Vol. 4, Issue I, 2025 (January – March)
International Journal of Politics & Social Sciences Review (IJPSSR)
Website: https://ijpssr.org.pk/ OJS: https://ojs.ijpssr.org.pk/ Email: ijpssrjournal@gmail.com
ISSN 2959-6467 (Online) :: ISSN 2959-6459 (Print)
ISSN 2959-6459 (ISSN-L)
Recognized by Higher Education Commission (HEC), Government of Pakistan

Investor Sentiments and Bitcoin Volatility: Empirical Evidence from Cryptocurrency Market

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Abstract

The present study goals to examine the impact of investors' sentiment, such as overconfidence, optimism, pessimism, and reasonable investor expectations, on Bitcoin currency. Therefore, daily Bitcoin trading data was taken from CoinMarketCap. The data period consists of January 2023 to December 2024. The unit root stationary, GARCH (1,1) model and ordinary least square (OLS) regression test were used. The unit root stationary (ADF) test results reveal that all variables are stationary at level. The GARCH (1,1) model suggests that the lagged trading volume has a considerable positive influence on the current Bitcoin trade volume. Further GARCH (1,1) results demonstrate that optimism has a positive significant impact on and pessimism has a negative significant influence on Bitcoin exchange volume. Whereas ordinary least square regression (OLS) models also show that optimism has a positive significant impact and pessimism has a negative impact on Bitcoin trade volume. The study has various suggestions for stakeholders, investors, policymakers, and researchers.

Keywords Bitcoin Currency, Investor Sentiments, Daily Exchange Data.

Introduction

Bitcoin analysis has gained a lot of devotion recently. This may be due to its unique qualities, ease, transparency, and increasing popularity. The digital currency sector has grown significantly since Satoshi Nakamoto's proposal of Bitcoin in 2009. Since April 2019, Bitcoin has evolved to become the most profitable and well-known cryptocurrency in the world. Because companies registered on stock exchanges already own Bitcoin, some financial institutions have begun to invest in the digital asset's value. Related to old approval currencies, the Bitcoin price is very volatile Bergsli et al. (2022). Transaction volume and frequency are key variables influencing volatility. Investors must consider these major variances while making investing decisions Kayal & Balasubramanian (2021). According to studies, Bitcoin's volatility follows a pro-cyclical pattern, growing in unison with increased global economic activity. Bitcoin's volatility responds differently to increasing unpredictability in the US stock market compared to gold.

In efficient market, securities prices replicate all available information and returns that are overhead or below average are unattainable Fama (1970). A useful starting point for researching modern finance theory is the efficient capital market hypothesis. The idea of "efficiency" describes the idea that investors cannot beat the market or have exceptional returns from capital market transactions in comparison to other investors. Nonetheless, there are countless real-time examples of market players experiencing disparate results. Therefore, the author believes that this variance in return variability is caused by the behavioral biases that result in these disparities in individual investor returns Oprean & Tanasescu (2014).

The study of behavioral finance looks at how psychological and emotional states affect financial and economic judgment Kengatharan & Kengatharan (2014). Since both behavioral finance and economics aim to understand how an individual's psychology influences their propensity to make decisions, they are connected. According to conventional finance, investors are rational people who make wise investment choices. Investors aim to select the best investment opportunity in order to maximize gain or profit, even during uncertain times (Kengatharan & Kengatharan, 2014).

Implication of the Study

The current study has added to the frame of prevailing knowledge by seeking to question the conventional wisdom on investors that supports the efficient market theory. The study also highlights the psychological factors that lead to irrational conduct and impact investors' decision-making processes. Further it practices secondary data to measure behavioral biases. While the primary data technique used in many researches offers important perceptions into the problems being studied, respondent biases are often common. Investors, researchers, market players, stockbrokers, and fund managers can also learn from this study that informational efficiency is not just dependent on data.

Literature Review

While behavioral finance theories seek to explain the causes of market inefficiencies and anomalies, traditional finance ideas (such as portfolio and EMH) try to clarify how financial markets are well-organized. Behavioral finance therefore explains how and why markets are ineffective (Mittal, 2022). All financial asset markets are prone to volatility due to illogical human behavior, according to study Kumar & Goyal (2016).

Urquhart (2019) Bitcoin's erratic price fluctuations, exponential returns, distinctive characteristics, and growing global usage all attest to the new cryptocurrency's adoption in recent years. The appeal of Bitcoin as an investment opportunity may have an impact on its price Baur & Dimpfl (2021). Karalevicius (2018) emphasized that only a few studies have used the mood of widely available textual content to predict BTC price fluctuations. (Anqi Liu, Hossein Jahanshahloo (2023) it was discovered that care and macroeconomic news had little effect on the price finding of Bitcoin. Furthermore, they demonstrated stronger news-based BTC mood, indicating that the futures market will play a more informative role.

According to behavioral experts, confidence is a conviction in one's own abilities. Overconfidence happens when a person overestimates their abilities Daniel & Hirshleifer, (2015). Overconfidence may have an influence on decision-making when managers overrate their ability to forecast future benefits. Overconfidence was discovered to have a considerable effect on investor decision-making Toma (2015). Previous performance and success may enhance confidence, as demonstrated by Gervais & Odean (2001). The study discovered that strong market returns increase investor confidence, even if they are dispersed over the whole market. Baker et al. (2023) the study found a one-way association between transaction size and return instability, supportive the market's overconfidence issue.

All behavioral errors, including pessimism, optimism, anxiety, and melancholy, contradict rational conduct. Stock markets include oddities, and few investors profit from their irrational behavior. In stock markets, individuals may display herding behavior to feel safe Oprean & Tanasescu (2014). Optimistic bias overestimates good outcomes based on investment prospects Kartini & Nahda (2021). Muradoglu & Harvey (2012) insufficient evidence shows that investors overreact to earnings news. In the French capital market, investors are more pessimistic than hopeful. This is because optimism requires time to be reinforced, but pessimism merely needs a tiny shock. This demonstrates how investors' views and beliefs influence their investment selections. Katper et al. (2019) optimism was found to have no significant influence on investing decisions.

According to this theory, while anticipating, mediators consider all necessary information without making systematic mistakes. Combining individual projections can result in correct market expectations. Recent study has found that agents lack the capacity to generate rational predictions, which contradicts this technique. Agents anticipate employing an adaptive rule based on their previous experience and realizations. A contemporary experimental research is being done through Banerjee (2011). Researchers disagree on how to express the cogent expectation philosophy in asset decisions. Our research observes whether past expectations and realizations can predict future stock prices. According to studies, investors are less prone to make related mistakes in an economy in which families are not totally rational Suresh G (2024).

Methodology

Daily Bitcoin trading data has taken from CoinMarketCap. CoinMarketCap ranks cryptocurrencies based on market capitalization. The largest cryptocurrency Bitcoin (BTC) has been selected. The data period consists of January 2023 to December 2024. GARCH (1,1) model test, unit root stationary and OLS regression model were used. This research analyzes how investors' sentiments like confidence, optimism, pessimism, and rational expectation impact on Bitcoin volatility.

Measurement of Variables

Behavioral biases are modeled using operational definitions from the appropriate literature (Oprean & Tanasescu, 2014; Rashid et al., 2022). They are given as mathematical discrepancies in this section.

Confidence

Investors' confidence in trading today is determined by comparing past day/week returns. If the prior day/week's return is non-negative better or equivalent to zero, the investor will feel comfortable trading; if the preceding day/week's return is adverse, the investor will be hesitant to trade.

Constructed on the above argument, we advise the following statement, stated in mathematical differences, for further practical examination.

$$R_{t-1} \geq 0 \rightarrow \text{There will be trading} \quad (1)$$

$$R_{t-1} < 0 \rightarrow \text{There will be no trading} \quad (2)$$

Rt−1 represents the preceding day's return of the Bitcoin (BTC) currency, or one day's trading volume.

Optimism

Positive investors set their profit target higher than their previous return, and they prediction future returns based on the earlier day's performance. Optimistic investors trade on days when the previous day's results exceed + one standard deviation, indicating optimism about future returns (Oprean & Tanasescu, 2014). Stockholders will not trade if the prior day's return was less than one average deviation from the mean.

Created on the above argument, we propose the following statement, stated in mathematical variations, for further empirical examination.

$$R_{t-1} \geq \bar{R} + \sigma \rightarrow \text{There will be trading} \quad (3)$$

$$R_{t-1} < \bar{R} + \sigma \rightarrow \text{There will be no trading} \quad (4)$$

Rt−1 represents the preceding day's return, R is the normal return for the period, and σ is the return's standard deviation.

Pessimism

The inquiry assesses pessimism using losses from the preceding day. If the previous days' return declines, he shall not trade. On the other side, if the return surpasses this least condition, investors often trade (Oprean & Tanasescu, 2014). Investors are more inclined to trade if the prior day's return exceeds or matches the difference between the mean and standard deviation. Otherwise, they may avoid trading.

Constructed on the above argument, we recommend the following statement, articulated in mathematical discriminations, for further empirical examination.

$$R_{t-1} \geq R - \sigma \rightarrow \text{There will be trading} \quad (5)$$

$$R_{t-1} < \bar{R} - \sigma \rightarrow \text{There will be no trading} \quad (6)$$

Rt−1 represents the preceding days' return, R is the normal gain for the period, and σ is the return's standard deviation.

Rational Expectation

Market equilibrium prices define future prospects, and new information has the potential to disturb this equilibrium. Asset values in a well-organized market represent all available information; yet, absorbing new information requires time. Some new material that distresses prices tends to alter investors' outlooks, which are based on balance prices. This means that investors occasionally make similar mistakes.

The mathematical expression operates as follows:

$$E(R) = R_{t-1} + \varepsilon_{t-1} \dots \dots (7)$$

E(R) is the anticipated return, Rt−1 is the preceding day's return, and εt−1 is the equation's error.

GARCH (1,1) Model

Bitcoin exchange volume is the GARCH model's dependent variable, with confidence, optimism, pessimism, and reasonable expectations serving as independent variables. Our GARCH models look at how investor sentiments impact Bitcoin volatility.

We would describe the GARCH Model equations are as follows:

- GARCH (1,1) Model on change in trade volume volatility of Bitcoin with behavioral biases on Mean Equation
- Bitcoin $_{(TVt)}$= $\alpha+\beta1Confidence_{(t)}+\beta2Optimism_{(t)}+\beta3Pessimism_{(t)}+\beta4RationalExpectation_{(t)} + \varepsilon t \dots \dots (8)$

Ordinary Least Square Regression Model

Bitcoin exchange volume is the GARCH model's dependent variable, with confidence, optimism, pessimism, and reasonable expectations serving as independent variables.

Investor sentiments' impact on Bitcoin Volatility

$$Bitcoin\ (_{Volume})_{Daily} = \beta_0 + \beta_1\, Confidence + \beta_2\, Optimism + \beta_3\, Pessimism$$

$$+ \beta_4\, Rational + \varepsilon t \dots \dots (9)$$

Result and Discussion

This segment summarizes, the Augmented Dicky Fuller Test for stationary, GARCH (1,1) Model and Regression Analysis.

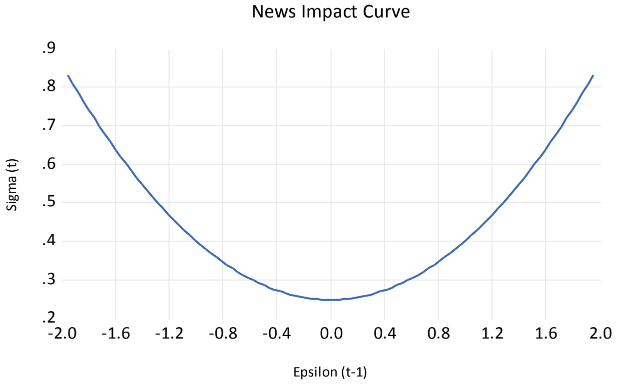
Table 1: GARCH (1,1) Model on change in trade volume volatility of Bitcoin with behavioral biases on Mean Equation

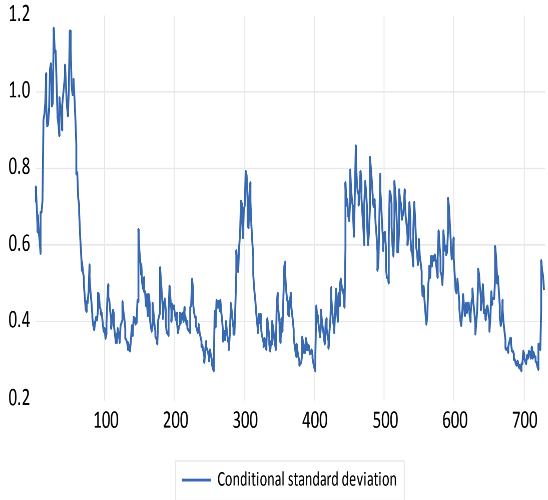
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.988825	0.067780	103.1107	0.0000
VOLUME(-1)	0.715203	0.000121	5932.812	0.0000
CONFIDENCE	-0.022725	0.036304	-0.625957	0.5313
OPTIMISM	0.249257	0.066391	3.754387	0.0002*
PESSIMISM	-0.248563	0.061406	-4.047890	0.0001*
Rational Expectation	0.264374	0.636122	0.415603	0.6777
	Variance Equation			
C	-0.000287	0.000263	-1.089862	0.2758
RESID(-1)^2	-0.005881	0.004056	-1.450043	0.1470
GARCH(-1)	1.007315	0.005400	186.5318	0.0000
R-squared	0.625211	Mean dependent var		23.86853
Adjusted R-squared	0.622612	S.D. dependent var		0.588584
S.E. of regression	0.361579	Akaike info criterion		0.779977
Sum squared resid	94.26287	Schwarz criterion		0.836786
Log likelihood	-274.5216	Hannan-Quinn criter.		0.801899
Durbin-Watson stat	1.915893			

****Source: Author own Calculation using, E-Views Software**
***Level of Significance 1%**
****Level of Significance 5%**

The constant term is significant at a 1% level (p<0.01), indicating a baseline effect of 6.99 units when all other variables are held constant. Lagged volume is extremely significant (p<0.01) and has a large coefficient (0.7152), suggesting strong persistence in the effect of past volume. The **Confidence** variable is not statistically significant (p>0.5313), implying that it does not substantially impact the dependent variable in this model. The optimism variable is significant at the 1% level (p<0.02), with a positive coefficient (0.2493), indicating that optimism positively influences the dependent variable.

The pessimism variable is significant at the 1% level (p<0.01), with a negative coefficient (-0.2486), meaning pessimism negatively affects the dependent variable. The **Rational Expectation** variable is not statistically significant (p>0.6777), suggesting it does not play a major role in this model. **C (Constant) is** not significant (p>0.2758). **RESID(-1)^2 has** Insignificant (p>0.1470), meaning past squared residuals do not affect current variance. **R-squared** model explains about 62.52% of the variance in the dependent variable, which is relatively good for financial models. **Adjusted R-squared (0.6226)** for the number of forecasters, this also indicates a good fit. **Durbin-Watson Statistic is 1.9159** close to 2, suggesting no strong autocorrelation in residuals. **Akaike Information Criterion value is 0.779977 and Schwarz Criterion value is 0.836786, and Hannan-Quinn Criterion value is 0.801899,** these values are useful for comparing the model with alternative specifications. Lower values generally indicate a better model fit.





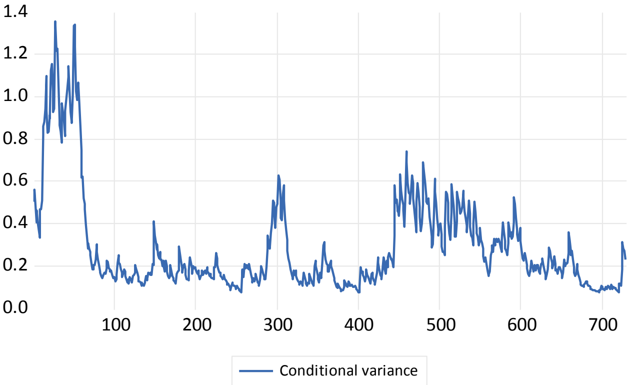


Fig.1 Conditional Variance, Conditional Standard Deviation, and News impact curve Graph for GARCH (1,1) Model

Table 2: Regression Analysis of Daily Data of Bitcoin

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	24.29458	0.104580	232.3056	0.0000
CONFIDENCE	0.001251	0.058705	0.021311	0.9830
OPTIMISM	0.526958	0.091487	5.759944	0.0000*
PESSIMISM	-0.558115	0.095793	-5.826264	0.0000*
Rational Expectation	-0.200574	0.962203	-0.208453	0.8349
R-squared	0.159079	Mean dependent var		23.86974
Adjusted R-squared	0.154427	S.D. dependent var		0.589090
S.E. of regression	0.541698	Akaike info criterion		1.618627
Sum squared resid	212.1546	Schwarz criterion		1.650154
Log likelihood	-584.1803	Hannan-Quinn criter.		1.630792
F-statistic	34.19299*	Durbin-Watson stat		0.577583
Prob(F-statistic)	0.000000*			

****Source: Author own Calculation using, E-Views Software**
***Level of Significance 1%**
****Level of Significance 5%**

The constant coefficient (C) is 24.29458, which is statistically significant (p-value < 0.01). This suggests that when all independent variables are zero, the dependent variable has an average value of approximately 24.29. The coefficient for confidence is 0.01, with a very high p-value (0.98), indicating it is not statistically significant. This suggests that confidence has no meaningful effect on the dependent variable in this model. The coefficient for optimism is 0.53, and it is highly significant (p-value < 0.01). This implies a strong and positive relationship between optimism and the dependent variable; a one-unit increase in optimism increases the dependent variable by approximately 0.53 units. The coefficient for pessimism is -0.558115, and it is also highly significant p-value < 0.01. This indicates a strong and negative relationship between PESSIMISM and the dependent variable; a one-unit increase in PESSIMISM decreases the dependent variable by approximately 0.56 units. The coefficient for Rational EXP is -0.200574, but it is not statistically important p-value > 0.83. This implies that Rational Expectation does not significantly influence the dependent variable in the model. This calculates the standard deviation of the residuals, indicating the typical distance among the observed and predicted values. The F-statistic and its p-value indicate that the overall regression model is statistically significant, which indicates that at least one of the independent variables has a substantial influence on the dependent variable.

Conclusion

The results of this study deliver valuable insights into the behavior of the analyzed variables (Confidence, Optimism, Pessimism, and Rational Expectation) and their effect on the dependent variable within the financial time series framework. Using the Augmented Dickey-Fuller (ADF) test, it was established that all variables are stationary, with consistent statistical properties over time, ensuring the reliability of time series modeling and forecasting. The constant term is significant at the 1% level, indicating a baseline effect of 6.99 units in the dependent variable when all independent variables are held constant. The lagged volume variable is highly significant (p<0.01) with a coefficient of 0.7152, indicating strong persistence of past effects, a common feature in financial data. **Optimism is** highly significant (p<0.01) with a positive coefficient (0.2493). A one-unit increase in optimism increases the dependent variable by approximately 0.53 units, indicating a robust positive relationship. **Pessimism** also highly significant (p<0.01) but with a negative coefficient (-0.2486), signifying a negative relationship where a one-unit increase in pessimism decreases the dependent variable by approximately 0.56 units.

These results highlight the contrasting roles of optimism and pessimism in influencing the dependent variable, emphasizing the importance of psychological factors in financial models. While confidence and rational expectations were not significant in this study, their inclusion enriches the understanding of behavioral dynamics in financial contexts.

The model provides a robust framework for interpreting time series data, with strong theoretical and empirical grounding. The findings can inform future studies, particularly in examining behavioral drivers of financial outcomes and their integration into predictive models. Further research could explore alternative specifications or additional variables to enhance explanatory power.

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