Market sentiment and the predictability of cryptocurrency risk premium using technical indicators

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Abstract

This paper investigates the predictability of cryptocurrency risk premium using technical indicators as predictor variables. It also evaluates the importance of periods of greed versus fear market sentiment on forecasting accuracy. By considering eight major digital coins, a sentiment index based on web-news is constructed for each currency using web scraping and textual analysis techniques. Out-of-sample results generally indicate the unpredictability of cryptocurrencies' excess returns. However, when the forecasts are disentangled into periods of greed versus fear sentiment, statistically significant predictions can be achieved. Technical predictors perform better during periods of greed market sentiment, where investors' opinions are less polarized, favoring trend-following strategies. This result is also supported by the economic value of the forecasts in an asset allocation exercise where a mean-variance investor chooses between investing in the risky asset and the risk-free rate. Robustness analyses further indicate that accurate out-of-sample forecasts are achieved in high volatility regimes, when investor sentiment has a greater impact on returns dynamics. Market participants may benefit from monitoring cryptocurrency market sentiment levels before selecting predictive variables for excess returns anticipation when developing investment strategies that use risk premium forecasts.

Keywords: Risk premium, Cryptocurrencies, Forecasting, Market sentiment, Technical analysis.

JEL Codes: C53, C58, G14, G17.

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1. Introduction

Accurate risk premium prediction helps investors make informed decisions, balance their portfolios, and manage potential risks effectively (Stein, 2024; Rapach et al., 2009; Xia, 2001). A well-assessed risk premium provides insights into the expected returns relative to the inherent risks, enabling more strategic investment planning and developing profitable market timing strategies (Hollstein et al., 2024; Yin, 2019; Avramov & Wermers, 2006). Risk premium prediction is particularly important in the cryptocurrency market, where considerable price fluctuations can occur rapidly, driven by factors such as regulatory changes, technological advancements, and market sentiment (Aysan et al., 2024; Arpaci, 2023; Meegan et al., 2021). Furthermore, understanding risk premium dynamic aids in the development of more robust financial models and enhances the overall stability and maturity of the cryptocurrency market, attracting a broader range of institutional and individual investors (Huang, 2024).

There has been an extensive discussion in the financial literature regarding the empirical evidence supporting the predictability of risk premium, especially in stock markets (Campbell & Shiller, 1988; Fama & French, 1988; Cochrane, 2008; Campbell & Thompson, 2008). The influential study by Welch & Goyal (2008) has reignited this debate by suggesting that equity risk premium is unpredictable. Since then, many researches focused on identifying in which conditions the equity premium is predictable (Yin, 2019; Tsiakas et al., 2020; Nonejad, 2022; Fernández et al., 2023; Kothari & O'Doherty, 2023; Goyal et al., 2023; Hollstein et al., 2024; Stein, 2024). Other studies dedicate to the construction and evaluation of new predictor variables and the development of more robust econometric methods (Yin, 2019; Tsiakas et al., 2020; Dichtl et al., 2021; Ciner, 2022; Wang & Zhou, 2023; Alexandridis et al., 2023). This paper contributes to this ongoing literature by exploring the predictability of cryptocurrencies excess returns.

Risk premium forecasting studies generally use technical and macroeconomic indicators as predictor variables[1]. For the case of cryptocurrencies, due to the absence of clearly (macro)economic fundamentals, technical variables would play a key role for excess returns prediction. The theoretical reasons why technical indicators are able to predict the risk premium are not yet well established in the literature. Neely et al. (2014) discuss four theoretical constructs to explain the predictive capacity of technical indicators: i) investors' access to information is asymmetrical – under this market friction, technical analysis is useful for identifying whether information has been fully incorporated into asset prices (Treynor & Ferguson, 1985); ii) investors are heterogeneous, with different responses to new information (Cespa & Vives, 2012); iii) investors underreact and overreact when incorporating new information (Barberis & Thaler, 2003); iv) investor sentiment affects price dynamics (Baker & Wurgler, 2006; Sze Nie Ung & Anderson, 2024).

Studies showed that investor sentiment is one of the mechanisms that moves asset prices away from their respective fundamental values. The ability of technical indicators to predict the risk premium could be explained by the ability of these indicators to anticipate changes in investor sentiment (Long et al., 1990; Baker & Wurgler, 2006; Huang et al., 2014; Gric et al., 2023). The predictive power of technical indicators has been confirmed for stock prices (Nazário et al., 2017; Lin, 2018; Dai et al., 2021) and also for cryptocurrency prices and returns (Svogun & Bazán-Palomino, 2022; Goutte et al., 2023; Bazán-Palomino & Svogun,

[1]Alternative variables are also considered, such as commodity prices (Nonejad, 2021, 2022), information extracted from options markets (Wang & Zhou, 2023), and the number of job postings divided by the employment level (Kothari & O'Doherty, 2023).

2023). Particularly for digital coins, market sentiment have played an important role on these assets' price dynamic (Li & Ma, 2024; Osman et al., 2024; Meyer et al., 2023).

Lin et al. (2023) found significant correlations between investor sentiment and volatility spillovers in the cryptocurrency market, highlighting the critical role of sentiment contagion in understanding market dynamics. Jo et al. (2020) showed that Bitcoin returns resembled returns to high sentiment beta stocks, and that Bitcoin's expected returns are low (high) when sentiment is high (low). More recently, Aysan et al. (2024) investigated the relationship between price jumps and news sentiment in cryptocurrencies. Their findings indicate that the release of information increases the probability of price jumps.

In this context, the aim of this paper is to evaluate the predictability of cryptocurrencies' risk premium using technical indicators as predictor variables. Eight of the most relevant digital coins are considered: Binance (BNB), Bitcoin (BTC), Dogecoin (DOGE), Ethereum (ETH), Litecoin (LTC), Stellar (XLM), Tron (TRX) and Ripple (XRP). The analysis covers the period from 2018 to 2023. Due to the high relevance of market sentiment in the digital coin market (Lin et al., 2023; Wang et al., 2022; Aysan et al., 2024), it is expected that technical indicators will provide accurate forecasts for the risk premium, as market sentiment helps to explain the predictive ability of technical analysis (Baker & Wurgler, 2006; Wang et al., 2022; Sze Nie Ung & Anderson, 2024). This work advances the literature on risk premium predictability by focusing on the cryptocurrency market, instead of considering only the equity market as most studies do. The methodology includes the classic bivariate regression approach using fourteen technical indicators as predictor variables, constructed based on moving average, volume, and momentum strategies (Welch & Goyal, 2008; Neely et al., 2014; Fernández et al., 2023). The predictability of the risk premium is assessed in out-of-sample predictive analyses to mimic real-world decision-making environments. The quality of the forecasts is measured in terms of accuracy. Predictions are statistically compared with the historical average benchmark.

In addition, using web scraping and textual analysis techniques, a news-based sentiment index is constructed for each evaluated cryptocurrency to disentangle the risk premium forecasting accuracy into periods of greed versus fear sentiment. This approach enables the verification of which market sentiment conditions allow technical indicators to yield better excess returns forecasts. For instance, Smith et al. (2016) showed that hedge fund managers who use technical analysis achieved higher performance during high-sentiment periods. Ding et al. (2023) and Picasso et al. (2019) relate the predictability of stock prices with market sentiment and the use of technical trading rules. Finally, forecasts are also evaluated in economic terms by considering an asset allocation exercise where the investor decides between investing in the risky asset and the risk-free rate. Jena et al. (2022) provided evidence of the market inefficiency of the most traded cryptocurrencies, revealing exploitable profitable trading opportunities. Thus, this paper evaluates these opportunities when forecasting the risk premium of cryptocurrencies and using these predictions in a portfolio allocation exercise.

To improve robustness, the quality of risk premium forecasts is also assessed during periods of different market volatility dynamics. Cryptocurrency volatility is estimated using regime-switching Markov GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models to define periods of low versus high volatility[2]. According to Baker & Wurgler (2006), a wave of investor sentiment has a greater impact on high-volatility stocks. Hence, high predictability of crypto risk premiums is expected during periods of heightened volatil-

[2]Wang et al. (2022) identified that technical indicators are powerful in forecasting Bitcoin volatility under different volatility regimes.

ity.

The findings showed that, in general, technical indicators are not good predictors of cryptocurrencies risk premium. However, when sentiment are disentangled into fear and greed, statistically accurate predictions are achieved. Technical indicators are better forecasters of excess returns during greed market periods, indicating that trend-following measures are more appropriate when investors have an optimistic outlook on the future – these conclusions hold true in economic terms. In fear market periods, investors' opinions are polarized, leading to price trend breakdowns and limiting the predictive power of technical indicators. When high volatility regimes are observed, the predictive capacity of technical indicators in forecasting the risk premiums of the evaluated digital currencies increases, confirming the major role of market sentiment for high volatile assets (Baker & Wurgler, 2006).

This study contributes to the literature and to the market practice. First, it enhances the body of work on the cryptocurrency market by relating sentiment with risk premium predictability. For the digital coin market, we provide new evidence that technical variables are relatively more useful in greed-sentiment periods for excess returns prediction. Second, this study expands the standard literature on risk premium forecasting to include cryptocurrencies. Given the relatively recent emergence of cryptocurrencies and the evolving nature of the market, there is limited research on the predictability of technical variables in this context over extended periods and not focusing solely on Bitcoin. Finally, we explore the practical implications of identifying periods where investors can achieve the highest accuracy in predicting the cryptocurrency risk premium. Our findings indicate that recognizing periods of higher predictive accuracy can significantly benefit investors, allowing them to make more informed decisions and optimize their investment strategies. This practical approach underscores the value of predictive accuracy in navigating the highly volatile and sentiment-based nature of the cryptocurrency market.

The remainder of this paper is structured as follows. Section 2 outlines the methodology, detailing: the data; the technical indicators used as predictive variables; the bivariate regression approach considered to assess risk premium predictability and how accuracy is measured; the construction of crypto sentiment indexes; and the modeling of volatility regimes. Section 3 focuses on the out-of-sample evaluations of risk premium forecasting in general conditions and in periods of high versus low sentiment. In Section 4, the economic benefits of forecasting the cryptocurrency risk premium are provided through an asset allocation exercise. Results are also evaluated under different volatility states in Section 5. Finally, Section 6 provides a summary of the key findings and proposes topics for future research.

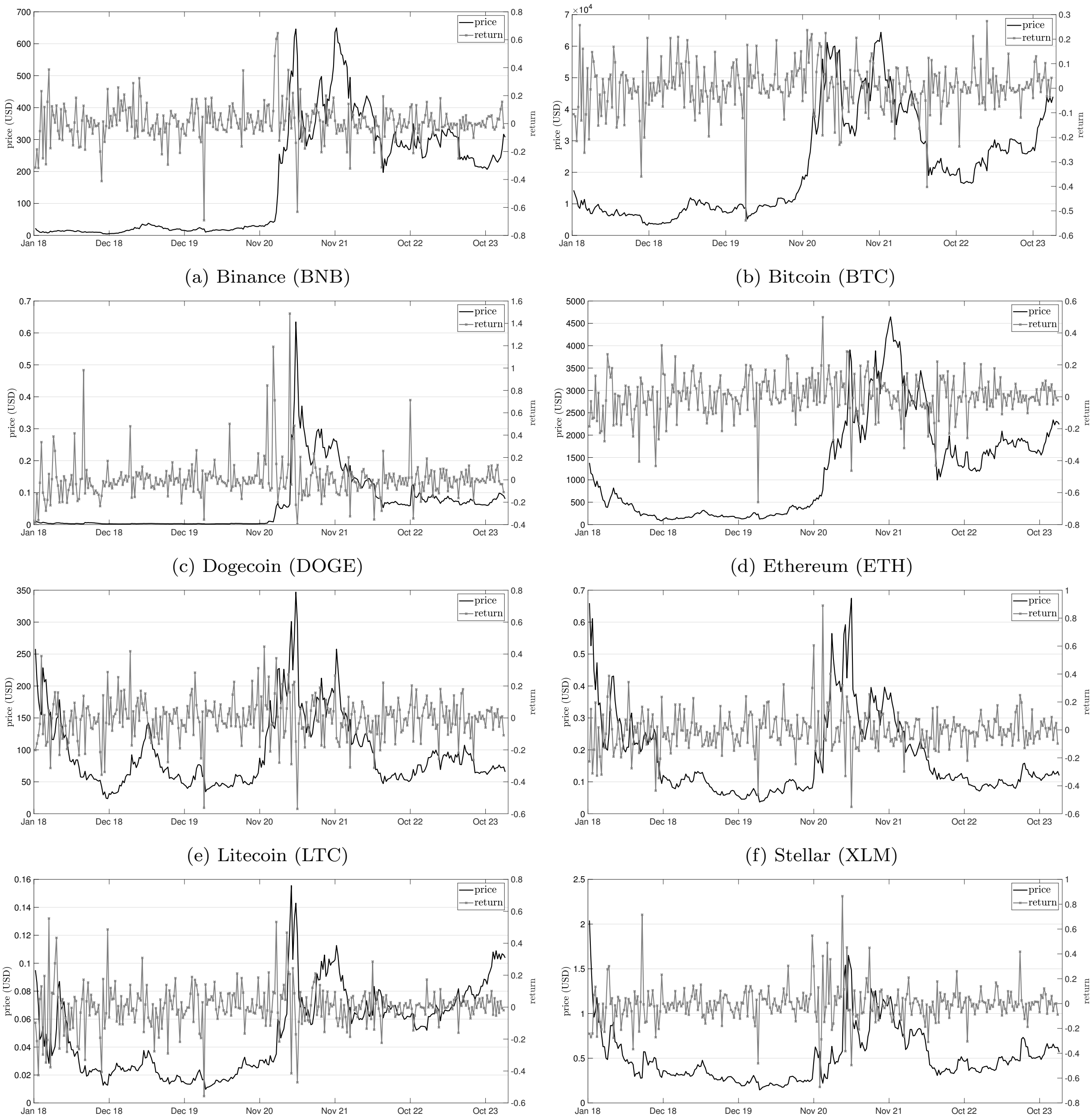
2. Methodology

2.1. Data

This study considers eight majorly traded cryptocurrencies: Binance (BNB), Bitcoin (BTC), Dogecoin (DOGE), Ethereum (ETH), Litecoin (LTC), Stellar (XLM), Tron (TRX) and Ripple (XRP). They were selected due to their representation of the cryptocurrency market, and the availability of historical data enough to produce a highest number of rolling out-of-sample forecasts. The data consists of weekly closing prices and volume (in USD) for the period from 1/1/2018 to 12/31/2023, totaling 313 observations (weeks)[3]. The clas-

[3]The sample starts in 2018, as historical data is available for all digital coins, and ends in 2023 according to data availability when the experiments were conducted. The data was extracted from Investing website: `https://www.investing.com/`.

sic risk premium forecasting literature typically utilizes monthly data, which may not be appropriate for cryptocurrencies due to their highly volatile nature. Hence, weekly data is employed in this study[4]. Figure 1 illustrates the price and log-return series of the selected cryptocurrencies from 2018 to 2023. The evolution of prices exhibits a clearly high volatile dynamic, which is reflected in the return's series through evidence of volatility clusters.



(a) Binance (BNB)

(b) Bitcoin (BTC)

(c) Dogecoin (DOGE)

(d) Ethereum (ETH)

(e) Litecoin (LTC)

(f) Stellar (XLM)

(g) Tron (TRX)

(h) Ripple (XRP)

Figure 1: Temporal evolution of prices and returns of the selected cryptocurrencies.

2.2. Technical indicators

Drawing from the established literature on predictive analysis of the risk premium in stock markets (Welch & Goyal, 2008; Neely et al., 2014; Liu, 2019; Fernández et al., 2023), fourteen technical indicators are utilized as predictor variables. These indicators are derived

[4]Experiments were also conducted using daily data, and the results are qualitatively similar.

from three trend-identification strategies. Buy decision signals (BS) are formulated based on these strategies. The initial strategy employs moving average rules (MA). At each time t, buy signals are generated ($BS_t^{\text{MA}} = 1$), or not ($BS_t^{\text{MA}} = 0$), based on the comparison between two moving averages:

$$\text{BS}_t^{\text{MA}} = \begin{cases} 1, & \text{if } \text{MA}_{s,t} \geq \text{MA}_{l,t}, \\ 0, & \text{if } \text{MA}_{s,t} < \text{MA}_{l,t}, \end{cases} \tag{1}$$

where $\text{MA}_{j,t} = (1/j)\sum_{i=0}^{j-1} P_{t-i}$, for $j = s, l$, P_t is the price at t, and s and t are the lengths of the short and long moving average windows, respectively. Moving average technical indicators are denoted as $\text{MA}(s, l)$.

The second strategy is grounded in momentum (MOM). Buy signals are generated according to the following:

$$\text{BS}_t^{\text{MOM}} = \begin{cases} 1, & \text{if } P_t \geq P_{t-m}, \\ 0, & \text{if } P_t < P_{t-m}. \end{cases} \tag{2}$$

Momentum indicators are denoted by $\text{MOM}(m)$ – the signals are computed according to the relationship in Eq. (2).

Lastly, to formulate a buying decision rule, the third strategy integrates price data and trading volume data as follows:

$$\text{BS}_t^{\text{VOL}} = \begin{cases} 1, & \text{if } \text{MA}_{s,t}^{\text{OBV}} \geq \text{MA}_{l,t}^{\text{OBV}}, \\ 0, & \text{if } \text{MA}_{s,t}^{\text{OBV}} < \text{MA}_{l,t}^{\text{OBV}}, \end{cases} \tag{3}$$

where $\text{OBV}_t = (1/j)\sum_{k=1}^{t} \text{VOL}_k \text{D}_k$, VOL_k is the trading volume in k, $\text{D}_k = 1$ if $P_k - P_{k-1} \geq 0$, $\text{D}_k = 0$ otherwise, and $\text{MA}_{j,t}^{\text{OBV}} = (1/j)\sum_{i=0}^{j-1} \text{OBV}_{t-i}$ for $j = s, l$.

The volume strategy is represented by variables denoted as $\text{VOL}(s, l)$.

Therefore, the fourteen technical analysis predictors considered are (Fernández et al., 2023; Liu, 2019; Neely et al., 2014): MA(1,9), MA(1,12), MA(2,9), MA(2,12), MA(3,9), MA(3,12), with $s = 1, 2, 3$ and $l = 9, 12$; MOM(9), MOM(12), with $m = 9, 12$; and VOL(1,9), VOL(1,12), VOL(2,9), VOL(2,12), VOL(3,9), VOL(3,12), with $s = 1, 2, 3$ and $l = 9, 12$.

2.3. Predictive approach

Employing technical indicators to assess the predictability of the cryptocurrencies' risk premium, the classic bivariate predictive regression is considered to compute out-of-sample forecasts (Welch & Goyal, 2008; Neely et al., 2014; Liu, 2019; Fernández et al., 2023):

$$\hat{r}_{t+1}^{p} = \hat{\gamma}_i + \hat{\lambda}_i x_{i,t}, \tag{4}$$

where r_t^p denotes the cryptocurrency risk premium at time t, calculated as the difference between the cryptocurrency return and the risk-free interest rate; $x_{i,t-1}$ represents one of the fourteen technical indicators at $t-1$, with $i = 1, 2, \ldots, 14$; $\hat{\gamma}_i$ and $\hat{\lambda}_i$ are the least squares estimates of the regression of $\{r_s^p\}_{s=2}^{t}$ on a constant and on $\{x_{i,s}\}_{s=1}^{t-1}$.

The forecasts are compared with the historical average (HA) – benchmark from the literature on equity risk premium predictability (Welch & Goyal, 2008; Campbell & Thompson, 2008; Ferreira & Santa-Clara, 2011; Neely et al., 2014). The HA is calculated as:

$$\hat{r}_{t+1}^{HA} = \left(\frac{1}{t}\right) \sum_{j=1}^{t} r_j^p. \tag{5}$$

Out-of-sample R_{OS}^2 and disentangled $R_{OS,c}^2$ are calculated as follows (Campbell & Thompson, 2008), respectively:

$$R_{OS}^2 = 1 - \frac{MSFE_i}{MSFE_0} = 1 - \frac{\sum_{t=1}^{T} (r_t^p - \hat{r}_t^p)^2}{\sum_{t=1}^{T} (r_t^p - \hat{r}_t^{HA})^2}, \tag{6}$$

$$R_{OS,c}^2 = 1 - \frac{MSFE_i}{MSFE_0} = 1 - \frac{\sum_{t=1}^{T} I_t^c (r_t^p - \hat{r}_t^p)^2}{\sum_{t=1}^{T} I_t^c (r_t^p - \hat{r}_t^{HA})^2}, \tag{7}$$

where $MSFE_i$ and $MSFE_0$ represent the mean squared forecast errors of the i model and of the historical average benchmark, respectively; I_t^c is an indicator variable with $c =$ fear sentiment (FS) and $c =$ greed sentiment (GS) and, alternatively, with $c =$ low volatility (LV) and $c =$ high volatility (HV).

Positive values of $R_{OS}^2/R_{OS,c}^2$ indicate that the predictive regression model performs better than the historical average. The statistical significance of $R_{OS}^2/R_{OS,c}^2$ is evaluated using the test proposed by Clark & West (2007). The adjusted MSFE statistic ($MSFE_{adj}$) (Clark & West, 2007) is used. This statistic tests the null hypothesis that the MSFE value of the historical average model is less than or equal to the MSFE value of the predictive regression models, which use technical indicators as predictor variables. The hypotheses are: $H_0: \ R_{OS}^2 \leq 0$ versus $H_1: \ R_{OS}^2 > 0$; and $H_0: \ R_{OS,c}^2 \leq 0$ versus $H_1: \ R_{OS,c}^2 > 0$. The effectiveness of the forecast models is evaluated through out-of-sample analyses, aiming to simulate real-time decision-making for investors.

2.4. Market sentiment

A news-based sentiment index was constructed for each evaluated cryptocurrency. The methodology used for this purpose follows two main steps: i) daily collection of news articles from web sources using a web scraping algorithm; and chronological organization and merging of articles based on their titles and descriptions; and ii) application of the FinBERT (A Large Language Model for Extracting Information from Financial Text) sentiment analysis model. Each of these steps is detailed below. The purpose of this analysis is to capture the market sentiment specifically for each cryptocurrency, rather than using a general index for all of them – such as the Fear & Greed Crypto Index, which major reflects the market sentiment for the Bitcoin. This approach aims to highlight the unique characteristics of each coin in terms of market sentiment.

2.4.1. News-based data collection

To structure the text corpus[5], we proceeded with the collection of daily publicly available news articles published by major web-based media outlets[6] between January 1, 2018, and December 31, 2023. The collection procedure was conducted using a web scraping algorithm developed in Python using the Selenium library[7]. The algorithm was designed to interact systematically with the prominent search engine, Google. The algorithm was developed to extract information deemed most relevant, as per the search engine's automatic classification, through the use of a specific keyword: "[Name of the Crypto] news" (for instance, "Bitcoin news"). The output of the code included key details such as title, description, publication date, news source name, and URL. The selection of Google as the primary source for data

[5]A corpus is a collection of authentic text or audio organized into datasets.

[6]Media outlets are defined as organizations or platforms that disseminate news and information to the public.

[7]For details see: `https://www.selenium.dev/documentation/`.

collection was justified by its predominant position as a global search engine, encompassing a wide variety of information sources (Lewandowski, 2015). This decision aims to ensure comprehensive and large representation of the news, thereby contributing to the robustness and generalization of the results obtained from the constructed corpus (Hoseinabadi & Sohrabi, 2024; Lewandowski, 2015). An example of word cloud for Bitcoin is illustrated in Figure B.1 in Appendix B – a word cloud is constructed using pre-processed text corpus.

2.4.2. Indexes construction

Following the data collection phase, we proceeded to the data preprocessing stage, where we structured the data by organizing the news articles chronologically and merging the title with the news description to use as input in the FinBERT classification model (Araci, 2019). Developed based on the BERT transformer, FinBERT was specifically designed for sentiment analysis in financial contexts (Sidogi et al., 2021), characterized by its ability to comprehend linguistic nuances intrinsic to the economic domain.

The decision to employ FinBERT in this study was motivated by the necessity to capture and understand the underlying sentiment within the collected financial texts, aiming to identify relevant patterns and trends for analysis, as well as the efficiency demonstrated by transformer architecture-based models (Huang et al., 2023). The integration of this model into our project was facilitated through the Hugging Face platform, which allowed us to utilize the pre-trained model for sentiment analysis task execution[8]. As the model output, we obtained the probability of each news input into our model falling into one of three categories: neutral, positive, and negative. The sentiment score was calculated through the positive-negative probability difference (Araci, 2019). Table B.1 in Appendix B shows the dataset sentiment summary in terms of processed data generated from FinBERT for each cryptocurrency. Figure B.2 in Appendix B illustrates the daily temporal evolution of the sentiment indexes for all the evaluated digital coins. Positive (negative) values of the indexes are associated with greed (fear) market sentiment.

2.5. Volatility regimes

Cryptocurrencies risk premium forecasts are also evaluated for different returns volatility regimes. This analysis provides robustness as market sentiment plays a more important role for high volatility assets (Baker & Wurgler, 2006). To define different volatility regimes for cryptocurrency returns, a regime-switching GARCH model is employed. Several studies in the literature have supported the existence of regime changes in the volatility dynamics of asset prices (Huang & Luo, 2024; Li et al., 2023; Zhang et al., 2019), particularly for cryptocurrencies (Bariviera, 2017; Balcombe & Fraser, 2017; Ardia et al., 2019; Maciel, 2021).

Let $y_t \in \mathbb{R}$ represent the log-return of the cryptocurrencies at time t, where $y_t = \ln(P_t) - \ln(P_{t-1})$, and P_t denotes the price at time t. Assuming that the volatility dynamics of log-returns have a zero mean, $\mathbb{E}[y_t] = 0$, and that y_t are not serially autocorrelated[9], the general specification of the Markov-Switching GARCH (MS-GARCH) model can be summarized as:

$$y_t | (s_t = k, \mathcal{I}_{t-1}) \sim \mathcal{D}(0, h_{k,t}), \tag{8}$$

where $\mathcal{D}(0, h_{k,t})$ represents a continuous distribution with a zero mean and a time-varying conditional variance $h_{k,t}$ in regime k, where $k = 1, \ldots, K$. The state variable s_t evolves

[8] The platform is available at: `https://huggingface.co/docs`.

[9] To ensure this, the data was pre-filtered using an AR(p) model, where p denotes the order of the autoregressive process.

according to a first-order ergodic homogeneous Markov chain with a finite number of states K, with transition probability matrix $\mathbf{P} \equiv p_{i,j}{}_{i,j=1}^{K}$, where $p_{i,j} \equiv \mathbb{P}[s_t = j | s_{t-1} = i]$ represents the probability of transitioning from state i to state j. Finally, $\mathcal{I}_{t-1}$ denotes the information set available up to time $t-1$, and the standardized innovations are defined as $y_t \equiv h_{k,t}^{1/2} \eta_{k,t}$, and $\eta_{k,t} \sim i.i.d.\ \mathcal{D}(0,1)$.

Following Haas et al. (2004), Maciel (2021), and Panagiotidis et al. (2022), the conditional variance of y_t is assumed to follow a GARCH-type model. Thus, conditionally on regime $s_t = k$, the GARCH-type conditional variance $h_{k,t} \equiv h(y_{t-1}, h_{k,t-1})$ is a function of past returns and past conditional variance. In this paper, the symmetric GARCH(1,1) method of Bollerslev (1986) is considered, with the following specification:

$$h_{t,k} \equiv \alpha_{0,k} + \alpha_{1,k} y_{t-1}^2 + \beta_k h_{k,t-1}, \tag{9}$$

for $k = 1, \ldots, K$, K is the number of regimes; and $\alpha_{0,k}, \alpha_{1,k}, \beta_k$ are the parameters to be estimated. To ensure positivity: $\alpha_{0,k} > 0$, $\alpha_{1,k} > 0$, and $\beta_k \geq 0$. Covariance-stationarity in each regime is obtained by requiring $\alpha_{1,k} + \beta_k < 1$. The unconditional variance of regime k is computed as $UV_k = [\alpha_{0,k}/(1 - \alpha_{1,k} - \beta_k)]$.

A GARCH model is selected due to its parsimonious results in modeling cryptocurrencies volatility dynamics, especially when volatility regimes are allowed to model the volatility generating process (Panagiotidis et al., 2022; Maciel, 2021). For the innovations, the standardized Student-t was selected as it provides lowest values of the Bayesian information criteria. Models were estimated via maximum likelihood. The identification of high versus low volatility regimes is carried out by ordering the states according to the unconditional variance of each GARCH-type process, from lower to higher values.

3. Market sentiment and crypto risk premium forecasting

To allow comparisons with seminal studies in the literature (Neely et al., 2014; Fernández et al., 2023), the initial estimation period considered data from 1/1/2018 to 1/1/2019 – a total of 53 weekly observations. Based on this window, the first one-step-ahead prediction was generated. From 1/7/2019 to 12/31/2023, a total of 248 out-of-sample predictions were obtained. The risk premium was calculated as the difference between the log-return of the cryptocurrecnies and the log-return of the risk-free interest rate. As in the papers by Welch & Goyal (2008), Neely et al. (2014), among others, the risk-free rate is represented by the weekly interest rate on three-month US treasury bills[10]. Tables A.1-A.8 in Appendix A provide the descriptive statistics for the dependent variable – the risk premium of the cryptocurrencies – and the independent variables – the buy signals obtained from the technical indicators – used in the regression models for all digital coins evaluated in this work. The Tables also include the statistics for the indicator variables that define periods of greed sentiment and high volatility regimes, i.e. when these variables assume a value of unity. The out-of-sample forecast results are considered, as they reflect the real conditions of decision-making in financial markets.

For cryptocurrencies risk premium out-of-sample predictions, Table 1-8 show the results for BNB, BTC, DOGE, ETH, LTC, XLM, TRX and XRP, respectively. For the entire period, the predictive ability of the technical indicators is measured by the values of R^2_{OS}. Positive values of $R^2_{OS}/R^2_{OS,c}$ indicate that the predictive regression outperforms the historical average. Using the Clark & West (2007) test, the statistical significance of $R^2_{OS}/R^2_{OS,c}$ is

[10]Data were extracted from `https://fred.stlouisfed.org/categories/116`.

evaluated[11]. The adjusted MSFE statistic ($MSFE_{adj}$) (Clark & West, 2007) was considered. The statistic evaluates the null hypothesis that the MSFE value of the historical average model is less than or equal to the MSFE value of the predictive regression models – the models that use technical indicators and macroeconomic indicators as predictor variables. The hypotheses are: $H_0: \ R^2_{OS} \leq 0$ versus $H_1: \ R^2_{OS} > 0$.

Considering the entire out-of-sample period, four out of the eight cryptocurrencies analyzed showed significant R^2_{OS} values at a significance level of at least 10%. For BTC (Table 2), DOGE (Table 3) and LTC (Table 5), almost all technical indicators provided statistically superior forecasts compared to those obtained from the historical average. For XRP 8), five out of the fourteen technical indicators resulted in significant R^2_{OS} values. In cases where R^2_{OS} values were statistically greater than zero, the vast majority exceeded 0.5%. For equity risk premium forecasting, Neely et al. (2014) indicates that R^2_{OS} values above 0.5% lead to predictions capable of generating economic gains in portfolio allocation based on the forecasts.

When we consider the disentangled R^2, the inferences are different across distinct market sentiment status. Accuracy is assessed when the market sentiment is greed ($R^2_{OS,GS}$) and when the market sentiment is fear ($R^2_{OS,FS}$). Greed (fear) sentiment is characterized when the constructed sentiment index assumes positive (negative) values. For the cases when accurate out-of-sample forecasts were achieved – BTC (Table 2), DOGE (Table 3) and LTC (Table 5) –, which coincides with greed market sentiment, almost all technical indicators provided statistically superior risk premium predictions to the historical average benchmark (at a significance level of at least 10%). When the sentiment of fear dominates investors' perceptions, digital coins excess returns are hard to anticipate. For XLM (Table 6), when market sentiment is disentangled into greed and fear, some technical indicators provide statistically significant forecasts in both statuses. Exceptions are TRX (Table 7) and XRP (Table 8), where significant predictions are found in moments of fear markets. Concerning the cryptocurrencies where the risk premium is predictable (BTC, DOGE, and LTC), better forecasts are obtained in periods of greed markets. The use of technical indicators, as predictive variables, is not adequate in periods of fear markets, as uncertainty rises and investors' opinions are more polarized, reducing the effect of trends in prices and hence the capability of trend-following technical indicators in anticipating changes in risk premium. These findings empirically support the relations suggested by Baker & Wurgler (2006) on the role of market sentiment for high volatile financial assets.

[11]For nested models, the Clark & West (2007) test is a modification of the Diebold & Mariano (1995) test. The benchmark predictor (historical average) is a special case of bivariate regressions. The historical average model assumes that the expected risk premium is constant, i.e.: $r^p_{t+1} = \alpha + e_{t+1}$, where α is a constant and e is a random error term.

Table 1: Out-of-sample predictive results for Binance (BNB).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	175.24									
MA(1,9)	177.07	-1.0443	0.4791	0.3160	0.6042	1.0615	0.1442	-3.5580	-0.3491	0.6365
MA(1,12)	177.21	-1.1230	0.5871	0.2786	1.1647	1.2709	0.1019	-4.6113	-0.4619	0.6779
MA(2,9)	177.66	-1.3766	0.5617	0.2871	0.8978	1.2465	0.1063	-4.8447	-0.5037	0.6928
MA(2,12)	176.79	-0.8821	0.4529	0.3253	1.1991*	1.2881	0.0989	-4.0557	-0.5289	0.7016
MA(3,9)	177.73	-1.4193	0.4407	0.3297	0.3940	1.0148	0.1551	-4.1844	-0.3870	0.6506
MA(3,12)	176.82	-0.9020	0.4848	0.3139	0.5632	0.9365	0.1745	-3.1362	-0.2088	0.5827
MOM(9)	176.07	-0.4719	0.6889	0.2454	0.2289	0.7321	0.2321	-1.5405	0.2543	0.3996
MOM(12)	176.31	-0.6103	0.2012	0.4203	0.6783	1.2041	0.1143	-2.5752	-0.4356	0.6684
VOL(1,9)	176.49	-0.7142	0.3914	0.3477	1.4905**	1.7824	0.0373	-4.0760	-0.5659	0.7143
VOL(1,12)	175.50	-0.1437	1.1767	0.1197	1.1697*	1.3993	0.0809	-2.1467	0.3573	0.3604
VOL(2,9)	177.80	-1.4588	0.6049	0.2726	-0.1934	0.8160	0.2073	-3.3883	0.0299	0.4881
VOL(2,12)	176.88	-0.9349	0.9661	0.1670	0.1955	1.0104	0.1562	-2.6586	0.3945	0.3466
VOL(3,9)	178.01	-1.5785	0.3539	0.3617	0.6170	1.0850	0.1390	-4.9263	-0.5323	0.7028
VOL(3,12)	176.24	-0.5696	0.7142	0.2376	0.6731	1.1434	0.1264	-2.4644	0.0494	0.4803

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0:\ R^2_{OS} \leq 0$ against $H_1:\ R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 2: Out-of-sample predictive results for Bitcoin (BTC).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	91.94									
MA(1,9)	90.62	1.4433***	2.5366	0.0056	3.0638***	2.6515	0.0040	-2.2266	0.3645	0.3578
MA(1,12)	91.23	0.7754**	2.1829	0.0145	1.8542**	2.2769	0.0114	-1.6679	0.2607	0.3971
MA(2,9)	91.46	0.5247**	2.2893	0.0110	1.6771***	2.3510	0.0094	-2.0850	0.3632	0.3582
MA(2,12)	91.46	0.5214**	2.2979	0.0108	0.8694**	2.1554	0.0156	-0.2669	0.8089	0.2093
MA(3,9)	91.30	0.7042**	2.3014	0.0107	1.1800**	2.1836	0.0145	-0.3735	0.7775	0.2184
MA(3,12)	91.51	0.4745**	2.2614	0.0119	0.7576**	2.1154	0.0172	-0.1667	0.8107	0.2088
MOM(9)	91.43	0.5624**	2.2355	0.0127	1.0309**	2.1324	0.0165	-0.4987	0.6930	0.2441
MOM(12)	90.69	1.3605***	2.3391	0.0097	1.9707**	2.2315	0.0128	-0.0215	0.7683	0.2212
VOL(1,9)	92.00	-0.0654	2.0885	0.0184	0.0084**	1.9414	0.0261	-0.2326	0.7787	0.2181
VOL(1,12)	91.52	0.4586**	2.1533	0.0156	0.9085**	2.0529	0.0200	-0.5602	0.6706	0.2513
VOL(2,9)	91.06	0.9665**	2.3104	0.0104	1.8813**	2.2813	0.0113	-1.1053	0.5608	0.2875
VOL(2,12)	91.50	0.4805**	2.1508	0.0157	0.8506**	2.0286	0.0213	-0.3576	0.7258	0.2340
VOL(3,9)	91.42	0.5684**	2.2033	0.0138	1.0756**	2.1161	0.0172	-0.5802	0.6393	0.2613
VOL(3,12)	91.54	0.4346**	2.1235	0.0169	0.8781**	2.0328	0.0210	-0.5699	0.6318	0.2638

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: \; R^2_{OS} \leq 0$ against $H_1: \; R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 3: Out-of-sample predictive results for Dogecoin (DOGE).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	345.61									
MA(1,9)	341.91	1.0719**	1.7560	0.0395	1.8857**	1.8468	0.0324	-2.9238	-0.0553	0.5220
MA(1,12)	342.27	0.9670**	1.7046	0.0441	1.6397**	1.6971	0.0448	-2.3359	0.2590	0.3978
MA(2,9)	341.97	1.0545**	1.8239	0.0341	1.9541**	1.9204	0.0274	-3.3628	-0.0494	0.5197
MA(2,12)	342.07	1.0248*	1.6443	0.0501	1.1844*	1.4034	0.0803	0.2415*	1.3223	0.0930
MA(3,9)	342.37	0.9393**	1.6850	0.0460	1.7708**	1.7720	0.0382	-3.1437	-0.0879	0.5350
MA(3,12)	342.26	0.9694**	1.6597	0.0485	1.3942*	1.5416	0.0616	-1.1166	0.7440	0.2284
MOM(9)	341.62	1.1567**	1.6934	0.0452	1.5169*	1.5387	0.0619	-0.6117	0.8982	0.1845
MOM(12)	349.43	-1.1052	1.4191	0.0779	-1.0773	1.0892	0.1380	-1.2422	1.7194	0.0428
VOL(1,9)	341.28	1.2530**	1.9313	0.0267	1.0168*	1.5034	0.0664	2.4128*	1.3981	0.0810
VOL(1,12)	342.97	0.7656*	1.3544	0.0878	1.0875*	1.4191	0.0779	-0.8147	0.0744	0.4704
VOL(2,9)	341.05	1.3192**	1.7502	0.0400	1.3279*	1.4666	0.0712	1.2766	1.1128	0.1329
VOL(2,12)	342.50	0.9013**	1.6546	0.0490	1.2446*	1.4903	0.0681	-0.7844	0.9585	0.1689
VOL(3,9)	340.65	1.4346**	1.6577	0.0487	1.8558*	1.5870	0.0563	-0.6336	0.5709	0.2840
VOL(3,12)	343.25	0.6832**	1.6461	0.0499	1.4327*	1.6182	0.0528	-2.9966	0.3177	0.3754

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 4: Out-of-sample predictive results for Ethereum (ETH).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	147.02									
MA(1,9)	147.09	-0.0488	1.4741	0.0702	0.0987	1.2740	0.1013	-0.5946	0.7419	0.2291
MA(1,12)	147.61	-0.4001	1.1487	0.1253	-0.0673	1.1161	0.1322	-1.6316	0.3461	0.3646
MA(2,9)	147.73	-0.4854	1.2286	0.1096	-0.0418	1.2513	0.1054	-2.1271	0.2224	0.4120
MA(2,12)	147.41	-0.2662	1.2315	0.1091	0.0050	1.1690	0.1212	-1.2699	0.4476	0.3272
MA(3,9)	147.71	-0.4690	1.2666	0.1026	-0.2202	1.2114	0.1129	-1.3899	0.4234	0.3360
MA(3,12)	147.36	-0.2311	1.2408	0.1073	-0.0591	1.1271	0.1299	-0.8676	0.5383	0.2952
MOM(9)	147.43	-0.2792	1.2789	0.1005	-0.4109	0.9997	0.1587	0.2085	0.8278	0.2039
MOM(12)	147.71	-0.4668	0.8042	0.2106	-0.0797	0.9090	0.1817	-1.8996	-0.0117	0.5047
VOL(1,9)	148.52	-1.0221	1.0598	0.1446	-1.0404	0.9306	0.1760	-0.9545	0.5492	0.2914
VOL(1,12)	148.12	-0.7498	1.0833	0.1393	-0.5163	1.0463	0.1477	-1.6138	0.3141	0.3767
VOL(2,9)	148.39	-0.9344	1.0893	0.1380	-0.4829	1.1303	0.1292	-2.6051	0.1626	0.4354
VOL(2,12)	147.69	-0.4521	1.1896	0.1171	-0.4165	1.0422	0.1487	-0.5838	0.6377	0.2618
VOL(3,9)	148.62	-1.0902	1.1352	0.1281	-0.8532	1.1092	0.1337	-1.9671	0.2770	0.3909
VOL(3,12)	147.62	-0.4100	1.4435	0.0744	-0.4835	1.2052	0.1141	-0.1381	1.0739	0.1414

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0:\ R^2_{OS} \leq 0$ against $H_1:\ R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 5: Out-of-sample predictive results for Litecoin (LTC).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	166.18									
MA(1,9)	164.38	1.0818**	1.7278	0.0420	0.3985	1.1556	0.1239	3.2682*	1.5617	0.0592
MA(1,12)	165.02	0.6950	1.2652	0.1029	-0.3398	0.5242	0.3001	4.0057**	1.9759	0.0241
MA(2,9)	164.74	0.8642*	1.3664	0.0859	0.3686	0.8681	0.1927	2.4501*	1.4495	0.0736
MA(2,12)	164.90	0.7704	1.2580	0.1042	-0.0376	0.6463	0.2590	3.3557**	1.7139	0.0433
MA(3,9)	164.32	1.1202*	1.3921	0.0819	1.0745	1.1021	0.1352	1.2667	1.0253	0.1526
MA(3,12)	165.72	0.2767	1.0186	0.1542	-1.0056	0.2456	0.4030	4.3798**	1.9810	0.0238
MOM(9)	165.60	0.3465	0.9392	0.1738	-0.5591	0.2902	0.3858	3.2441**	1.7545	0.0397
MOM(12)	164.05	1.2819*	1.3827	0.0834	1.8092*	1.4051	0.0800	-0.4055	0.1681	0.4332
VOL(1,9)	160.57	3.3775***	2.4667	0.0068	4.2566**	2.3065	0.0105	0.5646	0.8937	0.1857
VOL(1,12)	159.73	3.8786***	2.8184	0.0024	4.3934***	2.4854	0.0065	2.2315	1.3864	0.0828
VOL(2,9)	162.51	2.2093**	1.9773	0.0240	3.6482**	2.1622	0.0153	-2.3946	-0.3064	0.6204
VOL(2,12)	161.83	2.6161***	2.3326	0.0098	3.3859**	2.2219	0.0131	0.1531	0.7249	0.2343
VOL(3,9)	164.37	1.0878*	1.3894	0.0824	2.4859**	1.7175	0.0429	-3.3856	-0.6288	0.7353
VOL(3,12)	162.39	2.2816**	2.0585	0.0198	3.1416**	2.0249	0.0214	-0.4703	0.4878	0.3128

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: \ R^2_{OS} \leq 0$ against $H_1: \ R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 6: Out-of-sample predictive results for Stellar (XLM).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	177.92									
MA(1,9)	179.34	-0.7971	0.7095	0.2390	-0.6270	0.7424	0.2289	-2.0033	-0.0142	0.5057
MA(1,12)	179.52	-0.8990	0.4397	0.3301	-1.6153	-0.0719	0.5287	4.1800*	1.6289	0.0517
MA(2,9)	178.33	-0.2281	1.2607	0.1037	-0.9687	0.7008	0.2417	5.0229**	1.8698	0.0308
MA(2,12)	180.27	-1.3198	1.0908	0.1377	-2.3306	0.4181	0.3380	5.8469**	1.9282	0.0269
MA(3,9)	178.72	-0.4500	0.8638	0.1939	-1.4011	0.1212	0.4518	6.2941**	2.1574	0.0155
MA(3,12)	177.05	0.4925**	1.7060	0.0440	0.2687*	1.3056	0.0958	2.0792*	1.3381	0.0904
MOM(9)	179.55	-0.9147	1.1910	0.1168	-0.8561	0.9152	0.1800	-1.3301	0.9464	0.1720
MOM(12)	178.60	-0.3829	1.0834	0.1393	-0.7477	0.6651	0.2530	2.2034*	1.3096	0.0952
VOL(1,9)	177.56	0.2037	1.1567	0.1237	0.8905*	1.3780	0.0841	-4.6654	-0.5243	0.7000
VOL(1,12)	177.93	-0.0017	1.3817*	0.0835	1.0448*	1.6013	0.0547	-7.4215	-0.3840	0.6495
VOL(2,9)	178.39	-0.2616	1.2010	0.1149	0.4581*	1.3821	0.0835	-5.3644	-0.3616	0.6412
VOL(2,12)	179.47	-0.8713	1.0333	0.1507	-0.4490	1.0263	0.1524	-3.8661	0.1981	0.4215
VOL(3,9)	179.30	-0.7727	0.3414	0.3664	-0.7709	0.2536	0.3999	-0.7853	0.3002	0.3820
VOL(3,12)	179.77	-1.0379	0.5570	0.2888	-0.8193	0.5092	0.3053	-2.5878	0.2294	0.4093

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: \ R^2_{OS} \leq 0$ against $H_1: \ R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 7: Out-of-sample predictive results for Tron (TRX).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	131.43									
MA(1,9)	131.82	-0.2966	0.3691	0.3560	-0.0491	0.5312	0.2977	-1.4508	-0.7415	0.7708
MA(1,12)	131.82	-0.2943	0.3477	0.3640	-0.1732	0.4227	0.3363	-0.8590	-0.3717	0.6449
MA(2,9)	132.04	-0.4607	0.3298	0.3708	0.4088	0.9383	0.1740	-4.5153	-1.9211	0.9726
MA(2,12)	131.71	-0.2143	0.4261	0.3350	-0.1535	0.4336	0.3323	-0.4975	0.0040	0.4984
MA(3,9)	131.75	-0.2402	0.5035	0.3073	-0.0975	0.5449	0.2929	-0.9061	-0.1741	0.5691
MA(3,12)	132.02	-0.4462	0.5392	0.2949	-1.0870	0.2055	0.4186	2.5418*	1.4005	0.0807
MOM(9)	133.07	-1.2478	0.7582	0.2242	-2.7181	0.2178	0.4138	5.6086**	1.8042	0.0356
MOM(12)	132.51	-0.8176	1.0998	0.1357	-1.7743	0.6858	0.2464	3.6436*	1.4214	0.0776
VOL(1,9)	133.95	-1.9167	-0.0827	0.5329	-3.2098	-0.5682	0.7151	4.1135*	1.4591	0.0723
VOL(1,12)	134.61	-2.4212	0.3636	0.3581	-3.8957	-0.2147	0.5850	4.4544*	1.6131	0.0534
VOL(2,9)	134.72	-2.5040	0.0003	0.4999	-3.7088	-0.3735	0.6456	3.1140	1.2695	0.1021
VOL(2,12)	135.19	-2.8564	0.1282	0.4490	-4.0292	-0.2352	0.5930	2.6128	1.1900	0.1170
VOL(3,9)	131.76	-0.2494	0.8878	0.1873	-1.3179	0.3829	0.3509	4.7334*	1.5791	0.0572
VOL(3,12)	132.68	-0.9538	0.5929	0.2766	-1.9766	0.1721	0.4317	3.8153*	1.3674	0.0857

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: \ R^2_{OS} \leq 0$ against $H_1: \ R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 8: Out-of-sample predictive results for Ripple (XRP).

Predictor	Full Period				Greed sentiment			Fear sentiment		
	MSFE	R^2_{OS} (%)	MSFE$_{adj}$	p-value	$R^2_{OS,GS}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,FS}$ (%)	MSFE$_{adj}$	p-value
HA	212.09									
MA(1,9)	213.09	-0.4709	0.6242	0.2663	-1.3307	-0.0819	0.5327	0.0599	0.8255	0.2046
MA(1,12)	212.03	0.0276	1.0930	0.1372	-3.7923	-0.6260	0.7343	2.3853**	1.7637	0.0389
MA(2,9)	212.05	0.0194	1.0783	0.1404	-2.0759	-0.2802	0.6103	1.3126*	1.5563	0.0598
MA(2,12)	212.09	-0.0014	1.1725	0.1205	-2.1172	-0.1618	0.5643	1.3045*	1.5861	0.0564
MA(3,9)	211.26	0.3902*	1.3019	0.0965	-1.2299	0.0043	0.4983	1.3902*	1.6275	0.0518
MA(3,12)	210.73	0.6402**	1.6597	0.0485	-1.4672	0.7417	0.2291	1.9409*	1.4990	0.0669
MOM(9)	212.04	0.0225*	1.4016	0.0805	-1.1723	0.7916	0.2143	0.7599	1.1577	0.1235
MOM(12)	210.01	0.9784**	1.8586	0.0315	-1.7894	0.8844	0.1882	2.6867**	1.6537	0.0491
VOL(1,9)	212.07	0.0088	0.7886	0.2152	0.2840	0.7972	0.2127	-0.1610	0.4263	0.3349
VOL(1,12)	211.65	0.2046	0.8471	0.1985	-0.0310	0.4599	0.3228	0.3500	0.7116	0.2384
VOL(2,9)	213.14	-0.4944	0.7914	0.2144	-0.0319	1.0580	0.1450	-0.7799	0.2046	0.4190
VOL(2,12)	214.16	-0.9794	0.9105	0.1813	-0.8812	0.9399	0.1736	-1.0400	0.4550	0.3246
VOL(3,9)	214.23	-1.0116	1.0839	0.1392	-1.0926	0.9062	0.1824	-0.9617	0.6834	0.2472
VOL(3,12)	206.68	2.5496***	2.9420	0.0016	2.7261**	2.0178	0.0218	2.4406**	2.1527	0.0157

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Among the four cryptocurrencies that have positive values of R^2_{OS} for most technical indicators, BTC (Table 2), DOGE (Table 3), LTC (Table 5), and XRP (Table 8), distinct patterns can be observed. For DOGE and LTC, volume-based indicators stand out (provide highest accuracy), consistently performing better than the historical average – greater R^2_{OS} statistics are found in comparison with the remaining predictive indicators. For XRP, the R^2_{OS} values are similar for the variables based on moving average, momentum and volume. Similarly, for the BTC, all strategies also have significant R^2_{OS} values, however, indicators based on moving average have slightly higher statistics compared to momentum and volume strategies.

In periods of greed market, most cryptocurrencies present significant $R^2_{OS,GS}$ statistics: BNB (Table 1), BTC (Table 2), DOGE (Table 3), LTC (Table 5) and XLM (Table 6). BNB, LTC and XLM present the greatest $R^2_{OS,GS}$ for indicators based on volume strategy; particularly, all volume indicators display higher statistics in greed periods when compared to the values of the full period. For DOGE (Table 3), all technical indicators – except MOM(12) – have significant $R^2_{OS,GS}$ statistics, without notable differences among strategies (moving average, momentum and volume). For BTC, all indicators have positive and significant $R^2_{OS,GS}$ values, and they are always greater than those in the full period – particularly, moving average-based indicators performing better than other strategies (momentum or volume).

During fear sentiment periods, different behaviors are found for the four cryptocurrencies that display significant values of $R^2_{OS,FS}$. For LTC (Table 5), XLM (Table 6) and XRP (Table 8), moving averages and momentum-based technical indicators showed considerable $R^2_{OS,FS}$ statistics – in general, the higher values are from the moving average strategy. In Table 7, TRX cryptocurrency momentum indicators have the greatest values of $R^2_{OS,FS}$; however, volume-based indicators also perform consistently better than the historical average, with significant statistics. For all these currencies, technical indicators that have significant R^2_{OS} in the full sample analysis have respectively higher values of $R^2_{OS,FS}$.

In terms of practical implications, market agents who make investment decisions based on risk premium predictions must consider the unique characteristics of each cryptocurrency to use the most suitable technical indicator for each asset, since there is no single predictor that consistently performs well. On the other hand, periods of greed market are generally associated with better out-of-sample predictability perform for anticipating cryptocurrencies excess returns.

4. Economic gains of crypto risk premium forecasts

Using technical analysis indicators, the quality of risk premium predictions is evaluated in economic terms. These predictions are used in the composition of investment portfolios. The economic value of the predictions is measured by a metric called utility gain. This measure can be interpreted as the management fee an investor is willing to pay to access the additional information provided by the predictive model compared to the historical average model (benchmark). The utility gain is calculated according to the method proposed by Campbell & Thompson (2008). This method is also considered in the studies of Rapach et al. (2009), Ferreira & Santa-Clara (2011), and Neely et al. (2014).

Consider a risk-averse investor with a mean-variance expected utility function. Weekly, the investor allocates their resources into a portfolio composed of one risky asset and another risk-free asset. At time t, its utility is given by:

$$U_t = E[r_t] - \left(\frac{\phi}{2}\right) var(r_t), \tag{10}$$

where r_t is the portfolio return at time t, ϕ is the parameter that measures the degree of the investor's risk aversion – we set $\phi = 5$ as in Neely et al. (2014) –, and $E[\cdot]$ and $var(\cdot)$ are the expectation and variance operators, respectively.

Based on the information available up to time t, at the end of week t, the optimal proportion (w^*_{t+1}) allocated by the investor, over week $t+1$, in the risky asset (such as cryptocurrencies) is:

$$w^*_{t+1} = \left(\frac{1}{\phi}\right)\left(\frac{\hat{r}^p_{t+1}}{\hat{\sigma}^2_{t+1}}\right), \tag{11}$$

where $\hat{r}^p_{t+1}$ is the risk premium predicted at time $t+1$, obtained by the regression using technical indicators as independent variables; and $\hat{\sigma}^2_{t+1}$ is the estimated variance of the risk premium.

The proportion of wealth $(1 - w^*_{t+1})$ is allocated in the risk-free asset. The investment decision is made based on the current risk-free interest rate and the predicted risk premium ($\hat{r}^p_{t+1}$). The portfolio return at time $t+1$ is:

$$r_{t+1} = w^*_{t+1} r^p_{t+1} + (1 - w^*_{t+1}) r^f_{t+1}, \tag{12}$$

where r^f_{t+1} is the risk-free interest rate at time $t+1$.

As in Dangl & Halling (2012), Neely et al. (2014), and Nonejad (2022), the proportion of resources invested in the risky asset is restricted: $0 \leq w^*_t \leq 1.5$. The restriction is imposed to limit short selling and prevent leverage above 50%.

In the out-of-sample period, the investor achieves an average utility level equal to:

$$\bar{U} = \hat{\mu} + \frac{1}{2}\gamma\hat{\sigma}^2, \tag{13}$$

where, within the out-of-sample predictive period of size T_O, $\hat{\mu} = (1/T_O)\sum_{t=1}^{T_O} r_t$ and $\hat{\sigma}^2 = (1/T_O)\sum_{t=1}^{T_O}(r_t - \hat{\mu})^2$ are the mean and variance of the investor's portfolio returns, respectively.

For the out-of-sample period, the utility gain is calculated as the difference between the average utility produced under the predictive model ($\bar{U}$) and the average utility produced under the historical moving average model ($\bar{U}^b$). The predictive model uses technical analysis indicators to anticipate the risk premium. The historical moving average model uses the historical average as the predictor of excess return. The utility gain, $\Delta\bar{U}$, is then calculated as:

$$\Delta\bar{U} = 1.200 \cdot (\bar{U} - \bar{U}^b). \tag{14}$$

If $\bar{U} > \bar{U}^b$, the utility gain is positive. This means that the predictive model generates greater utility than the historical average model. Otherwise, a negative utility gain indicates that the historical average benchmark is economically superior to the predictive model. The utility gain is multiplied by 1.200 to express it in terms of average annualized gain (Campbell & Thompson, 2008; Neely et al., 2014).

Utility gains, for the full period, are generally positive concerning the majority of the technical indicators for BNB (Table 9), BTC (Table 10), DOGE (Table 11) and LTC (Table 13). Positive utility gains are also achieved for the full period for half of the predictors for XLM (Table 14) and XRP (Table 16). In those cases, it means that the forecasts are able to produce economic benefits to mean-variance investors that weekly allocate between cryptocurrencies and a risk-free asset. For ETH (Table 12) and TRX (Table 15), in the full period, utility gains are mostly negative. Discounting the transaction costs, the overall positive results still remain, confirm the economic benefits of the forecasts based on technical indicators.

Table 9: Economic gains of out-of-sample risk premium forecasts for Binance (BNB).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	0.6976	0.1127	1.6901	0.6299	0.3685	1.2060
MA(1,9)	1.2048	0.1181	1.4737	1.1954	1.9303	0.1763
MA(1,2)	0.6559	0.1114	1.6577	0.6387	1.8417	-0.9733
MA(2,9)	0.4441	0.1097	1.7228	0.4245	1.9346	-1.5832
MA(2,12)	0.9368	0.1122	1.5263	0.9253	2.0392	-0.5845
MA(3,9)	0.4401	0.1028	1.5796	0.4258	0.9697	-0.3316
MA(3,12)	0.5872	0.1052	1.5798	0.5727	0.8302	0.1925
MOM(9)	0.7822	0.1080	1.5766	0.7667	0.2162	1.4543
MOM(12)	1.4764	0.1208	1.2566	1.4741	0.9802	2.0592
VOL(1,9)	1.1245	0.1085	1.1700	1.1282	2.0294	-0.1365
VOL(1,12)	1.0309	0.1134	1.5780	1.0143	0.9851	1.0168
VOL(2,9)	0.1525	0.1013	1.7596	0.1285	0.3140	-0.1347
VOL(2,12)	0.4220	0.1037	1.7333	0.3985	0.5352	0.1983
VOL(3,9)	-0.2688	0.0816	1.5325	-0.2822	0.5370	-1.4022
VOL(3,12)	0.5410	0.0925	1.3313	0.5365	0.6217	0.3600

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

For all currencies with positive utility gains – with the exception of DOGE (Table 11) and LTC (Table 13) –, technical based-portfolios display slightly higher Sharpe Ratio values when compared to the benchmark (historical average-based portfolio). For DOGE and LTC, all fourteen technical indicators present higher Sharpe Ratio values than the base portfolio, indicating a clearly better risk-return trade-off. Additionally, for all digital coins, with exception of XLM (Table 14), portfolios based on technical indicators mostly present less turnover than the benchmark. In particular, concerning BTC results in Table 10, portfolios based on the technical indicators turnover is approximately one-third to one-half times higher than the historical average portfolio turnover amount.

When the sample is disentangled based on the market sentiment level, the utility gains are clearly superior in greed sentiment moments – in accordance with previous analyses on the $R^2_{OS,GS}$ statistics –, surpassing the gains concerning the full sample in most of the times, especially for BNB (Table 9), BTC (Table 10), DOGE (Table 11), LTC (Table 13) and XLM (Table 14). XRP (Table 16) is the only cryptocurrency that shows some positive values for the utility gains in the full sample, but with worsting performance in greed markets. In fear market periods, utility gains are generally lower when compared with periods where investors are greedy.

Similarly, as in the R^2_{OS} analyses, it is not possible to define the best technical predictor for all periods or even for all cryptocurrencies. For instance, in the full period, BTC (Table 10) shows positive values well distributed among strategies (mean average, momentum and volume); in periods of greed market sentiment, the higher utility gains are from portfolios using moving-average and momentum technical predictors.

In practice, utility gains results allow investors and portfolio managers to quantify the improvement, in terms of satisfaction or expected utility, that a strategy using technical indicators to forecast risk premium can provide compared to the historical average. The findings showed that the use of technical indicators offers significant economic value for cryptocurrency portfolios, especially in periods of greed sentiment.

Table 10: Economic gains of out-of-sample risk premium forecasts for Bitcoin (BTC).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	2.2469	0.1512	2.5352	2.1241	2.3796	1.9802
MA(1,9)	0.6587	0.1459	1.2443	0.7113	2.0518	-2.3540
MA(1,12)	0.1314	0.1281	1.1945	0.1867	1.2240	-2.2470
MA(2,9)	-0.0877	0.1210	1.0534	-0.0248	1.0404	-2.5357
MA(2,12)	-0.0520	0.1312	0.8892	0.0195	0.1499	-0.5125
MA(3,9)	0.1837	0.1342	1.0009	0.2497	0.4990	-0.5193
MA(3,12)	-0.0083	0.1401	0.8365	0.0662	0.0575	-0.1733
MOM(9)	-0.0878	0.1326	0.8747	-0.0157	0.1757	-0.6820
MOM(12)	0.8247	0.1498	1.3807	0.8709	1.5666	-0.8016
VOL(1,9)	-0.0571	0.1406	0.8493	0.0163	-0.2593	0.3611
VOL(1,12)	0.0029	0.1314	0.9891	0.0684	0.2658	-0.5892
VOL(2,9)	0.0598	0.1253	1.2542	0.1115	0.6204	-1.1719
VOL(2,12)	0.0272	0.1315	0.9853	0.0931	0.1600	-0.2830
VOL(3,9)	0.1117	0.1325	1.0883	0.1718	0.2381	-0.1846
VOL(3,12)	-0.0129	0.1418	0.8909	0.0578	0.1497	-0.3882

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

Table 11: Economic gains of out-of-sample risk premium forecasts for Dogecoin (DOGE).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	0.0072	0.0515	1.3204	-0.0670	-0.9680	2.2691
MA(1,9)	0.9945	0.0729	0.8654	1.0217	1.8012	-0.8788
MA(1,12)	1.2396	0.0834	0.8526	1.2676	1.5643	0.4813
MA(2,9)	0.6452	0.0599	0.8846	0.6712	1.6421	-1.6654
MA(2,12)	1.7398	0.1049	0.9335	1.7638	1.3764	2.5939
MA(3,9)	0.8581	0.0658	0.8353	0.8865	1.7820	-1.2853
MA(3,12)	1.4214	0.0913	0.8677	1.4483	1.6336	0.9271
MOM(9)	1.6732	0.1023	0.8613	1.7007	1.6310	1.7724
MOM(12)	1.8913	0.1116	1.2101	1.9006	0.5848	5.0548
VOL(1,9)	1.0625	0.0930	1.2262	1.0769	1.0964	1.0144
VOL(1,12)	0.9416	0.0735	0.9881	0.9627	1.2991	0.1082
VOL(2,9)	0.9665	0.0875	1.1029	0.9877	1.1496	0.5579
VOL(2,12)	1.1936	0.0852	0.9945	1.2146	1.1274	1.3508
VOL(3,9)	1.1137	0.0767	0.7884	1.1436	1.9712	-0.8765
VOL(3,12)	0.6071	0.0547	0.8656	0.6327	1.1674	-0.6949

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

Table 12: Economic gains of out-of-sample risk premium forecasts for Ethereum (ETH).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	3.2793	0.1558	1.7408	3.1800	3.6885	2.3801
MA(1,9)	-0.7477	0.1438	0.8263	-0.6953	-1.1140	0.0569
MA(1,12)	-1.3778	0.1219	0.6470	-1.3157	-1.8116	-0.4238
MA(2,9)	-1.4926	0.1197	0.5882	-1.4272	-2.0159	-0.3400
MA(2,12)	-1.1583	0.1273	0.7683	-1.1029	-1.5397	-0.3203
MA(3,9)	-1.4599	0.1155	0.6206	-1.3959	-1.9605	-0.3575
MA(3,12)	-1.2749	0.1203	0.7948	-1.2211	-1.6559	-0.4378
MOM(9)	-1.1727	0.1223	0.8884	-1.1240	-1.7886	0.1856
MOM(12)	-1.2316	0.1218	0.8443	-1.1804	-1.1781	-1.3527
VOL(1,9)	-1.6653	0.1231	0.5544	-1.5984	-1.9712	-0.9953
VOL(1,12)	-1.7494	0.1075	0.5603	-1.6827	-1.8687	-1.4918
VOL(2,9)	-1.8322	0.0960	0.6187	-1.7686	-2.0057	-1.4543
VOL(2,12)	-1.3047	0.1574	0.5408	-1.2369	-1.4608	-0.9664
VOL(3,9)	-1.6553	0.1213	0.5303	-1.5869	-1.7086	-1.5438
VOL(3,12)	-1.1260	0.1645	0.5615	-1.0594	-1.4021	-0.5221

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

Table 13: Economic gains of out-of-sample risk premium forecasts for Litecoin (LTC).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	0.2616	0.0429	0.6958	0.2196	-0.7043	3.1218
MA(1,9)	0.2760	0.0682	1.3387	0.2428	-0.2064	1.7133
MA(1,12)	0.4402	0.0672	1.0992	0.4198	-0.0057	1.7655
MA(2,9)	0.5456	0.0607	0.7754	0.5433	0.4035	0.9677
MA(2,12)	0.5501	0.0656	0.9194	0.5397	0.3198	1.2322
MA(3,9)	0.8171	0.0761	0.4444	0.8335	1.2842	-0.5725
MA(3,12)	0.2754	0.0606	1.0524	0.2576	-0.3013	1.9942
MOM(9)	0.5794	0.0653	0.8001	0.5759	0.3617	1.2261
MOM(12)	0.6634	0.0672	0.3228	0.6867	1.2982	-1.2212
VOL(1,9)	1.3325	0.1057	0.5565	1.3426	2.4548	-1.9869
VOL(1,12)	1.9445	0.1359	0.6033	1.9525	3.0211	-1.2407
VOL(2,9)	0.9406	0.1036	0.3177	0.9640	1.9840	-2.1473
VOL(2,12)	1.0943	0.0916	0.5534	1.1040	1.9980	-1.5824
VOL(3,9)	0.7013	0.0839	0.2649	0.7278	1.6982	-2.2500
VOL(3,12)	1.2490	0.1105	0.4727	1.2635	2.4090	-2.1809

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

Table 14: Economic gains of out-of-sample risk premium forecasts for Stellar (XLM).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	0.9315	0.0755	0.2562	0.9170	1.2036	0.0431
MA(1,9)	-0.2943	0.0438	0.2453	-0.2939	0.0483	-1.4077
MA(1,12)	-0.2996	0.0631	0.1173	-0.2920	-0.2728	-0.3878
MA(2,9)	-0.1316	0.0558	0.5592	-0.1492	0.5041	-2.1901
MA(2,12)	-0.0667	0.0605	0.6069	-0.0874	0.5939	-2.2066
MA(3,9)	0.0761	0.0897	0.3245	0.0718	0.4675	-1.1957
MA(3,12)	0.9007	0.1133	0.8065	0.8694	1.9601	-2.5141
MOM(9)	0.3873	0.0869	0.7538	0.3593	1.4625	-3.0807
MOM(12)	0.1967	0.1222	0.2220	0.1984	0.2497	0.0233
VOL(1,9)	0.1893	0.0783	0.5389	0.1734	0.7800	-1.7240
VOL(1,12)	0.5069	0.0921	0.8286	0.4754	1.8131	-3.6941
VOL(2,9)	0.0175	0.0673	0.7576	-0.0108	1.1413	-3.6036
VOL(2,12)	-0.2311	0.0581	0.8368	-0.2633	0.8509	-3.7166
VOL(3,9)	-0.0016	0.0767	0.3072	-0.0049	0.3327	-1.0882
VOL(3,12)	-0.2184	0.0508	0.5963	-0.2381	0.4822	-2.4866

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

Table 15: Economic gains of out-of-sample risk premium forecasts for Tron (TRX).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	2.0651	0.1256	0.7437	2.0237	2.4094	1.0816
MA(1,9)	-0.6448	0.1015	0.4809	-0.6311	-0.4206	-1.2861
MA(1,12)	-0.5622	0.1131	0.4274	-0.5455	-0.4456	-0.8976
MA(2,9)	-0.4714	0.1027	0.6979	-0.4701	0.0766	-2.0292
MA(2,12)	-0.3317	0.1214	0.5287	-0.3209	-0.3754	-0.2095
MA(3,9)	-0.7345	0.0892	0.5997	-0.7277	-0.5906	-1.1470
MA(3,12)	-0.7048	0.1709	0.2093	-0.6757	-0.9583	0.0177
MOM(9)	-0.2885	0.1530	0.3894	-0.2693	-0.6744	0.8144
MOM(12)	-0.3298	0.1299	0.4552	-0.3144	-0.4152	-0.0891
VOL(1,9)	-0.8694	0.0910	0.4703	-0.8555	-1.2942	0.3455
VOL(1,12)	-0.4096	0.1030	0.8669	-0.4181	-1.1893	1.8309
VOL(2,9)	-0.8478	0.0848	0.6004	-0.8419	-1.4570	0.8989
VOL(2,12)	-0.5541	0.0967	0.7799	-0.5586	-1.5248	2.2376
VOL(3,9)	0.4607	0.1566	0.6148	0.4681	-0.3028	2.6535
VOL(3,12)	0.0077	0.1247	0.6939	0.0108	-0.5848	1.7049

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

Table 16: Economic gains of out-of-sample risk premium forecasts for Ripple (XRP).

Preditor	Full period				Sentiment disentangled	
	$\Delta\bar{U}$	Sharpe	Turnover	$\Delta\bar{U}_{net}$	$\Delta\bar{U}_{GS}$	$\Delta\bar{U}_{FS}$
HA	1.2621	0.1116	0.2954	1.2453	1.6103	0.9361
MA(1,9)	-0.2271	0.1512	0.1335	-0.2180	-0.6289	0.1492
MA(1,12)	0.3264	0.1440	0.3416	0.3238	-0.3181	0.9304
MA(2,9)	-0.0122	0.1115	0.2865	-0.0117	-0.6899	0.6229
MA(2,12)	-0.0317	0.1191	0.2478	-0.0290	-0.4271	0.3385
MA(3,9)	0.1775	0.1405	0.2224	0.1820	-0.2822	0.6081
MA(3,12)	0.5103	0.1260	0.6019	0.4921	0.0011	0.9873
MOM(9)	-0.0385	0.0854	0.5907	-0.0561	-0.5929	0.4811
MOM(12)	1.2964	0.1391	0.8378	1.2692	1.5300	1.0805
VOL(1,9)	-0.5072	0.0709	0.1805	-0.5010	-0.5616	-0.4563
VOL(1,12)	-0.3011	0.1090	0.1387	-0.2922	-0.3717	-0.2349
VOL(2,9)	-0.1727	0.0935	0.2181	-0.1681	-0.1359	-0.2068
VOL(2,12)	0.0710	0.1044	0.3473	0.0683	0.1582	-0.0100
VOL(3,9)	0.6346	0.1273	0.5317	0.6223	0.5012	0.7599
VOL(3,12)	1.1594	0.1460	0.5049	1.1506	1.4882	0.8534

Notes: $\Delta\bar{U}$ is the utility gain in % per year; the turnover is the average monthly turnover of the predictive model portfolio; the Sharpe ratio is the ratio between the portfolio's excess return and the standard deviation of the portfolio's excess return; the net utility gain $\Delta\bar{U}_{net}$ (% per year) considers a transaction cost of 0.5% each trade; $\Delta\bar{U}_{GS}$ and $\Delta\bar{U}_{FS}$ are the utility gains disentangled for periods of greed and fear sentiment, respectively.

5. Volatility regimes and crypto risk premium forecasting

To verify the robustness of cryptocurrency risk premium predictability, out-of-sample accuracy is analyzed across periods of high and low volatility regimes. The volatility of digital coin returns is estimated using a Markov Switching GARCH (MS-GARCH) model. GARCH-family models are particularly powerful in addressing stylized facts of volatility – such as volatility clustering –, which are more pronounced in daily returns. Hence, volatility estimation is based on daily data. For each cryptocurrency, a MS-GARCH(1,1) model was estimated with two regimes ($K = 2$). Literature on modeling volatility regimes with MS-GARCH models for cryptocurrencies indicates that a two-regime approach yields more accurate results compared to single-regime or higher-regime models (Maciel, 2021; Panagiotidis et al., 2022). Our findings corroborate this by comparing the Bayesian Information Criteria (BIC) for different regime specifications ($K = 1, 2, 3, 4$). Similar experiments were conducted regarding the model structure, confirming that the (1,1) specification offers the most parsimonious results based on information criteria.

For each regime, the unconditional volatility was computed. The regime with higher (lower) unconditional volatility was defined as the high (low) volatility regime. Further, out-of-sample $R^2_{OS,c}$, as specified in Eq. (7), was analyzed using the indicator variable I^c_t, which equals unity when returns are in the high volatility regime and zero otherwise. The weekly values were calculated as the average of the daily values of the indicator variable within each week. Figure C.1 in Appendix C illustrates the temporal evolution of the smoothed probabilities, calculated using MS-GARCH models for each cryptocurrency. The probabilities indicate that the high volatility regime is more prevalent among the evaluated digital coins. BTC, STEL, TRON, and XRP volatilities alternate more frequently between high and low volatility regimes compared to other cryptocurrencies – see Figure C.1 in Appendix C.

Tables 17-24 provide the disentangled out-of-sample accuracy for BNB, BTC, DOGE, ETH, LTC, XLM, TRX, and XRP, respectively, across periods of high versus low volatility. Disentangled values of R^2 are computed when the returns are in the lower volatility regime ($R^2_{OS,LV}$) and when the returns are in the higher volatility regime ($R^2_{OS,HV}$). When R^2 is positive, the use of technical indicators as predictive variables results in more accurate forecasts than the historical average model for cryptocurrencies' risk premiums. Generally, for most digital coins and for most technical variables, $R^2_{OS,HV}$ is greater than $R^2_{OS,LV}$, indicating that technical indicators are better predictors in periods of heightened volatility. For Ripple (XRP) (see 24), higher values of R^2 are found in periods of lower volatility. For Litecoin (LTC) (Table 21) and for Stellar (XLM) (Table 22) although the R^2 values are not higher for a specific volatility regime, significant values are only observed during periods of high volatility.

When taking into account the significance of the R^2_{OS} values, inferences indicate that – using technical variables as predictors – the risk premium forecasts for Binance (Table 17), Ethereum (Table 20), and Tron (Table 23) are not statistically superior to the historical average approach, regardless of the volatility regime. For Bitcoin (Table 18), Dogecoin (Table 19), Litecoin (Table 21), and Stellar (Table 22), considering a significance level of at least 10%, most of the R^2_{OS} values indicate that statistically superior forecasts of the risk premium are achieved when compared to the historical average benchmark, especially in periods of heightened volatility. The only exception is Ripple (XRP) – see Table 24 –, where significant and positive values of R^2_{OS} are found in periods of lower volatility regime. This result can be explained by the frequent alternation between low and high volatility regimes during the evaluated period (see Figure C.1-(h) in Appendix C).

Generally speaking, the use of technical indicators for forecasting crypto risk premiums is associated with accurate results when the price return volatility is higher. This finding aligns with Baker & Wurgler (2006), who discussed that market sentiment has a greater impact on stocks with higher volatility. Since technical indicators can anticipate changes in market sentiment (Huang et al., 2014; Gric et al., 2023), the results indicate that accurate risk premium forecasts are achieved during periods of high volatility, confirming the role among market sentiment, volatility and technical analysis.

Table 17: Out-of-sample predictive results for Binance (BNB) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE_{adj}	p-value	$R^2_{OS,LV}$ (%)	MSFE_{adj}	p-value
MA(1,9)	-0.946	0.463	0.322	-2.098	0.127	0.450
MA(1,12)	-0.778	0.655	0.256	-4.838	-0.267	0.605
MA(2,9)	-1.074	0.605	0.272	-4.636	-0.149	0.559
MA(2,12)	-0.631	0.510	0.305	-3.588	-0.219	0.587
MA(3,9)	-1.152	0.507	0.306	-4.291	-0.326	0.628
MA(3,12)	-0.464	0.631	0.264	-5.615	-0.665	0.747
MOM(9)	0.119	0.914	0.180	-6.824	-1.135	0.872
MOM(12)	-0.660	0.198	0.422	-0.072	0.068	0.473
VOL(1,9)	-0.718	0.344	0.365	-0.672	0.310	0.378
VOL(1,12)	0.419*	1.288	0.099	-6.199	-0.305	0.620
VOL(2,9)	-1.038	0.697	0.243	-5.985	-0.403	0.656
VOL(2,12)	-0.467	0.991	0.161	-5.970	0.018	0.493
VOL(3,9)	-1.376	0.392	0.347	-3.759	-0.169	0.567
VOL(3,12)	-0.256	0.793	0.214	-3.944	-0.309	0.621

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0:\ R^2_{OS} \leq 0$ against $H_1:\ R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 18: Out-of-sample predictive results for Bitcoin (BTC) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE_{adj}	p-value	$R^2_{OS,LV}$ (%)	MSFE_{adj}	p-value
MA(1,9)	3.104*	1.606	0.054	0.516**	2.007	0.022
MA(1,12)	1.076	1.174	0.120	0.607**	1.857	0.032
MA(2,9)	2.716**	1.656	0.049	-0.700	1.711	0.044
MA(2,12)	2.354**	1.732	0.042	-0.502	1.722	0.043
MA(3,9)	1.789*	1.369	0.085	0.098**	1.879	0.030
MA(3,12)	3.021**	1.965	0.025	-0.948	1.584	0.057
MOM(9)	2.224**	1.734	0.041	-0.366	1.658	0.049
MOM(12)	0.227	0.860	0.195	1.994**	2.191	0.014
VOL(1,9)	3.433**	2.054	0.020	-2.020	1.310	0.095
VOL(1,12)	1.163*	1.389	0.082	0.065**	1.723	0.042
VOL(2,9)	1.842	1.223	0.111	0.477**	1.966	0.025
VOL(2,12)	1.346*	1.450	0.074	-0.003	1.698	0.045
VOL(3,9)	0.648	1.176	0.120	0.524**	1.884	0.030
VOL(3,12)	2.343**	1.816	0.035	-0.632	1.512	0.065

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0:\ R^2_{OS} \leq 0$ against $H_1:\ R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 19: Out-of-sample predictive results for Dogecoin (DOGE) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,LV}$ (%)	MSFE$_{adj}$	p-value
MA(1,9)	1.267**	1.727	0.042	-1.784	0.360	0.359
MA(1,12)	0.971*	1.539	0.062	0.915	1.196	0.116
MA(2,9)	1.395**	1.859	0.032	-3.930	-0.138	0.555
MA(2,12)	0.841*	1.375	0.085	3.714**	2.096	0.018
MA(3,9)	1.083*	1.625	0.052	-1.166	0.587	0.279
MA(3,12)	1.031*	1.538	0.062	0.063	0.994	0.160
MOM(9)	1.196*	1.524	0.064	0.586	1.200	0.115
MOM(12)	-0.199	1.435	0.076	-14.359	0.135	0.446
VOL(1,9)	1.487**	1.961	0.025	-2.172	0.082	0.467
VOL(1,12)	0.893*	1.383	0.083	-1.101	-0.040	0.516
VOL(2,9)	1.439**	1.710	0.044	-0.434	0.393	0.347
VOL(2,12)	1.290**	1.674	0.047	-4.777	0.009	0.496
VOL(3,9)	1.630**	1.673	0.047	-1.427	-0.108	0.543
VOL(3,12)	1.378**	1.839	0.033	-9.484	-1.143	0.874

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 20: Out-of-sample predictive results for Ethereum (ETH) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,LV}$ (%)	MSFE$_{adj}$	p-value
MA(1,9)	0.366	1.146	0.126	-2.276	1.022	0.153
MA(1,12)	0.121	0.939	0.174	-3.196	0.693	0.244
MA(2,9)	-0.295	0.825	0.205	-1.509	1.122	0.131
MA(2,12)	0.192	0.973	0.165	-2.728	0.796	0.213
MA(3,9)	-0.124	0.950	0.171	-2.322	0.937	0.174
MA(3,12)	0.298	1.022	0.153	-3.071	0.727	0.233
MOM(9)	0.122	0.981	0.163	-2.433	0.881	0.189
MOM(12)	-0.446	0.314	0.377	-0.578	1.000	0.159
VOL(1,9)	-1.124	0.564	0.286	-0.475	1.308	0.095
VOL(1,12)	-0.673	0.672	0.251	-1.164	1.098	0.136
VOL(2,9)	-0.629	0.779	0.218	-2.574	0.917	0.180
VOL(2,12)	-0.715	0.611	0.271	0.962*	1.526	0.063
VOL(3,9)	-1.247	0.580	0.281	-0.249	1.413	0.079
VOL(3,12)	-0.973	0.663	0.254	2.611**	2.052	0.020

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 21: Out-of-sample predictive results for Litecoin (LTC) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,LV}$ (%)	MSFE$_{adj}$	p-value
MA(1,9)	1.471*	1.531	0.063	0.315	0.932	0.176
MA(1,12)	1.579*	1.609	0.054	-1.049	0.267	0.395
MA(2,9)	1.263*	1.595	0.055	0.078	0.579	0.281
MA(2,12)	1.689**	1.734	0.041	-1.040	0.260	0.397
MA(3,9)	1.067*	1.607	0.054	1.225	0.746	0.228
MA(3,12)	1.200*	1.334	0.091	-1.544	0.174	0.431
MOM(9)	0.355	0.821	0.206	0.330	0.573	0.283
MOM(12)	0.027	0.469	0.320	3.757*	1.321	0.093
VOL(1,9)	1.041*	1.540	0.062	7.985**	1.929	0.027
VOL(1,12)	2.205**	1.924	0.027	7.179**	2.061	0.020
VOL(2,9)	1.048*	1.610	0.054	4.499*	1.331	0.092
VOL(2,12)	2.703***	2.406	0.008	2.444	1.127	0.130
VOL(3,9)	0.687*	1.309	0.095	1.879	0.881	0.189
VOL(3,12)	2.089**	2.047	0.020	2.661	1.135	0.128

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 22: Out-of-sample predictive results for Stellar (XLM) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,LV}$ (%)	MSFE$_{adj}$	p-value
MA(1,9)	0.068	0.631	0.264	-1.400	0.451	0.326
MA(1,12)	-3.117	-0.829	0.796	0.648*	1.351	0.088
MA(2,9)	2.249*	1.596	0.055	-1.956	0.490	0.312
MA(2,12)	-1.476	0.245	0.403	-1.211	1.183	0.118
MA(3,9)	-0.837	0.118	0.453	-0.180	0.994	0.160
MA(3,12)	0.350	0.649	0.258	0.592**	1.703	0.044
MOM(9)	-2.916	-0.060	0.524	0.481**	1.679	0.047
MOM(12)	-1.051	0.175	0.431	0.083*	1.346	0.089
VOL(1,9)	3.194**	1.899	0.029	-1.882	0.088	0.465
VOL(1,12)	2.874*	1.542	0.062	-2.008	0.594	0.276
VOL(2,9)	4.214***	2.417	0.008	-3.383	-0.111	0.544
VOL(2,12)	2.537**	1.499	0.067	-3.249	0.197	0.422
VOL(3,9)	0.225	0.581	0.281	-1.469	-0.006	0.503
VOL(3,12)	-1.629	-0.129	0.551	-0.626	0.830	0.203

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 23: Out-of-sample predictive results for Tron (TRX) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,LV}$ (%)	MSFE$_{adj}$	p-value
MA(1,9)	-0.171	0.460	0.323	-1.697	-0.959	0.831
MA(1,12)	-0.273	0.357	0.361	-0.531	-0.091	0.536
MA(2,9)	-0.121	0.570	0.284	-4.233	-1.720	0.957
MA(2,12)	-0.153	0.430	0.334	-0.896	-0.009	0.504
MA(3,9)	0.002	0.649	0.258	-2.931	-1.417	0.922
MA(3,12)	-0.589	0.456	0.324	1.139	0.877	0.190
MOM(9)	-1.501	0.640	0.261	1.569	1.038	0.150
MOM(12)	-0.703	1.051	0.147	-2.087	0.415	0.339
VOL(1,9)	-2.164	-0.143	0.557	0.831	0.986	0.162
VOL(1,12)	-2.423	0.361	0.359	-2.399	0.041	0.484
VOL(2,9)	-2.759	-0.060	0.524	0.326	0.718	0.236
VOL(2,12)	-3.250	-0.002	0.501	1.524	1.114	0.133
VOL(3,9)	-0.436	0.671	0.251	1.824	1.278	0.101
VOL(3,12)	-1.153	0.463	0.322	1.264	1.036	0.150

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

Table 24: Out-of-sample predictive results for Ripple (XRP) disentangled for different volatility regimes.

Preditor	High volatility			Low volatility		
	$R^2_{OS,HV}$ (%)	MSFE$_{adj}$	p-value	$R^2_{OS,LV}$ (%)	MSFE$_{adj}$	p-value
MA(1,9)	-1.617	-0.876	0.810	-0.282	0.878	0.190
MA(1,12)	-3.737	-0.836	0.798	0.646	1.473	0.070*
MA(2,9)	-2.982	-0.982	0.837	0.513	1.514	0.065*
MA(2,12)	-2.881	-0.935	0.825	0.472	1.578	0.057*
MA(3,9)	-2.702	-0.996	0.840	0.898	1.760	0.039**
MA(3,12)	-6.637	-0.946	0.828	1.836	2.284	0.011**
MOM(9)	-7.003	-1.162	0.877	1.177	2.042	0.021**
MOM(12)	-9.722	-1.284	0.900	2.737	2.508	0.006***
VOL(1,9)	-1.799	-0.982	0.837	0.306	1.199	0.115
VOL(1,12)	-2.983	-1.025	0.847	0.728	1.427	0.077**
VOL(2,9)	-3.822	-1.117	0.868	0.052	1.376	0.084**
VOL(2,12)	-5.388	-1.009	0.843	-0.255	1.479	0.070
VOL(3,9)	-6.005	-0.995	0.840	-0.191	1.622	0.052
VOL(3,12)	1.226	0.722	0.235	2.767	2.858	0.002***

Notes: MSFE error measures, R^2_{OS} values, $MSFE_{adj}$ statistics from Clark & West (2007) and the corresponding p-values are reported. For the hypothesis test $H_0: R^2_{OS} \leq 0$ against $H_1: R^2_{OS} > 0$, (*), (**), (***) indicate significance at 10%, 5% and 1%, respectively.

6. Conclusion

This paper evaluated the predictability of the cryptocurrency risk premium using technical indicators as predictor variables. It examined the importance of market sentiment in the predictive power of technical indicators, disentangling the accuracy of predictions into periods of greed and fear sentiment levels. In bivariate regression models, fourteen technical indicators based on moving average, momentum, and volume strategies were considered. From January 2018 to December 2023, out-of-sample predictive analyses were developed for eight of the major traded cryptocurrencies: Binance (BNB), Bitcoin (BTC), Dogecoin (DOGE), Ethereum (ETH), Litecoin (LTC), Stellar (XLM), Tron (TRX), and Ripple (XRP). For each cryptocurrency, a news-based market sentiment indicator was constructed based on web scraping and textual analysis methods to characterize periods of greed/fear sentiment. Robustness analyses were also conducted to validate the results in economic terms and under different volatility regimes.

The results indicated that, in general, the use of technical indicators as predictor variables does not generate superior predictions compared to the historical risk premium, the main benchmark in the risk premium forecasting literature. However, when market sentiment levels are taken into account, statistically significant predictions of the risk premium can be obtained. In periods of greed market sentiment, the predictive power of technical indicators in anticipating the risk premium of digital currencies is greater. The economic benefit of these predictions was also verified in a portfolio allocation exercise where a mean-variance investor decides, based on the risk premium predictions, to allocate their resources in risky and risk-free assets. Higher predictive power is also observed in high volatility regimes.

The findings provide relevant contributions to the literature on cryptocurrency markets and on risk premium predictability. The results highlight the theoretical justification for the predictive power of technical indicators, as these trend measures can anticipate changes in market sentiment levels, especially when investors are greedy. Additionally, it confirms, for cryptocurrencies, the discussion raised by Baker & Wurgler (2006) regarding the significant importance of market sentiment in explaining the returns of assets whose valuations are highly subjective and exhibit high volatility – technical indicators better predict the risk premium in regimes of heightened volatility. For market practice, the results indicate that cryptocurrency traders should monitor market sentiment patterns when considering technical indicators to predict the risk premium of digital currencies and use these predictions as an additional decision-making input for trading. Future work shall includes developing new predictor variables and considering more sophisticated forecasting models, such as those allowing for structural breaks in parameters.

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Appendix A. Variables descriptive statistics

Table A.1: Descriptive statistics of the Binance (BNB) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	0.0107	0.6479	-0.6923	0.1319	-0.0872	7.3930
$sent_t$	0.6047	1.0000	0.0000	0.4897	-0.4281	-1.8167
vol_t	0.7043	1.0000	0.0000	0.4571	-0.8955	-1.1982
MA(1,9)	0.5316	1.0000	0.0000	0.4998	-0.1265	-1.9840
MA(1,12)	0.5349	1.0000	0.0000	0.4996	-0.1399	-1.9804
MA(2,9)	0.5249	1.0000	0.0000	0.5002	-0.0998	-1.9900
MA(2,12)	0.5548	1.0000	0.0000	0.4978	-0.2206	-1.9513
MA(3,9)	0.5282	1.0000	0.0000	0.5000	-0.1131	-1.9872
MA(3,12)	0.5449	1.0000	0.0000	0.4988	-0.1801	-1.9676
MOM(9)	0.5548	1.0000	0.0000	0.4978	-0.2206	-1.9513
MOM(12)	0.5415	1.0000	0.0000	0.4991	-0.1667	-1.9722
VOL(1,9)	0.5482	1.0000	0.0000	0.4985	-0.1936	-1.9625
VOL(1,12)	0.5648	1.0000	0.0000	0.4966	-0.2613	-1.9317
VOL(2,9)	0.5515	1.0000	0.0000	0.4982	-0.2071	-1.9571
VOL(2,12)	0.5880	1.0000	0.0000	0.4930	-0.3577	-1.8720
VOL(3,9)	0.5382	1.0000	0.0000	0.4994	-0.1533	-1.9765
VOL(3,12)	0.5814	1.0000	0.0000	0.4942	-0.3300	-1.8911

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

Table A.2: Descriptive statistics of the Bitcoin (BTC) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	0.0058	0.2729	-0.5395	0.0974	-0.8648	4.2863
$sent_t$	0.6611	1.0000	0.0000	0.4741	-0.6808	-1.5365
vol_t	0.1196	1.0000	0.0000	0.3250	2.3446	3.4970
MA(1,9)	0.5017	1.0000	0.0000	0.5008	-0.0066	-2.0000
MA(1,12)	0.5017	1.0000	0.0000	0.5008	-0.0066	-2.0000
MA(2,9)	0.4983	1.0000	0.0000	0.5008	0.0066	-2.0000
MA(2,12)	0.5050	1.0000	0.0000	0.5008	-0.0199	-1.9996
MA(3,9)	0.4983	1.0000	0.0000	0.5008	0.0066	-2.0000
MA(3,12)	0.4950	1.0000	0.0000	0.5008	0.0199	-1.9996
MOM(9)	0.5316	1.0000	0.0000	0.4998	-0.1265	-1.9840
MOM(12)	0.5249	1.0000	0.0000	0.5002	-0.0998	-1.9900
VOL(1,9)	0.5847	1.0000	0.0000	0.4936	-0.3438	-1.8818
VOL(1,12)	0.5914	1.0000	0.0000	0.4924	-0.3717	-1.8618
VOL(2,9)	0.5515	1.0000	0.0000	0.4982	-0.2071	-1.9571
VOL(2,12)	0.5581	1.0000	0.0000	0.4974	-0.2341	-1.9452
VOL(3,9)	0.5548	1.0000	0.0000	0.4978	-0.2206	-1.9513
VOL(3,12)	0.5648	1.0000	0.0000	0.4966	-0.2613	-1.9317

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

Table A.3: Descriptive statistics of the Dogecoin (DOGE) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	0.0108	1.4876	-0.3961	0.1879	3.6044	20.9836
$sent_t$	0.7076	1.0000	0.0000	0.4556	-0.9130	-1.1664
vol_t	0.7342	1.0000	0.0000	0.4425	-1.0604	-0.8755
MA(1,9)	0.4684	1.0000	0.0000	0.4998	0.1265	-1.9840
MA(1,12)	0.4319	1.0000	0.0000	0.4962	0.2750	-1.9244
MA(2,9)	0.4551	1.0000	0.0000	0.4988	0.1801	-1.9676
MA(2,12)	0.4452	1.0000	0.0000	0.4978	0.2206	-1.9513
MA(3,9)	0.4751	1.0000	0.0000	0.5002	0.0998	-1.9900
MA(3,12)	0.4518	1.0000	0.0000	0.4985	0.1936	-1.9625
MOM(9)	0.4485	1.0000	0.0000	0.4982	0.2071	-1.9571
MOM(12)	0.4252	1.0000	0.0000	0.4952	0.3024	-1.9086
VOL(1,9)	0.4817	1.0000	0.0000	0.5005	0.0731	-1.9947
VOL(1,12)	0.4884	1.0000	0.0000	0.5007	0.0465	-1.9978
VOL(2,9)	0.4651	1.0000	0.0000	0.4996	0.1399	-1.9804
VOL(2,12)	0.4850	1.0000	0.0000	0.5006	0.0598	-1.9964
VOL(3,9)	0.4684	1.0000	0.0000	0.4998	0.1265	-1.9840
VOL(3,12)	0.4850	1.0000	0.0000	0.5006	0.0598	-1.9964

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

Table A.4: Descriptive statistics of the Ethereum (ETH) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	0.0054	0.4989	-0.6599	0.1279	-0.7527	3.7567
$sent_t$	0.6944	1.0000	0.0000	0.4614	-0.8438	-1.2881
vol_t	0.5615	1.0000	0.0000	0.4970	-0.2477	-1.9386
MA(1,9)	0.5150	1.0000	0.0000	0.5006	-0.0598	-1.9964
MA(1,12)	0.5482	1.0000	0.0000	0.4985	-0.1936	-1.9625
MA(2,9)	0.5316	1.0000	0.0000	0.4998	-0.1265	-1.9840
MA(2,12)	0.5415	1.0000	0.0000	0.4991	-0.1667	-1.9722
MA(3,9)	0.5183	1.0000	0.0000	0.5005	-0.0731	-1.9947
MA(3,12)	0.5349	1.0000	0.0000	0.4996	-0.1399	-1.9804
MOM(9)	0.5382	1.0000	0.0000	0.4994	-0.1533	-1.9765
MOM(12)	0.5249	1.0000	0.0000	0.5002	-0.0998	-1.9900
VOL(1,9)	0.5548	1.0000	0.0000	0.4978	-0.2206	-1.9513
VOL(1,12)	0.5714	1.0000	0.0000	0.4957	-0.2887	-1.9167
VOL(2,9)	0.5548	1.0000	0.0000	0.4978	-0.2206	-1.9513
VOL(2,12)	0.5648	1.0000	0.0000	0.4966	-0.2613	-1.9317
VOL(3,9)	0.5449	1.0000	0.0000	0.4988	-0.1801	-1.9676
VOL(3,12)	0.5714	1.0000	0.0000	0.4957	-0.2887	-1.9167

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

Table A.5: Descriptive statistics of the Litecoin (LTC) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	-0.0023	0.4468	-0.5698	0.1318	-0.3481	2.3977
$sent_t$	0.7475	1.0000	0.0000	0.4352	-1.1394	-0.7017
vol_t	0.5282	1.0000	0.0000	0.5000	-0.1131	-1.9872
MA(1,9)	0.4784	1.0000	0.0000	0.5004	0.0865	-1.9925
MA(1,12)	0.4585	1.0000	0.0000	0.4991	0.1667	-1.9722
MA(2,9)	0.4718	1.0000	0.0000	0.5000	0.1131	-1.9872
MA(2,12)	0.4651	1.0000	0.0000	0.4996	0.1399	-1.9804
MA(3,9)	0.4784	1.0000	0.0000	0.5004	0.0865	-1.9925
MA(3,12)	0.4684	1.0000	0.0000	0.4998	0.1265	-1.9840
MOM(9)	0.4651	1.0000	0.0000	0.4996	0.1399	-1.9804
MOM(12)	0.4518	1.0000	0.0000	0.4985	0.1936	-1.9625
VOL(1,9)	0.5548	1.0000	0.0000	0.4978	-0.2206	-1.9513
VOL(1,12)	0.5648	1.0000	0.0000	0.4966	-0.2613	-1.9317
VOL(2,9)	0.5449	1.0000	0.0000	0.4988	-0.1801	-1.9676
VOL(2,12)	0.5781	1.0000	0.0000	0.4947	-0.3162	-1.9000
VOL(3,9)	0.5548	1.0000	0.0000	0.4978	-0.2206	-1.9513
VOL(3,12)	0.5748	1.0000	0.0000	0.4952	-0.3024	-1.9086

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

Table A.6: Descriptive statistics of the Stellar (XLM) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	-0.0021	0.8901	-0.5509	0.1381	0.9995	7.5696
$sent_t$	0.7475	1.0000	0.0000	0.4352	-1.1394	-0.7017
vol_t	0.2292	1.0000	0.0000	0.4210	1.2883	-0.3403
MA(1,9)	0.4452	1.0000	0.0000	0.4978	0.2206	-1.9513
MA(1,12)	0.4551	1.0000	0.0000	0.4988	0.1801	-1.9676
MA(2,9)	0.4684	1.0000	0.0000	0.4998	0.1265	-1.9840
MA(2,12)	0.4585	1.0000	0.0000	0.4991	0.1667	-1.9722
MA(3,9)	0.4618	1.0000	0.0000	0.4994	0.1533	-1.9765
MA(3,12)	0.4551	1.0000	0.0000	0.4988	0.1801	-1.9676
MOM(9)	0.4917	1.0000	0.0000	0.5008	0.0332	-1.9989
MOM(12)	0.4252	1.0000	0.0000	0.4952	0.3024	-1.9086
VOL(1,9)	0.5382	1.0000	0.0000	0.4994	-0.1533	-1.9765
VOL(1,12)	0.5515	1.0000	0.0000	0.4982	-0.2071	-1.9571
VOL(2,9)	0.5316	1.0000	0.0000	0.4998	-0.1265	-1.9840
VOL(2,12)	0.5615	1.0000	0.0000	0.4970	-0.2477	-1.9386
VOL(3,9)	0.5415	1.0000	0.0000	0.4991	-0.1667	-1.9722
VOL(3,12)	0.5814	1.0000	0.0000	0.4942	-0.3300	-1.8911

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

Table A.7: Descriptive statistics of the Tron (TRX) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	0.0034	0.5336	-0.5576	0.1257	-0.1060	4.2648
$sent_t$	0.7475	1.0000	0.0000	0.4352	-1.1394	-0.7017
vol_t	0.7243	1.0000	0.0000	0.4476	-1.0036	-0.9928
MA(1,9)	0.5382	1.0000	0.0000	0.4994	-0.1533	-1.9765
MA(1,12)	0.5515	1.0000	0.0000	0.4982	-0.2071	-1.9571
MA(2,9)	0.5415	1.0000	0.0000	0.4991	-0.1667	-1.9722
MA(2,12)	0.5615	1.0000	0.0000	0.4970	-0.2477	-1.9386
MA(3,9)	0.5681	1.0000	0.0000	0.4962	-0.2750	-1.9244
MA(3,12)	0.5681	1.0000	0.0000	0.4962	-0.2750	-1.9244
MOM(9)	0.5814	1.0000	0.0000	0.4942	-0.3300	-1.8911
MOM(12)	0.5781	1.0000	0.0000	0.4947	-0.3162	-1.9000
VOL(1,9)	0.5748	1.0000	0.0000	0.4952	-0.3024	-1.9086
VOL(1,12)	0.5814	1.0000	0.0000	0.4942	-0.3300	-1.8911
VOL(2,9)	0.5581	1.0000	0.0000	0.4974	-0.2341	-1.9452
VOL(2,12)	0.5748	1.0000	0.0000	0.4952	-0.3024	-1.9086
VOL(3,9)	0.5847	1.0000	0.0000	0.4936	-0.3438	-1.8818
VOL(3,12)	0.5914	1.0000	0.0000	0.4924	-0.3717	-1.8618

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

Table A.8: Descriptive statistics of the Ripple (XRP) risk premium (r_t^p), the buy signals of the fourteen technical analysis predictors, and of the indicator variables to define greed market sentiment ($sent_t$) and high volatility regime (vol_t) in the period between January 2018 and December 2023.

Variable	Mean	Maximum	Minimum	Std. Dev.	Asymmetry	Kurtosis
r_t^p	0.0001	0.8646	-0.6715	0.1489	0.9443	7.8437
$sent_t$	0.5249	1.0000	0.0000	0.5002	-0.0998	-1.9900
vol_t	0.0233	1.0000	0.0000	0.1510	6.3264	38.0238
MA(1,9)	0.4684	1.0000	0.0000	0.4998	0.1265	-1.9840
MA(1,12)	0.4618	1.0000	0.0000	0.4994	0.1533	-1.9765
MA(2,9)	0.4718	1.0000	0.0000	0.5000	0.1131	-1.9872
MA(2,12)	0.4718	1.0000	0.0000	0.5000	0.1131	-1.9872
MA(3,9)	0.4684	1.0000	0.0000	0.4998	0.1265	-1.9840
MA(3,12)	0.4718	1.0000	0.0000	0.5000	0.1131	-1.9872
MOM(9)	0.5150	1.0000	0.0000	0.5006	-0.0598	-1.9964
MOM(12)	0.4751	1.0000	0.0000	0.5002	0.0998	-1.9900
VOL(1,9)	0.4651	1.0000	0.0000	0.4996	0.1399	-1.9804
VOL(1,12)	0.4917	1.0000	0.0000	0.5008	0.0332	-1.9989
VOL(2,9)	0.4518	1.0000	0.0000	0.4985	0.1936	-1.9625
VOL(2,12)	0.4618	1.0000	0.0000	0.4994	0.1533	-1.9765
VOL(3,9)	0.4485	1.0000	0.0000	0.4982	0.2071	-1.9571
VOL(3,12)	0.4651	1.0000	0.0000	0.4996	0.1399	-1.9804

Notes: predictors are based on moving average (MA), momentum (MOM) and volume (VOL) strategies.

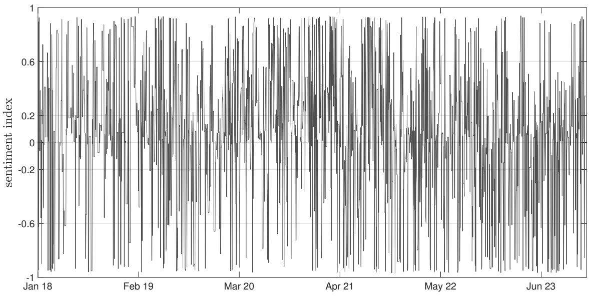
Appendix B. Sentiment analyses

Figure B.1: Bitcoin (BTC) world cloud for the corresponding pre-processed corpus using web-based news from 2017 to 2023.

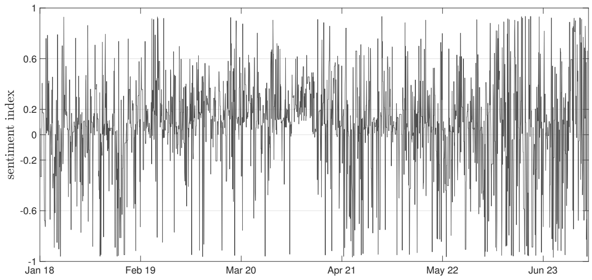
Table B.1: Dataset summary from web-scrapping and text analyses for the selected cryptocurrencies using data from January 1, 2018, to December 31, 2023.

Crypto	# outlets	# total news	Positive	Negative	Neutral
BNB	213	2546	746	651	1149
BTC	245	2866	576	486	1804
ADA	141	1473	610	276	587
DOGE	221	1677	565	364	748
ETH	291	2801	910	645	1246
LTC	170	1367	485	252	630
XLM	169	1090	419	142	529
TRX	149	1219	407	225	587
XRP	521	2736	693	685	1358

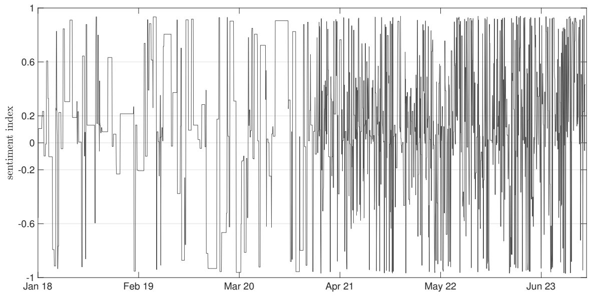
Notes: It includes the total number of sources/outlets (encompassing major web-based newspapers and other web-media outlets), the total count of collected news articles, and the breakdown of these news into positive, negative, and neutral sentiment categories.



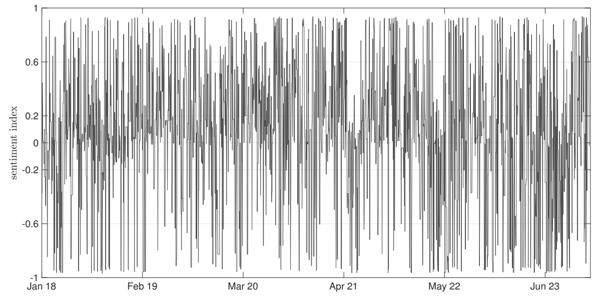
(a) Binance (BNB)



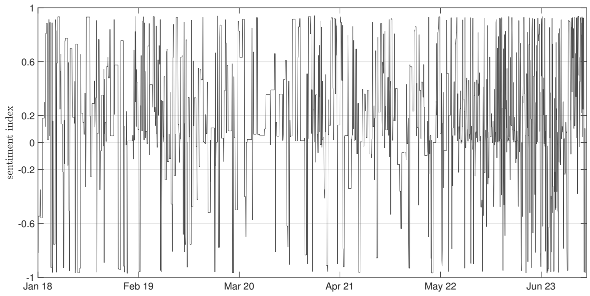
(b) Bitcoin (BTC)



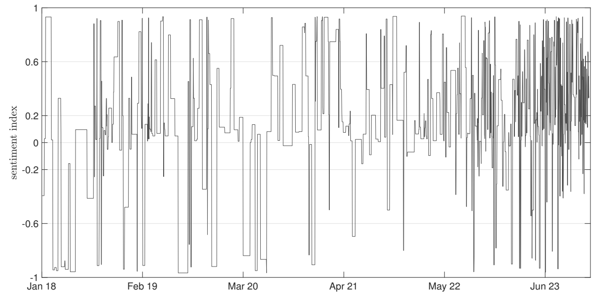
(c) Dogecoin (DOGE)



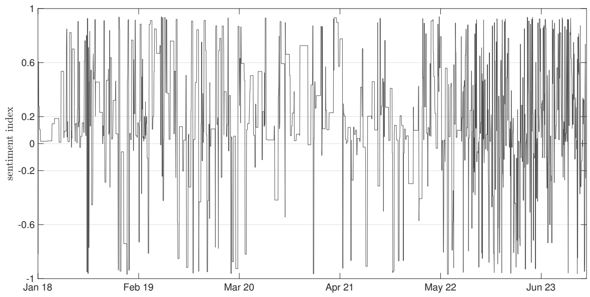
(d) Ethereum (ETH)



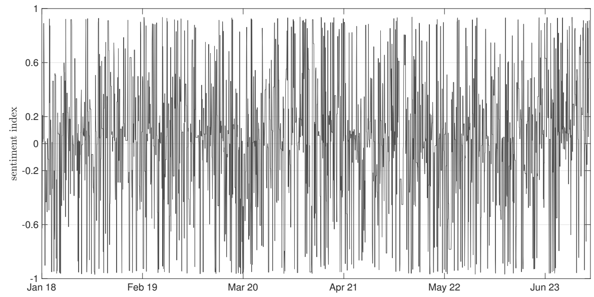
(e) Litecoin (LTC)



(f) Stellar (XLM)



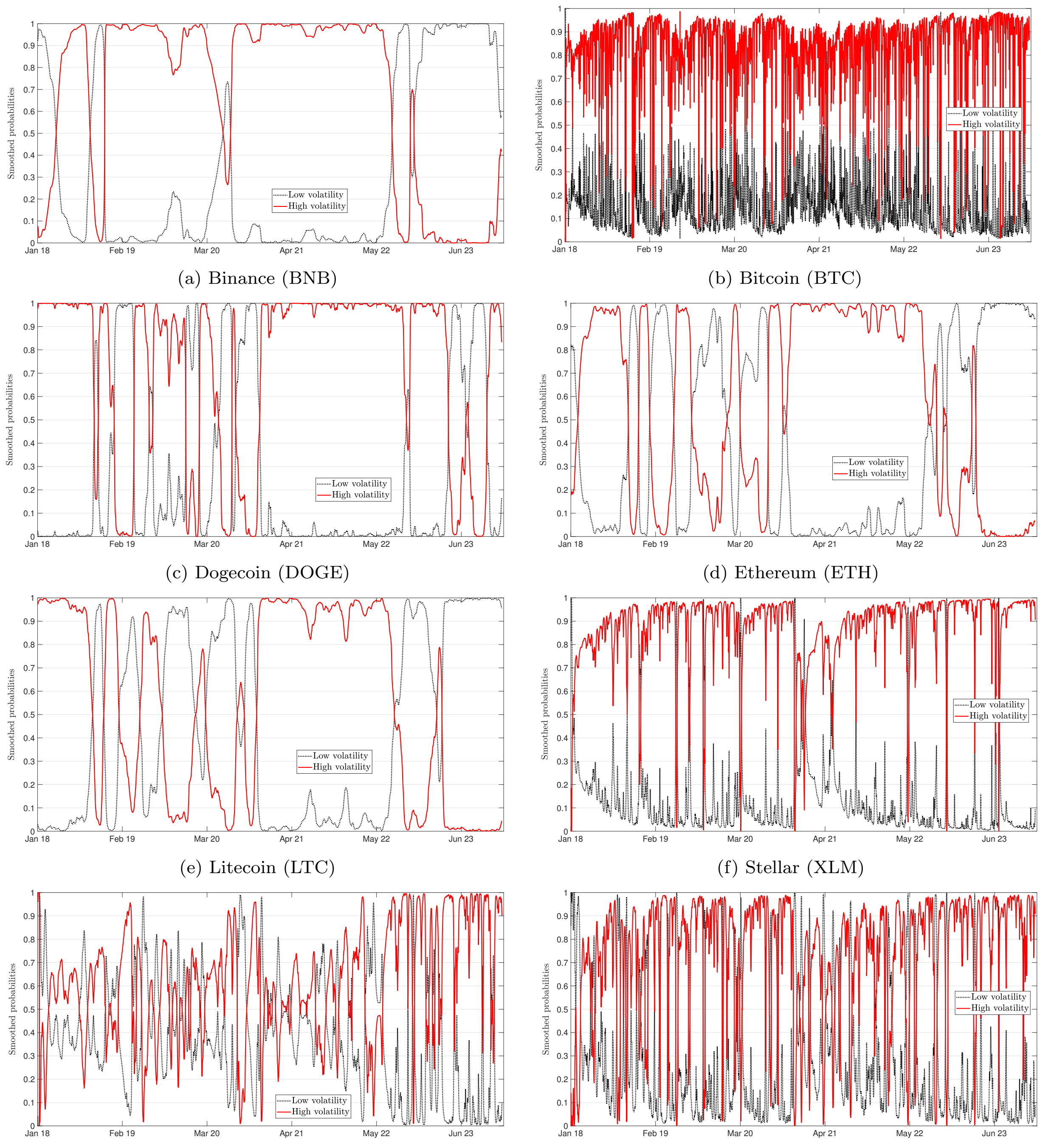
(g) Tron (TRX)



(h) Ripple (XRP)

Figure B.2: Temporal evolution of sentiment indexes for cryptocurrencies.

Appendix C. Smoothed probabilities for returns volatility regimes



(a) Binance (BNB)
(b) Bitcoin (BTC)
(c) Dogecoin (DOGE)
(d) Ethereum (ETH)
(e) Litecoin (LTC)
(f) Stellar (XLM)
(g) Tron (TRX)
(h) Ripple (XRP)

Figure C.1: Temporal evolution of smoothed probabilities extracted from MS-GARCH models for cryptocurrency returns.