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# Implied Volatility of Call Options and Abnormal Stock Returns: Evidence From Quantile Analysis of Abnormal Return Determinants

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**Abstract:**
The present study aims to assess the impact of implied volatility (IV) extracted from call option prices on abnormal stock returns. IV, as a critical market volatility index, plays an essential role in explaining investor behavior. The Black-Scholes model was used to extract IV, applying Brents method due to the absence of an explicit closed-form solution. In addition, daily call option trading data from the Tehran Stock Exchange (TSE) were utilized during 2016-24. Further, quantile multivariate regression, along with wild bootstrap resampling (1,000 repetitions), was employed for model estimation. Abnormal returns (ARs) were significantly associated with IV, illiquidity (ILLIQ), daily stock returns (RETs), and bid-ask spreads (SPREAD). However, ARs were negatively correlated with the logarithm of firm size (LogSIZE), historical option volatility ($\sigma$Option), logarithm of book-to-market(LogBM), implied volatility delta ($\Delta$IV), and idiosyncratic volatility (IDVOL). The historical stock volatility ($\sigma$Stock) and options-to-stocks volume ratio (O/S) demonstrated no significant association with ARs. The results highlighted the predictive power of IV and $\Delta$IV for future price movements. The study recommends market participants and portfolio managers to incorporate the abovementioned metric into investment decision-making processes.

*Keywords:*Implied Volatility, Call Options, Abnormal Returns, Quantile Regression.
*Classification:* MSC2010 or JEL Classifications: 62G08- 60H10- 62F40- 91G20.

# 1 Introduction

Contemporary financial markets, characterized by uninterrupted global interconnectedness, growing complexity, and rapid technological advancements, have evolved into highly dynamic yet uncertain environments. In such volatile settings, a systematic understanding of factors influencing asset valuation and price dynamics is no longer just a competitive advantage. Rather, it is considered as a crucial prereq-

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uisite for optimal risk management and effective decision-making among all of the stakeholders including financial policymakers, investors, and analysts. Such imperative is especially pronounced as investors seek profitable investment opportunities while safeguarding their capital against adverse market fluctuations [14].

The advent of financial derivative instruments, especially options contracts, has revolutionized risk management practices and trading opportunity utilization in capital markets. Options have rapidly become integral components of individual and institutional portfolios due to their unique capacity to provide investment flexibility and financial leverage. The nonlinear payoff structure is among defining features of such contracts, resulting in creating asymmetric responses to underlying asset price movements and volatility fluctuations, making options exceptionally reactive to shifts in market expectations regarding future volatility. A nonlinear payoff structure refers to a relationship in which variations in the underlying asset price lead to disproportionate or asymmetric gains and lossesa characteristic commonly observed in derivative instruments such as options, where even the slightest market fluctuations can exert disproportionate effects on option prices, while cash equity markets lack such sensitivity due to their linear return structure. These characteristics, along with combinatorial potential and customizable nature of options, enable these instruments to play an essential role in market expectation discovery, risk hedging, and speculative positioning [72], [48], [24].

Essential components in options market analysis include implied volatility (IV), which functions as a forward-looking index manifesting market expectations of future asset price fluctuations. Unlike historical volatility (HV) obtained from previous data, IV shows forecasting qualities, presenting valuable insights into investor sentiment.This characteristic renders IV an informative, anticipation-based metric for risk assessment and market analysis. Several studies underscored the capacity of IV to document information beyond historical stock data, validating the measure as a robust forecaster of future market behavior [16], [28], [59], [2], [10]. These results highlight the impact of derivative instruments, especially IV, on facilitating efficient information transmission and analyzing abnormal returns (ARs).

Abnormal stock returns, as another core element in capital markets and corporate finance, incorporate the portion of total stock returns which cannot be explained by systematic risk factors or market fluctuations, often originating from temporary market inefficiencies, firm-specific information, or unexpected events. Predicting and interpreting drivers of ARs can empower investors to identify arbitrage opportunities, resulting in achieving excess returns [23], [50], [36].

Based on recent evidence, financial markets respond to even subtle changes in disclosed information. Cashman et al. (2024) argued that linguistic modifications in annual reports of real estate investment trust (REIT) firms can impact stock returns [19]. In addition, Cashman et al. (2025) claimed that options markets serve as pricing mechanisms and adaptive information conduits facilitating data transmission to stock markets [20]. Further, Eksi and Roy (2025) reported that option prices show significant predictive power for non-fundamental market shocks and stock returns [34].

The exact mechanisms of information transmission between options and equity markets, especially regarding the IV-AR nexus, remain partially unresolved, despite empirical and theoretical progress in this field [71], [40], [36]. Such ambiguity is especially pronounced while evaluating the impact of IV on returns under varying distributional regimes (e.g., periods of extreme positive/negative return), warranting deeper investigation. To address this gap, quantile regression analysis was used to investigate the predictive power of call option IV in explaining and forecasting abnormal stock returns in the Tehran Stock Exchange (TSE).

The study focuses on strategic selective call options because such contracts manifest market optimism and bullish expectations, with their associated data presenting rich, accessible informational content. This approach enables a more precise analysis of the relationship between AR and IV, as well as facilitating the extraction of novel insights into positive market expectations, prospective formation of price bubbles, and investor reactions to upside potential(Upside potential measures the prospective capacity for an asset to appreciate in value, representing investment attractiveness and opportunities for profitability). The present study strengthens the theoretical foundations in the nexus between stock and option markets, as well as presenting valuable practical guidance for risk analysts, investors, and financial policymakers seeking to manage risk and identify opportunities in bullish capital market conditions.

Here, the theoretical foundations and research background is reviewed, followed by utilizing a quantile regression approach to present the impact of IV on different quantiles of the AR distribution with enhanced accuracy.

## 2 Theoretical foundations and research background

During the recent decades, financial derivatives have emerged as critical instruments for fostering financial market efficiency risk management, and optimal capital allocation. Within this domain, options have obtained a unique position among derivative instruments due to their ability to be customized to investors' needs, inherent flexibility, and leveraged structure [70], [73].

Intrinsic worth of options extends beyond their instrumental characteristics, serving as a crucial channel for transmitting latent market information. Empirical evidence reveals that option pricing may contain information which is not always fully manifested in the current price of the underlying asset. Such informational discrepancy transforms options into a powerful source for deriving investors' expectations about future market conditions [17], [21], [41], [62], [43], [6], [46], [49].

This informational characteristic of options can reveal risks and uncertainties earlier than the underlying asset price, especially embodied in the concept of IV. Indices such as the divergence between implied and realized volatility, which manifest market expectations of future volatility risk and tendency to pay a premium for its coverage, were significantly associated with future stock returns [57], [29], [42], [60], [55], [7]. This index manifests investors' risk appetite, as well as capturing future uncertainties and systemic risks, resulting in presenting forward-looking information about future market returns. Based on the recent studies, IV contains information beyond HV, which offers valuable insights about future volatility and its correlation with asset returns across various asset classes including bonds, currencies, equities, commodities, and the like [25], [37], [32], [38]. Additionally, information flows extracted from IV significantly increase the forecasting accuracy of economic returns and international realized volatility across all of the prediction horizons [54]. Generally, IVs outperform HVs in predicting future realized volatility [51].

Recent studies have underscored the asymmetry between IV and returns in options markets. For example, Chen et al. (2024) examined the dynamic relationship between IV and positive/negative returns by studying the options market data in China. They indicated that negative returns exert a significantly more pronounced impact on IV fluctuations relative to positive ones during the same period, corroborating the leverage effect phenomenon in China options market. The results represented that the data embedded in IV encode vital signals about investor expectations across the entire return spectrum, not just at the aggregate level [26].

Global financial literature extensively underscores the informational content of IVs and their forecasting power for future stock returns. However, studies in Iran emerging capital market yielded divergent results, revealing that IVs fail to reliably predict stock performance, where trading volume emerges as a more prominent factor [47]. In addition, Alavi Sheshtmand et al. (2024) adopted a reverse causality approach by focusing on the impact of abnormal stock returns on future return volatility while overlooking predictive variables extracted from derivatives markets such as IVs [1].
The aforementioned results highlight a significant challenge to understanding information flows and efficiency of Iran capital market, compelling an urgent reevaluation of analytical models and underlying hypotheses.

Beyond volatility and informational dimensions, derivatives market liquidity significantly impacts stock risk-return dynamics. Further, Deng et al. (2023) asserted that options liquidity associates with stock price crash risk, especially in firms with higher informed trading and greater short interest positions. These results highlight the significance of options liquidity as a catalyst for intensifying impacts on price crash risk, representing a novel mechanism for risk transmission from options to equity markets, transcending traditional explanations related to stock liquidity [30].

Options trading volume is regarded as another crucial metric for understanding predictive behavior in financial markets. A large number of studies have been conducted on information transmission between options and stock markets, with especial focus on the role of options volume in price discovery and information revelation. Therefore, the options-to-stocks volume ratio (O/S) often emerges as a reliable metric for understanding market risk structure and forecasting future stock returns [41], [69], [45], [63]. This metric reveals investor actions and expectations regarding the underlying asset which may not yet be fully incorporated in the stock market by capturing trading activity in derivatives markets.

Based on some studies, these metrics can present valuable predictive information beyond traditional stock market variables [9], [39], [49], [63]. Thus, ignoring such information flows and focusing solely on the stock market obscure key viewpoints regarding future market dynamics.

However, the core mechanisms underlying such predictability remain debated, one of which proposes that informed investors tend to apply options markets as their trading platform due to structural advantages such as higher financial leverage. Additionally, stock markets operate imperfectly in the presence of market constraints such as short interest bans, leading to incomplete manifestation of their private information signals in stock prices. Under such conditions, options markets may play a crucial role in price discovery by offering a comparative advantage in information transmission. Alternatively, some studies underscore a different mechanism where the return predictability based on options-IVs derive from low liquidity and temporary price pressures in stock markets, which fail to manifest in options prices, not from informational superiority of options markets. These two analytical viewpoints, which need not be mutually incompatible, may simultaneously impact information transmission between equity and options markets [30], [61].

Based on the efficient market theory, arbitrage opportunities emerge from price discrepancies when options pricing fails to fully manifest optimal market expectations regarding future volatility. Such opportunities should be rapidly eliminated by arbitrageurs through positioning in options and stock markets [58], [65]. However, theoretical models and empirical evidence show that institutional/structural constraints and arbitrage costs can impede immediate and full exploitation of such opportunities. Thus, the information embedded in options prices may be transmitted to stock prices with delays or incompletely. In this context, metrics such as idiosyncratic volatility (IDVOL), stock return volatility, and Amihud illiquidity measure (ILLIQ) are often used in financial literature as proxies for arbitrage costs [13], [67], [18].

The present study adopted a distinctive approach to address return dynamics by focusing on the above-mentioned discrepancies in domestic literature and considering the institutional and behavioral structure of Iran capital market. In addition, this study seeks to discuss whether IV, as a market expectations-derived metric, shows significant predictive or explanatory power for abnormal stock returns across different distribution levels employing a quantile regression framework.

The results extracted from the aforementioned approach can provide a scientific base for developing derivative market-based analytical instruments in emerging economies with incomplete information structures such as Iran. In fact, structures such as the Iranian capital market, which endure information asymmetry, informational inefficiencies, trading constraints, and behavioral volatility, need flexible modeling approaches like quantile regression to present more precise and multi-layered insights into variable relationships [52].

In such contexts, the classical modeling hypothesis regarding uniform independent variable effects on abnormal stock returns often conflicts with market realities. Therefore, quantile analysis provides a valuable opportunity to identify factors influencing ARs (during recessionary conditions and periods of strong market growth) by permitting focusing on extreme return behaviors at upper and lower levels. In addition, quantile regression exhibits robustness against volatility and outliers, capturing complex patterns without distorting results. Therefore, applying this technique in financial studies with nonlinear and dynamic nature can lead to a deeper insight into market mechanisms and predictive variables. The above-mentioned approach reveals heterogeneous impact of IV across different levels of ARs, providing valuable insights in the context of Iran financial market which experiences short-interest bans, severe shocks, and arbitrage constraints. Finally, this analytical framework can effectively complement IV analysis as a market expectations index, presenting a more precise understanding AR formation patterns.

# 3 Method

The present study is recognized as experimental in terms of objective, representing a retrospective analysis grounded in factual datasets regarding its essence and method. In such studies, cause-effect linkages between variables are assessed based on past events without the ability to control the independent variable.
This study aims to evaluate the presence of a significant relationship between IV and ARs.

## 3.1 Population and sample

The population included firms with tradable options listed in the TSE and Iran Over-the-Counter (OIC) during 2016-24. The firms were selected due to their commitment to transparent and regular disclosure of financial information, enabling access to comparable and reliable data. Given the population vastness, the sample was selected applying systematic elimination method to obtain reliable and precise results. The sample involved only firms meeting the following criteria.

- Firms with call options.
- Firms with accessible information about their industry.
- The firms should have at least 50 active trading days per year. This threshold was established based on the structural features of the Iranian options market to eliminate symbols with low liquidity.

Table 1: Names, symbols, and industries of the examined firms.

| Symbol | Firm name | Industry |
|---|---|---|
| HIWEB | Dadeh Gostar Asr Novin | Information and Communications |
| KHAVAR | Iran Khodro Diesel | Automotive Manufacturing and Parts |
| KHBAHMAN | Bahman Group | Automotive Manufacturing and Parts |
| KHPARS | Pars Khodro | Automotive Manufacturing and Parts |
| KHSAPA | SAIPA | Automotive Manufacturing and Parts |
| KHGOSTAR | Iran Khodro Investment Development | Automotive Manufacturing and Parts |
| KHUDRO | Iran Khodro | Automotive Manufacturing and Parts |
| SHPNA | Isfahan Oil Refining | Petroleum Products, Coke and Nuclear Fuel |
| VBSADER | Bank Saderat Iran | Banks and Financial Institutions |
| VBMELLAT | Bank Mellat | Banks and Financial Institutions |
| VTEJARAT | Bank Tejarat | Banks and Financial Institutions |
| SHASTA | Social Security Investment | Industrial Conglomerates |
| KOSAR | Kosar Insurance | Insurance |
| BASAMA | Saman Insurance | Insurance |
| ZOB | Esfahan Steel | Basic Metals |
| FOLAD | Esfahan's Mobarakeh Steel Company | Basic Metals |
| FMELI | National Iranian Copper Industries | Basic Metals |
| FSABA | Saba Persian Gulf Steel | Basic Metals |

- A minimum trading volume of 2,500 contracts was set for each call option to prevent low-trade contracts from entering the sample since some contracts are practically non-traded, failing to provide meaningful data.

Totally, 18 firms comprising 17,493 daily observations were selected as the final sample after applying the aforementioned criteria and constraints.Table 1 indicates the complete list of these firms and their respective industries. The limited number of firms derives from the structural constraints of the Iranian options market, which remains in early developmental stages, with options currently available only on a limited number of large firms listed on the TSE. Therefore, the small sample size represents the nascent nature of emerging options market in Iran, not researcher selection bias. To eliminate this obstacle and enhance estimation precision, daily data are used, along with Bootstrap method with 1,000 replications, to address statistical power concerns, resulting in creating multiple pseudo-random samples from the observed data, as well as providing more robust estimates of CIs and standard errors while decreasing the risk of influence from outliers or specific firms. Given the inherent limitations of the small sample size, the results should be interpreted with caution regarding generalizability and treated as primarily exploratory in nature.

Data were collected from the TSE database, audited financial statements, and reports published on the Codal website. Then, the data were cleaned, classified, and structured based on the intended variables. In the next step, they were processed and modeled employing a matrix network structure implemented in Python programming language. The study used quantile multivariate regression and EViews 13 software to analyze variable relationships. Unlike ordinary least squares (OLS) regression which only models the conditional mean of the dependent variable, quantile regression permits investigating variable effects across different distribution quantiles (e.g., median, first quartile or upper/lower percentiles). This approach is considered as semiparametric regarding distributional hypotheses, requiring neither homoscedasticity nor normality of errors.

## 3.2 Quantile regression model

The quantile model is defined as follows. The probability distribution function of the random variable Y is calculated as follows.

$$F(y) = \text{Prob}(Y \leq y) \tag{1}$$

The $\tau$-th quantile of Y is expressed as the following inverse function.

$$\text{Quant}(\tau) = \inf\{y : F(y) \geq \tau\}, \quad 0 \leq \tau \leq 1. \tag{2}$$

The sample median minimizes the following sum of absolute deviations for a random sample $\{y_1, \dots, y_n\}$ from Y.

$$\min_{\xi \in \mathbb{R}} \sum_{i=1}^{n} |y_i - \xi| \tag{3}$$

In addition, the $\tau$-th sample quantile $\xi(\tau)$, which simulates Quant $(\tau)$, can be formulated as the solution to the following optimization problem.

$$\min_{\xi \in \mathbb{R}} \sum_{i=1}^{n} \rho_\tau |y_i - \xi| \tag{4}$$

where

$$\rho_\tau(z) = z\left(\tau - I(z < 0)\right), \quad 0 < \tau < 1 \tag{5}$$

acts solely as the sample mean which minimizes the sum of squared errors.

$$\hat{\mu} = \arg\min_{\mu \in \mathbb{R}} \sum_{i=1}^{n} (y_i - \mu)^2 \tag{6}$$

Thus, the linear conditional mean function can be calculated by Equation (7).

$$\mathbb{E}(Y \mid X = x) = x'\beta \tag{7}$$

Finally, the linear conditional quantile function, $\text{Quant}(\tau \mid X = x) = x\beta'(\tau)$, can be estimated for each quantile by solving the following equation.

$$\hat{\beta}(\tau) = \arg\min_{\mu \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau\left(y_i - x_i'\beta\right) \tag{8}$$

where $\hat{\beta}(\tau)$ indicates the $\tau$-quantile regression coefficient [68], [66].
Heteroscedasticity was investigated utilizing the Breusch-Pagan test to validate the

use of quantile regression. Then, model quality was evaluated through goodness-of-fit and slope equality tests to ensure result compatibility with data structure. In the next step, result stability was examined through sensitivity analysis across dimensions such as extreme quantiles, window length, and data frequency shift from daily to weekly. Within this framework, the effect of the main variable on the dependent one was estimated across 1, 5, 10, and 20-day windows at the 0.05, 0.25, 0.5, 0.75, and 0.95 quantiles to capture behavioral fluctuations across all of the market conditions. In the next procedure, multicollinearity among explanatory variables was addressed through correlation analysis and variance inflation factor (VIF) calculation to ensure result robustness. Finally, regression models for the main independent variable were estimated with full data after outlier removal.

## 3.3 Goodness-of-fit test

Therefore, the linear model for the conditional mean function is calculated by Equation (9) [53].

$$\text{Quant}(\tau \mid X_i.\beta(\tau)) = X_i\beta'(\tau) \tag{9}$$

where the coefficient and data vectors are achieved as follows.

$$\begin{aligned} \beta(\tau) &= (\beta_0(\tau).\, \beta_1(\tau)')' \\ X_i &= (1,\, X_i'1)' \end{aligned} \tag{10}$$

In other words, Equation (9) can be written as follows.

$$\text{Quant}(\tau \mid X_i.\beta(\tau)) = \beta_0(\tau) + X_{i1}'\beta_1(\tau) \tag{11}$$

Thus, this criterion (0-1), measures the relative success of the model in fitting data for the $\tau$-th quantile as follows.

$$R^1(\tau) = 1 - \frac{S_1}{S_0} \tag{12}$$

$S_1$ : Loss function value for the model with independent variables.
$S_0$: Loss function value for the intercept-only model without independent variables.

$$R^1(\tau) = 1 - \frac{\min\limits_{\beta(\tau)} \sum\limits_i \rho_\tau\left(Y_i - X_i'\beta_1(\tau)\right)}{\min\limits_{\beta_0(\tau)} \sum\limits_i \rho_\tau\left(Y_i - \beta_0(\tau)\right)} \tag{13}$$

## 3.4 Slope equality test

Koenker and Bassett (1978) proposed this test to evaluate heteroscedasticity by addressing slope coefficient equality across quantiles [5], [52]. The results determined whether the estimated coefficients for independent variables differ statistically across different quantiles of the dependent variable. Slope equality test reveals

heterogeneous effects of independent variables at different points of the dependent variable distribution.
The null hypothesis of the test indicates the equality of regression coefficients for independent variables and their uniform effects across distribution points of dependent variable, while the alternative hypothesis represents statistically significant differences among the variables.

$$\begin{aligned} H_0: &\quad \beta_1(\tau_1) = \beta_1(\tau_2) = \cdots = \beta_1(\tau_k) \\ H_1: &\quad \exists\, j, l\ (j \neq l) \text{ such that } \beta_1(\tau_j) \neq \beta_1(\tau_l) \end{aligned}$$

## 3.5 Variables

The study variables are divided into three categories including dependent, independent, and control variables.

**Dependent variable:**

AR, calculated as the difference between actual and market return, stands as the dependent variable in this model. Such returns emerge when no accurate and transparent information exists about firm performance. In other words, information asymmetry leads to ARs, which are obtained applying Equation (14) [44].

$$AR_{it} = R_{it} - \mathbb{E}(R_{it}) \tag{14}$$

$AR_{it}$: Abnormal stock return
$R_{it}$: Actual return
$\mathbb{E}(R_{it})$: Expected return extracted from Equation (15),

$$\mathbb{E}(R_{it}) = \alpha_i + \beta_i R_{mt} \tag{15}$$

$R_{mt}$: represents market return calculated applying Equation (16),

$$R_{mt} = \ln \frac{I_{mt}}{I_{m0}} \tag{16}$$

where $I_{mt}$ and $I_{m0}$ indicate the market index at the end and beginning of period t, respectively.

**Independent variables:**

The independent variables incorporated in the model include O/S ratio, bid-ask spread (SPREAD), IV, implied volatility delta ($\Delta$IV), IDVOL, as well as historical stock and option volatility, all of which are defined and operationalized as follows. IV stands as a cornerstone concept in financial markets and derivatives, capturing market expectations of future underlying asset volatility. This metric can be extracted from fundamental option pricing models, especially the Black-Scholes model. The Black-Scholes framework is based on geometric Brownian motion

(GBM), which describes the stochastic behavior of stock prices over time. The stochastic differential equation (SDE) for non-dividend paying assets under this model takes the following form.

$$dS_t = \mu S_t\, dt + \sqrt{\sigma^2}\, S_t\, dw_t^s \tag{17}$$

$S_t$: Underlying asset price at time t
$\mu$: Drift rate (expected asset return)
$\sigma^2$: Variance
$dw_t^s$: Stochastic component (Wiener process/Brownian motion) showing random price fluctuations.

Employing this asset model, the Black-Scholes partial differential equation (PDE) for a European call option price C(t,S) is extracted as follows.

$$\frac{\partial C}{\partial t} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + r_f S \frac{\partial C}{\partial S} - r_f C = 0 \tag{18}$$

$C(t, S)$: Price of a European call option at time t for underlying asset S
$r_f$:Risk-free interest rate
$t$: Time to maturity
European options can only be exercised at maturity. Therefore, the terminal condition is established as follows

$$C(t = T, S) = (S_0 - K)^+ = \max(S_0 - K, 0) \tag{19}$$

$S_0$:Current underlying asset price
$K$: Option strike price

An analytical solution for European call option pricing exists as follows [11].

$$C = S_0 N(d_1) - K e^{-r_f T} N(d_2) \tag{20}$$

$N$: Cumulative distribution function (CDF) of the standard normal

$$\begin{aligned} d_1 &= \frac{\ln(S_0/K) + \left(r_f + \frac{\sigma^2}{2}\right) T}{\sigma\sqrt{T}} \\ d_2 &= d_1 - \sigma\sqrt{T} \end{aligned} \tag{21}$$

Given the call option price (C), strike price (K), current underlying asset price ($S_0$), risk-free rate ($r_f$), and time to maturity (T), the IV can be calculated utilizing the Black-Scholes inverse function ($BS^{-1}$) as follows [27].

$$\sigma^*(K, T) = BS^{-1}(C, S_0, T, r_f) \tag{22}$$

The aforementioned equation can be reformulated as the following optimization problem because no explicit algebraic solution exists for Equation (22) and a numerical iteration technique should be used to determine the IV $\sigma^*$.

$$g(\sigma^*) = BS(S, T, K, r_f, \sigma^*) - C(S, T; K) = 0 \tag{23}$$

Several methods can be used to solve the above-mentioned equation including Newton-Raphson, bisection, Brent's method, or hybrid approaches, each with unique limitations and advantages. For example, the Newton-Raphson method may fail to converge under conditions such as derivative discontinuities or poor initial guesses, while the bisection method typically shows linear convergence rates, despite its stability, leading to slower solutions compared to other techniques.

Here, Brents method was applied for root-finding. Brent's method is recognized as a hybrid algorithm which combines the advantages of the bisection with the efficiency of the secant approach and inverse interpolation (fast convergence). This method is widely used in financial calculations due to its high efficiency and stability over a wide range of functions. The method employs inverse parabolic interpolation based on the three most recent points to approximate the inverse function, mimicking the gradient of Newtons method [15].

$$\begin{aligned}\sigma_{k+1} = &\frac{\sigma_k\, g(\sigma_{k-1})\, g(\sigma_{k-2})}{(g(\sigma_k) - g(\sigma_{k-1}))\,(g(\sigma_k) - g(\sigma_{k-2}))} \\ &+ \frac{\sigma_{k-1}\, g(\sigma_{k-2})\, g(\sigma_k)}{(g(\sigma_{k-1}) - g(\sigma_{k-2}))\,(g(\sigma_{k-1}) - g(\sigma_k))} \\ &+ \frac{\sigma_{k-2}\, g(\sigma_{k-1})\, g(\sigma_k)}{(g(\sigma_{k-2}) - g(\sigma_{k-1}))\,(g(\sigma_{k-2}) - g(\sigma_k))}\end{aligned} \tag{24}$$

Quadratic interpolation is replaced with a secant-based approximation as follows when two consecutive approximations are identical $\sigma_k = \sigma_{k-1}$ [56]:

$$\sigma_{k+1} = \sigma_{k-1} - g(\sigma_{k-1}) \cdot \frac{\sigma_{k-1} - \sigma_{k-2}}{g(\sigma_{k-1}) - g(\sigma_{k-2})} \tag{25}$$

According to Cashman et al. (2022), $\Delta$IV equals IV minus volume-weighted average IV which is calculated as follows [22]

$$VWA = \sum_{i=1}^{a} IV \left( \frac{V_i}{\sum_{i=1}^{a} V_i} \right) \tag{26}$$

$VWA$ : Volume-weighted average implied volatility
$IV$:Implied volatility
$i$:Number of options in the target period
$V$:Trading volume of each option
According to Bali et al. (2011), IDVOL equals the standard deviation (SD) of market model residuals, which is calculated as follows. [8]

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{27}$$

$R_{it}$:RET of firm i at time t
$R_{mt}$:Daily value-weighted market index return
$\alpha_i$:Intercept and slope of the line which represents systematic risk
$\varepsilon_{it}$: Model residual whose SD serves as a measure for daily return IDVOL

$$\text{IDVOL} = \ln\big(\text{stdev}(\varepsilon_{it})\big) \tag{28}$$

Historical stock return volatility[1] serves to gauge uncertainty about future return fluctuations, which is calculated as the natural logarithm of the SD of daily equity returns.

$$\text{Volatility} = \ln\left(\text{Std Ret}_{it}\right) \tag{29}$$

$$\text{Std Ret}_{it} = \sqrt{\frac{1}{D_{it}-1}\sum_{1}^{D_{it}}\left(R_i - \overline{R}_i\right)^2} \tag{30}$$

$D_{it}$:Number of trading days in period t
$R_i$:RET, calculated as the natural logarithm of today price divided by yesterday price.

$$R_i = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{31}$$

$\overline{R}$: Mean daily return

The O/S ratio directly compares the intensity of options transactions relative to stock trading, both of which are normalized by the number of shares outstanding to allow meaningful comparison of trading activity across firms, irrespective of their market value over time, while accounting for changes in equity structure. This variable is calculated as follows ( [22], [49]).

$$\frac{O}{S}_{it} = OPVOL_{it} - EQVOL_{it} \tag{32}$$

$$OPVOL_{it} = \ln\left(\frac{\text{Option Volume}_{it} \times \text{size contract}}{\text{Number of shares Outstanding}_{it}}\right) \tag{33}$$

$$EQVOL_{it} = \ln\left(\frac{\text{Stock Volume}_{it}}{\text{Number of shares Outstanding}_{it}}\right) \tag{34}$$

[1] Historical option return volatility follows the same calculation method as stock return volatility, with the key distinction that its logarithmic returns are extracted from daily option prices rather than stock prices.

*Optionvolume*: Total number of option contracts traded for a specific stock during a daily time period.
*Stockvolume*: Total shares traded in the cash market during the same daily period.
Number of shares outstanding: Total shares of a firm held by identified shareholders during a daily period.
*Contractsize*: This standardized multiplier, which specifies the number of underlying shares equivalent to one options contract, varies depending on the type of underlying asset and standardization set by the securities exchange.
*Illiquidity*: This metric is utilized to examine the impact of price and illiquidity in the market. According to Amihud (2002), the illiquidity metric is calculated as the absolute value of daily stock return divided by the daily trading value in Rial terms [3]:

$$\text{ILLIQ} = \frac{1}{D_{iy}} \sum_{d=1}^{D_{iy}} \frac{|R_{iyd}|}{VOLD_{ivyd}} \tag{35}$$

$D_{iy}$:Number of trading days for stock i during the intended period
$R_{iyd}$:RET
$VOLD_{ivyd}$:Daily trading value in Rial terms
$Bid - askspread$: This metric, which serves as a proxy for information asymmetry, is considered as a critical instrument for distinguishing between measuring market liquidity and investors for an asset. According to Cashman et al. (2022), SPREAD is calculated as follows [22].

$$\text{Spread} = \ln\left(\frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|\text{Bid}_{it} - \text{Ask}_{it}|}{\left(\frac{\text{Ask}_{it}+\text{Bid}_{it}}{2}\right)}\right) \tag{36}$$

*Ask*: Daily closing ask price for stock i
*Bid*: Daily closing bid price for stock i
$D$: Number of days in period t with available bid-ask quotes.

**Control variables:**

**Book-to-market ratio (BM)**: According to Cashman et al. (2022), this ratio is calculated as the natural logarithm of the book value of equity at the end of the previous fiscal year divided by its market value, which is calculated by multiplying the number of outstanding shares by the year-end closing price per share [22].

$$LBM_t = \ln\left(\frac{E_{t-1}}{N \times P_{t-1}}\right) \tag{37}$$

$E_{t-1}$:Book value of equity at the end of fiscal year t-1
$P_{t-1}$: Closing stock price on the last trading day of year t-1
$N$:Number of shares outstanding in year t-1

**Firm size**: According to Doulou and Rajabi (2015), firm size is defined as the natural logarithm of daily market capitalization [33].

$$Lsize = \ln(N \times P) \tag{38}$$

$N$: Number of shares outstanding
$P$: Daily closing stock price

# 4 Results

Table 2 indicates descriptive statistics of research variables. As shown, the average abnormal return of sample firms during the study period is -0.009 (equivalent to a monthly decline of 0.9%), which may initially appear concerning. However, this value can be interpreted within the context of Iran capital market since emerging market characteristics and challenges such as informational inefficiencies, which impede immediate and full price adjustment, may partially explain this underperformance. In addition, macroeconomic conditions in Iran including international sanctions and high inflation rates have persistently pressured corporate cash flows and profitability which can create negative ARs even after controlling for systematic market risk, representing inability of firms to meet expected return thresholds in such a context. Mean, median, and skewness values show positive trends for IV, $\Delta$IV, option volatility, stock volatility, and IDVOL[2], which is regarded as an expected pattern, given economic uncertainties and shocks. ILLIQ exhibits positive descriptive statistics with extreme positive skewness (10.778), indicating market liquidity risk in Iran. This represents that a limited number of stocks suffer severe ILLIQ, while the majority demonstrate moderate market depth, imposing high trading costs on investors. The O/S ratio shows mean and median values of -6.025 and -5.919, respectively, with negative values attributable to logarithmic transformation, suggesting generally lower activity in options markets compared to underlying stocks. The mild negative skewness (-0.122) means near-symmetric distribution after log transformation, confirming its normalization effectiveness. As represented in Table 2, nearly all of the variables display fat tails and high kurtosis[3], justifying the methodological choice of quantile regression over conventional mean-based approaches such as OLS because this approach can lead to incomplete and even misleading conclusions in the presence of fat tails and skewness. Further, the Breusch-Pagan test results revealed the presence of heteroscedasticity (F-statistic = 391.81, $p < 0.05$), confirming the necessity of applying quantile regression.

Diagnostic tests were conducted after presenting the descriptive statistics for the variables to verify result stability and assess model sensitivity (Tables 3 and 4).

[2] The negative mean and median values stem from the logarithmic transformation, revealing that the raw volatility (pre-log) ranges between 0 and 1.

[3] Kurtosis values for the majority of variables significantly surpassed 3 (the normal distribution benchmark), representing heavily fat-tailed distributions.

Table 2: Descriptive statistics of research variables.

| variable | Mean | Median | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | Probability |
|---|---|---|---|---|---|---|---|---|---|
| AbRet | -0.0090 | -0.0090 | 0.3960 | -0.3270 | 0.0700 | 0.0830 | 5.7180 | 5403.4270 | 0.0000 |
| IV | 0.7510 | 0.6230 | 4.9960 | 0.0050 | 0.5350 | 2.9980 | 16.1050 | 151380.9000 | 0.0000 |
| IDVOL | -3.1730 | -3.1980 | -1.6730 | -5.0170 | 0.5840 | 0.0820 | 2.8360 | 39.4110 | 0.0000 |
| $\Delta$IV | 0.1680 | 0.0810 | 4.4870 | -1.6630 | 0.4280 | 3.0650 | 20.1590 | 241999.3000 | 0.0000 |
| O/S | -6.0250 | -5.9190 | 4.2480 | -14.8320 | 3.0250 | -0.1220 | 2.6940 | 111.8870 | 0.0000 |
| ILLIQ | 0.0620 | 0.0390 | 2.1240 | 0.0100 | 0.1580 | 10.7780 | 129.2010 | 11947287.0000 | 0.0000 |
| LBM | -0.6850 | -0.4350 | 1.8250 | -5.5640 | 1.2510 | -1.5480 | 7.2920 | 20409.1500 | 0.0000 |
| LSIZE | 33.8620 | 33.8050 | 36.3040 | 30.5500 | 1.1960 | -0.1830 | 2.1500 | 623.9760 | 0.0000 |
| RET | 0.0010 | 0.0000 | 0.1420 | -0.2290 | 0.0270 | 0.0570 | 3.0370 | 10.5800 | 0.0050 |
| $\sigma$(OPTION) | 0.6830 | 0.7010 | 1.7680 | -1.8660 | 0.3970 | -0.3520 | 3.4350 | 500.2620 | 0.0000 |
| $\sigma$(STOCK) | -2.2110 | -2.2830 | -0.5530 | -3.6950 | 0.4950 | 0.2720 | 3.2130 | 248.1540 | 0.0000 |
| SPREAD | -1.5450 | -1.3690 | -0.0110 | -9.7230 | 0.7650 | -2.0960 | 12.2250 | 74836.2500 | 0.0000 |
| N | 17493 | 17493 | 17493 | 17493 | 17493 | 17493 | 17493 | 17493 | 17493 |

As shown in Table 3, Almost all of the maximum pairwise correlation values are below 0.6, indicating no severe multicollinearity among the variables. The VIF values (1-4.5) represent only mild and non-critical multicollinearity. The correlation between IV and $\Delta$IV is relatively high ($\approx$0.8). However, the corresponding VIF value ($\approx$4.5) remains below the conventional threshold of 5, suggesting the insensitivity of the model to multicollinearity and validity of the regression structure.

Table 4 represents the IV coefficient estimates from OLS and quantile regression at the median percentile (q = 0.5). As presented, the IV coefficient is positive (0.0039) in the full sample, which turns negative (-0.0027) after outlier removal. However, the IV coefficient remains positive in both cases (0.0059 and 0.0033) under quantile regression at the median, showing the stability of the positive relationship between IV and ARs at the distribution center, confirming superior robustness of the quantile regression compared to OLS. Although Table 4 illustrates the median percentile, similar robustness checks have been performed across other quantiles, confirming the stability of the IV-AR relationship throughout the distribution.

Given the model validity, a quantile regression sensitivity analysis was conducted by altering window lengths and quantiles. Fig.1 illustrates the estimated IV coefficients across different window lengths and quantiles for both daily and weekly data. Star-shaped and circular points indicate coefficients significant at the 5% level and non-significant estimates, respectively, while shaded areas show the 95% CI.

In Panels A and B (coefficient vs. window length), the detailed results are as follows.

- In the daily data (Panel A), coefficients at the lower quantile (q=0.1) remain positive and significant across all of the windows. Coefficients at the higher

Table 3: VIF and maximum Pairwise correlation among independent variables.

| Variable | VIF | Correlated with (Highest) | Max Pairwise Correlation |
|---|---|---|---|
| IV | 4.468 | $\Delta$IV | 0.800 |
| IDVOL | 2.083 | $\sigma$(STOCK) | 0.692 |
| $\Delta$IV | 3.485 | IV | 0.800 |
| O/S | 1.407 | IV | -0.373 |
| ILLIQ | 1.907 | LSIZE | -0.295 |
| LBM | 1.241 | $\sigma$(STOCK) | -0.236 |
| LSIZE | 1.457 | $\sigma$(STOCK) | -0.303 |
| RET | 1.025 | $\Delta$IV | 0.139 |
| $\sigma$(OPTION) | 1.009 | $\sigma$(STOCK) | 0.181 |
| $\sigma$(STOCK) | 2.749 | IDVOL | 0.692 |
| SPREAD | 1.254 | O/S | 0.334 |

quantiles (q=0.75 and q=0.90) are negative and predominantly significant, while the median quantile (q=0.5) remains near zero without strong significance.

- In the weekly data (Panel B), the positive effect at q=0.1 is weaker and less significant, while the negative coefficients at higher quantiles, especially at q=0.9, are stronger and more significant. The confidence bands are wider in the weekly data, representing raised estimation uncertainty.

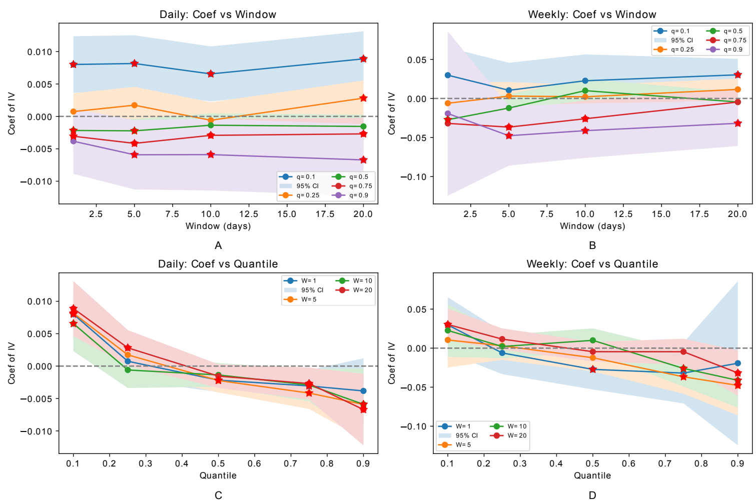


Figure 1: Quantile regression sensitivity analysis based on variations in quantiles and window length for daily and weekly data of the IV variable.

Panels C and D (coefficient vs. quantile) demonstrate the variation pattern of

Table 4: Robustness check of IV coefficients in OLS and quantile regression (Median, q=0.5) models with and without outlier removal.

| Model / Quantile | Independent Variable | Coefficient | Std. Error | t-stat | P-value |
|---|---|---|---|---|---|
| OLS Full | IV | 0.0039 | 0.001 | 3.945 | 0.000 |
| OLS No Outliers | IV | -0.0027 | 0.001 | -1.805 | 0.071 |
| Quantile 0. 5 Full | IV | 0.0059 | 0.001 | 7.180 | 0.000 |
| Quantile 0.5 No Outliers | IV | 0.0033 | 0.001 | 2.334 | 0.020 |

coefficients.

- In daily and weekly frequencies, coefficients decrease from lower quantiles (positive and often significant) toward higher ones (negative and frequently significant), revealing the asymmetric effect of IV.

- In the daily data (Panel C), coefficients for different windows are nearly overlapping with narrow confidence bands, representing higher reliability and stability of the results.

- In the weekly data (Panel D), negative coefficients at higher quantiles are more pronounced and significant (reaching approximately -0.1), while the wider confidence bands show raised estimation uncertainty.

Based on this sensitivity analysis, the effect of IV on returns highly depends on market conditions. Accordingly, the effect is positive and significant at lower quantiles (bearish markets), yet negative and significant at higher quantiles (bullish markets). Such an asymmetric effect is stronger yet accompanied by greater uncertainty in weekly horizons compared to daily ones, underscoring the significance of considering window length and time horizon in precise analysis. Additionally, the results present high sensitivity to extreme quantiles (0.1 and 0.9). However, the direction and sign of the effect remain stable across all of the quantiles and windows, confirming the robustness and validity of the results.

This nonlinear, state-dependent pattern aligns with features of the TSE such as severe short-term fluctuations, low liquidity, and a high presence of retail traders. During bearish conditions, a rise in IV functions as a "fear and risk" index, exerting a stronger influence on returns. During bullish conditions, IV frequently fails to function as a warning signal, and its effect sometimes turns weak or negative. Thus, simple linear analyses cannot explain such an asymmetry, necessitating the use of quantile regression.

The relationship between IV and abnormal stock returns was estimated within the framework of univariate to ten-variable models employing quantile regression. Table 5 indicates the significance levels, coefficients, and model validity metrics. Univariate analysis exhibited little evidence of a relationship between IV and abnormal stock returns although model 1 showed a positive IV coefficient, resulting in employing multivariate analyses. According to some researchers (e.g., [12] [35]), the following model specification was used to assess whether elevated IV, which captures rising perceived risk and market uncertainty, can lead to abnormal stock returns. The second and subsequent models showed that the IV coefficient increased after adding a variable to the univariate model, confirming the positive impact of IV on ARs. Table 5 presents the impact of other independent variables including O/S ratio, IDVOL, and call option $\Delta$IV on ARs across 11 different models. For instance, IDVOL demonstrates a consistently negative relationship with ARs in all of the models, which aligns with the results reported by Ang et al. (2006), declaring that stocks with higher IDVOL yield lower ARs in subsequent periods [4].

The O/S ratio shows a positive relationship with ARs in the majority of the models, contrasting with evidence presented by others in developed markets (e.g., Johnson and So, 2012) where O/S negatively forecasts future returns due to informed investors substituting options amid short-interest constraints [49]. In Iran, the absence of short-interest mechanisms and dominance of call option trading demonstrates that O/S primarily manifests bullish sentiment, defined as the collective positive expectations of investors regarding future asset price increases, which generate buying pressure and positive investor expectations.

Here, the coefficient of determination ($R^2$) was utilized to analyze the power of models to explain the expectations and predict abnormal stock returns. $R^2$, as a primary model fit measure, represents the percentage of variation in the dependent variable explained by the independent variables of the model. The initial model ($R^2$=0.0015) explained only 0.15% of variation through IV, while the final one ($R^2$=0.0333) exhibited substantially elevated explanatory capacity. The adjusted $R^2$ (Adj. $R^2$) was reported because $R^2$ may artificially inflate with additional independent variables. This metric presents a more realistic evaluation regarding the explanatory power of the model by considering the sample size and number of predictors. Here, Adj. $R^2$ values for the first and final models were 0.0014 and 0.0327, respectively, indicating that the model maintains comparable explanatory capability even after statistical adjustments.

Given the explanatory power of the model, slope equality test was conducted to investigate whether the effects of explanatory variables vary across different quantiles (table 5). The significant results (p-value=0.0000) confirmed heterogeneous effects across the AR distribution. The high test statistic after incorporating independent and control variables represented strong statistical significance, revealing fundamental heterogeneity in the independent-dependent variable relationships, validating the use of quantile regression to examine differential effects across AR levels.

$$\begin{aligned}\text{AbRet}_{it} = {} & \beta_0 + \beta_1 IV_{it} + \beta_2 IDVOL_{it} + \beta_3 \Delta IV_{it} + \beta_4 O/S_{it} + \beta_5 ILLIQ_{it} \\ & + \beta_6 LMB_{it} + \beta_7 LSIZE_{it} + \beta_8 RET_{it} + \beta_9 \sigma(OPTION)_{it} \\ & + \beta_{10} \sigma(STOCK)_{it} + \beta_{11} SPEARDit + \varepsilon_{it}\end{aligned} \tag{39}$$

Table 5: Stepwise quantile regression results of Equation (39) employing ARs as the performance metric.

| variable | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IV | Coefficient | 0.0060 | 0.0081 | 0.0216 | 0.0232 | 0.0243 | 0.0240 | 0.0229 | 0.0218 | 0.0240 | 0.0249 | 0.0253 |
| | Prob | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |
| IDVOL | Coefficient | | -0.0065 | -0.0086 | -0.0084 | -0.0097 | -0.0101 | -0.0107 | -0.0122 | -0.0117 | -0.0110 | -0.0109 |
| | Prob | | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |
| $\Delta$IV | Coefficient | | | -0.0193 | -0.0196 | -0.0212 | -0.0209 | -0.0200 | -0.0232 | -0.0265 | -0.0273 | -0.0265 |
| | Prob | | | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |
| O/S | Coefficient | | | | 0.0006 | 0.0005 | 0.0006 | 0.0005 | 0.0005 | 0.0004 | 0.0004 | 0.0002 |
| | Prob | | | | (0.0002)* | (0.0020)* | (0.0006)* | (0.0010)* | (0.0041)* | (0.0111)** | (0.0203)** | (0.1754) |
| ILLIQ | Coefficient | | | | | 0.0220 | 0.0220 | 0.0197 | 0.0203 | 0.0224 | 0.0221 | 0.0216 |
| | Prob | | | | | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |
| LBM | Coefficient | | | | | | -0.0013 | -0.0017 | -0.0018 | -0.0018 | -0.0018 | -0.0019 |
| | Prob | | | | | | (0.0005) | (0.0000) | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |
| LSIZE | Coefficient | | | | | | | -0.0010 | -0.0014 | -0.0008 | -0.0009 | -0.0011 |
| | Prob | | | | | | | (0.0321)** | (0.0021)* | (0.0773)*** | (0.0718)*** | (0.0237)** |
| RET | Coefficient | | | | | | | | 0.4696 | 0.4698 | 0.4690 | 0.4650 |
| | Prob | | | | | | | | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |
| $\sigma$(OPTION) | Coefficient | | | | | | | | | -0.0066 | -0.0066 | -0.0070 |
| | Prob | | | | | | | | | (0.0000)* | (0.0000)* | (0.0000)* |
| $\sigma$(STOCK) | Coefficient | | | | | | | | | | -0.0019 | -0.0025 |
| | Prob | | | | | | | | | | (0.2337) | (0.1228) |
| SPREAD | Coefficient | | | | | | | | | | | 0.0020 |
| | Prob | | | | | | | | | | | (0.0008) |
| $R^2$ | | 0.0015 | 0.0036 | 0.0065 | 0.0070 | 0.0089 | 0.0093 | 0.0094 | 0.0321 | 0.0330 | 0.0330 | 0.0333 |
| $Adj.R^2$ | | 0.0014 | 0.0035 | 0.0064 | 0.0068 | 0.0086 | 0.0089 | 0.0090 | 0.0317 | 0.0325 | 0.0325 | 0.0327 |
| $SET^{****}$ | coeficient | 158.4190 | 2756.475 | 2790.257 | 2799.450 | 2826.753 | 2861.562 | 2794.937 | 2840.063 | 2948.463 | 2815.865 | 2868.458 |
| | Prob | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |

*Note:* *Prob < 0.01; **Prob < 0.05; ***Prob < 0.10.
*Note:* ****The acronym SET refers to Slope Equality Test.

Quantile regression analysis was conducted applying EViews software to increase result precision and examine the robustness of estimated coefficients. Then, the Wild bootstrap method[4] with 1,000 replications was implemented in Python for statistical validation, followed by addressing coefficient sensitivity to sample variations (Table 6).

Table 6 indicates the estimated coefficients of independent variables across quantiles 0.1, 0.25, 0.5, 0.75, and 0.9. For example, the estimated IV coefficient at the 0.1 quantile was 0.0234 (p-value=0.0000), confirming its 1% statistical significance. Bootstrap validation yielded an identical estimate (0.0234) with a 95% confidence interval (CI) of (0.0165 - 0.0299), where the exclusion of zero confirmed the robustness of effects. Such consistency between parametric (quantile regression) and non-parametric (bootstrap) methods held for all of the model variables, confirming the reliability of the estimates.

Fig.2 displays the estimated coefficient variations across successive quantiles (from 0.1-0.9 at intervals of 0.1) for ARs, depicting the trend of coefficient variations and their CIs utilizing a blue curve and orange error bars, respectively,[5] representing the differing impacts of the variables across various levels of the dependent variable. As shown in Table 6 and Fig. 2, the observed data patterns in both representations align perfectly, reinforcing the validity of each other.

As illustrated, professional investors use the information embedded in IV to obtain ARs at low-to-median IV levels (quantiles 0.10.6) when the market appears less risky and calm. However, the market endures overreactions, panic, or herding behavior at high IV levels. In such conditions, all of the market participants know the heightened risk or impending drastic price changes. Thus, the market preemptively adjusts, forcing high IV information to no longer generate substantial ARs because all of the market players have already factored in these expectations. Such nonlinear behavior may arise from variations in investors reaction to volatility changes under calm conditions compared to turbulent market periods. Further,these results may represent informational inefficiencies of market during stress episodes or the impact of emotional behaviors.

$\Delta$IV functions as an index of unexpected changes in market expectations. As shown in Tables 5 and 6, along with Fig.2, a stronger negative relationship is found with ARs at low levels of $\Delta$IV, revealing the heightened sensitivity of market in low-risk conditions and overreaction to small changes in risk expectations. However, such negative relationship weakens at higher levels of $\Delta$IV, which may derive from

[4]Wild bootstrap is regarded as a nonparametric method which estimates the empirical distribution of model statistics through random sampling with replacement from the original data, allowing more accurate estimation without requiring restrictive hypotheses such as error normality or homoscedasticity. Here, 1,000 bootstrap iterations were performed per quantile, re-estimating model coefficients in each sample to calculate nonparametric confidence intervals and stability.

[5]The quantile coefficient shows statistical significance (at the 95% CI) when the CI band (the orange bar) excludes zero. However, the coefficient fails to achieve statistical significance when zero falls within the CI band.

defensive behavior by investors, liquidity constraints, market reaction saturation, or degraded informational transparency under high-volatility conditions.

Table 6: Estimated quantile regression coefficients and Wild bootstrap-derived CIs.

| EViews Estimates | | | | | | Wild Bootstrap Estimates | | |
|---|---|---|---|---|---|---|---|---|
| Var | Quant | Coeff | Std.Error | t-Statistic | P-value | Estimate | CI Lower | CI Upper |
| IV | 0.10 | 0.0234 | 0.0036 | 6.4770 | 0.0000 | 0.0234 | 0.0165 | 0.0299 |
| | 0.25 | 0.0227 | 0.0021 | 10.5639 | 0.0000 | 0.0227 | 0.0188 | 0.0271 |
| | 0.50 | 0.0253 | 0.0024 | 10.7131 | 0.0000 | 0.0253 | 0.0196 | 0.0294 |
| | 0.75 | 0.0129 | 0.0027 | 4.7259 | 0.0000 | 0.0129 | 0.0078 | 0.0178 |
| | 0.90 | 0.0133 | 0.0033 | 4.0295 | 0.0001 | 0.0133 | 0.0065 | 0.0196 |
| IDVOL | 0.10 | -0.0499 | 0.0018 | -27.032 | 0.0000 | -0.0499 | -0.0536 | -0.0463 |
| | 0.25 | -0.0344 | 0.0012 | -28.676 | 0.0000 | -0.0344 | -0.0365 | -0.0315 |
| | 0.50 | -0.0109 | 0.0012 | -8.916 | 0.0000 | -0.0109 | -0.0133 | -0.0085 |
| | 0.75 | 0.0237 | 0.0015 | 15.9159 | 0.0000 | 0.0237 | 0.0203 | 0.0263 |
| | 0.90 | 0.0484 | 0.0017 | 28.5313 | 0.0000 | 0.0484 | 0.0449 | 0.0519 |
| $\Delta$IV | 0.10 | -0.0279 | 0.0041 | -6.8343 | 0.0000 | -0.0279 | -0.0368 | -0.0211 |
| | 0.25 | -0.0257 | 0.0025 | -10.191 | 0.0000 | -0.0257 | -0.0316 | -0.0216 |
| | 0.50 | -0.0265 | 0.0025 | -10.474 | 0.0000 | -0.0265 | -0.0311 | -0.0210 |
| | 0.75 | -0.0133 | 0.0035 | -3.856 | 0.0001 | -0.0133 | -0.0195 | -0.0074 |
| | 0.90 | -0.0133 | 0.0042 | -3.1473 | 0.0017 | -0.0134 | -0.0211 | -0.0045 |
| O/S | 0.10 | 0.0004 | 0.0003 | 1.3754 | 0.169 | 0.0004 | -0.0002 | 0.0009 |
| | 0.25 | 0.0003 | 0.0002 | 1.9220 | 0.0546 | 0.0003 | 0.0000 | 0.0007 |
| | 0.50 | 0.0002 | 0.0002 | 1.3551 | 0.1754 | 0.0002 | -0.0001 | 0.0006 |
| | 0.75 | -0.0001 | 0.0002 | -0.4857 | 0.6272 | -0.0001 | -0.0005 | 0.0003 |
| | 0.90 | -0.0004 | 0.0003 | -1.4638 | 0.1433 | -0.0004 | -0.0009 | 0.0001 |
| ILLIQ | 0.10 | 0.0003 | 0.0132 | 0.0236 | 0.9812 | 0.0004 | -0.0094 | 0.0351 |
| | 0.25 | 0.0274 | 0.0038 | 7.2827 | 0.0000 | 0.0274 | 0.0098 | 0.0326 |
| | 0.50 | 0.0216 | 0.0047 | 4.5651 | 0.0000 | 0.0216 | 0.0139 | 0.0350 |
| | 0.75 | 0.0295 | 0.0073 | 4.0221 | 0.0001 | 0.0295 | 0.0100 | 0.0405 |
| | 0.90 | 0.0227 | 0.0030 | 7.5976 | 0.0000 | 0.0227 | 0.0173 | 0.0289 |
| LMB | 0.10 | -0.0067 | 0.0004 | -15.577 | 0.0000 | -0.0067 | -0.0074 | -0.0057 |
| | 0.25 | -0.0035 | 0.0005 | -6.6958 | 0.0000 | -0.0035 | -0.0047 | -0.0024 |
| | 0.50 | -0.0019 | 0.0004 | -4.8942 | 0.0000 | -0.0019 | -0.0028 | -0.0010 |
| | 0.75 | 0.0005 | 0.0006 | 0.7970 | 0.4255 | 0.0005 | -0.0009 | 0.0016 |
| | 0.90 | 0.0012 | 0.0005 | 2.5569 | 0.0106 | 0.0012 | 0.0000 | 0.0020 |
| LSIZE | 0.10 | -0.0013 | 0.0007 | -1.8726 | 0.0611 | -0.0013 | -0.0025 | 0.0004 |
| | 0.25 | -0.0022 | 0.0006 | -4.0126 | 0.0001 | -0.0022 | -0.0035 | -0.0012 |
| | 0.50 | -0.0011 | 0.0005 | -2.2619 | 0.0237 | -0.0011 | -0.0021 | 0.0000 |
| | 0.75 | 0.0055 | 0.0006 | 9.5107 | 0.0000 | 0.0055 | 0.0040 | 0.0064 |
| | 0.90 | 0.0058 | 0.0007 | 8.9226 | 0.0000 | 0.0058 | 0.0044 | 0.0072 |
| RET | 0.10 | 0.4332 | 0.0251 | 17.2860 | 0.0000 | 0.4331 | 0.3775 | 0.4770 |
| | 0.25 | 0.4848 | 0.0212 | 22.8867 | 0.0000 | 0.4848 | 0.4461 | 0.5348 |
| | 0.50 | 0.4650 | 0.0215 | 21.6168 | 0.0000 | 0.4650 | 0.4290 | 0.5122 |
| | 0.75 | 0.3874 | 0.0263 | 14.7092 | 0.0000 | 0.3874 | 0.3410 | 0.4390 |
| | 0.90 | 0.2661 | 0.0286 | 9.3134 | 0.0000 | 0.2664 | 0.2179 | 0.3214 |
| $\sigma$(OPTION) | 0.10 | -0.0048 | 0.0023 | -2.0963 | 0.0361 | -0.0048 | -0.0100 | -0.0007 |
| | 0.25 | -0.0071 | 0.0013 | -5.5655 | 0.0000 | -0.0071 | -0.0096 | -0.0044 |
| | 0.50 | -0.0070 | 0.0014 | -4.8930 | 0.0000 | -0.0070 | -0.0097 | -0.0041 |
| | 0.75 | -0.0087 | 0.0015 | -5.7752 | 0.0000 | -0.0087 | -0.0116 | -0.0057 |
| | 0.90 | -0.0007 | 0.0016 | -0.4469 | 0.655 | -0.0007 | -0.0038 | 0.0026 |
| $\sigma$(STOCK) | 0.10 | -0.0188 | 0.0023 | -8.1481 | 0.0000 | -0.0188 | -0.0231 | -0.0139 |
| | 0.25 | -0.0127 | 0.0018 | -6.9766 | 0.0000 | -0.0127 | -0.0163 | -0.0093 |
| | 0.50 | -0.0025 | 0.0016 | -1.5434 | 0.1228 | -0.0025 | -0.0057 | 0.0010 |
| | 0.75 | 0.0087 | 0.0018 | 4.7220 | 0.0000 | 0.0087 | 0.0051 | 0.0122 |
| | 0.90 | 0.0071 | 0.0020 | 3.5657 | 0.0004 | 0.0071 | 0.0033 | 0.0110 |
| SPREAD | 0.10 | 0.0009 | 0.0012 | 0.7346 | 0.4626 | 0.0009 | -0.0017 | 0.0033 |
| | 0.25 | 0.0021 | 0.0007 | 3.1114 | 0.0019 | 0.0021 | 0.0006 | 0.0032 |
| | 0.50 | 0.0020 | 0.0006 | 3.3490 | 0.0008 | 0.0020 | 0.0007 | 0.0031 |
| | 0.75 | 0.0022 | 0.0008 | 2.8316 | 0.0046 | 0.0022 | 0.0009 | 0.0039 |
| | 0.90 | 0.0016 | 0.0011 | 1.4419 | 0.1493 | 0.0016 | -0.0004 | 0.0037 |
| C | 0.10 | -0.2523 | 0.0252 | -9.9953 | 0.0000 | -0.2524 | -0.3100 | -0.2126 |
| | 0.25 | -0.1205 | 0.0191 | -6.3055 | 0.0000 | -0.1206 | -0.1557 | -0.0751 |
| | 0.50 | -0.0224 | 0.0157 | -1.4270 | 0.1536 | -0.0224 | -0.0557 | 0.0095 |
| | 0.75 | -0.0572 | 0.0170 | -3.3631 | 0.0008 | -0.0572 | -0.0857 | -0.0159 |
| | 0.90 | 0.0350 | 0.0199 | 1.7581 | 0.0787 | 0.0351 | -0.0051 | 0.0742 |

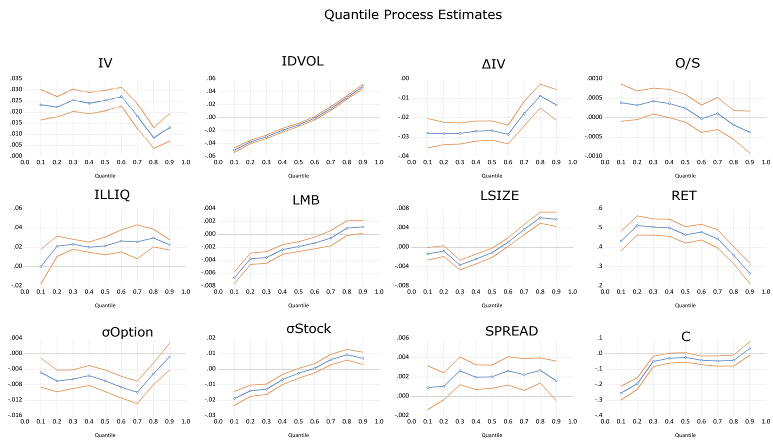


Figure 2: Coefficient plot related to effect of independent variables across different quantiles on ARs.

Based on the results, daily stock returns demonstrated a positive relationship with ARs across all of the quantiles. The IDVOL and logarithm of firm size (LogSIZE) exhibited negative effects at lower-to-median quantiles yet transition to positive effects at higher levels. The logarithm of book-to-market (LogBM) and historical stock volatility exhibited significant effects at extreme quantiles (low/high) yet insignificant near the median. Historical option volatility maintained uniformly negative significance. The SPREAD was insignificant at extremes yet significant at median levels. ILLIQ was insignificant at $\tau$=0.1 yet significant at other quantiles. The O/S ratio failed to retain statistical significance in Model 10 with SPREAD included, despite its significance in Models 19. The variance inflation factor (VIF) test was conducted to analyze the potential multicollinearity between the O/S and SPREAD with values of 1,4068 and 1,2543, respectively, both falling substantially below the critical threshold of 5, ruling out multicollinearity as the reason for insignificance of O/S after including the SPREAD. Rather, this result strengthened the possibility of informational overlap between the two variables, especially considering that the SPREAD, as a liquidity index, may capture a substantial portion of the information explained by O/S.

# 5 Discussion

Based on modern financial theories, call options reveal critical information about investors expectations regarding the future direction of stock prices due to their leveraged characteristics and high trading volumes, often before such information emerges in stock prices, potentially creating ARs [63]. IV, extracted from option prices, functions as a forward-looking risk expectation gauge, playing the role of a crucial informational source for ARs. Investors interpreting IV changes may predict future returns more effectively, especially during news shocks or market crises. Unlike backward-looking HV, IV is recognized as prospective, significantly related abnormal stock returns. In such context, sudden IV spikes indicate heightened perceived risk or market uncertainty, potentially driving prices away from equilibrium, leading to ARs. Several studies (e.g., [64], [17], [28], [31], [7]) have underscored the predictive role of IV in forecasting ARs across financial markets. However, Javidkia (2023) found that IV in Iran fails to show significant predictive power over future returns unlike developed markets [47]. Given the significance of IV as a latent informational source embedded in option prices and its role in generating informational advantages for investors, this study aims to evaluate the role of call option IV and $\Delta$IV in predicting ARs in the TSE and OIC market. Based on the results, IV and $\Delta$IV show significant predictive power for ARs in the Iranian capital market. Evidence consistent with developed markets can be achieved by using correct variable definitions and precise methodology. This relationship presents several practical applications for portfolio managers and Iranian investors. For example, fund managers can apply abnormal $\Delta$IV increases as warning signals for portfolio adjustments and risk management, while retail investors can incorporate high IV levels as indices of potential short-term ARs in their trading decisions. Given the currency/political-economic fluctuations and limited liquidity in Iran market, even relatively small changes in IV can provide valuable practical guidance for investment decision-making.

## 5.1 Limitations and recommendations

Like other empirical investigations in the field of finance, this study faces several challenges and limitations related to data quality and methodological hypotheses. However, the statistical methods applied such as Wild bootstrap or quantile regression are among the most reliable and widely used analytical instruments in financial literature, yielding robust results and valuable insights across numerous studies. The following section focuses on these limitations, as well as proposing recommendations for future works.

- *Geographical limitation of the study:* The present study exclusively focused on the TSE and Iran OTC due to its data constraints and objective. Thus, the results should be generalized to other jurisdictions by validation through complementary studies, especially in developed markets, owing to informational efficiency, market depth, structural differences, and trading mechanisms across financial markets.

- *Limitations in the quality and depth of derivatives market data:* Access to high-quality and accurate data on the Iranian options market remains a critical challenge, compounded by the insufficient depth of the derivatives market.

- *Hypotheses regarding statistical models:* Advanced statistical methods such as

Wild bootstrap and quantile regression were employed here. However, some of their fundamental hypotheses such as the absence of behavioral biases and data stationarity may not fully align with the dynamic context of Iran financial markets. Therefore, certain complex market dimensions such as investors' emotional behavior, external shocks, or structural changes may not be fully captured by the models.
Focusing on the aforementioned limitations in future studies can significantly foster the internal and external validity of the results, as well as their generalizability. In this regard, the following recommendations are presented.

- *Incorporating geopolitical factors and macroeconomic shocks into modeling:*Future studies should develop models which explicitly integrate variables such as shifts in economic policies, macroeconomic shocks, or geopolitical events in order to capture the dynamic relationship between IV and ARs more effectively.

- *Incorporating political and economic shocks into volatilityreturn analysis:*Future studies should address the impact of political or economic shocks on ARs, especially in emerging markets such as Iran.

- *Expanding the scope of analysis to commodity derivatives:*Examining similar relationships in commodity derivatives markets such as futures contracts on agricultural products, crude oil, or precious metals can provide valuable perspectives into the dynamics of volatility and returns in commodity markets, allowing comparisons with equity markets.

- *Applying diverse methods for estimating IV:*Using multiple approaches for extracting IV, instead of relying on a single method, can foster the robustness of results, offering a more comprehensive understanding of volatility mechanisms for researchers.

# 6 Conclusion

The results indicated that the effect of IV on ARs in the TSE shows an asymmetric and nonlinear nature. Specifically, investors react to IV changes strongly and positively at lower quantiles (0.10.3). Such an effect decreases at middle quantiles (0.60.8), while intensifying again at higher quantiles, representing that analyzing emerging markets necessitates using and quantile-focused and nonlinear models. From a practical perspective, high IV levels at lower quantiles can be interpreted as a downside risk warning, while their relative decrease at middle quantiles provides opportunities for short-term trading. Further, ARs may manifest market reactions to political and economic shocks. Overall, the results revealed the dominance of emotional behaviors and informational inefficiency in the TSE, which can explain abnormal fluctuations and high sensitivity of market to price shocks.

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