset transfers. Operating on decentralized peer-to-peer networks, they reduce vulnerabilities to manipulation and censorship. Bitcoin's value has soared dramatically, from mere cents to thousands of dollars, attracting investors and media attention and establishing cryptocurrencies as notable investment assets.

The rise of cryptocurrencies carries significant implications beyond finance. Their advantages include faster, cheaper transactions, increased financial access for the unbanked, and enhanced privacy and security. However, criticisms focus on extreme volatility, potential misuse for illicit activities, and high energy consumption. Regulators worldwide remain concerned with protecting investors and preventing abuses, fueling ongoing debates on balancing innovation and regulation.

Financial literature has increasingly examined cryptocurrencies, focusing on price and volatility dynamics and their determinants (Sovbetov, 2018; Katsiampa, 2019; Poyser, 2019). Studies highlight cryptocurrencies' hedge and safe-haven roles during market downturns (Bouri *et al.*, 2019; Paule-Vianez *et al.*, 2020), and analyze their speculative nature and bubble formation (Baur *et al.*, 2018; Corbet *et al.*, 2018). Research also explores interactions between cryptocurrencies and macroeconomic variables (Demir *et al.*, 2018; Kurka, 2019; Tiwari *et al.*, 2019).

Another literature strand focuses on how investor sentiment, the Financial Stress Index (FSI), and Economic Policy Uncertainty (EPU) shape cryptocurrency markets. Investor sentiment notably influences returns and volatility—positive sentiment drives prices up, while negative sentiment raises instability (Nasir *et al.*, 2019; Anamika and Subramaniam, 2022; Güler, 2023). FSI correlates with cryptocurrency returns, emphasizing Bitcoin's perceived safe-haven role during turmoil (Bouri *et al.*, 2018; Nur and Korkmaz, 2022; Yin *et al.*, 2024). EPU also predicts cryptocurrency volatility and returns, with Bitcoin and Ethereum acting as potential hedges during uncertain economic periods (Demir *et al.*, 2018; Paule-Vianez *et al.*, 2020; Mokni, 2021; Al-Shboul *et al.*, 2023). Despite this growing literature, critical gaps remain. Few studies specifically focus on explaining crises in cryptocurrency markets, which behave uniquely compared to traditional financial markets. While many analyze factors affecting returns and volatility, they often neglect the complex dynamics behind market disruptions. Furthermore, innovative measures of investor sentiment, such as direct indicators from Google Trends, are underutilized in forecasting models.

This study addresses these gaps by proposing a comprehensive framework combining a direct Google Trends–based investor sentiment measure with the Financial Stress Index and Economic Policy Uncertainty to explain crises in Bitcoin, Ethereum, and Ripple markets. Employing probit and logit models, the framework captures the interplay of behavioral and fundamental factors driving crises in major cryptocurrencies.

This research makes a significant contribution to financial forecasting and cryptocurrency market analysis. Theoretically, this study enriches academic literature by developing a comprehensive framework to explain crises in Bitcoin, Ethereum, and Ripple. By integrating behavioral finance, sentiment analysis, and macroeconomic indicators, it offers a novel approach to understanding and anticipating cryptocurrency market disruptions. Practically, it equips investors, portfolio managers, and policymakers with tools to assess and manage cryptocurrency crisis risks. Using indicators like the Financial Stress Index (FSI), Economic Policy Uncertainty (EPU) and Google Trends–based investor sentiment, the study provides early warning signals to improve forecasting and guide informed decisions.

Methodologically, the research employs robust probit and logit models to estimate crisis probabilities, demonstrating the value of combining behavioral and macro-financial variables. The inclusion of direct sentiment measures and dual-model estimation enhances empirical rigor and applicability.

At the societal level, these findings promote financial stability by enabling stakeholders to anticipate and mitigate crises, reducing sudden market crashes, minimizing losses, and reinforcing investor confidence for a more resilient financial ecosystem.

From a policy perspective, understanding the drivers of cryptocurrency crises allows regulators to implement timely interventions that protect the real economy from shocks and foster a more stable economic environment.

To our knowledge, this study is among the first to detect and predict cryptocurrency crises using an integrated framework that combines CMAX-based crisis detection, probit and logit models, Google Trends sentiment data, the Financial Stress Index (FSI), and Economic Policy Uncertainty (EPU). This novel methodology advances understanding of cryptocurrency vulnerabilities and offers valuable insights for investment and regulatory strategies in the evolving digital financial landscape.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 outlines the research methodology, and Section 4 describes the data. Section 5 presents the results and analysis. Finally, Section 6 provides the discussion and conclusions.

## 2. LITERATURE REVIEW

Previous studies have extensively examined the factors influencing cryptocurrency prices and volatility, highlighting the critical roles of investor sentiment, financial stress, and economic policy uncertainty.

### 2.1. Investor sentiment and the cryptocurrency market

Traditional financial theory was grounded in the concept of homo oeconomicus, assuming investors were fully rational, possessed perfect information, and always made utility-maximizing decisions based on objective risk-return assessments. However, behavioral finance challenged this framework by incorporating psychological and emotional biases that often drove market behavior, especially under uncertainty. This perspective was particularly relevant to the cryptocurrency market, which lacked intrinsic valuation anchors and was highly sensitive to investor moods and perceptions.

Empirical research increasingly emphasized the crucial role investor sentiment played in shaping cryptocurrency dynamics. Sentiment – whether constructed from fundamentals (rational) or driven by emotions and noise (irrational) – affected not only asset returns but also volatility and cross-asset spillovers.

Güler (2023) investigated the effect of investor sentiment on Bitcoin returns and volatility using several sentiment proxies within an EGARCH model framework. The study found that both rational and irrational components of sentiment significantly impacted Bitcoin price movements and volatility.

Anamika and Subramaniam (2022) analyzed survey-based Sentix data to study Bitcoin price responses. They reported that increased investor optimism boosted Bitcoin prices and caused sentiment spillovers to other cryptocurrencies, reinforcing Bitcoin's role as a benchmark asset.

Indirect investor sentiment, often constructed through internet search activity, was also widely studied. Nasir *et al.* (2019) applied VAR, copula models, and non-parametric methods on weekly data (2013–2017) and found a strong positive link between Google search volume for Bitcoin and its returns and trading volume, indicating that increased retail investor attention predicted market movements.

Akyildirim *et al.* (2021) analyzed sentiment transmission among the 13 largest cryptocurrencies using MarketPsych data. Their dynamic connectedness analysis showed that while altcoins dominated return spillovers, Bitcoin and Ethereum remained central in sentiment flow, reflecting their psychological influence.

Similarly, Bouri *et al.* (2021) applied Twitter-based sentiment data within a DCC-GARCH model to study volatility spillovers among 15 major cryptocurrencies. They found that extreme negative sentiment increased market volatility and interconnectedness, suggesting panic-driven contagion. Conversely, extreme positive sentiment reduced connectedness, allowing greater diversification. These findings demonstrated the asymmetric and nonlinear effects of sentiment on crypto market volatility.

Sun *et al.* (2023) used textual analytics on millions of posts from Chain Node, a major Chinese crypto investor forum, to construct a sentiment proxy. Their study suggested that cryptocurrency prices were more sensitive to sentiment-driven fluctuations than traditional stocks due to the absence of fundamental valuation anchors.

Building on behavioral indicators, Gurdgiev and O'Loughlin (2020) analyzed multiple sentiment measures – including the VIX, CBOE put-call ratio, and U.S. Equity Market Uncertainty Index – and found that investor sentiment significantly influenced crypto prices. They also provided tentative evidence that cryptocurrencies might serve as safe havens during economic uncertainty, though this effect was inconsistent during severe equity market crashes.

Bouteska *et al.* (2022) constructed a composite sentiment index using principal component analysis (PCA) on social media and financial data. Using vector autoregressive (VAR) models, they showed this index reliably predicted short-term Bitcoin returns, particularly during crises such as the COVID-19 pandemic, when emotions heavily influenced markets.

Overall, these studies highlighted investor sentiment's importance in the cryptocurrency market, revealing that both rational and irrational emotions significantly impacted asset returns and volatility.

### 2.2. Financial stress index and the cryptocurrency market

While investor sentiment significantly shaped cryptocurrency behavior, systemic financial stress was another vital factor that could amplify or mitigate market reactions. The Financial Stress Index (FSI) served as a comprehensive measure of global financial instability, capturing movements in interest rates, credit spreads, and market volatility. It functioned as a key barometer for investors and policymakers seeking to assess systemic risk and market vulnerability.

Recent empirical studies highlighted the FSI's significant role in cryptocurrency markets, particularly during times of heightened uncertainty.

For instance, Sun *et al.* (2023) employed a Vector Error Correction Model (VECM) to analyze Bitcoin price dynamics before and during the COVID-19 pandemic. Their results revealed that financial stress, alongside blockchain fundamentals (hashrate, transaction volume) and social media sentiment, significantly impacted Bitcoin in both the short and long term. This underscored the importance of combining macro-financial indicators and behavioral signals to understand price fluctuations.

Similarly, Bouri *et al.* (2018) investigated the dependence structure between the global FSI and Bitcoin returns from 2010 to 2017. They found right-tail dependence and significant Granger causality at distribution tails, suggesting that Bitcoin might have acted as a safe-haven asset during periods of extreme financial stress, even though its medium-term predictability remained limited.

Nur and Korkmaz (2022) applied GARCH and IGARCH models over a decade of data (2011–2021) and identified a positive volatility spillover from the FSI to Bitcoin. Their impulse-response analysis also confirmed a bidirectional relationship, indicating that cryptocurrency markets not only reacted to but also contributed to systemic stress, especially during periods of financial turbulence.

Yin *et al.* (2024) took a machine learning approach, employing a Graph Neural Network (GNN) to forecast the prices of Bitcoin, Ethereum, Litecoin, and Dash Coin, integrating Tether (USDT) and FSI data. Their findings emphasized that financial stress and its sub-components significantly enhanced predictive model performance, reinforcing the FSI's value in data-driven risk management strategies.

Zhang and Wang (2021) extended the analysis to cross-market comparisons, examining the effects of financial stress on Bitcoin and gold in both the U.S. and China. Their study, set against the backdrop of immigration crises and the China-U.S. trade conflict, found that both assets exhibited sensitivity to financial stress, particularly over short-term horizons – further confirming the responsive nature of cryptocurrencies to geopolitical and systemic shocks.

### 2.3. Economic policy uncertainty and the cryptocurrency market

Economic policy uncertainty (EPU) is a crucial macroeconomic risk factor that influences investment decisions, capital flows, and financial stability. As uncertainty surrounding government policies increases, investors often adjust their portfolios, which can lead to changes in asset prices, including those of cryptocurrencies. Due to the global nature of digital assets, EPU can generate spillover effects across different markets (Kang and Yoon, 2019).

The EPU index, originally developed by Baker *et al.* (2016), captures fluctuations in policy-related economic uncertainty and has become a widely used tool in analyzing financial market behavior. Demir *et al.* (2018), using vector autoregression (VAR) models, demonstrated a negative and significant relationship between EPU and Bitcoin returns, suggesting that high policy uncertainty prompts investors to reduce exposure to cryptocurrencies.

Mokni (2021) employed quantile regression and causality-in-quantiles approaches to show that EPU significantly predicted Bitcoin's returns and volatility across different market states, especially during periods of heightened turbulence. This reinforced the idea that cryptocurrency markets were sensitive to macro-level policy risks.

Yen and Cheng (2021), applying the heterogeneous autoregressive realized volatility (HAR-RV) model, found that China's EPU had a significant effect on the volatility of Bitcoin and Litecoin. Their findings emphasized the importance of region-specific uncertainty in shaping global cryptocurrency dynamics.

Huynh *et al.* (2021) used a nonlinear ARDL (NARDL) framework to explore asymmetries in the relationship between global EPU and Bitcoin's trading activity. They observed that higher EPU levels tended to suppress trading volumes and increase volatility, signaling heightened investor caution.

Paule-Vianez *et al.* (2020), utilizing GARCH and copula-based models, revealed that Bitcoin acted as a safe haven during periods of extreme EPU, with both returns and volatility responding positively to uncertainty shocks. Similarly, Al-Shboul *et al.* (2023), using the Diebold-Yilmaz volatility spillover framework, found that EPU contributed to cross-market volatility transmission between fiat currencies and cryptocurrencies, highlighting the growing integration of crypto markets into the global financial system.

Salisu *et al.* (2023) adopted a predictive regression framework to show that EPU served as a leading indicator for financial market volatility, while He *et al.* (2024), using a regime-switching model, demonstrated that although EPU had a limited influence on crypto markets in the short run, Bitcoin and Ethereum could still serve as short-term hedging instruments during periods of heightened uncertainty.

Despite extensive research on factors influencing cryptocurrency returns and volatility, limited attention has been given to the dynamics of cryptocurrency crises. In particular, there is a lack of empirical studies that integrate behavioral and macroeconomic factors – such as investor sentiment, financial stress, and economic policy uncertainty – in explaining crisis episodes in major cryptocurrencies like Bitcoin, Ethereum, and Ripple.

This study addresses this gap by systematically analyzing the drivers of cryptocurrency crises. By integrating both behavioral and macro-financial indicators, it aims to offer practical insights for investors and policymakers seeking to better anticipate and manage extreme market events.

## 3. METHODOLOGY

In this study, we first identify crisis periods in Bitcoin, Ethereum, and Ripple using the CMAX approach (current index level relative to historical maximum), as proposed by Patel and Sarkar (1998). We then examine the determinants of these cryptocurrency crises using both the probit and the logit models.

The following sections detail the implementation of the CMAX methodology and the specification of the econometric models employed in the analysis.

### 3.1. Cryptocurrency crisis detection: CMAX approach description and sensitivity analysis of threshold choice

This section describes the methodology used to detect cryptocurrency crises using the CMAX approach and presents a sensitivity analysis to validate the robustness of the chosen threshold level.

#### *3.1.1. CMAX methodology for crisis detection*

To detect **cryptocurrency crises**, we used the CMAX methodology suggested by Patel and Sarkar (1998). This method involves calculating the ratio of the current cryptocurrency price at time t to its maximum value over a specified period.

$$CMAX_{it} = P_{it} / \max\,[P_{it,lag}, \ldots, P_{it}] \quad (1)$$

where: $P_{it}$: the level of cryptocurrency price i at time t.

A cryptocurrency crisis is identified when the CMAX value for a specific cryptocurrency i at time t falls below the average CMAX for that cryptocurrency minus 1.5 standard deviations (which can be considered a threshold level).

The indicator representing the cryptocurrency crisis of cryptocurrency i at time t, Ci,t, is defined as:

$$C_{it}=1, \text{ if } CMAX_{it} < CMAX-1.5\,\sigma_i \quad (2)$$
$$C_{it}=0, \text{ otherwise}$$

Following the study by Ben Yaala and Henchiri (2024b, 2025a), we define the beginning date of the crisis, the trough date, the recovery date, and the amplitude as the key dimensions of the crisis.

The beginning of the crisis "the peak" corresponds to the day when the cryptocurrency price reaches its maximum prior to the day when the critical level is exceeded.

The trough date corresponds to the day on which the cryptocurrency price reaches its minimum level during the crisis.

The recovery date is defined as the day on which the cryptocurrency price regains its maximum level reached before the crash.

The duration of crises is the time elapsed between the date of the start of the crisis and the date of recovery of the loss.

The amplitude corresponds to the maximum loss observed during the crisis, i.e. the variation of the cryptocurrency price between the peak and the trough.

#### *3.1.2. Sensitivity analysis of threshold choice*

To ensure the robustness of our crisis identification approach using the CMAX method, we conducted a sensitivity analysis by varying the threshold level used to define a crisis. While the baseline threshold was set at 1.5 standard deviations below the average CMAX, we also tested alternative thresholds of 1.3 and 1.7 standard deviations.

### 3.2. Model selection, specification, and diagnostic checking

In this section, we describe the model selection process, specify the models used to analyze the risk of cryptocurrency crises, and discuss the diagnostic checks performed to ensure robustness.

#### *3.2.1. Model selection*

To analyze the risk of crises, we focus on limited dependent variable regression models suitable for binary outcomes. The dependent variable in our study is qualitative, taking the value 1 if a crisis occurs and 0 otherwise, which makes probit and logit models appropriate choices.

We initially consider both the probit and logit models due to their widespread use in binary outcome modeling:

- The probit model assumes that the error terms follow a standard normal distribution. It models the probability of crisis occurrence as:

$$\text{Prob}\ (\text{CRISIS}_i = 1 |\ X_i, \beta) = F\ (X_i' \ , \beta) \tag{3}$$

with:

F: distribution function of the reduced centered normal law

$X_i$: vector of exogenous variables

β: vector of parameters to be estimated.

- The logit model assumes a logistic distribution of the error terms. The probability function is given by:

$$\text{Prob}\ (\text{CRISIS}_i = 1 |\ X_i, \beta) = \Phi\ (X_i' \ , \beta) = \frac{1}{1+e^{-X_i' \ \beta}} \tag{4}$$

with:

Φ: logistic cumulative distribution function

**Variables description**

After presenting the general framework of the models, we proceed with a detailed description of all the variables used in the analysis.

- **Dependent variable**

The CRISIS variable is a binary variable and appears as the endogenous variable of the models. It takes the following two values:

$$\text{CRISIS}_t = \begin{cases} 1 & \text{For crisis periods} \\ 0 & \text{For quiet periods} \end{cases}$$

- **Explanatory variables**

The model's explanatory variables include various factors, such as stock market returns and volatility, the financial stress index, economic policy uncertainty, and behavioral variables like investors' optimistic and pessimistic sentiments.

**Cryptocurrency market performance: indicator of price acceleration**

To capture price acceleration, we incorporated year-on-year cryptocurrency price changes into our models. This measure is computed as the logarithmic ratio of the closing price at time *t* to the closing price at time *t – n*.

$$R_t = l\,n\left(\frac{P_t}{P_{t-n}}\right) \tag{5}$$

with:

$R_t$: The return of the cryptocurrency price on day (t).

$P_t$: The price of the cryptocurrency on day (t).

$P_{t-n}$: The price of the cryptocurrency on the day (t-n).

**Returns volatility**

In order to calculate the cryptocurrency volatility, we used the GARCH (1,1) modeling developed by Bollerslev (1986). The GARCH (1,1) process is written in the following form:

Mean equation: $R_t = \mu + \varepsilon_t$ (6)

Conditional variance equation: $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$ (7)

with:

$\sigma_t^2$ : is the conditional variance of the GARCH model.

εt: Are residues

ω, α and β: are coefficients and must satisfy the following conditions: $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$

**Optimistic and pessimistic investor sentiment**

To measure the optimistic and pessimistic sentiments of investors, we employed a direct measure obtained from the search volume of terms on Google Trends. Google Trends provides the search volume of words on a specific topic as a proportion of all searches within a given location and time frame, normalized to a scale of 0 to 100, where 100 signifies a high search activity.

To calculate the sentiment index, we curated two sets of twenty words each: one set comprising positive words and the other negative words, all relevant to the cryptocurrency domain. These sets were selected based on keywords such as "Cryptocurrency," "Bitcoin," "Digital Currency," "Ripple," "Blockchain," and "Ethereum."

Following a methodology similar to Da *et al.* (2011), we mitigated the effects of seasonality present in the time series of word search volume by regressing each term on daily binary variables and retained the residuals. Subsequently, we standardized each residual series by its standard deviation to ensure comparability across all series.

The subsequent step in constructing the sentiment indices involved identifying the most significant search terms for the crisis variable by examining the historical relationship between each term and the crisis variable. We selected the top 20 search terms (10 positive words and 10 negative words) with the highest correlation with the crisis variable.

Finally, we applied principal component analysis to the two groups of positive and negative words obtained from Google Trends to derive the optimistic and pessimistic sentiment of investors, as described in Da *et al.* (2015) and García Petit *et al.* (2019).

**The financial stress index**

To assess the influence of financial uncertainty on cryptocurrency crises, we employ the Financial Stress Index (FSI). The FSI, as conceptualized by Borio and Lowe (2002), is a composite measure that captures various dimensions of financial stress, including stock market volatility, credit spreads, interest rate spreads, banking sector health, liquidity measures, and exchange rate volatility. This index provides a comprehensive measure of the overall level of financial instability in the financial system.

**The economic policy uncertainty**

As a measure of Economic Policy Uncertainty (EPU), we utilized the daily US EPU index as developed by Baker *et al.* (2016) (available at policyuncertainty.com). This index is constructed based on the frequency of newspaper articles in the US that contain at least one of the following combinations of terms: “economy” or “economic”; “uncertain” or “uncertainty”; and “legislation”, “deficit”, “regulation”, “Congress”, “Federal Reserve”, or “White House”.

### *3.2.2. Model specification*

To analyze the explanatory factors behind cryptocurrency crises, we estimate a binary response model where the dependent variable indicates the presence (1) or absence (0) of a crisis. The probability that a crisis occurs at time t is modeled as a function of key economic and behavioral variables:

$$Pr(CRISIS_t=1)=f(\alpha_1+\beta_1(RETURN)_t+\beta_2(VOLATILITY)_t+\beta_3(OPTIMISM)_t+\beta_4(PESSIMISM)_t+\beta_5(FSI)_t+\beta_6(EPU)_t+\epsilon_{1,t}) \quad (8)$$

with:

CRISIS : Cryptocurrency crises
RETURN : Cryptocurrency return
VOLATILITY: Cryptocurrency volatility
OPTIMISM: Optimistic investor sentiment derived from Google Trends
PESSIMISM: Pessimistic investor sentiment derived from Google Trends
FSI: Financial stress index
EPU: Economic policy uncertainty

We apply both the probit and logit models to each of the three cryptocurrencies – Bitcoin, Ethereum, and Ripple – independently. This separate estimation strategy allows us to capture the distinct dynamics and sensitivities of each cryptocurrency to the selected explanatory variables.

### *3.2.3. Robustness checks*

To evaluate the performance of the estimated probit/logit models, we compared the predicted probabilities with the actual occurrence of cryptocurrency crises. As illustrated in Table no. 1, four scenarios can arise: correct crisis prediction (Type C), correct calm prediction (Type D), missed crisis (Type A error), and false alarm (Type B error). The goal is to minimize Type A and Type B errors while maximizing correct predictions.

In line with the methodologies proposed by Boucher (2004) and Coudert and Gex (2008), we present our evaluation results using two probability thresholds: 50% and 25%. These thresholds represent the minimum probability level at which a crisis signal is issued. A threshold of 50% reflects a stricter criterion – only higher predicted probabilities trigger crisis warnings, favoring specificity (reducing false positives). Conversely, a 25% threshold is more lenient, favoring sensitivity (reducing missed crises) by issuing warnings at lower predicted probabilities. Presenting results at both levels allows us to assess the trade-off between detecting true crises and avoiding false alarms, thus offering a more comprehensive evaluation of model performance.

**Table no. 1 – Performance evaluation of probit/logit models**

| | | Model prediction | |
|---|---|---|---|
| | | **Transmitted signal** | **No signal transmitted** |
| **Effective crises** | CRISIS=0 | Correct crisis announcement (C) | type A error; signal missing |
| | CRISIS=1 | type (B) error; false alarm | correct non-crisis announcement (D) |

*Source(s):* authors' own creation

## 4. DATA

Our sample comprises both fundamental data (returns, volatility, Financial Stress Index, and Economic Policy Uncertainty) and behavioral data (optimistic and pessimistic sentiment of investors obtained via Google Trends). All data were collected at daily frequencies. For returns and volatility, we considered the prices of three cryptocurrencies, Bitcoin, Ethereum and Ripple, obtained from the website investing.com. The direct measure of optimistic and pessimistic sentiment was derived from relevant positive and negative keywords extracted from Google Trends. The Financial Stress Index and Economic Policy Uncertainty were gathered from the website policyuncertainty.com.

Price data span from July 18, 2010, to December 31, 2023, for Bitcoin; from March 10, 2016, to December 31, 2023, for Ethereum; and from January 22, 2016, to December 31, 2023, for Ripple, to examine the factors determining crises in each cryptocurrency.

## 5. RESULTS

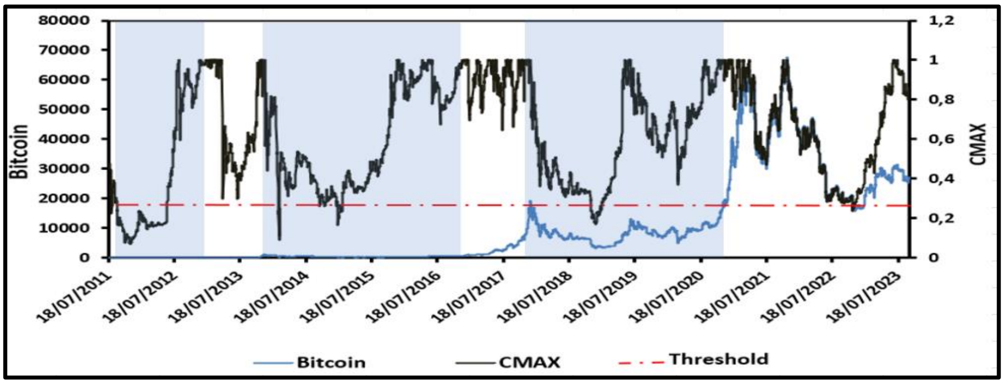
### 5.1. Cryptocurrency crises detection and analysis results

This section presents the results of crisis detection for Bitcoin, Ethereum, and Ripple using the CMAX method and evaluates the robustness of these results with respect to the choice of threshold.

#### *5.1.1. Cryptocurrency crises detection results*

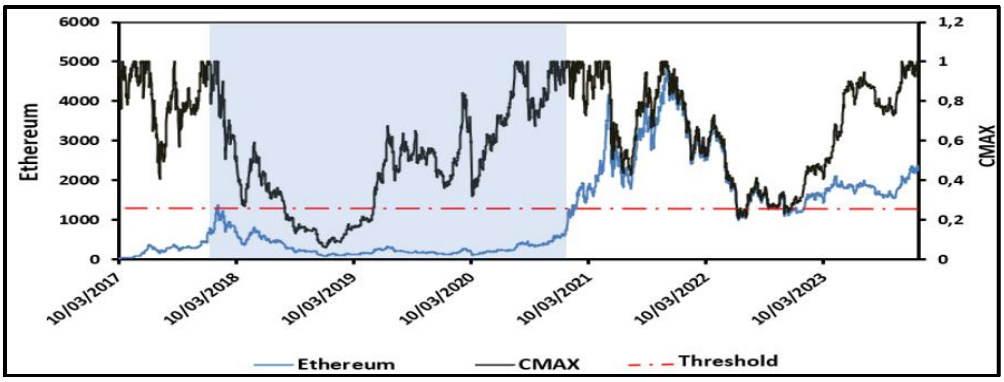
Using the CMAX method, we define the CMAX indicator as equals to 1 when cryptocurrency prices exhibit an upward trend over the analyzed period, indicating a bullish scenario. As prices decline, the CMAX value approaches 0. A crash is identified only when the price reaches its lowest point after exceeding a specified threshold.

Figures no. 1 to no. 3 illustrate the price trends of the cryptocurrencies and their alignment with the CMAX indicator.



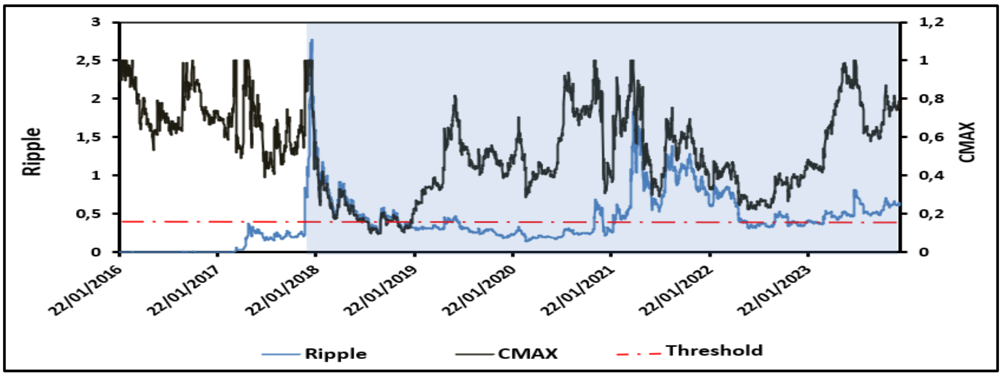

Source: authors' own creation

**Figure no. 1 – The relationship between the Bitcoin price and the CMAX indicator from 2011 to 2023**




Source: authors' own creation

**Figure no. 2 – The relationship between the Ethereum price and the CMAX indicator from 2017 to 2023**




Source: authors' own creation

**Figure no. 3 -The relationship between the Ripple price and the CMAX indicator from 2017 to 2023**

*5.1.1.1. Bitcoin crises identified*

Three major crises have marked the history of Bitcoin, each characterized by a significant drop in its price followed by a period of recovery. The first crisis, from 25/07/2011 to 12/01/2013, lasted 1 year, 5 months, and 18 days, with a magnitude of 6.05%. This crisis coincides with the European sovereign debt crisis, illustrating Bitcoin's vulnerability to major economic disruptions.

The second crisis, from 04/12/2013 to 02/03/2017, lasted 3 years, 2 months, and 26 days, and was marked by a magnitude of 10.09%, indicating a sharper decline and a slower recovery. This crisis was strongly influenced by the collapse of the Mt. Gox exchange in 2014, highlighting the impact of specific events within the cryptocurrency ecosystem on its volatility.

Finally, the crisis from 16/12/2017 to 30/11/2020 lasted 3 years, with a magnitude of 5%. This crisis occurred during a period of increased cryptocurrency regulation and the COVID-19 pandemic, which heightened uncertainty in financial markets.

Table no. 2 presents the three crises identified in Bitcoin.

**Table no. 2 – Crises identified by the CMAX approach in Bitcoin**

| The beginning of the crisis | The date of trough | The date of recovery | The duration of the crisis | | Magnitude (%) |
|---|---|---|---|---|---|
| | | | From the beginning of the crisis to the trough | From the trough to the recovery | |
| 25/07/2011 | 18/11/2011 | 12/01/2013 | 3 months and 23 days | 1 year, 1 month, and 25 days | 6.05 |
| 04/12/2013 | 21/02/2014 | 02/03/2017 | 2 months, and 17 days | 3 years, and 9 days | 10.09 |
| 16/12/2017 | 15/12/2018 | 30/11/2020 | 11 months, and 15 days | 2 years, and 15 days | 5 |

*Note*: The lapse of time between the beginning of the crisis and the date of the through correspond to the duration of the crash.

Source: authors' own creation

*5.1.1.2. Ethereum crises identified*

Applying the CMAX approach to the price of Ethereum, we identified a single crisis that began on January 13, 2018, and extended until January 24, 2021. This crisis, marked by a prolonged decline in prices of 15.47%, reached its lowest point on December 14, 2018. The crisis period lasted for 3 years and 27 days. This period was characterized by a series of regulatory crackdowns on cryptocurrencies globally and the economic disruptions caused by the COVID-19 pandemic, which contributed to significant market instability.

Table no. 3 presents the three crises identified in Ethereum.

**Table no. 3 – Crisis identified by the CMAX approach in Ethereum**

| The beginning of the crisis | The date of trough | The date of recovery | The duration of the crisis | | Magnitude (%) |
|---|---|---|---|---|---|
| | | | From the beginning of the crisis to the trough | From the trough to the recovery | |
| 13/01/2018 | 14/12/2018 | 24/01/2021 | 11 months, and 17 days | 2 years, 1 month, and 10 days | 15.47 |

*Note*: The lapse of time between the beginning of the crisis and the date of the through correspond to the duration of the crash.

Source: authors' own creation

*5.1.1.3. Ripple crisis identified*

The Ripple crisis, identified by the CMAX approach, began on January 17, 2018, and reached its lowest point on March 12, 2020. Lasting over two years, Ripple's value declined by 19.44%, with no recovery yet observed. This prolonged crisis highlights the significant and ongoing challenges Ripple has faced in recovering its market value.

Table no. 4 summarizes the crisis identified in Ripple.

**Table no. 4 – Crisis identified by the CMAX approach in Ripple**

| The beginning of the crisis | The date of trough | The date of recovery | The duration of the crisis | | Magnitude (%) |
|---|---|---|---|---|---|
| | | | From the beginning of the crisis to the trough | From the trough to the recovery | |
| 17/01/2018 | 12/03/2020 | Not yet | 02 years, 01 month, and 24 days | - | 19.44 |

*Note*: The lapse of time between the beginning of the crisis and the date of the through correspond to the duration of the crash.

Source: authors own work

Cryptocurrency crises highlight their sensitivity to global economic events and regulatory shifts, which significantly influence market stability and investor sentiment. External shocks – such as the European sovereign debt crisis or regulatory responses during the COVID-19 pandemic – underscore the strong link between cryptocurrencies and the broader financial environment.

***5.1.2. Robustness of crisis detection to threshold choice***

The results of the sensitivity analysis confirm that the crisis periods identified for Bitcoin, Ethereum, and Ripple remained consistent across various threshold values. This stability demonstrates that the CMAX method generates robust and reliable crisis signals. The fact that crisis detection is not dependent on a specific threshold reinforces the methodological soundness and credibility of our identification approach.

**5.2. Descriptive statistics analysis**

Table no. 5 presents the descriptive statistics for Bitcoin (Panel A), Ethereum (Panel B), and Ripple (Panel C). The variables include the frequency of crisis periods (expressed as a proportion of total trading days), daily returns and volatility (expressed in decimal form), investor sentiment indices—OPTIMISM and PESSIMISM (in index points)—as well as macroeconomic indicators, namely the Financial Stress Index (FSI) and Economic Policy Uncertainty Index (EPU), both measured in index units. In addition to central tendency and dispersion (mean and standard deviation), distributional characteristics such as skewness, kurtosis, and the Jarque-Bera test for normality are also reported.

Bitcoin experienced crises on 61.64% of trading days. Its average return is 0.0018 (equivalent to 0.18%) with a standard deviation of 0.0541 (5.41%). Returns are highly positively skewed (3.58) and extremely leptokurtic (156.94), suggesting frequent large positive deviations. Volatility averages 0.0424 (4.24%), with strong right skewness (6.42) and high kurtosis (76.03), reflecting substantial tail risk. The average investor sentiment indices are 4.17 (OPTIMISM) and 3.04 (PESSIMISM). FSI and EPU average 100.31 and 176.49, respectively, both showing leptokurtic behavior. All distributions significantly deviate from normality according to the Jarque-Bera test.

Ethereum has a crisis frequency of 44.55%. The average return is 0.00192 (0.192%) with a standard deviation of 0.0523 (5.23%). The return distribution is slightly negatively skewed (–0.60) and leptokurtic (12.91). Volatility averages 0.0497 (4.97%) and shows moderate skewness (1.50) and kurtosis (7.45). Sentiment indices average 4.01 (OPTIMISM) and 3.00 (PESSIMISM), with both distributions displaying leptokurtosis. FSI (100.15) and EPU (213.35) also show leptokurtic characteristics. All variables reject normality.

**Table no. 5 – Descriptive statistics**

| Variables | Mean | Max | Min | Std. Dev | Skewness | Kurtosis | Jarque Bera | Prob |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Descriptive statistics of Bitcoin** | | | | | | | | |
| CRISIS | 0.6164 | 1 | 0 | 0.4863 | -0.4788 | 1.2292 | 768.12 | 0.000 |
| RETURN | 0.0018 | 1.4741 | -0.8488 | 0.0541 | 3.5758 | 156.938 | 4501250 | 0.000 |
| VOLATILITY | 0.0424 | 0.5101 | 0.0132 | 0.0281 | 6.4231 | 76.0323 | 1042252 | 0.000 |
| OPTIMISM | 4.1719 | 7.4067 | -0.8621 | 1.2898 | 1.4194 | 4.98653 | 2275.582 | 0.000 |
| PESSIMISM | 3.0439 | 8.3713 | -0.4835 | 1.0072 | 2.5034 | 10.6378 | 15808.95 | 0.000 |
| FSI | 100.31 | 103.31 | 99.0589 | 0.6340 | 1.5750 | 6.85630 | 4699.424 | 0.000 |
| EPU | 176.49 | 428.98 | 90.3272 | 65.887 | 1.1927 | 4.22765 | 1364.274 | 0.000 |
| **Panel B: Descriptive statistics of Ethereum** | | | | | | | | |
| CRISIS | 0.4455 | 1 | 0 | 0.4971 | 0.2192 | 1.0481 | 414.739 | 0.000 |
| RETURN | 0.00192 | 0.2586 | -0.5896 | 0.0523 | -0.5959 | 12.906 | 10317.03 | 0.000 |
| VOLATILITY | 0.04973 | 0.1492 | 0.0172 | 0.0172 | 1.4964 | 7.4518 | 2981.868 | 0.000 |
| OPTIMISM | 4.01067 | 7.4067 | -0.8621 | 1.3745 | 0.9309 | 3.9356 | 449.9206 | 0.000 |
| PESSIMISM | 3.00280 | 8.3712 | -0.4835 | 1.1939 | 1.8775 | 7.2969 | 3374.545 | 0.000 |
| FSI | 100.152 | 101.91 | 99.0589 | 0.4851 | 0.9400 | 4.8726 | 729.6837 | 0.000 |
| EPU | 213.3454 | 428.98 | 105.5618 | 65.943 | 0.8034 | 3.4592 | 289.4178 | 0.000 |
| **Panel B: Descriptive statistics of Ripple** | | | | | | | | |
| CRISIS | 0.7534 | 1 | 0 | 0.4310 | -1.1760 | 2.383175 | 714.508 | 0.000 |
| RETURN | 0.00164 | 1.0279 | -0.6533 | 0.0669 | 2.05198 | 37.29171 | 144125.6 | 0.000 |
| VOLATILITY | 0.00509 | 0.4052 | 0.00129 | 0.0144 | 17.0815 | 408.3479 | 19994.47 | 0.000 |
| OPTIMISM | 4.11563 | 7.4067 | -0.8621 | 1.3638 | 1.00222 | 4.031833 | 614.1347 | 0.000 |
| PESSIMISM | 3.274388 | 8.3713 | -0.4835 | 1.1613 | 1.93509 | 7.523891 | 4282.815 | 0.000 |
| FSI | 100.1528 | 101.91 | 99.0589 | 0.4687 | 0.92883 | 4.951589 | 877.2100 | 0.000 |
| EPU | 199.1701 | 428.98 | 92.6370 | 70.383 | 0.76360 | 3.261701 | 290.1041 | 0.000 |

*Notes*: CRISIS variable represents the proportion of trading days classified as crisis periods, ranging from 0 to 1. RETURN and VOLATILITY are reported in decimal terms. OPTIMISM, PESSIMISM, FSI, and EPU are reported as index values.

Source: authors' own creation

Ripple exhibits the highest crisis frequency at 75.34%. The average return is 0.00164 (0.164%) with a standard deviation of 0.0669 (6.69%). Returns are positively skewed (2.05) and strongly leptokurtic (37.29). Volatility is lower on average (0.0051, or 0.51%) but extremely skewed (17.08) and highly leptokurtic (408.35), suggesting rare but severe price swings. Sentiment indicators average 4.12 (OPTIMISM) and 3.27 (PESSIMISM). FSI (100.15) and EPU (199.17) also display strong leptokurtosis. The Jarque-Bera test rejects normality for all variables.

Overall, all three cryptocurrencies exhibit leptokurtic return and volatility distributions, with Bitcoin and Ripple displaying particularly heavy tails – underscoring their vulnerability to extreme market events.

### 5.3. Estimation results of the probit and logit model explaining cryptocurrency crises and diagnostic checking results

We report the results of simultaneously estimating both probit and logit models to identify the economic and behavioral determinants of cryptocurrency crises, along with relevant diagnostic checks.

#### *5.3.1. Estimation result of probit model explaining cryptocurrency crises*

Table no. 6 presents the estimation results of the probit models, which reveal that the explanatory frameworks for Bitcoin, Ethereum, and Ripple crises are both statistically robust and well-specified. Each model demonstrates a strong goodness-of-fit, as evidenced by relatively high McFadden $R^2$ values and highly significant likelihood ratio (LR) statistics. These indicators support the reliability and validity of the models in capturing the key economic and behavioral determinants of cryptocurrency crises, thereby reinforcing confidence in the empirical findings.

Across all three cryptocurrencies, RETURN is negatively associated with the probability of crises. This indicates that higher returns reduce the likelihood of a crisis, likely because rising returns boost investor confidence and mitigate panic-driven sell-offs. This finding aligns with previous studies by Patel and Sarkar (1998), and Zouaoui *et al.* (2011), which also found a negative relationship between returns and crisis risk.

VOLATILITY emerges as a significant driver of crises across Bitcoin, Ethereum, and Ripple. The positive and significant association suggests that increased price fluctuations raise the probability of a crisis. Higher volatility often signals market uncertainty, instability, and speculative activity, making the market more susceptible to sharp corrections. These results are consistent with the findings of Choudhry (1996); Aggarwal *et al.* (1999); Fang (2001); Ben Yaala and Henchiri (2025b), who showed that elevated volatility increases the likelihood of financial crises.

The role of optimistic sentiment varies across the three assets. For Bitcoin and Ripple, excessive optimism significantly increases the probability of a crisis, implying that overconfidence and speculative behavior may inflate asset prices beyond their fundamentals, thereby increasing vulnerability to sudden reversals. This behavior reflects phenomena such as FOMO (fear of missing out) and momentum trading. These results are consistent with Anamika and Subramaniam (2022); Güler (2023), who found that optimistic sentiment positively affects returns and volatility through speculative trading. They are also supported by Ben Yaala and Henchiri (2024a), who emphasized the role of investor irrationality in predicting market crashes. However, optimism does not have a statistically significant effect on Ethereum crises, suggesting that Ethereum's investor base may be less influenced by emotional overreactions or speculative surges.

Pessimistic sentiment consistently exhibits a positive and significant effect on crisis probability across all three cryptocurrencies. Heightened pessimism increases risk aversion, often triggering widespread sell-offs and contributing to abrupt market downturns. These results support the findings of Bouri *et al.* (2021), who demonstrated that extreme investor sentiments, whether optimistic or pessimistic, significantly influence market volatility and the likelihood of crises.

The Financial Stress Index is positively associated with crisis occurrence in Bitcoin, Ethereum, and Ripple. Periods of elevated financial stress—characterized by tighter liquidity, credit constraints, and broader financial disruptions—tend to spill over into cryptocurrency markets. In such environments, investors often retreat from risky assets, amplifying the likelihood of sharp price declines. This result is consistent with the research of Bouri *et al.* (2018); Nur and Korkmaz (2022), who found that financial stress can trigger panic selling and increase the risk of cryptocurrency crises.

Economic policy uncertainty also plays a significant role in explaining cryptocurrency crises. The models reveal a strong and positive association between uncertainty and crisis occurrence for all three assets. Political and regulatory unpredictability weakens investor confidence and increases market volatility. While some investors may view cryptocurrencies as safe havens during uncertain periods, the speculative flows they attract can heighten market fragility and crisis susceptibility. These findings are supported by Demir *et al.* (2018); Mokni (2021), who showed that rising economic uncertainty drives both investor reallocation toward alternative assets and an increase in market volatility and crisis risk.

**Table no. 6 - Estimation result of probit model explaining cryptocurrency crise**

| **Variables** | **Coefficient** | **Prob** | **Average Marginal Effect** | **Interpretation of Marginal Effect** |
|---|---|---|---|---|
| **Estimation Results of the Probit Model Aiming to Determine the Explanatory Factors of Bitcoin Crises** | | | | |
| RETURN | -1.280543*** | 0.0010 | -0.343804 | A one-unit increase in return reduces the probability of a Bitcoin crisis by approximately 34.38 percentage points, suggesting that strong market performance significantly lowers the likelihood of a crisis. |
| VOLATILITY | 1.272397*** | 0.0000 | 0.341617 | Higher volatility increases crisis probability by 34.16 percentage points, suggesting that market uncertainty and price swings heighten perceived risk. |
| OPTIMISM | 0.083702*** | 0.0038 | 0.0022472 | Rising investor optimism increases crisis probability by 0.22 percentage points, possibly reflecting overconfidence and speculative behavior. |
| PESSIMISM | 0.015384*** | 0.0002 | 0.0041303 | Increased pessimism raises crisis probability by 0.41percentage points, reflecting sensitivity to negative investor sentiment. |
| FSI | 0.548133*** | 0.0001 | 0.147164 | A higher Financial Stress Index raises crisis probability by 14.72 percentage points, highlighting the influence of systemic macro-financial stress on Bitcoin stability. |
| EPU | 0.013790*** | 0.0000 | 0.003702 | Economic policy uncertainty increases crisis probability by 0.37 percentage points, suggesting that political and policy instability affects investor behavior. |
| C | 7.81031*** | 0.0000 | | |
| $R^2$ McFadden | | | 0.55 | |
| LR stat (prob) | | | 0.000 | |

| Variables | Coefficient | Prob | Average Marginal Effect | Interpretation of Marginal Effect |
|---|---|---|---|---|
| **Estimation Results of the Probit Model Aiming to Determine the Explanatory Factors of Ethereum Crises** | | | | |
| RETURN | -1.041807* | 0.0512 | -0.323188 | A one-unit increase in return marginally reduces the probability of an Ethereum crisis by approximately 32.32 percentage points. This implies that stronger market performance significantly lowers crisis risk. |
| VOLATILITY | 12.70908*** | 0.0000 | 3.94259 | A one-unit increase in volatility raises the probability of an Ethereum crisis by approximately 394.26 percentage points, indicating that Ethereum is highly sensitive to market instability. |
| OPTIMISM | 0.0082457 | 0.2216 | 0.00255 | Not statistically significant — suggests that optimism does not significantly predict Ethereum crises. |
| PESSIMISM | 0.0547422*** | 0.0032 | 0.016982 | A one-unit increase in pessimism raises the probability of an Ethereum crisis by about 1.70 percentage points, indicating that investor fear heightens vulnerability to crises. |
| FSI | 1.356534*** | 0.0006 | 0.420822 | A one-unit increase in the Financial Stress Index increases Ethereum crisis probability by 42.08 percentage points, showing that financial stress significantly affects crypto markets. |
| EPU | 0.0091144*** | 0.0000 | 0.002827 | A one-unit increase in Economic Policy Uncertainty raises the probability of an Ethereum crisis by approximately 0.28 percentage points, suggesting that macroeconomic or regulatory shocks contribute to crisis risk. |
| C | 9.107425*** | 0.0000 | | |
| $R^2$ McFadden | | | 0.47 | |
| LR stat (prob) | | | 0.0000 | |
| **Estimation Results of the Probit Model Aiming to Determine the Explanatory Factors of Ripple Crises** | | | | |
| RETURN | -2.493692*** | 0.0048 | -0.345482 | A one-unit increase in return reduces crisis probability by 34.55 percentage points. |
| VOLATILITY | 44.71839*** | 0.0000 | 6.195393 | Volatility greatly increases crisis risk by 619.54 percentage points, showing Ripple's high sensitivity to market swings |
| OPTIMISM | 0.1678186*** | 0.0049 | 0.02325 | Optimism raises crisis risk by 2.33 percentage points, suggesting investor overconfidence. |
| PESSIMISM | 0.1413014*** | 0.0000 | 0.0195762 | Pessimism increases crisis likelihood by 1.96 percentage points, reflecting fear-driven market sentiment. |
| FSI | 0.3974585*** | 0.0003 | 0.0550649 | Financial stress increases the probability of a Ripple crisis by 5.51 percentage points , |
| EPU | 0.0327339*** | 0.0000 | 0.004535 | Economic policy uncertainty raises crisis probability by 0.45 percentage points. |
| C | 08.24941*** | 0.0000 | | |
| $R^2$ McFadden | | | 0.51 | |
| LR stat (prob) | | | 0.0000 | |

*Notes:* *, ** and *** imply significance at the 10, 5 and 1 percent levels. Average Marginal Effects (AMEs) are computed using the Delta-method after estimating the Probit. The command margins, dydx(*) in Stata is used to derive the marginal effect of each explanatory variable on the probability of a crisis.

Source: authors' own creation

### *5.3.2. Estimation result of Logit model explaining cryptocurrency crises*

The estimation results of the logit models in Table no. 7, which aim to identify the determinants of crises in Bitcoin, Ethereum, and Ripple markets, reveal consistent and statistically significant relationships across all three cryptocurrencies. The McFadden $R^2$ values, ranging from

0.55 to 0.57, indicate a strong model fit, suggesting that the selected explanatory variables account for a substantial proportion of the variation in crisis occurrence. Across all models, return, volatility, pessimistic sentiment, financial stress, and economic policy uncertainty emerge as significant predictors. Specifically, higher returns are associated with a lower probability of crises, while increased volatility, greater pessimism, elevated financial stress, and heightened economic policy uncertainty significantly raise the likelihood of crisis episodes.

However, the effect of investor optimism, measured via Google Trends, appears to be cryptocurrency-specific. While optimism significantly increases crisis risk for Bitcoin and Ripple, it is not statistically significant for Ethereum, suggesting that positive investor sentiment does not play a decisive role in the occurrence of Ethereum crises. This heterogeneity highlights the importance of considering market-specific behavioral dynamics when analyzing the drivers of instability in cryptocurrency markets.

**Table no. 7 – Estimation result of Logit model explaining cryptocurrency crise**

| Variables | Coefficient | Prob | Average marginal effect | Interpretation of Marginal Effect |
|---|---|---|---|---|
| **Estimation Results of the Logit Model Aiming to Determine the Explanatory Factors of Bitcoin Crises** | | | | |
| RETURN | -2.095422*** | 0.0007 | -0.327037 | A one-unit increase in return decreases the probability of a Bitcoin crisis by 32.70 percentage points, indicating that stronger market performance reduces crisis risk. |
| VOLATILITY | 1.997939*** | 0.0000 | 0.311823 | A one-unit increase in volatility raises the likelihood of a Bitcoin crisis by 31.18 percentage points, highlighting that market instability significantly contributes to crisis occurrence. |
| OPTIMISM | 0.144596*** | 0.0011 | 0.225675 | Greater investor optimism raises the crisis probability by 2.26 percentage points, possibly due to speculative bubbles or overconfidence. |
| PESSIMISM | 0.026001*** | 0.0001 | 0.004056 | Pessimism increases the probability of a crisis by 0.41 percentage points, reflecting the influence of fear-driven investor reactions on market vulnerability. |
| FSI | 0.934974*** | 0.0000 | 0.145923 | A 1-unit rise in the Financial Stress Index increases crisis risk by 14.59 percentage points, confirming that systemic financial tension destabilizes Bitcoin markets. |
| EPU | 0.023144*** | 0.0000 | 0.003612 | A 1-unit increase in Economic Policy Uncertainty raises crisis probability by 0.36 percentage points, highlighting vulnerability to policy shifts. |
| C | 07.55290*** | 0.0000 | | |
| $R^2$ McFadden | | | 0.57 | |
| LR stat (prob) | | | 0.0000 | |
| **Estimation Results of the Logit Model Aiming to Determine the Explanatory Factors of Ethereum Crises** | | | | |
| RETURN | -1.796719* | 0.0481 | -0.33415 | A one-unit increase in return reduces the probability of an Ethereum crisis by approximately 33.42 percentage points indicating that positive performance helps mitigate crisis risk. |
| VOLATILITY | 21.52627*** | 0.0000 | 4.00343 | A one-unit increase in volatility increases the likelihood of an Ethereum crisis by |

| Variables | Coefficient | Prob | Average marginal effect | Interpretation of Marginal Effect |
|---|---|---|---|---|
| | | | | 400.34 percentage points, underscoring the strong sensitivity of Ethereum to market instability. |
| OPTIMISM | 0.0141687 | 0.2089 | 0.002635 | Not significant, — suggests that optimism does not significantly predict Ethereum crises. |
| PESSIMISM | 0.0912276*** | 0.0016 | 0.016966 | A one-unit increase in pessimism raises the probability of a crisis by 1.70 percentage points, indicating a notable influence of negative investor sentiment on Ethereum's risk profile. |
| FSI | 2.273135*** | 0.0004 | 0.422755 | A one-unit increase in the Financial Stress Index raises Ethereum crisis probability by 42.28 percentage points. |
| EPU | 0.015182*** | 0.0000 | 0.002823 | A one-unit increase in Economic Policy Uncertainty increases Ethereum crisis probability by 0.28 percentage points, highlighting the role of macroeconomic and regulatory shocks. |
| C | 8.9946152*** | 0.0000 | | |
| $R^2$ McFadden | | | 0.55 | |
| LR stat (prob) | | | 0.0000 | |
| **Estimation Results of the Logit Model Aiming to Determine the Explanatory Factors of Ripple Crises** | | | | |
| RETURN | -4.934835*** | 0.0048 | -0.3254279 | Higher returns reduce the probability of Ripple crises by approximately 32.54 percentage points, indicating a strong stabilizing effect. |
| VOLATILITY | 92.04943*** | 0.0000 | 6.070203 | An increase in volatility significantly raises the probability of Ripple crises by about 607.02%. |
| OPTIMISM | 0.3360511*** | 0.0049 | 0.02216099 | A one-unit increase in optimism raises the probability of crisis by 2.22 percentage points, suggesting a modest destabilizing effect. |
| PESSIMISM | 0.2485564*** | 0.0000 | 0.0163911 | A one-unit increase in pessimism increases crisis probability by 1.64 percentage points, highlighting a significant risk factor. |
| FSI | 1.034878*** | 0.0003 | 0.0136738 | A one-unit rise in the Financial Stress Index increases the probability of Ripple crises by 1.37 percentage points. |
| EPU | 0.0685409*** | 0.0000 | 0.0045199 | Economic Policy Uncertainty raises the probability of crisis by 0.45 percentage points, showing a strong link to policy shocks. |
| C | 07.15745*** | 0.0000 | | |
| $R^2$ McFadden | | | 0.56 | |
| LR stat (prob) | | | 0.0000 | |

*Notes:* *, ** and *** imply significance at the 10, 5 and 1 percent levels. Average Marginal Effects (AMEs) are computed using the Delta-method after estimating the Probit. The command margins, dydx(*) in Stata is used to derive the marginal effect of each explanatory variable on the probability of a crisis.

Source: authors' own creation

#### *5.3.3. Diagnostic checking results*

The performance analysis results from the double estimation of the Probit and Logit models for the three cryptocurrencies – Bitcoin, Ethereum, and Ripple – indicate that the models achieve high percentages of correctly predicted crisis episodes. At both the 50% and 25% significance thresholds, the false alarm rates (Type B errors) remain low, further confirming the reliability of the predictive frameworks. These findings underscore the robustness and validity of the estimated models in capturing the dynamics of cryptocurrency crises.

Table no. 8 presents the detailed performance results of the estimated models.

**Table no. 8 – Performance analysis results**

| | **Forecast error (%)** | | |
|---|---|---|---|
| | **Probit model** | | |
| | **Probit model for Bitcoin crises explaining** | **Probit model for Ethereum crises explaining** | **Probit model for Ripple crises explaining** |
| 50% threshold | | | |
| Type A[1] | 15.21 | 16.85 | 16.49 |
| Type B[2] | 09.74 | 10.01 | 09.87 |
| 25% threshold | | | |
| Type A[1] | 13.42 | 14.56 | 14.13 |
| Type B[2] | 07.12 | 09.64 | 08.49 |
| | **Logit model** | | |
| | **Logit model for Bitcoin crises explaining** | **Logit model for Ethereum crises explaining** | **Logit model for Ripple crises explaining** |
| 50% threshold | | | |
| Type A[1] | 14.81 | 16.42 | 16.05 |
| Type B[2] | 09.25 | 09.78 | 09.58 |
| 25% threshold | | | |
| Type A[1] | 13.15 | 14.22 | 13.89 |
| Type B[2] | 06.92 | 09.31 | 08.13 |

*Notes*: [1] Probability of having a crisis without any signal emitted
[2] Number of false signals among all signals

Source: authors' own creation

## 6. DISCUSSION AND CONCLUSION

This study investigates the determinants of crises in the cryptocurrency markets – specifically Bitcoin, Ethereum, and Ripple – by integrating economic fundamentals and behavioral factors such as returns, volatility, investor sentiment, financial stress, and policy uncertainty. Utilizing the CMAX method for crisis detection and probit/logit models for estimation, the research offers a comprehensive framework for understanding cryptocurrency market disruptions.

The crisis detection results reveal that Bitcoin experienced three major crises, Ethereum one prolonged crisis, and Ripple a persistent and unresolved crisis. These crises coincided with global financial shocks (e.g., the European sovereign debt crisis, COVID-19 pandemic), regulatory crackdowns, and exchange-specific events, reflecting the strong sensitivity of these markets to both macroeconomic conditions and internal vulnerabilities.

The estimation results from both the probit and logit models consistently show that returns act as a stabilizing factor across all three cryptocurrencies—Bitcoin, Ethereum, and Ripple. Higher returns are associated with a decreased probability of crisis, indicating that positive market performance enhances investor confidence and mitigates the likelihood of abrupt downturns. This underscores the importance of return trends as key indicators of market sentiment and perceived asset stability.

Conversely, volatility is identified as a significant driver of crises for all three assets. An increase in volatility reflects heightened market uncertainty and leads to amplified information asymmetry. Informed investors may preemptively adjust their portfolios by reducing their positions, while uninformed investors interpret the volatility as a sign of elevated risk. This dual reaction contributes to a collective decline in demand, intensifies panic behaviors, and raises the frequency of crises. Both models confirm that volatility plays a destabilizing role in cryptocurrency markets.

Regarding investor sentiment, the effects differ across assets. For Bitcoin and Ripple, both optimistic and pessimistic sentiments significantly increase the probability of crises. This reflects the speculative nature of these markets, where extreme positive sentiment can lead to overvaluation and bubble formation, while negative sentiment fuels fear-driven sell-offs. These dynamics align with behavioral finance theories, where emotional overreactions play a crucial role in market disruptions.

In contrast, for Ethereum, only pessimistic sentiment has a statistically significant effect on crisis occurrence. Optimistic sentiment does not appear to contribute meaningfully to crisis risk in this case, suggesting that Ethereum's market participants may be more resilient to euphoric speculation, or that its price dynamics are more fundamentally driven. The use of Google Trends to capture direct sentiment indicators further supports the explanatory power of investor behavior in crisis prediction across all three assets.

The Financial Stress Index (FSI) is another robust predictor, showing a positive and significant relationship with crisis risk in Bitcoin, Ethereum, and Ripple. During periods of elevated financial stress, investors tend to react more strongly to economic shocks, amplifying volatility and increasing the likelihood of market breakdowns. Additionally, financial stress reduces overall liquidity, making cryptocurrency markets more fragile and vulnerable to abrupt corrections.

Similarly, Economic Policy Uncertainty (EPU) significantly increases the probability of crises across all three cryptocurrencies. Political and regulatory uncertainty leads to ambiguous economic expectations, prompting disorderly portfolio adjustments and increased market volatility. Heightened EPU can also influence cryptocurrency regulation and investor behavior, exacerbating market instability. The positive association between EPU and crisis risk emphasizes the sensitivity of cryptocurrencies to the broader policy environment.

Finally, the diagnostic results of the probit and logit models confirm their robustness and predictive validity. Both models achieve high rates of correct crisis predictions and maintain relatively low false alarm rates across different threshold levels. These outcomes underscore the reliability of the selected variables—returns, volatility, sentiment, FSI, and EPU—in explaining and anticipating cryptocurrency market crises.

The implications of this study are multifaceted. Theoretically, it advances the understanding of cryptocurrency crises by confirming their presence in Bitcoin, Ethereum, and Ripple markets, and emphasizes the need to account for asset-specific dynamics in crisis analysis. Methodologically, it demonstrates the utility of advanced techniques—such as the CMAX method, probit and logit models—and highlights the value of integrating non-traditional indicators like Google Trends to capture investor sentiment.

Practically and politically, the findings offer valuable guidance for investors, regulators, and policymakers. Understanding how factors like volatility and sentiment contribute to crises can support more informed investment and regulatory decisions. Investors are encouraged to diversify portfolios and account for political and economic risks. Regulators should monitor sentiment and volatility indicators to detect early warning signs and implement timely interventions. Lastly, the importance of investor sentiment and policy uncertainty highlights the need for transparent communication and proactive regulation to foster stability in cryptocurrency markets.

This study offers valuable insights into cryptocurrency crises but has several limitations. It focuses on three major cryptocurrencies—Bitcoin, Ethereum, and Ripple—limiting generalizability. Future work should include a broader range of assets to verify these findings. While the CMAX method is widely used for crisis identification, it may miss some market distress nuances; combining it with methods like Markov-switching models could improve classification.

The use of probit and logit models assumes linear relationships, which may oversimplify market dynamics. Incorporating machine learning techniques such as random forests or neural networks could capture more complex patterns. Google Trends serves as a useful proxy for investor sentiment but may not capture its full complexity; supplementing it with social media data or surveys would enhance sentiment measurement.

The study does not consider other potentially relevant factors such as technological innovations, cyber-attacks, and governance policies, all of which can significantly influence cryptocurrency markets and their vulnerability to crises.

This analysis focuses on short-term crises, overlooking long-term structural changes. Future studies could apply time-varying or long-horizon models to reveal persistent vulnerabilities. Lastly, the study does not consider regulatory changes or region-specific policies, which can significantly affect markets. Including regulatory indicators would provide a deeper understanding of institutional impacts on crisis risk.

## ORCID

Sirine Ben Yaala https://orcid.org/0000-0002-3535-2669
Jamel Eddine Henchiri https://orcid.org/0000-0001-7675-056X

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