JOURNAL OF MANAGEMENT AND BUSINESS SOLUTIONS

Countercyclical Value at Risk Using Market Bubbles and Stock Market Crash Risk

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ABSTRACT

In this study, a countercyclical value-at-risk (VaR) measure was introduced and estimated using the market bubble in order to assess and predict the crash risk of the Tehran Stock Exchange. To estimate the countercyclical VaR, the long-term and equilibrium price trend was first calculated using Kaufman's Adaptive Moving Average, and based on this trend, the deviation from equilibrium was computed as the bubble index in the Tehran Stock Exchange. Subsequently, using the bubble index, a metric for inflation (compensation) of returns in the direction opposite to the bubble was introduced. On this basis, raw returns were transformed in a manner that incorporated the presence of bubbles in the market, and the bubble-adjusted value-at-risk measure was calculated using these transformed data. This study utilized daily data from the Tehran Stock Exchange index over the period 2015 to 2024. The findings indicate that the standard value-at-risk has a higher explanatory power for stock market crash risk compared to the countercyclical value-at-risk; however, interpretation of the model coefficients shows that the countercyclical VaR provides a more logically consistent explanation of the relational mechanism between value-at-risk and stock market crash risk.

Keywords: Value at Risk, Price Bubble, Stock Market Crash Risk, Countercyclical Risk.

Introduction

Asset price bubbles and their associated risks have long been among the most critical topics in financial economics, largely because of their capacity to distort market valuations, destabilize economic systems, and magnify systemic vulnerabilities. Financial markets are inherently susceptible to periods of excessive optimism, mispricing, and speculative booms that drive asset prices significantly above their fundamental values, often culminating in sharp reversals and market crashes. Recent developments in global and regional markets demonstrate that understanding the dynamics, formation mechanisms, and consequences of bubbles is essential for designing effective risk-assessment frameworks and regulatory responses. Contemporary research highlights that financial markets—particularly emerging and developing markets—are more prone to bubble formation due to structural inefficiencies, behavioral biases, and heightened exposure to macroeconomic volatility (1). From theoretical and empirical perspectives, assets may deviate from fundamental valuations when investors extrapolate

Article history:
Received 20 July 2025
Revised 13 October 2025
Accepted 20 October 2025
Published online 10 November 2025

How to cite this article:
Rohi, L., Nabavi Chashmi, S. A., & Nasrollahi, M. (2025). Countercyclical Value at Risk Using Market Bubbles and Stock Market Crash Risk. *Journal of Management and Business Solutions, 3*(6), 1-15. https://doi.org/10.61838/jmbs.94

recent price increases into the future, when liquidity surges fuel speculative demand, or when policy shocks create distortions that amplify risk-taking (2, 3).

The nature of bubbles has increasingly been examined through multiple analytical lenses, with scholars emphasizing their connection to systemic risk, volatility clustering, and contagion across markets. For example, Brunnermeier et al. (2020) argue that bubbles constitute an integral part of systemic risk transmission, given that they reflect misaligned expectations and excessive leverage, which together enhance the vulnerability of financial systems to abrupt crashes (4). Parallel research such as Zhang et al. (2023) shows that asset price bubbles can propagate systemic fragilities within interconnected financial institutions, especially in markets where banks and investment firms exhibit high exposure to speculative assets (5). These findings are consistent with global evidence indicating that bubbles often emerge in environments characterized by heightened uncertainty, macroeconomic shocks, or persistent deviations in market fundamentals (6).

Price bubbles are not only market-specific phenomena but often reflect broader macro-financial dynamics. Studies of energy, commodities, currency, and housing markets show widespread bubble formation across asset classes. In crude oil markets, speculation and uncertainty have been shown to trigger extreme price bubbles, particularly during crisis periods or geopolitical tensions (2, 7). Similar dynamics appear in copper markets, where periodically collapsing bubbles indicate recurrent speculative cycles linked to global demand fluctuations (8). Housing markets also display localized bubbles, driven by submarket dynamics, investor sentiment, and credit cycles, as evidenced by findings in the Greater Sydney housing market (9). Furthermore, recent cryptocurrency research shows persistent bubble episodes in Bitcoin and Ethereum, often coinciding with shifts in volatility regimes and speculative trading waves (10). These studies underscore the universality of bubble behavior across asset categories and highlight the importance of advanced detection and forecasting methods.

In emerging markets, including Iran, price bubbles represent even more complex and consequential phenomena. Scholars note that low market depth, concentrated ownership structures, and investor herding amplify the probability of bubble formation in these contexts (11). Research focusing on the Tehran Stock Exchange (TSE) finds that expectations, volatility shocks, and structural transformations play decisive roles in generating price bubbles. For instance, Izadi et al. (2021) identify the pivotal role of investor expectations, particularly in response to macroeconomic instability and currency fluctuations, in driving bubble formation in the Iranian stock market (12). Likewise, Mohammadi and Hoseini (2022) demonstrate that monetary policy shocks can propagate through asset markets and create conditions conducive to bubble formation, especially when policy interventions distort liquidity conditions (13). Bubble contagion is also evident between currency and stock markets in Iran, indicating a high degree of market interdependence (14, 15).

The behavioral components of bubble formation are similarly important in the Iranian context. Emotional shocks and sentiment-driven trading significantly influence bubble dynamics, as Rahmanian et al. (2019) show in their dynamic stochastic general equilibrium (DSGE) analysis, where investor optimism or panic contributes directly to deviations from fundamental valuations (16). Moreover, irregularities in stock price behavior—such as overreaction, underreaction, and herd behavior—are major predictors of bubble episodes in Iranian markets (17). These findings reinforce the view that bubble formation is a multidimensional process shaped by market microstructure, macroeconomic shocks, investor psychology, and expectations.

The global literature also offers advanced methodologies for detecting bubbles, serving as essential tools for understanding and quantifying market vulnerabilities. Traditional econometric tests, such as the right-tailed ADF tests standardized by Phillips and Yu, have been extended with covariates, volatility metrics, and structural break adjustments to improve detection accuracy (6). Recent innovations include the use of options-based bubble detection models, which leverage implied volatility patterns and derivatives pricing to reveal bubble characteristics not observable through spot prices alone (18). These methods underscore the increasing sophistication of bubble diagnostics and the importance of integrating diverse indicators—including volatility, liquidity cycles, and tail risk.

Tail risk, in particular, has emerged as a central indicator in bubble research. Jiang et al. (2020) demonstrate that extreme downside risk significantly influences asset pricing, particularly during bubble collapses when tail behavior intensifies (3). This resonates with the broader theoretical literature suggesting that bubbles tend to inflate the left-tail risk of return distributions by increasing vulnerability to abrupt price declines (1). Such findings have deep implications for risk-management frameworks, highlighting the need for dynamic and countercyclical risk measures that reflect market phases more accurately than static or unconditional metrics.

Amid these global and domestic insights, the Iranian economy faces additional bubble-inducing pressures stemming from chronic inflation, exchange rate volatility, and macroeconomic imbalances. For instance, empirical evidence from Ethiopia demonstrates that inflation and currency fluctuations may induce non-linear effects on economic activity and speculative behavior (19). Similar to Iran, these dynamics reflect how persistent macroeconomic instability can heighten uncertainty and distort investment decisions. Complementary research further shows that exchange rate volatility strongly affects inflation dynamics and may indirectly amplify bubble formation by altering expectations and risk-taking incentives (20). For Iran, given its structurally volatile exchange rate environment, the reciprocal relationship between inflation deviation and exchange rate fluctuations is especially relevant. Pirpour and Samsami (2025) confirm this relationship through a stochastic Mundell–Fleming model, demonstrating how exchange rate shocks may spill over into pricing behaviors and speculative cycles (21).

Given these circumstances, accurately measuring risk exposure during bubble periods becomes essential for both investors and regulators. Traditional value at risk (VaR) measures, while widely used, often underestimate downside risk during bubble expansion because they rely on historical volatility assumptions that fail to reflect the asymmetric and explosive nature of bubble dynamics. Scholars such as Mohammadi et al. (2023) and Faqih Kashani et al. (2024) emphasize the need for adaptive, bubble-sensitive risk metrics capable of incorporating market deviations from equilibrium (11, 14). International findings also highlight the limitations of standard VaR frameworks during periods of high uncertainty and tail dependence, calling for more robust approaches capable of capturing nonlinear distributional dynamics (8, 10).

Countercyclical risk assessment approaches have therefore gained increasing academic and practical attention. These approaches adjust risk estimates according to market conditions, thereby offering more realistic estimates of potential losses during bubble expansions and contractions. By incorporating deviations from equilibrium prices, countercyclical VaR frameworks attempt to capture the market's true latent risk, especially when speculative pressure artificially inflates asset prices (22). This view aligns with systemic risk approaches, which argue that monitoring deviations from fundamentals is crucial for building early warning indicators for market crashes (5).

In this context, the Tehran Stock Exchange—characterized by periodic speculative surges, sensitivity to macroeconomic shocks, and structural market inefficiencies—provides an important empirical setting for analyzing countercyclical risk metrics and exploring their performance relative to conventional VaR. Market dynamics in Iran display recurrent bubble cycles driven by exchange-rate shocks, speculative trading, and policy interventions. Research indicates that these shocks contribute to abrupt volatility clustering, systematic mispricing, and amplified tail risk (7, 13). Furthermore, contagion patterns between currency and equity markets suggest that risk cannot be fully captured unless bubble characteristics are explicitly integrated into risk measures (15).

Although the literature on bubble detection, contagion, and macro-financial instability in Iran has grown considerably, less attention has been paid to the development of bubble-adjusted risk metrics tailored to the local market structure. The gap is particularly significant given that the conventional VaR framework may misrepresent potential losses during bubble periods, especially in environments where structural breaks, expectations, and policy shocks play a defining role in shaping risk dynamics (12). Thus, integrating bubble indicators into risk estimations may provide more accurate and proactive assessments of stock market crash risk.

Given these observations, the present study seeks to contribute to the literature by measuring crash risk in the Tehran Stock Exchange through a countercyclical value-at-risk framework that explicitly incorporates bubble dynamics. This approach offers a novel perspective for evaluating risk during speculative periods and enables deeper understanding of the relationship between bubble behavior, volatility, and market vulnerability across time.

Therefore, the aim of this study is to evaluate and compare the explanatory power of value at risk (VaR) and countercyclical value at risk (BuVaR), constructed using market bubbles, in predicting stock market crash risk in the Tehran Stock Exchange.

Methods and Materials

The present research is applied in terms of objective and correlational in terms of its nature and method. Moreover, regarding the characteristics and direction of the data, it is ex-post facto and based on historical information. Given that this study aims to introduce and compute the bubble-adjusted value-at-risk metric as an indicator for measuring market risk in the Tehran Stock Exchange, the statistical population consists of the Tehran Stock Exchange Total Index, representing the market portfolio, which can appropriately reflect the price fluctuations of listed companies. In this study, daily data from the Tehran Stock Exchange Total Index were used, and the index information for the 10-year period 2015 to 2024 was collected and analyzed. Time-series data related to the Total Index were collected from the official website of the Tehran Stock Exchange. Microsoft Excel software was used for data organization and preliminary computations on the raw data, and the R software (version 4.3.3) was employed for data analysis and model estimation to determine value at risk and bubble-adjusted value at risk.

To address the research question, the effects of value at risk and countercyclical value at risk—constructed using the market bubble—were assessed separately in distinct regression models to evaluate their influence on stock price crash risk. The predictive power of each model in forecasting stock price crashes was then estimated and compared. For this purpose, regression models (1) and (2) were fitted separately for each of the value-at-risk criteria.

$$(1) \quad CR_t = \alpha_0 + \alpha_1 VaR_t + \alpha_2 RV_{[t-14:t]} + \alpha_3 MP_t + \alpha_4 PRM_t + \varepsilon_t$$

$$(2) \quad CR_t = \alpha_0 + \alpha_1 BuVaR_t + \alpha_2 RV_{[t-14:t]} + \alpha_3 MP_t + \alpha_4 PRM_t + \varepsilon_t$$

In these models, CR_t denotes stock market crash risk; $RV_{[t-14:t]}$ represents the 14-day return volatility of the index from day $t-14$ to day t; MP_t denotes the industry index on day t; and PRM_t denotes the market risk premium (the difference between the risk-free rate and the market return). VaR_t denotes value at risk, and $BuVaR_t$ denotes countercyclical value at risk using the market bubble.

To measure stock market crash risk, equation (3) was used in accordance with Habib, Hasan, and Jiang (2018):

$$(3) \quad CR = - \left[n(n-1)^{3/2} \Sigma W_\tau^3 \right] / \left[(n-1)(n-2)(\Sigma W_\tau^2)^{3/2} \right]$$

In this equation, *n* is the total number of periods examined for calculating crash risk. Also, *W* is computed daily as 1 plus the residual (ε_τ) of regression model (4):

(4) $r_\tau = \alpha_j + \beta_1 r_{(m,\tau-2)} + \beta_2 r_{(m,\tau-1)} + \beta_3 r_{(m,\tau)} + \beta_4 r_{(m,\tau+1)} + \beta_5 r_{(m,\tau+2)} + \varepsilon_\tau$

In equation (4), $r_{(m,\tau)}$ is the 14-day simple moving average of the market on day τ, and r_τ is the index return on day τ. Therefore, for the index on each day, there is a value $\varepsilon_{(j,\tau)}$ such that $W_\tau = 1 + \varepsilon_\tau$.

To calculate VaR_t, equation (5) was applied:

(5) $VaR = M \cdot Z_\alpha \cdot \delta \sqrt{T}$

In equation (5), *M* denotes the total invested value, Z_α is the α-percent quantile of the standard normal distribution, δ is the daily standard deviation of logarithmic index returns, and *T* is the time horizon for which VaR is calculated.

To compute countercyclical value at risk using the market bubble ($BuVaR_t$), the logarithmic return time-series was first decomposed into three components describing long-term trend (L_t), cycle (S_t), and noise (Z_t), according to equation (6):

(6) $X_t = L_t + S_t + Z_t$

While the trend component is driven by real economic growth, the noise component reflects realized trading activities under normal efficient-market conditions. Wong (2013) argues that the cycle component explains phenomena such as fat-tailed distributions or volatility clustering, which conventional VaR attributes to the noise term.

After extracting the cycle component from the original data, sequential Augmented Dickey–Fuller (ADF) tests on rolling windows of the cycle process were used to detect bubbles. Phillips (2018) confirmed the ADF framework as suitable for identifying bubbles. The test is repeatedly estimated for rolling subsamples, and the corresponding t-statistic for each subsample is compared with the right-tail critical value of the relevant distribution. Phillips (2018) define the start and collapse of explosive behavior as follows:

(7) $\hat{t}_e = \inf_{(s \geq t_0)} \{ s : ADF_s > cv_\beta^{adf}(s) \}$

(8) $\hat{t}_f = \inf_{(s \geq \hat{t}_e)} \{ s : ADF_s < cv_\beta^{adf}(s) \}$

In these equations, $\hat{t}_e$ and $\hat{t}_f$ denote the bubble origination and termination dates, respectively. Thus, the ADF test is applied on rolling windows of subsamples taken from the main sample, and the test statistic is compared against the critical value for each subsample. The first date at which the statistic exceeds the right-tail critical value of the corresponding t-distribution marks the bubble's formation, and the first subsequent date at which it falls below the critical value marks the bubble's collapse.

After identifying the bubble formation and collapse periods, the size of countercyclical bubbles in each bubble cycle must be computed. For this purpose, original data in each bubble period are compared with their expected value (a moving-average-based benchmark). Wong (2013) argues that moving averages are not suitable benchmarks during crash periods; instead, a rank-filtering process is proposed to extract a well-behaved price benchmark (μ_d). In this process, extreme price changes are removed, and historical prices are replaced such that the moving average of these values defines the benchmark price. Therefore, the deviation from the benchmark price representing bubble formation is calculated using equation (9):

(9) $B_d = X_d / \mu_d - 1$

In this equation, μ_d is the moving average of filtered historical prices, B_d is the bubble size on day d, and X_d is the latest price used in computing μ_d. The adaptive moving average satisfies the condition that in long-term growth periods, investments are not penalized by bubbles. Due to sustained trend growth, bubble magnitude declines and does not become negative during downturns; instead, benchmark prices fall in proportion to initial price declines. Thus, during crashes, inflation becomes negative, producing a downward bubble (Wong, 2014). Furthermore, the bubble moves synchronously with the market cycle, making it countercyclical. Accordingly, BuVaR co-moves with the market and often leads to identifying crashes or reversals (Wong, 2014).

After computing countercyclical bubbles, the returns used in VaR estimation must be adjusted using an inflation factor to ensure returns reflect the actual conditions shaped by market bubbles. Typically, the cycle component is combined with break, compression, or hybrid transformations to explain phenomena in asset-return series, and it is argued that price-series components can model actual market behaviors. The main goal of using the cycle is to asymmetrically inflate the distribution tail thickness: the larger the deviation of price from its benchmark—that is, the larger the bubble—the higher the crash risk. Therefore, the tail inflation must reflect this increased crash risk by multiplying the return distribution by an inflation factor. Wong (2014) defines this inflation factor as a response function that converts bubble B_d into the inflation factor Δ_d for each day d, as follows:

$$\Delta_d = \min\left(\Psi/(2\sigma_d),\ \exp\left\{ (|B_d| / B_{max})^{\omega} \times \ln(\Psi/(2\sigma_d)) \right\} \right) \quad (10)$$

Here, $\Delta_d \geq 1$, and ω is a curvature parameter determining the smoothness of variations in BuVaR. The inflation factor Δ_d grows with the bubble and, at $\omega = 2$, acts as a cap for the bubble—i.e., the factor cannot exceed this cap even if the bubble increases further. The factor is capped at $\Psi/(2\sigma_d)$. The ratio $\Psi/(2\sigma_d)$ approximates the shift from the current VaR, $2\sigma_d$, to Ψ. Empirically, Ψ is defined as the mean of the five largest losses and five largest gains in the entire asset-return sample (based on absolute daily returns). Empirical studies show that $\omega = 0.5$ provides the smoothest daily variation in BuVaR. Wong uses $2\sigma_d$ as an approximation for VaR; in this study, $2\sigma_d$ is replaced directly with VaR. B_{max} denotes the maximum absolute bubble value in the asset's history. Thus, Δ_d lies between VaR and its upper cap and adjusts each scenario multiplicatively on one side of the return distribution. The BuVaR method begins with the assumption that the distribution tails of financial variables are unknown and aims to provide a more accurate alternative to conventional VaR. Accordingly, bubbles identified in the St cycle must be compensated to prevent price crashes. Under this approach, return distribution X_t is adjusted to offset bubble effects. Under the BuVaR method, the return on day d is transformed using equation (11):

$$R_n = \begin{cases} \Delta_d R_n & \text{if } \operatorname{sign}(R_n) \neq \operatorname{sign}(B_t) \\ R_n & \text{if } \operatorname{sign}(R_n) = \operatorname{sign}(B_t) \end{cases} \quad (11)$$

Here, B_d is the bubble index and Δ_d is a function of B_d. Economically, this transformation compensates for the asymmetric crash risk that is not captured in the distribution of R_n and conventional VaR. Thus, if the bubble forms in an upward trend ($B_d > 0$), the negative side of the return distribution is transformed using the inflation factor (affecting long positions). If the bubble forms in a downward trend ($B_d < 0$), the positive side of the distribution is inflated (affecting short positions). Therefore, due to its countercyclical nature, BuVaR helps create a countercyclical capital buffer for market risk. As a result, calculating VaR based on the inflated returns in equation (11) leads to the estimation of countercyclical value at risk using the market bubble.

Findings and Results

The price bubble is a key determinant of the countercyclical value-at-risk (VaR) using the market bubble in this study. To identify price bubbles in the stock index, and consistent with Phillips (2018), sequential ADF tests were performed on 100-day rolling windows of observations, and the resulting test statistics were compared with their critical values at the 95% confidence level. These tests were conducted on the logarithmic returns of the index. Figure (1) illustrates the changes in index levels and their logarithmic returns over the research period.

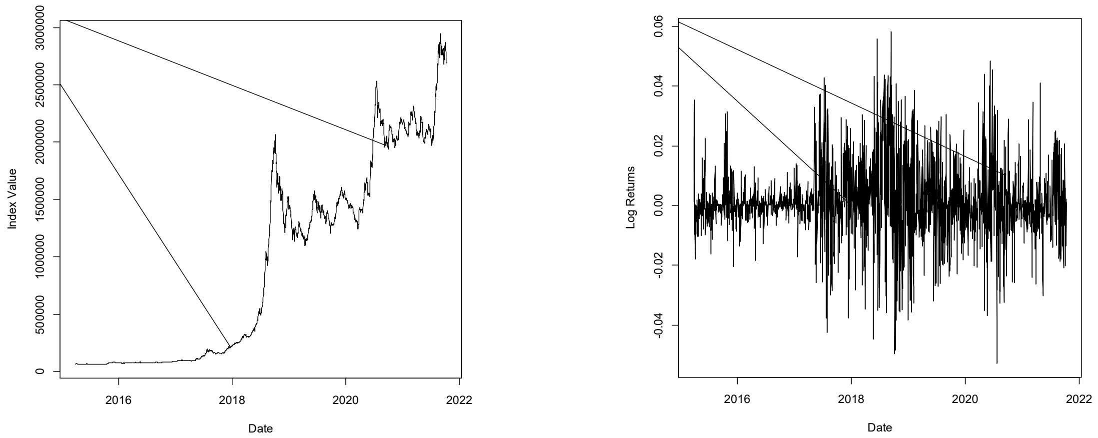

Figure 1. Time series of index values (left) and logarithmic returns (right) over the research period

Performing this test on the cyclical component of the logarithmic returns of the index resulted in the identification of 87 countercyclical price bubbles across all observations (Figure 2).

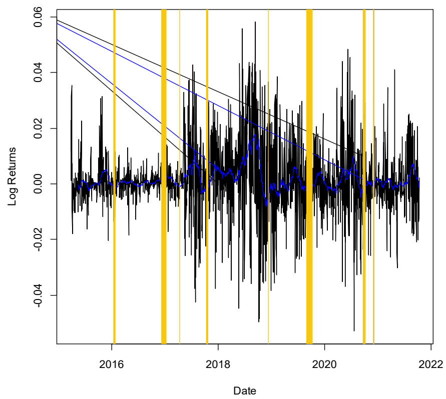

Figure 2. Price-bubble formation ranges (yellow bands), return trend (blue curve), and logarithmic returns (black curve)

As shown in Figure (2), the price bubbles formed periodically affect the logarithmic returns. The sequence of bubble-formation intervals (yellow bands) in Figure (2) indicates the bubble origination and collapse points on the index returns. To calculate the magnitude of the price bubble formed in each of the 87 bubble days, equation (9) was applied by comparing realized returns with their adaptive moving average. These bubble magnitudes were then used to compute the inflated returns using equation (11). In computing inflated returns, the five largest losses and the five largest gains (return boundary values), along with other inflation parameters, were applied on bubble-formation days. The values of each parameter are shown in Table (1).

Table 1. Initial parameter values in calculating inflated returns on bubble-formation days

Parameter	Value
Five largest losses	(−0.042535, −0.044628, −0.048277, −0.049496, −0.052912)
Five largest gains	(0.058109, 0.055670, 0.048421, 0.045494, 0.044004)
Ψ	0.001384897
ω	0.5
σ_d	0.00991066
∆_d	0.0698689

Accordingly, the inflated returns on bubble-formation days were computed through the inflation factor ∆_d. The computational results showed that the value of ∆_d in all bubble-formation periods was equal to Ψ/(2σ_d). Therefore, in computing inflated returns (equation 11), the inflation factor ∆_d was considered a constant coefficient.

After computing the inflated returns on bubble-formation days, the countercyclical value-at-risk and conventional value-at-risk were estimated using inflated returns and logarithmic returns, respectively, over the entire research period. Figure (3) shows the evolution of VaR and BuVaR over the research period.

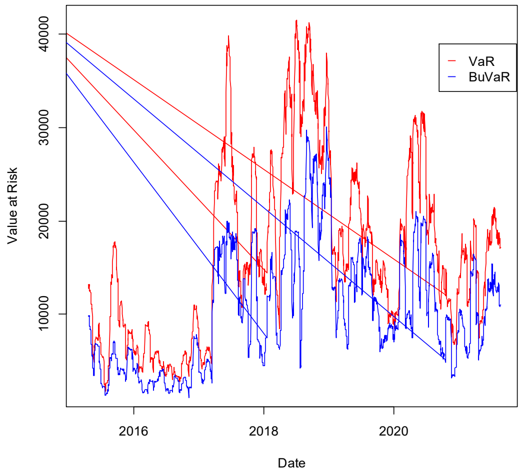

Figure 3. Value at Risk (VaR) and Countercyclical Value at Risk Using Market Bubble (BuVaR)

In computing both VaR metrics, the total investment value was set equal to 1,000,000 monetary units, and the VaR measures were calculated using 30-day rolling windows applied to the logarithmic and inflated returns. Figure (3) shows that countercyclical VaR using the market bubble is smaller than conventional VaR across the entire research period. This finding indicates that penalizing returns on bubble-formation days using the inflation factor ∆_d leads to lower investment value-at-risk. After estimating the values of both types of VaR, concentration and dispersion measures of the variables were examined to evaluate their overall statistical characteristics. A summary of the descriptive statistics of the model variables is presented in Table (2).

Table 2. Descriptive statistics of the research variables

Variable	Mean	Median	Maximum	Minimum	Standard Deviation
Price Bubble	2.83724	−0.95402	4842.537	−304.214	120.6675
Value at Risk	16606.39	15161.79	41509.80	1707.449	9633.7
Countercyclical VaR	5505.882	4360.241	16348.74	318.0496	3940.558
Stock Market Crash Risk	0.18370	0.26732	3.18611	−3.19645	0.93343
Total Index	2,952,762.2	2,987,117.2	2,944,637	61,163.70	861,645.2
Logarithmic Return	0.00069	0.00025	0.02523	−0.02298	0.00534
Industry Index	4434.275	5336.150	12,618.17	477.3	3721.669
Market Risk Premium	0.00119	0.00010	0.05942	−0.0522	0.01234
14-Day Volatility	0.00416	0.00376	0.01277	0.00032	0.00267

According to the indicators reported in Table (2), it is observed that the average price bubble of the stock index is 2.83724 units. The highest bubble value corresponds to 4 December 2023 (13/09/1402 in the Persian calendar), and the lowest value corresponds to 11 June 2018 (21/03/1397 in the Persian calendar). The value at risk of investment in the stock market for an investment of 1,000,000 monetary units is, on average, 16,606 units, and the countercyclical value at risk using the bubble for 1,000,000 monetary units is, on average, 5,505 units, which is approximately one third of the conventional value at risk. The average stock market crash risk is 0.1837, and the average value of the total index over the research period is 2,952,762. The mean logarithmic return of the index is 0.00069, and the average value of the industry index is 4,434.275. It is noteworthy that, given the importance of the rate of return and the interest rate as key risk factors in shaping overall market trends and the rise or fall of the total index, the banking industry index was used as the industry index. The average market risk premium over the research period is 0.00119, and the mean 14-day return volatility is 0.00416.

To answer the research question, the effects of two metrics—value at risk and countercyclical value at risk using the bubble—on stock market crash risk were tested through two separate regression models, and the explanatory power of these two models was compared. It should be noted that, due to significant structural changes in the index trend from 22 September 2019 onward (31/06/1398 in the Persian calendar), a dummy variable was employed to separate the effects of the variables in the regression model. The value of this dummy variable is equal to zero for periods before this date and equal to one for periods after it. Figure (4) illustrates the index movements separately for these two subperiods.

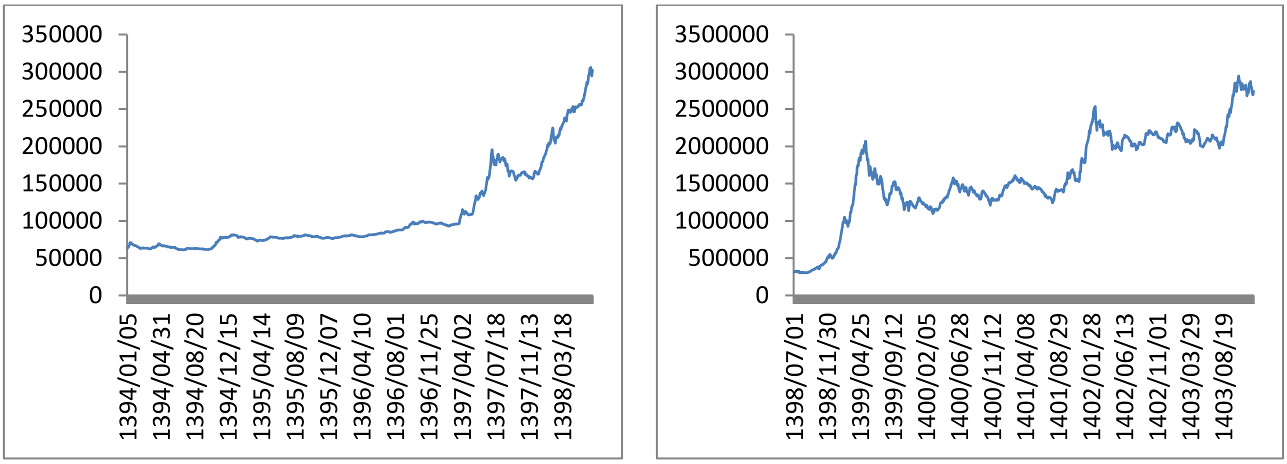

Figure 4. Index values in periods before (left) and after (right) 22 September 2019

Accordingly, the regression models under investigation were rewritten using equations (12) and (13) and then estimated.

$$CR_t = \alpha_0 + \alpha_1 VaR_t + \alpha_2 RV_{[t-14:t]} + \alpha_3 MP_t + \alpha_4 PRM_t + \alpha_5 Dum2019_t + \alpha_6 (Dum2019_t \times VaR_t) + \varepsilon_t \quad (12)$$

$$CR_t = \alpha_0 + \alpha_1 BuVaR_t + \alpha_2 RV_{[t-14:t]} + \alpha_3 MP_t + \alpha_4 PRM_t + \alpha_5 Dum2019_t + \alpha_6 (Dum2019_t \times BuVaR_t) + \varepsilon_t \quad (13)$$

Before final model estimation, the basic regression assumptions of the models were tested. Given that the significance levels obtained from the Breusch–Pagan–Godfrey and Breusch–Godfrey tests were smaller than the 0.05 error level, the assumptions of homoskedasticity and independence of the error terms in both models were not supported. Therefore, to mitigate the effects of heteroskedasticity and autocorrelation of the error terms on the estimation of regression coefficients, robust regression with HAC (heteroskedasticity and autocorrelation consistent) estimators was used. It should also be noted that, to enhance the predictive power of the model for stock market crash risk, the first-order lag of the dependent variable was included as the first explanatory variable in the model. This not only increased the model's ability to predict the dependent variable but also partly reduced the impact of autocorrelation in the error terms. Table (3) reports the estimation results of these two regression models, along with the diagnostic tests of basic assumptions and the model goodness-of-fit indices.

According to the results in Table (3), the significance level of both regression models testing this hypothesis is smaller than the 0.05 error level, confirming the overall significance of the regression models in explaining stock market crash risk. Based on the adjusted coefficients of determination of the two models, it is observed that the VaR-based model can explain 97.59% of the variation in stock market crash risk, whereas the countercyclical VaR-based model can explain 97.47% of the variation in stock market crash risk. Therefore, using a strict comparison, it can be concluded that conventional value at risk provides a slightly better prediction of stock market crash risk. Hence, the BuVaR metric did not outperform the VaR metric in identifying stock market crash risk.

Table 3. Estimation results of the research regression models

Model / Explanatory Variable	Value at Risk			Countercyclical Value at Risk		
	Coefficient	t-Statistic	Significance	Coefficient	t-Statistic	Significance
Stock Market Crash Risk (t−1)	0.922908	26.26088	0.000	0.928007	16.73361	0.000
Value at Risk	−0.0000457	−4.891564	0.000	−0.0000892	−6.098847	0.000
14-Day Volatility	59.22090	2.088616	0.0370	27.77723	1.419259	0.1561
First Difference of Industry Index	−0.001167	−1.803788	0.0715	−0.001247	−1.567754	0.1172
Market Risk Premium	2.226013	0.370773	0.7109	0.564792	0.091090	0.9274
Effect of Post-2019 Period	−0.345751	−2.415469	0.0159	−0.497195	−2.312556	0.0209
Post-2019 Effect × Value at Risk	0.0000319	4.487053	0.000	0.0000904	3.858021	0.0001
Constant	0.351033	5.344661	0.000	0.348018	4.301468	0.000

Basic assumptions and regression model diagnostics

Statistic	VaR Model	BuVaR Model
Adjusted R^2	0.975914	0.974711
Durbin–Watson Statistic	2.209125	2.211122
Likelihood Ratio Statistic	6507.130	6189.762
Model Significance	0.000	0.000
Breusch–Pagan–Godfrey Statistic	5.711120	2.328387
Breusch–Pagan–Godfrey Probability	0.000	0.0229
Breusch–Godfrey Statistic	4099.609	35.00361
Breusch–Godfrey Probability	0.000	0.000

In interpreting the regression coefficients, it should be noted that both value at risk (p-value = 0.000) and countercyclical value at risk (p-value = 0.000) have a statistically significant impact on stock market crash risk, and the moderating effect of the post-2019 period is also significant in this relationship. The estimated coefficients indicate that in the pre-2019 period (Dum2019 = 0), both value at risk and countercyclical value at risk have a negative and significant effect on stock market crash risk. However, in the post-2019 period (Dum2019 = 1), which coincides with a substantial rise in the index, value at risk has an effect equal to −0.00000138 ($\alpha_1 + \alpha_6$) on crash risk, whereas countercyclical value at risk shows an effect equal to 0.0000012 ($\alpha_1 + \alpha_6$) on crash risk. This result implies that, in the period after 2019, an increase in countercyclical value at risk is associated with a higher expected stock market crash risk, whereas according to conventional value at risk, in the post-2019 period, an increase in investment VaR is associated with a decrease in stock market crash risk—an outcome that is counterintuitive. Therefore, based on the interpretation of the regression coefficients, countercyclical value at risk appears to provide a more logically consistent explanation of stock market crash risk.

Discussion and Conclusion

The findings of this study shed important light on the dynamics of stock market crash risk in the Tehran Stock Exchange and the role played by bubble-adjusted risk indicators in explaining market vulnerabilities. The empirical results demonstrated that both conventional value at risk (VaR) and countercyclical value at risk (BuVaR) exert statistically significant effects on crash risk. However, their explanatory power and sign behavior differ across periods, particularly before and after the structural break identified in **2019**. Specifically, while the VaR-based model accounted for 97.59% of changes in crash risk, the BuVaR-based model explained 97.47%, leading at first glance to the conclusion that VaR performed marginally better. Yet, a deeper interpretation of the coefficients indicated that BuVaR offers a more logical and economically consistent explanation of crash behavior, especially in the post-2019 market environment characterized by rapid index growth and heightened speculative cycles.

This pattern aligns strongly with existing literature that emphasizes the limitations of conventional VaR during bubble episodes. Traditional VaR models rely on historical volatility and normality assumptions, often underestimating downside risk when markets experience speculative surges or abrupt deviations from fundamentals. Scholars have argued that tail behavior becomes more pronounced during bubble formation, meaning that risk assessments must incorporate these non-linearities (3). The results of this study confirm this perspective: when bubble dynamics intensified post-2019, VaR misleadingly suggested a decline in crash risk, whereas BuVaR—designed to capture bubble-driven distortions—reflected rising vulnerability. This outcome strongly supports the theoretical view that risk measures must adjust to market regimes, as volatility clustering and explosive price movements alter distributional properties in ways that static models cannot capture (1).

The findings also resonate with empirical research regarding bubble formation and collapse in emerging and transitional markets. For example, Izadi et al. showed that expectations and macroeconomic shocks significantly shape bubble episodes in Iran, particularly during periods of currency instability and inflationary pressure (12). Consistent with this, the current study revealed that the inflation-adjusted and bubble-correlated nature of market behavior after 2019 introduced a pronounced asymmetry in crash risk. Similarly, studies on bubble contagion between currency and equity markets highlight that cross-market interactions intensify speculative dynamics and alter risk transmission patterns (9, 14). The observed behavior of BuVaR in this study reflects this interconnected structure. As bubble magnitude increased, the countercyclical risk component grew accordingly, capturing more meaningful signals about systemic vulnerability than VaR.

International findings reinforce these conclusions. Research examining bubble contagion in commodity markets—such as the work by Gharib et al., which showed that COVID-19-related shocks contributed to cross-asset bubble spillovers in crude oil and gold markets—highlights that bubbles evolve in an interconnected and regime-dependent manner (22). This is consistent with the behavior seen in the Tehran Stock Exchange following structural economic events. Similarly, bubble detection in cryptocurrencies demonstrates that multiple bubble regimes frequently form and collapse, suggesting that asset prices undergo recurring phases of explosive behavior (10). The identification of 87 countercyclical bubbles in this study reflects these wider global patterns and highlights the necessity of models such as BuVaR that adjust to these cyclical deviations.

The stronger interpretive alignment of BuVaR with observed market dynamics is also consistent with the literature on bubble detection methodologies. Studies argue that the use of rolling ADF tests and adaptive moving averages improves the accuracy of identifying bubble regimes, particularly when markets experience structural breaks or abrupt shifts (6, 8). The use of these techniques in this research ensured that bubble cycles were identified with precision. In addition, Fusari et al. emphasized that bubble detection models benefitting from real-time adjustments provide better predictive accuracy than static measures based solely on historical price movements (18). Applying this logic, the countercyclical inflation factor used in BuVaR allowed risk estimates to respond more dynamically to deviations between realized prices and equilibrium benchmarks.

Moreover, the study's findings reflect the broader macro-financial context of Iran, where chronic inflation, exchange rate shocks, and policy-induced uncertainties characteristically fuel speculative trading waves. Research has noted that these macroeconomic distortions create environments conducive to repeated bubble episodes and heightened crash vulnerability. Pirpour and Samsami's analysis on the stochastic Mundell–Fleming model highlights the reciprocal influence of exchange-rate fluctuations and inflation deviations, a pattern that closely aligns with the bubble-induced distortions captured by BuVaR (21). Similarly, analyses of inflation and economic volatility in comparable contexts, such as Ethiopia, underscore how macroeconomic instability fosters speculative tendencies and destabilizes market expectations (19). The countercyclical behavior captured by BuVaR aligns tightly with these findings, suggesting that risk measures incorporating macro-volatility signals provide superior explanatory power relative to static measures such as VaR.

The results are further supported by literature investigating the behavioral underpinnings of bubble cycles. Studies show that emotional shocks, sentiment-driven trading, and investor expectations significantly influence bubble growth and collapse (16). These behavioral features often cause asymmetries in risk perception and lead to market overreactions or underreactions that are inadequately captured by conventional VaR. Because BuVaR integrates bubble magnitude directly into its inflation mechanism, it inherently captures the sentiment-driven, cycle-dependent aspects of market behavior, thereby reflecting crash risk more meaningfully.

Additionally, research on systemic risk in Chinese financial institutions notes that bubble formation magnifies systemic fragility by connecting micro-level price distortions to macro-level financial vulnerabilities (5). The findings of this study align with this systemic risk perspective, showing that in periods of speculative acceleration, traditional risk measures may become disconnected from actual systemic vulnerabilities. By contrast, BuVaR's sensitivity to directional price distortions makes it more adept at identifying the build-up of systemic pressures.

The contrast between pre-2019 and post-2019 behavior of VaR and BuVaR further emphasizes the importance of regime-sensitive risk measures. Before the structural break, both indicators negatively and significantly predicted crash risk, consistent with the notion that elevated risk exposure was associated with market stabilization rather than collapse. However, after 2019—with the heightened presence of speculative cycles—the two measures diverged sharply. VaR displayed a counterintuitive negative relationship with crash risk, suggesting that rising risk exposure reduced the likelihood of a crash. BuVaR, however, shifted sign appropriately, indicating that greater bubble-adjusted risk exposure increased crash vulnerability, in line with established economic theory and empirical observations in global bubble research (7). This divergence confirms the argument that traditional VaR fails under bubble-driven regimes and that bubble-adjusted metrics provide a more structurally realistic representation of market risk.

In conclusion, the results strongly support the theoretical framework asserting that bubble-sensitive and countercyclical risk metrics outperform traditional risk measures in environments characterized by speculative surges, macroeconomic instability, and structural market breaks. Although the statistical explanatory power of BuVaR is marginally lower than that of VaR, its behavioral, directional, and theoretical alignment with actual market dynamics makes it a more coherent and reliable indicator of crash risk under bubble conditions.

This study is limited by its focus on a single stock market, the Tehran Stock Exchange, which may reduce generalizability to other markets with different structural, regulatory, or microstructural characteristics. Additionally, reliance on historical price data and the assumption of consistent equilibrium benchmarks may overlook deeper fundamental value drivers not directly observable in price series. The use of daily data, although appropriate for volatility and crash-risk modeling, may miss high-frequency bubble signals or microsecond-level trading distortions. Furthermore, the identification of structural breaks—such as the one in 2019—relies on observable market outcomes rather than formal structural-break testing, which may introduce model-dependency in determining pre- and post-periods. Finally, the BuVaR framework requires multiple layers of decomposition and parameter tuning, which may introduce estimation uncertainty or sensitivity to the selection of smoothing windows and threshold values.

Future studies should explore bubble-adjusted risk measures across a broader set of markets, including developed and emerging economies, to assess cross-market robustness. High-frequency approaches could be integrated to detect intraday bubble behavior and crash signals. Researchers may also incorporate machine learning and nonlinear modeling techniques to enhance bubble detection accuracy and reduce false alarms. Additionally, future research could examine the role of fundamental factors such as earnings cycles, macroeconomic indicators, and investor sentiment indices in shaping bubble-adjusted risk dynamics. It may also be valuable to test hybrid risk models combining BuVaR with alternative tail-risk metrics to examine whether integrating multiple systemic risk indicators improves predictive accuracy for market crashes.

Market regulators should incorporate bubble-sensitive risk metrics into early warning systems for financial instability. Portfolio managers may consider employing countercyclical risk tools such as BuVaR to adjust leverage and exposure during speculative periods. Institutional investors could use bubble-detection signals to refine asset-allocation strategies, particularly in volatile emerging markets. Risk-management committees may also adopt dynamic capital buffers that respond directly to deviations from equilibrium prices, thereby strengthening resilience during market turbulence.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us carrying out this study.

Authors’ Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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