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Original Research

Delta Implied Volatility Spread, Short Selling, and Abnormal Stock Performance: Evidence from the Put-to-Call Volume Ratio in the Tehran Stock Exchange

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ABSTRACT
In recent years, derivatives markets have emerged as important sources of latent information about investor behavior, and their role in explaining stock return dynamics especially in emerging markets has gained growing attention. This study aims to assess how key derivatives-based indicators, including the delta implied volatility spread, the put-to-call volume ratio, and short-selling activity, influence abnormal stock returns in the Tehran Stock Exchange and Iran Fara Bourse from March 2016 to September 2024. To achieve a more precise understanding of how these variables shape different parts of the return distribution, we employ quantile regression and strengthen the robustness of the estimates using BCa and Wild bootstrap procedures. The empirical findings show that option-based indicators contain meaningful informational content, and their effects on abnormal returns differ substantially across quantiles. Furthermore, the interaction terms demonstrate that the joint presence of the delta–implied volatility spread, the normalized put-to-call ratio, and the intensity of short-selling activity significantly enhances the model's explanatory power in the extreme parts of the return distribution. Overall, the results suggest that incorporating derivatives-market indicators alongside advanced statistical techniques provides a deeper understanding of risk-transmission mechanisms and investor behavior in emerging markets during periods of heightened uncertainty and market adjustment.

1 Introduction

In recent decades, financial markets have become dynamic systems, due to the expansion of innovative instruments and the increasing complexity of investor behavior. Under such circumstances, the mechanisms of price formation and the discovery of asset values are regarded as one of the central

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challenges in financial economics. Although classical models such as the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH) have provided robust theoretical frameworks, empirical evidence suggests that abnormal returns are prevalent across many markets—particularly in emerging markets—indicating that the efficient market assumption does not always hold in practice [18-19, 22, 44]. Behavioral factors such as investor overreaction and underreaction, liquidity constraints, transaction costs, and information asymmetry can lead to deviations in prices from their fundamental values. These deviations, which result in returns exceeding those predicted by traditional models, create opportunities for investors while simultaneously challenging existing financial theories. This theoretical gap has motivated researchers and market participants to explore new sources of information that are capable of explaining and forecasting such abnormal returns. In this context, derivative instruments, particularly option contracts, have emerged as a vital and innovative source of information for forecasting future stock returns. Due to their inherent characteristics, these instruments encapsulate investors' expectations and overall market sentiment. Although the trading mechanisms of options play an essential role in explaining abnormal returns, analyzing these mechanisms alone cannot fully account for all market phenomena. Therefore, examining option market activity from a behavioral finance perspective is also crucial. Within the behavioral finance framework, investor sentiment and cognitive biases can cause asset prices to deviate from their intrinsic values. Consequently, the measurement and quantification of such sentiments has become central topics in behavioral finance research. To this end, researchers commonly employ three key proxies implied volatility (IV)**,** the put-to-call trading volume ratio, and short-selling activity as indicators of investor sentiment and market expectations [1, 11, 17, 36, 38]. Implied volatility (IV), derived from option prices, reflects investors' expectations about future volatility. Atmaz and Buffa (2023) show that disagreement among investors affects volatility derivative trading and shapes asset prices, while Białkowski et al. (2022) highlight that IV's relation to policy uncertainty can be complex. Together, these studies support using IV as an informative indicator of market expectations and perceived risk [2, 6]. The importance of implied volatility extends beyond its ability to forecast future fluctuations; it also serves as a powerful proxy for market sentiment. During periods of financial distress, investors tend to pay a higher premium for options to hedge against potential losses and protect their portfolios. This increased demand drives up option prices, and consequently raises the level of implied volatility [32].

Another key measure of implied volatility is the put-to-call volume ratio (PCR), which provides an additional reflection of investor behavior and sentiment in the options market. An increase in this ratio indicates a higher demand for put options relative to call options. From a behavioral finance perspective, investors tend to buy put options when they expect prices to decline or seek protection against potential price drops. Therefore, elevated PCR levels are interpreted as a signal of bearish sentiment in the market and can serve as a predictor of negative returns in the near future. Conversely, a declining PCR suggests bullish sentiment and a potential increase in prices. Furthermore, the PCR is also recognized as a contrarian indicator, such that extremely high levels are often associated with subsequent positive abnormal returns, while very low levels tend to precede negative abnormal returns in subsequent periods [31, 41].

The application of the PCR indicator is not limited to gauging market sentiment; it also plays a significant role in designing options trading strategies. Empirical evidence suggests that incorporating the PCR can not only enhance portfolio risk management but also generate abnormal returns compared to traditional strategies. This functionality arises from the fact that the PCR reveals dimensions of market sentiment and behavior that are often overlooked within the framework of traditional asset pricing models [31, 24].

Just as the PCR reflects investor sentiment, short-selling also conveys investors' bearish expectations regarding the future trajectory of asset prices. As a key mechanism in financial markets, short-selling allows traders to profit from declining asset prices and, through the creation of corrective selling pressure, helps align prices with their intrinsic values. In efficient markets without short-selling constraints, such activity typically reduces abnormal returns and enhances market informational efficiency. Moreover, the pressure generated by short-selling can serve as a predictive signal, providing valuable information about future price trends and investor expectations. However, the presence of restrictions or prohibitions on short-selling may hinder this corrective role, potentially leading to excessive optimism and the emergence of abnormal returns in the market [10, 26]. Within this context, the present study aims to provide a novel perspective on investor behavior by utilizing option-based indicators while considering the hypothetical mechanism of short-selling. Accordingly, the main contribution of this research can be articulated along two dimensions.

- The application of the modified O/S Johnson and So [29] index for calculating the PCR, which, through normalization based on the number of outstanding shares, mitigates constraints arising from firm size and trading intensity, thereby enabling meaningful comparisons across stocks with different characteristics.
- The analysis of the hypothetical short-selling mechanism in a market such as Iran, where no formal framework exists for conducting such activities.

The combination of these two dimensions provides a novel framework for examining collective investor behavior and predicting abnormal returns. Under such conditions, option-based indicators can serve as proxies for measuring negative expectations and investor biases while partially reflecting the informational role of short-selling, thereby contributing a significant scientific addition to the behavioral finance and derivatives literature.

Considering the importance of derivatives-based indicators in capturing investor sentiment, the main research question of this study is whether implied volatility, a newly introduced modified put–call ratio (PCR), and short-selling activity—individually or through their interaction effects—have predictive power for abnormal stock returns in the Tehran Stock Exchange and Iran Fara Bourse, and how these relationships vary across the return distribution. This study makes two key contributions. First, it introduces a modified PCR for the first time in the literature, integrating option-to-stock trading intensity into traditional sentiment measures. Second, it provides the first empirical implementation of a three-way interaction among short-selling activity, the delta-implied volatility spread, and the modified PCR, offering a novel mechanism to assess how sentiment-driven option pressures and short-selling jointly influence abnormal returns. Methodologically, the study combines option-derived measures with a hypothetical short-selling framework suitable for emerging markets and employs robust quantile regression techniques to capture heterogeneous effects across the return distribution.
The remainder of the paper is organized as follows: Section 2 presents the theoretical fundamentals and reviews the research background; Section 3 describes the methodology and variable construction; Section 4 reports the empirical findings; Section 5 outlines the limitations and provides recommendations; and Section 6 concludes the paper.

2 Theoretical Fundamentals and Research Background

One of the fundamental topics in financial economics is the examination of stock return behavior and the factors influencing it. In practice, investors are consistently in pursuit of achieving returns beyond expectations—commonly referred to as abnormal returns. Abnormal return denotes the difference between the actual return of a stock and its expected return as predicted by standard models such as the Market Model, the Capital Asset Pricing Model (CAPM), or the Fama–French Three-Factor Model. When the realized return exceeds the expected return, the abnormal return is positive; conversely, when it falls short, the abnormal return becomes negative. Examining this deviation is central to both the evaluation of asset-pricing models and the assessment of market informational efficiency.

In recent years, attention has increasingly shifted toward the role of derivatives markets in explaining the emergence of abnormal returns. Derivatives, and options in particular, function as dynamic arenas for aggregating private information and shaping investor expectations. Among the indicators derived from option prices, implied volatility stands out as a forward-looking measure that encapsulates the market's collective perception of future uncertainty and risk associated with the underlying asset. In essence, implied volatility reflects the consensus view of market participants about forthcoming price fluctuations and, as such, provides meaningful predictive insight into the direction of future returns [36, 38, 39, 43]. Empirical evidence further suggests that the relationship between implied volatility and subsequent stock performance is inherently asymmetric: negative returns tend to trigger sharper increases in implied volatility, while positive returns generally produce more moderate adjustments [33].

The relationship between implied volatility and abnormal returns can be articulated from various theoretical and empirical perspectives, the most prominent of which are as follows:

- **Predictive power beyond classical models:** Empirical research provides evidence that implied volatility possesses predictive capabilities for certain components of abnormal returns that cannot be explained by historical volatility or classical multi-factor models such as the Fama–French model [22]. In this regard, implied volatility serves as an informationally rich indicator, capturing forward-looking expectations and risk assessments that traditional backward-looking measures fail to encompass.
- **An independent risk factor:** Several studies have proposed that implied volatility can function as an independent risk factor within multi-factor asset pricing models, significantly enhancing their explanatory power in accounting for abnormal returns [40]. This suggests that market participants not only price assets based on conventional sources of systematic risk but also incorporate volatility-related risk premia derived from option markets.

Although in modern financial literature, implied volatility is widely recognized as a key indicator of market expectations [14, 33], more advanced analyses suggest that not only the absolute level of implied volatility but also the difference between call and put implied volatilities contains valuable predictive information [13,17, 30]. This difference—commonly referred to as the implied volatility spread —reflects the asymmetry in investors' expectations regarding the future return distribution of the underlying asset. From a behavioral finance perspective, this asymmetry is heavily influenced by investors' sentiment and their asymmetric risk-taking behavior. In a comprehensive study, Delisle et al. (2022) demonstrated that the implied volatility spread serves as a powerful predictor of future market returns. Their findings indicate that when this spread shifts toward more negative values—meaning that put implied volatility significantly exceeds call implied volatility—subsequent stock returns tend to decline markedly. This result underscores the notion that market fear, as embodied in the structure of implied volatility, can serve as a leading indicator of negative abnormal returns [14].

In addition to implied volatility, the put–call ratio (PCR) serves as a widely used proxy for investor sentiment in the derivatives market [27]. Elevated values of the PCR generally signal a predominance of bearish expectations and, particularly during periods of market stress, may indicate potential price reversals [37]. Despite its usefulness, the conventional PCR is subject to several limitations, as it does not adjust for differences in firm size, shares outstanding, or trading intensity. Building on the methodologies proposed by Cheshmen et al (2021) [8] and Johnson and So (2012) [29], the present study employs a modified PCR that normalizes option volumes by the number of underlying shares. This adjustment allows for more accurate cross-firm comparisons and enhances the reliability of sentiment-based analyses.

Beyond the options market, short-selling activity constitutes a central mechanism for price discovery and the revelation of negative information. Theoretically, in the absence of regulatory or institutional constraints, informed investors can engage in short selling of overvalued stocks to guide prices toward their fundamental levels. When such constraints exist—such as high borrowing costs or formal restrictions—the corrective function of short selling is impaired, creating conditions conducive to the persistence of abnormal returns [9, 34]. Empirical studies further indicate that short-selling pressure not only conveys valuable informational content but can also directly contribute to negative abnormal returns [20, 35]. Conversely, temporary short-selling bans, while generating short-term positive abnormal returns [4, 15], tend to reduce long-term market efficiency. Such interventions may shift selling pressure to alternative markets or amplify abnormal co-movements among targeted securities [5, 28].

In addition to derivative-based indicators and short-selling activity, firms' fundamental characteristics such as the book-to-market ratio (B/M), firm size, and past price trends exert a significant influence on abnormal return behavior. The book-to-market ratio serves as a measure of stock valuation, signaling the likelihood that a stock is overvalued or undervalued. Empirical studies indicate that stocks with low B/M ratios (growth stocks) are particularly susceptible to negative abnormal returns [21, 28]. Firm size similarly affects the formation of abnormal returns, as smaller firms—owing to lower liquidity and heightened sensitivity to information—tend to exhibit greater volatility and more pronounced abnormal reactions. Additionally, past price trends can provide predictive insight into future abnormal returns, reflecting the influence of investor behavior and psychological responses to prior market performance.

Although extensive research has examined implied volatility, implied volatility spread, put–call ratios, and short-selling individually, their joint effects on abnormal returns remain largely unexplored. This study addresses this gap by investigating the simultaneous influence of implied volatility, implied volatility spread, a newly introduced modified put–call ratio (PCR), and short-selling pressure on abnormal returns in the Iranian stock market. By analyzing these variables collectively, the paper uncovers latent relationships among market sentiment, informational dynamics, and return behavior, offering a novel perspective on asset pricing in emerging markets. Methodologically, the study employs regression analysis supplemented with advanced bootstrap techniques on historical market data, making it an applied-empirical, descriptive-analytical investigation designed to generate practical insights and support decision-making in the capital market.

3 Methodology

3.1 Population and Sample

The study population comprises companies listed with both call and put options on the Tehran Stock Exchange and Iran Fara Bourse during the period from April 2016 to September 2024. The statistical sample was determined using a systematic elimination method. Firms that did not satisfy the following criteria were excluded:

- Simultaneous availability of both call and put options.
- Availability of industry-specific information.
- Complete and continuous data for all research variables.
- A minimum of 50 active trading days per year.

Applying these selection criteria resulted in a final sample of 2,157 daily observations. The requirement for simultaneous call and put options notably reduced the sample size due to the relatively limited depth of the put option market on the Tehran Stock Exchange. However, this restriction ensures consistency in the computation of option-based variables and enhances the reliability and validity of the results. Data were sourced from audited financial statements, reports published through the CODAL system, and the databases of the Tehran Stock Exchange. Following collection, the data were cleaned, classified, and structured to align with the framework of the study variables, ensuring suitability for empirical analysis.

3.2 Variables

3.2.1 Dependent Variable

The dependent variable in this study is abnormal return, defined as the difference between a firm's realized stock return and the expected market return. Abnormal returns arise when information regarding a company's performance is incomplete or not fully transparent, creating conditions of information asymmetry that facilitate deviations from expected performance. This variable is computed according to Equation (1):

$$\mathrm{AR_{it}} = \mathrm{R_{it}} - \mathrm{E}(R_{\mathrm{it}}) \tag{1}$$

where $\mathrm{AR_{it}}$ represents the abnormal return of stock i in period t, R_{it} denotes the actual return of stock i in period t, and $\mathrm{E(R_{it})}$ is the expected return of stock i in period t, calculated using Equation (2).

$$\mathrm{E(R_{it})} = \alpha_\mathrm{i} + \beta_\mathrm{i}(\mathrm{R_{mt}}) + \varepsilon_i \tag{2}$$

$\mathrm{R_{mt}}$ represents the market return in period t, which is computed as specified in Equation (3).

$$\mathrm{R_{mt}} = \ln\frac{\mathrm{I_{mt}}}{\mathrm{I_{mo}}} \tag{3}$$

where I_{m0} and I_{mt} denote the overall stock index at the beginning and end of period t, respectively. ε_i is the error term representing the residual part of returns that cannot be explained by market movements.

3.2.2 Independent Variables

3.2.2.1 Implied Volatility Spread (Spread IV)

The difference between call and put implied volatilities serves as a key measure of market sentiment and a predictor of future volatility. This spread captures the market's directional bias, with positive values signalling a stronger inclination toward bullish movements and negative values indicating a tendency toward bearish expectations [3]. The implied volatility spread is calculated as follows:

$$\mathrm{SDIV} = \mathrm{IV}_{\mathrm{call}} - \mathrm{IV}_{\mathrm{put}} \quad (4)$$

where $IV_{\text{call},it}$ and $IV_{\text{put},it}$ denote the implied volatilities of the call and put options of stock i in period t, respectively. Implied volatility is typically estimated using the Black–Scholes option pricing model, according to which the theoretical value of a European call option is defined as follows [7, 42]:

$$\mathrm{C} = \mathrm{S_0 N(d_1)} - \mathrm{K}e^{-\mathrm{r_f T}}\mathrm{N(d_2)} \quad (5)$$

where:

$$\mathrm{d_1} = \frac{\ln\left(\frac{\mathrm{S_0}}{\mathrm{K}}\right) + \left(\mathrm{r_f} + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{\mathrm{T}}} \quad (6)$$

$$\mathrm{d_2} = \mathrm{d_1} - \sigma\sqrt{\mathrm{T}} \quad (7)$$

In the equations above, C represents the price of the call option, S_0 is the current price of the underlying asset, K denotes the strike price, r_f is the risk-free interest rate, and T represents the time remaining to maturity. When these variables are known, the implied volatility (σ) can be inferred from the observed market price of the call option. Specifically, implied volatility is obtained by inverting the Black–Scholes equation with respect to σ, as shown in Equation (8).

$$\sigma^*_{Call} = BS^{-1}(C;\ S_0.K.T.r_f) \quad (8)$$

Similarly, the implied volatility of a put option (IV_{put}) can be derived using the put–call parity relationship, which is expressed as follows:

$$P = C + Ke^{-r_f T} - S_0 \quad (9)$$

where p denotes the price of the put option. Given the observed market price of the call option and the corresponding model parameters, the theoretical value of the put option can be computed based on the put–call parity condition. Subsequently, the implied volatility of the put option (σ) is obtained by inverting the Black–Scholes equation with respect to σ.

$$\sigma^*_{put} = BS^{-1}(P;\ S_0.K.T.r_f) \quad (10)$$

Within the classical Black–Scholes framework, this relationship implies that the implied volatilities of put and call options are theoretically identical ($\sigma^*_{\text{put}} = \sigma^*_{\text{call}}$). In practice, however, market data often reveal discrepancies between the two. These differences arise from factors such as bid–ask spreads, cash settlement conventions, and the nonlinear shape of the volatility surface, which cause implied volatilities for puts and calls to diverge [12].

3.2.2.2 Implied Volatility Delta Spread (ΔIV)

To capture the difference between the implied volatilities of call and put options, the variable ΔIV is employed. This measure facilitates an assessment of the market's directional bias concerning movements in the underlying asset's price. A positive ΔIV indicates stronger optimism and expectations of price appreciation, whereas a negative value reflects market pessimism or an inclination toward hedging against downside risk. The ΔIV is defined as follows

$$S\Delta IV = \Delta IV_{call} - \Delta IV_{put} \tag{11}$$

where:

$$\Delta IV_{call} = \mathrm{IV}_{call} - IV_{VWA}^{call} \tag{12}$$

$$\Delta IV_{Put} = \mathrm{IV}_{put} - IV_{VWA}^{put} \tag{13}$$

$$IV_{VWA} = \sum_{i=1}^{a} \mathrm{IV}\left(\frac{\mathrm{V_i}}{\sum_{i=1}^{a} \mathrm{V_i}}\right) \tag{14}$$

where IV denotes the calculated implied volatility, IV_{VWA} represents the volume-weighted average implied volatility, i indicates the number of options in the given period, and V refers to the trading volume of each option.

3.2.2.3 Short Selling

Short selling is an advanced trading strategy through which an investor sells an asset not currently owned, aiming to profit from an anticipated decline in its price. Owing to Shariah compliance requirements, this strategy cannot be directly implemented in Islamic financial markets. Consequently, an alternative mechanism—commonly referred to as a commitment sale—has been introduced as a functional equivalent. Given the limited availability of data on commitment sale transactions, this study employs a dummy variable as a proxy for short-selling activity. The variable takes the value of 1 when a firm's return in a given period falls below the corresponding industry benchmark return, and 0 otherwise.

3.2.2.4 Put–Call Ratio (PCR)

The conventional put–call ratio (PCR), as presented in Equation (15), measures the relative trading volume of put options to call options.

$$\mathrm{PCR(Volume)} = \frac{Volume_{Put}}{Volume_{Call}} \tag{15}$$

However, this conventional indicator does not adjust for firm size—measured by the number of shares outstanding—or for the trading intensity of the underlying stock. As a result, comparisons across firms of different sizes or across varying market conditions may be distorted, potentially leading to biased interpretations. To address this limitation, the present study adopts a modified version of the PCR, as shown in Equation (16), in which option trading volumes are normalized by both the number of shares outstanding and the trading volume of the underlying stock. This normalization enables the adjusted index to capture investor sentiment more accurately and to provide a more consistent measure of the linkage between option trading activity and stock price dynamics compared with the traditional PCR.

$$\mathrm{PCR(O/S)} = \frac{(\frac{O}{S}_{it})_{Put}}{(\frac{O}{S}_{it})_{Call}} \tag{16}$$

Where:

$$\frac{O}{S_{it}} = \mathrm{OPVOL_{it}} - \mathrm{EQVOL_{it}} \tag{17}$$

$$\mathrm{OPVOL_{it}} = \ln\left(\frac{\text{Option Volume}_{it} \times \text{size contract}}{\text{Number of shares Outstanding}_{it}}\right) \tag{18}$$

$$\mathrm{EQVOL_{it}} = \ln\left(\frac{\text{Stock Volume}_{it}}{\text{Number of shares Outstanding}_{it}}\right) \tag{19}$$

where Option Volume denotes the total number of option contracts traded for a specific stock during a given daily period. Stock Volume represents the total number of shares exchanged in the spot (cash) market over the same interval. Number of Shares Outstanding refers to the total number of a firm's shares held by shareholders on that particular day. Contract Size is a standardized coefficient that specifies the number of underlying shares represented by a single option contract. This coefficient varies according to the characteristics of the underlying asset and the standardization conventions of the respective stock exchange.

3.2.3 Control Variables

3.2.3.1 Book-to-Market Ratio (B/M)

The book-to-market ratio for firms listed on the Tehran Stock Exchange is computed as the natural logarithm of the ratio of shareholders' equity to market value, as expressed below:

$$\mathrm{LBM_t} = \ln\left(\frac{\mathrm{E_{t-1}}}{\mathrm{N} \times \mathrm{P_{t-1}}}\right) \tag{20}$$

where E_{t-1}represents the book value of shareholders' equity at the end of the previous fiscal year, Ndenotes the number of common shares outstanding, and $P_{t-1}$is the closing price per share at the end of the previous fiscal year.

3.2.3.2 Momentum

Momentum is defined as the sequential movement of a stock's returns, measured by the cumulative return of stock $i$over the preceding 11 months. This variable captures the tendency for stocks with higher past returns to continue generating above-average returns, whereas stocks with lower historical returns are likely to exhibit comparatively weaker performance in subsequent periods.

$$Ret = \sum_{m=t-12}^{t-1} R_m \tag{21}$$

R_m: Stock return

3.2.3.3 Historical Stock Return Volatility

Historical stock return volatility is employed to measure the total risk associated with a firm's stock. This metric captures the degree of dispersion of past stock returns over a given period, reflecting the extent to which returns fluctuate around their mean. To compute this variable, the daily logarithmic returns of each stock are first calculated using the following formula:

$$R_i = \ln\left(\frac{p_{it}}{p_{it-1}}\right) \tag{22}$$

where p_{it} denotes the closing price of stock i on day t. The historical volatility of the stock is then obtained by computing the standard deviation of its daily returns over the specified period.

$$\text{Std Ret}_{it} = \sqrt{\frac{1}{D_{it}-1}\sum_{k=1}^{D_{it}}(R_{ik}-\bar{R_i})^2} \tag{23}$$

$$\text{Volatility} = \ln\left(\text{Std Ret}_{it}\right) \tag{24}$$

where D_{it} denotes the number of trading days in period t, R_{ik} is the daily return of stock i *on day* k, and $\bar{R_i}$ represents the average daily return of stock i over the same period.

3.2.3.4 Idiosyncratic Volatility

Investment risk and firm performance are central topics in financial research. A firm's total risk can be decomposed into systematic and idiosyncratic components. Systematic risk stems from macroeconomic factors—such as interest rates, inflation, and political developments—that are beyond managerial control, whereas idiosyncratic risk arises from firm-specific factors, including capital structure, operational efficiency, and managerial decisions, and can be mitigated through portfolio diversification. In this study, idiosyncratic risk is quantified as the standard deviation of the residuals obtained from the market model. Specifically, the daily return of stock i is regressed on the return of the market index using Equation (25):

$$R_{it} = \alpha_i + \beta_i(R_{mt}) + \varepsilon_{it} \tag{25}$$

where R_{it} denotes the daily return of stock i, R_{mt} is the daily return of the market index, β_i represents the sensitivity of the stock to market movements, α_i is the regression intercept, and ε_{it} is the regression residual (error term). The idiosyncratic volatility of the stock is then measured as the natural logarithm of the standard deviation of these residuals.

$$\text{IDVOL} = \ln\left(\text{stdev}\left(\varepsilon_{it_d}\right)\right) \tag{26}$$

3.2.3.5 Firm Size

Firm size is a key determinant of stock returns, reflecting a company's capacity to attract capital, its competitive position, and the stability of its economic activities. In this study, firm size is measured according to Equation (27) as the natural logarithm of the market value of shareholders' equity at the end of the fiscal year.

$$\text{Lsize} = \ln(N \times P) \tag{27}$$

where N denotes the number of outstanding shares of the company, and P represents the daily market price of the stock.

3.3 Research Model

The research model of this study is developed drawing on the frameworks of HangFu et al. (2024) [33], Cheshmen et al. (2021) [8], and Johnson and So (2012) [29]. The relationships between the independent variables, their interaction terms, and the dependent variable are analyzed using quantile regression, as specified in Model (28):

$$\begin{aligned} AR_{i,t} = \beta_0 + \beta_1 SDIV_{i,t} + \beta_2 S\Delta IV_{i,t} + \beta_3 short\ selling_{i,t} + \beta_4\, pcr(o/s)_{i,t} \\ + \beta_5\, pcr(Volume)_{i,t} + \beta_6 PCR(O/S)_{i,t} \times S\Delta iV_{i,t} \\ + \beta_7\, PCR(O/S)_{i,t} \times S\Delta iV_{i,t} \times short\ selling_{i,t} + \beta_8\, LBM_{i,t} + \beta_9\, MOM_{i,t} \\ + \beta_{10} \sigma Stock_{i,t} + \beta_{11}\, IDVOL_{i,t} + \beta_{12}\, Lsize_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (28)$$

where AR denotes the abnormal return, $SDIV$ is the implied volatility spread, $S\Delta IV$ represents the delta implied volatility spread, $Short\_Sell$ indicates short-selling activity, $PCR(O/S)$ is the ratio of put option volume to shares outstanding relative to call option volume to shares outstanding, PCR(Volume) denotes the ratio of put option volume to call option volume, LBM is the natural logarithm of the book-to-market ratio, MOM represents momentum, σ_{Stock} is historical stock return volatility, $IDVOL$ denotes idiosyncratic volatility, and $LSIZE$ is the natural logarithm of firm size.

3.3.1 Statistical Analysis Method

The computation and modeling procedures were implemented using matrix network structures in the Python programming environment. To examine the relationships among variables, EViews 13 and multivariate quantile regression were employed. Quantile regression is semi-parametric with respect to distributional assumptions and enables the assessment of variable effects across different points of the conditional distribution. Given that the coefficient distributions in quantile regression may deviate from normality and that heteroskedasticity may be present, advanced bootstrap techniques—including BCa-corrected bootstrap and Wild bootstrap—were applied to obtain robust estimates and to construct reliable confidence intervals for the regression coefficients.

3.3.1.1 BCa-Corrected Bootstrap

Among bootstrap methods, the percentile bootstrap is one of the simplest approaches for estimating confidence intervals. In this method, the empirical distribution of the estimators is constructed through repeated bootstrap sampling, and the confidence limits are determined based on the $\alpha/2$ and $1-\alpha/2$percentiles of the distribution. Its computational simplicity and minimal distributional assumptions have made it widely used in early empirical studies. However, when estimator distributions are asymmetric or biased, the percentile confidence interval may fail to provide adequate coverage and can produce misleading results. To address this limitation, the present study employs the bias-corrected and accelerated (BCa) bootstrap. By incorporating two adjustments—bias correction and acceleration—this method delivers more reliable and robust confidence intervals. The bias-correction factor, $\hat{z}_0$, represents the deviation between the original estimator and its bootstrap distribution, and is computed using the following formula:

$$\hat{z}_0 = \varphi^{-1}\left[\frac{\#\{\hat{\theta}_b^* < \hat{\theta}\}}{B}\right] \quad (29)$$

where $\{\hat{\theta}_b^*; b = 1, \ldots, B\}$are the bootstrap estimates, Bdenotes the number of repetitions, and $\phi^{-1}$is the inverse of the standard normal cumulative distribution function.

The acceleration factor, $\hat{a}$, which quantifies the rate of change of the estimator's standard error, is computed using the jackknife method as follows:

$$\hat{a}=\frac{\sum_{i=1}^{n} U_i^3}{6[\sum_{i=1}^{n} U_i^2]^{\frac{3}{2}}} \tag{30}$$

$$U_i = \hat{\theta}_{(0)} - \hat{\theta}_{(i)} \tag{31}$$

where $\hat{\theta}_{(i)}$denotes the estimator computed with the i-th observation omitted, and $\hat{\theta}_{(0)}$is the mean of the jackknife estimates.

Using these two parameters, the BCa bootstrap confidence interval at a confidence level of $1-\alpha$is calculated as follows (Equation 32):

$$\theta \in \left(\hat{\theta}^*_{[B(1-\frac{\tilde{\alpha}}{2})]} ; \hat{\theta}^*_{[B\left(\frac{\tilde{\alpha}}{2}\right)]}\right) \tag{32}$$

where $\tilde{\alpha}/2$and $1-\tilde{\alpha}/2$are defined as follows:

$$\frac{\tilde{\alpha}}{2} = \left[\hat{z}_0 + \frac{\hat{z}_0 + z_{\frac{\alpha}{2}}}{1-\hat{a}\left(\hat{z}_0 + z_{\frac{\alpha}{2}}\right)}\right] \tag{33}$$

$$1-\frac{\tilde{\alpha}}{2} = \left[\hat{z}_0 + \frac{\hat{z}_0 + z_{1-\frac{\alpha}{2}}}{1-\hat{a}\left(\hat{z}_0 + z_{1-\frac{\alpha}{2}}\right)}\right] \tag{34}$$

This approach facilitates the estimation of asymmetric and more accurate confidence intervals, while remaining robust to distributional assumptions and heteroskedasticity. In effect, it allows for a precise assessment of the relationships among variables and the quantification of coefficient uncertainty, thereby providing a reliable analysis of the effects of independent variables on quantile regression across different points of the conditional distribution [16].

3.3.1.2 Wild Bootstrap

To account for the high likelihood of heteroskedasticity in quantile regression residuals, the Wild bootstrap method was employed alongside the BCa approach. This technique is specifically designed for situations in which the errors are non-normally distributed or exhibit unequal variances. It operates on the principle that, instead of resampling observations, the residuals from the original model (e_i) are multiplied by a random variable $v_i^b$with mean zero and variance one. The simulated response values are then generated as follows:

$$y_i^b = \hat{y}_i + e_i.v_i^b \tag{35}$$

where $\hat{y}_i$denotes the predicted values from the original model. The regression model is subsequently refitted using the simulated data y_i^b, and the bootstrap estimator for the b-th iteration is obtained with the updated coefficients θ_b^*. This procedure is repeated Btimes, and the empirical distribution of $\theta_b^*$is used to calculate standard errors and construct confidence intervals.

4 Findings

This section presents and analyzes the empirical results of the study. Table 1 reports the descriptive statistics of the main variables. The data on abnormal returns indicate a positive median value (0.0071), suggesting that more than half of the observations are positive. In contrast, the mean return is slightly negative (-0.0021), reflecting the influence of a few extreme negative observations that lower the average. This pattern is typical in Tehran Stock Exchange data and reflects the coexistence of rare, severe loss events with predominantly positive daily returns. The implied volatility spread (SDIV) and delta implied volatility spread (SΔIV) exhibit positive and nearly identical means and medians, indicating a general market tendency toward heightened volatility. Both variables are approximately symmetrically distributed, although their kurtosis exceeds 3, suggesting the presence of occasional extreme observations in both tails. Given the observed skewness and kurtosis, the Jarque–Bera (JB) statistic is computed to evaluate the distributional properties of the variables. As reported in Table 1, the JB statistics are extremely large, with p-values equal to 0.0000 for all variables. These results provide clear statistical evidence against the null hypothesis of normality and confirm that the variables exhibit asymmetric and heavy-tailed distributions. The presence of asymmetry and heavy tails highlights the importance of employing robust or nonparametric methods in the subsequent statistical analyses. Descriptive statistics for the remaining variables are also presented in Table 1 for readers who wish to examine them in more detail.

Table 1: Descriptive Statistics of the Study Variables.

Variable	N	Mean	Median	Std - Dev	Skewness	Kurtosis	Jarque-Bera	prob
AR	2157	-0.0021	0.0071	0.0658	-6.588	77.429	513483.1	0.000
SDIV	2157	0.0670	0.0655	0.3179	-0.299	7.3508	1733.457	0.000
LMB	2157	-0.1218	-0.0235	0.8345	-3.7135	23.772	43733.45	0.000
LSIZE	2157	34.6464	35.1855	1.1543	-1.6269	4.3545	1116.462	0.000
MOM	2157	0.0637	-0.1905	1.3379	-2.0787	25.156	45671.34	0.000
IDVOL	2157	-3.1934	-3.0996	0.5127	1.6446	12.914	9805.076	0.000
σStock	2157	-2.3079	-2.3410	0.3795	2.2793	16.702	18740.57	0.000
Shortselling	2157	0.5568	1.0000	0.4969	-0.2286	1.0523	359.7456	0.000
SΔIV	2157	0.0722	0.0745	0.3371	0.1493	8.8060	3037.675	0.000
PCR(Volume)	2157	0.0344	0.0000	0. 641	3.3966	58.178	1.02E+8	0.000
PCR(O/S)	2157	-0.0052	0.0016	0.2088	-3.1687	21.551	1.17E+8	0.000
PCR(O/S) ×SΔIV	2157	-0.0006	0.0001	0.0193	-2.4054	17.049	76845193	0.000
PCR(O/S) ×SΔIV×Shortselling	2157	-0.0006	0.0000	0.0190	-2.5933	18.169	86287631	0.000

To examine potential multicollinearity among the explanatory variables in the quantile regression framework, we compute the Variance Inflation Factor (VIF) for all regressors and interaction terms. Although VIF is conventionally associated with OLS estimation, it is widely used as a diagnostic tool in quantile regression because it assesses linear dependence among regressors independently of the estimation procedure. As reported in Table 2, the VIF values for the core independent variables are well below the commonly accepted thresholds of 5 and 10, indicating that multicollinearity is not a material concern in the baseline specification. In contrast, the higher-order interaction terms—PCR(O/S) × SΔIV and PCR(O/S) × SΔIV × Shortselling—show elevated VIF values (35.16 and 38.08, respectively). Such inflation is expected, as interaction terms are mechanically correlated with their constituent variables. Importantly, the main effects remain stable and interpretable, and these high VIFs do not distort the variance structure of the primary regressors. Overall, the multicollinearity diagnostics confirm that the quantile regression models are well-conditioned for reliable coefficient estimation across quantiles. Furthermore, Augmented Dickey–Fuller (ADF) unit root tests (Table 2) show that all variables are stationary at the 5% significance level except LSIZE, which is stationary at the 10% level. Thus, the dataset is suitable for direct implementation of quantile regression without additional transformation.

Table 2: Variance Inflation Factors (VIF) and Augmented Dickey-Fuller (ADF) for Independent and Interaction Variables.

Variable	VIF	ADF Statistic	prob	Variable	VIF	ADF Statistic	prob
SDIV	3.28	-5.505	0.000*	σStock	3.79	-5.649	0.000*
LMB	1.14	-5.673	0.000*	Shortselling	1.09	-8.562	0.000*
LSIZE	1.18	-2.634	0.086**	SΔIV	3.08	-7.674	0.000*
MOM	1.24	-8.353	0.000*	PCR(Volume)	1.01	-29.520	0.000*
IDVoL	3.52	-5.820	0.000*	PCR(O/S)	3.37	-8.884	0.000*
PCR(O/S) ×SΔIV	35.16	-11.794	0.000*	PCR(O/S) ×SΔIV×Shortselling	38.08	-11.846	0.000*

*Stationary at 5% significance; **Stationary at 10% significance

Table 3 presents the results of eight estimated quantile regression models with abnormal return as the dependent variable. The baseline model, incorporating only the implied volatility spread (SDIV), yields a coefficient of -0.0127, significant at the 1% level. This suggests that a one-unit increase in the implied volatility spread of call and put options is associated with a decrease in abnormal returns. Contrary to findings in some developed markets, abnormal returns in the Iranian market exhibit an inverse relationship with implied volatility [23, 25]. This pattern can be attributed to the risk-averse behavior of investors, the inefficiency and limited depth of the capital market, and the significant influence of political–economic shocks on volatility. In other words, within the Iranian context, an increase in implied volatility is perceived not as an opportunity for higher returns but as a signal of heightened uncertainty and negative risk. The inclusion of control variables in Model 2 increases the adjusted R^2 from 0.0048 to 0.0818, indicating improved explanatory power. Subsequently, four variables—short selling, delta implied volatility spread (SΔIV), PCR(Volume), and PCR(O/S)—are introduced incrementally to assess changes in coefficients and model performance. In Model 3, the short-selling variable, operationalized as a dummy, exhibits a coefficient of -0.0384, significant at the 1% level, consistent with the expectation that increased short-selling activity exerts downward pressure on stock prices, resulting in negative abnormal returns. In Model 4, the $S\Delta IV$ variable demonstrates a positive and significant coefficient across all quantiles. An increase in this spread, reflecting higher implied volatility for call options relative to put options, indicates investor optimism and is thus positively associated with abnormal returns. In Models 5 and 6, the PCR(Volume) and PCR(O/S) variables are incorporated, with coefficients of -0.0015 and -0.0059, significant at the 1% and 10% levels, respectively. These findings suggest that reductions in these measures of option market sentiment generally correspond to increases in abnormal returns. In Models 7 and 8, which incorporate interaction effects, the interaction coefficients are generally significant, indicating that the influence of the examined variables on abnormal returns depends on the levels of other factors. In Model 7, the interaction coefficient is -0.0662, significant at the 1% level. This suggests that when investors' preference for put options exceeds that for call options—reflecting a more bearish market—combined with elevated information asymmetry, the downward pressure on abnormal returns is amplified.

Table 3: Quantile Regression Results for Model (28) with Abnormal Return as the Dependent Variable.

Variable	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
SDIV	-0.0127* (0.0013)**	-0.0155* (0.0006)**	-0.0072* (0.0071)**	-0.0198* (0.0009)**	-0.0196* (0.0009)**	-0.0199* (0.0007)**	-0.0197* (0.0007)**	-0.0195* (0.001)**
LMB		0.0013* (0.1976)	0.0028* (0.0005)**	0.0016* (0.2929)	0.0016* (0.2936)	0.0017* (0.2113)	0.0020* (0.0653)***	0.0019* (0.1095)
LSIZE		-0.0017* (0.065)****	-0.0014* (0.1499)	-0.0018* (0.0576)****	-0.0018* (0.0571)****	-0.0018* (0.0617)****	-0.0018* (0.0615)****	-0.0017* (0.0695)****
MOM		-0.0018* (0.0045)**	-0.0061* (0.0000)**	-0.0056* (0.0000) **	-0.0056* (0.0000) **	-0.0055* (0.0000) **	-0.0055* (0.0000) **	-0.0054* (0.0000) **
IDVOL		0.0355* (0.0000) **	0.0232* (0.0000) **	0.0218* (0.0000) **	0.0218* (0.0000) **	0.0218* (0.0000) **	0.0216* (0.0000) **	0.0217* (0.0000) **
σStock		-0.0085* (0.0443)***	-0.0257* (0.0000) **	-0.0239* (0.0000) **	-0.0239* (0.0000) **	-0.0238* (0.0000) **	-0.024* (0.0000) **	-0.0241* (0.0000) **
Short-selling			-0.0384* (0.0000)**	-0.0383* (0.0000)**	-0.0383* (0.0000)**	-0.0382* (0.0000)**	-0.0386* (0.0000) **	-0.0385* (0.0000) **
SΔIV				0.0127* (0.006)**	0.0127* (0.0059)**	0.0128* (0.0051)**	0.0124* (0.0059)**	0.0128* (0.0051)**
PCR (Volume)					-0.0015* (0.0000) **	-0.0014* (0.0000) **	-0.0015* (0.0000) **	-0.0015* (0.0000) **
PCR (O/S)						-0.0059* (0.09)****	0.0039* (0.004)**	0.0039* (0.0026)**
PCR (O/S) ×SΔIV							-0.0662* (0.0001)**	-0.2449* (0.032)***
PCR(O/S) ×SΔIV× Short-selling								0.1787* (0.1238)
R^2	0.0053	0.0844	0.2325	0.2359	0.235974	0.2374	0.2383	0.2385
Adj. R^2	0.0048	0.0818	0.229967	0.2330	0.2328	0.2339	0.2344	0.2342
Slope Equality Test	16.649* (0.0008)**	349.440* (0.0000) **	427.436* (0.0000) **	464.079* (0.0000) **	501.075* (0.0000) **	520.471* (0.0000) **	603.021* (0.0000) **	599.3385* (0.0000) **

Note: * indicates coefficients.
Note: **Prob < 0.01; ***Prob < 0.05; ****Prob < 0.10.

As reported in Table 3, the negative impact of this interaction is particularly pronounced in the lower quantiles of abnormal returns (0.25), indicating that weaker-performing stocks are more sensitive to the combined effects of investor pessimism and heightened informational risk. In contrast, this effect diminishes in the higher quantiles and loses statistical significance. These findings underscore that the magnitude and direction of variable effects vary across the conditional distribution of abnormal returns, highlighting the importance of examining interaction effects and non-mean-centered impacts concurrently. The adjusted R^2 values reported in Table 2 range from 0.0048 to 0.2342, demonstrating that the set of independent and control variables explains a substantial portion of the variation in abnormal returns.

Table 4: Estimated Quantile Regression Coefficients and Confidence Intervals Using Wild and BCa Bootstrap.

Variable	**Quantile**	**EViews-estimated results**		**Estimation results with Python (Wild Bootstrap method with 1500 iterations)**			**Estimation results with Python (BCa-Bootstrap method with 5000 iterations)**		
		Coefficient	**Prob.**	**Estimate**	**CI Lower (2.5%)**	**CI Upper (97.5%)**	**Estimate**	**CI Lower (2.5%)**	**CI Upper (97.5%)**
SDIV	0.1	0.061	0.000	0.061	0.032	0.099	0.061	0.034	0.102
	0.25	0.046	0.000	0.046	0.029	0.065	0.046	0.030	0.065
	0.5	0.004	0.560	0.004	-0.008	0.019	0.004	-0.008	0.018
	0.75	-0.011	0.050	-0.011	-0.022	-0.001	-0.011	-0.025	-0.003
	0.9	-0.019	0.001	-0.019	-0.030	-0.008	-0.019	-0.030	-0.008
LMB	0.1	-0.002	0.161	-0.002	-0.006	0.003	-0.002	-0.009	0.002
	0.25	0.001	0.459	0.001	-0.002	0.005	0.001	-0.002	0.004
	0.5	0.002	0.100	0.002	0.000	0.004	0.002	0.000	0.005
	0.75	0.001	0.028	0.001	0.000	0.003	0.001	0.000	0.003
	0.9	0.002	0.110	0.002	0.000	0.004	0.002	0.000	0.004
LSIZE	0.1	-0.002	0.280	-0.002	-0.005	0.003	-0.002	-0.007	0.001
	0.25	0.003	0.019	0.003	0.000	0.006	0.003	0.001	0.006
	0.5	0.000	0.758	0.000	-0.002	0.002	0.000	-0.002	0.001
	0.75	0.001	0.172	0.001	-0.001	0.002	0.001	0.000	0.002
	0.9	-0.002	0.070	-0.002	-0.003	0.000	-0.002	-0.004	0.000
MOM	0.1	0.009	0.002	0.009	0.004	0.014	0.009	0.004	0.014
	0.25	-0.002	0.013	-0.002	-0.004	-0.001	-0.002	-0.005	-0.001
	0.5	-0.003	0.000	-0.003	-0.004	-0.001	-0.003	-0.004	-0.001
	0.75	-0.002	0.000	-0.002	-0.003	-0.001	-0.002	-0.003	-0.001
	0.9	-0.005	0.000	-0.005	-0.008	-0.003	-0.005	-0.008	-0.003
IDVOL	0.1	-0.022	0.001	-0.022	-0.036	-0.010	-0.022	-0.034	-0.006
	0.25	-0.007	0.105	-0.007	-0.014	0.001	-0.007	-0.015	0.001
	0.5	0.008	0.006	0.008	0.002	0.014	0.008	0.002	0.014
	0.75	0.015	0.000	0.015	0.011	0.020	0.015	0.011	0.020
	0.9	0.022	0.000	0.022	0.018	0.027	0.022	0.017	0.027

σStock	0.1	-0.052	0.000	-0.052	-0.077	-0.013	-0.052	-0.100	-0.029
	0.25	-0.025	0.006	-0.025	-0.044	-0.005	-0.025	-0.041	-0.006
	0.5	-0.017	0.000	-0.017	-0.025	-0.009	-0.017	-0.024	-0.008
	0.75	-0.018	0.000	-0.018	-0.028	-0.009	-0.018	-0.025	-0.008
	0.9	-0.024	0.000	-0.024	-0.034	-0.014	-0.024	-0.038	-0.017
Shortselling	0.1	-0.039	0.000	-0.039	-0.048	-0.032	-0.039	-0.049	-0.032
	0.25	-0.053	0.000	-0.053	-0.059	-0.048	-0.053	-0.058	-0.048
	0.5	-0.037	0.000	-0.037	-0.042	-0.034	-0.037	-0.041	-0.034
	0.75	-0.035	0.000	-0.035	-0.037	-0.033	-0.035	-0.037	-0.033
	0.9	-0.039	0.000	-0.039	-0.042	-0.034	-0.039	-0.042	-0.034
SΔIV	0.1	-0.046	0.000	-0.046	-0.071	-0.024	-0.046	-0.080	-0.027
	0.25	-0.039	0.000	-0.039	-0.053	-0.025	-0.039	-0.055	-0.027
	0.5	-0.005	0.434	-0.005	-0.017	0.007	-0.005	-0.018	0.006
	0.75	0.007	0.096	0.007	-0.001	0.018	0.007	0.001	0.019
	0.9	0.013	0.005	0.013	0.003	0.020	0.013	0.005	0.023
PCR(Volume)	0.1	-0.060	0.000	-0.060	-0.073	0.002	-0.060	-0.084	-0.002
	0.25	-0.003	0.235	-0.003	-0.095	0.000	-0.003	-0.097	0.000
	0.5	0.000	0.156	0.000	-0.064	0.005	0.000	-0.002	0.073
	0.75	-0.001	0.000	-0.001	-0.005	0.066	-0.001	-0.003	0.069
	0.9	-0.001	0.000	-0.001	-0.006	0.063	-0.001	-0.035	0.061
PCR(O/S)	0.1	0.008	0.172	0.008	-0.066	0.070	0.008	-0.006	0.164
	0.25	-0.004	0.090	-0.004	-0.054	0.016	-0.004	-0.011	0.169
	0.5	-0.002	0.626	-0.002	-0.031	0.010	-0.002	-0.024	0.026
	0.75	0.000	0.962	0.000	-0.026	0.008	0.000	-0.021	0.022
	0.9	0.004	0.003	0.004	-0.040	0.019	0.004	-0.076	0.010
PCR(O/S) ×SΔIV	0.1	0.200	0.618	0.200	-0.660	1.814	0.200	-0.967	1.516
	0.25	0.375	0.006	0.375	-0.149	0.623	0.375	-0.097	1.080
	0.5	0.009	0.896	0.009	-0.427	0.296	0.009	-0.540	0.235
	0.75	0.031	0.977	0.032	-0.544	0.589	0.032	-0.578	0.487
	0.9	-0.245	0.032	-0.245	-0.323	0.655	-0.245	-0.671	-0.106
PCR(O/S) ×SΔIV× Shortselling	0.1	-0.482	0.251	-0.482	-2.184	0.646	-0.482	-1.871	0.933
	0.25	-0.460	0.001	-0.460	-0.826	0.319	-0.460	-1.295	0.036
	0.5	-0.059	0.506	-0.059	-0.385	0.452	-0.059	-0.593	0.275
	0.75	-0.075	0.945	-0.076	-0.665	0.522	-0.076	-0.605	0.551
	0.9	0.179	0.124	0.179	-0.717	0.428	0.179	0.038	0.815
C	0.1	-0.148	0.017	-0.148	-0.337	-0.038	-0.148	-0.308	-0.029
	0.25	-0.177	0.002	-0.177	-0.281	-0.054	-0.177	-0.311	-0.073
	0.5	0.024	0.467	0.024	-0.057	0.081	0.024	-0.048	0.084
	0.75	0.025	0.272	0.025	-0.014	0.083	0.025	-0.015	0.078
	0.9	0.129	0.000	0.129	0.066	0.194	0.129	0.064	0.190

The slope equality test, the results of which are reported in Table 3, reveals significance at the 1% level, confirming the presence of heterogeneous effects. This finding underscores the importance of employing a quantile regression framework to examine the impacts of variables across different points of the abnormal return distribution. To estimate parameters across different quantiles, in addition to quantile regression implemented in EViews, the BCa bootstrap (5,000 repetitions) and Wild bootstrap (1,500 repetitions) were employed to enhance the precision and reliability of the results. In Table 4, the estimated coefficients of the $SDIV$ variable at the 0.1, 0.25, 0.5, 0.75, and 0.9 quantiles are 0.061, 0.046, 0.004, -0.011, and -0.019, respectively. The corresponding p-values indicate statistical significance at most quantiles, with the exception of the 0.5 quantile, where the effect is not significant. Results obtained from the bootstrap methods further confirm the stability and robustness of the significant effects of this variable. A similar pattern of consistency is observed for other model variables. The agreement between the parametric quantile regression estimates and the nonparametric bootstrap results strengthens the reliability of the findings. The numerical values for the remaining variables are presented in Table 3 and can be referred to for more detailed analysis.

5 Limitations and Recommendations

While the findings of this study provide novel insights into the relationship between derivatives market indicators, short-selling constraints, and abnormal returns in the Iranian capital market, several limitations should be acknowledged. These include the absence of a formal short-selling framework, the limited depth of the derivatives market, the scarcity of high-quality trading data, and reliance on linear modeling approaches. Such factors may limit the generalizability of the results and warrant caution in extrapolation. Future research is encouraged to address these limitations by developing formal short-selling mechanisms, deepening derivatives markets, and employing higher-frequency data alongside nonlinear or multilevel modeling techniques. Specifically, researchers may:

1. Incorporate high-frequency market data, such as intraday transactions, to capture rapid price and volatility dynamics.
2. Apply nonlinear or regime-switching models, including Markov-switching or threshold models, to uncover asymmetric effects of derivatives-based indicators on abnormal returns.
3. Integrate behavioral or sentiment indicators to better account for investor psychology and market reactions.
4. Validate findings in other emerging markets to assess the robustness and generalizability of the results.

6 Discussion and Conclusions

Within the framework of behavioral finance, investor sentiment and cognitive biases play a central role in price volatility and deviations of asset prices from their intrinsic values. This study demonstrates that sentiment related indicators—including the implied volatility spread between call and put options, directional implied volatility, the put–call ratio (PCR), and short-selling activity—significantly influence abnormal returns in the Iranian capital market. The findings indicate that an overall increase in the implied volatility spread is generally associated with a decrease in abnormal returns, whereas higher call relative to put option volatility reflects investor optimism and is linked to positive abnormal returns. Short-selling activity exerts down-ward pressure on stock prices, reducing abnormal returns, while higher PCR values, indicative of bearish market sentiment, are also associated with lower abnormal returns. Furthermore, the results highlight the importance of examining the interactive effects among these variables. The simultaneous presence of market pessimism, elevated PCR, and heightened information asymmetry intensifies the downward pressure on abnormal returns. This suggests that analyzing each sentiment variable in isolation does not fully capture market behavior; simultaneous consideration of their interactions provides a more accurate understanding of market dynamics. These interactive effects vary across different market conditions, emphasizing the need for a comprehensive and integrated approach to sentiment-based measures. The results are consistent with evidence from other emerging and structurally constrained markets, where implied volatility and the put–call ratio primarily capture risk, uncertainty, and informational frictions rather than unconditional or mean-based return predictability [6, 41]. In contrast, evidence from developed markets indicates that option-based indicators particularly when conditioned on informed trading activity and specific market states may contain information predictive of future abnormal returns [38]. These cross-market differences are likely driven by variations in market structure, investor sophistication, market maturity, and the regulatory environment governing short-selling activities [4]. These insights have important policy and practical implications: regulators and policymakers can utilize derivatives-based indicators to monitor investor behavior and market risk, and to inform the development of short-selling regulations and risk management frameworks. Market participants can apply these indicators to guide investment decisions, portfolio management, and early detection of abnormal returns and heightened volatility. Overall, this study advances the understanding of market dynamics in emerging markets and provides a foundation for future research on investor behavior and the role of derivatives based indicators in predicting abnormal returns.

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