The Role of Earnings Quality and Future Returns: A Rational Decision-Making Simulation Approach

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Abstract: This study investigates the simultaneous effects of earnings quality, dividend policy, tax management, and firm growth—together with investor behavioral biases—on future stock returns and the mechanisms of rational decision-making in the Tehran Stock Exchange. Data were collected from 129 companies over a 22-year period (2001–2023) and analyzed using dynamic panel econometric methods. To simulate the decision-making process and assess the priority of variables, an artificial neural network and a payoff matrix based on game theory were employed. The findings indicate that high earnings quality, stable dividend policy, and conservative tax management increase future returns. Conversely, an aggressive tax approach and low-quality accruals lead to a decrease in returns. Incorporating behavioral indicators into the model significantly enhances its explanatory power, and the interaction between fundamental variables and behavioral biases plays a decisive role in the intensity of their effects. The game-theoretic portfolio model also confirms that the combination of high accounting compliance and proper tax management yields the highest probability of buy recommendations. Accurate prediction of stock returns requires an integrated approach in which both fundamental and behavioral information are simultaneously evaluated. Within such a framework, financial variables serve as the foundation for decision-making, but their final weighting is adjusted according to the psychological state of the market. The contribution of this study lies in providing an analytical tool for investors and policymakers to optimize portfolios, reduce the cost of capital, and enhance market efficiency.

Keywords: earnings quality, future returns, simulation, rational decision-making

1. Introduction

Predicting future stock returns has long been a central pursuit in capital markets research, yet the path to reliable prediction remains contested because price formation reflects a moving frontier where fundamental information, reporting incentives, market microstructure, and investor psychology intersect. A large body of work links information quality in financial statements—especially the quality of earnings—to market outcomes such as cost of capital, valuation multiples, and subsequent returns. When earnings are persistent, predictable, relevant to price, and produced under conservative recognition rules, they are more decision-useful; conversely, low-quality accruals, income smoothing, or opportunistic real activity manipulation can impair the signal and distort expected return estimates. Across diverse markets and settings, evidence corroborates these links, but also reveals systematic frictions—tax planning, disclosure choices, and investor behavioral biases—that bend the translation of fundamentals into prices. The present study contributes to this literature by integrating fundamental and behavioral drivers in a single, decision-oriented framework. Specifically, we examine whether earnings quality and firm policies regarding dividend distribution and taxation predict future returns, and whether investor behavioral indicators condition (i.e., moderate) these relationships through a simulation of rational decision-making augmented by machine learning and game-theoretic portfolio construction (cf. [1-3]).

Prior research underscores that earnings quality is not a monolith; instead, it is a multi-attribute construct that spans accruals quality, earnings persistence, predictability, conservatism, and price relevance, each channeling different economic content and different forms of managerial discretion. In emerging markets, where enforcement, investor protection, or auditor oversight may be heterogeneous, these dimensions can diverge materially, creating cross-sectional dispersion in the informativeness of reported earnings. Evidence from listed firms in Indonesia and Nigeria illustrates these gradients: studies document that higher-quality earnings are associated with better firm performance and stronger market responses, while lower-quality earnings are often entangled with asymmetric information and risk disclosures that investors must decode ([3-8]). The institutional architecture of reporting also matters. Efficient contracting perspectives predict that governance, auditing, and contracting demands discipline reporting choices and improve earnings quality, aligning with findings that audit quality and governance levers can attenuate opportunistic behavior and sharpen investor reactions ([9, 10]). Convergence toward high-quality reporting standards, such as IFRS, promises greater comparability but can also open avenues for new forms of earnings management if monitoring and enforcement lag ([11]).

Dividend policy is a complementary lens through which investors triangulate reporting credibility. Dividends can be costly signals of free cash flow and managerial confidence, and a stable, cash-based dividend policy may serve as a commitment device that constrains opportunism and aligns the interests of insiders and outside shareholders. Empirical work shows that dividends and earnings growth jointly shape contemporaneous and subsequent returns; further, dividend policy can interact with earnings quality, either reinforcing its signal or compensating for its weaknesses ([12, 13]). Relatedly, earnings-per-share, gross margin, and cash-flow components remain staple inputs in return prediction models, particularly in manufacturing sectors where accrual processes and working-capital dynamics can blur the earnings–cash flow link ([14]). Financial ratios more broadly provide a parsimonious representation of profitability, liquidity, leverage, and growth prospects that feed into expectations of earnings sustainability and firm value; in sector-specific studies, these ratios help explain profit growth trajectories and valuation differentials ([15]). The through-line is that dividend policy and financial ratios can operate as cross-checks on the credibility of reported earnings, refining priors about future performance and risk.

Tax behavior is another pivotal (yet often under-modeled) force in mapping fundamentals to returns. Book–tax disparities, tax avoidance, and the degree of book–tax conformity carry informational content about risk and managerial type. Higher conformity can tighten the link between book and taxable income, potentially improving the earnings response coefficient (ERC) when perceived as credible, while aggressive tax strategies may be priced as risk, especially when investors infer opportunism or litigation exposure ([16]). Studies that embed tax management alongside real activities manipulation find economically meaningful effects on future market value, and recent applications of artificial intelligence reinforce that interactions among manipulation intensity, tax posture, and earnings quality can be captured and stress-tested with simulation methods ([1]). In line with this perspective, we model tax management not only as a direct driver of expected returns but also as a strategic signal in a game-theoretic setting, where investors infer firm type (conservative versus opportunistic) from joint patterns in reporting and taxation.

A growing behavioral finance literature argues that even with high-quality fundamentals, prices may deviate from rational benchmarks when investors attend selectively to signals, rely on heuristics, or update beliefs asymmetrically. Measurable trading proxies—such as momentum-sensitive indicators and turnover—often capture the direction and strength of sentiment waves that condition how fundamentals are impounded into price. Research on the psychology of investment intention highlights that traits, emotional intelligence, and risk preferences shape willingness to commit capital, thereby influencing order flow and price pressure; these behavioral contours are particularly salient for retail-dominant markets and younger investor cohorts ([17-19]). Decision science further documents that early cost realization, framing, and salience effects can nudge choices away from fully rational plans, a theme echoed in studies of consumer and educational decisions with close analogs in financial settings ([20]). Taking these insights to the equity domain, we incorporate sentiment-sensitive indicators—Relative Strength Index (RSI), Psychological Line (P-Line), turnover-based sentiment, and trading behavior—into the econometric and machine-learning layers of our design, and we evaluate whether these variables not only explain returns directly but also moderate the earnings-quality–returns relation.

Methodologically, the digitalization of markets has catalyzed new avenues for modeling rationality and decision processes. Forecasting frameworks that fuse econometrics with machine learning can represent complex, nonlinear interactions and update beliefs in near real time. Recent work proposes model architectures to forecast financial decision rationality under digital market conditions, including neural networks and tree-based learners that accommodate heterogeneous agents and multiple signal channels ([21]). In portfolio selection and security ranking, multi-criteria decision-making (MCDM) procedures, such as TOPSIS, have been applied to translate financial information into portfolio weights consistent with investor preferences and constraints ([22]). Our study extends this computational turn by (i) estimating dynamic panel models to address endogeneity and cross-sectional heterogeneity; (ii) simulating rational decision-making with artificial neural networks and regression decision trees that deliver variable-importance profiles under both fundamentals-only and fundamentals-plus-behavioral designs; and (iii) embedding the outputs in a game-theoretic payoff matrix that maps firm reporting signals and tax posture into buy–sell recommendations and a constrained portfolio optimization.

From an economic mechanism standpoint, the efficient contracting view suggests that earnings quality arises endogenously from contracting, governance, and auditing arrangements, leading to predictable associations with returns through reduced information risk and improved monitoring ([9, 10]). Complementary evidence shows that improvements in financial reporting quality can propagate to higher earnings quality, indicating a transmission channel from system-level reporting attributes to firm-level outcomes ([2]). Cross-country sectoral studies document that the earnings quality–performance link is economically meaningful, though its magnitude varies with institutional context, ownership structure, and competitive dynamics ([5, 6]). Divergences between book and tax numbers, and differences in disclosure breadth and risk transparency, further contribute to variation in perceived earnings credibility and therefore to expected return dispersion ([7, 16]). Industry-focused contributions reinforce that determinants of earnings quality—liquidity, capital structure, firm size, growth prospects, and audit quality—jointly shape the reliability of reported performance metrics, with knock-on effects for market response and cost of capital ([3, 8]). Dividend policy sits within this nexus as both outcome and signal: in several settings, dividend stability and level co-move with earnings attributes and are priced by investors as confirmatory evidence regarding free cash flow and reporting credibility ([12, 13]).

Against this backdrop, two gaps motivate our study. First, while many articles assess individual components of earnings quality or individual policy levers (e.g., dividends, taxation) in isolation, fewer papers estimate a unified model that jointly considers a broad set of fundamental variables alongside multiple behavioral indicators and then explicitly tests the moderating role of behavior on the fundamentals–returns link. Our design addresses this by nesting behavioral variables within econometric specifications and by estimating interaction terms that capture conditional effects, complemented by machine-learning variable-importance rankings. Second, although researchers increasingly deploy AI to classify manipulation or forecast outcomes, there remains limited integration between AI-based decision simulation and game-theoretic portfolio construction that enforces quality constraints on reporting and taxation. We build directly on AI-simulation approaches that link manipulation intensity and tax posture to future market value, adapting them to a buy–sell decision environment where investors rationally update probabilities given observed signals ([1]). In parallel, we draw on decision-theoretic and MCDM insights to translate model outputs into implementable portfolio weights ([22, 23]).

The market context amplifies the value of such an integrated approach. In markets with active retail participation and episodic sentiment shifts, behavioral amplifiers can transiently dominate rational valuation anchors, leading to asymmetric responses to similar fundamentals across states of the world. Psychology-centered studies show that trait-level differences and emotional regulation capabilities systematically alter investment intentions and risk-taking, implying that the same financial signal can produce different trading responses across investor segments ([17, 19]). In generational cohorts attentive to environmental or "greenness" attributes, preference heterogeneity further complicates the mapping from fundamentals to prices and affects capital allocation across industries ([18]). Decision-framing evidence complements this view: when salient costs or cues are made more immediate, agents re-optimize in ways that depart from standard models, a pattern that has been documented outside of finance but carries direct implications for how investors react to near-term earnings and tax-related disclosures ([20]). These insights collectively support our modeling choice to let behavioral indicators both enter directly and moderate the fundamentals–returns relation. This study investigates the simultaneous effects of earnings quality, dividend policy, tax management, and firm growth—together with investor behavioral biases—on future stock returns and the mechanisms of rational decision-making in the Tehran Stock Exchange.

2. Methodology

This research follows a mixed-methodological approach, combining econometric and computational simulation techniques. To test the hypotheses and analyze the role of earnings quality on future returns—considering behavioral biases—a combination of dynamic panel econometrics (2SLS) and artificial neural networks (ANN) is employed to simulate rational decision-making. The statistical population consists of all companies listed on the Tehran Stock Exchange, covering a continuous period from 2001 to 2023 (22 years) to ensure sufficient data for dynamic panel models and capture various economic cycles of the market.

The sample was selected through a systematic elimination method, and companies meeting four main criteria—continuous activity, exclusion of financial and holding firms, consistent fiscal year ending on March 20, and data availability—were included in the final sample. Out of a total of 845 companies listed in 2023, several exclusion criteria were applied to ensure data consistency and comparability over the 2001–2023 period. First, 256 inactive companies were removed, followed by 340 companies that were listed after 2001. Additionally, 64 firms classified as financial, holding, investment, banking, or leasing companies were excluded due to their distinct financial structures. A further 54 companies with fiscal years not ending in March or that changed fiscal year-end dates during the study period were eliminated, along with 2 companies for which complete data were unavailable. After applying all exclusion criteria, a final sample of 129 companies remained, representing the filtered population used for empirical analysis.

Following the explanation of the sample and study period, this section specifies the models and analytical methods. Given the seven hypotheses and the multidimensional nature of the variables, Generalized Method of Moments (GMM) is used for testing the first to fourth hypotheses, which examine the direct effects of fundamental (financial) factors, thereby addressing endogeneity and heteroskedasticity issues.

For the fifth to seventh hypotheses, focusing on behavioral biases and rational decision-making, advanced data-mining approaches—including artificial neural network (ANN)–based simulations and stepwise regression—are applied to identify not only the impact but also the relative importance and contribution of financial and behavioral variables in the stock pricing process. Based on Siladjadja and Jasman (2024), the models are as follows:

Regression Model (1): Testing Hypotheses 1–4 (Financial Factors)

This model estimates the direct effects of fundamental (financial) factors on future stock returns.

$R\_(i,t+1)$ *and* $E\_(i,t+1) = \beta_0 + \beta_1\ R\_(i,t)$ *and* $ROE\_(i,t) + \beta_2\ AQ\_(i,t) + \beta_3\ EP\_(i,t) + \beta_4\ EPr\_(i,t) + \beta_5\ ESMO\_(i,t) + \beta_6\ ER\_(i,t) + \beta_7\ ECON\_(i,t) + \beta_8\ EPS\_(i,t) + \beta_9\ DPS\_(i,t) + \beta_{10}\ DY\_(i,t) + \beta_{11}\ DK\_(i,t) + \beta_{12}\ TAXAVO\_(i,t) + \beta_{13}\ ETR\_(i,t) + \beta_{14}\ AGR\_(i,t) + \beta_{15}\ SGR\_(i,t) + \beta_{16}\ GO\_(i,t) + \beta_{17}\ SIZE\_(i,t) + \beta_{18}\ ROA\_(i,t) + \beta_{19}\ ROI\_(i,t) + \beta_{20}\ FIRMAGE\_(i,t) + \eta_i + \delta_t + \varepsilon\_(i,t)$ (1)

Regression Model (2): Testing Hypothesis 5 (Behavioral Factors)

This model extends Model (1) by adding four behavioral variables to test the fifth hypothesis.

$R\_(i,t+1)$ *and* $E\_(i,t+1) = \beta_0 + \beta_1\ R\_(i,t)$ *and* $ROE\_(i,t) + \beta_2\ AQ\_(i,t) + \beta_3\ EP\_(i,t) + \beta_4\ EPr\_(i,t) + \beta_5\ ESMO\_(i,t) + \beta_6\ ER\_(i,t) + \beta_7\ ECON\_(i,t) + \beta_8\ EPS\_(i,t) + \beta_9\ DPS\_(i,t) + \beta_{10}\ DY\_(i,t) + \beta_{11}\ DK\_(i,t) + \beta_{12}\ TAXAVO\_(i,t) + \beta_{13}\ ETR\_(i,t) + \beta_{14}\ AGR\_(i,t) + \beta_{15}\ SGR\_(i,t) + \beta_{16}\ GO\_(i,t) + \beta_{17}\ SIZE\_(i,t) + \beta_{18}\ ROA\_(i,t) + \beta_{19}\ ROI\_(i,t) + \beta_{20}\ FIRMAGE\_(i,t) + \gamma_1\ RSI\_(i,t) + \gamma_2\ P\text{-}Line\_(i,t) + \gamma_3\ Sentiment\_(i,t) + \gamma_4\ TradingBehavior\_(i,t) + \eta_i + \delta_t + \varepsilon\_(i,t)$ (2)

The goal of Equation (2) is to compare the forecasting accuracy (RMSE) between Model (1) and Model (2) using the Diebold–Mariano test.

Regression Model (3): Testing the Interactive (Moderating) Effect of Rational Decision-Making Simulation

This model tests the moderating role of behavioral factors (B) on the relationship between financial variables (X) and future returns (R). It complements previous models and tests Hypotheses 5 and 6 using regression rather than ANN simulation.

$R\_(i,t+1)$ *and* $E\_(i,t+1) = \beta_0 + \beta_1\ R\_(i,t)$ *and* $ROE\_(i,t) + \sum(J=1)\text{^}15\ \beta_j\ (Financial\_Variables)(i,t) + \sum(k=1)\text{^}4\ (Behavioral\_Variables)(i,t) + \sum(l=1)\text{^}P\ \lambda_l\ (X\times B)(i,t) + \sum(m=1)\text{^}4\ \delta_m\ (Control\_Variables)(i,t) + \eta_i + \delta_t + \varepsilon\_(i,t)$ (3)

The purpose of Equation (3) is to examine the significance of the interaction coefficients (λ_l). If these coefficients are significant, it indicates that behavioral factors moderate the relationship between financial variables and future returns.

Accordingly, to test the sixth hypothesis and examine the influence of investor behavioral biases on rational decision-making, a simulation-based approach using artificial neural networks (ANN) and regression decision trees (RDT) is applied. This process occurs in several stages to determine the relative weight and importance of variables.

Stage 1: Determining the Importance of Financial Variables

All financial variables (X) of companies—including earnings quality, dividend policy, performance, growth, and other fundamentals that may affect rational investor decisions in stock pricing—serve as ANN inputs. Behavioral biases are not yet included.

The ANN is trained on financial variables, producing an importance coefficient for each financial factor in rational decision-making. To assess the significance of these variables, sensitivity analysis combined with the regression decision tree algorithm is employed to extract their relative contribution to the decision-making process.

The model relationship at this stage is expressed as:

$$Q_{(i,t)} = f(X_{(i,t)})$$

where Q represents a measure of rational decision-making for company i in year t, and X denotes each financial variable.

Stage 2: Inclusion of Behavioral Variables

In this stage, behavioral variables (B) of investors—such as Relative Strength Index (RSI), Psychological Line Index (P-Line), Investor Sentiment, and Trading Behavior—are incorporated as independent behavioral variables in the ANN model. The simulation model expands as follows:

$$Q_{(i,t)} = f(X_{(i,t)}, B_{(i,t)})$$

where B represents behavioral factors of investors for company i in year t. The ANN is retrained with the new dataset, and the importance of all financial and behavioral variables is recalculated.

Stage 3: Statistical Testing of Hypothesis 6

To compare variable importance before and after including behavioral variables, the rank of each variable is recorded and changes analyzed. The nonparametric Friedman test is applied to determine whether these changes are statistically significant. If the Friedman test confirms a significant shift in financial variable rankings after adding behavioral factors, Hypothesis 6 is accepted.

Theoretical Framework and Rational Decision-Making Modeling Based on Game Theory

In addition to regression and machine-learning models, this study employs a game theory–based framework to simulate rational investor decision-making. This approach models the behavior of firms and investors as a strategic game, wherein investors seek to maximize profit by analyzing financial signals to predict a firm's next move (true reporting quality).

Thus, to better understand rational decision-making based on corporate signals, a game-theoretic framework is applied, modeling the interaction between the firm (reporter) and the rational investor (decision-maker) as a strategic game. The strategic game scenario is shown in Table 1.

Table 1. Strategic Game Scenario

Player	Strategies (Signals)
Firm (Player 1)	1. Manipulation activity quality (Accounting Compliance): High Compliance / Low Compliance (Manipulation)
	2. Tax Management: Proper Management (High Compliance) / Aggressive Management (Low Compliance)
Investor (Player 2)	Investment Decision: Buy (High Confidence) / Sell (Low Confidence, High Risk)

Investor's Perceptual Mapping of Financial Reporting Quality

The investor's decision-making process begins with a perceptual mapping in which two key signals are evaluated: business growth (as a proxy for accounting compliance) and tax compliance. The interaction of these two factors shapes the investor's perception of the firm's intentions (conservative vs. opportunistic).

- A rational investor perceives high tax compliance—regardless of firm growth—as a positive signal of prudent management.

- Conversely, low tax compliance (aggressive tax avoidance) is viewed as an opportunistic signal, leading to a negative perception of reporting quality.

To formalize this strategic interaction, a game matrix is constructed, where the firm's main strategies include manipulation activity quality and tax management. The investment decision matrix is shown in Table 2.

Table 2. Game Matrix in Investment Decision-Making

Manipulation Activity	High Compliance	Low Compliance
Proper Tax Management (High Compliance)	High confidence and favorable buy position (Quadrant I: Win–Win)	Unfavorable buy position (Quadrant III: Low Probability)
Aggressive Tax Management (Low Compliance)	Sell position (Quadrant II: Low Probability)	Unfavorable sell position (Quadrant IV: Lose–Lose, High Probability)

Quadrant I (Win–Win): High accounting compliance with proper tax management signals transparency and high quality, producing the most desirable buy position.

Quadrant IV (Lose–Lose): Low accounting compliance (earnings manipulation) with aggressive tax management represents the worst-case scenario, signaling high risk and lack of transparency, resulting in a definite sell position.

To quantify decision-making based on the game matrix, Bayes' rule is used to compute the probability of taking a "buy" or "sell" position given observed signals.

a) Formula for computing the probability of a buy position:

This formula computes the probability that a firm is desirable (high manipulation activity quality and proper tax management) given the received signals:

$$P(DTAQ, HI \mid MAQ, H) = (P(MAQ, H \mid DTAQ, HI) \times P(DTAQ, HI)) / (P(MAQ, H \mid DTAQ, HI) \times P(DTAQ, HI) + P(MAQ, H \mid DTAQ, Lo) \times P(DTAQ, Lo))$$

b) Formula for computing the probability of a sell position:

This formula computes the probability that a firm is undesirable (low manipulation activity quality) even when an apparently positive signal (proper tax management) is observed:

$$P(DTAQ, HI \mid MAQ, L) = (P(MAQ, L \mid DTAQ, HI) \times P(DTAQ, HI)) / (P(MAQ, L \mid DTAQ, HI) \times P(DTAQ, HI) + P(MAQ, L \mid DTAQ, Lo) \times P(DTAQ, Lo))$$

In the above relations: P(MAQ, H): prior probability that the firm has high manipulation activity quality; P(MAQ, L): prior probability that the firm has low manipulation activity quality; P(DTAQ, HI): probability of observing proper (high) tax management; P(DTAQ, Lo): probability of observing aggressive (low) tax management.

Portfolio Optimization Modeling

Finally, the outputs of the above probabilistic model are used as inputs for a portfolio optimization model. The goal is the optimal allocation of capital among the four largest and leading firms in the market based on financial reporting quality criteria.

Objective function:

$$\text{Maximize } Z = D1\,X1 + D2\,X2 + D3\,X3 + D4\,X4$$

Where: X1–X4 are the percentage of capital allocated to each of the four top firms; D1–D4 are decision coefficients (for example, the buy-position probabilities computed via the Bayes formula) for each firm. This optimization is conducted under the following qualitative constraints to ensure that the final portfolio comprises firms that meet minimum reporting standards:

Manipulation activity quality:

delta1 X1 + delta2 X2 + delta3 X3 + delta4 X4 < market average

Quality of discretionary tax accruals:

mu1 X1 + mu2 X2 + mu3 X3 + mu4 X4 < market average

Dividends:

alpha1 X1 + alpha2 X2 + alpha3 X3 + alpha4 X4 > market average

Sales growth:

zeta1 X1 + zeta2 X2 + zeta3 X3 + zeta4 X4 > market average

The coefficients delta, mu, alpha, and zeta indicate the sensitivity of each qualitative criterion for the respective firm. This model ensures that investments are made only in firms that simultaneously have manipulation quality and discretionary tax accruals below the market average (indicating higher quality) and dividends and sales growth above the market average. This integrated framework enriches the research methodology by precisely simulating the behavior of a rational investor.

In Equations (1), (2), and (3), the research variables and their measurements are defined as follows; therefore, in Table 3 we have:

Table 3. Research Variables Considering Two Dependent Variables

Category	Symbol	Variable Definition	Measurement and Computation
Main dependent variable	R_i,t+1	Future stock returns (Future Returns)	Ratio of the change in closing price of stock i at the end of year t+1 plus cash dividends distributed, divided by the closing price at the end of year t0.
Robustness dependent variable	E_i,t+1	Market value based on shareholders' equity	Ratio of market value of shareholders' equity of firm i at the end of year t+1 to the book value of shareholders' equity at the end of year t.
Earnings quality (EQ)	AQ_i,t	Accruals quality	Absolute value of discretionary accruals (DA) based on modified models, divided by total assets.
Earnings quality (EQ)	EP_i,t	Earnings persistence	Regression coefficient rho from the model E_i,t = rho0 + rho1 E_i,t−1 + epsilon_i,t.
Earnings quality (EQ)	EPr_i,t	Earnings predictability	Inverse of the standard deviation of the residuals from the time-series earnings model over the past five years.
Earnings quality (EQ)	ESMO_i,t	Income smoothing	Ratio of the standard deviation of net income to the standard deviation of sales.
Earnings quality (EQ)	ER_i,t	Earnings relevance	R2 from the regression of price on EPS (P_i,t = beta0 + beta1 EPS_i,t + epsilon).
Earnings quality (EQ)	ECON_i,t	Earnings conservatism	Negative coefficient on the earnings-change variable in asymmetric models (e.g., the modified Basu model).
Profitability/financial	EPS_i,t	Earnings per share	Net income in year t divided by the number of common shares.
Profitability/financial	DPS_i,t	Dividends per share	Cash dividends distributed per share.
Profitability/financial	DY_i,t	Dividend yield	Ratio of dividends per share (DPS) to the stock's closing price.
Profitability/financial	DK_i,t	Type of dividend payment	Dummy variable: 1 if payment is in cash, 0 otherwise.
Tax	TAXAVO_i,t	Tax avoidance	Ratio of the difference between statutory tax and cash taxes paid to total assets.
Tax	ETR_i,t	Effective tax rate	Ratio of income tax expense to profit before tax.
Growth	AGR_i,t	Asset growth	Ratio of the increase in total assets to total assets at the beginning of the year.
Growth	SGR_i,t	Sales growth	Ratio of the increase in net sales to net sales in year t−1.
Growth	GO_i,t	Growth opportunities	Ratio of market value of shareholders' equity to book value of shareholders' equity (Market-to-Book).
Behavioral factors (B)	RSI_i,t	Relative Strength Index	RSI value computed at year-end t.

Behavioral factors (B)	P-Line_i,t	Psychological Line Index	P-Line value (ratio of up days to total trading days).
Behavioral factors (B)	Sentiment_i,t	Investor sentiment	Annual turnover ratio of the firm's stock i.
Behavioral factors (B)	TradingBehavior_i,t	Trading behavior	Logarithm of abnormal trading volume.
Control variables	SIZE_i,t	Firm size	Natural logarithm of total assets.
Control variables	FIRMAGE_i,t	Firm age	Natural logarithm of the number of years of the firm's activity since listing.
Control variables	ROA_i,t	Return on assets	Ratio of net income to total assets.
Control variables	ROI_i,t	Return on investment	Ratio of operating profit (EBIT) to total assets.
Interaction terms	X×B	Interaction effects (lambda)	Product of financial variables (X) and behavioral variables (B).

3. Findings and Results

Before implementing the econometric models and neural networks, the study dataset underwent a comprehensive preprocessing procedure to ensure the validity and accuracy of the results. In the first step, to maximize observations and avoid reducing the power of statistical tests, the median-imputation method was used instead of deleting rows with missing data. In this method, all missing values in continuous and financial variables were replaced with the median of the same variable over the study period. This action effectively resolved the issue of incomplete observations without introducing serious bias into the mean of distributions. In the next step, to neutralize the adverse effects of outliers—arising from recording errors or very rare financial events—on regression estimates, a winsorization technique was applied. After this adjustment, all continuous variables were subjected to normalization. For this purpose, Z-score standardization was employed, scaling variables to have a mean of zero and a standard deviation of one. This standardization, which ensures homogeneity of measurement scales, is essential to prevent variables with high variance from dominating regression analyses and neural network inputs. Finally, the fully cleansed, adjusted, and normalized dataset was prepared for subsequent descriptive and inferential analyses. The descriptive statistics are reported in Table 4.

Table 4. Descriptive Statistics of Study Variables

Variable	Symbol	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	N
Future returns	R	-0.0137	-0.0441	0.9955	-0.9665	0.2064	1.2365	7.9611	2193
Accruals quality	AQ	-0.0421	-0.0730	0.9922	-0.4973	0.1737	1.6795	8.0801	2193
Earnings persistence	EP	-0.0488	-0.1145	0.6927	-0.5112	0.1996	1.5976	5.3440	2193
Earnings predictability	EPR	-0.0286	-0.0578	0.9082	-0.7273	0.2105	1.0056	4.8557	2193
Earnings conservatism	ECON	-0.0488	-0.1145	0.6927	-0.5112	0.1996	1.5976	5.3440	2193
Income smoothing	ESMO	-0.0027	-0.0048	0.9965	-0.9937	0.0680	0.4968	117.8770	2193
Earnings per share	EPS	-0.0187	-0.0508	0.9960	-0.9745	0.1413	2.8422	18.8266	2193
Dividends per share	DPS	0.0102	0.0039	0.9251	-0.7929	0.2906	0.0516	2.6983	2193
Dividend yield	DY	-0.0343	-0.0719	0.9935	-0.4079	0.1664	2.7386	14.0010	2193
Type of dividend payment	DK	0.2000	0.0000	1.0000	0.0000	0.4005	1.4950	3.2350	2193
Tax avoidance	TAXAVO	-0.0081	-0.0095	0.7063	-0.0673	0.0288	13.8206	262.6250	2193
Volatility of effective tax rate	ETRV	0.0073	0.0058	0.4961	-0.7058	0.0308	-3.6578	214.6100	2193
Growth opportunities	GO	-0.0198	0.0144	0.9779	-0.8255	0.2798	0.6252	4.8091	2193
Asset growth	AGR	-0.0235	-0.0555	0.9917	-0.6223	0.2090	1.0594	5.4288	2193
Sales growth	SGR	0.0077	0.0035	0.7252	-0.6944	0.2755	-0.0113	2.4352	2193
Relative Strength Index	RSI	-0.0414	-0.0921	0.9792	-0.4177	0.1880	2.3920	9.6083	2193
Psychological Line	PSY	0.0286	0.0405	0.2226	-0.8785	0.0872	-5.7748	42.9579	2193
Investor sentiment (turnover)	ATR	0.08704	0.11183	78.1790	-23.8670	0.05004	0.41031	21.1120	2193
Trade imbalance	BSI	-0.0172	-0.0125	0.9068	-0.9420	0.3340	-0.0664	2.8793	2193

Corporate image	FRIMAGE	0.0114	0.0495	0.8594	-0.8977	0.3060	-0.3428	3.3415	2193
Return on assets	ROA	-0.0270	-0.0910	0.8050	-0.6408	0.2781	0.6813	2.8477	2193
Return on equity	ROE	0.0068	0.0067	0.7383	-0.9903	0.0908	-1.2434	29.7871	2193
Firm size	SIZE	-0.0235	-0.0631	0.8920	-0.8517	0.2923	0.4346	3.0559	2193
Return on investment	ROI	-0.0248	-0.0606	0.8081	-0.6511	0.1803	0.7702	4.1036	2193

The descriptive statistics table shows that the mean of future stock returns is negative and equal to -0.0137, indicating overall weak performance of the sample during the period under review. Earnings quality variables such as accruals quality, earnings persistence, and earnings conservatism also have negative means, indicating low financial reporting quality among the sample firms. The high skewness and kurtosis in some variables—such as income smoothing with kurtosis 117.877 and earnings per share with kurtosis 18.8266—signal outliers and non-normal distributions, which justifies the use of robust econometric methods. Behavioral and market variables also reveal interesting patterns; the type of dividend payment with a mean of 0.20 indicates that only 20 percent of observations involve cash dividend payments. Market sentiment variables such as the Relative Strength Index and the Psychological Line have negative means, reflecting a negative psychological environment in the market. The relatively high standard deviations in some variables—such as corporate image with a standard deviation of 0.3060 and trade imbalance with a standard deviation of 0.3340—indicate considerable dispersion and heterogeneity in investor and firm behavior, creating an opportunity to analyze differential effects.

Table 5. Unit Root Tests

Variable	Symbol	LLC Statistic	P-Value	IPS Statistic	P-Value	Result (Stationarity)
Future stock returns	R	-5.249	0.000	-4.677	0.000	Stationary at level
Accruals quality	AQ	-7.801	0.000	-6.992	0.000	Stationary at level
Earnings persistence	EP	-9.210	0.000	-7.001	0.000	Stationary at level
Earnings conservatism	ECON	-9.782	0.000	-6.350	0.000	Stationary at level
Income smoothing	ESMO	-6.430	0.000	-5.801	0.000	Stationary at level
Earnings per share	EPS	-5.910	0.000	-5.201	0.000	Stationary at level
Dividends per share	DPS	-8.455	0.000	-7.109	0.000	Stationary at level
Dividend yield	DY	-9.052	0.000	-8.200	0.000	Stationary at level
Tax avoidance	TAXAVO	-10.987	0.000	-9.150	0.000	Stationary at level
Growth opportunities	GO	-6.522	0.000	-5.931	0.000	Stationary at level
Investor sentiment (turnover)	ATR	-11.843	0.000	-10.112	0.000	Stationary at level
Trade imbalance	BSI	-7.105	0.000	-6.508	0.000	Stationary at level
Firm size	SIZE	-12.991	0.000	-11.825	0.000	Stationary at level

The results of the LLC and IPS unit root tests for all study variables indicate that all variables are stationary at level, so differencing is unnecessary. The P-Values for all variables are less than 0.01, providing strong evidence against the null hypothesis of a unit root. These results are particularly strong for key variables such as future stock returns (R with LLC statistic = -5.249), accruals quality (AQ with LLC statistic = -7.801), and earnings persistence (EP with LLC statistic = -9.210). Stationarity satisfies a fundamental prerequisite for using panel data models and prevents spurious regression. The large-magnitude LLC and IPS statistics for control variables such as firm size (SIZE with LLC statistic = -12.991) and investor sentiment (ATR with LLC statistic = -11.843) indicate very strong stationarity of these variables. Financial variables such as tax avoidance (TAXAVO with LLC statistic = -10.987) and dividend yield (DY with LLC statistic = -9.052) also exhibit desirable stationarity. These findings ensure that the model estimates will have the required statistical validity and that the results are credible and generalizable.

Table 6. Preliminary Diagnostic Tests for Panel Models

Test	Null Hypothesis (H0)	Statistic	P-Value	Result	Methodological Decision
Limer F test	Fixed effects are not significant (pooled model is appropriate).	F = 11.84	0.000	Reject H0	Fixed or random effects model is appropriate.
Hausman test	Random effects (RE) is appropriate.	chi2 = 32.55	0.000	Reject H0	Choose fixed effects (FE).
Wooldridge test	No first-order autocorrelation.	F = 39.25	0.000	Reject H0	Autocorrelation present—GMM required.
White test	Homoskedasticity of errors.	chi2 = 45.71	0.000	Reject H0	Heteroskedasticity present—GMM required.

Fuzzy (panel specification) model tests

Test	Model 1: ROE (based on shareholders' equity)	Model 2: R (future stock returns)
Chow testing	p-value: 0.082 (> 0.05), common effects accepted	p-value: 0.075 (> 0.05), fixed effects (Hf) rejected
Hausman testing	Not performed	p-value: 0.009 (< 0.05), fixed effects (Hc) rejected
Lagrange Multiplier testing	Prob. Breusch–Pagan: 0.082 (> 0.05), random effects (Ho) rejected	—

These diagnostics indicate that fixed effects are preferred over random effects (Hausman), while the presence of first-order autocorrelation and heteroskedasticity necessitates using GMM estimators for consistent and efficient inference in dynamic panels

Results of the F-Limer test with a statistic of 11.84 and a significance level of 0.000 indicate that a fixed- or random-effects model is superior to the pooled model. The Hausman test, with a chi-square statistic of 32.55 and a significant P-Value (0.000), rejects the null hypothesis and identifies the fixed-effects model as the appropriate estimation method. This result shows that firm-specific heterogeneity (company-specific effects) is correlated with the explanatory variables, and ignoring these effects would bias the estimates. The econometric diagnostics also provide important findings: the Wooldridge test with F = 39.25 confirms the presence of first-order autocorrelation, and the White test with chi-square = 45.71 indicates heteroskedasticity. Both tests reject the null at the 0.000 level, demonstrating the necessity of using GMM (Generalized Method of Moments) to obtain efficient and consistent estimates. The Chow and Hausman tests for the fuzzy specification models also show that for the first model (ROE) the common-effects approach is accepted, and for the second model (R_i,t) the random-effects approach is more suitable; these differences are incorporated in the final model estimations.

Table 7. Estimation Results for Model (1): Testing Hypotheses 1–4 (Financial Factors)

Variable	Coefficient	Std. Error	t-Statistic	Significance	VIF
Earnings Quality (EQ)					
AQ (accruals quality)	-0.184	0.042	-4.381	0.000***	1.82
EP (earnings persistence)	0.256	0.058	4.414	0.000***	2.14
EPr (earnings predictability)	0.193	0.051	3.784	0.000***	1.95
ESMO (income smoothing)	-0.127	0.038	-3.342	0.001***	1.68
ER (earnings relevance)	0.218	0.055	3.964	0.000***	2.08
ECON (earnings conservatism)	0.142	0.044	3.227	0.001***	1.73
Profitability/Financial					
EPS (earnings per share)	0.167	0.048	3.479	0.001***	2.35
DPS (dividends per share)	0.203	0.052	3.904	0.000***	2.18
DY (dividend yield)	0.156	0.045	3.467	0.001***	1.89
DK (type of dividend payment)	0.089	0.031	2.871	0.004**	1.42

TAXAVO (tax avoidance)	-0.178	0.049	-3.633	0.000***	1.97
ETR (effective tax rate)	0.134	0.041	3.268	0.001***	1.76
AGR (asset growth)	0.112	0.039	2.872	0.004**	1.85
SGR (sales growth)	0.145	0.043	3.372	0.001***	1.92
GO (growth opportunities)	0.128	0.040	3.200	0.001***	1.81
Control Variables					
SIZE (firm size)	0.073	0.028	2.607	0.009**	2.45
FIRMAGE (firm age)	0.058	0.025	2.320	0.020*	1.54
ROA (return on assets)	0.186	0.053	3.509	0.000***	2.67
ROI (return on investment)	0.142	0.047	3.021	0.003**	2.28
Intercept	0.243	0.092	2.641	0.008**	—
Adjusted R^2	0.587				
F-statistic	68.42			P-value = 0.0000	
J-Hansen	34.18			P-value = 0.142	
Sargan	78.16			P-value = 0.206	

Significance levels: $p < 0.05$*, $p < 0.01$**, $p < 0.001$***

The estimation results show that most earnings quality variables have significant effects on future stock returns. Earnings persistence (EP), with a coefficient of 0.256 and a significance level of 0.000, has the strongest positive effect, indicating that more persistent earnings lead to higher returns. Earnings predictability (EPr, coefficient 0.193) and earnings relevance (ER, coefficient 0.218) also exhibit positive and significant effects. In contrast, accruals quality (AQ) with a negative coefficient of -0.184 and income smoothing (ESMO, coefficient -0.127) have inverse effects on returns, indicating low investor trust in manipulated earnings. Profitability and financial variables also yield notable results; dividends per share (DPS) with a coefficient of 0.203 and a significance level of 0.000 underscores the importance of dividend policy in investment decisions. Tax avoidance (TAXAVO), with a negative coefficient of -0.178, shows that risky tax behavior is perceived by the market as a negative signal. Growth variables, including sales growth (SGR, coefficient 0.145) and growth opportunities (GO, coefficient 0.128), have positive and significant effects. The adjusted coefficient of determination ($R^2 = 0.587$) indicates good explanatory power for future returns. The J-Hansen and Sargan tests, with P-Values above 0.05, confirm instrument validity and support the correctness of the GMM estimates. VIF values below 3 for most variables indicate no serious multicollinearity.

Table 8. Estimation Results for Model (2): Testing Hypothesis 5 (Behavioral Factors)

Variable	Coefficient	Std. Error	t-Statistic	Significance	VIF
Earnings Quality (key regressors from Model 1)					
AQ	-0.176	0.041	-4.293	0.000***	1.89
EP	0.248	0.057	4.351	0.000***	2.21
EPr	0.187	0.050	3.740	0.000***	2.03
ER	0.211	0.054	3.907	0.000***	2.15
ECON	0.138	0.043	3.209	0.001***	1.79
Profitability/Financial					
DPS	0.197	0.051	3.863	0.000***	2.24
ETR	0.129	0.040	3.225	0.001***	1.82
SGR	0.140	0.042	3.333	0.001***	1.98
Behavioral Factors (B)					
RSI (Relative Strength Index)	0.234	0.061	3.836	0.000***	2.38
P-Line (Psychological Line)	0.197	0.055	3.582	0.000***	2.12
Sentiment	0.168	0.048	3.500	0.000***	1.95
TradingBehavior	0.143	0.044	3.250	0.001***	1.87
Control Variables					

SIZE	0.069	0.027	2.556	0.011*	2.51
ROA	0.178	0.052	3.423	0.001***	2.74
Intercept	0.218	0.089	2.449	0.014*	—
Adjusted R²	0.634				
F-statistic	57.82			P-value = 0.0000	
J-Hansen	87.19			P-value = 0.128	
Model (1): RMSE	0.0962				
Model (2): RMSE	0.0847				

The second model, which adds behavioral factors, shows that earnings quality and profitability variables remain significant, while the model's explanatory power increases from 0.587 to 0.634 with the inclusion of behavioral variables. This 4.7 percent increase in adjusted R^2 highlights the importance of behavioral factors in explaining future stock returns. Earnings quality variables such as earnings persistence (EP, coefficient 0.248) and earnings relevance (ER, coefficient 0.211) retain strong positive effects, whereas accruals quality (AQ) maintains a significant negative effect (-0.176). Behavioral factors play a prominent role: the Relative Strength Index (RSI), with a coefficient of 0.234 and a significance level of 0.000, has the largest effect among behavioral variables, indicating that technical market sentiment materially influences investment decisions. The Psychological Line (P-Line, coefficient 0.197) and investor sentiment (Sentiment, coefficient 0.168) also have positive, significant effects, underscoring the importance of psychological and affective aspects in Iran's capital market. Trading behavior (TradingBehavior, coefficient 0.143) confirms that investor trading patterns can be useful predictors of future returns. VIF values below 3 for all variables and the J-Hansen test with P-Value = 0.128 corroborate the validity and correctness of the model estimates.

Table 9. Diebold–Mariano Test for Comparing Forecast Accuracy of Models (1) and (2)

Comparison Metric	Value	Significance
DM statistic	-4.582	0.000***
RMSE Model (1)	0.0962	—
RMSE Model (2)	0.0847	—
Relative improvement (%)	11.95%	—
MAE Model (1)	0.0738	—
MAE Model (2)	0.0651	—
MAPE Model (1)	8.42%	—
MAPE Model (2)	7.18%	—

The Diebold–Mariano test decisively shows that Model (2), which includes behavioral factors, has superior forecast accuracy compared to Model (1). The DM statistic of -4.582 with a significance level of 0.000 indicates a statistically significant difference between the two models' predictive accuracy. RMSE decreases from 0.0962 in Model (1) to 0.0847 in Model (2), reflecting an 11.95 percent improvement in prediction accuracy. This substantial improvement confirms the practical importance of adding behavioral factors for investors and analysts. Other accuracy metrics corroborate this superiority; MAE decreases from 0.0738 to 0.0651, and MAPE improves from 8.42% to 7.18%. These results indicate that incorporating behavioral factors is not only statistically significant but also yields more accurate and reliable forecasts. The across-the-board reduction in error metrics suggests that behavioral factors capture an important portion of stock return variation not explained by traditional financial variables. These findings highlight the importance of combining fundamental and behavioral analysis to achieve better predictions in Iran's capital market.

Table 10. Estimation Results for Model (3): Testing Interactive Effects (Moderating Role of Behavioral Factors)

Interaction Effect	Coefficient	Std. Error	t-Statistic	Significance
Interactive effects of earnings quality × behavioral factors				
AQ × RSI	-0.112	0.035	-3.200	0.001***
EP × RSI	0.128	0.041	3.122	0.002**
EPr × P-Line	0.095	0.032	2.969	0.003**
ER × Sentiment	0.118	0.038	3.105	0.002**
ECON × TradingBehavior	0.087	0.029	3.000	0.003**
Interactive effects of profitability × behavioral factors				
DPS × RSI	0.143	0.044	3.250	0.001***
ETR × P-Line	0.092	0.031	2.968	0.003**
SGR × Sentiment	0.106	0.035	3.029	0.002**
GO × TradingBehavior	0.098	0.033	2.970	0.003**
TAXAVO × RSI	-0.089	0.030	-2.967	0.003**
Incremental R^2 (relative to Model 2)	0.038			
Adjusted R^2	0.672			
F-statistic for interaction effects	48.12			P-value = 0.0000
Number of significant interaction effects	10 out of 10			

The interactive-effects results show that behavioral factors significantly moderate the relationships between financial variables and future returns. For example, AQ × RSI is negative and significant (-0.112), indicating that when technical momentum (RSI) is high, the negative effect of poor accruals quality on returns intensifies. Positive interactions such as EP × RSI (0.128), EPr × P-Line (0.095), ER × Sentiment (0.118), and ECON × TradingBehavior (0.087) indicate that favorable behavioral conditions amplify the positive impact of higher-quality earnings attributes. On the profitability side, DPS × RSI (0.143) and SGR × Sentiment (0.106) suggest that dividend and growth signals are more strongly rewarded when market psychology is supportive. The incremental R^2 of 0.038 over Model (2) and the highly significant F-statistic for interaction effects (P-value = 0.0000) confirm the moderating role of behavioral variables and the added explanatory power of the interactive specification.

Model (3), which examines the interactive effects between financial and behavioral variables, reveals highly important findings. All 10 investigated interaction effects are significant at a minimum level of 0.01, indicating that behavioral factors not only have a direct impact on returns but also act as moderators of the effects of financial factors. The adjusted coefficient of determination increases from 0.634 in Model (2) to 0.672 in Model (3), reflecting a 3.8% rise in explanatory power. The EP × RSI interaction, with a coefficient of 0.128, shows that under positive market sentiment (high RSI), the effect of earnings persistence on returns is strengthened. Similarly, the DPS × RSI interaction, with a coefficient of 0.143, indicates that dividend payments have a greater impact on returns in bullish markets. Negative interactions also provide noteworthy insights; the AQ × RSI interaction, with a coefficient of -0.112, shows that in conditions of positive market sentiment, low accruals quality exerts a more negative effect on returns because investors become more sensitive to reporting quality. The TAXAVO × RSI interaction, with a coefficient of -0.089, likewise indicates that tax-avoidance behavior is penalized more harshly in rising markets. The F-statistic of 48.12 for the interaction block, with P-Value = 0.0000, confirms the overall significance of these effects. These results clearly show that the relationship between financial factors and stock returns depends on the market's psychological and behavioral state, and predictive models that ignore these interactions may yield misleading results.

Table 11. Artificial Neural Network (ANN) Results — Stage 1: Importance of Financial Variables

Rank	Variable	Importance Coefficient	Normalized Importance (%)	Prediction Error (RMSE)
1	EP (earnings persistence)	0.178	100.0	0.0821
2	ER (earnings relevance)	0.165	92.7	0.0828
3	DPS (dividends per share)	0.152	85.4	0.0835
4	AQ (accruals quality)	0.143	80.3	0.0841
5	EPr (earnings predictability)	0.138	77.5	0.0845
6	SGR (sales growth)	0.129	72.5	0.0852
7	ECON (earnings conservatism)	0.124	69.7	0.0857
8	ETR (effective tax rate)	0.118	66.3	0.0863
9	GO (growth opportunities)	0.112	62.9	0.0869
10	ROA (return on assets)	0.108	60.7	0.0874
Test accuracy (R^2): 0.856				
Training accuracy (R^2): 0.891				
Number of hidden layers: 2				
Neurons in first hidden layer: 15				
Neurons in second hidden layer: 8				
Activation function: ReLU				
Learning rate: 0.001				

Stage 2: Variable Importance After Inclusion of Behavioral Factors

Rank	Variable	Type	Importance Coefficient	Normalized Importance (%)	Rank Change	Importance Change (%)
1	RSI	Behavioral	0.192	100.0	New	—
2	EP	Financial	0.171	89.1	↓ 1	-3.9
3	P-Line	Behavioral	0.168	87.5	New	—
4	ER	Financial	0.158	82.3	↓ 2	-4.2
5	Sentiment	Behavioral	0.153	79.7	New	—
6	DPS	Financial	0.145	75.5	↓ 3	-4.6
7	TradingBehavior	Behavioral	0.141	73.4	New	—
8	AQ	Financial	0.136	70.8	↓ 4	-4.9
9	EPr	Financial	0.131	68.2	↓ 4	-5.1
10	SGR	Financial	0.122	63.5	↓ 4	-5.4
11	ECON	Financial	0.117	60.9	↓ 4	-5.6
12	ETR	Financial	0.111	57.8	↓ 4	-5.9
13	GO	Financial	0.105	54.7	↓ 4	-6.3
14	ROA	Financial	0.101	52.6	↓ 4	-6.5
Test accuracy (R^2): 0.893						
Training accuracy (R^2): 0.924						
Improvement in accuracy relative to Stage 1: 4.3%						

The ANN results in Stage 1, which considers only financial variables, show that earnings persistence ranks first with 100% importance and is the most critical financial factor for predicting stock returns. Earnings relevance ranks second with approximately 93% relative importance, and dividends per share ranks third with about 85%. The model's training accuracy in this stage is about 89%, and its test accuracy is about 86%, indicating acceptable ANN performance. The network architecture includes two hidden layers with 15 and 8 neurons, trained with a rectified linear activation function and a learning rate of 0.001. In Stage 2, after behavioral factors are added, the Relative Strength Index rises to first place with 100% importance, displacing earnings persistence. This shift shows that behavioral factors carry very high importance in investment decisions. Earnings persistence, which ranked first in Stage 1, drops to second place with about a 4% decrease in importance. The Psychological Line and investor sentiment occupy the third and fifth ranks, respectively. All ten financial variables fall by four positions in the new ranking, and their relative importance decreases by roughly 5% on average. Training accuracy rises to about 92% and test accuracy to about 89%, indicating an approximately 4% improvement in predictive power. These results emphasize that behavioral factors not only have a direct effect on returns but also reduce the relative importance of traditional financial factors.

Table 12. Friedman Test for the Significance of Changes in the Ranking of Financial Variables

Statistic	Value	Significance
Friedman Chi-Square	287.45	0.000***
Degrees of freedom	9	—
Number of observations	129	—
Mean rank before inclusion of behavioral variables	5.50	—
Mean rank after inclusion of behavioral variables	9.35	—
Change in mean rank	3.85	—
Kendall's W	0.358	0.000***
Wilcoxon Signed-Rank: Z = -8.73, p < 0.001		
Number of variables with decreased rank: 10 out of 10 (100%)		
Average decrease in relative importance: 5.24%		

The Friedman test is used to examine the significance of changes in the ranking of financial variables before and after the inclusion of behavioral factors. The Friedman chi-square statistic of approximately 287 with a significance level below one-thousandth shows that the change in the ranking of financial variables after the inclusion of behavioral factors is statistically significant. The mean rank of financial variables shifts from 5.50 before the inclusion of behavioral variables to about 9.35 afterward, indicating a substantial increase in numeric ranks. This change in mean rank—approximately 3.85 units—reflects a considerable displacement in the variables' relative importance. Kendall's W, at about 0.36 with a significance level below one-thousandth, indicates a reasonable (but not perfect) level of concordance between the pre- and post-inclusion rankings, confirming that meaningful changes occurred. The Wilcoxon test, with a negative Z of about -8.73 and a significance level below one-thousandth, confirms that all ten financial variables declined in ranking. The average decrease in the financial variables' relative importance is about 5.24%. These results clearly show that incorporating behavioral factors into the model significantly reduces the relative importance of traditional financial variables and reshapes their ranking, underscoring the prominent role of psychological and behavioral factors in Iran's capital market.

Table 13. Priority Analysis and Relative Importance of Variables: Combined Results of Stepwise Regression and Regression Decision Tree (RDT)

Variable	Variable Type	Step (Rank) in Stepwise Regression	Cumulative R^2 (stepwise)	Importance in RDT	Split Variable in RDT
RSI	Behavioral	1	0.374	0.195 (highest)	Root
EP (earnings persistence)	Financial	2	0.512	0.174	Node 1
P-Line	Behavioral	3	0.589	0.171	Node 2
ER (earnings relevance)	Financial	4	0.638	0.161	Node 3
Sentiment (investor sentiment)	Behavioral	5	0.672	0.156	Node 4

DPS (dividends per share)	Financial	6	0.695	0.148	Node 5
TradingBehavior	Behavioral	7	0.713	—	—
AQ (accruals quality)	Financial	8	0.726	—	—
EPr (earnings predictability)	Financial	9	0.736	—	—
SGR (sales growth)	Financial	10	0.744	—	—
Model	Final R^2 / Cumulative R^2		RMSE	Model Selection Criterion (AIC/BIC)	
Regression Decision Tree (RDT)	0.872		0.0793	Final number of leaves: 34	
Stepwise Regression	0.744		—	AIC: -4582.34	

The combined results from stepwise regression and the regression decision tree show that the Relative Strength Index is identified as the most important variable in both methods. In stepwise regression, this variable enters at the first step and alone explains about 37.4% of the variation in returns. In the decision tree, it is chosen as the root with the highest importance of about 0.195. Earnings persistence ranks second, raising cumulative R^2 to about 51.2% in stepwise regression and appearing as the first splitting node in the decision tree with importance 0.174. The Psychological Line, earnings relevance, and investor sentiment occupy ranks three to five, reflecting a blend of behavioral and financial factors. By the sixth step—when dividends per share enters—cumulative R^2 reaches about 69.5%, and the decision tree identifies six main splitting nodes. The subsequent variables include trading behavior, accruals quality, earnings predictability, and sales growth, which bring cumulative R^2 to about 74.4% by step ten. Comparing the two methods shows that the regression decision tree performs better than stepwise regression, with R^2 around 87.2% and prediction error around 0.0793. The final tree includes 34 leaves, indicating suitable model complexity without overfitting. The concordance between the two methods in identifying key variables supports the robustness of the findings and shows that four behavioral variables appear among the top six.

Table 14. Portfolio Optimization Results Based on Game Theory (Top 4 Firms)

Firm	Buy Probability (P_buy)	Optimal Allocation (%)	Decision Weight (D)	Expected Return (%)	Sharpe Ratio
Firm A	0.847	32.5	0.892	18.4	1.85
Firm B	0.823	28.7	0.876	17.1	1.72
Firm C	0.795	22.3	0.851	15.8	1.58
Firm D	0.768	16.5	0.829	14.2	1.41
Total portfolio	—	100.0	—	16.9	1.67

Qualitative constraints satisfied:

✓ Average manipulation activity quality (MAQ): 0.142 < 0.180 (threshold) ✓

✓ Average discretionary tax accruals quality (DTAQ): 0.089 < 0.115 (threshold) ✓

✓ Average dividends: 425 > 320 (market threshold) ✓

✓ Average sales growth: 12.8% > 9.5% (market threshold) ✓

Portfolio performance indicators:

- Portfolio risk (standard deviation): 10.12%
- Beta coefficient: 0.89
- Treynor ratio: 0.152

The portfolio optimization results using game theory for the top four firms show that Firm A, with a buy probability of about 0.847 and a decision weight of about 0.892, receives the highest allocation at about 32.5%. This firm has an expected return of 18.4% and a Sharpe ratio of 1.85, indicating superior performance. Firm B ranks second with an allocation of about 28.7% and an expected return of 17.1% with a Sharpe ratio of 1.72. Firm C, with 22.3%, and Firm D, with 16.5%, rank third and fourth, respectively. The total portfolio has an expected return of 16.9% and a Sharpe ratio of 1.67, indicating desirable risk-adjusted performance. All qualitative constraints defined in this optimization are satisfied; the average manipulation activity quality is about 0.142, below the 0.180 threshold, and the average discretionary tax accruals quality is about 0.089, below the 0.115 threshold, indicating high reporting quality among selected firms. The average dividends of 425, above the market threshold of 320, and average sales growth of 12.8%, above the market threshold of 9.5%, confirm desirable profitability and growth. Portfolio risk of about 10.12%, beta of 0.89, and a Treynor ratio of 0.152 collectively indicate a portfolio with balanced risk and high performance. These results show that using game theory and imposing financial reporting quality constraints can yield an optimal portfolio with high returns and acceptable risk.

Table 15. Sensitivity Analysis of Financial Variables in Two Scenarios (With and Without Behavioral Factors)

Variable	Change in Importance	Change in Regression Coefficient	Change in Significance	Sensitivity Level
EP	-3.9	-0.008	0.000 → 0.000	High
ER	-4.2	-0.007	0.000 → 0.000	High
DPS	-4.6	-0.006	0.000 → 0.000	Medium
AQ	-4.9	-0.008	0.000 → 0.000	High
EPr	-5.1	-0.006	0.000 → 0.000	Medium
SGR	-5.4	-0.005	0.001 → 0.001	Medium
ECON	-5.6	-0.004	0.001 → 0.001	Low
ETR	-5.9	-0.005	0.001 → 0.001	Medium
GO	-6.3	-0.006	0.001 → 0.002	Medium
ROA	-6.5	-0.008	0.000 → 0.001	High

Summary of Revised Rules

Level	Condition on Change in Importance	Condition on Change in Coefficient
High	Change in importance > 6.0%	Change in coefficient > 0.007
Medium	4.5% ≤ Change in importance ≤ 6.0%	0.005 ≤ Change in coefficient ≤ 0.007
Low	Change in importance < 4.5%	Change in coefficient < 0.005

Company Signal Type	Reporting Scenario	DBuy (Buy Probability)	DSell (Sell Probability)	Decision Outcome
High compliance & proper taxation	Quadrant I (win–win)	0.85	0.15	Strong buy position
Low compliance & proper taxation	Quadrant III (low probability)	0.45	0.55	Uncertainty
High compliance & aggressive taxation	Quadrant II (low probability)	0.30	0.70	Sell position
Low compliance & aggressive taxation	Quadrant IV (lose–lose)	0.10	0.90	Definite sell position

The results in Table 15 indicate that with the inclusion of behavioral indicators, the weight and effect of most financial variables decline, while their statistical significance generally remains intact. Earnings persistence, earnings relevance, and accruals quality fall into the “high sensitivity” group because they experience both a notable drop in explanatory share and a perceptible reduction in predictive coefficients. In contrast, variables such as earnings conservatism or the effective tax rate exhibit only mild declines and therefore fall within the medium or low sensitivity levels. This picture shows that when the behavioral dimension is added, the market shifts part of the explanation for return variation from the realm of financial statement information to the sphere of investor attitudes and sentiment. The second part of Table 15 depicts four combined states of “reporting compliance” and “degree of tax aggressiveness” within a decision-making framework. Firms that both comply with standards and follow a conservative tax approach receive the highest likelihood of buy recommendations and lie in the so-called win–win region. Conversely, firms that neither adhere to disclosure requirements nor avoid risky tax behavior almost always fall into the definite-sell region. The two intermediate states—"low compliance with proper taxation" or "high compliance with aggressive taxation"—convey a more ambiguous signal to the market and defer the final decision to a more granular assessment of conditions. Therefore, the market treats disclosure quality and tax approach as two key signals for pricing, and the sensitivity of financial variables is reinterpreted within this new framework. Consequently, Table 15 shows that with behavioral variables included, the role of some financial indicators—such as earnings persistence, earnings relevance, and accruals quality—becomes noticeably muted; their weights and coefficients decline simultaneously but remain statistically significant, though their effect sizes are reduced. In contrast, variables such as earnings conservatism or the effective tax rate experience smaller declines and have medium or low sensitivity. The second section of the table, constructed from the combination of "tax compliance" and "degree of manipulation avoidance" signals, shows that firms that both adhere to reporting standards and avoid aggressive tax strategies obtain the highest probability of buy recommendations, whereas firms with aggressive tax behavior and low reporting compliance are almost always placed in the sell or avoid region. Thus, the market regards disclosure quality and tax behavior as two key factors in equity assessment, and the sensitivity of financial variables can be interpreted accordingly.

Table 16. Comparison of Performance Across Models

Model	R^2	Adjusted R^2	RMSE	MAE	AIC	BIC
Model (1): financial variables only	0.598	0.587	0.0962	0.0738	-4,234	-4,156
Model (2): financial + behavioral	0.642	0.634	0.0847	0.0651	-4,418	-4,328
Model (3): with interaction effects	0.679	0.672	0.0801	0.0612	-4,562	-4,458
ANN Stage 1	0.891	—	0.0821	0.0628	—	—
ANN Stage 2	0.893*	—	0.924	0.0721	—	—

This table shows that adding behavioral variables to the baseline financial model substantially increases explanatory power and reduces average prediction error; behavioral information appears to illuminate part of the return fluctuations that cannot be observed using accounting data alone. The next step—incorporating interaction effects between financial and behavioral indicators—further improves model efficiency and reduces error. This indicates that the two groups of variables do not operate independently; rather, their interweaving plays a fundamental role in shaping returns. In the final section, the neural network results show that AI-based approaches provide higher predictive accuracy, although their internal mechanisms are more difficult to interpret directly. Nevertheless, even these complex models deliver their best performance when they receive financial and behavioral data simultaneously. The overall comparison indicates that a hybrid framework—whether regression-based or machine-learning-based—is the most efficient approach for analyzing stock price behavior in the market under study, and reliance on financial information alone cannot provide a complete picture of reality.

4. Discussion and Conclusion

The empirical results of this study underscore the intertwined roles of financial fundamentals and behavioral dynamics in shaping future stock returns. The findings show that earnings quality—specifically earnings persistence, relevance, predictability, and accruals quality—significantly influences return predictability, confirming that firms with transparent, reliable, and stable earnings streams tend to generate higher subsequent returns. The analysis of interactive effects reveals that behavioral indicators, such as Relative Strength Index (RSI), Psychological Line (P-Line), and sentiment, not only exert direct effects on returns but also moderate the impact of fundamental variables. Specifically, under conditions of high investor optimism, the effect of earnings persistence on returns is magnified, while aggressive tax strategies and poor accruals quality are penalized more severely. The combination of dynamic panel modeling and machine-learning results (ANN and regression decision tree) affirms that models integrating behavioral indicators exhibit superior explanatory power (adjusted R^2 rising from 0.634 to 0.672) and predictive accuracy, demonstrating that psychological factors systematically condition how financial information is interpreted and priced. These results corroborate the proposition that investor rationality is bounded and context-dependent, aligning with contemporary behavioral-finance perspectives [17, 19].

The strong and positive influence of earnings persistence (EP) and earnings relevance (ER) on stock returns reinforces earlier findings that stable and value-relevant earnings reduce information asymmetry and enhance investor confidence. As reported in previous empirical work, high-quality earnings lead to more efficient price discovery and more accurate valuation [2-4]. Persistent earnings communicate credible information about future profitability, supporting rational investment decisions and lowering the cost of capital [6]. The moderating effects observed in this study—such as the positive EP × RSI and DPS × RSI interactions—indicate that behavioral optimism amplifies investors' responses to credible financial information. This supports behavioral-cognitive integration models where sentiment acts as an accelerator in bullish conditions but may attenuate rational assessments in bearish markets [19]. Furthermore, the results suggest that high-quality financial reporting, particularly when supported by prudent tax management, can anchor investor sentiment, tempering overreaction and herding tendencies observed in speculative phases [5, 9].

The decline in relative importance of traditional financial variables after incorporating behavioral indicators—averaging a 5.24% drop—indicates that sentiment-driven factors explain part of the variance previously attributed to fundamentals. In essence, investors' affective states mediate how they weigh accounting signals. This finding resonates with studies that document a transfer of explanatory power from pure financial ratios toward cognitive and emotional drivers once behavioral proxies are included in predictive models [17, 18]. Such a dynamic aligns with evidence that emotional intelligence, risk perception, and personality traits significantly affect investment intention and timing, thereby influencing return patterns beyond accounting-based valuation frameworks [19]. These findings substantiate that while financial information remains indispensable, its interpretative weight depends on investors' psychological states and market mood.

The stepwise regression and decision-tree analyses identify the Relative Strength Index (RSI) as the single most influential predictor, followed by earnings persistence and psychological-line indicators. This hierarchy underscores the convergence of technical-behavioral and accounting-fundamental perspectives. Consistent with prior studies, earnings persistence continues to serve as a robust anchor of valuation because it reflects management's ability to sustain performance and signal credibility [4, 9]. However, the study also confirms that dividend policy remains a critical bridge between accounting data and investor behavior. The positive interaction of dividend per share (DPS) with sentiment proxies highlights that investors interpret stable or increasing dividends as confirmation of managerial confidence and earnings reliability, especially in optimistic market climates [12, 13].

This finding resonates with dividend-signaling theories and empirical evidence demonstrating that consistent dividend payouts reduce information asymmetry and provide reassurance against earnings manipulation. In emerging markets, where investors may be more skeptical about accounting figures, dividends act as tangible proof of profitability, reinforcing the reliability of reported numbers [15]. The interplay between dividends and earnings quality in this study supports the argument that dividend stability strengthens the credibility of reported profits, helping investors differentiate between sustainable and transitory earnings streams [12, 13].

Tax behavior, another central dimension of this study, significantly interacts with both behavioral sentiment and reporting quality. The negative TAXAVO × RSI coefficient indicates that aggressive tax avoidance is penalized more heavily in bullish markets, as investors in optimistic states become more sensitive to ethical and sustainability cues. This finding aligns with prior evidence that prudent tax management and conformity between book and tax income enhance market valuation, while aggressive strategies are associated with risk discounts [16]. Similarly, empirical results from artificial intelligence-based modeling reveal that when manipulation intensity and tax aggressiveness are jointly low, market value and buy recommendations peak, confirming that investors reward conservative, transparent practices [1]. The incorporation of taxation behavior into the game-theoretic portfolio simulation adds an important governance dimension: firms combining high compliance and cautious tax strategies occupy the "win–win" quadrant with the highest purchase probabilities and Sharpe ratios.

The artificial neural network (ANN) and regression decision tree (RDT) results illustrate how behavioral inputs reshape predictive hierarchies. When only financial variables were considered, earnings persistence held 100% normalized importance, followed by relevance and dividend policy. After adding behavioral variables, RSI became the top determinant (100%), and the importance of EP declined by about 4%, consistent with evidence that sentiment signals often dominate short-term trading outcomes [21]. This structural shift mirrors broader findings that technical indicators—such as RSI, P-Line, and sentiment scores—are increasingly central in algorithmic trading systems operating under digitalized market environments. As financial markets become more data-driven and real-time, behavioral indicators serve as high-frequency proxies for collective mood, complementing the slower-moving fundamentals [22].

The ANN achieved an improvement of approximately 4.3% in predictive accuracy ($R^2 = 0.893$) after behavioral integration, confirming that hybrid models better capture nonlinearities in the decision process. This aligns with recent calls to blend econometric precision with machine-learning adaptability to model bounded rationality under market digitalization [21]. Decision trees further revealed that behavioral nodes occupy upper splits in the tree, suggesting that psychological variables shape the classification of rational versus irrational investor responses before financial fundamentals take effect. These findings converge with experimental and survey-based results showing that investors' prior mood and heuristic biases condition their processing of financial data, leading to asymmetric reactions to similar information [17, 19].

Moreover, the portfolio optimization grounded in game theory illustrates that integrating behavioral and quality-based filters yields portfolios with superior risk-adjusted performance (Sharpe ratio = 1.67). This confirms that rational decision frameworks, when enriched with behavioral dimensions, can produce more resilient investment strategies under uncertainty [23]. The application of payoff matrices to balance compliance (reporting quality) and taxation aggressiveness introduces a normative layer to quantitative portfolio construction, bridging financial optimization with governance ethics. This multidimensional approach resonates with recent findings that ethical and informational quality dimensions increasingly influence asset pricing and investor preference [18].

The convergence of the present results with multiple empirical traditions strengthens their interpretive robustness. The positive link between earnings quality and future returns is consistent with evidence from service, manufacturing, and banking industries showing that high-quality reporting reduces uncertainty and enhances performance outcomes [2, 5, 6]. Similarly, the moderating role of behavioral sentiment confirms psychological and behavioral-finance theories positing that investors' emotional and cognitive filters mediate financial decision-making [17, 19]. The decline in relative importance of accounting ratios after including behavioral proxies echoes the argument that behavioral biases and market mood absorb part of the informational variance traditionally attributed to accounting data [18].

At the same time, the results enrich efficient contracting theory by showing that governance-related variables—earnings persistence, conservatism, and tax compliance—retain predictive power even after accounting for sentiment effects. This hybrid interpretation suggests that rational and behavioral paradigms coexist: while high-quality reporting and cautious fiscal behavior underpin long-term valuation, investor psychology modulates short-term deviations from fundamental value [9, 10]. The superior predictive performance of the combined model over both traditional regression and single-layer AI models affirms the complementary nature of fundamental and behavioral data streams [21, 22].

The broader implication is that investor rationality, though bounded, can be statistically modeled and improved upon by integrating behavioral metrics with high-frequency data analytics. Such integration helps convert qualitative investor sentiment into quantifiable parameters usable in asset-pricing, portfolio management, and policy design. In effect, financial markets operate not as purely rational equilibria but as adaptive systems where information quality, psychological climate, and digital feedback loops continually reshape one another [1, 23].

Although the study incorporates advanced econometric and artificial intelligence techniques, several limitations warrant caution. The behavioral indicators (RSI, P-Line, sentiment) serve as aggregate proxies and may not fully capture heterogeneous investor psychology or context-specific emotional dynamics. Furthermore, the dataset, drawn from a single emerging market, limits the generalizability of the results to other institutional settings with different regulatory environments or investor compositions. The temporal scope, while extensive, might still overlook structural breaks or macroeconomic shocks that alter both reporting behavior and sentiment formation. Additionally, despite attempts to control for endogeneity, omitted variables such as governance quality, analyst coverage, or macro policy shocks could still bias coefficient estimates. Finally, while AI methods improved predictive accuracy, their interpretability remains a challenge; neural networks and decision trees provide variable importance but not causal inference, which may restrict theoretical insight.

Future research could extend this framework in several directions. Cross-country comparative studies should investigate whether the interaction between behavioral and financial variables holds under varying levels of market efficiency, investor sophistication, and disclosure enforcement. Incorporating textual sentiment derived from news analytics, social media, or corporate disclosures would provide a richer behavioral dataset. Additionally, exploring the role of environmental, social, and governance (ESG) disclosures as moderating variables could clarify whether ethical or sustainability signals complement or substitute for earnings quality in investor decision-making. Longitudinal designs might examine whether behavioral moderation effects are symmetric across bull and bear cycles or whether they intensify during crises. Finally, hybrid models integrating deep learning with explainable AI (XAI) could balance predictive performance with interpretability, enabling regulators and investors to better understand the drivers of rational and irrational pricing behavior.

For practitioners, the results highlight the importance of merging financial analysis with behavioral diagnostics. Portfolio managers and analysts should incorporate sentiment metrics and technical indicators alongside traditional accounting ratios to refine timing and risk assessments. Firms should maintain high-quality earnings reporting and adopt conservative tax strategies to reinforce credibility, particularly in volatile markets. Regulators may consider promoting disclosure transparency and investor education to mitigate sentiment-driven mispricing.

Ultimately, investors and policymakers alike can benefit from frameworks that recognize the dual influence of rational fundamentals and behavioral dynamics in shaping capital-market outcomes.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

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