Analyzing the Dimensions and Components of an Optimal Investment Model Based on Stock Return Predictors and Risk Factors of Disruptive Traders

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Received: 2024-10-11 **Reviewed:** 2024-11-16 **Revised:** 2024-12-03 **Accepted:** 2024-12-29 **Published:** 2025-06-25

Abstract

This study analyzes the dimensions and components of an optimal investment model based on parameters for predicting stock returns and the risk factors associated with disruptive traders. The research adopts an applied post-event survey approach. Initially, the study identifies stock return predictor variables, followed by an examination of disruptive traders' risk factors, which are determined using behavioral errors and beta differences in trading. Subsequently, the study tests its assumptions by applying a combined regression model, integrating the risk factors of disruptive traders and the predictor variables of stock returns. Principal Component Analysis (PCA), the Generalized Supremum Augmented Dickey-Fuller (GSADF) test, and the logit method are utilized to assess the influence of disruptive traders on bubble formation in the Tehran Stock Exchange. The findings indicate that disruptive traders have a positive and significant effect on bubble occurrence. Specifically, a one-unit increase in optimistic sentiment, coupled with market disruption, raises the likelihood of bubble formation.

Keywords: *Optimal Investment, Stock Returns, Risk Factors, Disruptive Traders*

How to cite this article:

Alizadeh M, Aghasi S, Dalvi Esfahani M. (2025). Analyzing the Dimensions and Components of an Optimal Investment Model Based on Stock Return Predictors and Risk Factors of Disruptive Traders. Management Strategies and Engineering Sciences, 7(2), 1-8.

1. Introduction

Disruptive traders are individuals and entities that base their investment decisions on market sentiment and trade assets using unrelated or irrelevant information. These traders typically exhibit poor market timing, follow prevailing trends, and overreact to positive or negative news. Financial market experiences have demonstrated that disruptive traders, by acting on non-informative signals, cause significant fluctuations and deviations in asset values from their intrinsic worth. Given that the healthcare sector is one of the most critical indicators of a nation's economy, ensuring adequate access to healthcare services contributes to societal growth and development and plays a crucial role in achieving healthcare objectives. Therefore, designing and implementing an efficient and effective information system is essential for realizing these goals. One of the major challenges that hinder access to accurate information and mislead participants in the healthcare market is the presence of disruptive traders. These traders act on non-informative signals, causing substantial fluctuations and deviations in asset values from their intrinsic worth. In other words, asset prices diverge from their fundamental value [1, 2], and over time, such price increases and deviations are met with reverse expectations, often leading to sudden price declines and financial crises.

The stock market is inherently volatile, and investors are often exposed to various risks stemming from market inefficiencies, noise traders, and economic uncertainty. Research has shown that disruptive traders—those who trade based on misinformation or irrational behavior—can contribute to market bubbles and distort price efficiency [1]. The Tehran Stock Exchange (TSE), like other emerging markets, is particularly susceptible to such disruptions, making it an ideal case for analyzing the effects of noise trading on investment strategies.

Stock return predictors have been extensively studied in the literature, with factors such as liquidity, investor sentiment, and economic policy uncertainty playing pivotal roles [3, 4]. Liquidity, in particular, has been identified as a key determinant of market efficiency and stock valuation, influencing both short-term and long-term investment decisions [5]. High liquidity levels are often associated with reduced transaction costs and increased price stability, whereas illiquid markets are more susceptible to price manipulation by disruptive traders [6].

The relationship between stock returns and market liquidity is well-documented. Studies suggest that liquidity not only drives stock market returns but also interacts with investor risk aversion, shaping market dynamics [5]. Moreover, the role of investor sentiment has been highlighted as a crucial predictor of stock returns, with research indicating that sentiment-driven investors may exacerbate market fluctuations [7]. The interplay between these factors necessitates a comprehensive investment model that accounts for both rational and irrational market behaviors.

Economic policy uncertainty (EPU) is another critical factor influencing stock market performance. EPU can lead to increased volatility and reduced market confidence, affecting investment strategies and corporate financial decisions [4]. In emerging markets such as Iran, where political and economic conditions are often unpredictable, the impact of EPU on stock liquidity and return predictability cannot be overlooked. Furthermore, the increasing reliance on machine learning techniques for stock price prediction has revolutionized investment strategies. Advanced algorithms now enable investors to analyze vast datasets and identify patterns that traditional models might overlook [8]. Such technological advancements provide new avenues for mitigating risks associated with disruptive trading activities.

Disruptive traders, often referred to as noise traders, engage in speculative activities that can distort market efficiency. These traders operate on misinformation, rumors, or irrational exuberance, leading to asset mispricing and increased volatility [1]. Research suggests that noise trading is a significant factor contributing to the formation of speculative bubbles in financial markets, particularly in emerging economies where regulatory frameworks may be less stringent.

The presence of disruptive traders necessitates the development of robust risk management strategies to protect investors from potential losses. One approach involves leveraging accounting information proxies to assess stock valuation and mitigate excessive risk-taking [9]. Accounting-based metrics, such as earnings response coefficients and financial ratios, can provide valuable insights into a firm's financial health and resilience against market disruptions [10].

The availability and quality of financial information play a crucial role in shaping investment decisions. A well-informed investor can make strategic decisions based on comprehensive data analysis, reducing the likelihood of succumbing to market noise and speculation [11]. The internal information environment quality within firms is particularly important for tax risk reduction and overall financial stability.

Studies have shown that both static and dynamic factors influence stock market performance, with information asymmetry playing a key role in determining market outcomes [12]. In an efficient market, all relevant information should be reflected in stock prices, allowing investors to make rational decisions based on fundamental and technical analysis. However, in practice, information asymmetry often leads to market inefficiencies, creating opportunities for arbitrage and speculative trading.

An optimal investment model should incorporate multiple dimensions, including liquidity measures, investor sentiment indicators, and economic policy uncertainty metrics. Such a model must be dynamic, adapting to changing market conditions and investor behavior. Incorporating machine learning techniques can enhance the predictive accuracy of the model, enabling investors to identify potential market trends and mitigate risks effectively [8].

Furthermore, an optimal investment strategy should consider the impact of inflation as a moderating variable on investment risk and return. Inflationary pressures can erode purchasing power and affect corporate profitability, making it a critical factor in portfolio management [6]. By integrating inflation-related data into the investment model, investors can make more informed decisions that account for macroeconomic trends. Empowering market participants and healthcare policymakers with accurate insights into these factors can enhance transparency and facilitate market efficiency. The present study aims to investigate the impact of risk factors associated with disruptive traders on the healthcare sector.

2. Methodology

The present study is applied in nature in terms of its purpose and quantitative in terms of its methodology. It aims to assess the impact of disruptive traders on the healthcare sector. The research process involves several analytical steps.

In the first step, an emotionally combined variable and index are derived to explain the behavior of disruptive and emotional traders. Following the approach of numerous studies in this field, the principal component analysis (PCA) method is employed. This method reduces variables in a correlated multivariate space into a set of uncorrelated components, each of which is a linear combination of the original variables. The resulting uncorrelated components are referred to as principal components, which are derived from the eigenvectors of the covariance or correlation matrix. Regression of observed variables on latent variables provides factor loadings, which serve as weights for the structural factor definition.

In the second step, the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model is used to model and extract fluctuations in control variables. This model is chosen because the time series fluctuations of these variables may not respond symmetrically to positive and negative shocks. An asymmetric model, such as EGARCH, is therefore appropriate for analyzing the oscillatory behavior of these variables. The conditional variances of the EGARCH (p, q) model are calculated using the following formula:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_j \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \sum_{i=1}^{p} \alpha_j \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + v_t$$

In the third step, the Generalized Supremum Augmented Dickey-Fuller (GSADF) test is applied to the healthcare sector to identify factors affecting the sector. The test is conducted using the *rtadf* plugin in EViews software. The GSADF test is advantageous as it simultaneously accounts for nonlinear dynamics and structural breaks in the factors influencing the healthcare sector within a time series. As illustrated in Figure 1, in this test, the starting point (r_2) is allowed to vary within the range (0, r2-r0), and GSADF statistics are calculated as follows:

$$\mathrm{GSADF}(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} \{ADF_{r_1}^{r_2}\}$$

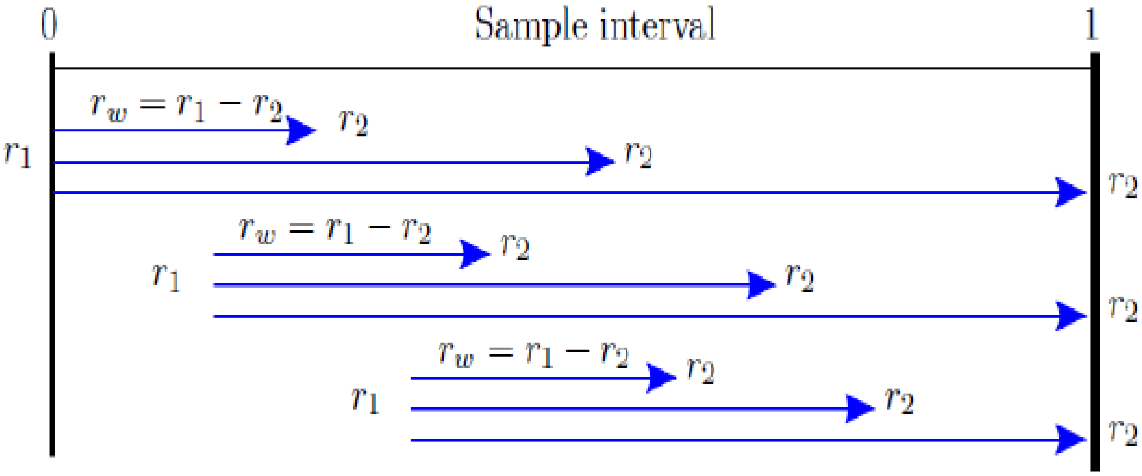

Figure 1: Description of the GSADF process

In the final step, the logistic regression (logit) model is employed to assess the influence of disruptive traders in the healthcare sector. The logit regression equation is formulated as follows:

$$\mathrm{Log}\left[{p_i}/{(1-p_i)}\right] = Z = \alpha + \sum_{i=1}^{k} b_i X_i$$

In this study, the dependent variable (z) represents the logarithm of the probability of health, while the independent variables (X_i) include control and emotional variables. Similar to the normal distribution function, the probability that y_i=1 is given by:

$$P(Y_i = 1 \mid X_i') = G(X_i'\beta) = \frac{1}{1+e^{-x_i'\beta}} = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}}$$

Conversely, the probability that y_i=0 is:

$$P(Y_i = 0|X_i) = 1 - P(Y_i = 1|X_i) = \frac{1}{1+e^{x_i\beta}}$$

Research Variables

1. Independent Variables

The independent variables include disruptive and emotional trading indicators:

A. Disruptive and Emotional Trading Indicators

Disruptive and emotional traders make decisions based on market sentiment rather than fundamental analysis. Therefore, an emotional index is used to capture their behavior. Emotional indicators reflect the sentiment of a group of traders and their optimism or pessimism regarding the current and future market conditions [13]. In this study, a composite emotional index is constructed using PCA, comprising several variables that represent emotional trading behavior. Seven variables were initially selected based on their prevalence in previous studies, data availability, and expert consultation. These variables are:

1. **Monthly volume of micro-transactions to the total stock market volume:** Smaller, less experienced investors are more prone to institutional investor influence. Micro-investors tend to trade based on sentiment-driven decisions.
2. **Monthly volume of online transactions to the total stock market volume:** During periods of high optimism, online trading volume increases, whereas during pessimistic phases, online trading volume declines. This variable was included following expert consultations.
3. **Monthly ratio of active trading accounts to total trading accounts:** Instead of newly opened accounts, which have been used in various studies

[14, 15], the number of active accounts (those with at least four transactions per month) was considered. This ratio indicates the market sentiment based on active participation.

4. **Average return of the first week of an initial public offering (IPO):** Baker and Wurgler (2006) identified this metric as a strong indicator of investor sentiment [16]. In Iran, due to regulatory price fluctuation limits, the first five trading days are considered.
5. **Monthly value ratio of inflows to investment funds relative to outflows:** Brown and Cliff (2004) suggest that investor movement between equity and fixed-income funds indicates their risk sentiment [17]. However, given the impact of monetary policies in Iran, only cash flows into stock investment funds are considered.
6. **Equity ratio in investment fund portfolios:** When market sentiment is high, fund managers allocate a higher proportion of their portfolios to stocks.
7. **Monthly volume of stock trading by institutional funds and portfolio companies to total market volume:** Institutional trading volume is used as a proxy for emotional trading tendencies among professional investors.

After conducting PCA, based on eigenvalues (percentage of variance explained by the first component) and factor loadings, three variables were retained in the final emotional index:

- Monthly volume of micro-transactions to total market volume (VS),
- Monthly volume of online transactions to total market volume (VO),
- Monthly volume of institutional trades to total market volume (VF).

2. Control Variables

The control variables in this study include inflation, Brent crude oil prices, gold prices (based on the old Freedom coin plan), liquidity, and exchange rates (USD to IRR). These variables are used both to control for fundamental economic influences on sentiment and to account for turbulence and uncertainty in the final model. Monthly data on inflation, liquidity, exchange rates, and gold prices were obtained from the Central Bank of Iran, while Brent crude oil prices were sourced from the U.S. Energy Information Administration.

3. Dependent Variable

The dependent variable in this study is a binary variable that represents health status in the pharmaceutical market. A value of zero indicates a lack of health, while a value of one indicates market health.

3. Findings and Results

The findings of the study are presented based on statistical analyses conducted through various methods, including principal component analysis (PCA), the EGARCH model, and logit regression.

Extraction of Emotional Composite Index

Using principal component analysis (PCA), a combined emotional orientation index was extracted. The first component was considered the primary indicator, with its selection based on the specific value (percentage of variance explained by the first component) and the operational load values (coefficients) of the variables. After an initial analysis, three variables were retained in the final model. These findings align with previous research indicating that emotional tendencies may be influenced by fundamental factors. To ensure the purification of emotional effects and eliminate fundamental factors, seasonal adjustments and an ARIMA model were applied.

Table 1. ARIMA Model Estimates for Emotional Trend Variables

Model & Variable	Coefficient	Standard Error	t-Statistic	Probability
VO - Online Trading Volume to Total Transactions				
C	-2.414	0.0669	-3.033	0.034
AR(1)	0.986	0.0124	43.301	0.000
MA(1)	-0.485	0.0195	-4.431	0.000
SIGMASQ	0.049	0.087	5.738	0.000
VS - Retail Trading Volume to Total Transactions				
C	-0.805	0.1549	-5.199	0.000
AR(1)	0.934	0.0676	15.0766	0.000
MA(1)	-0.603	0.1417	-4.262	0.001
SIGMASQ	0.042	0.061	6.925	0.000
VF - Trading Volume by Funds & Portfolio Companies to Total Market Transactions				

C	-4.161	0.118	-35.248	0.000
AR(1)	0.597	0.077	7.779	0.000
SIGMASQ	0.146	0.033	6.467	0.000

The total variance explained by the first component of the PCA model for the selected variables is provided in Table 2. The first component (PCA1) accounts for 71.37% of the total variance, indicating its strong explanatory power.

Table 2. Total Variance Explained by Common Components

Component	Eigenvalue	Percentage of Variance	Cumulative %
1	2.141	71.37%	71.37%
2	0.708	23.61%	94.98%
3	0.151	5.02%	100%

The estimated formula for the first component is:

SENTi=0.916·EVO+0.929·EVS+0.661·* EV

GSADF Test Results

The GSADF test was applied to examine explosive behavior in the market, and the results confirm the presence of explosive tendencies at all significance levels.

Table 3. GSADF Test Results

Variable	t-Statistic	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)
Health Index	3.689	1.606	1.089	0.847

The results indicate that the test statistic exceeds critical values at all levels, confirming the explosive behavior in the market and the influence of disruptive traders on market health.

Logit Regression Analysis

A logit regression model was employed to measure the effect of optimistic sentiment on market health. The results indicate that an increase in optimistic sentiment (OPTNEW) and its first lag (OPTNEW-1) have a positive and significant impact on market health at the 1% significance level. Additionally, liquidity and exchange rate fluctuations significantly increase market risk, while gold prices reduce the probability of market health.

Table 4. Logit Regression and Marginal Effects Analysis Results

Variable	Coefficient	Standard Error	t-Statistic	Probability	Marginal Effect
C	1.609	3.225	0.6177	0.000	0.000
OPTNEW	1.678	0.611	2.747	0.006	0.24
OPTNEW(-1)	1.955	0.588	3.326	0.009	0.28
LOG(GOLD)	-1.356	0.418	-3.244	0.012	-0.20
LOG(LIQ-1)	0.861	0.450	1.913	0.057	0.12
LOG(EXR-1)	0.655	0.352	1.861	0.063	0.10

The pseudo-R^2 value of 0.32 and the likelihood ratio (LR) statistic of 27.05 with a p-value of 0.000 confirm the significance of the model.

Summary of Findings

1. **Emotional Index:** The PCA model indicates that the first component explains 71.37% of the variance in the emotional index.
2. **Market Fluctuations:** The GSADF test provides strong evidence of explosive market behavior influenced by disruptive traders.
3. **Market Health Determinants:** Logit regression results show that optimistic sentiment significantly impacts market health. Liquidity and exchange rates increase market risk, whereas gold price fluctuations negatively impact market health.
4. **Marginal Effects:** A one-unit increase in optimistic sentiment raises the probability of market health by 24%, while gold price fluctuations reduce the likelihood by 20%.

These findings emphasize the critical role of emotional factors and external economic conditions in shaping market stability and highlight the need for targeted regulatory interventions to mitigate disruptive trading behaviors.

4. Discussion and Conclusion

This study aimed to examine the impact of disruptive traders on market dynamics using a quantitative research approach. To explain the behavior of disruptive traders, an emotional composite index was developed using the principal component analysis (PCA) method. Subsequently, the market health was assessed using the Generalized Supremum Augmented Dickey-Fuller (GSADF) test. Finally, the effect of disruptive traders on market health was evaluated through a regression model. In this model, turbulence and uncertainty associated with a series of competitor-related variables were incorporated as control variables.

The findings indicate that the effect of optimistic emotional orientation (Optnew) and its first lag [Optnew(-1)] on market health is statistically significant at the 1% probability level. These results align with the prior [18-20]. Additionally, an increase in liquidity and exchange rates is associated with a 12% and 10% increase, respectively, in market health risk. Conversely, rising gold prices reduce the likelihood of market health by 20%.

Based on the research findings and the significant impact of market health on emotional tendencies, it is recommended that policymakers implement various regulatory measures to mitigate the adverse effects of the widespread presence of sentiment-driven traders. Policy tools such as adjustments in market volatility limits, increased trading halts, and taxation policies should be considered. Furthermore, efforts to reduce emotional trading behavior in the market should include initiatives aimed at enhancing the financial literacy and market awareness of small-scale traders.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

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

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