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The Impact of Sentiment on Realized Higher-Order Moments in the S&P 500: Evidence from the Fear and Greed Index

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Abstract: This study empirically investigates the relationship between realized higher-order moments and the Fear and Greed Index as a measure of sentiments. We estimate daily realized moments for five different sentiment levels using 5-minute return data of the S&P 500 index from January 3, 2011, to September 18, 2020. We found that the Fear and Greed Index significantly impacts realized volatility during periods of extreme fear. Additionally, various sentiment indicators influence realized skewness and realized kurtosis. The VIX index significantly reduces realized skewness across all sentiment levels. Bearish and bullish sentiments have a significant negative relationship with negative realized skewness during periods of extreme fear and extreme greed. Conversely, the Fear and Greed index, bearish and bullish sentiments have a significant positive relationship with positive realized skewness. During extreme fear, the Fear and Greed index, bearish, and bullish sentiments have a significant negative relationship with realized kurtosis. These results remain consistent when considering the non-linear characteristics of the Fear and Greed Index during periods of extreme fear and extreme greed. These findings highlight the relevance of understanding sentiment in financial risk management and its significant relationship with asymmetric and extremity characteristics of asset returns.

Keywords: Fear and Greed Index; Realized Higher-Order Moments; Market sentiment; Asset Return Distribution; VIX Index

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1. Introduction

Recently, the global financial market has been marked by various turbulent events due to heightened levels of fear and greed among investors Albers [see, 1], Yang [see, 2]. These emotions, stemming from behavioural biases, have significantly impacted market dynamics and decision-making processes. For instance, the global financial crisis (2007–2008), the European debt crisis (2009–2010), and the COVID-19 pandemic-induced crash (2020) all highlighted the profound impact of investor sentiment on market outcomes Sarwar [3], Smales [4], Li *et al.* [5]. During these crises, fear spiked as investors grappled with uncertainty, leading to increased market volatility and risk aversion, while periods of optimism and greed triggered speculative behaviours that further destabilized markets Hollstein *et al.* [6], Elyasiani *et al.* [7].

The extant literature has predominantly focused on the relationship between investor sentiment and market returns, emphasizing metrics such as the CBOE Volatility Index (VIX) as a gauge of fear Sarwar [8], Smales [9]. However, these studies often ignore the critical role of higher-order moments such as skewness and kurtosis in capturing the full extent of sentiment-driven market behaviours. These moments are particularly relevant in assessing the asymmetric and extreme events that characterize financial markets during crises Tang and Shum [10], Amaya *et al.* [11]. Additionally, bullish and bearish sentiments, which represent market optimism and pessimism respectively, play a significant role in shaping investor behaviour and, consequently, market dynamics Smales [12]. While traditional analyses have focused on mean and volatility, the significance of skewness and kurtosis in understanding market dynamics cannot be ignored, particularly in explaining how fear, greed, and overall market sentiment (including bullish and bearish tendencies) influence market asymmetry and extremity Nieto *et al.* [13], Azimli and Kalmaz [14].

This study seeks to address these gaps by examining the impact of investor sentiment, as measured by the VIX, the CNN Fear-Greed Index, and bullish and bearish sentiment indices, on the realized volatility, realized skewness, and realized kurtosis of S&P 500 equity index. By utilizing high-frequency data, this study provides a granular understanding of how different levels of sentiment (extreme, normal, and neutral) drive market behaviour under varying conditions Elyasiani *et al.* [7], He and Hamori [15].

The results of this study show that in times of extreme fear, market volatility significantly increases. This is accompanied by a higher frequency of extreme negative returns, leading to more pronounced skewness and kurtosis. Conversely, periods of extreme greed and strong bullish sentiment are associated with increased positive skewness due to the price-driven capacity of investor confidence, resulting in a higher frequency of large positive outliers. When sentiment is neutral or bearish, volatility tends to stabilize volatility and the extremity and asymmetry in returns decreases. These findings offer valuable insights for investors and risk managers, highlighting the importance of accounting for higher-order moments in portfolio strategies, particularly in the context of persistent crises and uncertain market conditions Amaya *et al.* [11], Ahadzie and Jeyasreedharan [16].

This study contributes to the literature by extending the analysis beyond mean and volatility. It highlights the significant role skewness and kurtosis play in capturing the nuanced impact of investor sentiment on market behaviour. By utilizing indicators such as the VIX, CNN Fear-Greed Index, and sentiment indicators such as bullish and bearish indices, a more comprehensive assessment of how fear, greed, and overall market sentiment impact realized moments is provided. This offers new insights into the behavioural drivers of market dynamics Lo and Zhang [17], Kahneman [18].

The remainder of this study is organized as follows: Section 2 provides a theoretical and empirical review that aims to explain sentiment and realized moment relationships. Section 3 discusses the relevant theory for estimating higher-order moments. Section 4 presents the empirical data, the construction of higher-order moments, and the regression model used in this study. The empirical results are discussed in Section 5, and Section 6 concludes.

2. Literature Review

This section discusses the theories that explain the relationship between fear, greed, and the higher-order moments of equity markets, such as volatility, skewness, and kurtosis. The theoretical framework is grounded in key behavioural finance concepts, including prospect theory Kahneman [18], the optimal belief framework Ali *et al.* [19], the information asymmetry hypothesis Huang and Wang [20], and the adaptive market hypothesis Lo and Zhang [17]. These theories identify the primary drivers of market sentiment. Following the theoretical discussion, we review empirical studies that investigate the nexus between fear, greed, and market parameters, providing evidence of how these sentiments can be influenced by the mean, variance, and higher-order moments in the stock market.

2.1. Theoretical Review

The relationship between investor sentiments and realized moments of asset returns, specifically volatility, skewness, and kurtosis, can be explained by prospect theory. Prospect theory states that investors assign different weights to gains and losses, leading to deviations from rational expectations Kahneman [18]. Thus, during periods of uncertainty, cognitive biases and sentiments heavily influence investor decisions, resulting in suboptimal responses. Investors often adopt gambling strategies, driven by unrealistic optimism, high expectations, and overconfidence Jin and Zhou [21]. This behaviour manifests in market conditions where fear and greed significantly impact the realized moments, with fear leading to higher volatility and kurtosis, and greed increasing skewness through frequent extreme positive returns.

Similarly, the optimal belief framework developed by Brunnermeier and Parker [22] suggests that investors form beliefs based on a combination of neutral prospects and subjective sentiments. This framework shows that investors approach future utility optimistically, expecting gains due to their preference for skewed returns. Investors inherently hold biased likelihood assessments with imperfectly diversified portfolios, leading to a higher demand for more skewed assets, which typically yield lower returns. Brunnermeier *et al.* [23] observed over-investment in assets with skewed returns, while Ali *et al.* [19] noted that higher levels of fear correlate with higher expectations of future volatility. This implies that the attraction towards optimism coupled with poor decisions, drives investors' preference for skewed equities. Consequently, the anticipation of returns is influenced by other factors, such as skewness and kurtosis, which are relevant in portfolio decision-making. For instance, overly optimistic beliefs based on high levels of greed can inflate asset prices, increasing skewness, while high levels of fear can depress prices, raising volatility and kurtosis.

Additionally, the information asymmetry hypothesis suggests that variations in investor-based news result in market inefficiencies, while the risk-averse nature of investors represents heightened risk levels Huang and Wang [20]. This inconsistency induces anxiety in risk-averse investors with limited evidence, causing them to make irrational choices that further affect levels of fear and greed, increasing asymmetries. Thus, higher fear levels increase asymmetry as investors refrain from trading, increasing volatility and kurtosis. However, extreme greed can mitigate asymmetry as more investors participate in the market and potentially reducing skewness.

The adaptive market hypothesis (AMH) integrates behavioural elements into conventional finance theory, suggesting that market efficiency evolves based on varying circumstances and the personal biases of individual investors. According to the AMH, human behaviour is a complex mix of multiple decision-based systems, with logical reasoning being just one component Lo and Zhang [17]. Through the fight-or-flight mechanism, individual investors respond to varying and extreme risks, influenced by the skewness and kurtosis within the financial market. In this study, this analogy highlights how investors' fear and greed manifest under neutral or extreme conditions. Aggressive investors driven by greed optimistically respond to extreme market events, seeking higher returns by taking on more risk. However, fearful investors exhibit reserved behaviour during extreme events, recognizing that such situations often lead to significant losses.

Lo and Zhang [17] also argued that when collective wisdom outweighs mob mentality over prolonged periods, market returns reflect the former. However, diverse market conditions can trigger collective fear and greed, with the latter often leading to market bubbles and abrupt crashes. This phenomenon is reflected in the observed skewness and kurtosis in financial markets. We believe that AMH can help explain how investor fear and greed affect realized market moments under varying conditions. It is anticipated that during periods of extreme fear, market efficiency may deteriorate, leading to increased volatility and higher kurtosis. However, during neutral levels of sentiment, the market may exhibit traits closer to efficiency, with more stable volatility and lower skewness and kurtosis.

2.2. Empirical Review

This section discusses the empirical findings on how investor fear and greed may influence the financial market, with a focus on the analysis of mean, volatility, and higher-order moments.

2.2.1. Investor Fear and Greed: Mean & Volatility-Based Analysis

The extant literature documents the nexus between investor sentiment and financial market returns, consistently revealing an inverse pattern despite variations in sentiment metrics. Sarwar [3] found a robust adverse relationship between the peak volatility of the investor fear gauge (VIX) and U.S. equities, with a similar negative influence observed in the BRICS markets. This indicates that the VIX is an effective tool for assessing investor fear in the stock market. Further, Sarwar [8] observed a cross-asset influence of the VIX on U.S. and European equity markets in the post-market crisis period,

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suggesting market frictions and information processing limitations among European investors. Studies employing stochastic volatility and vector auto-regression models also suggest that fears of impending hurdles increase investor demand for hedges, which, in turn, affects equity returns Soydemir *et al.* [24], Todorov [25]. Additionally, Kumar and Rao [26] confirmed that the VIX adversely impacts all portfolios in the Indian equity market, with these effects showing persistent shocks. These findings are further supported by Shaikh and Padhi [27], who demonstrated that the VIX is a robust measure of investor fear in the Indian market, and by Smales [4], who found that increases in investor fear led to declining returns in the Australian equities, bonds, and currency markets.

Economou *et al.* [28] examined the relationship between equities in the U.S., U.K., and Germany and their respective VIX indices, finding an asymmetric reaction in the U.S. market. Sarwar and Khan [29] demonstrated that the VIX has an adverse predictive capacity on equities in emerging markets, with VIX shocks explaining a significant portion of equity variations. Chakraborty and Subramaniam [30] concluded that lower sentiment drives fear-based trading, leading to lower future returns, while Graham *et al.* [31] provided additional insights using web-based fear metrics. Studies conducted during the COVID-19 pandemic revealed that pandemic-related fear significantly impacted global equities. For instance, Li *et al.* [5] identified pandemic-based fear as a primary predictor of investor attention and volatility, and Duong *et al.* [32] showed the persistence of volatility in the Vietnam equity markets due to pandemic-induced fear. These findings highlight that volatility and fear from major markets, particularly the U.S., are significant drivers of global equity market volatility, with pronounced effects during crises Smales [9], Grima *et al.* [33], Narang *et al.* [34], Cupák *et al.* [35], Adekoya *et al.* [36].

2.2.2. Investor Fear & Greed and Higher-Order Moments

Given the dominance of risk and return-based analysis and the quest to validate the relevance of higher-order moments, Tang and Shum [10] examined the usefulness of global equity risk measures, particularly focusing on beta, skewness, and kurtosis under varying market conditions. Their study demonstrated that investors are compensated not only for systematic risk but also for unsystematic risk, indicating a preference for undiversified portfolios. It was found that investors tend to accept lower positive returns for positively skewed portfolios, with total risk positively related to realized returns in favourable conditions and negatively related in unfavorable conditions. Extending this work, Westerhoff [37] developed a behavioural stock market model driven by fear and greed, where optimistic beliefs lead to stock purchases and panic results in selling, causing alternating periods of low and high volatility.

Nieto *et al.* [13] showed that the variance risk premium responds to changes in the higher-order moments of market returns, linking investor fear with various economic and financial risk factors. In another study, Amaya *et al.* [11] analyzed weekly data from over 2,000 equity firms, finding that realized volatility decreases while skewness and kurtosis increase during periods of cross-sectional dispersion, indicating an inverse relationship between realized volatility and skewness. Meanwhile, Hollstein *et al.* [6] identified a highly integrated tail risk among emerging and developed markets, demonstrating the predictive power of the tail risk index in these markets.

Addressing limitations in the VIX, Elyasiani *et al.* [7] developed an Italian equity-based skewness index, which more accurately captures investor excitement (greed) than fear. Azimli and Kalmaz [14] found a link between RU-GPR and realized volatility, noting significant correlations in realized skewness and kurtosis across different markets. Additionally, Banerjee *et al.* [38] assessed the spillovers of higher moments between Shanghai International Energy and U.S. energy futures, highlighting substantial transmission during the pandemic and recent conflicts, underscoring the importance of higher-order moments in financial risk management.

Table 1 provides a comprehensive summary of the relationship between different sentiment levels ranging from Extreme Fear to Extreme Greed, and the observed volatility, skewness, and kurtosis in financial markets, based on both theoretical and empirical reviews.

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The table shows that sentiment-driven emotions, particularly fear and greed, significantly influence market dynamics. During periods of Extreme Fear, volatility, negative skewness, and kurtosis are significantly heightened, reflecting an increase in uncertainty and adverse investor reactions. This period also shows a significant decrease in positive skewness, indicating a high frequency of extreme negative returns and market downturns. In states of Fear, volatility, negative skewness and kurtosis still increase, while positive skewness decreases. When sentiment is Neutral, the market shows stable or slightly decreasing volatility, with skewness and kurtosis also remaining stable or showing minor changes. This reflects balanced market conditions, with no strong bias toward either fear or greed, resulting in fewer extreme fluctuations. Conversely, during periods of Greed, volatility either slightly increases or remains stable, while negative skewness decreases and positive skewness increases. This shift reflects a market where investors are generally optimistic, often engaging in speculative behaviour that drives the frequency of extreme positive returns, with a minimal or stabilizing impact on overall volatility. In situations of Extreme Greed, volatility may slightly decrease or remain stable, negative skewness decreases further, and positive skewness increases significantly. Kurtosis remains stable or slightly increases, suggesting fewer extreme negative returns and a prevalence of positive outliers. Understanding these dynamics provides valuable insights into how fear and greed influence investor behaviour and market outcomes, revealing underlying emotional drivers that traditional risk measures might ignore.

Table 1. Impact of investor sentiment on moments.

Sentiment Level	**Volatility**	**Negative Skewness**	**Positive Skewness**	**Kurtosis**
Extreme Fear	Significantly increases	Significantly increases	Significantly decreases	Significantly increases
Fear	Increases	Increases	Decreases	Increases
Neutral	Stable or slightly decreases	Stable or slightly increases	Stable or slightly decreases	Stable or slightly decreases
Greed	Slightly increases or stable	Decreases	Increases	Stable or slightly decreases
Extreme Greed	Decreases or slightly stable	Decreases	Significantly increases	Stable or slightly increases

This table summarizes the relationship between different sentiment levels and the observed volatility, skewness, and kurtosis based on the theoretical and empirical review.

2.3. Gaps in the Literature

This study contributes to the literature by investigating the relationship between investor sentiments, specifically fear and greed, and higher-order moments of asset returns, namely asymmetry (realized skewness) and extremity (realized kurtosis). Unlike previous studies that primarily focused on mean and volatility, our study emphasizes the importance of skewness and kurtosis in capturing the nuanced impacts of investor sentiments on market behaviour Tang and Shum [10], Amaya *et al.* [11], Hu and McInish [39]. By using high-frequency data, we capture relevant information that would otherwise have been ignored, providing a more granular understanding of how sentiments influence market dynamics Elyasiani *et al.* [7], He and Hamori [15].

Our approach diverges from prior research that predominantly focused on the VIX as a fear indicator, we employ the CNN Fear-Greed Index which allows us to capture both fear and greed. This approach shows that different sentiments have varying responses from market participants, especially during periods of significant stress Erdemlioglu and Gradojevic [40], John and Li [41]. By examining how extreme, normal, and neutral levels of fear and greed drive the realized volatility, skewness, and kurtosis of the S&P 500 index, this study provides comprehensive insights into the behavioural underpinnings of market movements Shaikh and Padhi [27], Dilmac *et al.* [42]. The results offer valuable insights for investors by highlighting how varying sentiments influence market asymmetry and extremity under different market conditions, thus advancing the understanding of investor decision-making in the presence of persistent crises and uncertainties Hollstein *et al.* [6], Adekoya *et al.* [36], Balcilar *et al.* [43].

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3. Higher-Order Realized Moments

In this section, we discuss the theoretical framework for estimating realized higher-order moments. Suppose the observed price follows a semi-martingale process on a filtered probability space (Ω, $\mathcal{F}$, $(\mathcal{F}t)t \geq 0$, $\mathbb{P}$) within a frictionless market where there is no arbitrage opportunities (see Back [44]). When accounting for jumps, the observed price can be described by a continuous-time semi-martingale jump-diffusion process:

$$p_t = \int_0^t \mu_D dt + \int_0^t \sigma_D dW_t + \sum_{k=1}^{N(t)} J(Q_k), \tag{1}$$

where μ_D is the diffusive mean, σ_D denotes the diffusive volatility process, dW_t is the increments of a Brownian motion W_t, $N(t)$ is a counting process, and $J(Q_k)$ are the non-zero jump increments (see Fleming and Paye [45] for further details). The quadratic variation for the jump-diffusion process is defined as:

$$QV_t = \int_0^t \sigma^2 Ddt + \sum k = 1^{N(t)} J^2(Q_k), \tag{2}$$

The first term on the right-hand side of Equation 2 is the integrated variance, and the second term is the sum of the squared jumps (variance of the jump component). In the absence of jumps, Equation 2 simplifies to a pure diffusion model with continuous sample paths, as the jump component becomes zero. For this jump-diffusion process, it is assumed that μ_D and σ_D are jointly independent of W_t. The integrated variance (IV) for this process is defined as $IV_t \equiv \int_0^t \sigma_D^2 dt$, equating to the quadratic variance (QV).

In high-frequency finance, realized variance (RV) is employed as a proxy for sample variance, replacing the traditional use of squared returns at low frequencies. It is well-documented that realized variance is a more robust estimator of volatility (see Andersen and Bollerslev [46], Andersen *et al.* [47], Hansen and Lunde [48,49], Barndorff-Nielsen and Shephard [50], Andersen *et al.* [51]). The discrete-time high-frequency returns over the holding-interval h is defined as:

$$r_{i,h} = p_{i,h} - p_{i-1,h}, \quad i = 1, 2, ..., N \tag{3}$$

where h is the holding-interval (trading day), $p_{i,h}$ is the i-th high-frequency log price for the holding-interval h, and N is the number of infill observations for each sampling-interval τ, partitioned into equal lengths such that $\tau \equiv (b-a)/N$ and $[a,b] \subset h$. The RV is defined as the sum of squared high-frequency returns:

$$RV_{i,h} = RM(2)i, h \equiv \sum i = 1^N r_{i,h}^2 \to \int_0^t \sigma^2 Ddt + \sum k = 1^{N(t)} J^2(Q_k), \quad \text{as} \quad N \to \infty \tag{4}$$

The RV is an efficient estimator of the quadratic variation, converging to the QV as the number of observations (N) approaches infinity ($RV_{[a,b]}^{(N)} \to QV_{[a,b]}$ as $N \to \infty$; see Andersen and Bollerslev [46], Barndorff-Nielsen and Shephard [52]). Notably, in the absence of jumps, RV converges to IV.

Following Amaya *et al.* [11], Ahadzie and Jeyasreedharan [53], and Ahadzie and Jeyasreedharan [54], the third and fourth realized moments are defined as:

$$\begin{aligned} RM(3)_{i,h} &\equiv \sum_{i=1}^{N} r_{i,h}^3 \to \sum_{k=1}^{N(t)} J^3(Q_k), \quad as \quad N \to \infty \\ RM(4)_{i,h} &\equiv \sum_{i=1}^{N} r_{i,h}^4 \to \sum_{k=1}^{N(t)} J^4(Q_k), \quad as \quad N \to \infty \end{aligned} \tag{5}$$

According to Amaya *et al.* [11], the third realized moment converges to the sum of cubic jumps, and the fourth realized moment converges to the sum of quartic jumps. This implies that the realized third higher-order moment captures the sum of cubic jumps, while the realized fourth higher-order

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moment captures the sum of quartic jumps. For $RM(4)$, only the magnitude of the jumps is relevant, not their direction. These jump-driven convergences align with the findings of Kim and White [55], who demonstrated that estimates of higher moments of high-frequency data distributions are significantly influenced by the presence of jumps.

Following Amaya *et al.* [11], Ahadzie and Jeyasreedharan [53,54], RS is defined as the cubic intra-day returns normalized by the square root of RV cubed, and RK is the sum of the quartic high-frequency returns normalized by RV squared:

$$RS_{i,h} = \frac{\sqrt{N}\sum_{i=1}^{N} r_{i,h}^3}{RV_{i,h}^{3/2}} \quad (6)$$

$$RK_{i,h} = \frac{N\sum_{i=1}^{N} r_{i,h}^4}{RV_{i,h}^2} \quad (7)$$

For negative realized skewness ($RS(-)$) and positive realized skewness ($RS(+)$), the definitions are:

$$RS(-)i,h = \frac{\sqrt{N}\sum i = 1^N r_{i,h}^3 \mid r_{i,h} < 0}{RV_{i,h}^{3/2} \mid r_{i,h} < 0} \quad (8)$$

$$RS(+)i,h = \frac{\sqrt{N}\sum i = 1^N r_{i,h}^3 \mid r_{i,h} > 0}{RV_{i,h}^{3/2} \mid r_{i,h} > 0} \quad (9)$$

Amaya *et al.* [11] showed that realized skewness and realized kurtosis do not converge to the sample skewness and sample kurtosis. The sample skewness and kurtosis include diffusive skewness and diffusive kurtosis components. Thus, the normalized third realized moment (realized skewness) captures the normalized direction and magnitude of the cubic jumps, while the normalized fourth realized moment (realized kurtosis) captures the normalized magnitude of the quartic jumps. Consequently, the information contained in realized skewness and realized kurtosis differs from that of sample skewness and sample kurtosis, typically computed from long samples of low-frequency return data (e.g., daily, weekly, or monthly return series).

4. Data and Methodology

In high-frequency literature, it is common to use returns sampled at a 5-minute frequency as a proxy for unbiased high-frequency return data in the U.S. market Andersen *et al.* [51], Andersen and Bollerslev [56], Huang and Tauchen [57]. This approach balances microstructure noise and variance bias. According to Bandi and Russell [58], it is important to compute realized variance with unbiased intra-day return data, as using contaminated return data can significantly accumulate noise, resulting in biased estimates. Therefore, this study uses 5-minute last-traded prices of the S&P 500 index.

The high-frequency data was obtained from the DataScope Refinitiv database, covering the period from January 3, 2011, to September 18, 2020, and includes trading days between 9:30 am and 4 pm. This results in a sample of 78 intra-day prices per day. We exclude weekends and overnight returns from the data. Intra-day returns were computed as the change in the logarithm of the closing prices of successive days. Daily realized moments were computed from the 5-minute high-frequency returns data, yielding 2,535 daily observations. Daily data for the US stock market volatility index (VIX Index) were downloaded directly from the CBOE website[1]. The US AAII investor sentiment survey data for bearish and bullish sentiments and the US dollar index (USDX) were downloaded from DataStream, while the Fear and Greed index was downloaded from Medium[2].

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1 Available at:https://www.cboe.com/tradable_products/VIX/VIX_historical_data/
2 Available at: https://medium.com/@polish.greg/fear-and-greed-index-python-scraper-96e71e57dbd0x

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Table 2 reports the relationship between various sentiment levels (extreme fear, fear, neutral, greed, and extreme greed) and the dependent variables; realized volatility, realized skewness, negative realized skewness, positive realized skewness, and realized kurtosis. Using ANOVA and Bartlett's tests, we test whether these variables' means and variances differ significantly across sentiment levels.

The Hypotheses for ANOVA is defined as follows:

Null Hypothesis (H0): The means of the variable are equal across the different sentiment levels.

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$$

Alternative Hypothesis (H1): At least one of the means of the variable is different across the sentiment levels.

$$H_1 : \text{At least one } \mu_i \neq \mu_j$$

The Hypotheses for Bartlett's Test is defined as follows:

Null Hypothesis (H0): The variances of the variable are equal across the different sentiment levels.

$$H_0 : \sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2 = \sigma_5^2$$

Alternative Hypothesis (H1): At least one of the variances of the variable is different across the sentiment levels.

$$H_1 : \text{At least one } \sigma_i^2 \neq \sigma_j^2$$

The ANOVA results show significant differences in the means of each variable across sentiment levels, indicated by F-statistics and corresponding significant p-values. For instance, realized volatility shows an F-statistic of 17.300 (p-value = 0.000), realized skewness an F-statistic of 24.070 (p-value = 0.000), positive realized skewness an F-statistic of 25.440 (p-value = 0.000), negative realized skewness an F-statistic of 5.860 (p-value = 0.000), and realized kurtosis an F-statistic of 22.260 (p-value = 0.000). We reject the null hypothesis that the means of the variables are equal across sentiment levels, this suggests that fear and greed sentiment significantly impact realized moments.

Moreover, Bartlett's tests show unequal variances across sentiment levels for all variables, as evidenced by chi-square statistics and significant p-values as well. Specifically, realized volatility has a chi-square value of 34.769 (p-value = 0.000), realized skewness a chi-square value of 268.447 (p-value = 0.000), positive realized skewness a chi-square value of 370.080 (p-value = 0.000), negative realized skewness a chi-square value of 32.461 (p-value = 0.000), and realized kurtosis a chi-square value of 379.005 (p-value = 0.000). We reject the null hypothesis of equal variances, implying significant heteroscedasticity.

The relevance of these results shows the influence of fear and greed sentiment on market behaviour, which aligns with the findings presented in Table 1. For example, higher sentiment levels such as extreme greed is associated with higher realized kurtosis, indicating more extreme returns. This variability and extremity in returns can significantly affect risk management and investment strategies. The rejection of the null hypothesis for both tests across all dependent variables suggests the need for financial models to account for sentiment-driven market dynamics, as these psychological factors can lead to significant deviations from traditional risk and return expectations. Hence, the results empirically support investigating fear and greed-driven realized moment relationships.

To investigate the relationships between realized moments and the Fear and Greed index, we estimate Equation 10 using the following quantile regression:

$$RM_t = \alpha_\tau + \beta_\tau X_t + \epsilon_{t,\tau} \tag{10}$$

where the subscript t denotes time (t = 1,...,T), τ represents the quantile level, and ϵ is the error term. RM represents the realized moment (i.e., realized volatility (RV), realized skewness (RS), negative realized skewness ($RS(-)$), positive realized skewness ($RS(+)$), and realized kurtosis (RK)). X is a vector of predictors, including the Fear and Greed index (FGI), US dollar index (USDX), bearish and bullish sentiments, and return data. The coefficients α_τ and β_τ are estimated for each quantile τ.

Table 2. Summary Statistics and Hypothesis Testing Results by Sentiment Level.

Variable	Sentiment Level	Mean	Std. Dev.	ANOVA F-Statistic	Prob $\geq$ F	Bartlett's Test Chi-Square	Prob $\geq$ chi2	Accept/Reject H_0
RV	Extreme Fear	0.002895	0.001431	17.300	0.000	34.769	0.000	Reject
	Fear	0.003123	0.001836					
	Neutral	0.003657	0.001751					
	Greed	0.003556	0.001822					
	Extreme Greed	0.003621	0.001722					
RS	Extreme Fear	-0.702	1.252	24.070	0.000	268.447	0.000	Reject
	Fear	-0.201	1.950					
	Neutral	-0.042	2.378					
	Greed	0.436	2.461					
	Extreme Greed	0.580	2.803					
RS(-)	Extreme Fear	-3.445	1.041	5.860	0.000	32.461	0.000	Reject
	Fear	-3.293	0.986					
	Neutral	-3.454	1.056					
	Greed	-3.270	0.903					
	Extreme Greed	-3.186	0.827					
RS(+)	Extreme Fear	2.602	0.720	25.440	0.000	370.080	0.000	Reject
	Fear	2.927	1.253					
	Neutral	3.179	1.489					
	Greed	3.281	1.592					
	Extreme Greed	3.562	1.964					
RK	Extreme Fear	7.926	5.958	22.260	0.000	379.005	0.000	Reject
	Fear	10.047	9.834					
	Neutral	12.608	12.108					
	Greed	12.848	13.123					
	Extreme Greed	15.098	16.055					

This table report the means and standard deviations for each sentiment level and dependent variables (thus, RV is realized volatility, RS is realized skewness, RS(-) is negative realized skewness, RS(+) is positive realized skewness, and RK is realized kurtosis), along with the F-statistic, p-value for the ANOVA, Bartlett's Test Chi-Square value, and its p-value. The main objective is to test whether the means of these variables differ significantly across the sentiment levels. Extreme Fear is defined as FGI $\leq$ 24, Fear is defined as 25 $\leq$ FGI $\leq$ 44, Neutral is defined as 45 $\leq$ FGI $\leq$ 55, Greed is defined as 56 $\leq$ FGI $\leq$ 75, and Extreme Greed is defined as FGI $\geq$ 76. The results of RV is multiplied by 100.

Figure 1 shows how higher-order moments, such as realized variance, realized skewness, and realized kurtosis, provide insights into the behaviour of financial markets, specifically the S&P 500 returns. We observe that realized kurtosis has sharp fluctuations, which indicates market stress. These fluctuations often coincide with extreme events or periods of heightened uncertainty, which can precede significant market movements. Realized skewness and its components, negative skewness and positive skewness, offer valuable perspectives on market sentiment. Negative skewness moves with the bearish sentiment, suggesting a tendency toward negative returns, while positive skewness indicates bullish sentiment, pointing to positive return tendencies. Lastly, realized variance is closely linked to market volatility.

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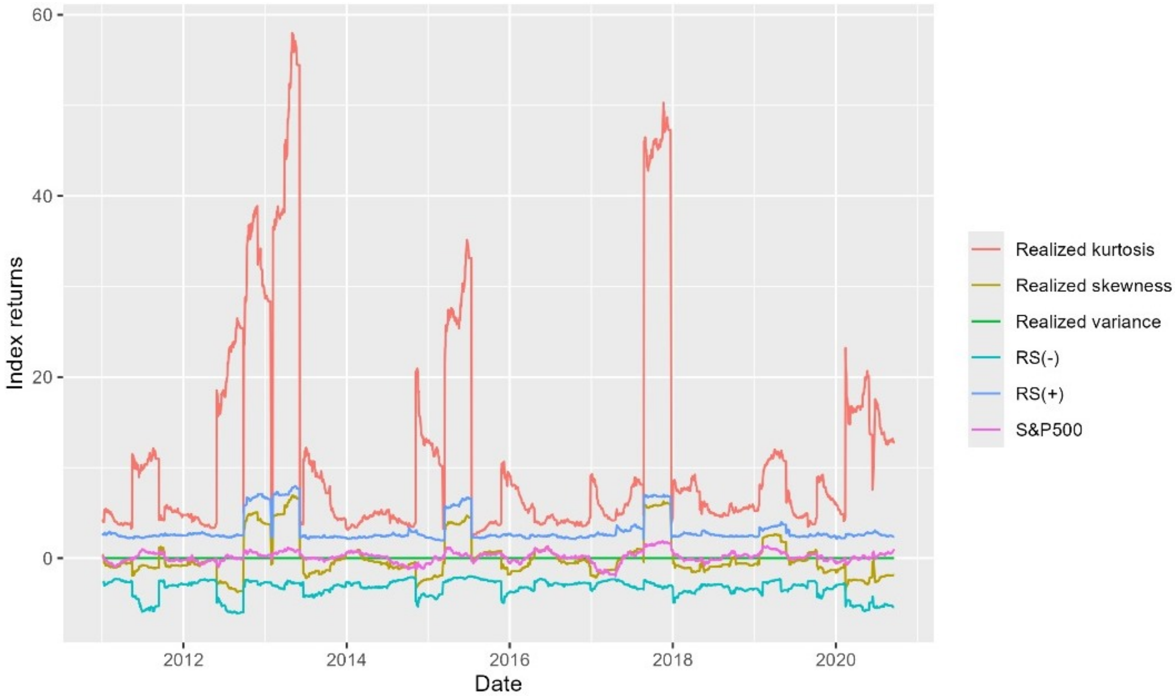

Figure 1. This graph reports the relationship between S&P 500 index and realized higher-order moments across time. The moments realized variance, realized skewness (both positive and negative), and realized kurtosis.

5. Results

5.1. Fear and Greed-Realized Moment Relationship

In this section, we investigate the empirical relationship between realized moments and the Fear and Greed Index while controlling for other market sentiment indicators. Table 3 reports the quantile regression results across different sentiment levels and provides the relationships between various predictors and realized volatility.

At the extreme fear sentiment level, the results show significant relationships between several predictors. We note that the FGI index has a significant negative coefficient of -4.5E-07 at the 1% significance level, indicating that increased fear reduces realized volatility. This finding contrasts with the general understanding that fear typically increases volatility, suggesting a unique dynamic in extreme fear conditions. Typically, fear is associated with increased volatility as investors react to uncertainty and potential losses, leading to more volatile market conditions (see Smales [12], Whaley [59]). However, the unique dynamic relationship observed in the extreme fear conditions suggests that in rare scenarios, heightened fear may lead to more cautious behaviour and reduced volatility contrasting the typical reaction to fear. The USDX has a positive and significant coefficient of 3.06E-07 at the 1% significance level, suggesting that an increase in USDX increases realized volatility, likely due to increased market uncertainty, as suggested by Ehrmann *et al.* [60]. The VIX index has a significant positive coefficient of 3.04E-07 at the 1% significance level, indicating that higher market volatility (as measured by VIX) tends to increase realized volatility, consistent with studies Grima *et al.* [33], Whaley [59], Da *et al.* [61], Szczygielski *et al.* [62], who identified VIX as a reliable measure of market sentiment and volatility. The return variable has a significant negative coefficient of -2.3E-06 at the 1% significance level, suggesting that higher returns decrease realized volatility, contrasting with the general finding by studies Duong *et al.* [32], Narang *et al.* [34], Andersen *et al.* [63], Vasileiou [64], that noted that higher returns are usually associated with higher volatility due to increased speculative trading. The bearish and bullish sentiments are insignificant at this sentiment level, indicating that extreme fear sentiment may overshadow other sentiment influences.

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For the fear sentiment level, the FGI index has a positive and significant coefficient of 2.01E-07 at the 5% significance level, indicating that increased fear is associated with increased realized volatility. The USDX has a positive but not statistically significant relationship with a coefficient of 1.01E-07. The bearish and bullish sentiments, the VIX, and return variables are insignificant in this quantile.

The FGI index is insignificant in the neutral sentiment level, with a coefficient of -1.5E-09. The USDX has a significant positive relationship with a coefficient of 7.54E-07 at the 1% significance level. The VIX index also shows a significant positive coefficient of 5.85E-07 at the 5% significance level, reinforcing the importance of market volatility in influencing realized volatility. The bearish sentiment, bullish sentiment, and return variables are insignificant in this sentiment level, suggesting a more stable market condition where these factors are less impactful.

At the greed sentiment level, the FGI index has a positive but insignificant coefficient of 5.12E-08. The USDX has a negative but insignificant relationship with a coefficient of -4.8E-08. The bearish sentiment has a significant negative coefficient of -8.9E-07 at the 5% significance level, indicating that increased bearish sentiment reduces realized volatility. This contrasts with the findings of Brown and Cliff [65], who note that bearish sentiment often increases volatility, likely due to panic selling and market pessimism. The VIX index has a significant negative coefficient of -5.1E-07 at the 1% significance level, suggesting that higher market volatility decreases realized volatility, which may appear contradictory but could indicate market stabilization mechanisms during greed sentiment periods. The return variable shows a significant positive relationship with realized volatility, with a coefficient of 9.01E-06 at the 1% significance level, aligning with the general understanding that higher returns can increase market activity and volatility, as noted by studies Narang *et al.* [34], Andersen *et al.* [63], Vasileiou [64].

For the extreme greed sentiment level, the FGI index has a positive but insignificant coefficient of 9.17E-08. The USDX has a positive but insignificant relationship with a coefficient of 7.79E-08. The VIX index shows a significant negative coefficient of -6.4E-07 at the 1% significance level, indicating that higher market volatility decreases realized volatility, which may reflect a market correction mechanism during extreme greed periods. The return variable has a significant positive coefficient of 7.21E-06 at the 5% significance level, suggesting that higher returns increase realized volatility. The bearish and bullish sentiments are insignificant at this sentiment level, implying that during extreme greed, other factors like market volatility and returns have more pronounced effects.

The results show how different economic indicators and sentiment indices uniquely influence realized volatility across various sentiment levels. The FGI index and sentiments significantly impact volatility during periods of extreme fear and fear, indicating investor sentiment strongly influences market behaviour. The USDX affects volatility during extreme fear and neutral sentiment levels, highlighting its critical role in market uncertainty. The VIX index consistently impacts volatility across sentiment levels, showing the importance of market volatility in shaping realized volatility. The return variable's persistent relationship with volatility during extreme fear, greed, and extreme greed highlights its ongoing impact on market dynamics. These insights provide a deeper understanding of how various factors shape market behaviour in response to various sentiments.

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Table 3. Quantile regression across sentiment levels where the dependent variable is realized volatility.

Sentiment Level	Predictor	Coefficient	Std. Error	t-value	P-value
Extreme Fear	FGI	-4.5E-07	6.5E-08	-6.919	0.000
	USDX	3.06E-07	4.95E-08	6.178	0.000
	BEARISH	1.24E-07	8.97E-08	1.387	0.166
	BULLISH	9.07E-08	8.31E-08	1.091	0.276
	VIX	3.04E-07	6.53E-08	4.657	0.000
	return	-2.3E-06	8.59E-07	-2.703	0.007
	cons	-1.6E-05	7.73E-06	-2.124	0.034
	Number of obs	411			
	Pseudo R^2	0.152			
Fear	FGI	2.01E-07	8.95E-08	2.250	0.025
	USDX	1.01E-07	5.86E-08	1.716	0.087
	BEARISH	3.73E-08	1.46E-07	0.256	0.798
	BULLISH	6.17E-08	1.28E-07	0.481	0.630
	VIX	4.73E-08	1.05E-07	0.449	0.654
	return	-4.3E-07	8.54E-07	-0.499	0.618
	cons	-3.8E-06	1.04E-05	-0.364	0.716
	Number of obs	593			
	Pseudo R^2	0.012			
Neutral	FGI	-1.5E-09	4.82E-07	-0.003	0.998
	USDX	7.54E-07	2.06E-07	3.654	0.000
	BEARISH	-7.2E-07	5.57E-07	-1.285	0.199
	BULLISH	-1.9E-07	4.15E-07	-0.464	0.643
	VIX	5.85E-07	2.7E-07	2.166	0.031
	return	2.44E-06	2.52E-06	0.966	0.335
	cons	-2.1E-05	3.96E-05	-0.539	0.590
	Number of obs	428			
	Pseudo R^2	0.061			
Greed	FGI	5.12E-08	2.37E-07	0.216	0.829
	USDX	-4.8E-08	1.71E-07	-0.279	0.780
	BEARISH	-8.9E-07	4.21E-07	-2.110	0.035
	BULLISH	4.84E-07	3.3E-07	1.466	0.143
	VIX	-5.1E-07	1.82E-07	-2.827	0.005
	return	9.01E-06	2.1E-06	4.284	0.000
	cons	4.93E-05	2.81E-05	1.757	0.079
	Number of obs	807			
	Pseudo R^2	0.094			
Extreme Greed	FGI	9.17E-08	3.07E-07	0.298	0.766
	USDX	7.79E-08	2.22E-07	0.351	0.726
	BEARISH	-6.4E-07	6.31E-07	-1.020	0.309
	BULLISH	-4.6E-07	5.61E-07	-0.824	0.411
	VIX	-6.3E-07	1.5E-07	-4.228	0.000
	return	7.21E-06	2.92E-06	2.470	0.014
	cons	9.4E-05	5.01E-05	1.876	0.062
	Number of obs	296			
	Pseudo R^2	0.326			

This table reports the quantile regressions where realized volatility is the dependent variable. The data spans January 3, 2011, to September 18, 2020, where FGI is the Fear and Greed index, USDX is the US dollar index, BEARISH is the bearish index, and BULLISH is the bullish index, VIX is the CBOE volatility index. Extreme Fear is defined as FGI ≤ 24, Fear is defined as $25 \leq$ FGI ≤ 44, Neutral is defined as $45 \leq$ FGI ≤ 55, Greed is defined as $56 \leq$ FGI ≤ 75, and Extreme Greed is defined as FGI ≥ 76. For each sentiment level, a quantile regression is run within the range when the values of Extreme Fear correspond to q = 0.10, Fear to q = 0.20, Neutral to q = 0.50, Greed to q = 0.70, and Extreme Greed to q = 0.90.

Table 4 reports the quantile regression results across different sentiment levels and provides insights into the relationships between various predictors and realized skewness.

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At the extreme fear sentiment level, we note that the FGI index has a positive and insignificant coefficient of 6.99E-05. The USDX has a positive and significant coefficient of 0.011 at the 1% significance level, suggesting that an increase in USDX increases realized skewness. The bearish sentiment has a significant negative coefficient of -0.056 at the 1% significance level, indicating that increased bearish sentiment reduces realized skewness. The VIX index has a significant negative coefficient of -0.030 at the 1% significance level, indicating that higher market volatility reduces realized skewness, consistent with the role of VIX as a fear gauge Whaley [59]. The return variable has a significant positive coefficient of 1.724 at the 1% significance level, suggesting that higher returns increase realized skewness. This contradicts the findings of [11], who revealed that assets with less (more) skewness are compensated with higher (lower) returns.

For the fear sentiment level, the FGI index has a negative and insignificant coefficient of -4.93E-04. The USDX has a positive but insignificant relationship with a coefficient of 0.004. The bearish sentiment has a negative coefficient of -0.025, which is insignificant. The bullish sentiment shows a positive coefficient of 0.028 at 10% significance level. The VIX index has a significant negative coefficient of -0.058 at the 1% significance level. The return variable shows a significant positive relationship with realized skewness, with a coefficient of 1.190 at the 1% significance level, supporting the relationship between returns and skewness as observed in broader market dynamics (see Boyer and Vorkink [66]).

In the neutral sentiment level, the FGI index is insignificant, with a coefficient of -0.005. The USDX has a positive but insignificant relationship with a coefficient of 0.001. The bearish sentiment has a significant positive coefficient of 0.079 at the 1% significance level, and the bullish sentiment also shows a significant positive coefficient of 0.071 at the 1% significance level. The VIX index has a significant negative coefficient of -0.083 at the 1% significance level. The return variable shows a significant positive relationship with realized skewness, with a coefficient of 1.684 at the 1% significance level.

At the greed sentiment level, the FGI index has a negative but insignificant coefficient of -0.022. The USDX has a significant negative relationship with a coefficient of -0.070 at the 1% significance level. The bearish sentiment has a significant negative coefficient of -0.072 at the 5% significance level, indicating that increased bearish sentiment reduces realized skewness. The VIX index has a significant negative coefficient of -0.031 at the 5% significance level. The return variable shows a significant positive relationship with realized skewness, with a coefficient of 3.312 at the 1% significance level.

For the extreme greed sentiment level, the FGI index has a negative but insignificant coefficient of -0.041. The USDX has a significant negative relationship with a coefficient of -0.189 at the 1% significance level. The bearish sentiment has a significant negative coefficient of -0.543 at the 1% significance level, indicating that increased bearish sentiment reduces realized skewness. The bullish sentiment also shows a significant negative coefficient of -0.183 at the 1% significance level. The VIX index has a significant negative coefficient of -0.055 at the 1% significance level. The return variable has a significant positive coefficient of 1.786 at the 1% significance level.

The results show that the VIX consistently reduces realized skewness across sentiment levels, highlighting its stabilizing role during market volatility. Bearish sentiment lowers skewness, especially during extreme greed, while USDX increases skewness under extreme fear but decreases it during extreme greed. Higher returns consistently increase realized skewness, suggesting asymmetry in positive returns.

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Table 4. Quantile regression across sentiment levels where the dependent variable is realized skewness.

Sentiment Level	Predictor	Coefficient	Std. Error	t-value	P-value
Extreme Fear	FGI	6.99E-05	0.005	0.015	0.988
	USDX	0.011	0.004	3.131	0.002
	BEARISH	-0.056	0.007	-8.483	0.000
	BULLISH	-0.001	0.006	-0.183	0.855
	VIX	-0.030	0.005	-6.305	0.000
	return	1.724	0.063	27.376	0.000
	cons	-0.793	0.567	-1.400	0.162
	Number of obs	411			
	Pseudo R^2	0.385			
Fear	FGI	-4.93E-04	0.012	-0.043	0.966
	USDX	0.004	0.008	0.487	0.626
	BEARISH	-0.025	0.019	-1.312	0.190
	BULLISH	0.028	0.016	1.692	0.091
	VIX	-0.058	0.014	-4.315	0.000
	return	1.190	0.110	10.849	0.000
	cons	-1.456	1.340	-1.087	0.278
	Number of obs	593			
	Pseudo R^2	0.149			
Neutral	FGI	-0.005	0.018	-0.253	0.800
	USDX	0.001	0.008	0.091	0.927
	BEARISH	0.079	0.021	3.758	0.000
	BULLISH	0.071	0.016	4.510	0.000
	VIX	-0.083	0.010	-8.181	0.000
	return	1.684	0.095	17.702	0.000
	cons	-4.233	1.492	-2.836	0.005
	Number of obs	428			
	Pseudo R^2	0.266			
Greed	FGI	-0.022	0.020	-1.078	0.281
	USDX	-0.070	0.015	-4.803	0.000
	BEARISH	-0.072	0.036	-2.017	0.044
	BULLISH	-0.029	0.028	-1.023	0.306
	VIX	-0.031	0.015	-1.993	0.047
	return	3.312	0.179	18.549	0.000
	cons	11.498	2.383	4.826	0.000
	Number of obs	807			
	Pseudo R^2	0.388			
Extreme Greed	FGI	-0.041	0.033	-1.240	0.216
	USDX	-0.189	0.024	-7.901	0.000
	BEARISH	-0.543	0.068	-7.961	0.000
	BULLISH	-0.183	0.061	-3.012	0.003
	VIX	-0.055	0.016	-3.408	0.001
	return	1.786	0.316	5.661	0.000
	cons	44.813	5.413	8.279	0.000
	Number of obs	296			
	Pseudo R^2	0.527			

This table reports the quantile regressions where realized skewness is the dependent variable. The data spans January 3, 2011, to September 18, 2020, where FGI is the Fear and Greed index, USDX is the US dollar index, BEARISH is the bearish index, and BULLISH is the bullish index, VIX is the CBOE volatility index. Extreme Fear is defined as FGI ≤ 24, Fear is defined as $25 \leq$ FGI ≤ 44, Neutral is defined as $45 \leq$ FGI ≤ 55, Greed is defined as $56 \leq$ FGI ≤ 75, and Extreme Greed is defined as FGI ≥ 76. For each sentiment level, a quantile regression is run within the range when the values of Extreme Fear correspond to q = 0.10, Fear to q = 0.20, Neutral to q = 0.50, Greed to q = 0.70, and Extreme Greed to q = 0.90.

In Table 5, we report the quantile regression results across different sentiment levels and discuss the relationships between various predictors and negative realized skewness.

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At the extreme fear sentiment level, we observe that the FGI index has a negative coefficient of -0.002, but it is insignificant. The USDX has a positive and significant coefficient of 0.025 at the 1% significance level, suggesting that an increase in USDX increases negative realized skewness. The bearish sentiment has a significant negative coefficient of -0.074 at the 1% significance level, indicating that increased bearish sentiment reduces negative realized skewness. The VIX index has a significant negative coefficient of -0.056 at the 1% significance level, indicating that higher market volatility reduces negative realized skewness. The return variable has a significant positive coefficient of 0.272 at the 1% significance level, suggesting that higher returns increase negative realized skewness, which aligns with the concept that higher returns can lead to increased asymmetry in the distribution of returns (see Boyer *et al.* [67]).

For the fear sentiment level, the FGI index has a positive coefficient of 0.010, but it is insignificant. The USDX has a negative but insignificant relationship with a coefficient of -0.004. The bearish sentiment has a positive coefficient of 0.019, which is insignificant. The bullish sentiment shows a positive coefficient of 0.031, which is also insignificant. The VIX index has a significant negative coefficient of -0.121 at the 1% significance level. The return variable shows a significant negative relationship with negative realized skewness, with a coefficient of -0.368 at the 5% significance level.

In the neutral sentiment level, the FGI index is insignificant, with a coefficient of -0.012. The USDX has a negative but insignificant relationship with a coefficient of -0.004. The bearish sentiment has a significant positive coefficient of 0.037 at the 5% significance level, and the bullish sentiment also shows a significant positive coefficient of 0.029 at the 5% significance level. The VIX index has a significant negative coefficient of -0.094 at the 1% significance level. The return variable is insignificant.

At the greed sentiment level, the FGI index has a negative but insignificant coefficient of -0.004. The USDX has a significant positive relationship with a coefficient of 0.009 at the 1% significance level. The bearish sentiment has a negative coefficient of -0.009 at a 10% significance level. The bullish sentiment has a significant negative coefficient of -0.024 at the 1% significance level. The VIX index has a significant negative coefficient of -0.015 at the 1% significance level. The return variable is insignificant.

For the extreme greed sentiment level, the FGI index has a negative but insignificant coefficient of -0.003. The USDX has a significant positive relationship with a coefficient of 0.005 at the 1% significance level. The bearish sentiment has a significant negative coefficient of -0.015 at the 1% significance level, indicating that increased bearish sentiment reduces negative realized skewness. The bullish sentiment also shows a significant negative coefficient of -0.039 at the 1% significance level. The VIX index has a significant negative coefficient of -0.012 at the 1% significance level. The return variable has a significant negative coefficient of -0.077 at the 1% significance level, suggesting that higher returns reduce negative realized skewness.

The findings show that VIX consistently reduces negative realized skewness, mitigating downside risk during extreme fear and greed. Additionally, bearish and bullish sentiments reduce negative skewness during extreme fear and greed. This reflects a potential market correction mechanism, where extreme optimism is tempered by sentiment dynamics.

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Table 5. Quantile regression across sentiment levels where the dependent variable is negative realized skewness.

Sentiment Level	Predictor	Coefficient	Std. Error	t-value	P-value
Extreme Fear	FGI	-0.002	0.006	-0.368	0.713
	USDX	0.025	0.005	5.150	0.000
	BEARISH	-0.074	0.009	-8.604	0.000
	BULLISH	-0.026	0.008	-3.229	0.001
	VIX	-0.056	0.006	-8.918	0.000
	return	0.272	0.083	3.288	0.001
	cons	-2.784	0.743	-3.747	0.000
	Number of obs	411			
	Pseudo R^2	0.438			
Fear	FGI	0.010	0.017	0.581	0.562
	USDX	-0.004	0.011	-0.385	0.700
	BEARISH	0.019	0.028	0.689	0.491
	BULLISH	0.031	0.025	1.239	0.216
	VIX	-0.121	0.020	-5.930	0.000
	return	-0.368	0.165	-2.238	0.026
	cons	-3.885	2.011	-1.932	0.054
	Number of obs	593			
	Pseudo R^2	0.188			
Neutral	FGI	-0.012	0.016	-0.735	0.463
	USDX	-0.004	0.007	-0.603	0.547
	BEARISH	0.037	0.019	1.958	0.051
	BULLISH	0.029	0.014	2.096	0.037
	VIX	-0.094	0.009	-10.360	0.000
	return	0.072	0.085	0.848	0.397
	cons	-2.954	1.336	-2.211	0.028
	Number of obs	428			
	Pseudo R^2	0.108			
Greed	FGI	-0.004	0.003	-1.486	0.138
	USDX	0.009	0.002	4.679	0.000
	BEARISH	-0.009	0.005	-1.827	0.068
	BULLISH	-0.024	0.004	-6.309	0.000
	VIX	-0.015	0.002	-6.953	0.000
	return	-0.007	0.024	-0.303	0.762
	cons	-1.624	0.325	-5.005	0.000
	Number of obs	807			
	Pseudo R^2	0.083			
Extreme Greed	FGI	-0.003	0.002	-1.795	0.074
	USDX	0.005	0.001	3.719	0.000
	BEARISH	-0.015	0.004	-3.897	0.000
	BULLISH	-0.039	0.003	-11.437	0.000
	VIX	-0.012	0.001	-13.549	0.000
	return	-0.077	0.018	-4.341	0.000
	cons	-0.183	0.303	-0.603	0.547
	Number of obs	296			
	Pseudo R^2	0.255			

This table reports the quantile regressions where negative realized skewness is the dependent variable. The data spans January 3, 2011, to September 18, 2020, where FGI is the Fear and Greed index, USDX is the US dollar index, BEARISH is the bearish index, and BULLISH is the bullish index, VIX is the CBOE volatility index. Extreme Fear is defined as FGI $\leq$ 24, Fear is defined as 25 $\leq$ FGI $\leq$ 44, Neutral is defined as 45 $\leq$ FGI $\leq$ 55, Greed is defined as 56 $\leq$ FGI $\leq$ 75, and Extreme Greed is defined as FGI $\geq$ 76. For each sentiment level, a quantile regression is run within the range when the values of Extreme Fear correspond to q = 0.10, Fear to q = 0.20, Neutral to q = 0.50, Greed to q = 0.70, and Extreme Greed to q = 0.90.

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Table 6 reports the quantile regression results across different sentiment levels and discusses the relationships between various predictors and positive realized skewness.

At the extreme fear sentiment level, we note that the FGI index has a negative and significant coefficient of -0.005 at the 1% significance level, indicating that increased fear reduces positive realized skewness. The USDX has a positive but insignificant coefficient of 0.001. The bearish sentiment has a significant positive coefficient of 0.008 at the 1% significance level, and the bullish sentiment also shows a significant positive coefficient of 0.007 at the 1% significance level. This suggests that both bearish and bullish sentiments increase positive realized skewness. The VIX index is insignificant, while the return variable has a significant negative coefficient of -0.081 at the 1% significance level, indicating that higher returns reduce positive realized skewness.

For the fear sentiment level, the FGI index has a positive and significant coefficient of 0.004 at the 5% significance level. The USDX has a positive and significant relationship with a coefficient of 0.004 at the 1% significance level. Both the bearish and bullish sentiments exhibit significant positive coefficients of 0.010 and 0.004 at the 1% and 5% significance levels, respectively. The VIX index has a significant positive coefficient of 0.004 at the 5% significance level, indicating that higher market volatility increases positive realized skewness. The return variable shows a significant negative relationship with positive realized skewness, with a coefficient of -0.037 at the 1% significance level.

The FGI index is insignificant in the neutral sentiment level, with a coefficient of 0.007. The USDX has a positive but insignificant relationship with a coefficient of 0.008. The bearish sentiment has a positive coefficient of 0.015, which is insignificant. The bullish sentiment shows a positive coefficient of 0.021 at 10% significance level. The VIX index is insignificant, and the return variable is also insignificant. These results suggest that during neutral sentiment periods, the predictors do insignificantly impact positive realized skewness.

At the greed sentiment level, the FGI index has a negative but insignificant coefficient of -0.036. The USDX has a significant negative relationship with a coefficient of -0.058 at the 1% significance level. The bearish sentiment has a negative but insignificant coefficient of -0.057, and the bullish sentiment is insignificant. The VIX index has a negative but insignificant coefficient of -0.019. The return variable shows a significant positive relationship with positive realized skewness, with a coefficient of 1.471 at the 1% significance level, suggesting that higher returns increase positive realized skewness. This is supported by findings from Conrad *et al.* [68] on the relationship between returns and skewness.

For the extreme greed sentiment level, the FGI index has a negative but insignificant coefficient of -0.019. The USDX has a significant negative relationship with a coefficient of -0.181 at the 1% significance level. The bearish sentiment has a significant negative coefficient of -0.531 at the 1% significance level, indicating that increased bearish sentiment reduces positive realized skewness. The bullish sentiment also shows a significant negative coefficient of -0.220 at the 1% significance level. The VIX index has a significant negative coefficient of -0.036 at the 1% significance level. The return variable has a significant positive coefficient of 0.625 at the 1% significance level, suggesting that higher returns increase positive realized skewness.

The results show the asymmetry effects of bearish and bullish sentiments on positive realized skewness across sentiment levels. While both sentiments significantly increase positive realized skewness during periods of extreme fear and fear, they exhibit a negative effect during periods of extreme greed, where both bearish and bullish sentiments reduce positive realized skewness. This suggests that during periods of heightened market fear, investors' actions driven by both negative and positive sentiment contribute to an increase in positive skewness, while in times of extreme greed, these sentiments suppress positive skewness, reflecting different market dynamics under varying emotional extremes.

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Table 6. Quantile regression across sentiment levels where the dependent variable is positive realized skewness.

Sentiment Level	Predictor	Coefficient	Std. Error	t-value	P-value
Extreme Fear	FGI	-0.005	0.001	-3.707	0.000
	USDX	0.001	0.001	1.109	0.268
	BEARISH	0.008	0.002	4.230	0.000
	BULLISH	0.007	0.002	3.951	0.000
	VIX	0.002	0.001	1.280	0.201
	return	-0.081	0.019	-4.255	0.000
	cons	1.754	0.171	10.235	0.000
	Number of obs	411			
	Pseudo R^2	0.136			
Fear	FGI	0.004	0.001	2.442	0.015
	USDX	0.004	0.001	4.589	0.000
	BEARISH	0.010	0.002	4.007	0.000
	BULLISH	0.004	0.002	2.060	0.040
	VIX	0.004	0.002	2.505	0.013
	return	-0.037	0.014	-2.661	0.008
	cons	1.351	0.170	7.933	0.000
	Number of obs	593			
	Pseudo R^2	0.054			
Neutral	FGI	0.007	0.013	0.528	0.598
	USDX	0.008	0.006	1.446	0.149
	BEARISH	0.015	0.015	0.989	0.323
	BULLISH	0.021	0.011	1.901	0.058
	VIX	0.001	0.007	0.106	0.915
	return	0.128	0.068	1.877	0.061
	cons	0.106	1.066	0.099	0.921
	Number of obs	428			
	Pseudo R^2	0.021			
Greed	FGI	-0.036	0.026	-1.398	0.163
	USDX	-0.058	0.019	-3.115	0.002
	BEARISH	-0.057	0.046	-1.239	0.216
	BULLISH	0.013	0.036	0.370	0.711
	VIX	-0.019	0.020	-0.936	0.349
	return	1.471	0.229	6.431	0.000
	cons	11.623	3.053	3.807	0.000
	Number of obs	807			
	Pseudo R^2	0.157			
Extreme Greed	FGI	-0.019	0.014	-1.387	0.167
	USDX	-0.181	0.010	-18.308	0.000
	BEARISH	-0.531	0.028	-18.846	0.000
	BULLISH	-0.220	0.025	-8.793	0.000
	VIX	-0.036	0.007	-5.325	0.000
	return	0.625	0.130	4.792	0.000
	cons	46.606	2.238	20.828	0.000
	Number of obs	296			
	Pseudo R^2	0.466			

This table reports the quantile regressions where positive realized skewness is the dependent variable. The data spans January 3, 2011, to September 18, 2020, where FGI is the Fear and Greed index, USDX is the US dollar index, BEARISH is the bearish index, and BULLISH is the bullish index, VIX is the CBOE volatility index. Extreme Fear is defined as FGI $\leq$ 24, Fear is defined as 25 $\leq$ FGI $\leq$ 44, Neutral is defined as 45 $\leq$ FGI $\leq$ 55, Greed is defined as 56 $\leq$ FGI $\leq$ 75, and Extreme Greed is defined as FGI $\geq$ 76. For each sentiment level, a quantile regression is run within the range when the values of Extreme Fear correspond to q = 0.10, Fear to q = 0.20, Neutral to q = 0.50, Greed to q = 0.70, and Extreme Greed to q = 0.90.

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Table 7 reports the quantile regression results across different sentiment levels and provides critical insights into the relationships between various predictors and realized kurtosis.

At the extreme fear sentiment level, we note that the FGI index has a significant negative coefficient of -0.051 at the 1% significance level, indicating that increased fear reduces the extremeness of return distributions. This is consistent with findings by Baker and Wurgler [69] who show that investor sentiment significantly impacts market returns and their distributions. The USDX has a positive and significant coefficient of 0.022 at the 5% significance level, suggesting that a stronger USDX increases realized kurtosis, likely due to increased market uncertainty. This finding is supported by Ehrmann *et al.* [60], who explore the international financial transmission mechanisms and suggest that fluctuations in the US DOLLAR can significantly affect market conditions and uncertainty. In the cases of bearish and bullish sentiments, we observe significant positive coefficients of 0.119 and 0.112 at the 1% significance level, respectively, indicating that these sentiments contribute to higher realized kurtosis. The VIX index has a significant negative coefficient of -0.045 at the 1% significance level, suggesting that higher market volatility tends to reduce realized kurtosis. Andersen *et al.* [63] provide evidence of the impact of volatility on the return distribution's higher moments, which is consistent with this finding. The return variable has a significant positive coefficient of 0.333 at the 5% significance level, indicating that returns increase the extremeness of the distribution during extreme fear.

For the fear sentiment level, the FGI index has a positive but not statistically significant coefficient of 0.010. The USDX has a significant positive relationship with a coefficient of 0.036 at the 1% significance level. Both the bearish and bullish sentiments exhibit significant positive coefficients of 0.041 and 0.062 at the 5% and 1% significance levels, respectively, suggesting that these sentiments increase realized kurtosis. The VIX index is insignificant in this quantile. The return variable shows a significant positive relationship with realized kurtosis, with a coefficient of 0.394 at the 1% significance level.

In the neutral sentiment level, the FGI index is insignificant, with a coefficient of -0.133. Similarly, the USDX is insignificant. The bearish sentiment has a negative coefficient of -0.388 and the bullish sentiment has a negative coefficient of -0.283, both not statistically significant. The VIX index shows a significant positive coefficient of 0.357 at the 1% significance level, indicating that market volatility increases realized kurtosis. The return variable is insignificant.

At the greed sentiment level, the FGI index has a negative but insignificant coefficient of -0.244. The USDX has a significant negative relationship with a coefficient of -0.607 at the 1% significance level. The bearish sentiment has a significant negative coefficient of -0.982 at the 5% significance level, indicating that increased bearish sentiment reduces realized kurtosis. The bullish sentiment and VIX are insignificant. The return variable shows a significant positive relationship with realized kurtosis, with a coefficient of 11.558 at the 1% significance level.

For the extreme greed sentiment level, the FGI index has a negative and insignificant coefficient of -0.172. The USDX has a highly significant negative relationship with realized kurtosis, with a coefficient of -1.314 at the 1% significance level. The bearish sentiment has a significant negative coefficient of -4.075, and the bullish sentiment also shows a significant negative coefficient of -1.602 at the 1% significance level, respectively. The VIX index shows a significant negative coefficient of -0.287 at the 5% significance level, indicating that higher market volatility reduces realized kurtosis. The return variable has a significant positive coefficient of 7.629 at the 1% significance level, suggesting that returns increase the extremeness of the distribution during extreme greed.

In summary, the results show how different sentiment indices uniquely influence realized kurtosis across various conditions. During periods of extreme fear and fear, the FGI index and sentiments (bearish and bullish) significantly impact realized kurtosis, indicating changes in the extremeness of return distributions. The USDX has a significant effect, particularly during extreme fear and extreme greed, highlighting its crucial role in market uncertainty. The VIX index consistently influences kurtosis across sentiment levels, this highlights the importance of market volatility in shaping return

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distributions. The return variable maintains a significant positive relationship with realized kurtosis, emphasizing its persistent impact on return extremeness across different sentiment conditions. The results suggest that understanding the influence of investor sentiment on return distributions leads to more precise risk assessments and enhances the accuracy of predictive models.

Table 7. Quantile regression across sentiment levels where the dependent variable is realized kurtosis.

Sentiment Level	Predictor	Coefficient	Std. Error	t-value	P-value
Extreme Fear	FGI	-0.051	0.012	-4.264	0.000
	USDX	0.022	0.009	2.417	0.016
	BEARISH	0.119	0.017	7.226	0.000
	BULLISH	0.112	0.015	7.306	0.000
	VIX	-0.045	0.012	-3.724	0.000
	return	0.333	0.158	2.107	0.036
	cons	-4.224	1.422	-2.969	0.003
	Number of obs	411			
	Pseudo R^2	0.080			
Fear	FGI	0.010	0.013	0.793	0.428
	USDX	0.036	0.008	4.247	0.000
	BEARISH	0.041	0.021	1.973	0.049
	BULLISH	0.062	0.018	3.375	0.001
	VIX	0.011	0.015	0.701	0.483
	return	0.394	0.123	3.209	0.001
	cons	-3.386	1.499	-2.258	0.024
	Number of obs	593			
	Pseudo R^2	0.026			
Neutral	FGI	-0.133	0.220	-0.607	0.544
	USDX	0.028	0.094	0.293	0.769
	BEARISH	-0.388	0.254	-1.526	0.128
	BULLISH	-0.283	0.189	-1.497	0.135
	VIX	0.357	0.123	2.899	0.004
	return	0.652	1.151	0.567	0.571
	cons	28.340	18.054	1.570	0.117
	Number of obs	428			
	Pseudo R^2	0.060			
Greed	FGI	-0.244	0.236	-1.036	0.301
	USDX	-0.607	0.170	-3.567	0.000
	BEARISH	-0.982	0.418	-2.348	0.019
	BULLISH	-0.352	0.328	-1.075	0.283
	VIX	-0.128	0.181	-0.708	0.479
	return	11.558	2.090	5.530	0.000
	cons	126.066	27.892	4.520	0.000
	Number of obs	807			
	Pseudo R^2	0.150			
Extreme Greed	FGI	-0.172	0.244	-0.706	0.481
	USDX	-1.314	0.176	-7.455	0.000
	BEARISH	-4.075	0.501	-8.130	0.000
	BULLISH	-1.602	0.446	-3.594	0.000
	VIX	-0.287	0.119	-2.414	0.016
	return	7.629	2.320	3.288	0.001
	cons	336.144	39.794	8.447	0.000
	Number of obs	296			
	Pseudo R^2	0.468			

This table reports the quantile regressions where realized kurtosis is the dependent variable. The data spans January 3, 2011, to September 18, 2020, where FGI is the Fear and Greed index, USDX is the US dollar index, BEARISH is the bearish index, and BULLISH is the bullish index, VIX is the CBOE volatility index. Extreme Fear is defined as FGI ≤ 24, Fear is defined as $25 \leq \text{FGI} \leq 44$, Neutral is defined as $45 \leq \text{FGI} \leq 55$, Greed is defined as $56 \leq \text{FGI} \leq 75$, and Extreme Greed is defined as FGI ≥ 76. For each sentiment level, a quantile regression is run within the range when the values of Extreme Fear correspond to q = 0.10, Fear to q = 0.20, Neutral to q = 0.50, Greed to q = 0.70, and Extreme Greed to q = 0.90.

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5.2. Robustness Test: Quantile Regressions with Non-Linear Effects

In Table 8, we report the result for the quantile regressions with non-linear effects of Fear and Greed Index (FGI) during periods of extreme fear and extreme greed. The analysis focuses on realized volatility (RV), realized skewness (RS), negative realized skewness (RS(-)), positive realized skewness (RS(+)), and realized kurtosis (RK) as the dependent variables. The non-linear effect is captured by including the squared term of the FGI in the regression model of Equation 10.

Table 8. Quantile regression with non-linear effects focusing on extreme fear and extreme greed sentiment levels.

Sentiment Level : Extreme Fear						Sentiment Level : Extreme Greed					
Dependent Variable	**Predictor**	**Coefficient**	**Std. Error**	**t-value**	**P-value**	**Dependent Variable**	**Predictor**	**Coefficient**	**Std. Error**	**t-value**	**P-value**
RV	FGI	-2.4099E-07	3.17415E-07	-0.759	0.448	RV	FGI	-1.7988E-07	1.0473E-05	-0.017	0.986
	FGI^2	-6.99524E-09	1.14098E-08	-0.613	0.540		FGI^2	1.60572E-09	6.1876E-08	0.026	0.979
	USDX	3.04373E-07	5.55956E-08	5.475	0.000		USDX	9.08976E-08	2.178E-07	0.417	0.677
	BEARISH	9.9135E-08	1.00546E-07	0.986	0.325		BEARISH	-6.27661E-07	6.3823E-07	-0.983	0.326
	BULLISH	8.87201E-08	9.32592E-08	0.951	0.342		BULLISH	-4.66088E-07	5.5978E-07	-0.833	0.406
	VIX	3.34928E-07	7.33067E-08	4.569	0.000		VIX	-6.32988E-07	1.4706E-07	-4.304	0.000
	return	-2.12938E-06	9.63981E-07	-2.209	0.028		return	7.26003E-06	2.9039E-06	2.500	0.013
	cons	-1.74238E-05	8.84158E-06	-1.971	0.049		cons	1.04162E-04	4.3413E-04	0.240	0.811
	Number of obs	411					Number of obs	296			
	Pseudo R^2	0.154					Pseudo R^2	0.326			
RS	FGI	0.017	0.023	0.753	0.452	RS	FGI	0.684	1.139	0.601	0.549
	FGI^2	-0.001	0.001	-0.747	0.456		FGI^2	-0.004	0.007	-0.652	0.515
	USDX	0.011	0.004	2.896	0.004		USDX	-0.184	0.024	-7.757	0.000
	BEARISH	-0.055	0.007	-7.752	0.000		BEARISH	-0.548	0.069	-7.902	0.000
	BULLISH	-0.002	0.007	-0.234	0.815		BULLISH	-0.179	0.061	-2.947	0.003
	VIX	-0.029	0.005	-5.588	0.000		VIX	-0.058	0.016	-3.604	0.000
	return	1.675	0.068	24.486	0.000		return	1.893	0.316	5.994	0.000
	cons	-0.915	0.628	-1.458	0.146		cons	14.450	47.209	0.306	0.760
	Number of obs	411					Number of obs	296			
	Pseudo R^2	0.386					Pseudo R^2	0.528			
RS(-)	FGI	-0.019	0.027	-0.694	0.488	RS(-)	FGI	-0.079	0.071	-1.100	0.272
	FGI^2	0.001	0.001	0.542	0.588		FGI^2	0.000	0.000	1.041	0.299
	USDX	0.024	0.005	5.079	0.000		USDX	0.005	0.001	3.411	0.001
	BEARISH	-0.075	0.009	-8.723	0.000		BEARISH	-0.011	0.004	-2.558	0.011
	BULLISH	-0.026	0.008	-3.288	0.001		BULLISH	-0.036	0.004	-9.304	0.000
	VIX	-0.056	0.006	-9.034	0.000		VIX	-0.012	0.001	-12.066	0.000
	return	0.254	0.082	3.095	0.002		return	-0.068	0.020	-3.454	0.001
	cons	-2.595	0.753	-3.446	0.001		cons	2.758	2.962	0.931	0.353
	Number of obs	411					Number of obs	296			
	Pseudo R^2	0.438					Pseudo R^2	0.256			
RS(+)	FGI	-0.010	0.007	-1.534	0.126	RS(+)	FGI	0.139	0.479	0.289	0.773
	FGI^2	0.000	0.000	0.652	0.515		FGI^2	-0.001	0.003	-0.325	0.745
	USDX	0.001	0.001	1.177	0.240		USDX	-0.184	0.010	-18.491	0.000
	BEARISH	0.008	0.002	3.903	0.000		BEARISH	-0.540	0.029	-18.494	0.000
	BULLISH	0.007	0.002	3.706	0.000		BULLISH	-0.228	0.026	-8.919	0.000
	VIX	0.001	0.002	0.930	0.353		VIX	-0.036	0.007	-5.357	0.000
	return	-0.090	0.020	-4.430	0.000		return	0.604	0.133	4.544	0.000
	cons	1.778	0.187	9.498	0.000		cons	40.790	19.858	2.054	0.041
	Number of obs	411					Number of obs	296			
	Pseudo R^2	0.137					Pseudo R^2	0.466			
RK	FGI	-0.171	0.048	-3.544	0.000	RK	FGI	-3.505	9.212	-0.380	0.704
	FGI^2	0.004	0.002	2.245	0.025		FGI^2	0.019	0.054	0.349	0.727
	USDX	0.015	0.008	1.801	0.072		USDX	-1.420	0.192	-7.414	0.000
	BEARISH	0.096	0.015	6.299	0.000		BEARISH	-4.241	0.561	-7.555	0.000
	BULLISH	0.097	0.014	6.800	0.000		BULLISH	-1.624	0.492	-3.299	0.001
	VIX	-0.028	0.011	-2.552	0.011		VIX	-0.274	0.129	-2.122	0.035
	return	0.469	0.147	3.193	0.002		return	7.607	2.554	2.978	0.003
	cons	-1.989	1.346	-1.477	0.140		cons	495.887	381.869	1.299	0.195
	Number of obs	411					Number of obs	296			
	Pseudo R^2	0.087					Pseudo R^2	0.469			

This table reports the quantile regressions with non-linear effects focusing on extreme fear and extreme greed sentiment levels. The data spans January 3, 2011, to September 18, 2020, where FGI is the Fear and Greed index, USDX is the US dollar index, BEARISH is the bearish index, and BULLISH is the bullish index, VIX is the CBOE volatility index. RV is realized volatility, RS is realized skewness, RS(-) is negative realized skewness, RS(+) is positive realized skewness, and RK is realized kurtosis. Extreme Fear is defined as FGI ≤ 24 and Extreme Greed is defined as FGI ≥ 76. For each sentiment level, quantile regression is run within the range when the values of Extreme Fear correspond to q = 0.10, and Extreme Greed to q = 0.90.

For the extreme fear sentiment level, with realized volatility as the dependent variable, we observe that the coefficients of FGI and its squared term are statistically insignificant. This indicates that the non-linear effects of FGI do not impact realized volatility under extreme fear conditions. The USDX index, has a positive and significant effect at the 1% level, suggesting that a stronger USDX index increases realized volatility, consistent with the results discussed in Table 3. The bearish and bullish indices have a positive but insignificant relationship with realized volatility. The VIX index shows a positive and significant relationship with realized volatility at the 1% level, indicating that higher

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market volatility increases realized volatility. The return variable has a significant negative coefficient, suggesting that higher levels of return tend to reduce realized volatility, possibly due to the stabilizing effect of high returns on market expectations.

For the extreme greed sentiment level, with realized volatility as the dependent variable, the coefficients for the FGI and its squared term are insignificant. This suggests that the non-linear effects of FGI do not impact realized volatility under extreme greed conditions. The USDX index is also insignificant. The bearish and bullish indices have a negative but insignificant relationship with realized volatility. The VIX index has a significant negative coefficient, suggesting that higher market volatility decreases realized volatility during extreme greed. This finding shows the unique market reaction to volatility in periods of extreme fear and extreme greed. The return variable shows a significant positive relationship, indicating that higher returns increase realized volatility.

With realized skewness as the dependent variable under extreme fear, the FGI and its squared term are insignificant. However, the USDX index is positively significant, suggesting that a stronger USDX index increases realized skewness. Bearish sentiment has a significant negative effect, indicating that increased bearish sentiment reduces realized skewness. The bullish index, on the other hand, has a negative but insignificant relationship with realized skewness. The VIX index shows a negative and significant relationship, indicating that higher market volatility reduces realized skewness. The return variable has a significant positive relationship with realized skewness, indicating that higher returns increase realized skewness.

For realized skewness under extreme greed, the FGI and its squared term are insignificant. The USDX index is significant and negative, indicating that a stronger USDX index decreases realized skewness. Both bearish and bullish sentiments have significant negative effects, indicating that these sentiments reduce realized skewness during extreme greed. The VIX index is also negative and significant. The return variable shows a significant positive relationship, suggesting that higher returns increase realized skewness. This shows that in periods of extreme greed, investors experience significant positive returns while periods of extreme fear lead to significant negative returns.

For negative realized skewness under extreme fear, the FGI and its squared term are insignificant. The USDX index is positive and significant, indicating that a stronger USDX index increases negative realized skewness. Both bearish and bullish sentiments have significant negative effects, suggesting that these sentiments reduce negative realized skewness. The VIX index is negative and significant, and the return variable shows a significant positive relationship, suggesting that higher returns increase negative realized skewness.

For negative realized skewness under extreme greed, the FGI and its squared term are also insignificant. The USDX index is positive and significant, indicating that a stronger USDX index increases negative realized skewness. Both bearish and bullish sentiments have significant negative effects. The VIX index is negative and significant. The return variable shows a significant negative relationship, suggesting that higher returns reduce negative realized skewness.

With positive realized skewness under extreme fear, the FGI and its squared term are insignificant. The USDX index is insignificant as well. While both bearish and bullish sentiments have significant positive effects, indicating that these sentiments increase positive realized skewness. The VIX index is insignificant. The return variable shows a significant negative relationship, suggesting that higher returns reduce positive realized skewness.

For positive realized skewness under extreme greed, the FGI and its squared term are insignificant. The USDX index is significant and negative. Both bearish and bullish sentiments have significant negative effects. The VIX index is negative and significant. The return variable shows a significant positive relationship, suggesting that higher returns increase positive realized skewness.

For realized kurtosis under extreme fear, the FGI is significant and negative, indicating that increased fear reduces realized kurtosis. The FGI squared term is positive and significant. This shows the significant non-linear dynamic effect FGI has with realized kurtosis, suggesting a threshold effect, where extreme fear first stabilizes return distributions (lower kurtosis), but beyond a certain point, it amplifies tail risks, leading to a fatter-tailed distribution (higher kurtosis). The USDX index is significant at a 10% level. Both bearish and bullish sentiments have significant positive effects. The VIX index is negative and significant. The return variable shows a significant positive relationship, suggesting that higher returns increase realized kurtosis.

For realized kurtosis under extreme greed, the FGI and its squared term are insignificant. The USDX index is significant and negative. Both bearish and bullish sentiments have a significant negative relationship with realized kurtosis. The VIX index is negative and significant. The return variable shows a significant positive relationship, suggesting that higher returns increase realized kurtosis.

In summary, the results show that during periods of extreme greed, higher market volatility (VIX) reduces realized volatility, skewness, and kurtosis, suggesting that extreme optimism dampens market distortions and stabilizes the distribution of returns, contrary to typical expectations of heightened volatility and risk during such periods. This implies that investor sentiment can significantly alter market dynamics, leading to unexpected stabilization even when volatility is perceived to be high.

6. Conclusion

This study investigates the relationship between realized higher-order moments and the Fear and Greed Index. Using 5-minute return data from January 3, 2011, to September 18, 2020, we estimate daily realized moments for the US stock market index (S&P 500 index).

Our findings show how different economic indicators and sentiment indices influence market behaviour under varying conditions. We note that the Fear and Greed index significantly impacts realized volatility during periods of extreme fear and fear, reflecting the strong impact of investor sentiment on market dynamics. The USDX index plays a critical role in market uncertainty, particularly, affecting volatility during extreme fear and neutral sentiment levels. Additionally, the VIX index consistently impacts volatility across all sentiment levels, this suggests the relevance of market volatility in shaping realized volatility. The return variable has a persistent relationship with volatility during extreme fear, greed, and extreme greed which highlights its ongoing impact on market dynamics.

For realized skewness, we note that the USDX index and returns consistently impact skewness across various sentiment levels, while bearish and bullish sentiments tend to reduce skewness during periods of greed. We observe that during periods of extreme fear and fear, the Fear and Greed index, bearish, and bullish sentiments significantly increase positive realized skewness. Also, during extreme greed, the bearish and bullish sentiments tend to reduce positive skewness. The VIX index generally reduces skewness across most sentiment levels but increases positive realized skewness during fear sentiment and reduces it during greed sentiment. These relationships highlight the complex role market sentiment plays in shaping the asymmetric nature of asset return distributions.

Our results also reveal significant variations for realized kurtosis across different sentiment conditions. We note that the Fear and Greed index, and the bearish and bullish sentiments significantly impact realized kurtosis during extreme fear and fear periods, this shows changes in the extremeness of return distributions. The USDX index significantly affects kurtosis positively and negatively during extreme fear and extreme greed periods, respectively. The VIX index has a significant negative relationship with realized kurtosis during extreme fear and extreme greed periods. The return variable has a significant positive relationship with realized kurtosis across all sentiment levels, highlighting its persistent impact on return extremeness. The results remain consistent when controlling for the non-linear attributes of the Fear and Greed index during periods of extreme fear and extreme greed. These relationships show the significant and unique role market sentiment plays in shaping the extremity nature of asset return distributions.

The findings are important for financial risk management and modeling, as they show that varying sentiment levels significantly affect the relationship between market sentiments and realized moments. This suggests that understanding these dynamics allows investors and risk managers to better anticipate market behaviour and adjust their strategies accordingly.

The limitations of this study include: (i) the focus on the US index rather than individual stocks was determined by the availability of high-frequency data for the estimation of higher-order moments in the considered period, and (ii) the availability of the Fear and Greed index.

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