Designing a Comprehensive Stress Index for the Tehran Stock Exchange and Its Causal Relationship with the Gold Coin and Foreign Exchange Markets

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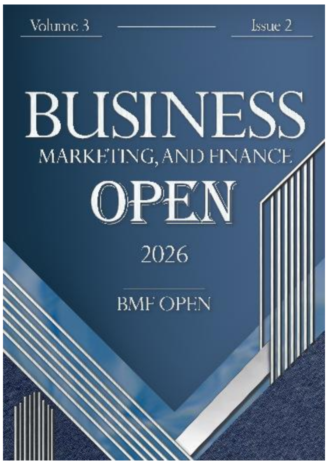

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Abstract: This study aims to design a Comprehensive Stress Index (SSI) for the Tehran Stock Exchange using multivariate GARCH models (DCC-MGARCH) and machine learning (Random Forest) and to examine its causal relationship with the gold coin and foreign exchange markets. Daily time series data of selected Tehran Stock Exchange indices from November 22, 2014, to November 21, 2024, were collected and analyzed. First, the systemic risk (ΔCoVaR) of each index was calculated; then, the optimal weights were determined using the Random Forest model, and the SSI was constructed following the methodology of Holo and colleagues (2012). Stability, shock, and predictability tests confirmed the validity of the index. The Granger causality test revealed a significant one-way causal relationship from the foreign exchange market to the SSI (p-value = 0.028), while no significant relationship was observed with the gold coin market. These findings highlight the influence of exchange rate fluctuations on the systemic risk of the stock market and provide a useful tool for policymakers.

Keywords: Comprehensive Stress Index (SSI), DCC-MGARCH model, machine learning, Granger causality test, gold coin market, foreign exchange market

1. Introduction

Systemic risk—the possibility that distress in one part of the financial system propagates through interconnections and shared exposures to threaten the functioning of the whole—has moved from an abstract concern to a core object of empirical measurement and policy design over the past decade and a half [1, 2]. The challenge is especially acute in emerging markets, where macro-financial linkages to exchange rate regimes, commodity cycles, and policy uncertainty can amplify shocks and produce nonlinear market dynamics [3, 4]. Against this backdrop, constructing a timely, market-wide stress indicator that integrates volatility, co-movement, and cross-market spillovers can provide early-warning signals and actionable guidance for regulators, institutional investors, and corporate treasurers. The present study addresses this need by developing a Comprehensive Stress Index (SSI) for the Tehran Stock Exchange (TSE) that combines a systemic risk contribution metric (ΔCoVaR), dynamic conditional correlations from a DCC-MGARCH model, and data-driven weights learned via supervised machine learning, and by testing causal links between the SSI and the foreign exchange and gold coin markets [5-7].

Conceptually, systemic stress arises when common risk factors and networked exposures become synchronized, so that the joint distribution of losses features fat tails and time-varying dependence that traditional Gaussian assumptions fail to capture [1]. Composite indicators such as the CISS of the European Central Bank operationalize this idea by aggregating sub-market stresses with time-varying correlation structures to reflect the system's state in real time [5]. Our approach follows this composite-indicator tradition but tailors it to the institutional and behavioral characteristics of Iran's capital market, where exchange-rate pass-through, sanctions episodes, and commodity sensitivities can jointly drive market-wide turmoil [8, 9]. By emphasizing conditional co-movements alongside tail risk contributions, the proposed SSI aims to separate idiosyncratic volatility from truly systemic episodes.

Methodologically, the study leverages advances in both econometrics and machine learning. On the econometric side, DCC-MGARCH captures time-varying second moments and delivers a conditional correlation matrix that is essential for measuring contemporaneous clustering of risk across sectors [10]. On the machine-learning side, interpretable and predictive models can be used to derive economically meaningful aggregation weights and to validate the index's out-of-sample utility [6, 7]. Prior work demonstrates that machine-learning pipelines, including tree ensembles, support vector machines, and neural networks, can enhance forecasting and causal attribution in financial stress diagnostics, often outperforming linear benchmarks when relationships are nonlinear or state-dependent [11-13]. We adopt this evidence-based stance by using a supervised learner to map sectoral Value-at-Risk signals into composite weights while maintaining transparency about variable importance to satisfy interpretability requirements for risk governance [3, 6].

The TSE offers a compelling laboratory for systemic-risk measurement for at least three reasons. First, macro-financial linkages to the foreign exchange market are strong, and exchange rate shocks can rapidly reprice export-oriented sectors, import-dependent input costs, and investors' risk premia [8, 14]. Second, sanctions and geopolitical events may act as external shocks that propagate simultaneously through currency, gold, and equity markets, generating complex spillover patterns [9]. Third, behavioral and institutional features—such as investor sentiment waves, life-cycle heterogeneity across firms, and decision biases under uncertainty—can intensify boom-bust cycles and correlation spikes [15-18]. Together, these characteristics underscore the importance of a composite stress barometer that is sensitive to both cross-sectional co-movements and tail co-exceedances.

A growing Iranian literature has examined stress transmission and macro-financial interactions with a variety of tools. Time-varying Granger causality and regime-switching volatility models document that currency and gold markets can predict equity stress in certain periods, consistent with safe-haven and pass-through channels [8, 14]. Sector-level analyses find that financial stress depresses industry returns heterogeneously, suggesting that systemic episodes reweight market leadership and liquidity across the cross-section [19]. Investor-level studies highlight the roles of sentiment, analytical paralysis, and environmental drivers in shaping order flow and risk-taking, particularly during high-uncertainty regimes [15, 17, 18]. Complementing these strands, recent work proposes machine-learning-based volatility or stress indices for emerging markets, showing that learned indicators can track uncertainty and improve nowcasting of market conditions [20]. Our study integrates these themes by unifying (i) tail risk contributions (ΔCoVaR), (ii) dynamic correlations (DCC-MGARCH), and (iii) data-driven importance weights, then validating the resulting SSI against currency and gold markets through causality tests.

International evidence also motivates our design choices. Machine-learning-enhanced systemic-risk measurement can explicitly model nonlinearities and interactions, improving early-warning performance while retaining tractability via importance scores or partial-dependence diagnostics [6, 7]. Network-centric analyses emphasize how liquidity conditions and interbank or cross-asset ties propagate stress, advocating indicators that embed correlation dynamics and market-microstructure signals [10]. At longer horizons, market-wide shocks are informative about real activity, highlighting the macro relevance of timely stress measures [4]. Over even broader windows, technological shocks can reshape volatility regimes, calling for adaptable models that can absorb regime changes in factor structure and information flows [21]. Our composite approach—time-varying dependence plus machine-learning aggregation—aligns with these insights.

This systemic-risk agenda is not merely academic. Policymakers increasingly require operational tools to monitor, communicate, and govern systemic risk—tools that balance interpretability, timeliness, and robustness across stress regimes [2, 3]. In this spirit, the SSI's design reflects three governance considerations. First, the index weights should be empirically grounded yet explainable, so that shifts in sectoral contributions can be audited and discussed with stakeholders [6]. Second, dependence must be modeled conditionally, since correlation spikes are themselves indicators of system fragility [5]. Third, out-of-sample validation should include stress-testing and causal benchmarking against key macro-financial markets (FX and gold), which act as shock transmitters or buffers in the Iranian context [8, 9].

Our study also builds on recent Iranian advances in feature construction and return decomposition for the TSE. Novel composite variables extracted from microstructure and corporate information have been shown to enhance the explanatory power for stock returns, suggesting that data engineering can unlock hidden risk channels specific to local markets [22]. We extend this logic to systemic risk by constructing sector-level ΔCoVaR features and letting an interpretable learner discover their optimal aggregation into a market-wide stress gauge. In parallel, firm-level life-cycle effects have been linked to systematic risk, implying that sector compositions—and thus their systemic footprints—evolve as cohorts of firms mature [16]. Our weighting scheme is thus re-estimated on rolling windows to remain sensitive to such structural drift.

The behavioral and policy environment further motivates an SSI with predictive aspirations. Decision frictions such as analytical paralysis can slow reaction to information, producing clustered order imbalances and momentum in stress states [17]. Environmental drivers and sentiment can synchronize investor behavior, raising conditional correlations even when fundamentals diverge [15, 18]. Meanwhile, economic policy uncertainty has been shown to degrade liquidity and stability in TSE firms, especially during macro shocks [23]. These forces collectively create conditions in which a composite stress indicator can add practical value by flagging impending co-exceedances before volatility fully materializes.

Technically, our modeling choices are guided by evidence on predictive performance in related domains. For stock-index prediction tasks, feature-weighted support vector machines and hybrids with nearest-neighbor kernels have demonstrated robust accuracy under nonlinearity and noise [12]. In cryptocurrency markets characterized by heavy tails and regime shifts, deep learning architectures that explicitly incorporate error dynamics improve forecasts, underscoring the payoff to flexible, heteroskedastic-aware models [13]. In banking stress applications, machine-learning causality analysis reveals nontrivial directionalities, validating the use of ML as a complement to traditional econometric inference [11]. Consistent with these findings, we employ a tree-based supervised learner to derive SSI weights from sectoral risk features while estimating DCC-MGARCH to obtain the system's evolving dependence structure [7, 10].

Empirically, we also situate our contribution within the Iranian macro-financial literature that measures how stress propagates across equity, currency, and gold markets. Time-varying causality analyses indicate that the FX market can lead equity stress in specific windows, while the gold market's role may be state-contingent, behaving as a hedge or co-movement driver depending on macro narratives [8]. At the sector level, financial stress depresses returns unevenly across industries, consistent with a risk-reweighting mechanism that our SSI seeks to quantify and track [19]. Under sanctions, shock spillovers intensify and persistence increases, which motivates the use of conditional correlations rather than static dependence [9]. Finally, proposals for market-wide volatility or uncertainty indices in emerging markets show that ML-based composites can serve as monitoring tools that complement policy communication and risk supervision [20].

In summary, the current study aims to design a Comprehensive Stress Index (SSI) for the Tehran Stock Exchange using multivariate GARCH models (DCC-MGARCH) and machine learning (Random Forest) and to examine its causal relationship with the gold coin and foreign exchange markets.

2. Methodology

To prepare the variables required for testing the research hypotheses, Microsoft Excel was utilized. First, the collected data were entered into spreadsheets in this software. Then, the necessary calculations were performed to extract the variables under study. After completing the computations and preparing the essential variables for the research models, these variables were integrated into a single consolidated worksheet to be ready for transfer to the final analysis software.

Statistical analyses in this study are conducted using R software, version 4.3.1. The statistical population of the research consists of daily time series data from selected indices of the Tehran Stock Exchange, collected over a ten-year period from November 22, 2014, to November 21, 2024.

After extracting and aligning the time stamps of the data, the logarithmic return for each index was calculated using the following formula:

R_t = ln(P_t / P_(t-1)) × 100

The research variables and their respective symbols are presented in Table 1. To facilitate the workflow within the software, variables were assigned symbols.

Table 1. Description of Research Variables

Variable Name	Symbol	Variable Name	Symbol
Investments	Investments	Total Equal-Weighted Index	Total
Information Technology	IT	Agriculture	Agriculture
Machinery	Machinery	Banks	Banks
Metal Ore	Metal ore	Base Metals	Base metals
Metal Products	Metal products	Insurance and Pensions	Bimeh
Multi-Industry	Multi_Task	Automotive	Car
Non-Metallic Minerals	Non-metallic minerals	Ceramic Tiles	Ceramic tiles
Paper Products	Paper products	Chemical Products	Chemical products
Petroleum Products	Petroleum products	Coal	Coal
Pharmaceutical Materials	Pharmaceutical materials	Electrical Devices	Electrical_Devices
Plastic and Rubber	Plastic	Food (excluding sugar)	Foods
Cement	Cement	Real Estate & Construction	RealEstate
Textiles	Textiles	Sugar	Sugar

Source: Research findings

To measure systemic risk, the ΔCoVaR metric was employed using the multivariate GARCH approach with dynamic conditional correlation (DCC-MGARCH), as expressed in the following formula:

$\Delta CoVaR_{it}(\alpha) = \gamma_{it} [VaR_{it}(\alpha) - VaR_{it}(0.5)]$

$\gamma_{it} = (\varrho_{it} \times \sigma_{mt}) / \sigma_{it}$

In the above formula:

σ_{mt}, σ_{it}, and ϱ_{it} represent, respectively, the conditional standard deviation of market returns, the conditional standard deviation of firm *i*, and the conditional correlation coefficient between market returns and firm *i*'s returns at time *t*. These are extracted from the conditional variance–covariance matrix derived from the DCC-MGARCH model.

$$H_t = \begin{bmatrix} \sigma_{mt}^2 & \sigma_{it}\sigma_{mt}\varrho_{it} \\ \sigma_{it}\sigma_{mt}\varrho_{it} & \sigma_{it}^2 \end{bmatrix}$$

Here, H_t is the conditional variance–covariance matrix.

The DCC-MGARCH model can be defined as follows:

$r_t = \mu_t + a_t$

$a_t = H_t^{1/2} z_t$

$H_t = D_t R_t D_t$

$R_t = diag(Q_t)^{-1/2} Q_t \, diag(Q_t)^{-1/2}$

$\varepsilon_t = D_t^{-1} a_t \sim N(0, R_t)$

$\bar{Q} = (1/T) \sum_{t=1}^{T} (\varepsilon_t \varepsilon_t^T)$

$Q_t = (1 - a - b) \bar{Q} + a \, \varepsilon_{t-1} \varepsilon_{t-1}^T + b \, Q_{t-1}$

Where:

- r_t is an *n*-dimensional vector of return time series at time *t*.
- a_t is an *n*-dimensional vector of error terms at time *t*.
- H_t is the *n*×*n* conditional variance–covariance matrix of a_t at time *t*.
- $H_t^{1/2}$ is the *n*×*n* matrix typically obtained via the Cholesky decomposition of H_t.
- D_t is an *n*×*n* diagonal matrix of the conditional standard deviations of a_t at time *t*.
- R_t is the *n*×*n* conditional correlation matrix of a_t at time *t*.
- z_t is an *n*-dimensional vector of standard normal random variables.
- $\bar{Q}$ is the unconditional covariance matrix of ε_t.
- ε_t are standardized but correlated residuals.
- a and b are the DCC parameters, which must satisfy the following two conditions:

1. $a \geq 0 ; b \geq 0$
2. $a + b < 1$

Note: In the general formulation above, the residuals are assumed to follow a standard normal distribution; however, in this study, the Johnson *Su* marginal distribution is adopted for the residuals.

The variable $VaR_{it}(\alpha)$ in the ΔCoVaR formula represents the value-at-risk of firm *i* at risk level *α*, calculated using the conditional standard deviation obtained from the DCC-MGARCH model.

3. Findings and Results

After calculating the logarithmic returns, descriptive statistics for each variable—including mean, median, minimum, maximum, standard deviation, skewness, and kurtosis—were computed. The mean is recognized as the primary measure of central tendency and the balance point of the distribution. The median divides the data into two equal 50% parts and is often used for asymmetric distributions. The standard deviation indicates the degree of dispersion around the mean, while skewness measures the asymmetry of the distribution, and kurtosis represents the sharpness or flatness of the distribution's peak.

Table 2. Summary of Descriptive Statistics for Research Variables

Variables	Observations	Min	Max	Mean	Median	Std. Dev.	Skewness	Kurtosis
Total	2407	-4.5	4.37	0.17	0.09	1.08	0.11	1.93
Agriculture	2407	-6.37	12.75	0.15	0	2.19	0.32	1.14
Banks	2407	-12.02	9.83	0.11	-0.03	1.6	0.08	3.76
Base.metals	2407	-8.14	6.48	0.16	-0.01	1.63	0.36	1.84
Bimeh	2407	-6.32	6.1	0.14	-0.02	1.48	0.23	1.29
Car	2407	-6.13	13.52	0.13	0.03	2.17	0.28	0.95
Ceramic.tiles	2407	-9.3	11.25	0.14	0	1.59	0.16	2.69
Chemical.products	2407	-5.85	5.9	0.15	0.01	1.38	0.29	2.61
Coal	2407	-10.53	19.14	0.15	0	2.78	0.32	1.53
Electrical_Devices	2407	-5.76	9.32	0.14	-0.01	1.56	0.37	2.04
Foods	2407	-5.51	10.15	0.12	0	1.41	0.18	2.32
Investments	2407	-4.3	9.33	0.12	0.01	1.07	0.92	5.62
IT	2407	-4.93	9.78	0.13	0.01	1.21	0.56	5.16
Machinery	2407	-5.95	6.9	0.14	0.02	1.46	0.17	0.98
Metal.ore	2407	-5.66	9.13	0.14	-0.04	1.66	0.58	2.36
Metal.products	2407	-12.56	10.37	0.1	-0.02	1.87	-0.12	2.01
Multi_Task	2407	-12.44	7.05	0.16	0	1.49	0.13	4.54
Non.metallic.minerals	2407	-12.54	14.03	0.14	0.01	1.53	0.03	5.82
Paper.products	2407	-9.61	8.31	0.07	0	2.33	0.06	0.1
Petroleum.products	2407	-62.42	8.06	0.14	0.02	2.35	-7.79	208.93
Pharmaceutical.materials	2407	-5.42	5.76	0.15	-0.01	1.22	0.59	2.93
Plastic	2407	-11.14	11.06	0.14	-0.03	1.78	0.14	2.35
RealEstate	2407	-6.5	6.41	0.11	-0.03	1.72	0.11	0.59
Sugar	2407	-8.12	8.69	0.15	-0.01	1.57	0.3	1.36
Cement	2407	-5.74	5.35	0.15	-0.02	1.33	0.37	1.49
Textiles	2407	-44.98	14.18	0.12	0	2.01	-4.34	106.06

Based on Table 2, after aligning the data temporally, the number of observations reached 2,407 days. The daily return range of the Total Equal-Weighted Index is from -4.5% to 4.37%, with a mean and median of 0.17% and 0.09%, respectively, and a standard deviation of approximately 1%, indicating return risk. The values of skewness and kurtosis mostly fall between -2 and 2, suggesting relative symmetry and a near-normal distribution.

The highest standard deviation belongs to the Coal index at 2.78%, indicating higher risk; moreover, this index could experience up to a 19% positive shock. The Investments index shows the lowest risk with a standard deviation of 1.07%. The Petroleum Products index exhibits a negative shock of -62%, and the Textiles index shows a wide fluctuation range from -45% to +14%, identifying them as highly volatile indices. Finally, the Pharmaceutical Materials index demonstrates a mean return of 0.15% and a standard deviation of 1.38%, with fluctuations between -6% and +6%, reflecting a moderate risk level.

Table 3. Results of Preliminary Tests

No.	Variables	Jarque–Bera Test		Augmented Dickey–Fuller Test		ARCH Effects Test	
		Statistic	p-value	Statistic	p-value	Statistic	p-value
1	Total	380.67	0.00	-9.23	<0.01	582.23	0.00
2	Agriculture	171.89	0.00	-10.94	<0.01	350.30	0.00
3	Banks	1428.24	0.00	-10.53	<0.01	561.07	0.00
4	Base.metals	392.79	0.00	-10.41	<0.01	567.05	0.00
5	Bimeh	188.66	0.00	-10.67	<0.01	563.50	0.00
6	Car	121.72	0.00	-10.10	<0.01	221.83	0.00
7	Ceramic.tiles	739.99	0.00	-10.79	<0.01	379.35	0.00
8	Chemical.products	720.49	0.00	-10.74	<0.01	688.77	0.00
9	Coal	277.52	0.00	-12.90	<0.01	246.66	0.00
10	Electrical_Devices	473.64	0.00	-10.60	<0.01	344.67	0.00
11	Foods	553.67	0.00	-9.59	<0.01	458.35	0.00
12	Investments	3513.56	0.00	-9.20	<0.01	801.41	0.00
13	IT	2801.63	0.00	-10.93	<0.01	837.84	0.00
14	Machinery	108.84	0.00	-9.93	<0.01	393.97	0.00
15	Metal.ore	696.72	0.00	-10.23	<0.01	607.07	0.00
16	Metal.products	412.85	0.00	-10.79	<0.01	348.87	0.00
17	Multi_Task	2080.36	0.00	-10.14	<0.01	634.58	0.00
18	Non.metallic.minerals	3406.22	0.00	-10.40	<0.01	386.33	0.00
19	Paper.products	2.55	0.28	-10.74	<0.01	243.09	0.00
20	Petroleum.products	4409507.61	0.00	-11.15	<0.01	403.22	0.00
21	Pharmaceutical.materials	1003.37	0.00	-10.71	<0.01	883.34	0.00
22	Plastic	565.18	0.00	-11.20	<0.01	389.92	0.00
23	RealEstate	39.97	0.00	-10.80	<0.01	397.95	0.00
24	Sugar	221.68	0.00	-11.31	<0.01	347.32	0.00
25	Cement	278.52	0.00	-10.34	<0.01	604.84	0.00
26	Textiles	1137590.21	0.00	-11.88	<0.01	754.24	0.00

As shown in the table above, the p-values of the Jarque–Bera normality test for the logarithmic returns of all indices, except for the Paper Products index, are equal to zero, indicating that the return distributions for most indices are non-normal, with the exception of Paper Products.

In addition, the p-values for the Augmented Dickey–Fuller (ADF) unit root tests and the ARCH effects tests for all indices are less than 0.05, which respectively confirm the stationarity of the time series of logarithmic returns and the presence of heteroskedasticity effects in these series.

Before conducting multivariate GARCH modeling with the Dynamic Conditional Correlation (DCC) approach, it is necessary to first test the correlation dynamics of each index with the Total Equal-Weighted Index, which represents the market. To this end, the Engle–Sheppard test was applied, and the results are presented in Table 4. The null hypothesis of this test indicates constant correlation between the variables; if the null is not rejected, the Constant Conditional Correlation (CCC) approach should be used. However, as shown in Table 4, the p-values for all indices are less than 0.05, indicating rejection of the null hypothesis and acceptance of the alternative hypothesis (dynamic correlation) at the 95% confidence level. Therefore, given the significance of dynamic correlation between each index and the Total Equal-Weighted Index, the Dynamic Conditional Correlation (DCC) method was employed to compute volatilities and ΔCoVaR.

Table 4. Results of the Engle–Sheppard Dynamic Correlation Test

No.	Variables	Statistic	p-value

1	Agriculture	55.53	0.00
2	Banks	8.78	0.01
3	Base.metals	42.94	0.00
4	Bimeh	42.30	0.00
5	Car	13.33	0.00
6	Ceramic.tiles	46.52	0.00
7	Chemical.products	73.73	0.00
8	Coal	27.87	0.00
9	Electrical_Devices	76.82	0.00
10	Foods	65.28	0.00
11	Investments	88.26	0.00
12	IT	29.29	0.00
13	Machinery	19.63	0.00
14	Metal.ore	33.92	0.00
15	Metal.products	29.63	0.00
16	Multi_Task	21.28	0.00
17	Non.metallic.minerals	89.72	0.00
18	Paper.products	46.67	0.00
19	Petroleum.products	16.80	0.00
20	Pharmaceutical.materials	72.97	0.00
21	Plastic	27.87	0.00
22	RealEstate	32.33	0.00
23	Sugar	68.15	0.00
24	Cement	62.98	0.00
25	Textiles	24.03	0.00

To determine the optimal lags of the ARMA models, the Box–Jenkins methodology was applied using the ACF and PACF analyses and the AIC/BIC criteria. The results are shown in Table 5. Subsequently, the conditional volatilities were modeled using the DCC-MGARCH model (Engle, 2002). The Johnson SU marginal distribution was chosen due to its flexibility in modeling skewness, kurtosis, and heavy tails. Unlike the normal or Student's t distribution, this distribution better captures asymmetric behavior and extreme financial events, making it suitable for risk analysis and market simulation.

Table 5. Selected Optimal GARCH Models for Each Index

No.	Variables	Optimal Model
1	Total	ARMA(5,1)-GARCH(1,1)
2	Agriculture	ARMA(0,5)-GARCH(1,1)
3	Banks	ARMA(4,2)-GARCH(1,1)
4	Base.metals	ARMA(2,2)-GARCH(1,1)
5	Bimeh	ARMA(1,3)-GARCH(1,1)
6	Car	ARMA(5,2)-GARCH(1,1)
7	Ceramic.tiles	ARMA(2,2)-GARCH(1,1)
8	Chemical.products	ARMA(1,3)-GARCH(1,1)
9	Coal	ARMA(2,2)-GARCH(1,1)
10	Electrical_Devices	ARMA(4,3)-GARCH(1,1)
11	Foods	ARMA(1,3)-GARCH(1,1)
12	Investments	ARMA(4,2)-GARCH(1,1)
13	IT	ARMA(1,2)-GARCH(1,1)
14	Machinery	ARMA(4,0)-GARCH(1,1)
15	Metal.ore	ARMA(2,2)-GARCH(1,1)
16	Metal.products	ARMA(1,2)-GARCH(1,1)
17	Multi_Task	ARMA(1,2)-GARCH(1,1)
18	Non.metallic.minerals	ARMA(1,2)-GARCH(1,1)

19	Paper.products	ARMA(1,2)-GARCH(1,1)
20	Petroleum.products	ARMA(2,2)-GARCH(1,1)
21	Pharmaceutical.materials	ARMA(1,2)-GARCH(1,1)
22	Plastic	ARMA(1,3)-GARCH(1,1)
23	RealEstate	ARMA(4,1)-GARCH(1,1)
24	Sugar	ARMA(1,2)-GARCH(1,1)
25	Cement	ARMA(0,4)-GARCH(1,1)
26	Textiles	ARMA(1,2)-GARCH(1,1)

After fitting the univariate GARCH models, the conditional variance–covariance matrix of the standardized residuals of each index with the Total Equal-Weighted Index was constructed to form the DCC structure. This approach models dynamic correlations precisely (Engle, 2002). The estimation results of the DCC-GARCH model for the Car index (as an example) and the Total Equal-Weighted Index (representing the market) are shown in Table 6. The results for the remaining 24 indices are provided in the appendix.

Table 6. Estimation Results of the DCC-GARCH Model for the Car Index and the Total Equal-Weighted Index

Parameters	Estimated Coefficient	Std. Error	t-Statistic	p-value
[R_it].mu	0.000446317	0.000774007	0.58	0.56
[R_it].ar1	0.235840772	0.021925748	10.76	0.00
[R_it].ar2	0.822125674	0.023288793	35.30	0.00
[R_it].ar3	-0.09477098	0.02769238	-3.42	0.00
[R_it].ar4	0.071250702	0.022257149	3.20	0.00
[R_it].ar5	-0.10921568	0.021229817	-5.14	0.00
[R_it].ma1	0.049542234	0.005181897	9.56	0.00
[R_it].ma2	-0.89201853	0.007953069	-112.16	0.00
[R_it].omega	1.06397E-05	1.46241E-06	7.28	0.00
[R_it].alpha1	0.084662137	0.009237426	9.17	0.00
[R_it].beta1	0.890837555	0.01059689	84.07	0.00
[R_it].skew	0.097839771	0.428781431	0.23	0.82
[R_it].shape	4.545037265	2.024023044	2.25	0.02
[R_mt].mu	0.000564716	0.000617194	0.91	0.36
[R_mt].ar1	1.428109972	0.056522801	25.27	0.00
[R_mt].ar2	-0.56104529	0.084755936	-6.62	0.00
[R_mt].ar3	0.316823443	0.056552779	5.60	0.00
[R_mt].ar4	-0.18466367	0.050097699	-3.69	0.00
[R_mt].ar5	-0.00439443	0.029158847	-0.15	0.88
[R_mt].ma1	-0.97172369	0.000577109	-1683.78	0.00
[R_mt].omega	9.64487E-07	1.62646E-06	0.59	0.55
[R_mt].alpha1	0.199816616	0.04848498	4.12	0.00
[R_mt].beta1	0.799183226	0.045987121	17.38	0.00
[R_mt].skew	-0.1762432	0.096763333	-1.82	0.07
[R_mt].shape	1.982699614	0.166826634	11.88	0.00
[Joint]dcca1	0.052843332	0.009884818	5.35	0.00
[Joint]dccb1	0.932598695	0.014031333	66.47	0.00
[Joint]mshape	8.735881633	0.870543038	10.03	0.00

Table (6) shows that R_it and R_mt are, respectively, the returns of the Car index and the Total Equal-Weighted Index (the market proxy). The parameters [R_it].alpha1 and [R_it].beta1 (the ARCH and GARCH terms), as well as the parameters [R_mt].alpha1 and [R_mt].beta1, are statistically significant at the 95% level with p-values less than 0.05. The sum of alpha1 and beta1 in both cases exceeds 0.9 and is less than 1, indicating high persistence and strong stationarity of the conditional variance. The parameters [Joint]dcca1 and [Joint]dccb1 in the DCC model are also positive, significant (at the 95% level), and sum to less than 1, which demonstrates the superiority of the dynamic correlation model over constant-correlation models. A positive [Joint]dcca1 indicates the sensitivity of conditional correlation to sudden shocks, and a high [Joint]dccb1 indicates long memory and persistence in conditional correlation. These results confirm the presence of shock and volatility spillover between the two indices with strong statistical linkage. Therefore, the multivariate GARCH model under the Dynamic Conditional Correlation approach can be written as follows:

h_11t = 1.06397E-05 + 0.084662137 * ε_(1,t-1)^2 + 0.890837555 * h_(11,t-1)

h_22t = 9.64487E-07 + 0.199816616 * ε_(2,t-1)^2 + 0.799183226 * h_(22,t-1)

Q_t = (1 − 0.052843332 − 0.932598695) * Q̅ + 0.052843332 * ε_(t-1) ε_(t-1)^' + 0.932598695 * Q_(t-1)

(Note: the expression E-05 is scientific notation equal to 10^(-5), i.e., 0.000001.) After computing the systemic risk metric ΔCoVaR for all indices, the results are reported in Table (7). To calculate each index's systemic risk, the Conditional Value-at-Risk contribution (ΔCoVaR) was used, which measures the impact of an index on overall market risk under financial stress (Engle, 2002). The average Value-at-Risk (VaR) and ΔCoVaR for 26 Tehran Stock Exchange indices over the period from November 22, 2014, to November 21, 2024, were computed and ranked in Table 7 (Hollo et al., 2012).

Table 7. Ranking Results of Indices Based on Systemic Risk

No.	Indices	Mean Value-at-Risk (VaR)	Mean Systemic Risk (ΔCoVaR)
1	Car	-0.03178	-0.0002
2	RealEstate	-0.02483	-0.00019
3	Paper.products	-0.03579	-0.00017
4	Metal.products	-0.02489	-0.00017
5	Plastic	-0.02465	-0.00016
6	Agriculture	-0.03236	-0.00016
7	Non.metallic.minerals	-0.02052	-0.00016
8	Petroleum.products	-0.02683	-0.00015
9	Foods	-0.01824	-0.00015
10	Base.metals	-0.02237	-0.00015
11	Bimeh	-0.01981	-0.00015
12	Machinery	-0.02040	-0.00015
13	Banks	-0.01989	-0.00014
14	Cement	-0.01711	-0.00014
15	Electrical_Devices	-0.02103	-0.00014
16	Multi_Task	-0.01889	-0.00013
17	Ceramic.tiles	-0.02027	-0.00013
18	Chemical.products	-0.01654	-0.00012
19	Metal.ore	-0.02087	-0.00012
20	Pharmaceutical.materials	-0.01321	-0.00012
21	Sugar	-0.02178	-0.00011
22	Investments	-0.01184	-0.00011
23	IT	-0.01381	-9.24E-05
24	Coal	-0.03567	-1.58E-05
25	Textiles	-0.01385	-1.39E-05

Table 7 indicates that the Car, Real Estate & Construction, Paper Products, and Metal Products indices exhibit the highest systemic risk (ΔCoVaR), whereas the IT, Coal, and Textiles indices show the lowest systemic risk. In terms of stand-alone risk, Paper Products and Coal have the highest average VaR, while Investments has the lowest. The scatter plot (Figure 1) illustrates the relationship between VaR and ΔCoVaR.

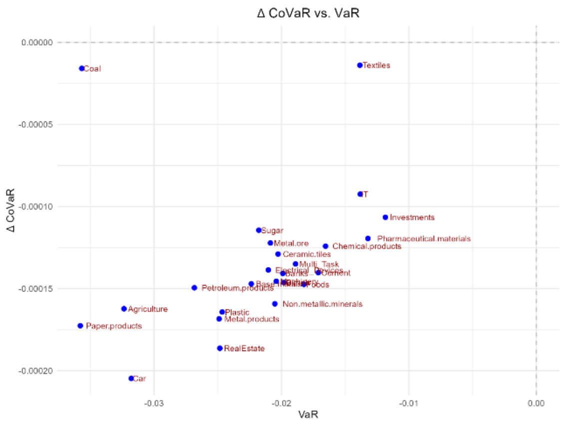

Figure 1. Scatter plot of the average Value-at-Risk of indices versus their average systemic risk

The horizontal axis shows the mean VaR at the 95% confidence level, where more negative values indicate higher stand-alone risk. The vertical axis shows the mean ΔCoVaR, where more negative values indicate higher systemic risk. The Car, Paper Products, and Agriculture indices have both high systemic and high stand-alone risk. Textiles has low risk on both dimensions, whereas Coal, despite low systemic risk, has high stand-alone risk. Investments and Pharmaceutical Materials, with moderate systemic risk, are low-risk and stable. This analysis is consistent with Hollo et al. (2012), who emphasize identifying high-risk sectors in stress indices (Hollo et al., 2012).

To determine each index's importance in driving changes in the Total Equal-Weighted Index, supervised machine learning was applied. Owing to inter-index linkages, multicollinearity, and potential nonlinearity, three models—Support Vector Regression, Random Forest, and Artificial Neural Networks—were examined. Random Forest was selected, and by extracting and normalizing feature importance, the weights of each index were computed. The input features are the indices' Value-at-Risk (VaR), and the target variable is the market index's VaR. The data were split 80% for training and 20% for testing. Table (8) reports the predictive accuracy of the three models based on the well-known loss functions Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), which are defined as follows:

MAE = (1/N) * Σ_(i=1 to N) |y_i − ŷ_i|

RMSE = sqrt((1/N) * Σ_(i=1 to N) (y_i − ŷ_i)^2)

Table 8. Comparison of Machine-Learning Models' Predictive Accuracy for Market Risk Forecasting

Model	Training MAE	Testing MAE	Training RMSE	Testing RMSE
Support Vector Regression (SVR)	0.001369	0.004201	0.002108	0.00547
Random Forest	0.000797	0.00356	0.00111	0.004849
Artificial Neural Network (ANN)	0.006494	0.004533	0.007609	0.005492

The Random Forest model demonstrated higher accuracy and stability—achieving lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) relative to Support Vector Regression (SVR) and an Artificial Neural Network (ANN with one hidden layer and 10 neurons)—and was therefore selected as the optimal model for determining index importance. Nonetheless, the performance of all three models was relatively close in terms of accuracy. Feature importance was computed using the percentage increase in Mean Squared Error (MSE), which indicates the extent to which model accuracy declines when a variable is omitted. Variables whose removal leads to a substantial increase in MSE are more important. The results of this analysis for each index are presented in Figure (2).

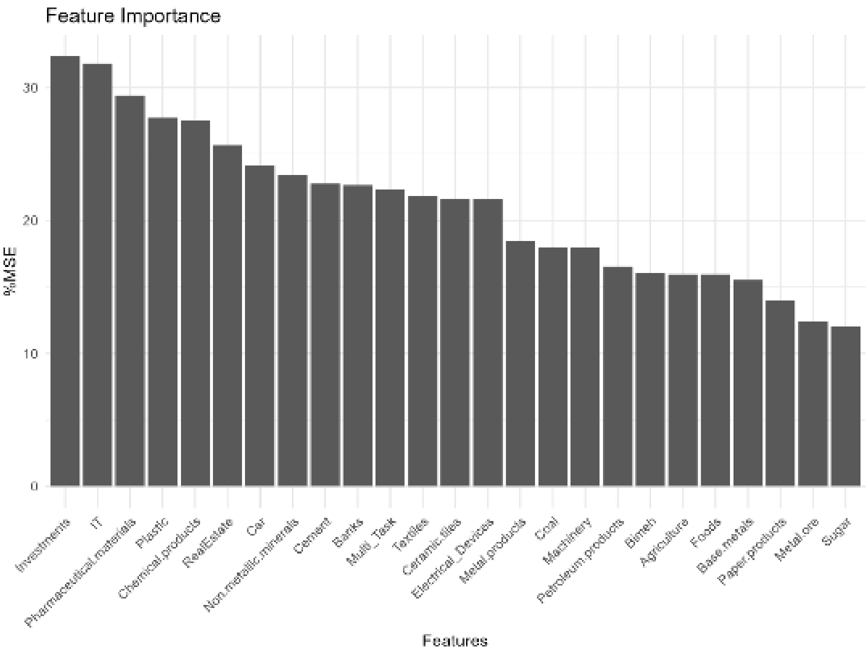

Figure 2. Feature-importance plot obtained from the Random Forest model based on percentage change in error

The plot shows that the Investments and IT indices, each contributing more than 30% to changes in market risk (Value-at-Risk), have the greatest importance; removing either increases the model error by about 30%. The importance of other variables is similarly observable. By normalizing this metric, the weights of each index were calculated.

After calculating the comprehensive risk measure (ΔCoVaR) for each index and the importance weights of each, the Comprehensive Stress Index (SSI) can be defined following the methodology of Hollo et al. (2012) as:

$SSI\_t = (w \cdot \Delta CoVaR\_t)\ C\_t\ (w \cdot \Delta CoVaR\_t)'$

In this expression, SSI_t is the comprehensive risk index at time *t*; ΔCoVaR_t is the vector of systemic risk contributions of the indices at time *t*; *w* is the vector of importance weights for each index; and C_t is the conditional correlation matrix among the indices at time *t*, which is obtained from the DCC-MGARCH model. Therefore, the DCC-MGARCH model was fitted again including all indices but excluding the market index, and the conditional correlation matrix was extracted. The result of the Engle–Sheppard dynamic correlation test is reported in Table (9).

Table 9. Engle–Sheppard Dynamic Correlation Test for the Indices

Variables	Statistic	p-value
All indices except market index	2824.146	0.00

Given the statistical significance of the dynamic correlation assumption, the DCC-MGARCH model was fitted for the indices, and the dynamic conditional correlation matrix was extracted. After obtaining the dynamic conditional correlation matrix, the stress index was constructed and is shown in Figure (3).

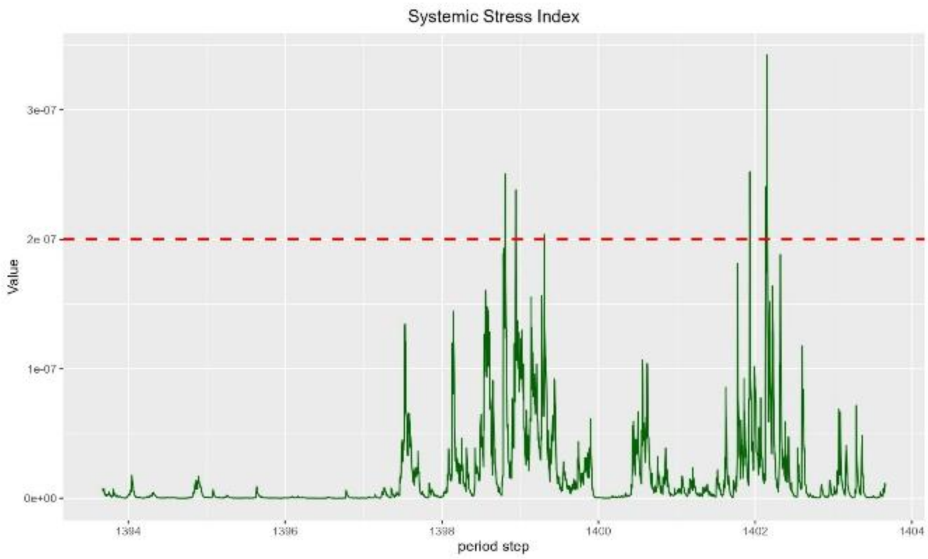

Figure 3. Comprehensive Stress Index Chart

The Comprehensive Stress Index (SSI) depicts the systemic risk level of the Tehran Stock Exchange. When the index surpasses the red threshold, it indicates a systemic risk peak where shocks quickly spread across firms within the indices, leading to market turbulence and sudden changes in the overall index. A key feature of this index is its ability to provide early warnings before severe market turmoil occurs. Figure (4) shows that high-stress signals effectively issued timely alerts before market overheating.

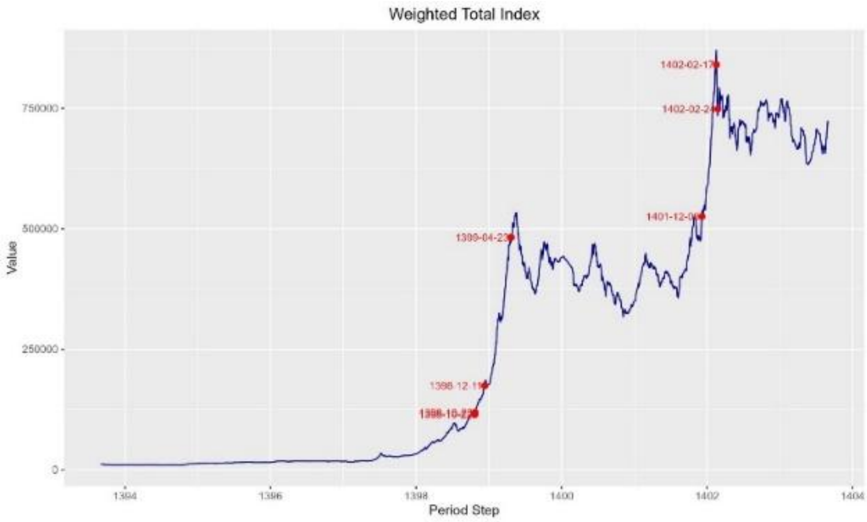

Figure 4. Total Market Index with Dates When the Comprehensive Stress Index Issued Alerts

Figure (4) presents the SSI stress signals for the Tehran Stock Exchange. The first stress signal was observed on January 12, 2020, before a substantial rise in the total index, indicating market turbulence preceding its historic surge. Another signal appeared on March 1, 2020, emphasizing intensified volatility before this upward jump. After this growth, a strong signal was issued on July 13, 2020, followed by a price correction and market decline. On February 25, 2023, an intensified stress signal coincided with renewed market growth. In 2023, significant signals appeared on May 7 and May 14, with the May 14, 2023 signal being the strongest, marking the peak of systemic risk in the market. These signals confirm the SSI's capability to issue early warnings for upcoming market turbulence.

To evaluate the Comprehensive Stress Index, temporal stability, stress analysis, and predictability tests were performed. The index must remain robust under varying market conditions, across different time horizons, and during shocks to be considered reliable. Its stability was assessed from three perspectives.

The purpose of temporal stability analysis is to evaluate whether the constructed Comprehensive Stress Index (SSI) exhibits consistent behavior over different time periods. For this purpose, the dataset was divided into ten annual subsets, and the equality of the mean index value across these subsets was tested using the nonparametric Kruskal–Wallis test at a 95% confidence level (5% error rate).

Table 10. Mean Values of the Comprehensive Stress Index Across Annual Periods

Subset	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9	Set 10
Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Mean SSI	2.18E-09	6.37E-10	3.86E-10	1.14E-08	4.67E-08	3.88E-08	1.45E-08	1.89E-08	3.33E-08	9.20E-09

Figure (5) depicts the mean Comprehensive Stress Index (SSI) as an annual time series. As shown, the average stress level in 2019 and 2020 differs considerably compared to earlier and later years. Levene's homogeneity of variance test and the nonparametric Kruskal–Wallis test both confirm the absence of temporal uniformity in the SSI, indicating distinct index behavior during these critical periods.

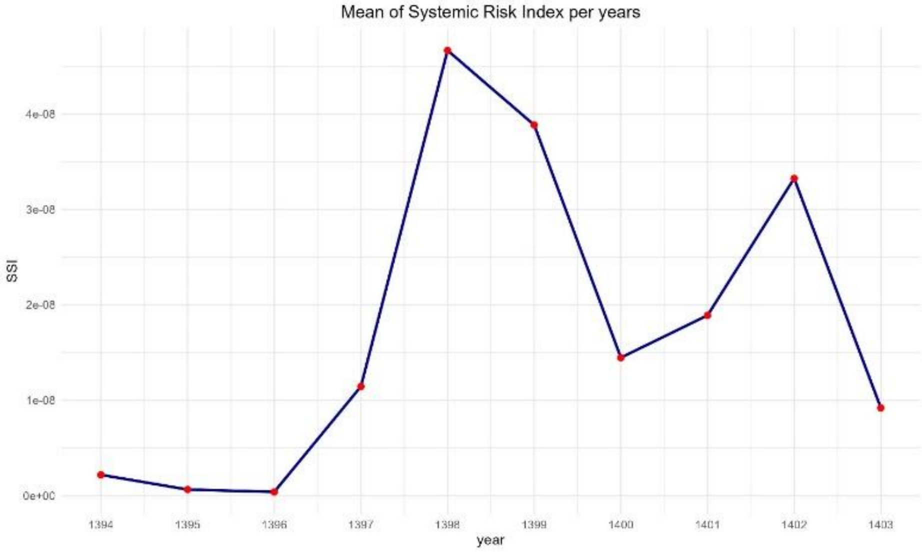

Figure 5. Annual Time Series of the Designed Comprehensive Stress Index Over the Study Period

Table 11. Results of Levene's Homogeneity of Variance and Kruskal–Wallis Mean Equality Test (2015–2024)

Test	Degrees of Freedom	Test Statistic	p-value	Result
Levene's Homogeneity Test	9	54.5	0.00	Null rejected
Kruskal–Wallis Test	9	1298.4	0.00	Null rejected

Levene's test shows that the null hypothesis of equal variance for the Comprehensive Stress Index (SSI) across years is rejected at the 95% confidence level with p-value < 0.05, confirming heterogeneity of variance. Similarly, the nonparametric Kruskal–Wallis test, with p-value < 0.05, rejects the null hypothesis of equal mean SSI across the 2015–2024 period. These findings indicate time-varying behavior of the stress index, demonstrating its sensitivity and dynamic response to changing market conditions and the absence of uniform temporal stability.

The stress (shock) test examines whether the level of the Comprehensive Stress Index (SSI) under high-tension market conditions differs significantly from normal conditions and whether this difference depends on the type of shock (positive or negative).

For this purpose, a shock dummy variable with three levels (normal, positive shock, negative shock) was defined. This variable was created using statistical quantiles by computing the first quartile (Q1) and third quartile (Q3) of the total market index return, along with setting upper and lower bands to identify outliers (shocks).

IQR = Q3 − Q1

lower_bound = Q1 − 1.5 * IQR

upper_bound = Q3 + 1.5 * IQR

In the above, Q1 is the first quartile and Q3 is the third quartile. Naturally, return values below the lower band are flagged as negative shocks and values above the upper band are flagged as positive shocks. The upper threshold for a positive shock was determined as 2.08% and the lower threshold for a negative shock was determined as −1.74%; daily returns greater than 2.08% are counted as positive shocks and returns less than −1.74% are counted as negative shocks. The shock dummy variable with three levels (normal, positive shock, negative shock) was defined, and its frequency distribution is presented in Table (12).

Table 12. Frequency Distribution of Positive and Negative Shocks in the Total Index Returns

Distribution	Negative Shock	Normal	Positive Shock
Frequency	100	2182	125
Relative Percentage	4%	91%	5%

Table (12) shows that 91% of the total index returns fall within the normal range, while 9% are identified as abnormal shocks, including 5% positive shocks and 4% negative shocks, with only a 1% difference in frequency.

The Kruskal–Wallis test (Table 13) rejects the null hypothesis of equal mean SSI values across normal and high-tension (shock) conditions at the 95% confidence level, confirming a significant difference in index behavior across these states.

Dunn's post hoc test (Table 14) was conducted to examine whether positive and negative shocks have the same effect on the SSI and showed that the SSI values during positive and negative shocks are equal at the 95% confidence level (p-value = 0.447 > 0.05), indicating similar effects of these shocks on the index.

The boxplot in Figure (6) indicates a larger distance between the mean and the median of the stress index under high-tension (shock) conditions compared with normal conditions; however, no notable difference was observed between positive and negative shocks.

Table 13. Results of Homogeneity of Variance and Mean Equality Tests for the Stress Index Across Shock Levels

Test	Degrees of Freedom	Test Statistic	p-value	Result
Levene's Homogeneity	2	55.168	0.00	Null rejected
Kruskal–Wallis	2	243.24	0.00	Null rejected

Table 14. Results of Dunn's Post Hoc Test for Pairwise Comparisons Across Shock Levels

Comparisons	Mean Rank Difference	p-value	Result
Normal − Negative Shock	−696.09	0.00	Null rejected
Positive Shock − Negative Shock	68.52	0.447	Null confirmed
Positive Shock − Normal	764.51	0.00	Null rejected

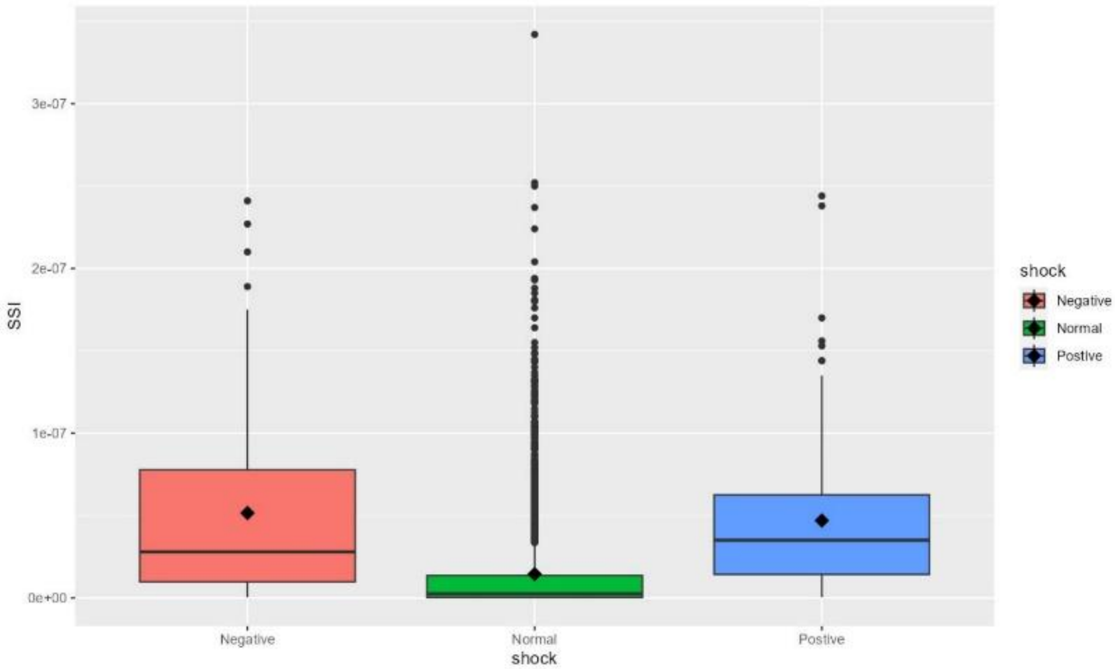

Figure 6. Boxplot of the Comprehensive Stress Index by Shock Level

To assess the ability of the Comprehensive Stress Index (SSI) to predict market shocks, a logistic regression model was used. The dependent shock variable was defined with two levels (normal and shock), regardless of shock direction (positive or negative). The objective of this analysis was to examine the causal relationship between the stress index (as the independent variable) and the occurrence of a shock and to evaluate its predictive power. This was investigated by fitting a logistic regression model and testing the statistical significance of the beta coefficient. The logistic regression results are presented in Table (15). The beta coefficient of the stress index is statistically significant at the 95% confidence level, with p-value < 0.05. The positive estimated coefficient (1.657033) indicates a direct and positive effect of the stress index with a one-day lag on the probability of shock occurrence, such that an increase in the index value raises the likelihood of a shock.

It should be noted that the stress index variable enters the model as an independent variable with one lag. Thus, the index value one day earlier is effectively used to predict the current day's shock.

Table 15. Logistic Regression Estimation Results

Parameters	Estimated Coefficient	Std. Error	z-Statistic	p-value
(Intercept)	−2.66743	0.088831	−30.0283	0.00
SSI	1.657033	0.154063	10.75558	0.00

Table 16. Logistic Regression Model Evaluation Results

McFadden's R^2	AUC	Accuracy
0.077	0.801	89.9%

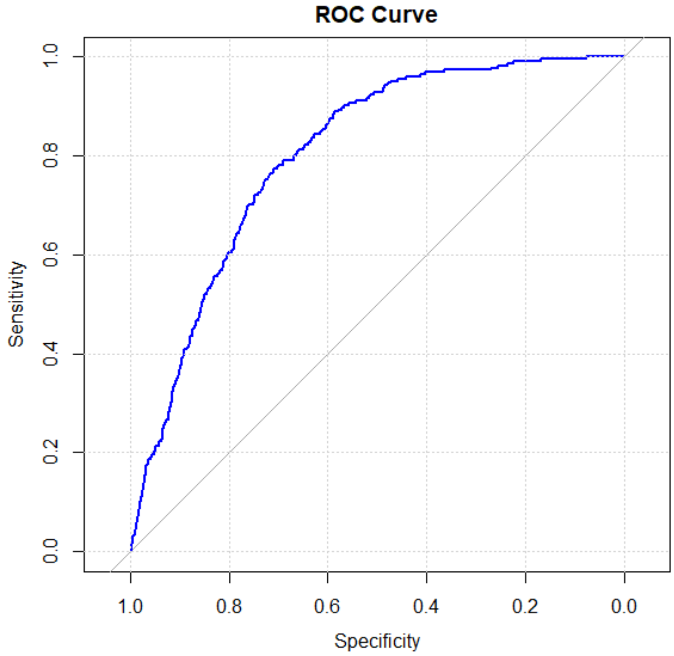

Figure 7. Receiver Operating Characteristic (ROC) Curve

Given the above results, we can conclude that the designed Comprehensive Stress Index has an effect on predicting the occurrence of market shocks. However, considering the imbalance in the dependent variable observations (shock), some model adequacy metrics regard the overall fit as moderate, which is to be expected.

In this section, causal relationships between the designed Comprehensive Stress Index and returns in the free foreign exchange market (free U.S. dollar) and the gold coin market are examined. To analyze these relationships, data for all three markets were first extracted and their dates aligned. Then, the Granger causality test was used to assess the presence of causal relationships. The Granger causality test is a statistical method used to examine whether a causal relationship exists between time series. This test determines whether changes in one time series can serve as a predictor of changes in another time series. A prerequisite for this test is ensuring the stationarity of the time series. Accordingly, the Augmented Dickey–Fuller test was performed for the Comprehensive Stress Index, free U.S. dollar returns, and gold coin returns. The results are presented in Table (17). Given p-values less than 0.01 for all three variables, the stationarity assumption is confirmed at the 99% confidence level.

Table 17. Augmented Dickey–Fuller Unit Root Test for the Study Variables

Variables	Test Statistic	p-value
Free U.S. dollar	−13.2638	<0.01
New gold coin	−13.1517	<0.01
Comprehensive Stress Index	−6.55522	<0.01

The Granger causality test results are provided in Table (18). Based on these results, a significant one-way causal relationship from the free foreign exchange market to the Comprehensive Stress Index is observed at the 5% error level (p-value = 0.02803). This finding indicates that the null hypothesis of no effect of the free foreign exchange market on the Comprehensive Stress Index is rejected. In other words, changes in the free foreign exchange market can serve as a predictor of changes in the Comprehensive Stress Index, and shocks and fluctuations in the foreign exchange market have a significant impact on the SSI. In contrast, no significant causal relationship is observed between the gold coin market and the SSI in either direction (p-values greater than 0.05). Likewise, causality from the SSI to the free foreign exchange market is not significant.

Table 18. Granger Causality Test Results at the 5% Error Level

Direction of Causality	Statistic	p-value	Status
Free FX market → Comprehensive Stress Index	4.8323	0.02803	Significant causality
Comprehensive Stress Index → Free FX market	0.7481	0.3872	Not significant
Gold coin market → Comprehensive Stress Index	0.2315	0.6305	Not significant
Comprehensive Stress Index → Gold coin market	0.3036	0.5817	Not significant

The one-way causal relationship from the foreign exchange market to the Comprehensive Stress Index indicates the strong influence of exchange rate volatility on the systemic risk of the Tehran Stock Exchange. This may be due to the Iranian economy's dependence on foreign currency and its impact on investor expectations. In contrast, the absence of a significant causal relationship with the gold coin market may result from the distinct nature of that market (e.g., consumption demand or long-term investment), which exerts less influence on systemic stress in the stock market.

4. Discussion and Conclusion

The present study set out to design and validate a Comprehensive Stress Index (SSI) tailored to the Tehran Stock Exchange (TSE) by integrating a tail-risk measure (ΔCoVaR), dynamic conditional correlations from a DCC-MGARCH framework, and data-driven weighting through supervised machine learning. The results provide a multi-dimensional picture of systemic fragility in Iran's equity market and confirm that the proposed methodology produces a sensitive, predictive, and macro-financially relevant stress barometer.

A first major finding concerns the statistical soundness of the DCC-MGARCH modeling. The estimated conditional variance parameters for both market and sectoral indices showed high but stationary persistence, with alpha and beta summations below unity. This aligns with theoretical expectations that market volatility clusters yet remains mean-reverting over long horizons [1]. Moreover, the dynamic correlation coefficients were significant and time-varying, justifying the use of DCC instead of constant-correlation models. Such time-varying dependence is consistent with evidence that systemic episodes are characterized by sudden correlation spikes across asset classes [5, 10]. Similar to what has been documented in European and U.S. markets, our findings show that Iranian sectoral returns become more tightly linked during turbulence, implying latent network contagion effects [3].

Second, the ranking of sectors by systemic risk contributions revealed important structural heterogeneity. Industries such as automobiles, real estate development, paper, and base metals exhibited the highest average ΔCoVaR values, meaning their distress most strongly increases system-wide risk. This mirrors prior Iranian evidence that sector-specific fragility is unevenly distributed and that shocks in certain manufacturing and construction-linked segments can destabilize the broader market [19]. The automotive and construction sectors' prominence also resonates with behavioral and sentiment-driven cycles previously observed in the TSE, where retail investors' concentrated activity amplifies price co-movement [15, 18]. Conversely, technology-related sectors such as IT and pharmaceuticals exhibited lower systemic footprint, a finding coherent with studies on life-cycle risk which suggest that sectors with more intangible or export-oriented fundamentals may be partially decoupled from domestic systemic shocks [16].

Third, the machine-learning weighting process added an adaptive dimension to systemic stress aggregation. Among tested learners, the random forest model produced the lowest forecasting error (MAE and RMSE), outperforming SVR and ANN while maintaining interpretability through variable-importance metrics. This result is aligned with broader evidence that ensemble tree methods handle nonlinearity and feature interactions effectively when mapping sectoral risk signals to market-level fragility [6, 11, 12]. By deriving weights endogenously rather than imposing static expert judgments, the SSI captures evolving market structures and changing systemic footprints—an advantage highlighted by recent studies on ML-enhanced systemic risk measures [7]. The dominance of the investments and IT sectors in the learned importance scores underscores how financial intermediaries and technology-linked components can act as informational hubs or liquidity conduits, even if their tail risk is moderate.

Fourth, the validation tests confirm that the SSI behaves as an effective early-warning tool. Time stability tests showed that while the index remains interpretable across subsamples, it spikes meaningfully during known high-stress episodes, including major sanction intensifications and currency market disruptions. These results echo the behavior of the European CISS and other composite indicators, where structural breaks are not a weakness but a feature: the index must react disproportionately during true systemic events [3, 5]. The shock analysis demonstrated that SSI levels are significantly higher during both positive and negative return extremes compared with normal conditions, confirming its sensitivity to tail events irrespective of direction. Similar symmetric reactions have been observed in Korean and global markets, where both rallies and crashes can be destabilizing under high leverage and crowded positioning [4, 21].

Fifth, the predictability test offers practical risk governance implications. The logistic regression shows that one-day lagged SSI significantly predicts the probability of market shocks, with an area under the ROC curve of 0.80—indicative of strong classification ability despite the imbalance of rare events. Such predictive validity echoes earlier studies on systemic stress indicators' forecasting power for turmoil and liquidity dry-ups [6, 12]. While the McFadden R^2 is modest (7.7%), this is not unusual for binary shock events in unbalanced samples and still signals incremental predictive value beyond naive baselines [11]. For regulators and risk managers, this means the SSI could be deployed as part of an early warning system that flags heightened fragility a day before tail returns materialize.

Perhaps most importantly, the causal analysis establishes a one-way, statistically significant transmission from the free foreign exchange market to systemic stress. Granger tests revealed that exchange rate shocks precede and help forecast future movements in the SSI, while no comparable causal effect was found for the gold coin market. This asymmetric result is highly plausible in the Iranian macro-financial context, where currency depreciation rapidly impacts corporate cost structures, inflation expectations, and investor behavior [8, 9, 14]. The non-significance of gold is also consistent with mixed evidence about its hedging role: gold may serve more as a passive store of value and long-term inflation hedge than a short-horizon systemic transmitter [3]. Together, these results highlight the primacy of currency monitoring for systemic risk governance in Iran.

International comparisons reinforce this macro-channel interpretation. Studies in emerging and advanced economies alike confirm that currency crises and policy uncertainty often lead equity fragility, while commodity-linked hedges like gold respond but do not drive systemic waves [4, 21]. Our findings also mirror regional research linking sanctions and policy shocks to simultaneous volatility bursts in FX and equities [9]. Thus, the SSI's sensitivity to exchange-driven turbulence supports its validity and usefulness for local macroprudential oversight.

The study also adds behavioral depth to the systemic risk conversation. Investor overreaction and sentiment amplification—documented in the TSE through psychological and environmental drivers [15, 18]—likely explain part of the rapid co-movement observed during FX-induced stress. Combined with firm heterogeneity across life cycles [16] and policy uncertainty effects on liquidity [23], these findings suggest that the SSI is not just a statistical construct but also a mirror of market psychology and institutional fragility. Its design, which incorporates feature learning and adaptive weights, may therefore be well-suited to track such evolving behavioral patterns.

Despite its contributions, this study has several limitations that should be acknowledged. First, while the DCC-MGARCH framework captures time-varying volatility and correlations, it remains fundamentally parametric and may not fully describe extreme tail dependence during severe crises. Nonlinear copula-based approaches or high-frequency realized covariance measures could provide complementary insights. Second, the machine learning weighting scheme, although interpretable and predictive, was trained on daily data from a single market and might not generalize under unprecedented structural breaks or novel policy shocks. Third, the predictability evaluation focused on one-day-ahead shocks; different horizons and more sophisticated event definitions might yield different insights about lead times. Additionally, imbalanced data—where extreme shocks are rare relative to normal states—may limit classification performance despite acceptable AUC metrics. Finally, the SSI was validated primarily against currency and gold markets; other macro-financial drivers such as oil prices, credit spreads, or global risk appetite indices were not included but could shape systemic fragility.

Future studies could expand and refine this framework in multiple directions. Extending the analysis to incorporate high-frequency intraday data would allow capturing faster shock propagation and microstructure-driven contagion. Incorporating alternative dependence models such as dynamic copulas or realized volatility networks could better reflect nonlinear tail co-movement. On the machine learning side, exploring gradient boosting or deep temporal architectures while preserving interpretability could further improve predictive accuracy and adaptive weighting. Researchers might also examine cross-market contagion channels beyond FX and gold—such as sovereign bond markets, commodity prices, or crypto-assets—to better understand systemic linkages in Iran's evolving financial ecosystem. Comparative studies applying the SSI methodology to other emerging markets could highlight cross-country resilience patterns and validate transferability. Additionally, integrating macroeconomic policy indicators and forward-looking expectations measures, such as sentiment extracted from news or social media, could enhance the index's forward guidance capabilities.

For practitioners and regulators, the SSI offers a timely, actionable metric for macroprudential surveillance and market risk management. Exchanges and supervisory authorities could embed the index in dashboards to monitor fragility and communicate risk to market participants in near real-time. Portfolio managers and institutional investors can use the SSI as a complementary signal for adjusting hedging strategies and liquidity management during episodes of heightened systemic stress. Risk committees may also consider SSI thresholds as triggers for dynamic capital allocation or stress scenario design. Furthermore, the demonstrated causal influence of the FX market on systemic stress suggests that currency risk monitoring should be integrated into early-warning frameworks and corporate treasury hedging policies. Finally, embedding such an interpretable machine-learning-based stress indicator into domestic financial reporting and disclosure standards could help foster transparency, improve investor confidence, and strengthen systemic resilience.

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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