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Financial literacy, investor sentiment, and Bitcoin returns: Panel evidence from the Eurozone

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ABSTRACT

This study investigates the moderating role of financial literacy in the relationship between investor sentiment and Bitcoin returns in the Eurozone context. Using monthly panel data for 15 Eurozone countries from 2012 to 2024, we focus on Bitcoin as a representative cryptocurrency alongside key macro-financial variables. A three-layered empirical approach is employed to capture long-run equilibrium relationships, country-specific short-run coefficients, and heterogeneous effects across the return distribution through pooled least squares, panel Autoregressive Distributed Lag (ARDL), and quantile regression methods. The findings primarily reveal that investor sentiment has a significant positive impact on Bitcoin returns, and financial literacy strengthens the impact of sentiment on returns in the aggregate long run and the country-specific short run. This indicates that sentiment-induced effects on cryptocurrency return are significantly stronger in more financially literate environments. Short-run dynamics show rapid error correction of Bitcoin returns. The study's novel contribution is integrating financial literacy into the sentiment–returns nexus for the cryptocurrency market.

1. Introduction

Cryptocurrency has significantly transformed the digital financial landscape, offered new investment opportunities, and posed unique market and economic challenges (Agosto et al., 2022). With over 300 million users globally and a market capitalization exceeding $1.2 trillion, the cryptocurrency ecosystem has evolved from a niche innovation to a modern financial domain (Buy Bitcoin Worldwide, 2023). As the dominant asset, Bitcoin accounts for more than 54 % of the market share, attracting investors and traders (Crypto Economy, 2023).

Despite its technological sophistication, cryptocurrency markets are heavily influenced by behavioral factors. Social media sentiment, news cycles, and speculative patterns create price swings beyond underlying value (Bouteska et al., 2022; Güler, 2023; Naeem et al., 2021). In this context, financial literacy, defined as possessing the knowledge and skills to enable conscious and effective money management, becomes crucial (Kumari, 2020). The Organization for Economic Co-operation and Development (OECD, 2023, p.13) conceptualizes financial literacy as a combination of "financial awareness, knowledge, skills, attitudes and behaviours necessary to make sound financial decision and ultimately achieve financial well being". Investors with adequate financial literacy are better equipped to navigate the highly volatile cryptocurrency markets and mitigate potential losses, whereas those with insufficient financial literacy may lack the necessary tools to manage such risks effectively (Hayashi & Routh, 2025). This phenomenon raises an important question: can financial literacy act as a moderating force in a digital market dominated by perception and emotion? Understanding how individual knowledge influences investor sentiment has become increasingly relevant, especially in light of events such as the FTX collapse, the Terra-Luna crash, and the broader crypto winter of 2022–2023 (Vidal-Tomás et al., 2023; Briola, Vidal-Tomás, Wang, & Aste, 2023).

Investor sentiment refers to investors' subjective attitudes or emotional biases toward a financial asset, such as stocks or cryptocurrencies. It is shaped by market conditions, media signals, and behavioral factors, and can significantly influence speculative behavior, investment demand, and asset pricing dynamics (Anamika et al., 2023; Güler, 2023). Sentiment plays a critical role in shaping investor decisions in conventional stock markets and in emerging asset classes such as cryptocurrencies (Dias et al., 2022; Mai et al., 2022). Market

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optimism often initiates price rallies, while declining sentiment is associated with sharp downturns and increased volatility (López-Cabarcos et al., 2021). Although these dynamics are discussed from an equity market perspective, their implications for cryptocurrency markets remain underexplored despite these assets' highly speculative nature and instability (Güler, 2023; Mokni et al., 2022).

Bitcoin appears highly responsive to shifts in public mood and speculative attention, raising concerns over rational decision-making in these rapidly evolving markets (Güler, 2023; Wang, 2024). Studies have examined volatility spillovers, hedging strategies during crises (Yousaf & Ali, 2020), and cryptocurrency market efficiency under various statistical models (Palamalai et al., 2021). Bouteska et al. (2022) and Ben Hamadou et al. (2025) highlight the nonlinear and volatile relationship between investor sentiment and cryptocurrency returns. Recent research has also employed AI-based sentiment analysis to assess stakeholder perceptions (Jayawardhana & Colombage, 2025). It is important to note, however, that the role of financial literacy as a moderating force in sentiment-return dynamics remains underexplored.

The literature on financial literacy has focused primarily on traditional financial products and basic investment decisions (Arriqoh & Zoraya, 2024; Cascavilla, 2024), with limited attention to digital assets. Moreover, the interaction between financial literacy and investor sentiment in cryptocurrency markets remains absent, particularly across diverse regulatory and cultural environments such as the Eurozone (Carbó-Valverde et al., 2023; Singh & Gulia, 2024). No prior study has systematically examined how financial literacy moderates behavioral factors in cryptocurrency markets. While prior studies analyzed market efficiency and sentiment effects (Naifar & Altamimi, 2023; Philippas et al., 2019), less attention has been paid to how individual-level knowledge shapes investor responsiveness to market sentiment in the cryptocurrency domain.

This gap is significant given the speculative dynamics and information asymmetry that characterize digital assets. Accordingly, this study addresses the following research question: Does financial literacy moderate the relationship between investor sentiment and cryptocurrency returns? The empirical approach of this study is designed to investigate this relationship, particularly to assess the moderating effect of financial literacy.

We employ a three-tier econometric framework consisting of pooled least squares, panel ARDL, and quantile regression models. In addition, several diagnostic methods are applied to validate the reliability and consistency of the results across specifications and quantiles. After testing the dataset, the findings primarily reveal that investor sentiment significantly impacts Bitcoin returns, and financial literacy strengthens the impact of sentiment on returns in both the aggregate long run and the country-specific short run.

This paper contributes to the literature by offering a cross-country empirical assessment of how financial literacy moderates the impact of investor sentiment on cryptocurrency returns, focusing on 15 Eurozone countries with varying economic and regulatory frameworks. This comparative analysis is particularly relevant given the increasing calls for region-specific investor protection policies in volatile digital markets. We integrate behavioral finance and financial education by operationalizing sentiment and financial literacy within a unified econometric framework. This study offers stakeholders, academicians, and policymakers valuable insights by integrating behavioral finance and financial literacy dimensions. The findings can inform financial education strategies and regulatory responses, helping to mitigate sentiment-driven risks and promote more informed engagement with digital assets. It also offers practical insights for regulators and educators by identifying conditions under which financial literacy attenuates speculative sentiment effects.

The remainder of the paper is organized as follows. Section 2 reviews the literature on investor sentiment and returns to identify the research gap. Section 3 explains the applied methods and provides mathematical formulations. Section 4 presents and interprets the findings. Section 5 discusses the outcomes and their policy implications. Finally, Section 6 concludes with limitations and future research directions.

2. Related literature

With technological advancements, various investment instruments have evolved to meet the diverse risk appetites of a broader investor base. As a result, investors' preferences have changed in the face of diversified asset types. Prospect Theory, which states that investors' gains and losses should be evaluated based on reference points such as increasing financial products, changing investor preferences, and the amount of capital held by investors, has also contributed to the development of theories related to behavioral finance (Kahneman & Tversky, 1979). The theory emphasizes that investors may display more irrational behavior due to their tendency to avoid risk. Focusing on the interaction between limited arbitrage theory, investor sentiment theories, and financial markets, behavioral finance argues that investors are influenced by factors such as emotion and financial literacy when making investment decisions. Prior literature regarding investor sentiment is mainly classified into two domains: i) the relationship between investor sentiment and stocks (stock market returns), and ii) the relationship between investor sentiment and crypto assets (cryptocurrencies). At the same time, studies have examined the effect of financial literacy on investor decisions in stock markets. In this section, the studies conducted within the scope of the subject are briefly reviewed.

2.1. Relationship between investor sentiment and stocks

Previous research on the relationship between investor sentiment and stock performance has primarily concentrated on how sentiment influences stock returns. Baker and Wurgler (2006) analyzed the impact of sentiment on the cross-section of returns and found that future returns are systematically related to sentiment indicators present at the beginning of the period. Similarly, Bathia and Bredin (2016) showed that value stocks are susceptible to shifts in investor sentiment, with high (low) sentiment levels predicting lower (higher) future returns across G7 markets. Ding et al. (2019) further disentangled sentiment effects, demonstrating a negative association between long-term sentiment and stock returns, while short-term sentiment exhibited a positive contemporaneous correlation with returns. These findings suggest an inverse relationship between sentiment and long-term or future returns. Contrary to these findings, Alburaythin et al. (2024) examined arbitrage limits and the role of investor sentiment on stock prices in nine UK stock market anomalies. The results showed that five stock market anomalies tended to generate higher returns during strong investor optimism. Likewise, Wang (2024) focused on the effect of investor sentiment on stock market returns and concluded that this effect is market-specific.

Financial literacy plays a critical role in shaping investor behavior and stock market outcomes. Numerous studies have explored investor sentiment, financial literacy, and the influence of investors' behavioral attitudes on stock market returns. A study conducted in China found that overconfidence in financial literacy positively affects stock market participation, while distrust has an adverse effect (Xia et al., 2014). Shiller (2015) also noted that individuals' overconfidence in intuitive judgments plays a key role in understanding speculative bubbles. Consequently, investors' overconfidence and mood significantly influence asset pricing and market participation. Mouna and Jarboui (2015a, 2015b) stated that the portfolio returns of small investors in Tunisia are affected by behavioral biases, and that their level of experience can reduce such biases; limited financial literacy appears to be a significant determinant of weak portfolio diversification.

Guiso et al. (2008) examined the role of trust, concluding that individuals with low trust are less likely to participate in the stock market; they suggested that stock ownership could be expanded through education about stock markets. Daniel et al. (1998) found that overconfident and knowledgeable investors paid more attention to specific signals than to previous ones, which caused stock prices to overreact. On the other hand, Karolyi (2016) examined the role of cultural distance in explaining foreign bias in international portfolio investments and stated that country-based investments made by global investors in emerging markets show even more negative sensitivity to cultural distance. Falamarzi et al. (2023) also noted that individuals in some cultures display higher risk-taking levels than those in other cultures. This difference in risk-taking tendencies is an influential factor in investment decision-making.

However, contrary to these studies, research has found that investors' attitudes toward risk positively affect overconfidence. Conversely, the effect of investors' financial literacy (investors' knowledge about company performance and macroeconomic conditions) is blocked by their attitudes toward risk, and therefore, financial literacy has no effect on overconfidence (Arifin & Soleha, 2019). Rasool and Ullah (2020) reported a negative relationship between individual investors' behavioral biases and financial literacy; as financial literacy increased, the likelihood of encountering behavioral biases decreased. Prasad et al. (2021) found a significant positive relationship between financial literacy and individual investor decisions (return, risk, market analysis). Similarly, Paramita and Henny (2022) documented that financial literacy (financial attitude, financial knowledge, and financial behavior) has a positive effect on investment decisions, emphasizing that investors with a good level of financial literacy are better able to optimize profits and minimize risks when making stock investment decisions. From the aforementioned research, it can be derived that investors' financial literacy is an important factor in addition to investor sensitivity regarding stock returns.

2.2. Relationship between investor sentiment and crypto assets

Existing literature predominantly investigates the influence of investor sentiment on the returns of major cryptocurrencies such as Bitcoin and Ethereum. Quantile regression is commonly employed to capture heterogeneity across different return distributions. Eom et al. (2019) focused on the statistical properties and predictability of Bitcoin returns and volatility and suggested that investor sentiment increases the predictability of the future state of Bitcoin volatility. Mokni et al. (2022) used the quantile autoregressive regression model in their study and found a significant and positive relationship between Bitcoin returns and investor sentiment, emphasizing that returns positively affect sentiment. Using a similar method, several other studies reported diverse outcomes—for example, a non-linear association between investor sentiment and Bitcoin volatility and returns (Dias et al., 2022); increased sentiment is associated with increases in Bitcoin prices, while decreased sentiment is associated with decreases in Bitcoin prices (Koutmos, 2023). In addition, Güler (2023) used the EGARCH model and stated that investor confidence positively affects Bitcoin returns and conditional volatility, especially after the COVID-19 pandemic. In contrast, Naifar and Altamimi (2023) examined the effects of global confidence and COVID-19 news on the dynamics of Bitcoin returns during the pandemic and ascertained that such news negatively affected Bitcoin returns during extreme decline periods (quantile regression). Moreover, they found that the effects of this news on Bitcoin returns are heterogeneous and generally negative (quantile-on-quantile regression).

Recently, machine learning techniques have also been applied to explore this relationship. Ben Hamadou et al. (2025) developed a Bitcoin returns forecasting model employing various methods, including one-dimensional convolutional neural networks, bidirectional long short-term memory (LSTM) networks, and support vector machines, demonstrating that investor sentiment notably improved predictive performance during the COVID-19 period. Cryptocurrencies attracted significant investor interest during this time, partly due to their perceived safe haven properties (Tarchella et al., 2024). Additional research themes include the relationship between investor sentiment and cryptocurrency market risk (Lin et al., 2023), jump risk determinants in Bitcoin prices (He & Wang, 2023), and interdependencies between cryptocurrencies and investor confidence (Long et al., 2024).

With advances in financial technologies, interest in cryptocurrency investment has surged, driven by expectations of high returns, hedging, diversification, and safe haven benefits. Several studies support the hedge hypothesis for cryptocurrencies. Dyhrberg (2016), using asymmetric GARCH methodology, showed that Bitcoin can hedge stock exposure on the Financial Times Stock Exchange (FTSE) Index and, in the short term, the US dollar, indicating hedging features akin to gold. Bouri, Gupta, et al. (2017) found that Bitcoin can hedge against global uncertainty by employing quantile regression. However, Bouri, Molnár, et al. (2017) concluded that Bitcoin is a weak hedge for major global stock indices, gold, oil, bonds, and the US dollar index but can function effectively as a diversifier. Bitcoin's role as a speculative asset is also well-documented; Baur et al. (2018) noted that Bitcoin is generally uncorrelated with traditional assets during regular and turbulent times, underpinning its speculative appeal. Corbet et al. (2018) found that this speculative characterization remains despite the introduction of futures trading. Shahzad et al. (2019) identified that Bitcoin, gold, and a commodity index exhibit weak safe haven properties for the global stock market under extreme conditions. However, their safe haven roles vary across emerging, developed, US, and Chinese markets and fluctuate over time.

Aggregately, Bitcoin serves both hedging and speculative functions for investors. Wang et al. (2021) affirmed Bitcoin's hedging efficacy in certain developed and emerging markets, while Tarchella et al. (2024) highlighted its increased preference amid the COVID-19 period. Nonetheless, opposing views exist: Nguyen and Pham (2025) reported that Bitcoin and Ethereum were ineffective hedges in major Asian emerging markets during COVID-19, with Ethereum hedging only for Pakistan. Acikgoz (2025) also argued that Bitcoin lacks hedging and safe haven qualities across developed and emerging markets. Conlon et al. (2024) stated that Bitcoin is a strong hedge against the US dollar but a weak safe haven over short horizons.

Multiple studies confirm the conditional presence and variability of the safe haven feature. Tarchella and Dhaoui (2021) argue that Bitcoin's safe haven status depends on market conditions and investment horizons. Wang et al. (2021) emphasize Bitcoin's hedging and diversification benefits across select markets. Diniz-Maganini et al. (2021) demonstrated Bitcoin's safe haven function for the MSCI World Index. Feder-Sempach et al. (2024) view Bitcoin as a weak safe haven in financial distress. Liu and Yuan (2024) note its hedging role across stock, bond, and foreign exchange markets alongside safe haven functions during turmoil. Ullah et al. (2024) show Bitcoin's safe haven properties in the Russian market, highlighting adequate diversification with traditional assets.

Studies on investor sentiment related to cryptocurrencies vary broadly in asset coverage—including Bitcoin, Ethereum, Dogecoin, Ripple, DeFi tokens, CEX tokens, Stellar, and NEM (Lin et al., 2023; Long et al., 2024). However, Bitcoin remains the primary focus (Bouteska et al., 2022; Dias et al., 2022; He & Wang, 2023; Koutmos, 2023; Mokni et al., 2022). Understanding the relationship between investor sentiment and the cryptocurrency market is crucial for policymakers to inform decisions and strategies. Mai et al. (2022) state, "Bitcoin is the only asset whose trade sentiment can create exceptional economic gains." Consequently, Bitcoin is considered representative of the broader cryptocurrency market in studying the moderating role of financial literacy on the investor sentiment-return relationship.

This study addresses a significant gap in financial literacy, behavioral factors, and cryptocurrency research. Prior cryptocurrency studies extensively examined sentiment effects (Huang et al., 2021; Philippas et al., 2019) and market efficiency questions (Nadarajah & Chu, 2017; Urquhart, 2016). Meanwhile, financial literacy research focused primarily on traditional financial products and basic investment decisions (Lusardi & Mitchell, 2014; Van Rooij et al., 2011). To our knowledge, no prior study has systematically examined how financial literacy moderates behavioral factors in cryptocurrency markets. This gap is particularly significant given the unique characteristics of cryptocurrency markets. We address this gap by examining the pivotal question: Does financial literacy moderate the relationship between investor sentiment and cryptocurrency returns? We hypothesize that financial literacy could moderate investor sentiment and affect Bitcoin returns. To empirically test this hypothesis and ensure the robustness of our findings, this study employs a three-layered comprehensive econometric approach—namely, pooled least squares, panel ARDL, and quantile regression models. Additionally, various diagnostic methods are applied for dataset validation and result robustness.

3. Data and method

3.1. Data description and nature

This study uses monthly panel data of 15 Eurozone countries, including Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, and Spain, from June 2012 to December 2024, with 2211 observations. Bitcoin return (BTC) is the predicted variable, and FINTINST is the primary predictor variable, defined as the interaction term between investor sentiment and financial literacy. Additionally, macroeconomic variables such as gold returns, exchange rate, interest rate, and the VIX volatility index are included as control factors (Table 1). We restrict the sample to 15 countries with consistent coverage for the investor sentiment indicator and the OECD/INFE financial literacy measure. Regarding financial literacy data, Latvia and Lithuania have missing monthly observations in the dataset. Specifically, Latvia lacks data from June 2012 to April 2014 (23 months), and Lithuania has missing values from June 2012 to December 2014 (31 months).

Growth rate transformation is applied to all variables to ensure stationarity and meaningful interpretation in percentage change terms. Fig. 1 shows time series plots of the transformative growth rate first differences and reveals differing levels of volatility and dynamic behavior across variables. BTC and VIX exhibit pronounced volatility clustering, while INRST demonstrates a persistent, mean-reverting pattern. The visual assessment supports the need for econometric methods that account for data heterogeneity, persistence, and potential non-stationarity.

Table 2 documents the summary of data nature based on various measures—i.e., measures of central tendency, measures of dispersion, and measures of distribution shape. Bitcoin returns show a positive

Table 1
Description of selected variables.

Variable	Description	Source
INVSENT	Euro Zone, Business Surveys, Sentix, Investors Sentiment	LSEG Data & Analytics
FINLIT	Financial Literacy. OECD/INFE 2023 International Survey of Adult Financial Literacy	Organisation for Economic Co-operation and Development (OECD)
FINTINST	Interaction Term (FINTINST = INVSENT * FINLIT)	
BTC	Bitcoun Return	Investing.com
GOLDR	Gold Return	Investing.com
ERUS	Exchange Rate (USD to Euro)	Investing.com
INRST	Interest Rate. Long-Term Government Bond Yields: 10-Year: Main (Including Benchmark) for Euro Area (19 Countries), Percent, Monthly, Not Seasonally Adjusted	Federal Reserve Bank of St. Louis
VIX	CBOE Volatility Index	Investing.com
FINSTR	St. Louis Fed Financial Stress Index, Index, Weekly, Not Seasonally Adjusted	Federal Reserve Bank of St. Louis

Source: Authors

mean (0.0630) and standard deviation (0.2570), indicating moderate volatility. The distribution of BTC returns is positively skewed (1.77) and leptokurtic (kurtosis = 13.17), which signifies extreme positive movements. The interaction term (FINTINST) demonstrates a high mean (108.31) and dispersion (267.84), with extreme skewness (7.69) and kurtosis (84.98). These measures denote the volatile and asymmetric nature of BTC returns and the heterogeneous impact of FINTINST. The Jarque–Bera normality test rejects the null hypothesis of normality for all variables at the 1 % significance level, except for ERUS ($p = 0.928$). The test indicates that most series deviate from normality ($p < 0.01$), particularly BTC, FINTINST, INRST, and VIX, suggesting potential asymmetry and fat tails in the data distribution. These distributional properties support employing empirical models that address non-normality and distributional asymmetry, such as quantile regression.

Before regression modeling, the sample variables are tested for stationarity using panel unit root tests. We apply multiple tests, including Im, Pesaran & Shin (IPS), Levin, Lin & Chu (LLC), and Fisher-type ADF and PP tests, each with different assumptions about cross-sectional independence and trend components. All tests are based on the following general autoregressive specification:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \sum_{p=1}^{P} \phi_{ip} \Delta y_{i,t-p} + \varepsilon_{it} \tag{1}$$

Appendix I reports that the sample variables—i.e., BTC, FINTINST, GOLDR, ERUS, INRST, VIX, and FINSTR—are stationary at level. Although the Breitung test fails to reject the null hypothesis for ERUS, it does not undermine the overall stationarity conclusion because of uniform support from the other methods. These findings indicate that all series are integrated of order zero, I(0). Despite the dataset being stationary in levels, we adopt the panel ARDL framework following Pesaran et al. (1999) due to its flexibility in modeling dynamic relationships (Nkoro & Uko, 2016; Pesaran et al., 1999). In this scenario, the model does not estimate a long-run cointegrating vector, but it remains valid for capturing short-run lagged effects and heterogeneous adjustment dynamics across countries.

3.2. Variable selection and justification

We select the Eurozone for several reasons—i.e., common currency environment (the euro), economic size, market development, and educational factors (e.g., investor sentiment and financial literacy). From the Eurozone, only 15 countries are chosen due to their data availability for both investor sentiment and financial literacy variables. Regarding the dependent variable, Bitcoin is considered representative of all cryptocurrencies, as used in prior literature (Bouteska et al., 2022; Koutmos, 2018; Koutmos et al., 2021; Zhang et al., 2023). The interaction term of investor sentiment and financial literacy is included as a primary independent variable to capture how the effect of investor sentiment might fluctuate across sample countries depending on their level of financial literacy. Several studies have used these two variables separately to predict stock returns (Alburaythin et al., 2024; Xia et al., 2014). In terms of control variables, we include gold return (Ben Hamadou et al., 2025; Dias et al., 2022), exchange rate (EUR/USD) (Dias et al., 2022), interest rates (Basher & Sadorsky, 2022), VIX (Dias et al., 2022), and financial stress (Ben Hamadou et al., 2025).

3.3. Estimation steps and model specification

The empirical framework is designed to incrementally test the relationship between investor sentiment and cryptocurrency returns, particularly to assess the moderating effect of financial literacy. We employ three main techniques to ensure the robustness of the findings—namely, pooled least squares, panel ARDL, and quantile regression models. In addition, several methods are applied to check the dataset and the robustness of the outcomes.

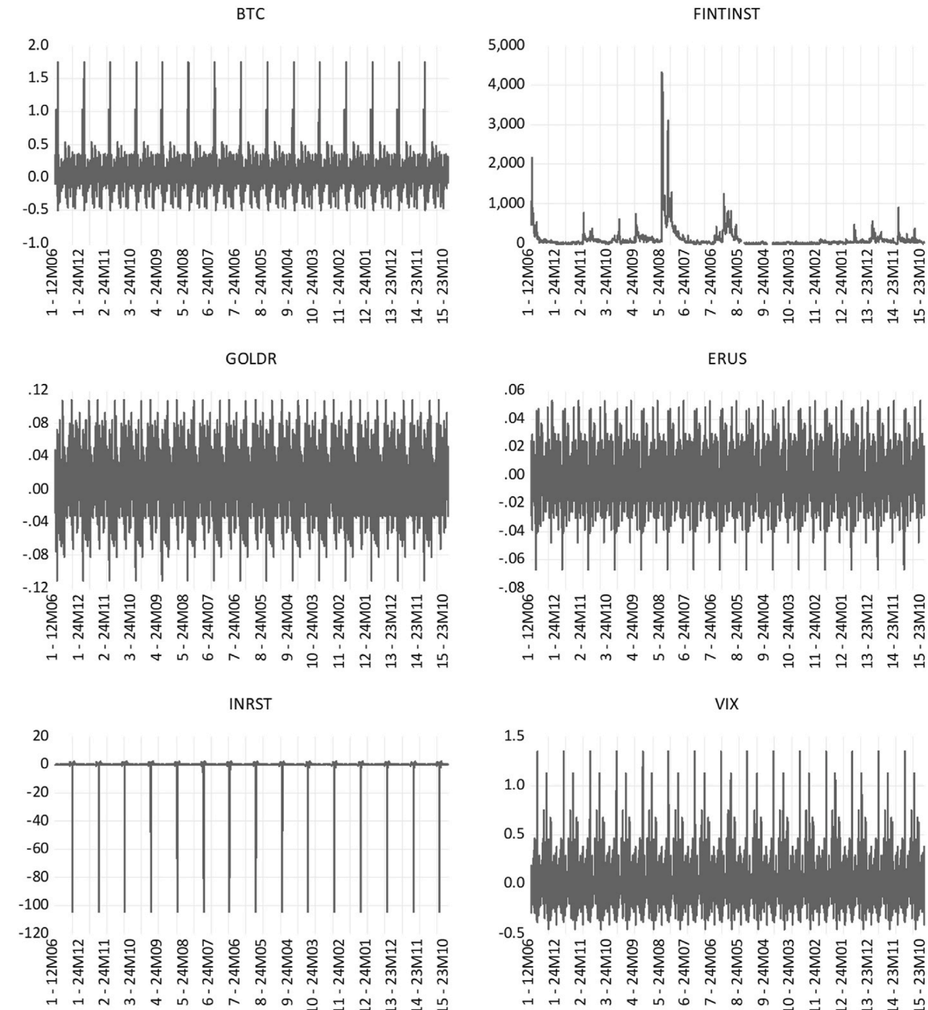

Fig. 1. Time-series plots of endogenous and exogenous variables.
Source: Authors

Table 2
Descriptive statistics.

Particulars	BTC	FINTINST	GOLDR	ERUS	INRST	VIX
Mean	0.063032	108.3082	0.004588	−0.001023	−0.676050	0.029446
Median	0.053786	36.93300	−8.27E-05	−0.001246	−0.024650	−0.008571
Std. Dev.	0.257032	267.8400	0.041305	0.020900	8.641076	0.272059
Skewness	1.770568	7.688215	0.209431	−0.003512	−11.97033	1.470066
Kurtosis	13.16683	84.98198	2.816102	2.960420	144.6686	7.345232
Jarque-Bera	10677.66	640957.9	19.27846	0.148863	1901749.	2535.779
Probability	0.000000	0.000000	0.000065	0.928271	0.000000	0.000000

Note: This table reports the descriptive statistics for all variables used in the panel ARDL estimation over 2012M06–2024M12. BTC represents the monthly returns of Bitcoin, and FINTINST is the interaction term between investor sentiment and financial literacy. GOLDR, ERUS, INRST, and VIX denote gold returns, exchange rate, interest rate, and market volatility index, respectively. The statistics include measures of dispersion (standard deviation), central tendency (mean, median), and distribution shape (skewness, kurtosis).Source: Authors.

3.3.1. *Pooled least squares (LS)*

We begin with simple pooled panel regressions (panel least squares) as a baseline. The pooled OLS treats the data as one large combined cross-section or time series, initially ignoring country-specific effects or dynamics. The basic form of the model is as follows:

$$Y_i = \alpha + \beta X_i + \varepsilon_i \tag{2}$$

With this method, we gradually proceed to develop the main LS model.

Model 1: BTC as the dependent variable, with investor sentiment as the independent variable.

$$\mathrm{BTC}_{it} = \alpha + \beta_1 \mathrm{INVSENT}_{it} + \varepsilon_{it} \tag{3}$$

Model 2: BTC as the endogenous variable, with financial literacy as the exogenous variable.

$$\mathrm{BTC}_{it} = \alpha + \beta_1 \mathrm{FINLIT}_{it} + \varepsilon_{it} \tag{4}$$

Model 3: BTC as the predicted variable and the interaction term as the predictor variable.

$$\mathrm{BTC}_{it} = \alpha + \beta_1(\mathrm{INVSENT} \times \mathrm{FINLIT})_{it} + \varepsilon_{it} \tag{5}$$

Model 4: BTC as the response variable, with the interaction term as the key regressor variable (and macro controls: gold, exchange rate, interest rate, and VIX).

$$\mathrm{BTC}_{it} = \alpha + \beta_1 \mathrm{FINTINST}_{it} + \beta_2 \mathrm{GOLDR}_{it} + \beta_3 \mathrm{ERUS}_{it} + \beta_4 \mathrm{INRST}_{it} + \beta_5 \mathrm{VIX}_{it} + \varepsilon_{it} \tag{6}$$

3.3.2. Panel ARDL model

We employ a panel ARDL model to analyze primarily the impact of FINTINST on BTC returns. In an ARDL (p, q1, q2, …) model, the dependent variable is regressed on its p-lagged and q-lagged values of each independent variable. A distinct advantage of ARDL is that we can include variables of different integration orders (I(0) or I(1)) and obtain unbiased long-run coefficients even in relatively short samples. We utilize a panel ARDL framework with the Pooled Mean Group (PMG) estimator (Pesaran et al., 1999). This approach allows short-run coefficients and error variances to differ across countries while constraining long-run coefficients to be equal. The PMG approach provides an error-correction representation of the ARDL model, from which both short-run dynamics and long-run relationships are inferred.

In general form, for a given dependent variable Y_{it} and a set of regressors X_{it}, the ARDL model can be written as:

$$Y_{it} = \alpha_i + \sum_{j=1}^{p} \phi_j\, Y_{i,t-j} + \sum_{m=1}^{M} \sum_{k=0}^{q_m} \beta_{m,k}\, X_{m,i,t-k} + \varepsilon_{it} \tag{7}$$

where i indexes country (i = 1, …,15 for each Eurozone member) and t represents year. α_i captures country-specific fixed effects. The term with ϕ_j includes lags of the dependent variable, and the terms with $\beta_{m,k}$ include contemporaneous and lagged values of each of the M independent variables X_m. The lag orders p and q_m are chosen based on the Akaike Information Criterion and diagnostics to ensure serially uncorrelated residuals. In practice, given the annual data and sample size, we include a limited number of lags (typically 1 lag of the response variable and 0–1 lag of the regressor variables) to conserve degrees of freedom.

We re-parameterize the ARDL into an Error Correction Model (ECM) form. The ECM highlights the short-run adjustments and the speed at which variables return to equilibrium after a shock. The ECM form is given by:

$$\Delta \mathrm{Y}_{it} = \sum_{j=1}^{p-1} \lambda_j\, \Delta \mathrm{Y}_{i,t-j} + \sum_{m=1}^{M} \times \sum_{k=0}^{q_m-1} \gamma_{m,k}\, \Delta \mathrm{X}_{m,i,t-k} + \psi\left(\mathrm{Y}_{i,t-1} - \theta_0 - \sum_{m=1}^{M} \theta_m \mathrm{X}_{m,i,t-1}\right) + \varepsilon_{it} \tag{8}$$

where Δ denotes year-over-year differences (short-run changes). The coefficient ψ on the term in parentheses is the error-correction coefficient, which should be negative and statistically significant if a long-run equilibrium exists. The term $\mathrm{Y}_{i,t-1} - \theta_0 - \sum_{m=1}^{M} \theta_m \mathrm{X}_{m,i,t-1}$ represents the previous period's deviation from the long-run equilibrium relationship between Y and X; the parameter ψ measures the speed of adjustment – for instance, $\psi = -0.2$ would indicate that 20 % of the deviation is corrected each year. The $\gamma_{m,k}$ coefficients capture the short-run impact of changes in independent variables on ΔY, while the θ_m (embedded in the error-correction term) are the long-run coefficients of the cointegrating relationship. We report short- and long-run estimates in the results tables for straightforward interpretation.

This study estimates the ARDL-ECM model to address the research question. This model examines how financial literacy moderates the impact of investor sentiment on Bitcoin returns.

$$\Delta BTC_{it} = \alpha_i + \lambda_i\big(BTC_{i,t-1} - \theta_1 FINTINST_{i,t-1} - \theta_2 GOLDR_{i,t-1} - \theta_3 ERUS_{i,t-1} - \theta_4 INRST_{i,t-1} - \theta_5 VIX_{i,t-1}\big) + \text{short-run terms} + \varepsilon_{it} \tag{9}$$

3.3.3. Quantile regression

While the panel ARDL addresses average long-run effects and short-run adjustments, quantile regression (QR) allows us to explore how the impact of sentiment (and its moderation by literacy) might differ across the distribution of Bitcoin return outcomes. This is important since cryptocurrency returns are highly non-normal and often exhibit asymmetry—the determinants of extreme crashes might differ from those of mild moves or extreme booms. The QR model developed by Koenker and Bassett (1978) is presented as follows:

$$Q_{y_t}(\tau|X_t) = \alpha_\tau + X_t'\beta_\tau \tag{10}$$

We estimate cross-sectional quantile regressions for the panel at five quantiles, namely the 10th, 25th, 50th (median), 75th, and 90th percentiles of the Bitcoin return distribution. The quantile regression model specification mirrors the full Model 4 from OLS, but applied quantile-by-quantile.

$$Q_\tau\{BTC_{it}|X_{it}\} = \alpha(\tau) + \beta_1(\tau)\mathrm{FINTINST}_{it} + \beta_2(\tau)\mathrm{GOLDR}_{it} + \beta_3(\tau)\mathrm{ERUS}_{it} + \beta_4(\tau)\mathrm{INRST}_{it} + \beta_5(\tau)\mathrm{VIX}_{it} \tag{11}$$

3.3.4. Robustness test

We perform robustness tests to ensure the findings are not spurious outcomes of specific model choices. As part of the process, we reapply the panel ARDL approach by replacing the VIX with the St. Louis Fed Financial Stress Index to observe whether the results remain consistent. After replacing this variable, we run the model based on the following specification:

$$\Delta BTC_{it} = \alpha_i + \lambda_i\big(BTC_{i,t-1} - \theta_1 FINTINST_{i,t-1} - \theta_2 GOLDR_{i,t-1} - \theta_3 ERUS_{i,t-1} - \theta_4 INRST_{i,t-1} - \theta_5 FINSTR_{i,t-1}\big) + \text{short-run terms} + \varepsilon_{it} \tag{12}$$

4. Results and discussion

Testing the dataset through the primary methods (pooled least squares, panel ARDL, and quantile regression) provides multifaceted insights that answer the research question—i.e., Does financial literacy moderate the relationship between investor sentiment and cryptocurrency returns? In addition, findings from other methods, considered for robustness tests, bolster the core results and justify the primary objective of this study. This section begins by presenting the static pairwise relationship between the sample variables.

4.1. Pairwise correlation structure

To comprehend the direction and strength of linear relationships between variables, the pairwise Pearson correlation coefficients are presented in Table 3. It is observed that none of the pairwise correlations are particularly high in absolute value—the largest is about 0.3786 between GOLDR and ERUS. BTC returns have a weak positive correlation with FINTINST (0.0518) and ERUS (0.0704), and a weak negative correlation with INRST (−0.0999) and VIX (−0.1737). These outcomes signify that Bitcoin returns tend to be slightly higher when sentiment (with the moderation of financial literacy) and exchange rates are higher, and lower when interest rates or market volatility are higher.

4.2. Pooled least squares

We ascertain several insights from the pooled LS results (four models) to examine the determinants of Bitcoin returns. These models

Table 3
Correlation matrix.

Variables	BTC	FINTINST	GOLDR	ERUS	INRST	VIX
BTC	1.00000					
FINTINST	0.05175	1.00000				
GOLDR	0.00545	-0.01197	1.00000			
ERUS	0.07039	0.01132	0.37861	1.00000		
INRST	-0.09989	0.01440	0.11554	-0.10231	1.00000	
VIX	-0.17368	-0.02543	-0.00243	-0.23409	0.14998	1.00000

Pearson correlation coefficients.

Source: Authors

are developed gradually based on "forward selection" methods—i.e., systematically building our regression model by adding the most impactful predictor at each step until no significant improvement is observed (Table 4). Before testing the moderating effect of the interaction term, we consider investor sentiment and financial literacy to observe their impact on Bitcoin returns separately in the first two models.

Model 1 shows that investor sentiment alone has a positive and statistically significant effect on Bitcoin returns at the 5 % level ($\beta = 0.0029$). This coefficient indicates that higher investor sentiment is associated with statistically greater Bitcoin returns, holding other variables constant. However, the adjusted R^2 is significantly low (0.0021), denoting that only 0.21 % of the variation in BTC returns can be explained by investor sentiment. In Model 2, we find no statistically significant impact of financial literacy on Bitcoin returns. For this reason, the third model is employed to test the moderating effect of financial literacy on the relationship between investor sentiment and Bitcoin returns. Model 3 introduces the interaction term (FINTINST) without the main effects and observes a positive and significant coefficient ($\beta = 0.00005$, $p = 0.0149$). This indicates that the combination of high sentiment and financial literacy coincides with higher Bitcoin returns. It is noticeable that the economic effect (in other words, adjusted R^2) remains significantly low. The model implicitly assumes that any sentiment effect emerges only through the interaction (and similarly for literacy). This restricted specification implies that the effect of investor sentiment is dependent on financial literacy, thus motivating further investigation by adding some control variables.

Model 4 represents the most comprehensive specification, integrating the FINTINST interaction term and key macroeconomic and market control variables, including gold return, exchange rates, interest rates, and volatility index. In this model, the coefficient of FINTINST remains positive and statistically significant (0.00005, p-value = 0.0199). It bolsters and justifies the primary finding (Model 3)—i.e., financial literacy moderates the relationship between investor sentiment and Bitcoin returns, even after controlling for macroeconomic and volatility dynamics. A substantially improved explanatory power, with an adjusted R^2 of 0.0366, is observed regarding the model's fitness. This indicates that the sample endogenous variables can explain approximately 3.7 % of the variation in BTC returns. The highly significant F-statistic (p-value = 0.0000) confirms this comprehensive model's overall statistical validity and predictive capacity.

The pooled LS regressions provide preliminary evidence that financial literacy significantly moderates the relationship between investor sentiment and Bitcoin returns. R^2 and adjusted R^2 values suggest increasing explanatory power across models, with the full specification providing the best model fit. However, since this model neither accounts for heterogeneity across countries (each country might have its own mean return or structural differences) nor dynamics (lagged effects), the study advances to more sophisticated panel time-series models—i.e., panel ARDL approach.

Table 4
Pooled least squares regression results.

Variable	Model 1	Model 2	Model 3	Model 4
Sentiment	0.0029* (0.0166)	–	–	–
FINLIT	–	0.0000 (1.0000)	–	–
FINTINST	–	–	0.00005* (0.0149)	0.00005* (0.0199)
GOLD	–	–	–	0.0337 (0.8132)
ERUS	–	–	–	0.2908 (0.3144)
INRST	–	–	–	−0.0022* (0.0004)
VIX	–	–	–	−0.1480* (0.0000)
R^2	0.0026	0.0000	0.0027	0.0388
Adj. R^2	0.0021	−0.0004	0.0022	0.0366
F-statistic	5.7488 (0.0165)	4.10E-13 (0.9999)	5.9316 (0.0149)	17.7882 (0.0000)

Note: *significance level ($p < 0.05$). This table presents the results of panel least squares regressions estimating the effects of investor sentiment, financial literacy, and their interaction on Bitcoin (BTC) returns across four model specifications. Each cell reports the estimated coefficient and its associated p-value in parentheses. All regressions are estimated with robust standard errors using unbalanced panel data from 15 countries spanning June 2012 to December 2024.Source: Authors.

4.3. Panel ARDL approach

Table 5 presents the estimated coefficients for an Error Correction Model (ECM) from the panel ARDL approach. The results provide insight into equilibrium relationships and short-term adjustments between Bitcoin returns and their determinants. This framework is essential for understanding how deviations from long-term trends are corrected over time.

In the long run, the coefficients of all exogenous variables are statistically significant at the 1 % level. Noticeably, the interaction term has a positive and statistically significant impact on Bitcoin returns ($\beta = 0.000077$, $p = 0.0105$), indicating that financial literacy augments the effect of investor sentiment on returns. For instance, if financial literacy is higher by 10 units in one country relative to another, the long-run impact of a given sentiment level on BTC returns would be higher by 0.077 % ($0.000077*10 = $0.00077). Although this number is trivial per unit, the combined effect of large sentiment movements and substantial literacy differences could be noticeable. The direction of the outcome (positive sign) aligns with the pooled regressions and suggests that in more financially literate markets, positive sentiment correlates with higher returns. This supports the hypothesis that financial literacy moderates investor sentiment and affects higher cryptocurrency returns.

Among the macro-financial variables, gold returns, interest rates, and market volatility negatively affect BTC returns. These signify that Bitcoin and gold are partial substitutes in portfolio allocation, and that it is sensitive to tightening financial conditions and risk aversion. On the other hand, the exchange rate shows a strong positive influence ($\beta =$

Table 5
Results of long- and short-term coefficients of ARDL-ECM.

Variable	Coefficient	Std. Error	t-Statistic	P-value
Long Run Equation				
FINTINST	0.000077	3.00E-05	2.559933	0.0105
GOLDR	−0.95355	0.293297	−3.25113	0.0012
ERUS	6.02633	0.562892	10.70602	0.0000
INRST	−0.0087	0.001208	−7.21902	0.0000
VIX	−0.35177	0.053105	−6.624	0.0000
Short Run Equation				
COINTEQ01	−0.93413	0.005647	−165.418	0.0000
Δ(FINTINST)	0.000139	0.000258	0.540516	0.5889
Δ(FINTINST(-1))	0.00031	0.000724	0.427064	0.6694
Δ(FINTINST(-2))	−0.00043	0.000501	−0.86424	0.3876
Δ(GOLDR)	1.324338	0.047852	27.67586	0.0000
Δ(GOLDR(-1))	0.272406	0.033635	8.098934	0.0000
Δ(GOLDR(-2))	−0.78419	0.065013	−12.064	0.0000
Δ(ERUS)	−5.88008	0.638212	−9.21649	0.0000
Δ(ERUS(-1))	−5.12694	0.064317	−79.713	0.0000
Δ(ERUS(-2))	−2.02719	0.061092	−33.1826	0.0000
Δ(INRST)	0.005536	5.70E-05	97.17878	0.0000
Δ(INRST(-1))	0.003522	4.89E-05	71.96666	0.0000
Δ(INRST(-2))	0.002465	8.73E-05	28.22477	0.0000
Δ(VIX)	−0.14368	0.025688	−5.58418	0.0000
Δ(VIX(-1))	−0.08419	0.013626	−6.01142	0.0000
Δ(VIX(-2))	−0.0237	0.005479	−4.32523	0.0000
Constant (C)	0.061829	0.002524	24.49671	0.0000

Note: This table presents the estimated long-run and short-run coefficients from the Panel ARDL model (ARDL(1, 3, 3, 3, 3, 3)), with Bitcoin returns (ΔBTC) as the dependent variable. The coefficient of the lagged error correction term (COINTEQ01) is also reported. Significance levels: $p < 0.01$ (), $p < 0.05$ (), $p < 0.10$ (). Source: Authors.

6.026, $p < 0.001$). Euro appreciation positively correlates with higher Bitcoin returns; in other words, Bitcoin serves as a long-term hedge against currency depreciation.

In the short run, the error correction term (COINTEQ01) reveals the adjustment mechanism and signifies how quickly the variables correct deviations and return to long-term equilibrium. The coefficients refer to the impact of the changes in the exogenous variables on the change in cryptocurrency returns. The ECT coefficient is −0.9341 ($p < 0.0001$), indicating that any deviation from the long-run equilibrium is adjusted by about 93.4 % in the next month, a considerably fast adjustment speed. This significant negative ECT validates the presence of a long-run relationship. It is worth mentioning that changes in the interaction term are not significant in any of the lags in the short run. The absence of significant short-term effects suggests that monthly fluctuations in sentiment do not directly impact Bitcoin returns within the same period. This implies that the moderating influence of financial literacy on investor sentiment primarily manifests in the long-run equilibrium.

To ensure the moderation finding (ascertained from the panel ARDL model) is statistically robust, we conducted a formal Wald test on the long-run coefficient of FINTINST (Table 6). The test provides an F-statistic of 6.553 ($p = 0.0105$) and an equivalent Chi-square of 6.553 ($p = 0.0105$), which confirms the rejection of the null hypothesis. This outcome validates that the interaction term has a statistically significant long-run effect on Bitcoin returns; in other words, financial literacy has a positive and significant long-run moderating effect on the relationship between investor sentiment and Bitcoin returns.

Table 6
Moderation effect.

Statistic	Value	p-value
F-statistic	6.553	0.0105
Chi-square	6.553	0.0105
Coefficient	0.0000769	(SE = 0.00003)

Note: This Wald test assesses the null hypothesis that the long-run coefficient of the interaction term between investor sentiment and financial literacy (FINTINST) equals zero (H_0: FINTINST = 0). Source: Authors.

4.4. Cross-section short-term coefficient

In the pooled panel estimation (Table 5), we ascertain no significant short-run effect of the interaction term at the aggregate level; however, opposite statistically significant cross-sectional heterogeneity is found when coefficients are estimated separately for each Eurozone country. Table 7 disaggregates the short-run coefficients from the panel ARDL model, providing country-specific estimates for Δ(FINTINST) and the ECT across 15 sample countries.

This granular analysis reveals that the short-run coefficient for Δ(FINTINST) is statistically significant (p-value = 0.0000) for all 15 individual countries (Table 7). The country-level findings indicate that short-term fluctuations in the interaction term have an immediate heterogeneous impact on Bitcoin returns. Nine countries, including Cyprus (0.000308), Estonia (0.001058), Greece (0.0000673), Ireland (0.001486), Latvia (0.000817), Malta (0.002125), the Netherlands (0.000285), and Spain (0.000495), show a positive short-run relationship, where an increase in Δ(FINTINST) is associated with an immediate increase in Bitcoin returns. On the other hand, six countries, such as Finland (−0.000421), France (−0.000220), Germany (−0.000296), Italy (−0.000162), Lithuania (−0.001955), Luxembourg (−0.000686), and Portugal (−0.000812), exhibit a negative association (Table 8).

This directional variance indicates the influence of heterogeneous external factors at the country level. Local market structures, regulatory environments, or prevailing investor behavioral biases within each country probably mediate how the short-term relationship between investor sentiment and financial literacy explains Bitcoin return movements. Furthermore, the ECT consistently remains highly significant and negative across all 15 countries, which signifies a rapid adjustment to long-run equilibrium within the current period for all respective national cryptocurrency markets.

4.5. Quantile regression analysis

While the prior method, i.e., panel ARDL, examines average long-run effects and average short-run adjustments, quantile regression (QR) investigates the impact of the interaction term across diverse quantiles of Bitcoin return outcomes. Table 9 presents how independent variables

Table 7
Country-level short-run coefficient estimates from the panel ARDL model.

Country	Δ(FINTINST)	ECT
Cyprus	0.000308 (0.0000)	−1.000929 (0.0000)
Estonia	0.001058 (0.0000)	−0.927163 (0.0000)
Finland	−0.000421 (0.0000)	−0.929725 (0.0000)
France	−0.000220 (0.0000)	−0.921220 (0.0000)
Germany	−0.000296 (0.0000)	−0.926498 (0.0000)
Greece	0.0000673 (0.0000)	−0.928105 (0.0000)
Ireland	0.001486 (0.0000)	−0.924823 (0.0000)
Italy	−0.000162 (0.0000)	−0.922790 (0.0000)
Latvia	0.000817 (0.0000)	−0.964969 (0.0000)
Lithuania	−0.001955 (0.0000)	−0.926873 (0.0000)
Luxembourg	−0.000686 (0.0000)	−0.913569 (0.0000)
Malta	0.002125 (0.0000)	−0.944331 (0.0000)
Netherlands	0.000285 (0.0000)	−0.927557 (0.0000)
Portugal	−0.000812 (0.0000)	−0.928257 (0.0000)
Spain	0.000495 (0.0000)	−0.925072 (0.0000)

Note: This table reports the short-run coefficients from the panel ARDL model, estimated separately for each of the 15 Eurozone countries in the sample. The dependent variable is the first-differenced monthly return of Bitcoin (D(BTC)). The primary explanatory variables include the interaction term between investor sentiment and financial literacy (D(FINTINST)). ECT denotes the error correction term reflecting the speed of adjustment toward the long-run equilibrium. All coefficients are reported along with their corresponding p-values in parentheses. Source: Authors.

Table 8
Direction and significance of country-level short-run effects.

Particulars	C	D(FINTINST)	D(GOLDR)	D(ERUS)	D(INRST)	D(VIX)	T*
Cyprus	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Estonia	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Finland	✓(−)	✓(−)	✓(+)	✓(−)	✓(+)	✓(+)	5(3/2)
France	✓(−)	✓(−)	✓(+)	✓(−)	✓(+)	✓(+)	5(3/2)
Germany	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Greece	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Ireland	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Italy	✓(−)	✓(−)	✓(+)	✓(−)	✓(+)	✓(+)	5(3/2)
Latvia	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Lithuania	✓(−)	✓(−)	✓(+)	✓(−)	✓(+)	✓(+)	5(3/2)
Luxembourg	✓(−)	✓(−)	✓(+)	✓(−)	✓(+)	✓(+)	5(3/2)
Malta	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Netherlands	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
Portugal	✓(−)	✓(−)	✓(+)	✓(−)	✓(+)	✓(+)	5(3/2)
Spain	✓(−)	✓(+)	✓(+)	✓(−)	✓(+)	✓(+)	5(4/1)
T*	15	15 (8/7)	15 (15/0)	15 (0/15)	15 (15/0)	15 (15/0)	

Note: Dependent Variable: D(BTC). If significant (p-value<0.05), then coefficient(positive) = "✓", otherwise, coefficient(negative) = " × ". T* indicates the total sign of the coefficient (positive/negative). COINTEGRATION= C. The rightmost column summarizes the number of statistically significant short-run coefficients across the five exogenous variables for each country. The bottom row summarizes the number of significant coefficients across all 15 countries by variable.

influence Bitcoin returns across different points of its conditional distribution. Unlike traditional mean-based regression (e.g., OLS or pooled ARDL), quantile regression addresses non-normality and distributional asymmetry in the sample dataset and allows for examining the heterogeneous effects of predictors on low (e.g., $\tau = 0.10, 0.25$), median ($\tau = 0.50$), and high (e.g., $\tau = 0.75, 0.90$) Bitcoin returns.

The interaction term shows a heterogeneous, nuanced impact across diverse quantiles. It is observed that the impact of FINTINST on Bitcoin returns is not statistically significant at the lower and median quantiles (e.g., $\tau = 0.10, 0.25, 0.50$); however, it becomes significant and positive at $\tau = 0.75$ (coefficient = 0.000029, p-value = 0.0328). The result signifies that the positive moderating effect of financial literacy on sentiment becomes more pronounced when Bitcoin returns are already in the higher range (75th percentile). However, this effect loses significance at the top quantile ($\tau = 0.90$).

4.6. Robustness test and model selection justification

To ensure the robustness of the ascertained findings from the core methods, the panel ARDL model is re-estimated by replacing the VIX variable with a Financial Stress Index (FINSTR) to observe whether the results remain the same or similar. The long-run FINTINST impact on Bitcoin return remains positive and significant (Appendix III). This signifies that changing the variable from VIX to FINSTR does not fundamentally alter the key findings and overall integrity of the panel ARDL model. In other words, the model fit did not change even after changing the variable, which confirms the robustness of the panel ARDL model.

To justify the employed panel ARDL model selection, the optimal lag is systematically determined using established information criteria. In this process, we allow statistical software to select the lags instead of manually selecting them. The Akaike Information Criterion (AIC) is considered to choose the best-fitted model, which is the model with the minimum AIC value. As a result, the ARDL (1, 3, 3, 3, 3, 3) specification is identified as the most appropriate model (Appendix II). The selected model implies that the endogenous variable is required with one lag, whereas all exogenous variables are incorporated with three lags. The selected model specification ensures robust and efficient estimation of long-run equilibrium relationships and the short-run adjustment mechanisms.

5. Discussion

The study's primary findings answer the research question, comply with the objective, and reject the null hypothesis of this study. Thus, we critically discuss their implications in the context of existing literature and theory to synthesize the market dynamics regarding investors and policyholders.

Initially, this study shows that investor sentiment has a significant impact on Bitcoin returns in the Eurozone context, which aligns with previous studies in the cryptocurrency domain (Bouteska et al., 2022; Koutmos, 2023; Mokni et al., 2022) that found investor sentiment-driven effects. A growing body of literature in behavioral finance that emphasizes the role of investor mood and non-fundamental factors in asset pricing also supports this context of the finding (Baker & Wurgler, 2007; Shiller, 2015). In the baseline pooled LS regression (Model 1), the coefficient for investor sentiment is positive and significant ($p < 0.05$). This outcome confirms that investor optimism is positively associated with higher Bitcoin returns, emphasizing that general investor sentiment plays a role even in a globally traded, decentralized asset such as Bitcoin. It is not just technical or supply and demand factors inherent to the crypto ecosystem.

In this relationship, financial literacy emerges as a novel and

Table 9
Quantile regression results across selected quantiles.

Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
FINTINST	0.000000 (1.0000)	0.000013 (0.4494)	0.000027 (0.1051)	0.000029 (0.0328)	0.000074 (0.3037)
GOLDR	−0.276019 (0.4023)	0.624057 (0.0042)	1.063399 (0.0000)	0.579637 (0.0002)	−0.437634 (0.0023)
ERUS	0.636003 (0.1346)	0.510045 (0.0435)	−0.740501 (0.0577)	−1.284538 (0.0000)	1.860389 (0.0000)
INRST	−0.004853 (0.0000)	−0.003701 (0.0000)	−0.002685 (0.0000)	−0.001432 (0.0000)	0.000662 (0.0005)
VIX	−0.017494 (0.0611)	−0.128781 (0.0000)	−0.212112 (0.0000)	−0.200833 (0.0000)	−0.069966 (0.0347)
C	−0.192121 (0.0000)	−0.071584 (0.0000)	0.050483 (0.0000)	0.175333 (0.0000)	0.324576 (0.0000)

Note: This table reports the estimated coefficients from Quantile Regression models for Bitcoin Returns across selected quantiles (τ). The dependent variable is monthly Bitcoin returns. The columns represent different conditional quantiles of the dependent variable's distribution. Values in parentheses are the corresponding p-values. Statistical significance is typically assessed at the 5 % level.

important factor that moderates investor sentiment's influence on cryptocurrency returns. The positive coefficient on the interaction term (investor sentiment * financial literacy) in both pooled LS and long-run ARDL implies that fluctuations in investor sentiment lead to more significant Bitcoin return volatilities in environments with higher average financial literacy. Although this finding might initially contradict the expectation that financially literate investors would mitigate irrational market behaviors, it suggests that a distinct mechanism is operating within the cryptocurrency market's unique landscape.

Several reasons could drive this nature of the market and its participants. Since higher financial literacy is associated with greater participation and market access (Van Rooij et al., 2011), individuals with significant financial literacy might be willing to invest in cryptocurrencies when positive sentiment drives demand and price upward, and vice versa. Notably, the quantile regression method indicates that the amplification effect is more evident on the upside ($\tau = 0.75$) than on the downside (Table 9). In addition, financially literate investors might use more advanced trading tools—e.g., derivatives, margin trading, and algorithmic strategies—to act on sentiment. When sentiment is bullish and a literate investor is convinced of an uptrend, they might employ leverage or derivative exposure to Bitcoin. In contrast, investors with low financial literacy might either not invest at all (due to a lack of knowledge) or invest in smaller amounts. Furthermore, higher-income or excessively wealthy investor groups with financial literacy could influence market dynamics. When the market is optimistic, more capital can flow into speculative and volatile investments in a high-literacy country. Another contributing factor could be the inherent greed of investors. Mokni et al. (2022) reveal a bidirectional significant relationship between investor greed and Bitcoin returns—i.e., investor greed positively influences Bitcoin returns and vice versa.

Ascertaining financial literacy as a significant moderator of sentiment effects is the core contribution of this study, which challenges traditional assumptions in financial literacy literature. Financial literacy theory suggests that higher financial knowledge should reduce behavioral biases and improve investment decisions (Lusardi & Mitchell, 2014). However, the results reveal a more complex relationship consistent with sophisticated investor overconfidence theory. Daniel et al. (1998) show that overconfident investors, who often possess higher financial knowledge, trade more aggressively on their information signals. Similarly, overconfidence among sophisticated investors may increase trading activities and access risk-taking behavior (Barber & Odean, 2001).

Along with aggregate findings from panel ARDL, the moderating role of financial literacy is also explicitly observed at the country level with a heterogeneous directional nature. This diverse direction could be due to the institutional and cultural factors that influence financial behavior. Guiso et al. (2008) show that the cultural attribute of trust plays a role in individuals' decisions to engage with financial markets. On the other hand, Karolyi (2016) finds that greater cultural distance may be associated with unfamiliarity and can lead to investing less in foreign markets. It is important to clarify that the measure of financial literacy is at an aggregate level. This study compares the sentiment-return relationship between a presumably lower-scoring country, such as Greece or Portugal, and a country with high financial literacy scores, such as Germany. Given its positive moderation, Bitcoin may be more sensitive to attitude changes in Germany than in a country with lower literacy levels.

Consistent with recent developments in behavioral asset pricing models, the quantile regression results show that the financial literacy moderating effect varies systematically across market situations. However, the statistically significant relationship is observed in the upside ($\tau = 0.75$) quantile rather than the downside. This behavior aligns with the Prospect Theory (Kahneman & Tversky, 1979), which suggests that individuals make decisions under risk by focusing on changes relative to a reference point (gains and losses).

5.1. Policy implications and contribution

As observed, investor sentiment significantly impacts cryptocurrency returns, and financial literacy considerably moderates this relationship. It seems evident that efforts to improve financial literacy contribute to better decision-making and investor protection. However, financial literacy alone may not be sufficient for such a volatile and speculative market unless strengthened by comprehensive risk education since we ascertain that a more financially literate investor may result in more noticeable boom-bust cycles. Although financial literacy is widely acknowledged to improve financial outcomes (Lusardi & Mitchell, 2011), the results of this study suggest that it may have unintended consequences when applied to behavior in speculative markets. Therefore, financial literacy programs should address behavioral biases and risk management rather than focusing solely on financial instrument knowledge.

Education alone is not sufficient to ensure optimal decisions and avoid the speculative nature of such a volatile market. Regulatory initiatives and actionable plans are necessary to protect investors from sudden market fluctuations. In this process, the regulatory body should consider tracking investor sentiment indicators and financial literacy levels as part of their risk assessment for the market. It is assumed that as a country's population becomes more financially literate and crypto-friendly, investor sentiment tends to be bullish. In that case, regulators might anticipate larger inflows to crypto and possibly more volatility or financial system exposure. On the other side, improved financial literacy might help investors better navigate downturns to avoid panic selling due to an understanding of volatility. Although the study's findings do not demonstrate a significant moderating effect during downturns, it is reasonable to assume that knowledgeable investors would not sell at a loss as quickly as less educated ones due to emotional panic. The claim suggests that financial literacy could exert a stabilizing influence during market downturns. Even if the extreme quantile analysis did not yield statistically significant evidence, it is plausible that it might mitigate the potential severity of crashes.

The study's country-specific short-run results indicate notable differences worth exploring qualitatively. For instance, why would Cyprus and Estonia immediately react positively to the interaction term, whereas Germany and France show a negative one? In smaller countries, the fraction of investors who are financially literate and engaged in crypto might be relatively small but active. This signifies that literate investors significantly move the market when investor sentiment is high by providing a positive short-run impulse. Conversely, the cryptocurrency market is typically broader and more diversified in larger economies. Here, financially literate investors constitute a smaller fraction of overall market participation, or they might be quicker to realize gains, potentially dampening short-run momentum or even contributing to an adverse immediate effect. Furthermore, national cultural attitudes may play a role in the nature of investors' investments.

This study addresses a significant gap in the intersection of financial literacy, behavioral factors, and cryptocurrency research. Prior cryptocurrency studies extensively examined sentiment effects (Huang et al., 2021; Philippas et al., 2019) and market efficiency questions (Nadarajah & Chu, 2017; Urquhart, 2016). Meanwhile, financial literacy research focused primarily on traditional financial products and basic investment decisions (Lusardi & Mitchell, 2014; Van Rooij et al., 2011). To our knowledge, no prior study has systematically examined how financial literacy moderates behavioral factors in cryptocurrency markets. This gap is particularly significant given the unique characteristics of cryptocurrency markets. We address this gap by examining the moderating role of financial literacy in the relationship between investor sentiment and Bitcoin returns and ascertaining its significant role in the cryptocurrency market.

6. Conclusion and future direction

This study investigates whether financial literacy moderates the relationship between investor sentiment and Bitcoin returns. A multifaceted empirical framework is employed to comprehend this nexus in 15 Eurozone countries over 2012–2024. The applied econometric methods elucidate that financial literacy strengthens the influence of sentiment on returns. This pattern is observed across multiple analytical dimensions: in the long run for aggregate data, in the short run at the country level data, and notably, within higher quantiles ($\tau = 0.75$) of the aggregate data. The results comprehensively answer the research question and support the hypothesis robustly.

Aggregately, the study finds a significant positive effect of investor sentiment on Bitcoin returns. When investors are optimistic, cryptocurrency prices tend to rise, and vice versa. This effect persists even after controlling for macroeconomic factors, which confirms the robustness of the findings and signifies the significant influence of market psychology in the cryptocurrency market. Although financial literacy alone does not directly predict crypto returns, it moderates how sentiment affects returns. We find robust evidence that higher financial literacy strengthens the impact of sentiment on Bitcoin returns in the long run. In other words, bullish sentiment in countries with more financially educated investors increases crypto returns significantly. The equilibrium adjustment in cryptocurrency markets is notably rapid, which suggests that despite their high volatility, prices are not irrationally detached from underlying values. Instead, they tend to realign swiftly in response to prevailing investor sentiment and fundamental market indicators.

This research contributes to the literature by revealing the complex role of financial literacy in highly volatile markets such as cryptocurrency. On one hand, financial knowledge empowers individuals to make more informed decisions and reduces their vulnerability to fraud or avoidable mistakes. On the other hand, it can foster a sense of confidence that leads some investors to engage more actively in speculative behavior. From a theoretical perspective, these findings contribute to the behavioral finance literature by emphasizing the importance of investor heterogeneity—particularly in financial literacy and market sophistication—as a critical determinant of asset pricing dynamics. Traditional finance models often assume homogeneous rational agents or distinguish between noise traders and arbitrageurs. However, our results suggest a more nuanced reality. Even sophisticated investors, often labeled arbitrageurs, may participate in trend-following behavior rather than correcting mispricing, especially in markets where fundamental values are difficult to define—such as cryptocurrencies.

Despite the study's robust findings, several limitations should be noted. First, our measure of financial literacy is aggregate; individual-level data would better capture how knowledge shapes sentiment responses. Second, the study relies on a general sentiment index due to limited historical crypto-specific sentiment data. Future research could incorporate sources such as Twitter or Google Trends to test the robustness of the ascertained results. Lastly, while we focus on Bitcoin, generalizing to other cryptocurrencies—especially those with different use cases or investor profiles—requires caution. Therefore, researchers should expand the scope by including other cryptocurrencies operating on the Bitcoin blockchain, potentially using principal component analysis to capture common dynamics. A comparative analysis across multiple blockchain ecosystems—such as Bitcoin and Ethereum—could offer deeper insights into how sentiment and literacy effects vary across different technological and market structures.

Future researchers can also conduct surveys linking individuals' financial literacy, sentiment toward crypto, and trading behavior. In this process, developing a cryptocurrency-centric financial literacy scale would benefit and validate our macro findings and provide more direct causation evidence. Another area is exploring the role of media and information—does more financial news coverage (financially literate investors likely consume more news) strengthen sentiment transmission? Furthermore, cross-country studies beyond the Eurozone, including emerging markets where literacy varies widely, could yield interesting contrasts.

In conclusion, this study emphasizes that investor sentiment and financial literacy significantly influence cryptocurrency markets, similar to traditional markets. Understanding these behavioral drivers and their interaction with investor capabilities becomes crucial as crypto becomes more integrated into the financial system. It is worth mentioning that education alone is not sufficient to alleviate the speculative behavior of investors; instead, a balanced approach that combines financial literacy improvements with safeguards against overconfidence is recommended. Therefore, promoting financial literacy grounded in robust risk management principles and accompanied by efforts to curb excessive risk-taking and greed-driven behavior may contribute to fostering a more stable and resilient cryptocurrency market.

Author contribution form

Dr. Rashed Jahangir: Conceptualization, Methodology/Study design, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review and editing, Visualization, Supervision, Project administration.

Dr. Gülfen Tuna: Conceptualization, Methodology/Study design, Validation, Investigation, Writing – review and editing, Supervision, Project administration.

Hümeyra Koç: Validation, Formal analysis, Investigation, Writing – original draft, Writing – review and editing.

Muhammad Hassan Abbas: Validation, Formal analysis, Investigation, Writing – original draft, Writing – review and editing.

Declaration of generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this study, the authors used OpenAI's service to refine language clarity, improve academic tone, and enhance logical structure. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix I. Unit root test results

Variable	Test Method	Test Statistic	p-value	Decision
BTC	Levin, Lin & Chu (LLC)	−17.0581	0.0000	Reject H_0
	Im, Pesaran & Shin (IPS)	−18.4753	0.0000	Reject H_0
	ADF - Fisher Chi-square	389.293	0.0000	Reject H_0
	PP - Fisher Chi-square	1065.230	0.0000	Reject H_0
FINTINST	Levin, Lin & Chu (LLC)	−1.9163	0.0277	Reject H_0
	Im, Pesaran & Shin (IPS)	−8.7290	0.0000	Reject H_0
	ADF - Fisher Chi-square	148.926	0.0000	Reject H_0

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(*continued*)

Variable	Test Method	Test Statistic	p-value	Decision
	PP - Fisher Chi-square	493.125	0.0000	Reject H_0
GOLDR	Levin, Lin & Chu (LLC)	−11.1842	0.0000	Reject H_0
	Im, Pesaran & Shin (IPS)	−15.4097	0.0000	Reject H_0
	ADF - Fisher Chi-square	300.287	0.0000	Reject H_0
	PP - Fisher Chi-square	1262.540	0.0000	Reject H_0
ERUS	Levin, Lin & Chu (LLC)	−2.0539	0.0200	Reject H_0
	Breitung t-stat	0.3202	0.6256	Fail to reject H_0
	Im, Pesaran & Shin (IPS)	−12.6497	0.0000	Reject H_0
	ADF - Fisher Chi-square	208.524	0.0000	Reject H_0
	PP - Fisher Chi-square	1147.950	0.0000	Reject H_0
INRST	Levin, Lin & Chu (LLC)	−21.8988	0.0000	Reject H_0
	Breitung t-stat	−19.2970	0.0000	Reject H_0
	Im, Pesaran & Shin (IPS)	−15.7257	0.0000	Reject H_0
	ADF - Fisher Chi-square	281.061	0.0000	Reject H_0
	PP - Fisher Chi-square	1197.220	0.0000	Reject H_0
VIX	Levin, Lin & Chu (LLC)	−8.5055	0.0000	Reject H_0
	Breitung t-stat	−19.6476	0.0000	Reject H_0
	Im, Pesaran & Shin (IPS)	−22.1351	0.0000	Reject H_0
	ADF - Fisher Chi-square	453.301	0.0000	Reject H_0
	PP - Fisher Chi-square	1381.000	0.0000	Reject H_0
FINSTR	Levin, Lin & Chu (LLC)	−11.0748	0.0000	Reject H_0
	Breitung t-stat	−11.2917	0.0000	Reject H_0
	Im, Pesaran & Shin (IPS)	−6.1197	0.0000	Reject H_0
	ADF - Fisher Chi-square	85.9715	0.0000	Reject H_0
	PP - Fisher Chi-square	281.8950	0.0000	Reject H_0

Note: The null hypothesis for each test assumes the presence of a unit root. Levin, Lin & Chu (LLC) assumes a standard unit root process, while IPS, ADF-Fisher, and PP-Fisher allow individual unit root processes. The Breitung test offers additional robustness. P-values less than 0.01, 0.05, and 0.10 are considered statistically significant at the 1 %, 5 %, and 10 % levels, respectively. Results indicate that all variables are stationary at level (I(0)), thus satisfying the conditions for panel ARDL estimation. Source Authors.

Appendix II. Model selection criteria table

Model	LogL	AIC*	BIC	HQ	Specification
3	179.180029	0.075146	0.760948	0.326032	ARDL(1, 3, 3, 3, 3, 3)
15	215.251249	0.083448	0.887946	0.377756	ARDL(4, 3, 3, 3, 3, 3)
7	184.153612	0.084469	0.809836	0.349829	ARDL(2, 3, 3, 3, 3, 3)
11	196.544383	0.086895	0.851827	0.366729	ARDL(3, 3, 3, 3, 3, 3)
2	68.998161	0.091122	0.579096	0.269637	ARDL(1, 2, 2, 2, 2, 2)
1	2.557673	0.0999	0.390047	0.206044	ARDL(1, 1, 1, 1, 1, 1)
16	226.557409	0.10083	0.984459	0.424068	ARDL(1, 4, 4, 4, 4, 4)
6	90.635406	0.101687	0.629227	0.294676	ARDL(2, 2, 2, 2, 2, 2)
10	268.91964	0.102386	1.056111	0.469965	ARDL(4, 4, 4, 4, 4, 4)
12	101.079158	0.105924	0.673029	0.313387	ARDL(3, 2, 2, 2, 2, 2)
4	115.160777	0.106778	0.713448	0.328715	ARDL(4, 2, 2, 2, 2, 2)
5	6.469994	0.112089	0.439921	0.230827	ARDL(2, 1, 1, 1, 1, 1)
14	229.448065	0.112085	1.035283	0.449263	ARDL(2, 4, 4, 4, 4, 4)
8	243.349274	0.113111	1.075871	0.465315	ARDL(3, 4, 4, 4, 4, 4)
9	9.783853	0.117205	0.490353	0.256167	ARDL(3, 1, 1, 1, 1, 1)
13	17.589012	0.127765	0.536608	0.277331	ARDL(4, 1, 1, 1, 1, 1)

Appendix III. Panel ARDL with financial stress index (robustness check)

Variable	Coefficient	Std. Error	t-Statistic	P-value
Long Run Equation				
FINTINST	0.000083	3.07E-05	2.686463	0.0073
GOLDR	−0.827398	0.301679	−2.742649	0.0062
ERUS	6.037587	0.552701	10.92379	0.0000
INRST	−0.007720	0.001218	−6.336935	0.0000
FINSTR	−0.007342	0.012436	−0.590374	0.5550
Short Run Equation				
COINTEQ01	−0.938405	0.006552	−143.2271	0.0000
Δ(FINTINST)	0.000189	0.000247	0.766194	0.4437
Δ(FINTINST(-1))	0.000201	0.000326	0.616408	0.5377
Δ(FINTINST(-2))	−0.000572	0.000491	−1.165190	0.2441
Δ(GOLDR)	1.083623	0.045249	23.94820	0.0000

(*continued on next page*)

(*continued*)

Variable	Coefficient	Std. Error	t-Statistic	P-value
Δ(GOLDR(-1))	−0.059386	0.035376	−1.678374	0.0934
Δ(GOLDR(-2))	−0.889001	0.068662	−12.94771	0.0000
Δ(ERUS)	−5.511923	0.068673	−80.26359	0.0000
Δ(ERUS(-1))	−4.521284	0.072267	−62.56355	0.0000
Δ(ERUS(-2))	−2.021433	0.062975	−32.09890	0.0000
Δ(INRST)	0.004805	6.11E-05	78.69120	0.0000
Δ(INRST(-1))	0.002302	5.35E-05	42.98566	0.0000
Δ(INRST(-2))	0.001919	7.32E-05	26.21413	0.0000
Δ(FINSTR)	−0.097662	0.048765	−2.002678	0.0451
Δ(FINSTR(-1))	−0.019394	0.002864	−6.767323	0.0000
Δ(FINSTR(-2))	0.000491	0.001764	0.278106	0.7810
Constant (C)	0.049553	0.002616	18.94123	0.0000

References

Acikgoz, T. (2025). Gold and Bitcoin as hedgers and safe havens: Perspective from nonlinear dynamics. *Resources Policy, 102*, Article 105489. https://doi.org/10.1016/j.resourpol.2025.105489

Agosto, A., Cerchiello, P., & Pagnottoni, P. (2022). Sentiment, Google queries and explosivity in the cryptocurrency market. *Physica A: Statistical Mechanics and Its Applications, 605*, Article 128016. https://doi.org/10.1016/j.physa.2022.128016

Alburaythin, Y., Fifield, S., & Paramati, S. (2024). Interaction between investor sentiment, limits to arbitrage and the returns of stock market anomalies: Evidence from the UK stock market. *The European Journal of Finance*. https://doi.org/10.1080/1351847X.2024.2377363

Anamika, Chakraborty, M., & Subramaniam, S. (2023). Does sentiment impact cryptocurrency? *The Journal of Behavioral Finance, 24*(2), 202–218. https://doi.org/10.1080/15427560.2021.1950723

Arifin, Z., & Soleha, E. (2019). Overconfidence, attitude toward risk, and financial literacy: A case in Indonesia stock exchange. *Review of Integrative Business and Economics Research, 8*(Supplementary Issue 4), 144–152. https://sibresearch.org/uploads/3/4/0/9/34097180/riber_8-s4_10_k19-110_144-152.pdf.

Arriqoh, D., & Zoraya, I. (2024). The effect of financial literacy on Gen-Z crypto investment decision through herding behavior as mediator. *Manajemen Dan Bisnis, 23*(1), 1–12. https://doi.org/10.24123/mabis.v23i1.737

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance, 61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *The Journal of Economic Perspectives, 21*(2), 129–151. https://doi.org/10.1257/jep.21.2.129

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics, 116*(1), 261–292. https://doi.org/10.1162/003355301556400

Basher, S. A., & Sadorsky, P. (2022). Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility? *Machine Learning with Applications, 9*, Article 100355. https://doi.org/10.1016/j.mlwa.2022.100355

Bathia, D., & Bredin, D. (2016). An examination of investor sentiment effect on G7 stock market returns. In *In Contemporary issues in financial institutions and markets* (pp. 99–128). Routledge. https://doi.org/10.4324/9781315749730.

Baur, D., Hong, K., & Lee, A. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money, 54*, 177–189. https://doi.org/10.1016/j.intfin.2017.12.004

Ben Hamadou, F., Mezghani, T., Zouari, R., & Boujelbène-Abbes, M. (2025). Forecasting bitcoin returns using machine learning algorithms: Impact of investor sentiment. *EuroMed Journal of Business, 20*(1), 179–200. https://doi.org/10.1108/EMJB-03-2023-0086

Bouri, E., Gupta, R., Tiwari, A., & Roubaud, D. (2017a). Does bitcoin hedge golabal uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters, 23*, 87–95. https://doi.org/10.1016/j.frl.2017.02.009

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. (2017b). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters, 20*, 192–198. https://doi.org/10.1016/j.frl.2016.09.025

Bouteska, A., Mefteh-Wali, S., & Dang, T. (2022). Predictive power of investor sentiment for Bitcoin returns: Evidence from COVID-19 pandemic. *Technological Forecasting and Social Change, 184*, Article 121999. https://doi.org/10.1016/j.techfore.2022.121999

Briola, A., Vidal-Tomás, D., Wang, Y., & Aste, T. (2023). Anatomy of a stablecoin's failure: The Terra-Luna case. *Finance Research Letters, 51*, Article 103358. https://doi.org/10.1016/j.frl.2022.103358

Buy Bitcoin Worldwide. (2023). 63+ cryptocurrency statistics, facts & trends. https://buybitcoinworldwide.com/cryptocurrency-statistics/.

Carbó-Valverde, S., Cuadros-Solas, P. J., & Rodríguez-Fernández, F. (2023). Cryptocurrency ownership and biases in perceived financial literacy. In *Social science research network*. https://doi.org/10.2139/ssrn.4509931. *SSRN 4509931*.

Cascavilla, A. (2024). Between money and speculative asset: The role of financial literacy on the perception towards Bitcoin in Italy. *Journal of Economic Psychology*. , Article 102716. https://doi.org/10.1016/j.joep.2024.102716

Conlon, T., Corbet, S., & McGee, R. (2024). Enduring relief or fleeting respite? Bitcoin as a hedge and safe haven for the US dollar. *Annals of Operations Research, 337*(1), 45–73. https://doi.org/10.1007/s10479-024-05884-y

Corbet, S., Lucey, B., Peat, M., & Vigne, S. (2018). Bitcoin Futures—what use are they? *Economics Letters*, (172), 23–27. https://doi.org/10.1016/j.econlet.2018.07.031

Crypto Economy. (2023). Bitcoin (BTC) reaches 54% dominance ahead of 2024 halving. Retrieved from https://crypto-economy.com/bitcoin-reaches-54-dominance-ahead-of-2024-halving/.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance, 53*(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077

Dias, I. K., Fernando, J. M. R., & Fernando, P. N. D. (2022). Does investor sentiment predict bitcoin return and volatility? A quantile regression approach. *International Review of Financial Analysis, 84*, Article 102383. https://doi.org/10.1016/j.irfa.2022.102383

Ding, W., Mazouz, K., & Wang, Q. (2019). Investor sentiment and the cross section of stock returns: New theory and evidence. *Review of Quantitative Finance and Accounting, 53*, 493–525. https://doi.org/10.1007/s11156-018-0756-z

Diniz-Maganini, N., Diniz, E. H., & Rasheed, A. A. (2021). Bitcoin's price efficiency and safe haven properties during the COVID-19 pandemic: A comparison. *Research in International Business and Finance, 58*, Article 101472. https://doi.org/10.1016/j.ribaf.2021.101472

Dyhrberg, A. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters, 16*, 139–144. https://doi.org/10.1016/j.frl.2015.10.025

Eom, C., Kaizoji, T., Kang, S., & Pichl, L. (2019). Bitcoin and investor sentiment: Statistical characteristics and predictability. *Physica A: Statistical Mechanics and Its Applications, 514*, 511–521. https://doi.org/10.1016/j.physa.2018.09.063

Falamarzi, H., Fathi, Z., & Shafii, H. (2023). The influence of culture on investors' financial decision-making styles and unplanned decisions to avoid uncertainty, power distance. *International Journal of Finance & Managerial Accounting, 8*(30), 19–30. https://doi.org/10.30495/ijfma.2022.61649.1667

Feder-Sempach, E., Szczepocki, P., & Bogołębska, J. (2024). Global uncertainty and potential shelters: Gold, bitcoin, and currencies as weak and strong safe havens for main world stock markets. *Financial Innovation, 10*(1), 67. https://doi.org/10.1186/s40854-023-00589-w

Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *The Journal of Finance, 63*(6), 2557–2600. https://doi.org/10.1111/j.1540-6261.2008.01408.x

Güler, D. (2023). The impact of investor sentiment on bitcoin returns and conditional volatilities during the era of Covid-19. *The Journal of Behavioral Finance, 24*(3), 276–289. https://doi.org/10.1080/15427560.2021.1975285

Hayashi, F., & Routh, A. (2025). Financial literacy, risk tolerance, and cryptocurrency ownership in the United States. *Journal of Behavioral and Experimental Finance*. , Article 101060. https://doi.org/10.1016/j.jbef.2025.101060

He, C.-W., & Wang, Y.-J. (2023). Bitcoin price jumps and investor sentiment indicators. *Applied Economics Letters, 30*(18), 2626–2630. https://doi.org/10.1080/13504851.2022.2102122

Huang, Y., Duan, K., & Mishra, T. (2021). Is bitcoin really more than a diversifier? A pre- and post-COVID-19 analysis. *Finance Research Letters, 43*, Article 102016. https://doi.org/10.1016/j.frl.2021.102016

Jayawardhana, A., & Colombage, S. (2025). Will the cryptocurrency exuberance last? An empirical assessment using AI and the ARDL approach. *Borsa Istanbul Review, 25*(3), 568–586. https://doi.org/10.1016/j.bir.2025.02.005

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263–291. https://doi.org/10.2307/1914185

Karolyi, G. A. (2016). The gravity of culture for finance. *Journal of Corporate Finance, 41*, 610–625. https://doi.org/10.1016/j.jcorpfin.2016.07.003

Koenker, R., & Bassett, J. G. (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society*, 33–50. https://doi.org/10.2307/1913643

Koutmos, D. (2018). Bitcoin returns and transaction activity. *Economics Letters, 167*, 81–85. https://doi.org/10.1016/j.econlet.2018.03.021

Koutmos, D. (2023). Investor sentiment and bitcoin prices. *Review of Quantitative Finance and Accounting, 60*, 1–29. https://doi.org/10.1007/s11156-022-01086-4

Koutmos, D., King, T., & Zopounidis, C. (2021). Hedging uncertainty with cryptocurrencies: Is bitcoin your best bet? *Journal of Financial Research, 44*(4), 815–837. https://doi.org/10.1111/jfir.12264

Kumari, D. (2020). The ımpact of fınancıal lıteracy on ınvestment decısıons: Wıth specıal reference to undergraduates ın western provınce, srı lanka. *Asian Journal of Contemporary Education, 4*(2), 110–126. https://doi.org/10.18488/journal.137.2020.42.110.126

Lin, X., Meng, Y., & Zhu, H. (2023). How connected is the crypto market risk to investor sentiment? *Finance Research Letters, 56*, 1–10. https://doi.org/10.1016/j.frl.2023.104177, 104177.

Liu, P., & Yuan, Y. (2024). Is bitcoin a hedge or safe-haven asset during the period of turmoil? Evidence from the currency, bond and stock markets. *International Review of Financial Analysis, 96*, Article 103663. https://doi.org/10.1016/j.irfa.2024.103663

Long, S., Chatziantoniou, I., Gabauer, D., & Lucey, B. (2024). Do social media sentiments drive cryptocurrency intraday price volatility? New evidence from asymmetric TVP-VAR frequency connectedness measures. *The European Journal of Finance, 30*(13), 1470–1489. https://doi.org/10.1080/1351847X.2024.2314085

López-Cabarcos, M.Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., & Šević, A. (2021). Bitcoin volatility, stock market and investor sentiment. Are they connected? *Finance Research Letters, 38*. https://doi.org/10.1016/j.frl.2019.101399

Lusardi, A., & Mitchell, O. S. (2011). Financial literacy around the world: An overview. *Journal of Pension Economics and Finance, 10*(4), 497–508. https://doi.org/10.1017/S1474747211000448

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *American Economic Association: Journal of Economic Literature, 52*(1), 5–44. https://doi.org/10.1257/jel.52.1.5

Mai, D., Pukthuanthong, K., & Zhou, G. (2022). Investor sentiment and asset returns: Actions speak louder than words. SSRN 4281161 https://doi.org/10.2139/ssrn.4281161.

Mokni, K., Bouteska, A., & Nakhli, M. S. (2022). Investor sentiment and bitcoin relationship: A quantile-based analysis. *The North American Journal of Economics and Finance, 60*, 1–17. https://doi.org/10.1016/j.najef.2022.101657, 101657.

Mouna, A., & Jarboui, A. (2015a). A study on small investors' sentiment, financial literacy and stock returns: Evidence for emerging market. *International Journal of Accounting and Economics Studies, 3*(1), 10–19. https://doi.org/10.14419/ijaes.v3i1.4098

Mouna, A., & Jarboui, A. (2015b). Financial literacy and portfolio diversification: An observation from the Tunisian stock market. *International Journal of Bank Marketing, 33*(6), 808–822. https://doi.org/10.1108/IJBM-03-2015-0032

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters, 150*, 6–9. https://doi.org/10.1016/j.econlet.2016.10.033

Naeem, M. A., Mbarki, I., & Shahzad, S. J. H. (2021). Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. *International Review of Economics & Finance, 73*, 496–514. https://doi.org/10.1016/j.iref.2021.01.008

Naifar, N., & Altamimi, S. (2023). Asymmetric impact of investor sentiment and media coverage news on bitcoin returns. *Managerial Finance, 49*(8), 1342–1354. https://doi.org/10.1108/MF-08-2022-0400

Nguyen, B. K. Q., & Pham, D. T. N. (2025). Investing during a Fintech revolution: The hedge and safe haven properties of Bitcoin and Ethereum. *Research in International Business and Finance, 73*, Article 102599. https://doi.org/10.1016/j.ribaf.2024.102599

Nkoro, E., & Uko, A. K. (2016). Autoregressive distributed lag (ARDL) cointegration technique: Application and interpretation. *Journal of Statistical and Econometric Methods, 5*(4), 63–91. https://www.scienpress.com/Upload/JSEM/Vol%205_4_3.pdf.

Palamalai, S., Kumar, K. K., & Maity, B. (2021). Testing the random walk hypothesis for leading cryptocurrencies. *Borsa Istanbul Review, 21*(3), 256–268. https://doi.org/10.1016/j.bir.2020.10.006

Paramita, P., & Henny, R. (2022). The effect of fınancıal lıteracy on stock investment decısıons. *Eurasia: Economics & Business, 7*(61), 56–65. https://econeurasia.com/issue-2022-07/article_07.pdf.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association, 94* (446), 621–634. https://www.tandfonline.com/doi/epdf/10.1080/01621459.1999.10474156?needAccess=true.

Philippas, D., Rjiba, H., Guesmi, K., & Goutte, S. (2019). Media sentiment and herding behavior in cryptocurrency markets: An empirical study. *Finance Research Letters, 30*, 29–35. https://doi.org/10.1016/j.frl.2019.03.008

Prasad, S., Kiran, R., & Sharma, R. (2021). Influence of financial literacy on retail investors' decisions in relation to return, risk and market analysis. *International Journal of Finance & Economics, 26*(2), 2548–2559. https://doi.org/10.1002/ijfe.1920

Rasool, N., & Ullah, S. (2020). Financial literacy and behavioural biases of individual investors: Empirical evidence of Pakistan stock exchange. *Journal of Economics, Finance and Administrative Science, 25*(50), 261–278. https://doi.org/10.1108/JEFAS-03-2019-0031

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis, 63*, 322–330. https://doi.org/10.1016/j.irfa.2019.01.002

Shiller, R. J. (2015). *Irrational exuberance* (3rd ed.). Princeton University Press https://www.torrossa.com/en/resources/an/5559001.

Singh, M. A., & Gulia, S. (2024). Financial literacy in the age of cryptocurrencies: Challenges and opportunities. *Nanotechnology Perceptions*, 3858–3860. https://doi.org/10.62441/nano-ntp.vi.3605

Tarchella, S., & Dhaoui, A. (2021). Chinese jigsaw: Solving the equity market response to the COVID-19 crisis: Do alternative asset provide effective hedging performance? *Research in International Business and Finance, 58*, Article 101499. https://doi.org/10.1016/j.ribaf.2021.101499

Tarchella, S., Khalfaoui, R., & Hammoudeh, S. (2024). The safe haven, hedging, and diversification properties of oil, gold, and cryptocurrency for the G7 equity markets: Evidence from the pre-and post-COVID-19 periods. *Research in International Business and Finance, 67*, Article 102125. https://doi.org/10.1016/j.ribaf.2023.102125

Ullah, M., Sohag, K., Doroshenko, S., & Mariev, O. (2024). Examination of Bitcoin Hedging, diversification and safe-haven ability during financial crisis: Evidence from equity, bonds, precious metals and exchange rate markets. *Computational Economics*, 1–33. https://doi.org/10.1007/s10614-024-10710-5

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters, 148*, 80–82. https://doi.org/10.1016/j.econlet.2016.09.019

Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics, 101*(2), 449–472. https://doi.org/10.1016/j.jfineco.2011.03.006

Vidal-Tomás, D., Briola, A., & Aste, T. (2023). FTX's downfall and Binance's consolidation: The fragility of centralised digital finance. *Physica A: Statistical Mechanics and Its Applications, 625*, Article 129044. https://doi.org/10.1016/j.physa.2023.129044

Wang, W. (2024). Investor sentiment and stock market returns: A story of night and day. *The European Journal of Finance, 30*(13), 1437–1469. https://doi.org/10.1080/1351847X.2024.2306942

Wang, P., Zhang, H., Yang, C., & Guo, Y. (2021). Time and frequency dynamics of connectedness and hedging performance in global stock markets: Bitcoin versus conventional hedges. *Research in International Business and Finance, 58*, Article 101479. https://doi.org/10.1016/j.ribaf.2021.101479

Xia, T., Wang, Z., & Li, K. (2014). Financial literacy overconfidence and stock market participation. *Social Indicators Research, 119*, 1233–1245. https://doi.org/10.1007/s11205-013-0555-9

Yousaf, I., & Ali, S. (2020). The COVID-19 outbreak and high frequency information transmission between major cryptocurrencies: Evidence from the VAR-DCC-GARCH approach. *Borsa Istanbul Review, 20*, S1–S10. https://doi.org/10.1016/j.bir.2020.10.003

Zhang, D., Sun, Y., Duan, H., Hong, Y., & Wang, S. (2023). Speculation or currency? Multi-Scale analysis of cryptocurrencies—the case of bitcoin. *International Review of Financial Analysis, 88*, Article 102700. https://doi.org/10.1016/j.irfa.2023.102700