Journal of Mathematics and Modeling in Finance (JMMF)
Vol. 6, No. 2, Summer & Fall 2026
Research paper

Analysis of Risk Trends, Capital Structure Stability, and Profitability Potential of Iranian Listed Companies Using Numerical Risk Scoring and Fuzzy Logic

Zahra Heydari Marbari[1], **Effat Golpar-Raboky**[2], **Seyedeh Narges Mirei**[3]

[1] Undergraduate Student, Department of Computer Science, University of Qom, Qom, Iran.
zahrazhi1382@gmail.com

[2] Associate Professor-Faculty Member, Department of Mathematical Sciences, University of Qom, Qom, Iran.

g.raboky@qom.ac.ir

[3] Assistant Professor-Faculty Member, Department of Computer Science, University of Qom, Qom, Iran.

n.mirehi@qom.ac.ir

Abstract:
This study analyzes the trend of risk and profitability of 60 Iranian listed companies during the period of 2015 to 2022. The research data was extracted from the audited financial statements of these companies and includes key financial variables such as Debt to Equity ratio, Current Ratio, Return on Assets (ROA), Return on Equity (ROE), Net Profit Margin, Operating Margin, and Asset Turnover. After normalizing the indicators and numerical scoring based on weighted average, the risk level of the companies was calculated. Then, using a fuzzy logic model, the impact of liquidity and asset variables on profit before tax was analyzed. The results show that most companies are at a medium to low risk level, and in some companies, an upward trend in risk has been accompanied by a decrease in profitability. The application of the fuzzy model has been able to better model the non-linear and complex relationships between financial indicators and can be useful for assessing profitability potential. In addition, to assess the stability of companies' capital structure, fluctuations in the debt-to-equity ratio were analyzed using a 3-year moving average.

Keywords: Financial risk, Profitability potential, Fuzzy logic, Iran stock exchange, Capital stability.
Classifications: 03E72, 91G70, 91B84.

1 Introduction

The capital market, as one of the most important pillars of any country's financial system, plays a fundamental role in resource mobilization and optimal capital allocation. In this market, the correct analysis of companies' risk and profitability is of paramount importance from the perspective of investors, analysts, and policymakers; because incorrect decisions can lead to significant financial losses. On the other hand,

[2] Corresponding author
Received: 12/10/2025 Accepted: 31/01/2026
https://doi.org/10.22054/jmmf.2026.88826.1225

the dynamism and complexity of financial variables mean that evaluating risk and profitability based solely on a single indicator is insufficient, and a multidimensional approach is needed.

Classical risk assessment methods are usually based on financial ratios and simple quantitative models. However, such methods are unable to accurately represent the nonlinear and complex relationships between financial indicators and companies' profitability. In recent years, the use of intelligent approaches such as fuzzy logic has emerged as an effective tool in modeling uncertainty and explaining ambiguous relationships between financial variables.

The present study focuses on 60 Iranian listed companies from 2015 to 2022, analyzing the trend of risk and profitability. In this regard, key financial ratios were first extracted, and companies' risk scores were calculated using normalization and weighted average methods. Then, to more accurately analyze the impact of liquidity and asset variables on earnings before tax, a fuzzy model was used. Additionally, as a supplementary analysis, fluctuations in the debt-to-equity ratio over the study period were examined to also consider the stability of companies' capital structure.

The main objective of this research is to present a hybrid framework of quantitative and qualitative methods for assessing the risk and profitability potential of listed companies, thereby providing a more comprehensive picture of their financial status and health.

2 Literature Review

The analysis of corporate risk and profitability has always been a central topic in the financial domain. Traditional approaches typically rely on individual financial ratios and linear models, which are unable to capture the nonlinear and complex relationships among financial variables. In this context, fuzzy logic, first introduced by Lotfi A. Zadeh (1965), has emerged as a powerful tool for modeling uncertainty and ambiguity in financial data. The concept of fuzzy sets provides a theoretical foundation for handling imprecision and linguistic variables in financial analysis [6].

Fuzzy logic has been applied in various financial areas, including risk assessment, bankruptcy prediction, and stock valuation, enabling more precise and flexible analyses [1].

Research [2] introduced a multi-criteria fuzzy system for stock valuation and was able to simultaneously consider the effect of multiple variables in decision-making. A comparison with the current research shows that although both use fuzzy logic for multi-dimensional modeling, the focus of the present study is on combining numerical risk scoring with a fuzzy model and predicting profit before tax.

Theoretical studies repeatedly emphasize the importance of asset volatility and capital structure. Studies such as [3, 4] have shown that asset volatility and financial leverage directly affect company risk and investor returns. Increased leverage leads to higher volatility, with an estimated elasticity of volatility to leverage of approximately 20%. These findings justify the inclusion of the “volatility of debt-to-equity ratio” in this study and highlight the importance of examining the stability of corporate financial structures.

Global studies also demonstrate that hybrid models, which combine fuzzy logic with statistical or machine learning techniques, significantly improve the accuracy of risk and profitability analyses. For instance, research combining fuzzy multi-criteria systems has enabled stock valuation by simultaneously considering multiple variables [2, 7]. These hybrid approaches provide a robust framework for financial modeling under uncertainty and serve as a foundation for the present research, which integrates multidimensional analysis with numerical risk scoring and profit-before-tax prediction

In Iran, numerous studies have applied fuzzy logic in the capital market, including ranking of companies’ shares [8], portfolio selection using fuzzy methods [9], and stock price prediction with hybrid models [10]. These studies confirm the efficiency of fuzzy logic in the Iranian market and demonstrate the feasibility of portfolio optimization and stock prediction using local data.

Furthermore, studies such as [5, 11] have highlighted that risk assessment based solely on numerical indicators cannot adequately represent the complexities and uncertainties present in financial data. This underscores the importance of applying fuzzy logic in the current study, as financial ratios with similar numerical values may have different impacts on risk assessment and profit prediction.

Finally, risk management in other domains, such as cybersecurity and industrial systems, illustrates the applicability of combined risk and fuzzy approaches [12], providing additional justification for integrating multiple methods in financial risk and profitability modeling.

Research Gap and Innovation

The innovation of this study lies in the integration of three components:

(i) Numerical risk scoring

(ii) Capital structure volatility analysis

(iii) Fuzzy modeling for predicting profit before tax over 2015–2022

This approach allows the model to be compared with traditional methods and enables the identification of patterns specific to the Iranian market.

3 Research method

3.1 Preliminary Analysis and Study Period:

The study covers the period 2015–2022 (1394–1401 in the Iranian calendar). This period was selected for several reasons:

- **Data availability:** Financial information of companies from 2015 onward is complete and reliable.
- **Long-term trends:** The 8-year period allows the examination of risk and profitability trends, as well as fluctuations in financial structure.
- **Economic shocks:** This period includes different phases of economic growth and recession in Iran, including sanctions and currency depreciation, which may affect the volatility patterns of financial indicators.
- **Comparison with previous studies:** Aligning the study period with other research facilitates comparative analysis.

After extracting raw data, the data were examined using two methods:

(i) Examining the correlation between nominal values such as total assets and total liabilities.

(ii) Examining the correlation between financial ratios calculated from the combination of these data.

The purpose of the first step was mainly to assess the initial quality of the data, while the purpose of the second step was to meaningfully analyze economic relationships.

To better understand the relationships between financial indicators and prevent severe multicollinearity between variables, a correlation matrix of the main features of the dataset was calculated at this stage of the analysis. Calculating correlations allowed us to identify the degree of linear dependence between indicators. High correlation between some variables can indicate their similar impact on profitability, and if severe, it may interfere with subsequent analyses. Therefore, examining these correlations was considered a preliminary step for validating models and interpreting final results.

3.2 Numerical Risk Scoring:

To calculate the numerical risk score for each company, seven key financial indicators were initially selected: debt-to-equity ratio (D/E), current ratio, return on assets (ROA), return on equity (ROE), net profit margin (NPM), operating margin, and asset turnover.

These indicators were then normalized to the range $[0, 1]$ to make values with different units comparable. Subsequently, the risk score for each company was calculated using an equally weighted average. In this method, all indicators had the same weight, and the final risk score represented the company's risk level in the range of 0 (lowest risk) to 1 (highest risk).
These scores were used as the main input for the fuzzy logic model to analyze pre-tax profit forecasting and examine the impact of risk and other financial indicators on profitability.

3.3 Fuzzy Logic:

To investigate the simultaneous effect of two key financial indicators, namely liquidity ratio and risk score, on companies' earnings before tax, a fuzzy logic approach was employed. These variables were chosen because liquidity indicates a company's ability to meet short-term obligations and its capacity to perform financial operations, while risk reflects the level of uncertainty and the probability of loss in a company's activities. Earnings before tax was considered the main indicator of financial performance because it shows the company's true ability to create value before the impact of tax policies. Given the nonlinear and ambiguous nature of the relationships between these variables, the use of fuzzy logic allows for their precise and simultaneous analysis. In this framework, liquidity and risk were defined as inputs and earnings before tax as the output of the model (Figure 5). In this study, up to this point, instead of fully designing rules, the focus has been on displaying and interpreting the three-dimensional relationships between variables, which shows the combined behavior of the variables and their effects on profitability and provides a basis for analyzing the results.

Furthermore, in subsequent studies, fuzzy logic was used to evaluate the profitability potential of companies. Fuzzy logic is capable of modeling the uncertainty and range of changes in financial variables and provides more accurate results compared to classical methods.

Data Preparation and Normalization

To harmonize input variables and prevent dominance of any single variable in the fuzzy model, all inputs Risk Score, Current Ratio, and Total Assets were normalized to the range $[0, 1]$ using Min-Max Scaling:

$$\frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

This normalization is compatible with the Mamdani fuzzy model and ensures interpretability of membership functions.

Weighting and Risk Score Calculation

Seven financial ratios related to corporate risk were selected. Given the lack of strong empirical evidence for differential weighting and to avoid researcher bias, **equal weighting** was applied:

$$RiskScore = \sum_{i=1}^{n} \frac{1}{n} X_i \tag{2}$$

This approach increases the reproducibility of the model and ensures that inputs are consistently derived from market data.

Fuzzy Inputs and Membership Functions

The model uses three main inputs and one output:

- **Inputs: Risk Score**, Current Ratio (Liquidity), Total Assets
- **Output**: Earnings Before Tax (Profit)

For each variable, three membership functions were defined (triangular/trapezoidal) based on data distribution:

- Inputs: Low, Medium, High
- Output: Low Profit, Medium Profit, High Profit

Input:

$$x = [x_1, x_2, x_3] = [risk - score, debt - to - equity, net - profit - margin]$$

where, x_1 **(risk -score)** represents the company's financial risk level, x_2 **(debt-to-equity)** is the debt to equity ratio and x_3 **(net-profit-margin)** is the net profit margin.

Each of these variables, based on the range of empirical data, was mapped to fuzzy sets such as weak, medium, and strong using fuzzy membership functions.

The choice of membership functions ensures **simplicity and interpretability**.

Fuzzy Rule Base

The fuzzy rule base is considered the most important part of a fuzzy logic system, and other system components are used to implement these rules. This base includes a set of IF-–THEN fuzzy rules that express expert knowledge in fuzzy language. For example:

If **risk-score** is low, **debt-to-equity** is medium and **net-profit-margin** is high, then profitability potential is strong.

Mathematically, for each rule τ, the rule's activation degree is calculated using the following relationship:

$$\alpha^{\tau} = \min(\mu_{A^{\tau}}(x_1), \mu_{A^{\tau}}(x_2), \mu_{A^{\tau}}(x_3)) \tag{3}$$

where $\mu_{A^{\tau}}(x_i)$ represents the membership degree of input variable x_i in the fuzzy set corresponding to rule τ.

Fuzzy Inference Process

The fuzzy inference process is responsible for establishing the relationship between input and output variables using defined rules. This process is carried out using the Mamdani fuzzy logic principle, which uses a combination of min and max operators to combine rules.

For a set of M fuzzy rules, the overall fuzzy output is obtained by aggregating the individual rule outputs using the maximum operator:

$$\mu_{B'}(y) = \max_{\tau=1,\ldots,M} \min(\alpha^{\tau}, \mu_{B^{\tau}}(y)) \tag{4}$$

where, $\mu_{B^{\tau}}(y)$ is the original membership function of the output fuzzy set associated with rule τ and $\mu_{B'}(y)$ is the aggregated membership function represents the final fuzzy output of the system.

Fuzzification

In a fuzzy logic system, inputs can be real or linguistic variables, but the fuzzy inference engine is only capable of processing fuzzy sets. Therefore, real variables must be fuzzified before entering the inference engine; this process is called fuzzification.

Fuzzification means converting each real variable into one or more fuzzy sets with membership degrees between 0 and 1. As a result, several fuzzy interpretations of each input are generated, providing a mapping from the real domain to the fuzzy space for the inference engine.

Example: The input variable $risk - score$ can be divided into three fuzzy sets: low, medium, and high. For instance, a company with a $risk - score = 0.38$ might have a membership of 0.7 in the medium set and 0.3 in the low set. This information allows the fuzzy inference engine to produce the appropriate fuzzy output based on the defined rules.

Defuzzification

Since the output of the fuzzy system is a fuzzy value, it is necessary to convert this output into a precise numerical value. In this research, the Centroid Method was used for defuzzification, which calculates the final output value y^* as follows:

$$y^* = \frac{\int \mu_{B'}(y) y dy}{\int \mu_{B'}(y) dy} \tag{5}$$

This step is the part that quantifies the output of the fuzzy logic and allows for numerical comparison between companies.

Sensitivity Analysis

To evaluate the robustness of the model:

(i) **Membership function shapes:** Triangular functions were changed to trapezoidal. Output changes remained within 5˘8%, indicating stability.

(ii) **Input weighting:** Scenarios with increased weights for liquidity or risk were tested; equal weighting produced the most consistent results.

Pseudo-Code of Fuzzy Process

Algorithm : Fuzzy Logic-Based Profitability Potential Assessment

Input: Dataset with financial indicators for each company

Output: Profitability potential score for each company (ProfitPotential[i])

(i) Begin

(ii) Load dataset

(iii) Select relevant financial indicators

(iv) Normalize all inputs to [0,1] using Min-Max scaling

(v) Compute RiskScore = mean(normalized risk variables)

(vi) Define membership functions for:

(vii) -Risk

(viii) -Liquidity

(ix) -Assets

(x) -Profitability Potential

(xi) Define fuzzy rules: $R_1, R_2, ..., R_n$

(xii) For each company i :

(xiii) Fuzzify inputs

(xiv) Apply fuzzy rules using Mamdani inference

(xv) Aggregate outputs

(xvi) Defuzzify using Centroid method $\rightarrow$ ProfitPotential[i]

(xvii) EndFor

(xviii) Perform sensitivity analysis

(xix) Generate and report results including surface plots

(xx) End

At the end of the fuzzy inference process, the final output value is numerically calculated using the centroid method. In the results section, the distribution of companies based on this output and its correlation analysis with actual net profit are presented.

In addition to the fuzzy logic model, a supplementary analysis of the fluctuations in companies' capital structure, focusing on the debt-to-equity ratio, was also conducted to examine the stability and financial behavior of companies during the study period, which will be discussed further. (Figure 6)

3.4 Capital Structure Stability:

To analyze the stability of companies' financial structures and identify hidden risks arising from financing fluctuations, this study examined an index called capital structure stability.

This index was designed to complement the numerical fuzzy risk assessment by analyzing changes in companies' debt-to-equity ratios during the period 2015 to 2022.

The reason for using this analysis was that a mere examination of the debt ratio or numerical risk score does not provide a complete picture of the stability or instability of companies' financial structures. Some companies may have a moderate or low-risk score; however, their reliance on debt can experience severe fluctuations and sudden changes over time, which indicates a hidden risk. For this purpose, the annual change in the debt ratio for each company was first calculated:

$$\Delta D = D_t - D_{t-1} \tag{4-1}$$

where D_t is the company's debt ratio in year t and is an indicator of the company's reliance on debt in year t. D_{t-1} is the debt ratio of the same company in the previous year $(t-1)$, and ΔD indicates the intensity of the increase or decrease in reliance on debt.

Given that annual fluctuations in the debt ratio, due to data limitations, did not have sufficient interpretability on their own, a three-year moving average was used. This method allows for smoothing changes and a more accurate and meaningful measurement of debt ratio fluctuations over a period of time.

Now, to have fluctuations over a specific time frame (3 years), we calculate the standard deviation of annual changes in moving windows (3 years). Let's assume ΔD_i is the annual change in the debt ratio in year i, ΔD is the average change in the debt ratio in the three-year window under consideration, and n is the number of windows, which we considered as $n = 3$. In this case, the formula for the standard deviation in the moving window is:

$$\sigma_t = \sqrt{\frac{1}{n} \sum_{i=t-n+1}^{i} (\Delta D - \Delta D_i)^2} \tag{4-2}$$

where, σ_t represents the standard deviation of changes in the debt ratio over years t, $t-1$, and $t-2$. The output of this value is a time series of three-year moving fluctuations in the debt ratio changes.

For a more precise analysis, the average fluctuation, standard deviation, maximum, and minimum fluctuation indices were also calculated. The average fluctuation for the entire study period of the company is:

$$MeanRollingVol = \sum_t \frac{1}{T} \sigma_t \tag{4-3}$$

where T is the total number of 3-year windows available in the data and σ_t is the standard deviation of changes in the debt ratio in the moving window corresponding to year t. To calculate the standard deviation of moving volatility ($StdVol$), the following formula is used:

$$MeanRollingVol = \frac{1}{T-1}\sqrt{\sum_t (\sigma_t - MeanRollingVol)^2} \tag{4-4}$$

We used it. We obtain the maximum (MaxVol) and minimum (MinVol) moving volatility in the desired time range from the following relationships:

$$MaxVol = \max_t \sigma_t, \; MinVol = \min_t \sigma_t \tag{4-5}$$

The results showed that some companies, despite having a moderate risk score, exhibited high volatility in their capital structure, indicating the presence of hidden risk in their reliance on debt financing. In contrast, several companies with relatively high risk scores demonstrated greater stability in their debt ratio fluctuations.

4 Results and Data Analysis

In this section, we first examine the statistical characteristics and correlation relationships among the main variables, and then present and analyze the results obtained from processing the financial data and implementing the fuzzy model. The correlation matrix of the raw data (Figure 8 in appendix A) indicates a strong correlation ($r = 0.96$) between certain variables such as current assets and total assets.

This highlights the necessity of data standardization and transforming them into financial ratios to ensure comparability, which is a completely natural step in such analyses.

The findings of the present study, which are based on the analysis of the correlation matrix, indicate that there are significant linear relationships among certain key financial ratios. Specifically, return on assets (ROA) shows the highest positive correlation with operating profit margin ($r = 0.61$), while debt-to-equity ratio exhibits the strongest negative correlation with return on equity (ROE) ($r =$ ˘0.83). In addition, the weakest correlations are observed between return on equity and asset turnover ($r = 0.01$), and between net profit margin and asset turnover ($r =$ ˘0.19), the latter being an indicator of efficiency. This suggests that, in the current sample, the companies' strategies were mainly focused on profitability per unit of sales rather than on rapid asset turnover, indicating the independence of these two variables from each other. This correlation framework provides a clear understanding of the data structure prior to modeling.

According to the values shown in Figure 1, the correlations among the independent variables do not exceed the strong threshold level (0.83). Therefore, there is no serious concern regarding multicollinearity if these variables are used together in a regression model.

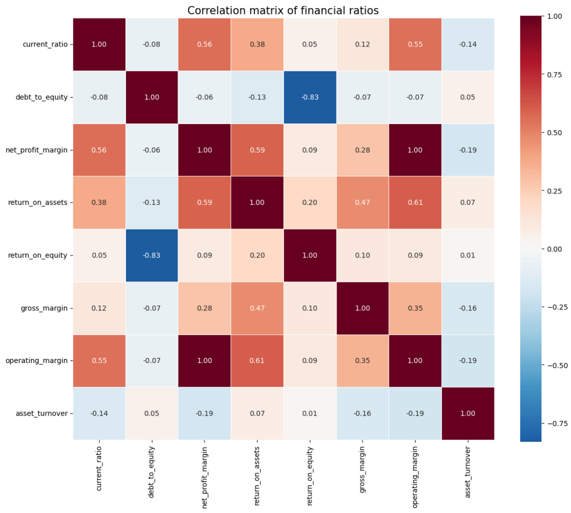

Figure 1: Correlation matrix of financial ratios

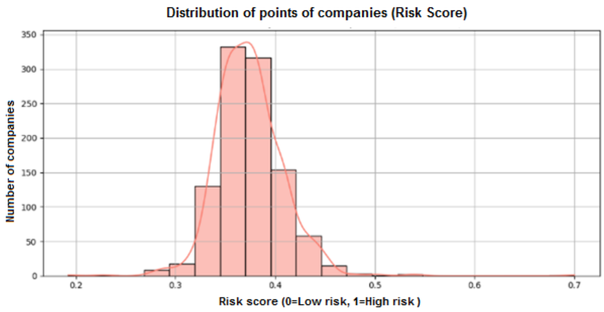

Figure 2: Distribution of companies' risk score

Figure 2 presents the histogram and kernel density estimation (KDE) plot, illustrating the distribution of companies' risk scores ranging from 0 (very low risk) to 1 (very high risk). Most companies have scores between 0.3 and 0.4, indicating a low to moderate level of risk. The distribution is approximately bell-shaped with a slight right skew, showing that high-risk companies (risk score > 0.5) are relatively few. This figure helps to better understand and compare the overall risk levels among companies.

Risk and Profitability Trend Analysis

During the observed period, most companies exhibited low to moderate risk levels, with risk scores predominantly within the 0.3˘0.4 range. The trend analysis reveals that sharp increases in debt (D/E), decreases in return on assets (ROA) and return on equity (ROE), as well as the presence of accumulated losses, were consistently associated with declining or negative net profitability.

Specifically, whenever the risk score approaches higher values, the company's profitability tends to decrease, indicating a clear inverse relationship between risk and profitability. This analysis provides a practical framework for comparing firms and predicting profitability using the fuzzy modeling approach.

To demonstrate this relationship and the practical application of the proposed framework, two sample companies were selected as case studies, and their risk and profitability trends are illustrated in Figures 3 and 4.

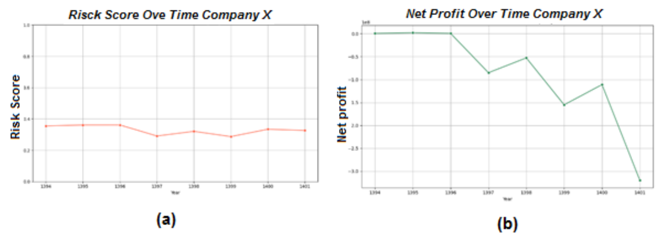

Figure 3: Trend of net profit changes

Figure 3 illustrates that, despite short-term fluctuations, the company's risk score has exhibited an overall upward trend (see Figure 3-a). In contrast, Company $X's$ net profit has experienced a significant decline according to the above chart, falling from 0 in 2019 to -3 in 2021 (Figure 3-b). This pattern further confirms that an increase in a company's risk level can be a predictor of a decrease in future profitability.

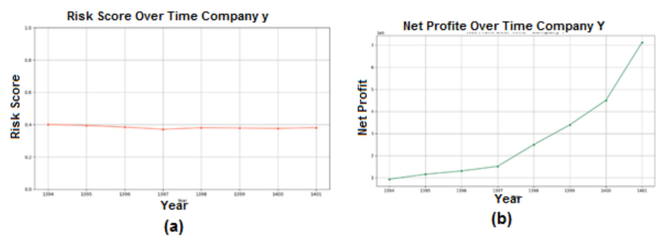

Figure 4: Trend of risk score changes

Figure 4 illustrates a similar pattern for Company Y. The risk score of this company over the examined period exhibits a relatively stable trend with a slight downward fluctuation, while the net profit shows an upward trend during the same period (for the full net profit chart, Figure 4-b). This pattern may be attributed to factors such as effective risk management, improved operational efficiency, or entry into new markets. Indeed, Company Y demonstrates that although there is generally an inverse relationship between risk and profitability, companies that can manage risk intelligently may still increase their profitability even under controlled risk conditions.

Furthermore, in the fuzzy model, companies' pre-tax profit is strongly influenced by the combination of liquidity and risk level. The highest profit values were observed when liquidity was in a medium to relatively high range and the risk level was low, creating positive profit peaks and highlighting the importance of maintaining liquidity balance along with risk management.

In contrast, in regions with high risk, even increased liquidity could not prevent profit reduction, and pre-tax profit decreased significantly, indicating that companies are still vulnerable under high-risk conditions, even with abundant cash resources. The combination of low liquidity and high risk resulted in the greatest losses, reflecting the high sensitivity of financial performance to resource scarcity and risk pressures.

Under conditions of very high liquidity, the surface tended to flatten, indicating reduced profit volatility and relative stability; however, the negative effect of risk remained significant, and complete profit stability was not guaranteed. These results clearly emphasize the importance of simultaneously managing liquidity and risk to enhance company profitability and show that merely increasing liquidity without careful risk control does not ensure sustainable profits. The findings also provide a clear message for financial managers: optimal use of liquidity and risk reduction are key to improving efficiency, sustainability, and resilience of profitability in response to economic and financial market fluctuations.

Figure 5 illustrates that companies' pre-tax profits are influenced by the combination of liquidity and risk levels. The highest profits occur when liquidity is at a medium-to-high level and risk is low, creating positive profit peaks and highlighting the importance of balancing liquidity with effective risk management. Conversely, in high-risk areas, even increased liquidity could not prevent profit declines, and the combination of low liquidity and high risk resulted in the largest losses. Under conditions of very high liquidity, the plot exhibits a relatively flat profile, indicating reduced profit volatility; however, the negative impact of risk remains significant. These findings emphasize that simultaneous management of liquidity and risk is

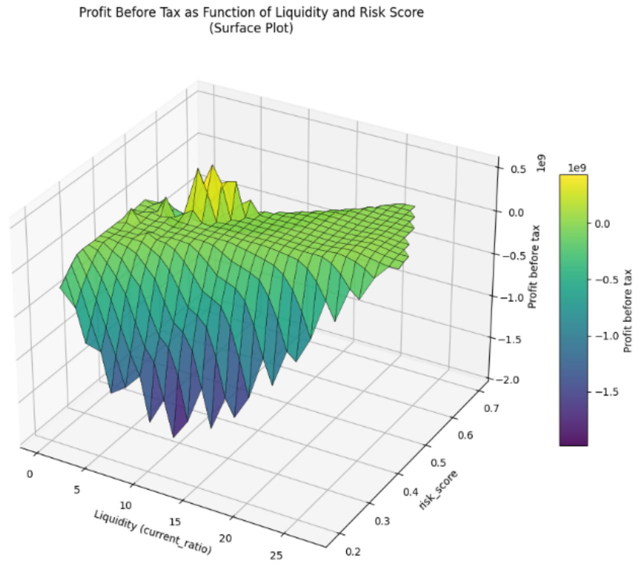

Figure 5: 3D plot of pre-tax profit vs. liquidity and risk

essential for achieving sustainable profitability. The results of applying the fuzzy

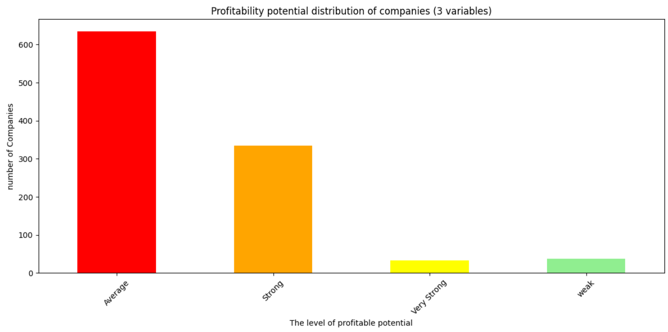

Figure 6: Fuzzy distribution of companies companies profitability

inference model to $1,040$ observations showed that companies were classified into four fuzzy categories in terms of profitability potential. As shown in Figure 6, the largest proportion belonged to the Average group, accounting for approximately 61.1% of all companies. This was followed by the Strong group with 32.1%, while only 3.7% of companies were classified as Weak and 3.2% as Very Strong.

Furthermore, the analysis of the relationship between the fuzzy profitability potential score and the actual net profit of the companies revealed a positive but weak correlation ($r = 0.185$) between the two variables.

This result indicates that the fuzzy model was able to predict the general trend of profitability to some extent, yet non-financial factors and external conditions also play a significant role in determining actual profits.

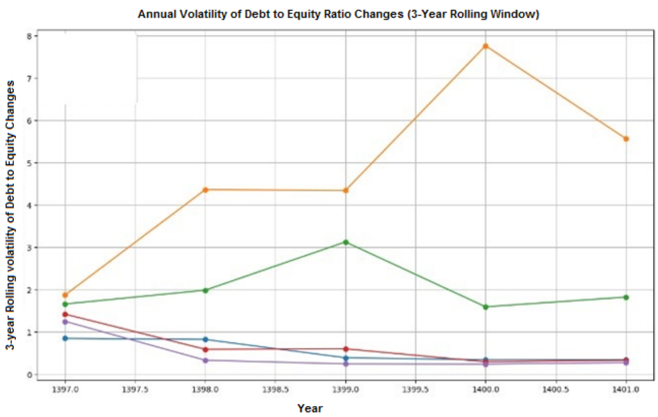

Figure 7: Annual volatility chart

Figure 7 illustrates the annual fluctuations in the debt-to-equity ratio using a three-year moving window. As observed, these fluctuations between 2018 and 2022 for a sample of the studied companies exhibit different patterns. Some companies experienced higher volatility, indicating greater changes in capital structure and, potentially, higher financial risk. This indicator can serve as an important input in the comprehensive assessment of corporate risk.

These findings emphasize that combining the numerical scoring of the fuzzy model with an analysis of capital structure volatility provides a more accurate and comprehensive view of companies' financial risk. It can also facilitate better interpretation of the fuzzy model outputs and help identify companies with stable or turbulent financial management.

5 Discussion and Conclusion

The results of this study demonstrate that the proposed fuzzy logic-based framework provides a flexible and robust tool for evaluating the profitability potential of companies under uncertain and volatile market conditions. Compared to traditional risk assessment methods, such as numerical scoring, ratio analysis, or statistical regression models, the fuzzy system effectively captures the nonlinear and interactive effects of risk, liquidity, and asset structure on profitability. While conventional approaches typically assume linear relationships and rely primarily on historical financial ratios, the fuzzy model explicitly accommodates uncertainty and imprecision inherent in financial data and market behavior.

Traditional methods, including Altman's Z-score, debt-to-equity ratio analysis, and three-year moving average volatility measures, are effective at identifying financial distress and broad risk trends but often fail to capture the combined influence of multiple interacting factors, especially when relationships are nonlinear. In contrast, the fuzzy model translates expert knowledge and heuristic rules into a computational framework, enabling the identification of companies with high, medium, or low profitability potential even when individual financial indicators provide ambiguous signals.

The study also highlights **market-specific patterns in Ira**n, where currency fluctuations, economic sanctions, and high inflation have intensified volatility in debt and asset structures. As illustrated in Figure 6, companies exhibit distinctly different patterns of debt-to-equity ratio volatility, indicating substantial differences in capital structure stability. Firms with higher volatility typically face greater uncertainty in financial management, which adversely affects profitability potential. This phenomenon is particularly pronounced in the Iranian market due to regulatory constraints, market inefficiencies, and external systemic shocks that are less prevalent in more stable international markets.

Furthermore, ranking companies based on their fuzzy profitability potential scores provides a relative assessment that complements absolute financial measures. Although the correlation between the fuzzy score and actual net profit is modest ($r = 0.185$), this suggests that the fuzzy system serves more effectively as a **qualitative evaluation and early warning tool**, rather than a precise predictive mechanism. Such qualitative modeling aligns with the nature of emerging markets like Iran, where financial data may be incomplete, noisy, or heavily influenced by non-financial factors such as managerial quality, access to financing, and government policy interventions.

In comparison with recent scientific advances, the fuzzy logic framework aligns with modern hybrid approaches that integrate **machine learning, expert systems, and soft computing** for risk and profitability assessment. While deep learning and ensemble models may achieve high predictive accuracy, they require large datasets and often lack interpretability. The fuzzy approach, by contrast, provides explicit, transparent rules, enhancing interpretability for analysts and investors an important advantage in markets where regulatory oversight and investor confidence depend on analytical clarity.

In addition to profitability analysis, fuzzy logic has demonstrated significant potential in forecasting risks and future disruptions. As discussed in prior research [12], fuzzy inference systems can identify potential threats by learning from historical and real-time data patterns. This capability has been applied in fields such as network security to predict cyber-attacks, and similarly can be used in finance to anticipate credit risk, market volatility, or early signs of corporate distress.

Finally, the findings suggest that incorporating additional variables such as the three-year volatility of the debt-to-equity ratio shown in Figure 6 alongside qualitative factors like management quality or industry dynamics may enhance the model's predictive power. Integrating fuzzy logic with traditional scoring systems and advanced statistical techniques creates a comprehensive analytical architecture that improves the detection of hidden risks and supports more informed investment decision-making in environments characterized by uncertainty and structural instability.

1 Appendix A

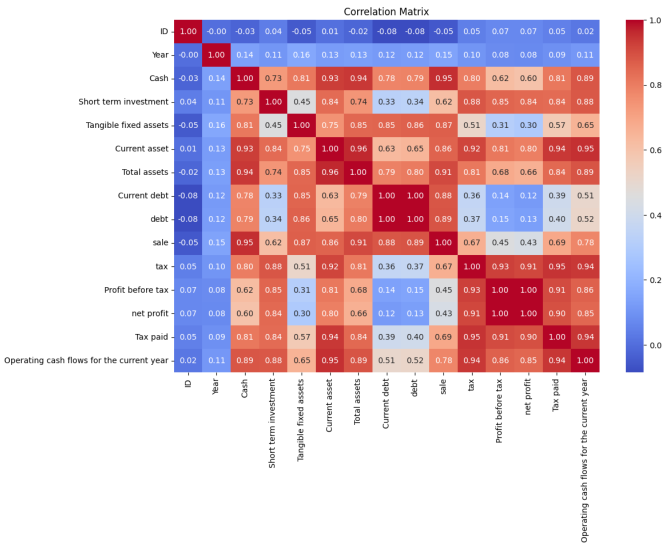

Figure 8: Correlation matrix of the raw data (nominal values)
(Source: Research findings)

Bibliography

[1] M. Sǎnchez-Roger, M. D. Oliver-Alfonso and C. Sanchis Pedregosa, *Fuzzy Logic and*

Its Uses in Finance: A Systematic Review exploring its potential to deal with banking crises, Mathematics, 7(11) (2019), 1091.

[2] S. HAŠKOVĂ, P. ŠULEŘ AND R. KUCHĂR, *A Fuzzy Multi-Criteria Evaluation System for Share Price Prediction: A tesla case study*, Mathematics, 11(13) (2023), pp. 3033.

[3] J. CHOI AND M. RICHARDSON, *The volatility of a firm's assets and the leverage effect*, Journal of Financial Economics, 121(2) (2016), 254-277.

[4] D. KRYGIER AND A. VILHELMSSON, *Equity Volatility and Leverage–Loan Level Evidence*, Available at SSRN 3722492, (2020).

[5] M. GALLAB, , H. BOULOIZ, Y. L. ALAOUI, AND M. TKIOUAT, *Risk assessment of maintenance activities using fuzzy logic*, Procedia Computer Science, 148 (2019), pp. 226–235.

[6] L. A. ZADE, *Fuzzy sets*, Information and Control, 8(3) (1965), pp. 338–353.

[7] S. M. CHEN, *Fuzzy multiple criteria decision-making methods and applications*, Information Sciences, 128(1-4) (2000), pp. 1–18.

[8] D. FARID,AND M. POURHAMIDI, *Classifying Stocks of Listed Companies on Tehran Stock Exchange Using Fuzzy Cluster Analysis*, Financial Accounting Research, 4(3) (2012), pp. 105-128.

[9] M. MIRLOHI, AND N. MOHAMMADI TODESHKI, *Portfolio Optimization Using Hierarchical and Denotation Clustering in Tehran Stock Exchange*, Journal of Investment Knowledge, 9(34) (2020), pp. 333-354.

[10] M. MASJED-MOUSAVI, M. MIR SAJAD, S. KHALAFI, A. SEPIDEH, Z. ASHRAFI, AND B. ZAHRA, *Stock price prediction in the securities exchange market using a neuro-fuzzy network* [Article in Persian], Journal of Accounting Management and Economic Affairs, 2(11) (2025), pp. 22–35. https://lajournal.ir/fa/paper.php?pid=171

[11] S. BAHRAMI, A. SOTOUDEH, N. JAMSHIDI, AND M. R. ELMI, *Environmental risk assessment of Kermanshah petrochemical complex using FMEA method*, Advanced Environmental Sciences, 16(3) (2018), pp. 1-24.

[12] H. I. KURE, S. ISLAM, M. GHAZANFAR, A. RAZA, AND M. PASHA, *Asset criticality and risk prediction for an effective cybersecurity risk management of cyber-physical system*, Neural Computing and Applications, 34(1) (2022), 493-514.

How to Cite: Zahra Heydari Marbari[1], Effat Golpar-Raboky[2], Seyedeh Narges Mirei[3], *Analysis of Risk Trends, Capital Structure Stability, and Profitability Potential of Iranian Listed Companies Using Numerical Risk Scoring and Fuzzy Logic*, Journal of Mathematics and Modeling in Finance (JMMF), Vol. 6, No. 2, Pages:1–19, (2026).