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Research paper

The predictive power of mispricing Stocks based on financial and governance criteria, using linear and nonlinear models (CART, LASSO, PINSVR)

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Abstract:
This paper introduces a predictive model for stock mispricing by examining the financial and governance factors that influence it. The model utilizes panel data from 133 companies listed on the Tehran Stock Exchange, selected through systematic elimination, during the years 2013 to 2022. It compares the predictive capabilities of these factors and evaluates the learning and predictive power of linear and nonlinear models using CART, LASSO, and PINSVR algorithms, which are considered artificial intelligence models in the fields of data mining and pattern recognition. The results indicate a significant difference in the error rates between linear and nonlinear models in predicting stock mispricing, suggesting that linear models, especially in times of high volatility, are less effective. Additionally, based on the Mean Absolute Error (MAE), the prediction of stock mispricing using corporate governance metrics generally indicates lower accuracy compared to financial metrics, even in nonlinear algorithms.

Keywords: stock mispricing, financial factors, governance factors, linear and nonlinear models
Classification: M41, C02, C38.

1 Introduction

Market volatility and crashes in the securities market have a significant impact on other financial markets and assets; creating an unfavorable environment that breeds skepticism among the public and shareholders towards the stock market. This skepticism can lead to capital flight from productive sectors and may transfer crises from the financial sector to the real economy. Often, there is a preceding period of rising stock prices before any stock market crash. Both the rise and fall in stock prices indicate a divergence between the current price and its fundamental

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value, reflecting mispricing.

Mispricing is a phenomenon stemming from the weaknesses of capital markets. Poor quality and information asymmetry are key characteristics of an incomplete market, serving as significant factors in the misevaluation of stocks. When a financial asset is mispriced, and its stock price is significantly higher than its discounted expected cash flows, a price bubble occurs (see more [31]).

Typically, the mispricing of assets leads to a sudden drop in prices, ultimately resulting in a stock market crash. Therefore, identifying the factors influencing stock mispricing can help market participants predict future stock returns more accurately and recognize the formation of price bubbles in a timely manner. It also allows them to maintain lower-risk stocks in their portfolios and thereby reduce the risk of price declines (see [7]).

Given that investors' valuations and their entry into capital markets are realized through stock pricing, along with the critical importance of capital markets and their dynamic impact on the overall economies of countries, it is crucial to address stock mispricing. When company stock prices deviate from their fundamental values and are priced above or below their intrinsic values, it can result in detrimental effects on the company, shareholders, the capital market, and ultimately the entire economy (see [31]).

Market anomalies, including excess returns that cannot be justified by asset pricing models or the occurrence of price bubbles in the Tehran Stock Exchange during the years 2009, 2011, 2012, 2013, 2017 and 2019, reflect instances of market mispricing and market inefficiency, leading to shareholder dissatisfaction. It is therefore critical to investigate what factors can influence stock mispricing and how to predict this phenomenon.

In an environment where many influencing variables are unknown, and their relationships are nonlinear and complex, traditional econometric tools and models are no longer sufficient for data analysis. It is essential to use powerful tools capable of examining, analyzing, predicting, and making decisions in place of human intervention (see [21]). Moreover, advanced linear models provide reasonable predictions for short-term and medium-term periods, whereas stock behavior adheres to non-linear patterns, with linear models only capturing part of the markets stock behavior [1]. Recently, financial mathematics has garnered significant attention due to its extensive connections with economics and financial markets, while artificial intelligence (AI) and machine learning (ML) have made remarkable advancements in various fields, especially in tackling complex and expansive issues. Financial markets have also witnessed a growing trend in the use of trading algorithms for investment decision-making. AI and ML are particularly appealing to financial researchers due to their superior and more consistent capabilities compared to statistical methods in [30]. Thus far, researchers have utilized AI algorithms to predict events such as financial information quality rankings, future company performance, investment efficiency, liquidity forecasting, company internal control effectiveness, corporate value, earnings smoothing, financial distress, bankruptcy, and systematic risk estimation, acknowledging the high predictive power and pattern recognition ability of AI. This study, recognizing the importance of stock pricing in capital markets and its impact on the risk of price declines and financial and economic crises, seeks to elucidate the effects of certain financial and governance factors on stock mispricing. Using AI algorithms alongside linear and nonlinear models, it aims to find a predictive pattern for this phenomenon in the Tehran Stock Exchange, representing the innovative aspect of this research. The main objectives of this paper consist of investigating the role of corporate governance criteria, financial information, and a combined approach including both corporate governance and financial information in stock mispricing, and finding linear and nonlinear algorithms for predicting stock mispricing. The research questions have been formulated as follows:

- What is the predictive power of influential financial and governance components in stock mispricing?
- How do linear and nonlinear models perform in predicting stock mispricing?

2 Theoretical foundations and literature review

Based on the Efficient Market Hypothesis (EMH) proposed by Fama and et al. in [15], one of its fundamental pillars is the Rational Expectations Theory. This theory suggests that investors' expectations about the future play a crucial role in shaping the current prices of securities. These expectations are formed based on optimal forecasts of the future, using all available information. Essentially, the price of a security reflects the optimal prediction of its intrinsic (true) value. When the intrinsic value and the stock price deviate from what investors expect under normal circumstances, this indicates stock mispricing ([6]). Additionally, according to a valuation model known as the buy low, sell high strategy, investors aim to acquire undervalued stocks (mispriced low) and sell overvalued stocks (mispriced high). Therefore, stock mispricing is a persistent phenomenon in the market, highlighting the importance of examining the factors that may influence it (see more [45]).

2.1 Financial components and Stock mispricing

The primary goal of financial statement analysis-is to compare statements across different companies-in order to assess the performance of a company over time and forecast its future, informing decisions regarding the buying or selling of its stock. Fluctuations in financial ratios can be viewed as signals for investment decisions. The quality of information presented to the market in the form of financial statements is reflected in the stock price of the company, leading to either correct or incorrect pricing of securities in the stock market (see [3]). Managers often have incentives to conceal or delay the disclosure of bad news while accelerating the release of good news. Since the responsibility for preparing financial statements lies with the management of the business unit, and considering their direct access to information and the power to choose to account methods, there exists the potential for financial statement manipulation (see [40]). Based on a model discussed by Jin and Myers in [18], from a historical cost accounting perspective, it is argued that managers in opaque financial markets can utilize historical cost accounting to hide or delay the disclosure of bad news. Hutton and et al. used discretionary earnings management as a measure of specific company opacity (see [20]). Manipulating the information environment not only leads to agency problems but also makes it challenging for investors to rationally analyze information, hindering their trading decisions and subsequently resulting in mispriced assets in the capital market (see more details in [14]). This asymmetric approach to information disclosure also has a limited lifespan, as hidden information will eventually be revealed, potentially leading to significant negative returns, often referred to as stock price crashes (see [26]). Kim and Zhang, in [24], demonstrated that a lack of transparency in company-specific financial reporting significantly increases the risk of future downturns. Additionally, the quality of accounting information is one of the strongest deterrents to the risk of a downturn, as found by Zhang et al. in [50]. As for financial components, activity ratios indicate how efficiently and effectively a company's resources are utilized. Managers with poor performance attempt to manipulate the information environment in order to create misleading valuations in the capital market. Leverage ratios measure the amount of resources obtained from debt. A higher financial leverage increases the dispersion of net income and provides a strong incentive for managers to utilize various mechanisms, such as earnings management, to steer the company's stock price towards their targeted objectives. Profitability ratios reflect the success of a business unit in generating profit, while earnings volatility and returns serve as tools for assessing the risk associated with potential future changes in the companys condition. This factor serves as a benchmark for evaluating the information asymmetry within the company and will exacerbate the mispricing of stocks. Additionally, the distribution of dividends to shareholders reduces the resources under managerial control and consequently diminishes managerial power, thereby helping to mitigate managerial opportunistic behavior and addressing the agency problem.

2.2 Corporate governance and Stock mispricing

A significant portion of stock mispricing is attributed to a lack of transparency at the corporate level (see [29]). Nanda and Narayanan in [28] and Healy and Palepu in [19] argue that mispricing results from information asymmetry, which is a clear indication of agency problems. One of the assumptions of agency theory is that individuals tend to act in their self-interest; the primary interest of individuals is to maximize their wealth, while concepts such as loyalty, ethics, and similar ideals are not included in this theory (see more details [13]). Agency theory posits that managers do not maximize shareholder returns unless appropriate governance structures are established to safeguard the interests of stakeholders in large corporations. This idea has been given by Jensen et al. in [17]. The issue of corporate governance began to gain attention in the 1990s in advanced industrial countries such as the UK, Australia, and several European nations. Corporate governance is defined as having legitimacy, accountability, and competency in the realm of policy and service provision while respecting the law and human rights. This concept is readily understandable through the Cadbury Report, which outlines how corporate governance controls and manages corporate activities (see [21]). However, it is stated that governance can be either good or bad, effective or ineffective (see [4]). Corporate governance serves as a tool for shareholders, creditors, and other stakeholders to protect their interests against the threats posed by market fluctuations and financial crises, and it can play a vital role in the stability of financial markets and economic development. Some researchers such as Darvish and Bani Mahd in [11], have presented contentious findings regarding the relationships between corporate governance, corporate financial performance, and market value. They emphasize that a strong corporate governance system is an important tool for reducing conflicts of interest between stakeholders and management, and it is recognized as a crucial factor in the stability and economic growth of financial markets. For instance, in terms of governance components, an increase in the financial expertise and experience of the audit committee within companies, along with their tenure and background, leads to better and more effective judgments in the area of internal controls, which is one of the mechanisms of corporate governance. Active oversight by state managers and institutional investors, as one of the mechanisms of corporate governance, reduces managerial opportunistic and biased behavior, enhances informational transparency, improves the quality of disclosures, and mitigates the risk of price bubbles in company stocks.

In light of all the aforementioned factors, identifying the financial and governance components that can effectively reduce transparency issues, agency problems, information asymmetry, expectation formation, and stock mispricing, as well as improving the mechanisms of corporate governance oversight, will contribute to the resolution of stock pricing anomalies and further reduce the investment decision-making risks for investors in the capital market. Li et al. investigated the relationship between real earnings management and stock price crash risk, focusing specifically on emerging market economies. They also examined the impact of internal controls and institutional ownership on corporate governance. The study found that managers, affected by information asymmetry and a tendency to withhold bad news, contribute to stock mispricing and sudden drops in a company's stock price. Additionally, the research indicated that effective corporate governance practices can help reduce stock price crash risk (see [26]). The connection between risk management and corporate governance was examined from environmental, social, and governance (ESG) perspectives. In addition, Baker, Boulton, Braga-Alves, and Morey conducted a study on underpricing in initial public offerings (IPOs) for 7,446 companies listed on stock exchanges in 36 countries from 2008 to 2018, in [8]. According to sensitivity analyses, countries with more transparent financial disclosures and stronger standards for social responsibility and shareholder protection experience lower frequencies of underpricing in IPOs.

Verma et al. explored how pricing errors are influenced by the sentiments of individual and institutional investors (see more details [43]). The results showed that pricing errors persist and stock prices consistently deviate from their true values. These deviations are influenced by expectations shaped by both individual and institutional investors, considering risk factors and market noise. Interestingly, institutional investors seem to be more influenced by rational factors compared to individual investors. They also have a significant influence in correcting pricing errors caused by unpredictable shifts in sentiment. In a study, Yang, Ho, Shen, and Shi in [47], used ranking data for disclosures to examine the relationship between the quality of information disclosure and stock mispricing in emerging markets. The findings demonstrated that companies with higher disclosure rankings tend to experience less deviation of market prices from their fundamental values. Particularly, firms operating in highly competitive industries exhibit a stronger link between disclosure ranking scores and stock misvaluation, highlighting the importance of information disclosure in reducing stock mispricing.

Additionally, [51] explored the effects of investor sentiment and accounting information on stock prices, demonstrating that investor sentiment could alter expected profit growth and required returns, thereby impacting stock prices. However, the influence of sentiment was distinctly different during periods of pessimism compared to periods of optimism. Accounting information and investor preferences also have a substantial effect on stock prices. Research [2] conducted an empirical examination of the impact of auditor conservatism in preventing stock mispricing. The results indicated that auditors play a key role in enhancing the quality of accounting information and financial statements, thus influencing capital market guidance and its fluctuations resulting from stock mispricing. Consequently, auditor conservatism not only protects their reputation but may also align market stock values closer to their fundamental values.

Another study [32] aimed to investigate the effect of investor opinion divergence on stock mispricing, considering the role of financial information quality and information asymmetry in the Iranian capital market. It was suggested that a significant portion of stock mispricing can be attributed to a lack of informational transparency at the company level. By improving the quality of disclosed information, information asymmetry between insiders and outsiders is diminished, ultimately enabling investors to rely on accurate information for trading, which can bring stock pricing closer to its intrinsic value and reduce mispricing.

Research [38] analyzed the anatomy of noise trading and pricing errors caused by the entry of uninformed traders in the Tehran Stock Exchange. The results revealed that the influx of uninformed traders creates noise, leading to deviations of asset prices from their fundamental values and resulting in pricing errors. Noise traders often resemble irrational investors who hold incorrect and irrational beliefs about the future returns of risky assets, reacting to signals that are disconnected from future cash flows. Noise trading has a positive and significant effect on the level of stock pricing errors, with pricing errors varying across different levels of the book-to-market (B/M) ratio.

Additionally, a study examining 180 listed companies [33] classified the components of company complexity into three main criteria and 13 indicators. It demonstrated that the elements of informational complexity, including divergence, negative operating cash flows, accrual items, consolidated financial statements, standard deviation of operating cash flows, and standard deviation of changes in net operating assets, have a positive and significant impact on stock mispricing. Among the components of operational complexity, three indicatorslength of the operating cycle, export sales ratio, and product diversitywere found to have a positive and significant relationship with stock mispricing; however, no significant relationship was observed between the level of production technology and stock mispricing in Iran. Finally, the results indicated that the components of governance complexity, including political connections, CEO tenure, and ownership concentration, have a positive and significant relationship with stock mispricing.

Research [49] aimed to investigate the impact of financial information quality on stock mispricing of companies listed on the Tehran Stock Exchange. It revealed that the quality of financial information has a significant negative effect on stock mispricing. Additionally, stock liquidity and the book-to-market ratio of the companies were found to have a significant negative impact, while institutional ownership had a significant positive effect on stock mispricing. Furthermore, variables such as financial leverage, liquidity, price-to-earnings ratio, and company size did not show significant effects on stock mispricing. Therefore, providing high-quality information by companies can influence investor decision-making and behavior in the market, thereby reducing stock mispricing. Moreover, minimizing management incentives and increasing informational transparency can help decrease stock price deviations.

3 Research methodology

This research is analytical in terms of objectives, quantitative in terms of execution process, and practical in terms of outcomes. To achieve the research objective, the statistical population consists of all publicly traded companies in the Iranian capital market. The sample includes all companies listed on the Tehran Stock Exchange, selected through a systematic elimination method.

– Companies that meet all five criteria are included in the research sample, while those that do not are excluded.

- Companies must have been accepted on the Tehran Stock Exchange before the year 2013 and remain active in the market until the end of the year 2022 (to ensure panel and homogeneous data).
- To enhance the comparability of companies and maintain panel and homogeneous data, companies should not change their fiscal year or type of activity during the period from 2013 to 2022, and their fiscal year-end must be March 19 (29 Esfand).
- Companies with separate reporting structures, such as investment firms and financial intermediaries (including leasing companies, insurance firms, holding companies, banks, and financial institutions), are excluded from the sample.
- Companies must not have trading interruptions exceeding three months, as these interruptions can result in gaps in the required statistical data.
- Their financial information must be accessible for the period from 2013 to 2022.

Considering the above limitations, 133 companies from 22 industries were selected as the sample for the years 2013 to 2022. Additionally, 26 financial criteria (as detailed in Table 1) and 13 corporate governance criteria (as detailed in Table 2) were considered as independent variables. For collecting relevant information regarding the background and theoretical foundations, library research was employed. For gathering statistical data, the financial statements of companies listed on the Tehran Stock Exchange and computerized databases (RahaVard Novin software) were utilized, alongside consulting the Codal website during the specified years. Ultimately, to determine the significance of the independent variables and eliminate redundant variables, the Relief-F algorithm [35] was employed. For indexing the dependent variable and presenting a comprehensive model for measuring it, a factor analysis approach was used to build the model and examine the predictive capabilities of financial and governance components in the mispricing of stocks. Moreover, to compare the predictive abilities of linear and nonlinear models in this context, the prediction algorithms CART, LASSO [41], and PINSVR [46] were utilized.

4 Research variables

4.1 Independent variables of the study

In this research, corporate governance criteria and financial criteria are considered as independent variables, which were collected through a library method. Several of the collected components were eliminated due to limitations in extracting their stock market data, while others were removed because they were identified as redundant variables according to the Relief-F variable selection method. The operationalization of the independent variables is shown in Tables 1 and 2.

Row	Components	Evaluation Method	Criterion	Ref.
1	Quick Ratio	Quick Ratio $= \frac{\text{Current Assets} - \text{Inventories}}{\text{Current Liabilities}}$	Criteria for Performance Obligations	[32]
2	Debt Ratio	Debt Ratio $= \frac{\text{Total Liabilities}}{\text{Total Assets}}$	Criteria for Performance Obligations	[27]
3	Current Debt Ratio	Current Debt Ratio $= \frac{\text{Current Liabilities}}{\text{Total Liabilities}}$	Criteria for Performance Obligations	[27]
4	Average Collection Period	Average Collection Period $= \frac{\text{Accounts Receivable}}{\text{Average Daily Credit Sales}}$	Activity Criteria	[27]
5	Asset Turnover Ratio	Asset Turnover Ratio $= \frac{\text{Net Sales}}{\text{Total Assets}}$	Activity Criteria	[27]
6	Fixed Asset Turnover Ratio	Fixed Asset Turnover Ratio $= \frac{\text{Net Sales}}{\text{Fixed Assets}}$	Activity Criteria	[27]
7	Current Assets to Total Assets Ratio	$\frac{\text{Current Assets}}{\text{Total Assets}}$	Activity Criteria	[27]
8	Net Profit Margin Ratio	Net Profit Margin Ratio $= \frac{\text{Net Profit}}{\text{Sales}}$	Profitability Criteria	[27]
9	Gross Profit Margin Ratio	Gross Profit Margin Ratio $= \frac{\text{Gross Profit}}{\text{Sales}}$	Profitability Criteria	[27]
10	Stock Return	$K_t = \frac{(P_t - P_{t-1}) + D_t + \frac{(P_t - P'_t) * N_c}{N_t} + \frac{N_e * P_t}{N_t}}{P_{t-1}}$ K_t = Total return on equity relative to the initial stock price P_t = Stock price at the end of the financial year P_{t-1} = Stock price at the beginning of the financial year D_t = Gross cash dividend per share P'_t = Nominal value of the share N_c = Number of shares increased through reserves or retained earnings N_e = Number of shares increased through cash contributions N_t = Number of shares before capital increase	Profitability Criteria	[15]
11	Sales Growth Rate	Sales Growth Rate $= \frac{\text{Current Year Sales} - \text{Previous Year Sales}}{\text{Previous Year Sales}}$	Sustainability Criteria	[25]
12	Tobins Q Ratio	Tobins Q Ratio $= \frac{\text{Market Value of the Company} + \text{Book Value}}{\text{Book Value of Assets}}$	Market Criteria	[15]
13	Market Value Added	Market Value Added = Market Value of the Company − Invested Capital Invested Capital = Fixed Assets (after deducting accumulated depreciation)+ (Current Assets − Current Liabilities)	Market Criteria	[22]
14	Systematic Risk	$\beta = \frac{\text{Cov (Stock Returns, Market Returns)}}{\text{Var (Market Returns)}}$	Other Financial Criteria	[42]
15	Company Size	Company Size = Natural Logarithm of Market Value of the Company	Other Financial Criteria	[42]

Table 1: Operationalization of independent research variables (Financial Components)

Table 2: Operationalization of Independent Research Variables (Governance Components)

Row	Components	Evaluation Method	Criterion	Ref.
1	Independence of the Audit Committee	Number of Non-Executive Members divided by Total Members of the Audit Committee	Audit Components	[36]
2	Board Independence	Number of Non-Executive Directors divided by Total Board Members	Board Components	[36]
3	Financial Expertise of the Board	Number of Financial and Accounting Specialists divided by Total Board Members	Board Components	[36]
4	Institutional Ownership	Percentage of Shares Held by Any Individual or Entity with More Than 5% of Issued Shares	Transparency and Disclosure Components	[21]
5	Managerial Ownership	Percentage of Shares Held by Board Members	Transparency and Disclosure Components	[36]

4.2 Dependent Variable of the Study

In this study, mispricing of stocks is considered the dependent variable. The mispricing of a company's stock is measured as the deviation of the company's equity value from its intrinsic or fundamental value [29]. Accordingly, six alternatives have been utilized to measure stock mispricing. Five metrics (the price-to-intrinsic-value ratio, the total capital-to-attributed capital ratio, the company's fundamental value, the natural logarithm of the market value of stocks to the median book value of stocks, and abnormal stock returns) are employed to measure stock mispricing, while the final metric is an index that combines all the measures and presents a comprehensive model for assessing stock mispricing [29]. The assessment of mispricing consists of the following measures:

Market Price to Intrinsic Value Ratio (Int-Price)

The absolute value of the natural logarithm of the ratio between the stock price and its intrinsic value serves as an indicator of mispricing [29]. The stock price to intrinsic value ratio is measured using the residual income model [12]. To calculate residual income, the following formula for excess net income is applied:

$$X_t^a = X_t - R_e B_{t-1} \tag{1}$$

where X_t is the net income belonging to common shareholders, R_e is the cost of equity, and B_{t-1i} is the book value of common equity at the end of period B_{t-1}.

In this study, the cost of equity (R_e) is measured based on the Gordon Growth Model as follows:

$$R_e = \frac{DPS_t}{P_{t-1}} + g_t \tag{2}$$

where

$$g_t = ROE_t \times \left[\frac{1 - DPS_t}{EPS_t}\right] \tag{3}$$

with DPS_t as the cash dividend paid per share, P_{t-l} as the price of the stock at the beginning of the year, g_t as the dividend growth rate, ROE_t as the return on equity, and EPS_t as earnings per share. To estimate the intrinsic value of the stock, it is necessary first to calculate the persistence coefficient of retained earnings (W). To compute the persistence coefficient of retained earnings in the dynamic earnings model, following [12], a correlation model based on time series is used as follows:

$$X_{t+1}^a = \alpha_t - W_t X_t^a + e_{it+1} \tag{4}$$

The estimation of intrinsic value V_t is operationalized as follows based on the model [12]

$$V_t = B_t + \frac{(X_t - \mathrm{R_e} B_t - 1)\,\theta}{1 + \mathrm{R_e} - \theta} \tag{5}$$

Where X_t is the net income belonging to common shareholders, R_e is the cost of equity, and B_{t-1} is the book value of common equity at the end of period B_{t-1}.

Total capital to assigned value ratio (lnCapital):

The stock mispricing of a company is calculated as the absolute value of the natural logarithm of the total capital of the company to its assigned value. The assigned value of capital is derived from the product of the company's sales and the median of the capital-to-size ratio in the relevant industry ([29] and [9]):

$$\text{Mispricing } = \left|\ln \left(\frac{\text{Capital }_{i,t}}{I\text{ (Capital }_{i,t})}\right)\right|, \tag{6}$$

where Capital $l_{i,t}$ is the total capital of the company (the market value of equity plus the book value of the company's debts), and I (Capital $_{i,t}$) is the product of the company's sales and the median capital-to-size ratio in the relevant industry divided by the company's sales.

To calculate the median capital, the capital of each company is divided by the company's sales, and the results from all companies in a given year are used to determine the median. Consequently, one median is obtained for each year (using the companies present in a specific industry; for example, if there are five companies in an industry, the median of those five companies is calculated), and this process continues in the following years [42].

Fundamental Value of the Company (F)

The fundamental value of a company is measured based on the difference between market value and fundamental value as follows, according to models [29] and [34]

$$\ln\left(M_{it}\right) = \left|\alpha_{0it} + \alpha_{1it}\ln\left(B_{it}\right) + \alpha_{2it}\ln(NI)_{it}^{+} + \alpha_{3it}I(<0)\ln(NI)_{it}^{+} + \alpha_4\left(LEV_{it}\right) + e_{it}\right| \tag{7}$$

where:

- $\ln\left(M_{it}\right)$ is the natural logarithm of the market value of company ii in year t,
- $\ln\left(B_{it}\right)$ is the natural logarithm of the book value of assets of company ii in year t,
- $(NI)_{it}^{+}$is the net income of company ii in year t,
- $I(<0)\ln(NI)_{it}^{+}$is a dummy variable that equals one if company ii incurs a loss in year t, and zero otherwise,
- LEV_{it} is the financial leverage of company ii in year t, calculated as total debt over the sum of debt and equity.

In the above model, the calculation of mispricing is based on the residual e and the error of the model.

Natural logarithm of market value of equity to median book value of equity ($\ln(MB)$)

In this model, the natural logarithm of the market value of equity to the median book value of equity in the industry serves as a measure of mispricing [29]. The deviation of the market-to-book value ratio from the industry norm may indicate mispricing of the stock [44].

$$\text{Mispricing }_i = \left| \ln \left(\frac{(MB)_i}{\text{Median}(MB)_{j,t}} \right) \right| \tag{8}$$

where:

- Mispricing represents the mispricing of stock,
- $MB_{i,t}$ is the market-to-book value ratio of the common equity of company i,
- Median (MB), is the median market-to-book value ratio of common equity in the industry.

Abnormal Stock returns (ARET)

This model, which is the result of the difference between stock returns and market returns, indicates stock mispricing [29]. Market return is calculated as the difference between the market index of the current period and the market index of the previous period, divided by the market index of the previous period.

Finally, by utilizing the five aforementioned measures of mispricing and employing a factor analysis approach, a comprehensive model for measuring stock mispricing has been developed.

5 Data analysis

5.1 Factor analysis for mispricing indexing

Factor analysis has been utilized for indexing stock mispricing and providing a comprehensive model for measuring stock mispricing. Factor analysis is a technique used to reduce a large number of variables into fewer factors, typically employed when there are numerous interrelated variables and it is necessary to identify the underlying structure or patterns in the data. This technique, assisted by the STATA software, extracts the maximum shared variance from all variables and consolidates them into a single common score. This score is then used as an index representing all variables for further analysis.

5.2 Identifying the importance of independent variables based on Relief-F in Stock mispricing

Relief-F provides a method for selecting useful information from a large amount of redundant, incomplete, and excess data. This method is an algorithm based on weighting independent variables, whose idea is inspired by sample-based algorithms. For regression problems, feature weights represent the importance of each feature in predicting the continuous dependent variable. Positive weight: Indicates that the feature is useful in improving the accuracy of the regression model [35]. Negative weight: Suggests that this feature may contribute to prediction error or have an adverse effect on the model's accuracy. Figure 1 shows the algorithm of this method.

Relief(D, S, *NoSample*, *Threshold*)
(1) $T = \phi$
(2) Initialize all weights, W_i, to zero.
(3) For $i = 1$ to *NoSample*/* Arbitrarily chosen */
  Randomly choose an instance x in D
  Finds its *nearHit* and *nearMiss*
  For $j = 1$ to N
    $W_j = W_j - diff(x_j, nearHit_j)^2 + diff(x_j, nearMiss_j)^2$
(4) For $j = 1$ to N
    If $W_j \geqslant Threshold$
      Append feature f_j to T
(5) Return T

Figure 1: Relief Algorithm

In this study, it has been employed to select independent variables and eliminate redundant ones. For the variable of stock mispricing:

From the perspective of corporate governance criteria, the variables selected were "Board Independence," "Audit Committee Independence", "Managerial Ownership", "Board Financial Expertise" and "Institutional Ownership".

From the perspective of financial information criteria, the selected variables included "Tobin's Q", "Market Value Added", "Return on Equity", "Company Size", "Systematic Risk", "Fixed Asset Turnover Ratio", "Debt Ratio", "Sales Growth Rate", "Current Assets to Total Assets Ratio", "Current Debt Ratio", "Total Asset Turnover Ratio", "Average Collection Period", "Gross Profit Margin", "Current Ratio" and "Net Profit Margin".

From the perspective of a combined approach, the selected variables included "Tobin's Q", "Market Value Added", "Return on Equity", "Company Size", "Systematic Risk", "Board Independence", "Fixed Asset Turnover Ratio", "Current Assets to Total Assets Ratio", "Audit Committee Independence" and "Total Asset Turnover Ratio".

5.3 CART, LASSO, and PINSVR prediction algorithms

The selected independent variables for model construction are fed into the least absolute shrinkage and selection operator (LASSO) algorithm, the non-parametric, non-linear Support Vector Regression (SVR) algorithm, and the Classification and Regression Trees (CART) algorithm. The LASSO algorithm falls under linear regression algorithms [41]. Although there are numerous linear regression algorithms, LASSO presents two primary advantages. Firstly, this algorithm aims to select as few independent variables as possible while discarding irrelevant ones. Secondly, it has a convex model, which can be viewed as a convex optimization problem that can be solved using the Lagrange function. In addition to these features, LASSO includes a parameter that allows for a trade-off between minimizing variable usage and minimizing the squared prediction error. The non-parametric, non-linear SVR algorithm utilizes a non-parametric one-sided loss function, which provides a solid capability for addressing market volatility. Furthermore, this algorithm has both linear and non-linear versions, which are created through the kernel trick [46]. Decision trees represent a method in machine learning for structuring algorithms and modeling decisions and their outcomes. The CART algorithm is used for training and constructing decision trees. To conduct the training and evaluation phases of the algorithms, these algorithms are applied for the current and the subsequent year under the following scenarios:

- Corporate governance independent variables with the dependent variable of Stock mispricing,
- Financial information independent variables with the dependent variable of Stock mispricing,

and

- Combined independent variables of corporate governance and financial information with the dependent variable of Stock mispricing.

5.4 Data splitting methods and model evaluation criteria

For training the models, it is essential to initially divide the company-year sample set into training and validation data and test data [5]. The training and validation data are used for learning the model parameters and hyperparameters, while the test data are utilized for evaluating the predictive performance of the models. To enhance the effectiveness and efficiency of model predictions, this study employs a 10-Fold Cross-Validation approach [5]. In this study, a total of 133 companies from the years 2013 to 2022 have been analyzed, resulting in a total of 1,330 company-year samples. As illustrated in Figure 2, these samples are divided into 10 iterations with shuffled evaluation samples. Specifically, from the 1,330 samples, 133 samples are selected as evaluation data in the first iteration, with the remaining data divided into 9 segments for training and validation. The combination of these 9 segments and the 1 segment forms the components of the 10-Fold Cross-Validation method. Without loss of generality, for the second iteration, the data from the second segment serves as evaluation data, while the other segments act as training and validation data. This process is repeated in the same manner for a total of ten iterations. Using the 10-Fold Cross-Validation methodology and relying on the training-validation dataset, a model is learned for each iteration. In simpler terms, during the first iteration, each model independently learns its parameters and hyperparameters based on the 9 training-validation segments as explained in the previous section and constructs its model. To assess how well these models have learned from the training-validation data, the exact 9 segments are fed back into the trained models to predict stock mispricing. Subsequently, using evaluation criteria, which will be introduced further, such as Mean Squared Error (MSE), the predictive errors and the actual values of the stock mispricing variable are measured. This value is recorded as the learning error for the first iteration. This process is repeated for the remaining segments, yielding ten MSE error values. The average of these errors is recorded as the learning phase error for each model. Figure 1. It shows the selection steps of two training and test data sets with 10 cross-validation.

After splitting the firm-year observations into two groups for training-validation and testing using 10-fold cross-validation, two evaluation metricsMean Absolute Error (MAE) and Mean Squared Error (MSE)have been employed to assess both linear and nonlinear models. These metrics are calculated using Equations 9 and 10.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - d_i| \tag{9}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - d_i)^2 \,. \tag{10}$$

Figure 2: Selection steps of two training and test datasets with 10-point cross-validation

5.5 Evaluating the ability of learning and predicting models

In the training phase of linear and non-linear models after learning, the training-validation data, excluding the dependent variable, is provided again to predict the stock mispricing variable. Subsequently, the predictive performance and learning error of these models are assessed by calculating two error metrics: Mean Absolute Error (MAE) and Mean Squared Error (MSE). The same process is carried out independently and in parallel for each category of metrics. The error metrics from the training phase are presented in Table 3.

Table 3: Examining the learning ability of models using two error evaluation criteria MAE and MSE in the training phase

Training stage						
Criterion	corporate governance		Financial information		A hybrid approach	
MAE	current year	next year	current year	next year	current year	next year
Liner PINSVR	0.79 ± 0.005	0.817 ± 0.007	0.375 ± 0.003	0.716 ± 0.005	0.384 ± 0.003	0.721 ± 0.005
Nonliner PINSVR	0.67 ± 0.005	0.674 ± 0.005	0.109 ± 0.001	0.496 ± 0.003	0.199 ± 0.002	0.535 ± 0.005
Lasso	0.79 ± 0.007	0.816 ± 0.008	0.374 ± 0.012	0.715 ± 0.006	0.384 ± 0.008	0.721 ± 0.006
CART	0.777 ± 0.01	0.816 ± 0.007	0.148 ± 0.008	0.611 ± 0.027	0.221 ± 0.01	0.639 ± 0.031

Training stage						
Criterion	corporate governance		Financial information		A hybrid approach	
MSE	current year	next year	current year	next year	current year	next year
Liner PINSVR	0.992 ± 0.012	1.046 ± 0.018	0.26 ± 0.014	0.828 ± 0.011	0.384 ± 0.031	0.847 ± 0.11
Nonliner PINSVR	0.744 ± 0.011	0.767 ± 0.011	0.024 ± 0.001	0.447 ± 0.007	0.069 ± 0.001	0.517 ± 0.01
Lasso	0.992 ± 0.012	1.045 ± 0.018	0.259 ± 0.017	0.826 ± 0.011	0.282 ± 0.012	0.846 ± 0.012
CART	0.965 ± 0.023	1.038 ± 0.018	0.04 ± 0.004	0.645 ± 0.042	0.085 ± 0.007	0.698 ± 0.051

The results derived from the examination of the table indicate that:

a. Considering the range of the dependent variable, the Mean Absolute Error (MAE) for the corporate governance metric is significantly higher than that of the financial information approach and the combined approach. This suggests that predictions using corporate governance metrics generally exhibit lower accuracy, even in non-linear algorithms.

b. A comparison of the MAE errors for the current and subsequent years shows that the non-linear PINSVR, CART decision tree, linear PINSVR, and Lasso algorithms have a respective superiority over each other. Among the linear algorithms, there is not much difference, with their errors being approximately close to one another.

c. The significant difference in error rates between linear and non-linear models in predicting stock mispricing indicates that linear models are not particularly effective in this context.

d. The error for the current year is less than that of the subsequent year. When the prediction error for stock mispricing in the current year is lower than that for the next year, this signifies greater difficulties associated with long-term predictions.

In the testing phase, the test data that was set aside during the 10-fold cross-validation process is input into the trained models to evaluate their predictive power on samples that the model has not previously encountered. The goal of this assessment is to measure the model's ability to generalize to new data. It is expected that the difference between the errors in the training phase and the testing phase will be minimal, as significant differences would indicate the occurrence of overfitting or underfitting. While the testing phase error may be slightly higher or lower than the training phase error, the key issue is a small and rational difference between the two. Such minor differences indicate that the model has effectively learned the underlying patterns in the data and demonstrates stable performance in both phases. This provides reassurance that the model possesses adequate generalization capabilities and can perform well when faced with new data. In Table 4, similar to the training phase, the mean and standard deviation of all errors based on corporate governance metrics, combined approach metrics, and financial information metrics are presented. As observed, the difference between the errors reported in the upper and lower tables is minimal, hence the phenomenon of overfitting has not occurred, and all discussions presented in the training phase hold true in the evaluation phase as well.

Considering that the Mean Squared Error (MSE) consists of the mean error and its variance, this error metric has been employed for comparing the algorithms, while the Mean Absolute Error (MAE), which is merely an average, has not been taken into account. Furthermore, due to the linear and nonlinear nature of the algorithms, each category has been examined separately. A comparison of the results presented in Tables 3 and 4 reveals that in linear models, the financial information criteria, the hybrid approach, and corporate governance have sequentially constructed better linear models. Overall, it can be stated that there is not much difference in the errors presented by the two linear algorithms. However, the error for the nonlinear algorithm is significantly lower than both, with financial information-based criteria, the hybrid approach, and corporate governance constructing better nonlinear models, respectively. The nonlinear PINSVR algorithm demonstrates better accuracy than the CART decision tree algorithm.

Table 4: Mean and deviation of error criteria to check the prediction ability of models in the testing phase

Testing stage						
Criterion	corporate governance		Financial information		A hybrid approach	
MAE	current year	next year	current year	next year	current year	next year
Liner PINSVR	0.79 ± 0.005	0.817 ± 0.061	0.375 ± 0.028	0.716 ± 0.046	0.283 ± 0.011	0.721 ± 0.044
NonLiner PINSVR	0.67 ± 0.042	0.674 ± 0.044	0.109 ± 0.01	0.496 ± 0.031	0.199 ± 0.015	0.535 ± 0.047
Lasso	0.794 ± 0.049	0.821 ± 0.061	0.382 ± 0.027	0.728 ± 0.046	0.389 ± 0.026	0.73 ± 0.046
CART	0.778 ± 0.048	0.815 ± 0.058	0.148 ± 0.018	0.612 ± 0.051	0.223 ± 0.019	0.638 ± 0.055
Liner PINSVR	0.992 ± 0.109	1.046 ± 0.16	0.26 ± 0.123	0.828 ± 0.099	0.283 ± 0.102	0.848 ± 0.1
Nonliner PINSVR	0.744 ± 0.097	0.767 ± 0.094	0.024 ± 0.006	0.447 ± 0.064	0.069 ± 0.009	0.517 ± 0.088
Lasso	1.003 ± 0.112	1.057 ± 0.162	0.296 ± 0.193	0.863 ± 0.108	0.301 ± 0.122	0.878 ± 0.112
CART	0.968 ± 0.098	1.038 ± 0.157	0.04 ± 0.01	0.646 ± 0.111	0.086 ± 0.017	0.693 ± 0.112

5.6 Weights of linear models: PINSVR and LASSO

The weights of the linear PINSVR model for corporate governance and financial information criteria, as well as the hybrid approach, have been calculated based on the linear PINSVR model mentioned in Equation 11 [46]

$$f(x) = \frac{1}{2}\left(f_1(x) + f_2(x); lkbvdzf + f_2(x)\right) = \frac{1}{2}\left(w_1 + w_2\right)^T x + \frac{1}{2}\left(b_1 + b_2\right), \quad (11)$$

The upper and lower bounds of the regression model are calculated as follows:

$$f_1(x) - g_1(x) = \left(w_1 - w_3\right)^T x + b_1 - b_3 \quad (12)$$

$$f_2(x) + g_2(x) = \left(w_2 + w_4\right)^T x + b_2 + b_4 \quad (13)$$

Independent variables for predicting stock mispricing have been input into the Lasso algorithm with the linear model according to Equation 6. Initially, using 10 -fold cross-validation, the data was divided into training and evaluation datasets, and after executing the Lasso learning process, the weights of the linear model for this algorithm were calculated for both the current year and the following year in Equation14 [5]

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \quad (14)$$

The results indicate that the Nonlinear-PINSVR model has performed better than linear models in predicting actual values due to its nonlinear capabilities. It has also been able to model fluctuations adequately. The differences among the various models, especially at critical points and during periods of high volatility (such as in the years 2016 and 2021), become more pronounced, as linear models are unable to accurately model these fluctuations. The Lasso and Linear-PINSVR models generally yield similar results, with their prediction errors exceeding that of Nonlinear-PINSVR; however, they have modeled fluctuations better than the decision tree. The decision tree model does show closer performance to actual values at some points, but it also exhibits high volatility, which is associated with significant errors in certain cases. The models Lasso, Linear-PINSVR, and CART have not provided accurate forecasts, reinforcing the results discussed in the previous section. In summary, nonlinear models such as Nonlinear-PINSVR can achieve better accuracy in predicting stock mispricing due to their improved ability to model the complexities inherent in the data. Linear models, particularly in conditions of severe volatility, demonstrate lower effectiveness. As stated in previous sections, corporate governance criteria are unsuitable for predicting stock mispricing.

6 Discussion and conclusion

Mispricing is a phenomenon rooted in the weaknesses of the capital market. When a financial asset is mispriced, and the price of a share significantly exceeds its discounted expected cash flow value, a price bubble emerges. Typically, mispricing of assets leads to a sudden drop in prices and ultimately a stock market crash. Therefore, identifying the factors influencing stock mispricing can assist market participants in maintaining lower-risk stocks in their portfolios through more accurate forecasting of future stock returns and timely detection of price bubbles, thereby reducing the risk of price declines. This study aims to develop a model for predicting the phenomenon of stock mispricing based on financial and governance criteria within the Tehran Stock Exchange, and it also examines and compares the predictive power of linear and nonlinear models. The results indicate that predictions incorporating corporate governance criteria generally exhibit lower accuracy, even within nonlinear algorithms. The high error associated with corporate governance criteria may stem from their inadequate alignment with the complexities present in the data, or insufficient modeling of the dependent variable, highlighting the need to rethink the use of this criterion compared to other approaches. One reason for this could be the nature of the independent variables, most of which are binary. A comparison of the predictive abilities of the LASSO, PINSVR, and CART algorithms in forecasting stock mispricing reveals that the nonlinear PINSVR outperforms the CART decision tree, followed by the linear PINSVR and LASSO models. However, there is not much difference observed among the linear algorithms. The existence of differences among the algorithms is entirely natural, as it is improbable to find a specific algorithm that provides the best response across all global issues. Consequently, in some cases, one linear algorithm may outperform another. An algorithm might perform well for one problem, while another does not, and the opposite may occur for a different problem. The learning power of linear models is significantly low, which is well-demonstrated by both errors. Furthermore, the considerable discrepancy in the error rates of linear and nonlinear models in predicting stock mispricing indicates that linear models are not particularly effective in this regard. This conclusion arises from the inherent complexity of the input space and the nonlinear characteristics present in the issue's data, which relates to the intrinsic nature and complex dynamics of the stock market. Indeed, the nonlinear nature of the relationships among variables in the issue of stock mispricing restricts the use of linear models, preventing them from accurately modeling the underlying relationships and patterns. Thus, nonlinear models, due to their enhanced capability to comprehend and utilize these complexities, exhibit superior performance in forecasting stock mispricing. It is practically impossible to identify suitable linear models that can compete with the performance of nonlinear models, and linear models tend to exhibit lower effectiveness, especially in conditions of high volatility. Based on the results, the forecasting error for stock mispricing for the current year is less than that for the following year, indicating greater difficulty in long-term forecasts. In other words, as the time interval for predictions increases, uncertainty and complexity also rise, leading to forecasts that are less precise and further from reality. Various factors, such as market volatility, economic changes, and various uncertainties, significantly impact the accuracy of long-term predictions. The findings of the present study align with [39], which demonstrates the superior performance of nonlinear forecasting models compared to linear models. However, these results do not coincide with [23], which indicate no significant difference between linear and nonlinear models in forecasting stock price indices on the Tehran Stock Exchange.

Given that in recent years, artificial intelligence and machine learning have made significant advances across various fields, particularly in complex and extensive issues, they have attracted considerable attention from researchers in diverse financial topics, including pricing optimization, multi-stage portfolio investment, and risk management. Furthermore, financial markets have witnessed a growing trend in the use of trading algorithms for investment decision-making. Therefore, it is recommended that financial market analysts utilize mathematical models similar to those employed in this study for forecasting financial issues. It can be argued that a significant portion of stock mispricing is attributable to a lack of information transparency at the corporate level, and higher-quality financial information can reduce stock mispricing. Therefore, it is recommended that regulatory bodies such as the Audit Organization and the Securities and Exchange Organization require companies to improve the quality of their accounting information, ensure transparency, and publish reports regarding corporate governance criteria similar to those identified in this study. This would help prevent discrepancies between the intrinsic value and the market value of companies' stocks. In this regard, special attention should also be given to the role of incentive policies and financial penalties. Considering that the impact of corporate governance on stock mispricing may vary across different time periods and be influenced by changes in corporate governance, it is recommended that future researchers examine the effects of political, economic, and social conditions in Iran on stock mispricing and the factors influencing it.

Many factors (particularly the country's inflationary conditions and the lack of adjusted financial statements) have an impact on the research findings, and controlling for them is beyond the researcher's capability.

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