Financial Stability Risk and Determining the Difference in Investment Horizons Between Passive and Active Investors: A Portfolio-Based Leptokurtic Distribution Test

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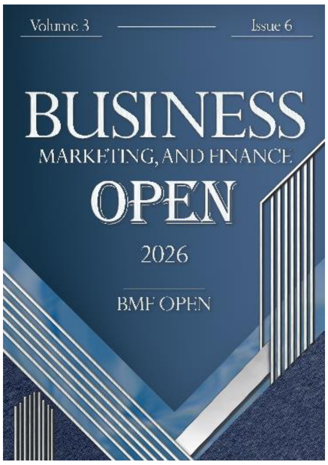

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Abstract: The purpose of this study was to evaluate financial stability risk and determine the difference in investment horizons between passive and active investors through the application of a leptokurtic distribution test and portfolio construction. Using the leptokurtic basis in the empirical distribution of financial returns and quantile regression, the study first examined the normality level of the data and subsequently investigated the difference between the overall stock market index (TEPIX) as the benchmark index and the financial stability index "TEBFS." In addition to identifying the most influential criterion affecting financial stability risk through Root Mean Square Error (RMSE), Mean Square Error (MSE), and the coefficient of determination (R^2), the study also determined the difference between the investment horizons of passive investors based on quantile regression compared with the investment horizons of active investors in constructing the Sortino portfolio (E) and the Markowitz portfolio (F). The study period, in terms of collecting data related to the financial stability risk of banks listed on the Tehran Stock Exchange, covered 2018 to 2022. The results of the leptokurtic distribution function indicated that all coefficients related to the "TEPIX" and "TEBFS" indices were significant within this distribution function. In fact, the significance of the conditional variance coefficient of banking system financial stability returns based on the "TEBFS" index demonstrates that all identified criteria affecting the measurement of financial stability in the banking system possess the required capability for risk determination. Furthermore, the findings revealed that since the Conditional Value at Risk fluctuation "ΔCoVaR" calculated for the "TEBFS" index was negative, concentrating on the identified criteria and developing them as an evaluation model provides a more reliable basis than the overall stock market index (TEPIX) within technical analysis processes for investors. Finally, the results demonstrated that the construction of the Sortino portfolio (E) by passive investors, based on a longer-term investment horizon for evaluating banks' financial stability risk, was more desirable than the construction of the Markowitz portfolio (F) by active investors.

Keywords: Investment Horizon, Leptokurtic Distribution, Quantile Regression

1. Introduction

Financial stability has become one of the central concerns of banking, capital market analysis, and macro-financial governance because banks are not only financial intermediaries but also channels through which liquidity shocks, credit contraction, market volatility, regulatory pressure, and investor expectations are transmitted to the wider economy. The banking system's stability depends on the interaction of internal balance-sheet indicators, market-based risk measures, regulatory frameworks, liquidity conditions, managerial stability, and investor behavior. In emerging markets, where financial markets are often exposed to higher volatility, policy uncertainty, and structural inefficiencies, the evaluation of banking stability requires methods that can capture non-normal return distributions, asymmetric risk, tail dependence, and differences in investors' time horizons. Recent studies emphasize that financial stability cannot be understood solely through traditional accounting indicators; rather, it must be examined through a multidimensional framework that includes systemic risk, market risk, liquidity risk, regulatory quality, financial inclusion, and portfolio formation behavior [1-4].

Banks listed in capital markets are especially important because their financial stability is evaluated simultaneously by regulators, shareholders, depositors, and investors. In such settings, market-based signals such as stock returns, volatility, trading turnover, and risk spillovers may reveal information about the resilience or fragility of banking institutions. The literature shows that systemic risk in the banking industry is closely connected to market risk and that market indicators can explain part of the vulnerability of banks during unstable periods [1]. Similarly, macro-financial models of contagion demonstrate that financial systems may become fragile when shocks are transmitted across interconnected agents and institutions, making risk measurement a central tool for anticipating instability [2]. This issue is particularly relevant for banking systems in emerging markets, where bank stability is affected by internal risk management, regulatory reforms, political risk, and capital market dynamics [5-7].

Financial stability in banks is also shaped by institutional and regulatory conditions. Evidence from developing economies indicates that bank regulations matter for financial stability because capital adequacy, supervision, liquidity requirements, and risk-control mechanisms influence banks' ability to absorb shocks [4]. Post-crisis regulatory experiences, including strengthened supervision and trust-building reforms, also show that the sustainability of banking stability depends on the credibility of regulatory institutions and the effectiveness of monitoring systems [8]. Basel-related reforms further highlight the importance of harmonizing capital requirements and risk-sensitive supervision to reduce systemic vulnerability [6]. However, regulatory frameworks alone are insufficient when market volatility, liquidity shortages, and investor behavior create new forms of instability. For this reason, empirical models of bank stability increasingly combine accounting-based variables with market-based and econometric risk measures.

Liquidity risk is another key determinant of banking stability. Banks are exposed to liquidity shocks through deposits, interbank lending, loan growth, and market turnover, and such shocks may influence both the stability of individual banks and the systemic resilience of the banking sector. Comparative evidence from Islamic, conventional, and hybrid banks confirms that liquidity risk exposure differs across banking models and is affected by balance-sheet structure, funding sources, and institutional conditions [9]. Studies on Islamic banking further show that financial stability is linked to intellectual, structural, and institutional dimensions of banking performance [10]. In addition, research on Sukuk market development suggests that financial risks may have asymmetric long-run effects, implying that financial stability analysis should account for nonlinear and asymmetric responses rather than assuming uniform effects across market conditions [11]. These findings reinforce the need for models capable of evaluating conditional volatility, non-normal return behavior, and downside risk in bank-related portfolios.

In the Iranian banking and capital market context, financial stability is influenced by both firm-level and market-level factors. Research on Iranian banks shows that dividend policy can affect financial stability, suggesting that internal financial decisions are associated with the stability profile of banking institutions [12]. Other evidence indicates that cash flow risk management contributes to financial stability, emphasizing the role of liquidity planning and internal financial control mechanisms [13]. Competition, capital adequacy, and losses during crisis periods have also been examined as determinants of banking stability, demonstrating that the Iranian banking system requires risk assessment models that can integrate market performance, capital structure, and crisis sensitivity [14]. Moreover, managerial stability and earnings stability may affect systematic risk, especially when risk management serves as a moderating mechanism [15]. These studies collectively suggest that financial stability risk in Iranian banks should be evaluated through a combined framework that links banking indicators to capital market behavior.

The relationship between financial inclusion, financial development, and banking stability has also attracted growing attention. Financial inclusion can strengthen the banking system by expanding deposit bases, improving access to financial services, and increasing the depth of financial markets, but it may also introduce additional risks when credit expansion is not accompanied by proper supervision. Studies in developing countries show that financial inclusion and institutional factors play a significant role in banking stability [16]. Evidence from the MENA region also indicates that financial inclusion and financial development are closely related to financial stability, although their effects may depend on the institutional and macroeconomic environment [17]. Similarly, dynamic panel evidence shows that financial inclusion, banking stability, and economic growth are interrelated, which means that instability in banks can weaken broader economic performance, while growth and inclusion can reshape banking-sector resilience [18]. These findings indicate that bank stability is not merely a micro-level concern but a broader financial-system issue.

At the same time, the behavior of investors in capital markets affects how banking risk is priced, interpreted, and transformed into portfolio decisions. Investors differ in their risk perception, behavioral biases, demographic characteristics, and investment horizons, and these differences influence their preference for active or passive strategies [19]. Passive investors often seek long-term exposure, lower transaction costs, and relatively stable portfolio performance, whereas active investors attempt to exploit short-term market inefficiencies and abnormal returns. The rise of passive investing has become a major phenomenon in global capital markets, and systematic reviews show that passive strategies have altered market liquidity, price discovery, and portfolio management practices [20]. However, passive investment may also create concentration in intraday liquidity, especially when many investors follow similar index-based or rule-based strategies [21]. Therefore, distinguishing passive and active investors requires attention not only to portfolio returns but also to risk exposure, trading horizon, and market conditions.

The active–passive distinction becomes particularly important during bull and bear market conditions. Evidence from emerging markets shows that the performance of passive and active investment strategies may differ depending on market regimes, suggesting that the superiority of either strategy is conditional rather than universal [22]. Active stock selection may provide benefits for diversified investors when managers can identify mispriced assets, control downside risk, or respond quickly to changing market conditions [23]. At the same time, uncertainty-based portfolio studies show that active and passive portfolios may be compared through tracking error and risk-adjusted measures, rather than through average returns alone [24]. In the Tehran Stock Exchange, evidence on individual investors also shows that the performance of active and passive investors differs when evaluated through portfolio studies and own-benchmark abnormal return approaches [25]. Therefore, in markets such as Iran, where bank stocks are exposed to financial stability risk, it is necessary to examine whether passive or active investment horizons provide a more reliable basis for portfolio formation.

Investment horizon is a critical concept in this debate because it determines how investors respond to short-term volatility, long-term value creation, and downside risk. Studies on mental accounting and portfolio selection in the Tehran Stock Exchange show that investors' stock selection is affected by their investment time horizon, meaning that long-term and short-term investors may classify risk and return differently [26]. Institutional shareholders' investment horizons can also affect managerial short-termism, indicating that long-term investors may discipline managerial behavior differently from short-term investors [27]. In other financial markets, speculative behavior and capital-gain expectations illustrate that time horizon can reshape investment incentives and risk-taking behavior [28]. Accordingly, in evaluating the financial stability risk of bank stocks, it is not sufficient to estimate risk coefficients; it is also necessary to determine whether such coefficients support active short-term portfolio strategies or passive long-term portfolio strategies.

From a methodological perspective, financial stability risk should be assessed using models that account for volatility clustering, heavy tails, non-normal distributions, and conditional dependence. Financial returns usually do not follow a normal distribution; instead, they often exhibit skewness, excess kurtosis, and extreme observations. This makes leptokurtic distribution analysis and conditional volatility models particularly relevant. The use of GARCH-family models enables researchers to estimate conditional variance and detect risk behavior that ordinary mean-based models may overlook. In banking stability analysis, such techniques are useful because financial shocks often appear first in volatility patterns before becoming visible in accounting indicators. Moreover, systemic risk assessment requires attention to tail events and conditional losses, which can be captured through measures such as Value at Risk and Conditional Value at Risk. These tools are especially relevant when financial stability is assessed in relation to the whole capital market index and a constructed banking financial stability index.

Quantile regression provides an additional advantage because it estimates relationships at different points of the conditional distribution rather than focusing only on the conditional mean. This is particularly suitable for financial stability studies because extreme downside conditions, not average conditions, are often the main concern of regulators and investors. In the context of banking-sector risk, quantile regression can reveal how bank-specific stability indicators behave under lower-tail or upper-tail market conditions. It also allows the comparison of different portfolio structures by examining whether the effect of banking stability criteria changes across value and growth stock quintiles. When combined with Conditional Value at Risk fluctuation, quantile regression can provide a stronger basis for comparing the TEPIX benchmark index with a bank-specific financial stability index such as TEBFS. This approach is consistent with the broader literature emphasizing that banking stability is multidimensional, nonlinear, and sensitive to systemic and market-based risk factors [1, 2, 29].

Portfolio formation models also provide a useful basis for distinguishing active and passive investor behavior. The Markowitz mean–variance portfolio is generally consistent with active investment logic because it emphasizes the trade-off between expected return and variance, making it attractive for investors who seek to optimize short-term risk-return combinations. By contrast, the Sortino portfolio focuses on downside risk rather than total volatility, making it more aligned with investors who prioritize protection against unfavorable returns and long-term financial stability. This distinction is important in bank-stock investment because financial stability risk is inherently asymmetric: positive volatility may not harm investors, while downside volatility can signal distress, contagion, or systemic fragility. Therefore, comparing Markowitz and Sortino portfolios within a quantile regression framework can clarify whether active or passive investors are better positioned to evaluate the financial stability risk of bank stocks.

The present study addresses this gap by integrating financial stability indicators, leptokurtic distribution analysis, quantile regression, and portfolio-based investor classification. While previous studies have examined banking stability, financial inclusion, regulatory frameworks, liquidity risk, active and passive investment, and investment horizons separately, fewer studies have connected these dimensions within a single empirical framework for bank stocks in the Tehran Stock Exchange. The novelty of this study lies in evaluating the financial stability risk of listed banks through a constructed banking financial stability index and comparing it with the overall capital market index, while simultaneously identifying whether passive investors using the Sortino portfolio or active investors using the Markowitz portfolio benefit from a more reliable investment horizon. By combining banking stability criteria with market-based risk measures and portfolio construction, the study contributes to both financial stability literature and investment management research.

Accordingly, the aim of this study is to evaluate financial stability risk and determine the difference in the investment horizons of passive investors compared with active investors through a portfolio-based leptokurtic distribution test and quantile regression analysis of banks listed on the Tehran Stock Exchange.

2. Methodology

In terms of objective, the present study is applied research, and with respect to its nature, it should be classified as correlational research. In this process, the identified quantitative indicators were examined using a nonlinear GARCH model in order to determine the Generalized Error Distribution (GED) or Student's t-distribution and the conditional variance of financial stability returns within the banking system. Accordingly, the leptokurtic distribution, as a type of probability distribution, was employed to identify the differences between the data collected from financial stability indicators and the overall stock market index. Subsequently, the Conditional Value at Risk fluctuation ($\Delta CoVaR$)was calculated at error levels of 0.05 and 0.01 to determine which regression-based index provides a more reliable basis for assessing financial stability risk. Thereafter, Root Mean Square Error (RMSE), Mean Square Error (MSE), and the coefficient of determination (R^2)were used to calculate the financial stability risk of the banking system based on the identification of the most influential indicator. Finally, based on the Markowitz and Sortino portfolios, the difference between the investment horizons of passive and active investors was determined in terms of volatility trading behavior. In this process, the Fama and French model {Fama & French, 1993} was applied to all banking stocks constituting investors' portfolios, based on equal and random weighting of investment horizons over a five-year period from 2018 to 2022, represented by the symbols $Q_1$and Q_5.

Model Specification

In the present study, based on the studies of {Asif & Nasir, 2023}, {Boucly et al., 2023}, and {Atellu et al., 2021}, eight factors affecting the evaluation of financial stability risk in bank stocks, according to the operational definitions presented in Table 1, constituted the basis for model development.

Table 1. Operational Definitions of the Indicators Affecting the Enhancement of Banks' Financial Stability

Row	Identified Indicator	Abbreviation	Operational Definition
1	Shareholders' Equity	Equity	Book value of total shareholders' equity
2	Liquidity Turnover	Turnover Ratio	Total market transaction value divided by the average total market value over a specific period
3	Loans and Advances to Banks	Loans and Advances to Banks	Outstanding loans and advances granted to other banks at the end of the period
4	Mortgage Loans	Mortgage Loans	Outstanding mortgage facilities at the end of the period
5	Current Deposits	Customer Deposit Current	Total balance of customers' current deposit accounts at the end of the period

6	Long-Term Deposits	Customer Deposit Saving Term	Total balance of customers' short-term and long-term deposits at the end of the period
7	Legal Reserves	Bank Reserves	Total bank deposits held at the central bank at the end of the period
8	Bank Loan Growth	Bank LOAN Grow	Increase in banking facilities divided by the opening balance of facilities

Subsequently, based on the operational definitions of each indicator affecting the evaluation of banks' financial stability risk, the following relationships were specified to examine the empirical results of the study in line with the formulated research questions. In other words, through the construction of a nonlinear GARCH model, an attempt was made to explain the factors affecting financial stability risk in the banking system. For this purpose, it was first assumed that $P_t$represents the study index and $r_t$denotes the return rate corresponding to the benchmark index. Accordingly, the continuously compounded return rate was calculated according to Equation (1):

$$r_t = 100[\log(p_t) - \log(p_{t-1})]$$

Equation (1)

In this equation, $t$represents daily observations. In order to formulate the model as a nonlinear GARCH process, the return series $r_t$was expressed as follows:

$$r_t = \delta + \varepsilon_t = \delta + \eta_t\sqrt{h_t}$$

Equation (2)

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

Equation (3)

In these equations, the conditions $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$must hold so that, based on the positivity of variance and the error process, the square root of the conditional variance can be represented by the standardized residual process (η_t), which lies between zero and unit variance. Generally, not all time-series data satisfy the condition of positive variance. In such cases, a modified GARCH model known as the "leverage effect" model must be employed. In fact, the leverage effect constitutes a type of asymmetric GARCH model that allows the conditional variance to respond differently to positive and negative shocks. To obtain this model, the following relationship must be considered:

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2\left[1 - I_{\{\varepsilon_{t-1}>0\}}\right] + \xi\varepsilon_{t-1}^2 I_{\{\varepsilon_{t-1}>0\}} + \beta_1 h_{t-1}$$

Equation (4)

Where $I_{\{\omega\}}$denotes the indicator coefficient of the relationship, and the function ωsatisfies $0 < \omega \leq 1$, becoming zero under negative skewness conditions. To overcome the skewness frequently observed in financial returns within GARCH regression models, the identified parameters were modeled based on the logarithm of the conditional variance as follows:

$$\ln(h_t) = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \xi\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_1 \ln(h_{t-1})$$

Equation (5)

Therefore, based on the theoretical relationships provided to achieve a model with an appropriate probability distribution, all identified indicators had to be estimated within the framework of both mean and variance equations so that the leptokurtic distribution could be calculated accordingly. On the other hand, quantile regression was also employed to better evaluate banking stability risk through the creation of a balanced return index relative to the banking stability index. For this purpose, the $CoVaR$criterion was used to calculate financial stability risk within the national banking system. Consequently, the overall stock market index (TEPIX) was utilized as the benchmark index because the objective of the study was to evaluate the financial stability risk of banks listed on the Tehran Stock Exchange. In addition, the financial stability index derived from the modeled indicators and denoted as "TEBFS" was used as the regression benchmark. Accordingly, $CoVaR$should be considered as a function of tail dependence between two probabilistic risk values, namely Value at Risk (VaR)and Expected Maximum Loss ($VaR(a)$), over a given time horizon at the confidence level $(1-a)$, which can be modeled as follows:

$$Pr(X^i \leq VaR_a^i) = \alpha$$

Equation (6)

In this equation, X^irepresents the return of the banking system (the banks under study). The probability that the return is less than or equal to VaRequals α. Furthermore, $CoVaR_q^{(jparalleli)}$is equal to VaR_q^j(representing the entire economy or capital market), conditional upon an event affecting the banking sector, such as $C(R^i)$. This event occurs when the return of the banking index (R^i)is less than or equal to the banking system VaR. Therefore, $CoVaR_q^{(jparalleli)}$is defined as follows:

$$Pr(R^j \leq CoVaR_q^{(j\|C(R^i))}) = q$$

Equation (7)

The Conditional Value at Risk fluctuation ($\Delta CoVaR$)represents the marginal impact of the banking system on the total risk of the economy under conditions in which the banking system is in distress. Therefore, the Conditional Value at Risk fluctuation is equal to the difference between the $CoVaR$of the overall economy when the banking system is in crisis conditions (i.e., at the 1% Value at Risk level) and the $CoVaR$of the overall economy when the banking system is at the 50% Value at Risk level. In other words, Equation (8) must be considered:

$$\Delta CoVaR_q^{(j\|i)} = CoVaR_q^{(j\|R^i=VaR_q^i)} - CoVaR_q^{(j\|R^i=VaR_{50}^i)}$$

Equation (8)

Based on these explanations, the final model for evaluating financial stability risk between the overall stock market index "TEPIX" and the banking system financial stability index "TEBFS" was specified as follows:

$$RTEBFS_{(q\cdot t)}^{system} = \alpha_q^{(system\|i)} + \gamma_q^{(system\|i)} TEPIX_{(t-1)} + \beta_q^{(system\|i)} BANK_{(q\cdot t)}^{(system\|i)}$$

Equation (9)

$$\begin{aligned} BANK_{(q\cdot t)}^{(system\|i)} &= \sum_{k=1}^{n} [\vartheta_1 + \vartheta_2 Equity_{it} + \vartheta_3 TurnoverRatio_{it} + \vartheta_4 LoansAndAdvancesToBanks_{it} \\ &+ \vartheta_5 MortgageLoans_{it} + \vartheta_6 CustomerDepositCurrent_{it} + \vartheta_7 CustomerDepositSavingTerm_{it} \\ &+ \vartheta_8 BankReserves_{it} + \vartheta_9 BankLOANGrow_{it} + \varepsilon_{it}] \end{aligned}$$

Equation (10)

In the above equations, $RTEBFS_{(q\cdot t)}^{system}$represents the financial stability risk of the national banking system; $\gamma_q^{(systemparalleli)} TEPIX_{(t-1)}$denotes the overall stock market index based on the previous period's return rate; and $\beta_q^{(systemparalleli)} BANK_{(q\cdot t)}^{(systemparalleli)}$represents the identified financial stability indicators of the national banking system. It should be noted that the present study employed the average daily data of the overall stock market index $TEPIX_{(t-1)}$based on the previous period return rate, together with the identified bank financial stability indicators $BANK_{(q\cdot t)}^{(systemparalleli)}$, over the period from 2018 to 2022. Subsequently, the portfolio formation process for distinguishing passive investors from active investors is elaborated.

Markowitz Portfolio

The Markowitz portfolio is based on the "mean–variance" model, which utilizes the mean as a criterion for evaluating returns and financial stability risk variance, while standard deviation and variance are defined as measures of risk under the assumption of normally distributed returns {Dallagnol et al., 2009}. The Markowitz portfolio suggests that investors, in addition to maximizing returns to the greatest extent possible, seek certainty regarding investment risks. To justify this argument, the model asserts that if investors were solely interested in maximizing expected returns, they should allocate their investments exclusively to the single stock with the highest expected return. However, this investment behavior can be explained by the fact that investors simultaneously consider both risk and return. Therefore, investors seeking to maximize expected returns while minimizing uncertainty (i.e., risk) must balance these two conflicting objectives in such a way that the value of their investments increases in the short term rather than focusing solely on long-term returns {Baptista, 2012}. Consequently, the formation of a Markowitz portfolio may be regarded as representative of active investors' behavior, based on the following assumptions.

First, these investors attempt to maximize their expected utility according to their degree of risk tolerance, such that the marginal utility curve of wealth does not decline. Therefore, active investors focusing on short-term returns employ the expected mean–variance framework in constructing their portfolios. Accordingly, their indifference curves are considered functions of expected return and expected variance.

Second, investors classified within this portfolio structure do not necessarily possess a specific level of risk control and superior returns because they generally exhibit higher risk tolerance compared with other investors. On this basis, such investors typically focus on two factors in portfolio construction:

(a) High expected return, which constitutes the desirable factor.

(b) Return uncertainty, which constitutes the undesirable factor.

To determine portfolio selection according to the Markowitz method, which minimizes variance for a specified return level, the following linear programming model must be used:

$$\min\ z = \delta_p^2$$

Equation (11)

$$\bar{R}_p = \sum_{j=1}^{n} W_j\,\bar{R}_j$$

Equation (12)

$$\sum_{j=1}^{n} W_j = 1$$

Equation (13)

$$W_j > 1$$

Where: $W_j$is the weight of stock $i$in the portfolio; $\bar{R}_p$is the expected return of the portfolio; $\bar{R}_j$is the return of stock i; and $\delta_p^2$is the variance of portfolio returns. The variance of portfolio returns is calculated according to Equation (14):

$$\delta_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i\, w_j\, cov(\bar{r}_i, \bar{r}_j)$$

Equation (14)

Sortino Portfolio

In this portfolio, performance evaluation is based on undesirable risk assessment rather than standard deviation (SD). In other words, if Xdenotes the portfolio return variable and $f(x)$represents the probability skewness function of this variable, while μdenotes the mean and $r$represents the minimum acceptable return (MAR), then the Sortino portfolio can be expressed as follows {Mamoghli & Daboussi, 2008}:

$$SOR = \frac{(\mu - r)}{\sigma}$$

Equation (15)

Where σrepresents the semi-standard deviation of returns below the target return, defined as:

$$\sigma^2 = \int_{-\infty}^{r} (r - x)^2 f(x) dx$$

Equation (16)

Since the objective of the present study was the evaluation of financial stability risk, Equation (17) was employed:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} (\max\{R_f - R_{ij}\})^2}$$

Equation (17)

Therefore, the Sortino portfolio adjusts average returns relative to undesirable financial stability risk in portfolio construction. Accordingly, the "IMNEX" index was used to evaluate stock returns in this portfolio structure. This index was designed on a weighted basis and incorporates several adjustments. The index was calculated according to Equation (18):

$$IMNEX_t = \frac{\sum_{i=1}^{n} NAV_{it} \times NU_{it}}{C_t}$$

Equation (18)

Where $n$represents the number of stocks constituting the portfolio; NAV_{it}denotes the net asset value of stock $i$at time t; NU_{it}represents the number of shares of stock $i$at time t; and $C_t$is the base value at time t, assumed to equal 1000. As implied by the nature of this portfolio, passive investors in the capital market attempt to select stocks that yield higher returns over long-term investment horizons in order to benefit from more reasonable profits through the control of market fluctuations under financial stability conditions. This approach is therefore comparable to the behavior of passive investors in capital markets. Consequently, in constructing the two portfolios based on quantile regression as the most desirable framework for evaluating banking system financial stability risk, the distinction between value stocks and growth stocks, which forms the basis for differentiating active investors from passive investors, must be considered.

Distinguishing Value Stocks from Growth Stocks

To distinguish the risk of value stocks from growth stocks as the common basis for constructing both the Markowitz and Sortino portfolios, the identified indicators for evaluating financial stability risk within the banking system were used as the testing criteria. Accordingly, in response to the second and third research questions, and for the purpose of better differentiating the Markowitz portfolio $(F)$from the Sortino portfolio (E), portfolios ranging from $Q1$to $Q5$were formed so as to create a spectrum extending from value stocks $(Q1)$to growth stocks $(Q5)$. The stock classification process was performed based on the identified financial stability risk indicators, such that stocks with lower coefficients were categorized as value stocks because their investors consider higher levels of financial risk as a basis for long-term investment decisions, unlike growth stocks. On this basis, passive investors can be identified through a value-stock-oriented approach.

3. Findings and Results

First, the statistical properties of the time series were examined based on the function of each index under study. For this purpose, the kurtosis and skewness statistics of the probability distribution of index returns were calculated. In addition, the Jarque–Bera test was used to examine the normality hypothesis of the probability distribution of returns for the two indices, "TEPIX" and "TEBFS." The Jarque–Bera test statistic follows a chi-square distribution (χ^2).

Table 2. Statistical Properties of the Time Series of the Indices Under Study

Statistic	Mean	Skewness	Kurtosis	Jarque–Bera	Anderson–Darling	Cramér–von Mises
"TEPIX" Index	0.00112	0.364743	7.76703	3123.242	36.0982152	7.918721
p-value				0.000000	0.000000	0.000000
"TEBFS" Index	-0.000145	0.318789	9.82251	1419.445	44.6552768	9.319827
p-value				0.000000	0.000000	0.000000

The results obtained from the preliminary tests show that the skewness of the "TEBFS" index is 0.318789 and its kurtosis is 9.82251, indicating that the probability distribution of returns for the "TEBFS" index is a leptokurtic distribution and is right-skewed relative to the normal distribution. Moreover, the calculated Jarque–Bera statistic is 1419.445, based on which the hypothesis of normality for the probability distribution of index returns is rejected. Generally, according to the Jarque–Bera test, in time series with serial autocorrelation, the normality hypothesis of the distribution is rejected (Thomakos & Wang, 2003); therefore, alternative tests should be used. Accordingly, to address the serial autocorrelation problem in the time-series data of this study, the Anderson–Darling and Cramér–von Mises tests were applied. Since the significance coefficients of both tests are below the 0.05 error level, the stationarity test of the data for both indices can be conducted after resolving the serial autocorrelation problem in the time-series data. The reason for conducting this test is that time-series estimation is possible through the stationarity of data levels. For this purpose, the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests were used. The results presented in Table 3 show that the returns of both indices have no unit root, indicating the stationarity of the time-series data.

Table 3. Results of the Unit Root Test for the Research Variables

Model Index	Test Statistic	Critical Coefficients	Critical Values	Stationarity Test Statistic
"TEPIX" Index	-21.7768	-3.88713	1%	Augmented Dickey–Fuller (ADF) test statistic
		-3.51672	5%	
		-3.22091	10%	
"TEBFS" Index	-19.0729	-2.76628	1%	Phillips–Perron (PP) test statistic
		-1.89723	5%	
		-1.54678	10%	

Another important point regarding the results of the time-series stationarity tests is that both model tests were estimated without an intercept, which makes it possible to estimate the data for the leptokurtic distribution function and quantile regression.

A) Leptokurtic Distribution

A leptokurtic distribution is a type of probability distribution that describes a dataset with an above-normal number of extreme or outlier values. Statistically, it is a distribution with a higher degree of kurtosis than the normal distribution. Kurtosis measures the shape of the distribution and its deviation from the normal distribution. A normal distribution has zero excess kurtosis, meaning that it has a bell-shaped curve without outliers. In contrast, a leptokurtic distribution has kurtosis greater than zero, indicating a higher peak and fatter tails than the normal distribution. This means that the distribution has a greater concentration of data around the mean and a higher probability of extreme values at the tails of the distribution. Therefore, to determine this distribution, the conditional variance of financial stability returns in the banking system must be calculated through the ARMA–EGARCH(1,1) model using the Generalized Error Distribution or Student's *t*-distribution. Accordingly, as shown in Table 4, the unconditional variance must be estimated to determine the leptokurtic distribution. As noted earlier, the distribution interval of this test was calculated based on the developed Equations (2) to (5).

Table 4. Unconditional Variance of the Leptokurtic Distribution

Mean Equation										
$r_t = \delta_0 + \delta_1 r_{t-1} + \delta_2 \varepsilon_{t-1} + \varepsilon_t$										
Variable	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6	ϑ_7	ϑ_8	DW	SBC
Coefficients ("TEBFS")	0.084	0.176	0.251	0.124	0.651	0.097	0.213	0.172	1.89	-6.365
p-values	0.028	0.001	0.019	0.002	0.000	0.031	0.015	0.001	—	—
Variance Equation										
$\ln(h_t) = \alpha_0 + \alpha_1 \left\lvert \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right\rvert + \xi \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_1 \ln(h_{t-1})$										
Variable	α_0	α_1	ξ	β_1	GED					
Coefficients ("TEPIX")	-0.3281	0.2108	0.1201	0.8782	0.8001					
Test Statistics	-4.545	8.287	4.191	198.763	39.265					

The results of the leptokurtic distribution function indicate that all coefficients of the "TEPIX" and "TEBFS" indices are significant in this distribution function. In fact, the significance of the conditional variance coefficient of financial stability returns in the banking system based on the "TEBFS" index indicates that all identified effective criteria for measuring financial stability in the banking system possess the required capability for determining risk, because, according to Figure 1, the normal distribution has greater kurtosis relative to the "TEPIX" index.

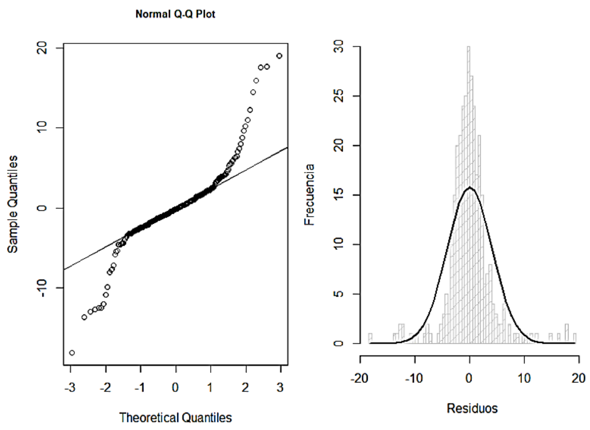

Figure 1. Leptokurtic Distribution Function Diagram

As is evident, the normal distribution is determined within the range of 15, and the leptokurtic distribution function related to the "TEBFS" index has greater kurtosis than the "TEPIX" index. Subsequently, based on the estimated conditional variance of index returns, the probabilistic Value at Risk (VaR)must be estimated at the 95% confidence level.

B) Quantile Regression

Unlike linear regression, whose objective is limited to estimating the mean of the dependent variable, quantile regression seeks a combination of one or more quantiles of the dependent variable based on a standard threshold.

To calculate the Conditional Value at Risk fluctuation ($\Delta CoVaR$), the significance of each of the "TEPIX" and "TEBFS" indices must be calculated at the error levels of 0.05 and 0.01 based on Equation (11).

$$\Delta CoVaR_{q,t}^{i} = \hat{\beta}_q\left(\widehat{Var}_{q,t}^{i} - \widehat{Var}_{0.5,t}^{i} - \widehat{Var}_{0.1,t}^{i}\right)$$

Equation (11)

Accordingly, Table 5 presents the quantile regression estimation based on this process.

Table 5. Quantile Regression Estimation at Error Levels of 0.05 and 0.01

Variable	$\alpha_q^{(system\Vert i)}$	$BANK_{(q\cdot t)}^{(system\Vert i)}$	$TEPIX_{(t-1)}$	Pseudo-R^2	Quasi-LR	Error Level	$\Delta CoVaR$
"TEPIX" Index	0.0005	0.3198	0.2987	0.23	1010.768	0.05	0.265
Test statistic / *p-value*	3.15	14.54	8.19		0.000		$\Delta CoVaR_f$
"TEBFS" Index	-0.091	0.2901	0.3651	0.19	89.652	0.01	-0.652
Test statistic / *p-value*	-9.02	2.187	5.29		0.000		$\Delta CoVaR_g$

The results presented in the regression model show that both indices have an appropriate significance level in estimating financial stability risk in the banking system. However, since the calculated Conditional Value at Risk fluctuation ($\Delta CoVaR$)for the "TEBFS" index is negative, it can be inferred that focusing on the identified criteria and developing them as an evaluation model provides a more reliable basis for investors' technical analysis processes than the overall stock market index (TEPIX).

Figure 2. Financial Stability Risk Index in the Banking System at Error Levels of 0.05 and 0.01

As Figure 2 also shows, there is no significant difference between the error levels of 0.05 and 0.01 in estimating the regression model related to banks' financial stability risk, and it can therefore be considered an analytical tool for the estimated statistical coefficients. Finally, in order to determine the most important identified criterion in calculating the financial stability risk of the national banking system, the evaluation criteria of Root Mean Square Error (RMSE), Mean Square Error (MSE), and the coefficient of determination (R^2)must be used.

Table 6. Determination of the Most Influential Financial Stability Risk Criterion

Effective Criteria	Scale	$\alpha_q^{(system\Vert i)}$	$BANK_{(q\cdot t)}^{(system\Vert i)}$	$TEPIX_{(t-1)}$	Pseudo-R^2	Quasi-LR	RMSE	MSE	R^2	Rank
ϑ_2	TEPIX	0.013	0.008	0.043	0.031	0.074	0.046	0.174	0.665	Third
	TEBFS	0.042	0.039	0.062	0.059	0.092				
ϑ_3	TEPIX	0.019	0.010	0.038	0.027	0.064	0.055	0.193	0.694	First*
	TEBFS	0.080	0.053	0.044	0.063	0.052				
ϑ_4	TEPIX	0.012	0.009	0.056	0.154	0.116	0.042	0.173	0.641	Fourth
	TEBFS	0.093	0.124	0.147	0.189	0.156				
ϑ_5	TEPIX	0.007	0.012	0.035	0.044	0.024	0.031	0.152	0.443	Seventh
	TEBFS	0.047	0.063	0.078	0.052	0.101				
ϑ_6	TEPIX	0.242	0.217	0.289	0.315	0.548	0.041	0.169	0.603	Fifth
	TEBFS	0.264	0.204	0.256	0.341	0.647				
ϑ_7	TEPIX	0.076	0.112	0.143	0.105	0.202	0.043	0.121	0.312	Eighth
	TEBFS	0.083	0.061	0.049	0.077	0.094				
ϑ_8	TEPIX	0.064	0.014	0.070	0.088	0.111	0.037	0.148	0.485	Sixth
	TEBFS	0.145	0.098	0.122	0.139	0.202				
ϑ_9	TEPIX	0.487	0.263	0.275	0.412	0.439	0.053	0.189	0.687	Second
	TEBFS	0.078	0.289	0.272	0.218	0.367				
Mean sum of final model coefficients		0.0435	0.1648	0.5662						

Accordingly, based on the sum of the coefficients of the model developed using the two indices "TEPIX" and "TEBFS," it is determined that the liquidity turnover criterion (Turnover Ratio) has a greater effect than the other identified criteria in evaluating the financial stability risk of the banking system. As shown in Figure 3, the range of all identified criteria lies within $-0.2 < BANK_{(q \cdot t)}^{(system \| i)} < 0.2$, indicating that all criteria have an approximately equal effect on evaluating financial stability risk.

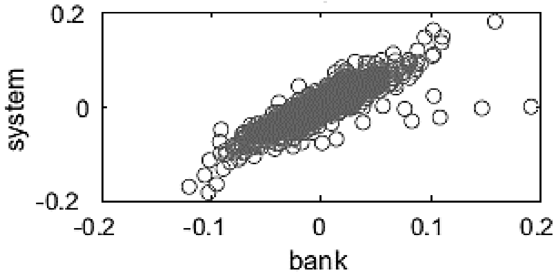

Figure 3. Determined Range for Evaluating the Criteria Affecting $BANK_{(q \cdot t)}^{(system \| i)}$

Subsequently, in order to distinguish between the two portfolios considered in this study based on quantile regression as the desirable basis for evaluating financial stability risk, two criteria—random weights and equal weights—must be considered separately. Therefore, based on the Fama and French (1993) model, all stocks constituting investors' portfolios are initially assumed to have equal weights and must then be incorporated into the Markowitz (F) and Sortino (E) models. Accordingly, one growth portfolio and one value portfolio are formed each year. Moreover, random weights are first generated through a vector of random values based on the number of stocks constituting the portfolio within each quintile, so that the values follow a normal distribution; in other words, the sum of all evaluation criteria for each vector equals one in order to prevent deviation in portfolios with random weights. The reason for this procedure is that, due to the large number of portfolios formed during each year and over the research period, at least one equal-weight portfolio must be formed in the Markowitz (F) and Sortino (E) evaluations to make comparison possible. In other words, each year, ten growth portfolios and ten value portfolios were constructed with random weights, and given the five-year study period, 50 portfolios were randomly generated for comparison. This method has two advantages. First, it increases the sample size; second, it shows whether the selection of a value or growth portfolio differs in performance under any stock-weighting structure. On this basis, the effective criteria for evaluating financial stability risk must be considered according to the distinction between value stocks and growth stocks as the basis for differentiating active investors' approach from passive investors' approach within the framework of quantile regression. Accordingly, Table 7 presents the results of this hypothesis based on the distinction between growth stocks and value stocks according to the two portfolios, Markowitz (F) and Sortino (E), as the basis for evaluating the difference between active and passive investors' approaches.

Table 7. Difference Between Active and Passive Investors' Approaches

Portfolio	Fold	Criteria	Q1	Q2	Q3	Q4	Q5	MSE	MAE	R^2
Markowitz Portfolio (F)	ϑ_2	Equal weights	0.176	0.102	0.187	0.214	0.206	0.021	0.101	0.204
		Random weights	0.194	0.218	0.303	0.363	0.321			
	ϑ_3	Equal weights	0.076	0.093	0.116	0.149	0.232	0.030	0.106	0.285
		Random weights	0.104	0.096	0.130	0.176	0.304			

	ϑ_4	Equal weights	0.066	0.054	0.083	0.109	0.152	0.028	0.107	0.220
		Random weights	0.103	0.118	0.140	0.137	0.214			
	ϑ_5	Equal weights	0.076	0.112	0.143	0.105	0.202	0.043	0.121	0.312
		Random weights	0.083	0.061	0.049	0.077	0.094			
	ϑ_6	Equal weights	0.183	0.109	0.192	0.223	0.217	0.028	0.108	0.219
		Random weights	0.201	0.230	0.315	0.387	0.405			
	ϑ_7	Equal weights	0.018	0.010	0.063	0.142	0.139	0.031	0.106	0.278
		Random weights	0.054	0.112	0.139	0.152	0.188			
	ϑ_8	Equal weights	0.074	0.061	0.089	0.117	0.261	0.054	0.177	0.427
		Random weights	0.167	0.210	0.318	0.359	0.532			
	ϑ_9	Equal weights	0.016	0.037	0.065	0.079	0.101	0.029	0.111	0.237
		Random weights	0.081	0.093	0.117	0.109	0.162			
Mean quantile regression coefficients in Markowitz portfolio formation								0.033	0.117	0.272

Portfolio	Fold	Criteria	Q1	Q2	Q3	Q4	Q5	MSE	MAE	$\boldsymbol{R^2}$
Sortino Portfolio (E)	ϑ_2	Equal weights	0.074	0.061	0.089	0.117	0.261	0.054	0.177	0.427
		Random weights	0.167	0.210	0.318	0.359	0.532			
	ϑ_3	Equal weights	0.311	0.328	0.405	0.443	0.516	0.062	0.182	0.511
		Random weights	0.273	0.226	0.296	0.353	0.584			
	ϑ_4	Equal weights	0.016	0.037	0.065	0.079	0.101	0.029	0.111	0.237
		Random weights	0.081	0.093	0.117	0.109	0.162			
	ϑ_5	Equal weights	0.066	0.054	0.083	0.109	0.152	0.028	0.107	0.220
		Random weights	0.103	0.118	0.140	0.137	0.214			
	ϑ_6	Equal weights	0.076	0.112	0.143	0.105	0.202	0.043	0.121	0.312
		Random weights	0.083	0.061	0.049	0.077	0.094			
	ϑ_7	Equal weights	0.076	0.093	0.116	0.149	0.232	0.030	0.106	0.285
		Random weights	0.104	0.096	0.130	0.176	0.304			
	ϑ_8	Equal weights	0.113	0.156	0.219	0.308	0.414	0.038	0.126	0.323
		Random weights	0.063	0.090	0.115	0.135	0.210			
	ϑ_9	Equal weights	0.266	0.197	0.307	0.209	0.317	0.055	0.165	0.378
		Random weights	0.215	0.166	0.293	0.155	0.228			
Mean quantile regression coefficients in Sortino portfolio formation								0.042	0.219	0.336

According to the test of the second hypothesis, it was found that the mean absolute error (MAE) of the Sortino portfolio (E) is higher than that of the Markowitz portfolio (F). This means that, considering the differentiation of investors' approaches in constructing their portfolios through growth stocks and value stocks, there is a significant difference between the two portfolios under random weighting. Moreover, given the random weights in both portfolios, it was found that the Sortino portfolio, due to having higher weight ratios, provides more reliable returns than the Markowitz portfolio in investors' portfolio formation decisions. By contrast, because the Markowitz portfolio obtained lower coefficient ratios in quantile regression, it is considered a basis for constructing a value-stock portfolio, according to which investors inclined toward this portfolio pursue short-term returns in their investments. In addition, the difference in the prediction percentage of R^2between the two portfolios shows that both portfolios are capable of predicting probabilities and incorporating other influential data into investment returns. However, the $R^2$of the Sortino portfolio (E) is higher than that of the Markowitz portfolio (F), which indicates greater investor reliability in evaluating the financial stability risk of bank stocks through quantile regression. This also reflects the functional nature of passive investors' approach in constructing bank-stock portfolios through financial stability risk control, because the coefficients of the stocks formed in the investment portfolio show a greater tendency to move toward returns formed along the $Q5$spectrum. This indicates a stronger tendency to invest in growth stocks, which are regarded as reflecting longer-term investment approaches in bank stocks. In other words, it was determined that the formation of the Sortino portfolio (E) by passive investors based on quantile regression is more desirable than the formation of the Markowitz portfolio (F) by active investors in evaluating banks' financial stability risk. Therefore, it should be stated that the aggregate mean coefficients of the Sortino portfolio within the quantile regression framework have higher accuracy in predicting passive investors' approaches compared with active investors' approaches in evaluating the effective financial stability risk criteria of banks listed in the capital market, as shown in Figure 4.

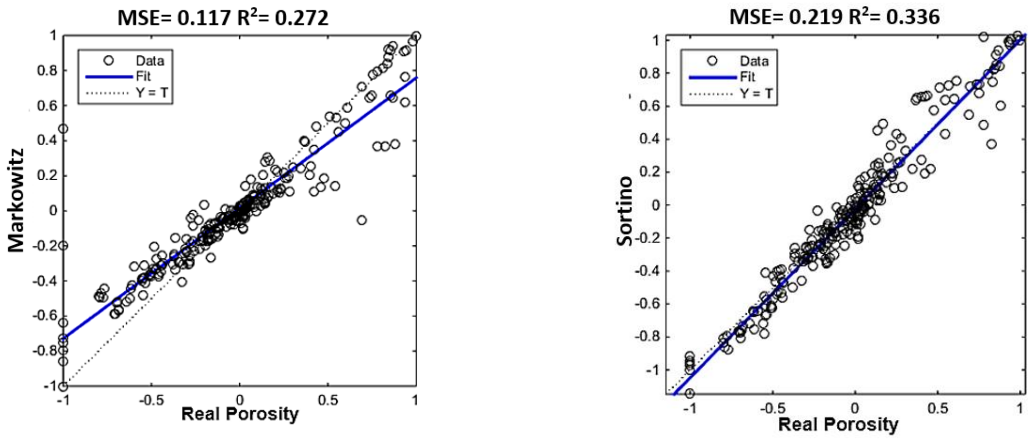

Figure 4. Significant Difference in Portfolio Formation Coefficients Through Quantile Regression

Furthermore, the ranking of the identified financial stability risk evaluation criteria by the two portfolios shows that in the Markowitz portfolio (F), banks' legal reserves held at the central bank (ϑ_8), and in the Sortino portfolio (E), liquidity turnover (ϑ_3), constitute the basis for differentiating investors' approaches through quantile regression.

4. Discussion and Conclusion

The present study aimed to evaluate the financial stability risk of banks listed on the Tehran Stock Exchange and to determine the difference between the investment horizons of passive and active investors through a leptokurtic distribution framework, quantile regression, and portfolio analysis. The findings demonstrated that the return distributions of both the “TEPIX” and “TEBFS” indices were non-normal and characterized by positive skewness and high kurtosis, indicating the existence of leptokurtic distributions. Furthermore, the Jarque–Bera, Anderson–Darling, and Cramér–von Mises tests confirmed the rejection of normality assumptions for the time-series data. These findings indicate that the return behavior of banking-sector financial stability indicators is associated with fat tails and a higher probability of extreme fluctuations than predicted by normal distributions. Such results are consistent with the broader financial stability literature, which emphasizes that banking systems and capital markets are frequently exposed to nonlinear and asymmetric risks that cannot be properly captured by conventional normal-distribution models [1, 2]. The existence of leptokurtic distributions in the banking system also confirms that the behavior of financial returns in emerging markets is highly sensitive to market shocks, liquidity disruptions, and investor reactions.

The significance of the conditional variance coefficients estimated through the ARMA–EGARCH(1,1) model further demonstrated that the identified indicators of banking stability possess substantial explanatory power in evaluating financial stability risk. This result suggests that financial stability in banks is not solely dependent on macroeconomic variables, but is also strongly associated with internal banking indicators such as equity, liquidity turnover, deposits, loan growth, reserves, and interbank lending relationships. These findings align with studies emphasizing the importance of regulatory structures, liquidity management, and internal financial policies in determining banking stability [4, 5]. In addition, the findings support the argument that banking-sector vulnerability emerges through the interaction of institutional and market-based variables rather than through isolated accounting indicators. The significance of the “TEBFS” index indicates that a combined index derived from banking stability criteria may provide a more precise representation of banking-system risk compared with relying solely on the general capital market index.

Another important finding of the study was that the Conditional Value at Risk fluctuation ($\Delta CoVaR$)estimated for the “TEBFS” index was negative, whereas the value estimated for the “TEPIX” index was positive. This finding suggests that the banking-system financial stability index has stronger explanatory power for identifying downside systemic risk than the overall capital market index. In practical terms, the negative ($\Delta CoVaR$)indicates that fluctuations in banking stability indicators contain information regarding crisis transmission and systemic vulnerability that may not be fully reflected in the broader market index. This result is highly consistent with studies demonstrating that systemic risk originates from interconnected financial relationships and tail dependencies between financial institutions and capital markets [1, 2]. The findings also support the view that banking-system stability should be assessed through sector-specific indicators capable of identifying conditional risk spillovers rather than through aggregate market measures alone.

The results of the quantile regression analysis revealed that both indices were statistically significant in estimating financial stability risk; however, the explanatory power of the “TEBFS” index was stronger in lower-tail conditions. This indicates that banking-sector financial stability is more effectively explained through quantile-based estimation frameworks that capture extreme market conditions. Unlike ordinary least squares regression, which focuses on average relationships, quantile regression is capable of identifying how risk behaves under adverse conditions. The present findings therefore reinforce the methodological argument that financial stability assessment should incorporate tail-risk estimation and nonlinear econometric techniques. Similar conclusions have been reached in studies emphasizing that market instability and banking fragility are often concentrated in lower quantiles and crisis periods rather than in average market states [11, 29]. Accordingly, the present study contributes to the literature by demonstrating that quantile regression provides a more reliable framework for evaluating the financial stability risk of banks listed in emerging capital markets.

Among the identified criteria affecting banking-system stability, liquidity turnover (Turnover Ratio) was found to be the most influential factor in evaluating financial stability risk. This finding suggests that market liquidity and transaction flow play a central role in shaping investors' perceptions of banking stability. High liquidity turnover reflects the dynamic interaction between investor demand, market participation, and confidence in banking-sector performance. This result is compatible with studies indicating that liquidity risk and cash flow management significantly influence banking resilience and market stability [9, 13]. Moreover, the finding confirms that liquidity-related indicators are not only operational measures but also signals of broader systemic confidence within the banking sector. In periods of uncertainty, liquidity turnover may therefore serve as an early warning indicator for changes in banking-system risk.

The findings also demonstrated that all identified financial stability criteria had relatively similar ranges of influence, indicating that banking stability is a multidimensional phenomenon shaped by the interaction of several financial indicators. This result supports the argument that financial stability cannot be reduced to a single ratio or performance indicator. Instead, banking stability reflects the combined influence of equity structure, deposits, reserves, lending behavior, liquidity turnover, and growth in banking facilities. This multidimensional interpretation is consistent with studies highlighting the interconnected relationship between financial inclusion, banking development, competition, and institutional quality in determining banking stability [16-18]. Consequently, policymakers and investors should avoid relying exclusively on isolated indicators when evaluating the risk profile of banks.

A major contribution of the study relates to the distinction between passive and active investors through the comparison of the Sortino portfolio and the Markowitz portfolio. The results showed that the Sortino portfolio exhibited higher MAE and R^2values than the Markowitz portfolio, indicating stronger predictive accuracy and greater reliability in evaluating banking-system financial stability risk. This finding suggests that passive investors, who focus on downside risk and long-term investment horizons, are more successful in evaluating the stability of bank stocks than active investors who primarily emphasize short-term return optimization. The result is theoretically meaningful because the Sortino portfolio framework focuses specifically on downside volatility rather than total variance. In financial stability analysis, downside risk is more relevant than symmetrical volatility because investors are generally more concerned about losses arising from banking fragility than about positive return fluctuations.

The superiority of the Sortino portfolio in explaining financial stability risk is aligned with studies emphasizing the growing importance of passive investment strategies in modern capital markets [20]. Passive investors tend to prioritize long-term stability, lower transaction frequency, and reduced exposure to speculative fluctuations. Such behavior may explain why the Sortino portfolio performed better under quantile regression conditions associated with downside risk. In contrast, the Markowitz portfolio, which is based on mean–variance optimization, may be less effective in environments characterized by leptokurtic distributions and asymmetric risk structures. These findings are also compatible with evidence showing that active and passive investment strategies perform differently under volatile market conditions and that passive strategies may provide more stable outcomes during periods of uncertainty [22, 24].

The movement of portfolio coefficients toward the $Q5$spectrum further indicated that investors exhibited stronger preferences for growth stocks than for value stocks in the context of long-term investment horizons. This finding suggests that passive investors may associate growth-oriented banking stocks with greater long-term financial stability and more sustainable returns. Such behavior is consistent with studies on investment horizons and mental accounting, which indicate that investors classify stocks differently depending on their perception of long-term risk and return [26, 27]. The stronger tendency toward growth-stock portfolios may also reflect expectations regarding the future expansion of banking-sector profitability, technological adaptation, and institutional resilience.

At the same time, the Markowitz portfolio was found to be more closely associated with short-term investment behavior and value-stock orientation. This result implies that active investors tend to pursue short-term abnormal returns and respond more rapidly to market volatility and pricing fluctuations. Such findings are consistent with evidence showing that active stock selection strategies may generate advantages under specific market conditions but are often associated with higher exposure to uncertainty and short-term volatility [23]. The lower predictive accuracy of the Markowitz portfolio in the present study indicates that mean–variance optimization may be less suitable for evaluating financial stability risk in banking sectors characterized by asymmetric shocks and systemic uncertainty.

Another notable finding concerns the ranking of financial stability criteria across the two portfolio structures. In the Markowitz portfolio, legal reserves held at the central bank (ϑ_8)represented the most influential criterion, whereas in the Sortino portfolio, liquidity turnover (ϑ_3)was identified as the dominant factor. This distinction suggests that active and passive investors interpret banking stability through different financial dimensions. Active investors appear to prioritize regulatory and reserve-based protection mechanisms, likely because such indicators provide short-term assurances against market shocks. By contrast, passive investors emphasize liquidity turnover because it reflects long-term market confidence, transaction continuity, and sustainable participation in the banking sector. This interpretation aligns with studies emphasizing the role of liquidity concentration, institutional conditions, and long-term investment behavior in shaping portfolio outcomes [21, 28].

The findings of the present study also have important implications for banking governance and financial policy. Since the "TEBFS" index demonstrated stronger explanatory power than the general market index, regulators and financial analysts may benefit from constructing specialized banking stability indices based on sector-specific indicators. Such indices can improve the monitoring of systemic risk and provide investors with more reliable signals regarding the stability of bank stocks. In addition, the superiority of the Sortino portfolio suggests that investment strategies emphasizing downside risk control may contribute to more stable capital allocation in banking sectors. This issue is particularly important in emerging markets, where financial systems are often exposed to macroeconomic volatility, political uncertainty, and liquidity shocks [7, 15].

Overall, the findings confirm that the financial stability risk of banks listed on the Tehran Stock Exchange is characterized by nonlinear, leptokurtic, and asymmetric behavior that cannot be fully explained through traditional mean-based models. The study demonstrates that quantile regression, conditional volatility modeling, and downside-risk portfolio analysis provide a stronger framework for evaluating banking-system stability and differentiating passive and active investors' approaches. The evidence further indicates that passive investors relying on the Sortino portfolio possess a more reliable long-term framework for evaluating banking-sector stability than active investors relying on the Markowitz portfolio. Consequently, the study contributes to the financial stability literature by integrating systemic risk analysis, investor behavior, portfolio theory, and nonlinear econometric modeling within a unified analytical framework.

One limitation of the present study was that the analysis was restricted to banks listed on the Tehran Stock Exchange over a five-year period. Therefore, the results may not fully capture the long-term structural dynamics of banking stability across different economic cycles. In addition, the study relied primarily on market-based and accounting-based indicators, while some macroeconomic and geopolitical variables that could affect systemic banking risk were not incorporated into the model. Another limitation was the dependence on historical data, which may reduce the ability of the model to fully account for unexpected structural breaks or extraordinary economic crises.

Future studies may expand the present framework by comparing banking stability risk across different countries and financial systems, particularly between developed and emerging economies. Researchers may also examine the interaction between banking stability and behavioral finance variables such as investor sentiment, herding behavior, and speculative trading. In addition, future research could employ machine learning algorithms, network analysis, and dynamic panel methods to improve the prediction of systemic banking risk and compare their explanatory power with quantile regression and GARCH-based approaches.

From a practical perspective, the findings suggest that financial regulators should develop specialized banking stability indices capable of identifying downside systemic risk more accurately than aggregate market indicators. Bank managers should also strengthen liquidity management and turnover-related policies because liquidity turnover was identified as the most influential factor in evaluating financial stability risk. Furthermore, investors may improve long-term portfolio performance by adopting downside-risk-oriented strategies such as the Sortino portfolio, particularly when investing in banking-sector stocks exposed to systemic volatility and asymmetric market shocks.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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