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RESEARCH PAPER

Investigating The Asymmetric Relationship between Tehran Stock Market Return Cycles and Investor Sentiments Regime

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Abstract
Behavioral economics and financial literature suggest that there are two distinct types of stock market investors who conduct differently. A portion of these investors operate professionally and conduct fundamental analyses. A second type of investor is one whose investment decisions are influenced by conjecture and market sentiment. Therefore, it is essential to the evolution of the stock market to examine the behavior of the second category of investors. This research examines the asymmetric relationship between investor sentiment and market returns on the Tehran Stock Exchange. To achieve this, data from 2010Q1 to 2021Q4 are analyzed using a Markov switching method of vector autocorrelation. According to the findings of this study, the joint probability distribution function between the Tehran Stock Exchange market and investor sentiment has two regimes. Regime 0 (bull market with optimistic sentiments) and Regime 1 (bear market with pessimistic sentiments) are the two regimes. The study’s findings indicate that the increase in investor sentiment during a bull market has no significant effect on the increase in stock returns and that the stock market influences investor sentiment. This is the transaction’s trend-following (herd) behavior. This substantiates the elevated prices on the Iranian capital market. The results for regime 1 (bear market) indicate that stock market pessimism is causally related to causality. The stock market stagnates due to pessimism regarding the stock market.
Keywords: Bear Market, Bull Market, Investor Sentiment, Markov Switching Causality Model.
JEL Classification: C58, D81, G41.

1. Introduction
According to financial economic theories, capital market investors always conduct themselves rationally. According to a study by Baker et al. (1997), capital market investors evaluate economic and fundamental indicators to maximize profits and create wealth. However, according to behavioral economists, price deviations from fundamental values are the result of investors’ sentiments and positive or negative news. Merton (1980) was the first to

investigate the relationship between stock price changes over time and a variety of related factors. They questioned conventional asset pricing models because investor sentiment plays no role in determining asset prices. Mood, tone, and sentiment, according to Edelen et al. (2010), can influence the market in ways that do not reflect fundamentals or changes in the investment opportunity. Consequently, it makes sense for professionals to monitor their asset portfolios for any potential adjustments, even in the absence of fundamental information. Regardless of cash flow prospects or fundamental measures, investor sentiment can rapidly permeate the market and influence investors' risk aversion and portfolio selection. A recent study by Schmidt (2017) suggests that traders' preferences for a particular stock are frequently influenced by their desires, cognitive errors, and sentimental responses. This group of traders makes investment decisions based on their sentiments rather than on fundamental information, resulting in a consistent pattern of abnormal returns on financial investments. Friedman (1953) demonstrated that in competitive markets, fair competition results in equilibrium securities with fair prices that reflect only fundamental values. Lin et al. (2018) note that non-professional traders are removed from the markets using their rational counterparts through the process of arbitrage. Professional institutional investors who are deemed rational utilize less-skilled retail investors who are deemed noise traders as part of the removal process. According to Barrot et al. (2016), mispricing can be exploited by the trading run's increased liquidity, which is accompanied by cacophony. Therefore, the presence and influence of irrational speculators on the financial markets can at best be considered temporary. The process described above explains why traditional asset pricing frameworks do not account for the influence of sentiments. This demonstrates that rare pricing is a temporary phenomenon that arbitrageurs can rapidly and at minimal cost correct. As a rebuttal, Lin et al. (2018) assert that the process of exploiting mispricing does not always occur instantly. In other words, noise traders may participate in the market for an extended period. Following this argument, Toffler et al. (2017) discovered that incorrect pricing occurs during periods of elevated sentiments as the number of noise traders rises. This has resulted in a rise in market volatility and sentimental traders, causing equities to become more speculative. Due to herd behavior, noise merchants trade collectively based on their sentiments. Consequently, trading volumes rise sharply, leading to an increase in market volatility. Mispricing occurs in an environment where sentiment traders have become more prevalent. Similar to Toffler et al., Shen et al. (2017) assert that noise traders typically enter the market during periods of high sentiment. They suggest that the reason for this behavior of noise traders is that they interpret fundamental signals (fundamental information) through the lens of periods of extreme optimism. According to Xu and Chang (2015), when sentiment and expectations reverse, price bubbles collapse due to the liquidation of portfolios by sentiment traders. As a consequence of this process, financial markets become unstable. It is argued by Alfano et al. (2015) that sentiments affect not only noise traders but also informed investors and merchants. Moreover, DeVault et al. (2019) demonstrate that rational investors demand speculative equities during periods of elevated sentiment. According to a 1999 study by Nofsinger & Sias, institutional investors are more likely to receive positive feedback than individual investors, and the institutional herd has a greater impact on prices than the individual herd. Due to institutional investors' tendency to follow trends, there is little cross-trading with noise traders. The reversal of sentiment may result in prolonged extreme volatility in the financial markets. These behaviors are likely the result of the noise trader's risk and arbitrage limits.

The discussions reveal that there are two perspectives on the relationship between the stock market and the sentiments of investors. According to the first viewpoint, there is no relationship between the stock market and sentiments. According to the second viewpoint, investor sentiment significantly influences stock market returns. Therefore, the performance of the stock market can be predicted based on the sentiments of investors. The causality between the stock market and the sentiments of investors appears to be an aspect of the relationship between sentiments and the stock market that is not adequately explained. According to research, optimism is typically associated with prosperous periods on the stock market, whereas pessimism is typically associated with instability and stagnation. Consequently, it is uncertain which factor accounts for the other variable. The questions are: Does investor sentiment contribute to stock market growth? Does the prosperity of the stock market inspire investor optimism? It is necessary to conduct research in this regard. To clarify the relationship between the stock market and the sentiments of investors, it is necessary to calculate the probabilities of both variables together. Specifically, this study seeks to determine whether investor sentiments have asymmetric effects on the market; is it affected by market conditions? The most innovative aspect of this research is how this question is addressed. According to the reviewed studies, no endeavor has been made to differentiate between optimism and pessimism. There has been no consideration of the stock market's recession and growth conditions. In addition, linear indicators have been used to study the effects of sentiments on stock market returns. The current research uses the Hodrick-Prescott filter to isolate and detrend investors' sentiments. In addition, using Markov switching causality, we examined the relationship between investor sentiment and bull and bear market stock market returns. Other studies did not consider the conditions of the stock market in increasing sentiments and only considered the one-way nonlinear relationship between sentiments and stock market returns, whereas the present research focuses on the role of the stock market in creating sentiments. This study investigates the asymmetric bilateral relationship between the Tehran Stock Exchange and investor sentiment. This paper will then discuss a literature review on the subject, research methodology, analysis and experimental results, and conclusions.

2. Nonlinear Relationship between Investor Sentiment and Stock Market Returns

Investor sentiment has been examined from two distinct angles. According to the first theory, sentiments are a transient phenomenon due to the mechanism of market equilibrium and the presence of arbitrage. The second approach contends that noise traders expose the stock market to market risks due to the unpredictability of their trading decisions. As a consequence of the unpredictability of the trader's choices, sentiments can always influence the stock market. In addition to the question "Do sentiments play a significant role in stock market returns or not?", there is also the issue of how sentiments influence stock market returns. This question's answer is subject to divergent opinions. Brown & Cliff (2005) demonstrate that a rise in optimism can result in an exaggerated rise in market value. In difficult economic circumstances, investors' pessimistic beliefs may result in a decline in asset values. As a result of arbitrage restrictions and short-selling restrictions, behavioral models indicate that sentimental overpricing occurs more frequently than underpricing. Arbitrage, according to De Long et al. (1990), entails both fundamental risk and noise trader risk (sentimental traders). In the meantime, short-term selling restrictions eliminate negative market sentiment and permit a substantial price increase (Chang et al., 2007). According to Nagel (2005), the majority of high-level professional investors do not engage in short sales and are unable to trade at exceedingly high prices. When adverse investors reduce stock prices below fundamental values, only long-term institutional investors, such as the majority of mutual funds, can increase the value of underpriced stocks. Moreover, in times of crisis or a precipitous decline in stock prices, legislators frequently prohibit the sale of securities and impose stringent restrictions on short selling (Lamont, 2005). This prevents the market price from experiencing significant declines (Baker et al., 2007). The cited evidence suggests that the degree to which prices deviate from the fundamental price and, consequently, rectify the incorrect price, is greater during economic expansions than contractions. The average value of the sentiment index is lower at the time of economic expansion, but it is generally rising. During economic contractions, on the other hand, the sentiment index has a higher average value but generally falls (Baker and Wergler, 2006).

Consequently, investors are likely to receive a flurry of positive news indicating an improved economic outlook during prosperous times. Additionally, this may indicate a more optimistic outlook for future capital flows. In difficult circumstances, negative economic news or disappointing information about corporations may come public. Therefore, it is natural to observe a rise in investor sentiment during periods of economic expansion and vice versa.

3. Criteria for Measuring Investors' Sentiments

Because investor sentiment is not explicitly quantifiable, researchers have resorted to a variety of methods to estimate investor sentiment. The discount on limited investment funds is one of the most important and frequently employed sentiment indicators. Zweig (1973) uses a limited version of discount investment funds as an indicator of investor sentiment. Individual investors, in his opinion, are the primary traders of limited investment funds. Using weekly discount data from 24 hedge funds between 1966 and 1970, it was discovered that buy-sell signals derived from discount data could be used to generate trading strategies that produced superior returns on the Dow Jones Industrial Average. Lee et al. (1991) estimated an index based on 20 limited investment funds utilizing monthly discount data between July 1956 and December 1985. According to their findings, the returns of small businesses are more closely related to discount rates than those of large businesses. Qiu & Welch (2004) prefer survey information such as the Michigan Consumer Confidence Index, the Board of Directors' Consumer Confidence Index, and the UBS/GALLUP Investor Optimism Index. Brown & Cliff (2004) measured sentiment using American Association of Individual Investors survey data. Brown & Cliff (2004) utilized sentimental measures, such as the ARMS index, which represents the ratio of advancing to declining equities. Baker & Stein (2004) argue that market liquidity can be used as a measure of sentiment, and they employ turnover to support this claim. In conclusion, a variety of sentimental measures accurately reflect the volatile character of investors' sentiments. All of these metrics share certain characteristics in common. Initially, it is commonly believed that individual investors are more influenced by their sentiments than by their rationality. Second, the majority of these actions target the complete market rather than individual stock sentiment.

4. Trading Volume as an Indicator of Investors' Sentiments

Several models provide evidence that investor heterogeneity regarding the allocation or interpretation of information influences trading volume. Harris and Ravio (1993) investigate how public information can generate trading volume if it is interpreted differently by investors. According to them, both public and private information can be used to generate trading volume. If public knowledge prevails, a rise in trading volume should enhance market liquidity. When private information predominates, an increase in trading volume will diminish liquidity because private information creates information asymmetry between investors. According to Wang (1994), trading volume is comprised of two components: investors' risk appetite and speculative requirements. Using this model, there are two groups of investors: those with distinct information regarding the expected return of traded assets and those with identical information. Investors' risk demands are determined by the relationship between the expected return on traded assets and the return on non-traded assets. As a result of speculative demand, investors with more knowledge can make better choices. As superior information can result in information asymmetry among investors, the trading volume reflects their speculative demands, which can reduce liquidity. According to Ross (1989), the free arbitrage economy contains 37 predictive measures of asset prices, and the variance of price changes is proportional to the flow of information. Additionally, investor optimism may also contribute to a high volume of trading. According to Baker and Stein (2004), a high trading volume indicates that market participants are overconfident. It is also possible for investors with rational expectations of asset prices and those with distorted expectations to hold divergent views.

Trading volume is likely to reflect investor sentiment. Baker and Austin (2004) were the first to formally model their relationship. Second, existing theories suggest that investor sentiment is naturally related to trading volume. According to Baker and Austin (2004), there are rational investors and overly confident investors. There is a negative correlation between the price performance of the underlying stock and both types of investors, but overconfident investors are more influenced by the information they possess. There are restrictions on the market regarding short-selling and transacting with private information. In times of elevated investor sentiment, overconfident investors tend to react less to insider trading information and place a greater emphasis on pricing performance. Their transactions enhance the share price and diminish the effect of transaction prices. A high price effect results in a reduced return, whereas a low price effect attracts a greater trading volume.

Due to market restrictions on borrowing and selling, rational investors are unable to deal with overconfident investors' transactions. Moreover, when investor sentiment is extremely elevated, overconfident investors dominate the market, resulting in high liquidity and trading volumes. Consequently, a rise in trading volume indicates the participation of overconfident investors in the market and an improvement in investor sentiment. Existing theories suggest that investor sentiment and trading volume are closely related. As defined by Zweig

(1973), Lee et al. (1991), Baker and Stein (2004), and Brown and Cliff (2005), investor sentiment is the difference in valuation between a group of rational investors and a group of irrational investors. In other words, investor heterogeneity increases as investor sentiment rises. Alternately, the literature on volume suggests that investor heterogeneity contributes to trading volume (Karpov, 1986; Harris and Ravio, 1993). Therefore, it can be presumed that trading volume will increase/decrease when investor sentiment rises/falls.

Dai Wang (2018) examined the connection between investor sentiment and feedback trading in a study. This phenomenon is defined as a trading strategy consisting of purchasing when the market price falls and selling when the market price rises. According to the study, traders with positive feedback and relatively high sentiments trade more frequently. The stability of the American market is maintained by positive feedback transactions. Consequently, it displaces prices from their fundamental value and heightens volatility. Consequently, positive feedback trading tends to increase market volatility during periods of intense sentimental intensity when the number of positive feedback traders is high (Charteriz and Rupand, 2017).

Table 1. A Summary of Research Conducted on the Effects of Investor Sentiments on the Stock Market

Author	Methodology and the field of study	Results
Zawai et al. (2011)	Panel model using the logit method over the 1995-2009 period in European and American countries; The consumer confidence index is used as an indicator of investors' sentiments.	The sentiment of investors is a reliable indicator of the overvaluation of securities.
Zhang et al. (2010)	VAR(S) model; Chinese stock market from November 1997 to December 2007; The value of transactions is an indicator of sentiment.	The impact of sentiments on stock prices is positive, while their fluctuations have a negative effect.
Linchong et al. (2012)	Investigation of the causal relationship between sentiments and economic conditions using the VAR method and Granger causality; Analysis of the Markov Switching Method used to detect recessions and booms in the United States from January 1966 to December 2007; The consumer confidence index represents the sentiment index.	During periods of economic prosperity, the only explanation for stock market returns is sentiments. In the United States, economic recession is associated with stock market recession, and economic prosperity is associated with stock market prosperity. This observation is extended to the stock market.
Chen et al. (2013)	Panel threshold model, 11 Asian countries and from 1996 to 2010; Investor sentiment is reflected in the volume of trading.	If investor sentiment exceeds a certain threshold, stock returns will improve.
Uyghur and Tash (2014)	GHARCH, United States, Japan, Hong Kong, United Kingdom, France, Germany, and Turkey over the period 2000-2011; Trading volume is a proxy for investor sentiment.	Investor sentiment increases during periods of low sentiment, which reduces volatility, while it increases conditional volatility during periods of high sentiment. In other words, periods of intense sentiment impair the mean-variance relationship. Therefore, investor sentiments increase volatility and have a negative effect on returns when sentiments are high.
Ney et al. (2015)	Quantile panel method, Chinese stock market and the period 2005-2013; Baker and Wurgler's composite index measures sentiment.	Stocks with higher short-term returns are more susceptible to investor sentiment changes. However, it is detrimental for stocks with lower long-term returns. The reverse effect confirms the prevalence of an overreaction in the Chinese stock market. This is because when investors are optimistic about the stock's outlook, it will trade at a higher price.
Aydoghan (2017)	TGHARCH; The stock markets of America, England, France, Germany, Italy, Spain, Ireland, Greece and Turkey; Using consumer confidence data as a proxy for sentiment index.	Based on the results of this study, bad news (negative profit shocks) has a greater impact than good news (positive profit shocks). The findings reveal that high sentiments should weaken the mean-variance relationship. The results confirm that the increasing participation of sentiment traders in periods of high sentiment leads to a weakening of positive mean-variance trading and creates an anomaly.
Namori et al. (2018)	TGHARCH The stock market of the USA, England, France, Germany, Italy, Spain, Ireland, Greece, and Turkey; Using consumer confidence data as a proxy for sentiment index.	According to the findings of this study, bad news (negative profit shocks) has a greater impact than good news (positive profit shocks). The findings of this study reveal that high sentiments should weaken the mean-variance relationship. The results confirm that the increased participation of sentiment traders in periods of high sentiment leads to a weakening of positive mean-

Author	Methodology and the field of study	Results
		variance trading and creates an anomaly.
Namori et al. (2018)	Panel smooth transition regressive (PSTR); Period 1987-2014 G7 countries.	According to the findings of this study, the first regime is characterized by the dominance of fundamental principles in the stock market and the absence of sentimental influences on the stock price or return. The second regime is the regime in which there are investors' sentiments and this feeling increases stock returns. The third market regime is characterized by excessive sentimental dominance by investors. In this circumstance, as opposed to the second regime, this excessive optimism decreases efficiency.
Chakraborty and Subramaniam (2020)	Quantile causality, India; Over the 2012-2018 period; Monthly data format; A market-based measure (MMI) and a survey-based measure (CSI) have been used for investor sentiment.	Based on the results of this study, it appears that lower quantiles are associated with lower returns due to less sentiment. As a consequence of the lower sentiment, investors are increasingly inclined to sell out of fear. When it is abundant [0.60-0.80], it generates stock returns that indicate a positive market sentiment and higher returns. At much higher levels [0.80-0.95], it results in negative stock returns. This demonstrates that extreme optimism results in a decline in stock returns and a return to their actual rate.
Gang Hee et al. (2020)	OLS method and linear quantile Daily data in the period 2008-2014 of the Chinese stock market.	The OLS results are consistent with the linear quantile regression results. It is only found that there is a significant nonlinear relationship between pessimistic sentiment and stock return volatility, while the relationship between optimism and stock return is not significant.
Yildirim et al. (2021)	NARDL United States stock market in the period from 1985 to 2017 and the form of monthly data.	Short- and long-term investor sentiment and stock prices are positively correlated. Long-term, the diminution of investor sensitivity to macroeconomic fluctuations (optimism) has a greater positive impact on stock prices than a negative impact.
Wenzhao Wang (2021)	Fixed effects panel method, global evidence; In the period 2001-2015; The sentiment index is the consumer confidence index.	The results demonstrate that negative sentiment has a positive impact on the stock returns of developed markets. Moreover, negative sentiments have a negative effect on the stock returns of developing nations. In contrast, high sentiments in developed markets have negative effects, and the same is true for high sentiments in emergent markets, albeit with greater intensity.
Dahmene et al. (2021)	Panel smooth regression, developed countries; In the period 2010-2014 in the form of monthly data; The sentiment index is the consumer confidence index.	The results show that in all the studied countries, investors' sentiments have asymmetrically affected the returns of the stock market. This study shows that the effects of sentiment not only depend on the stock market cycle, but these effects differ from country to country.
Cevik et al. (2022)	Quantiles regression and PVAR METHOD- G-20 countries; weekly data from March 2020 to May 2021 - Google Search Volume Index for terms related to the coronavirus disease (COVID-19) and COVID-19 vaccine as a proxy for sentiment	An increase in positive investor sentiment leads to an increase in stock returns while negative investor sentiment decreases stock returns at lower quantiles. Also, negative sentiment increases volatility, whereas positive sentiment reduces volatility.

Author	Methodology and the field of study	Results
He (2022)	quantile regressions; The American Association of Individual Investors (AAII) sentiment is used as investor sentiment،	results show that the sentiment has a significant negative effect on the time-varying risk-return tradeoff across all quantiles. So a negative individual sentiment associated with bad news has a stronger impact than a positive individual sentiment associated with good news.
Gao and Zhao (2023)	two-layer network models; The sample ranges from June 4, 2019, to December 31, 2021 for China	Results indicate the relationship between investor sentiments and stock price jumps based on two-layer network models. They found that strong two-way spillover effects confirm investor sentiment and jump volatility among green industries.
Nadiri and Panahian (2024)	Var regression, The sample ranges from 2011 to 2019 monthly data for iran China	impulse response shows that the market participants who make rational decisions based on fundamental analysis and other relevant information have a greater influence on market movements than those who make decisions based on emotions or other non-fundamental factors.
Dadar et al. (2023)	Panel Smooth Transition Regression (PSTR) model, period of 15 Years (2005-2019) for the Tehran Stock market	The findings of this study indicate the importance of monitoring investor sentiment and avoiding overconfidence in one's investment decisions

Source: Research finding.

A review of studies conducted in this field indicates that the sentimental states of investors have asymmetric effects on the stock market. According to the majority of studies, negative sentiments are a significant cause of stock market stagnation. Positive sentiments, on the other hand, play a crucial role in generating prosperity in the stock market. Nevertheless, several studies indicate that investor sentiments only have a positive influence during economic expansion. During a stock market crisis, however, investor sentiment does not play the same role. In contrast, some studies indicate a negative relationship between investor sentiment and stock market returns. In addition to these results, a small number of studies have demonstrated that stock market prosperity enhances optimism. No study in the foreign literature simultaneously demonstrates the relationship between these two variables and differentiates market conditions from sentiments. This field has been studied from two distinct perspectives in foreign studies. Either the sentiment variable is divided into a number of phases and its effects on the stock market are studied, or the stock market cycle is identified and the general effects of sentiments (undifferentiated) on various market conditions are measured. This is the first study to distinguish between stock market cycles and various sentimental states, and then investigate the relationship between these variables. Furthermore, a review of relevant literature on Iran’s economy reveals that the majority of studies contemplate a linear relationship between sentiments and stock market returns. The separation of sentiments has received insufficient attention in these investigations. In addition, they did not mention the separation of stock market business cycles. This can result in an incorrect hypothesis and erroneous conclusions. This study aims to address the deficiencies of international and domestic research based on the issues mentioned. In addition, we intend to elucidate the connection between sentiments and the stock market.

To clarify the research innovations, our study is compared with three previous studies, demonstrating that our study enhances and complements them. The first study we differentiate from is Nadiri and Panahian's research titled "Rational and Irrational Sentiments of Investors and Stock Market Returns: Evidence from the Tehran Stock Exchange Market." While Nadiri's study employed a linear approach and the VAR method to investigate the relationship between investors' sentiments and stock market returns during a specific period, our study introduces significant nuances. We emphasize the pronounced negative impact of negative sentiments compared to positive ones on stock market returns. Another study we distinguish ourselves from is Dadar et al.'s research titled "Threshold Effect in the Relationship Between Investors' Inclinations and Stock Returns: A Soft Panel Regression Model." despite using a non-linear methodology, Dadar's study solely focused on sentiments' effects on the stock market. The categorization of regimes in their study was based solely on sentiments, with no attention given to the state and cycles of the stock market. In contrast, our study takes into account the well-established proxy in financial and behavioral economics studies—the consumer confidence index—which indicates that the state of the stock market significantly influences sentiments. This consideration is a key element in our research.

Our study demonstrates a deep understanding of the asymmetric impact of sentiments on the stock market during different bull and bear cycles, a dimension absent in other studies. In terms of methodology, our research is preferable to others. Dadar's study suggests that investor sentiments, upon crossing a threshold, lead to weakened returns. However, it overlooks the reciprocal relationship between stock market returns and investors' sentiments. In other words, just as sentiments affect stock market returns, stock market returns also influence investors' sentiments—a dynamic relationship not explored in Dadar's study.

Most studies underscore the existence of herd behavior in markets lacking proper investment knowledge and culture. Herd behavior primarily involves following market trends and paying attention to the impact of returns on increasing sentiments. Given the prevalent trend-following characteristics in the Iranian stock market and the propensity of Iranian investors to make uninformed decisions, disregarding the stock market's cycles in assessing sentiments is an oversight. The key distinction between our study and Dadar's study lies in our investigation of the two-way asymmetric dynamic relationship between these variables, while Dadar's study examined only a one-way asymmetric relationship. The third study we differentiate ourselves from is a 2022 research titled "Asymmetric Impacts of Individual Investor Sentiment on the Time-Varying Risk-Return Relationship in the Stock Market. This study, much like the previous two, has adopted a one-sided approach to sentiments within the capital market. Employing quantile regression, this study demonstrates that pessimistic sentiments exert a more significant negative influence than positive sentiments. In light of this hypothesis, our study aims to explore the influence of stock market returns on the generation of both pessimism and optimism among investors. The primary hypothesis of our study posits that investors' sentiments constitute a dependent variable influenced by the stock market—a factor hitherto unaddressed in any of the previous studies. None of the referenced studies investigate sentiments as a dependent variable influenced by the stock market, providing our research with an advantage in reflecting the presence of herd behavior in the Iranian stock market, a phenomenon associated with investors following market trends due to lower levels of knowledge and financial literacy.

5. Methodology

This study utilizes stock market return and trading volume (as a proxy for sentiment) as its two variables. To calculate the stock market return, the difference between the logarithm of the present index of the total market (TEPIX) and the interval of this index is considered. The method of Hodrick-Prescott's filter is used to differentiate between pessimistic and optimistic investor sentiments. Using this filter, the trading volume trend is examined and it is determined under what conditions investor sentiments dominate the stock market. The volume of trading has been computed using the Hodrick-Prescott filtering method and Eviews 12 software to isolate positive and negative impulses (positive and negative shocks).

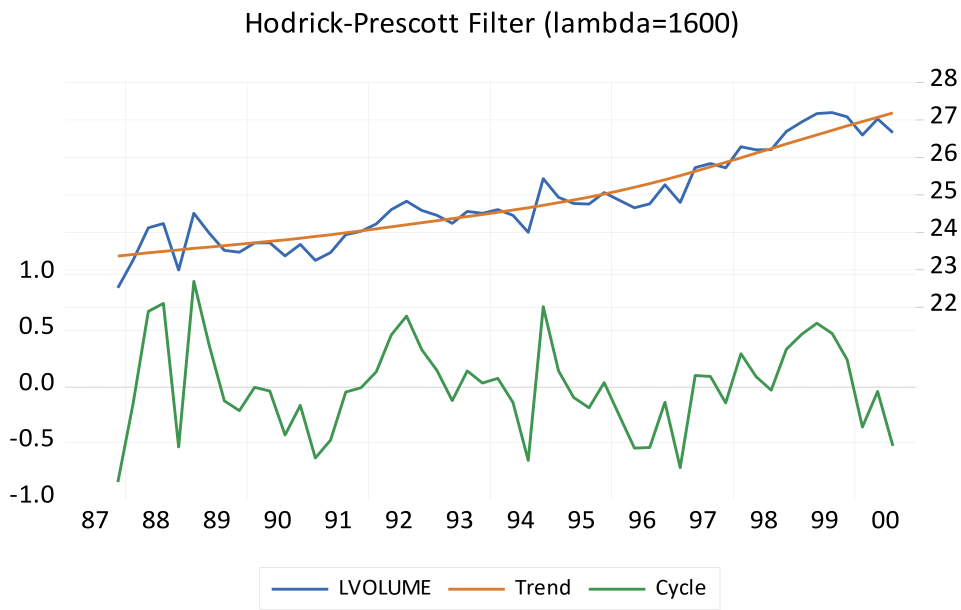

Figure 1. Separation of Investors' Sentiments from Trading Volume Trends Using Hodrick-Prescott's Method

Source: Research finding.

It was stated in the section on theoretical foundations that rational and irrational investors characterize the stock market. When investor sentiment improves, irrational investors enter the market, and the volume of trading increases and becomes more aggressive. Conversely, when sentiments decline, the number of investors declines, and only rational individuals are typically present on the market (there is a high likelihood that rational individuals will also abandon the market). According to the depicted diagram, the shocks of the logarithm of trading volume follow both positive and negative trends. It is conceivable to refer to these jolts as sentimental shifts. The Markov switching method is used to determine the relationship between investor sentiment and the shocks of the logarithm of trading volume.

6. MS-VAR Regression Model

By economic theory, the behavior of certain time series variables is nonlinear. In nonlinear models, the model's parameters are typically determined by the variables or by distinct regimes. Consequently, they will evolve. In nonlinear models, it is considered that the behavior of the variable being modeled differs and varies depending on the situation. Based on the rate at which it changes state, a nonlinear model can be divided into two main groups. There are nonlinear models (such as STAR models and artificial neural networks, ANNs) in which the shift from one state to another occurs gradually and gradually. The flexibility of this technique is an advantage. Using this method, a permanent change or several temporary changes are feasible. It is possible to repeatedly experience these alterations for a brief period. This model also autonomously determines the precise time of structural changes and malfunctions. The increasing use of these models in the economy (Fallahi, 2011) can be attributed to the ability of MS models to explain the behavior of economic variables, which frequently alter the status (regime).

In Markov switching models, the desired time series process is assumed to be a function of an unobservable random variable (S_t) known as the regime or state the desired time series process was in at time *t*. S_t is an integer random variable. The probability that a specific value of S_t equals j depends solely on the previous period's performance. In such a case:

$$P\{S_t= j|S_{t-1} = i, S_{t-2} = K,\dots S_{t-n} = n\}=p\{ S_t= j/ S_{t-1} = i \}=P_{ij} \qquad (1)$$

Such a process is a Markov chain with n regimes and P_{ij} as the probability of transition. Here, P_{ij} denotes the probability of shift from regime *i* to regime *j* (Hamilton, 1989).

$$P = \begin{bmatrix} P11 & P12 & Pn1 \\ P12 & P22 & Pn2 \\ P1n & P2n & Pnn \end{bmatrix} \qquad (2)$$

The element in the *i*th row and *j*th column of the matrix (P_{ij}) represents the likelihood of experiencing regime *j* following regime *i*. As an example, p12 in the second row and first column indicates the probability of switching from regime 1 to regime 2 (Hamilton, 1989). According to the principles of Markov switching, it is also possible to construct economic models as follows:

$$(rt|\varphi t\text{-}1) \sim \begin{cases} f(\theta t^{(1)}) & p1,t \\ f(\theta t^{(2)}) & (1\text{-}p1,t) \end{cases} \qquad (3)$$

One of the possible conditional distributions with a normal distribution is f(θ). $\emptyset t(i)$ represents the vector of parameters that define the distribution in the *i*th regime. The expression $p1$, t = Pr{st = $1|\varphi t-$ 1} represents the predicted probability. Here, $\varphi t{-}1$ represents the information at time $t{-}1$ (Zareei et al., 2022). The vector of time-varying parameters can be decomposed into three components:

$$\theta t^{(i)} = (\mu t^{(i)}, ht^{(i)}, vt^{(i)}) \quad (4)$$

where μt(i) ≡ E($rt|\varphi t{-}1$) is the conditional mean, $ht^{(i)}$ is the conditional variance, and $vt^{(i)}$ is the parameter of the conditional distribution. For the estimation of the Markov switching model, the model's state type must be specified. Depending on which of these equations is dependent on the state variable, the following general circumstances apply:

Table 2. General Markov Switching Models

Model	Equation	Error term distribution
Msm1(m)-ar(p)	$\Delta yt-\mu(St)=\sum_{i=1}^{p}\alpha t(\Delta y_{t-i}-\mu(S_{t-i}))+\varepsilon_t$	$\varepsilon_t \sim IID(0،\delta^2)$
Msm2(m)-ar(p)	$\Delta yt=c(St)+\sum_{i=1}^{p}\alpha t(\Delta y_{t-i})+\varepsilon_t$	$\varepsilon_t \sim IID(0،\delta^2)$
Msm3(m)-ar(p)	$\Delta yt=C+\sum_{i=1}^{p}\alpha t(\Delta y_{t-i})+\varepsilon_t$	$\varepsilon_t \sim IID(0،\delta^2)$
Msm4(m)-ar(p)	$\Delta yt=C+\sum_{i=1}^{p}\alpha t(S_t)(\Delta y_{t-i})+\varepsilon_t$	$\varepsilon_t \sim IID(0،\delta^2)$

Source: Hamilton, 1989.

By combining the first and second modes with the second and third modes, it is possible to create models with greater detail. In these models, it is feasible for the various equation components to depend on the regimes. Table 3 summarizes the various Markov switching model modes.

Table 3. Partial Models of Markov Switching

		MSM		MSI	
		μVariable	**μConstant**	**C Variable**	**Constant C**
Constant α1	Constant σ2	MSM-AR	Linear AR	MSI	Linear AR
	Variable σ2	MSMH-AR	MSH-AR	MSIH-AR	MSH-AR
Variable α1	Constant σ2	MSMA-AR	MSA-AR	MSIA-AR	MSA-AR
	Variable σ2	MSMAH-AR	MSH-AR	MSIH-AR	MSAH-AR

Source: Hamilton, 1989.

According to Luo et al. (2014), economic variables or price indices can be divided into two or more regimes using Markov switching, and each regime has a distinct average growth rate. The regime determines the time sequence of the autoregressive custom regression under the behavior of the series in the mean and variance.

$$y_t=u_{st}+\emptyset(L)(Y_{t-1}-u_{st-1})+u_t \quad , u_t\sim NID(0,\sigma^2_{st})$$
$$\emptyset(L)=\emptyset L+\emptyset_2 L^2+\ldots+\emptyset_q L^q \quad (5)$$

The interval operator L is determined using AIC and SBC criteria. Each of the growth regimes' potential growth rates and variances of fluctuations can be expressed as follows:

$$u_{st}=u_0(1-S_t)+u_1 S_t$$
$$\sigma_{st}=\sigma_0(1-S_t)+\sigma_1 S_t \qquad (6)$$
$$S_t=0 or 1$$

μ0 and μ represent two distinct regimes' prospective growth rates. σ0 and σ1 are the variances of fluctuations used to characterize the variation in each regime. Depending on whether the components of the MS-AR pattern are fixed or variable, the pattern can be defined differently. Utilizing diagnostic statistics, the definition is utilized to determine the optimal pattern. Krolzig (1997, 1998, and 1999) transformed Hamilton's original MS-AR model into the multivariate MS-VAR and MS-VEC models. An MS-VAR is used to analyze the characteristics of emerging and developing economies in light of the possibility of structural failures and changes in economic direction.

Krolzig (1998) investigated the generalization of the vector autoregressive model. In a generalization of the average-adjusted VAR (p) model, he described a Markov switching vector autoregressive model of finite-order p with regime M.

$$y_t - u_{st} = A_t(S_t)\big(y_{t-1} - u(S_{t-1})\big) + \cdots + A_P(S_t)\big(y_{t-p} - u(S_{t-p})\big) + e_t$$
$$e_t \sim NID\left(y, \sum S_t\right) \qquad (7)$$

$\mu(s_t), A_1(s_t), \ldots, A_p(s_t), \sum s_t$ are functions related to parameter transfer.

7. Experimental Results

Before approximating the model using the unit root test, it is crucial to verify the unit root of the variables. This test was conducted using the augmented Dickey-Fuller (ADF) unit root test. The results are summarized in Table 4.

Table 4. Augmented Dickey-Fuller Test (ADF)

Variable	t	p-value	Results
Stock market returns	-5.43	0.00	Stationary at the level
Logarithm of trading volume	-5.62	0.00	Stationary at the level

Source: Research finding.

The Markov switching model is then used to determine the optimal number of lags for the model's principal estimation. The outcomes are shown in the table below. In this table, Akaike's criterion indicates the number of one interruption, whereas Schwarz[1] and Henan's criterion[2] indicates the number of 0 optimal lags.

1. Schwarz information criterion
2. Hannan-Quinn information criterion (HQC)

Table 5. Determining the Number of Optimal Lags

Lags	LR	FPE	AIC	SC	HQ
0	NA	83.76	10.10	10.18*	10.13
1	10.46*	78.44*	10.03*	10.27	10.12*
2	3.81	84.90	10.11	10.50	10.26
3	5.21	88.55	10.15	10.70	10.36
4	1.44	101.30	10.28	10.98	10.55

Source: Research finding.

After analyzing the experimental results, it is necessary to determine the number of optimal regimes. Regarding this, the LR test is used to determine the number of optimal regimes in the Markov switching model. Notably, Krolzig (1997) asserts that the test of the combined Markov switching model cannot be conducted due to the presence of perturbing parameters. In this regard, the optimal number of regimes will be determined based on the researcher's knowledge of the variable conditions (Fallahi, 2013). Additionally, the Akaike criterion is used to determine the optimal model. The model with two regimes and two lags has the lowest Akaike criterion value. It is therefore estimated using two lags and two regimes.

Table 6. The Main Results of Estimation of Markov Switching VAR

	Estimation of stock market return equation		Estimation of investors' sentiment equation	
	Regime 0	Regime 1	Regime 0	Regime 1
Lag 1 stock returns	1.53928***	0.148717***	0.0153554***	0.00017644
Lag 2 stock returns	-0.316833	0.213990**	0.00257018	0.00441564
Lag 1 cycle of sentiments	-6.20154	-16.5056***	-0.283427	0.537156***
Lag 2 cycle of sentiments	0.497848	1.33964	-0.0099190	-0.0296891
Intercept	17.0106**	-1.85232	0.0704433	-0.220948***

Source: Research finding.

Note: *** The coefficients are significant at the statistical level of 0.00. ** The coefficients are significant at the statistical level of 0.05. * The coefficients are significant at the statistical level of 0.1.

To comprehend the key findings, it is necessary to define the properties of regimes 0 and 1. This will allow us to better comprehend the connection between investor sentiment and stock market returns. The intercepts of estimates allow for the specification of the characteristics of each regime. According to Hamilton, the width of a business cycle with a negative starting point implies stagnation, while a positive starting point indicates economic growth. In regime 0, the width from the origin is positive for both variables, while in regime 1, it is negative. Accordingly, regime 0 represents optimistic feelings affiliated with the stock market's prosperity. Regime 1 represents the pessimistic sentiments associated with the stock market's stagnation. According to research, this analysis remains true for Markov switching, but not for MS-VAR; therefore, it is preferable to calculate the average data of each dependent variable in each regime to determine the characteristics of each. Table 7 provides a comparison of the averages of each variable in each regime. Positive sentiments are associated with regime 0 of the stock market's prosperity. Regime 1 of a recession is associated with pessimistic sentiment.

Table 7. Calculation of the Average Stock Returns and Sentiments in Regimes 1 and 0

	Average stock market returns	Average investor sentiments
Regime 0	31.46179	0.283717
Regime 1	2.215876	-0.13781

Source: Research finding.

As a consequence of the stock market's return, the estimation indicates that investor sentiment increases in regime 0. In other words, in regime 0, the causality runs from the stock market returns to the sentiments of investors. The most important reason is that non-professionals tend to follow market trends, which intensify during prosperous times. As a result, the return of the stock market contributes to an improvement in investor sentiment. This result is consistent with the research conducted by Gang Hee et al. (2020), Jiashun et al. (2017), and Kardan et al. The cumulative coefficients indicate that in the regime 0 or bull regime, an increase in investor sentiment leads to a decline in stock returns (although the effect is not statistically significant). This result is consistent with the findings of Chakraborty & Subramaniam (2020) for the Indian stock market, Hela Namouri et al. (2018) for the stock markets of the G7 countries, and Brenna Aydogan (2017) for the stock markets of the United States, England, France, Germany, Italy, Spain, Ireland, Greece, and Turkey, who concluded that an increase in investor sentiments in a booming market results in the creation of anomalies and a decrease in stock returns.

The estimation of the coefficients, on the other hand, indicates that stock market returns have a significant effect on investor sentiment in regime 1. In regime 1, stock market returns are reduced due to investor sentiment. This result is consistent with the findings of Chakraborty and Subramaniam (2020), Ni et al. (2015), and Nikbakht et al. (2015), as well as Hemmati et al. (2020). Importantly, the joint probability distribution function of the two regimes demonstrates that optimistic sentiments are associated with bull markets, and pessimistic sentiments are associated with stagnant markets, which is consistent with the vast majority of domestic and foreign studies.

8. Post-Estimation Tests

A follow-up evaluation of the tests is required to guarantee the estimation's primary results. In this regard, the following table outlines the linear test against nonlinearity, the normality test, and the autocorrelation test.

Table 8. Results of the Tests after Estimating

Test	Test statistics	Probability value	Result
Linearity LR-test Chi-2	175.55	0.000	The null hypothesis of linear relationships between test variables is rejected.
Vector normality	2.3306	0.6752	The normality test is not rejected.
Vector ARCH 1-1	0.52690	0.7166	The absence of variance heterogeneity is accepted.
Vector portmanteau (12)	22.155	0.7741	The absence of autocorrelation is accepted.

Source: Research finding.

The results of the tests indicate that the principal estimate is accurate. The possibilities associated with the shift of regimes are evaluated in the following section. The results of the potential outcomes are presented in Table 9:

Table 9. Transfer Probability between Regimes

	Regime 0,t	Regime 1,t
Regime 0,t+1	0.36334	0.41397
Regime 1,t+1	0.63666	0.58603

Source: Research finding.

The results of the regime shift indicate that the probability of remaining in regime 0 is 0.36334%. Moreover, the likelihood of a shift from a zero to a recessionary regime is 63%. The probability of transitioning from Regime 1 to Regime 0 is estimated to be 0.41%. The probability of remaining in regime 1 is 0.58%.

According to the results of classifying the seasons into zero, one, and two regimes, the stock market spent the majority of the years in a recession. Alternatively, regime 1 dominated the market.

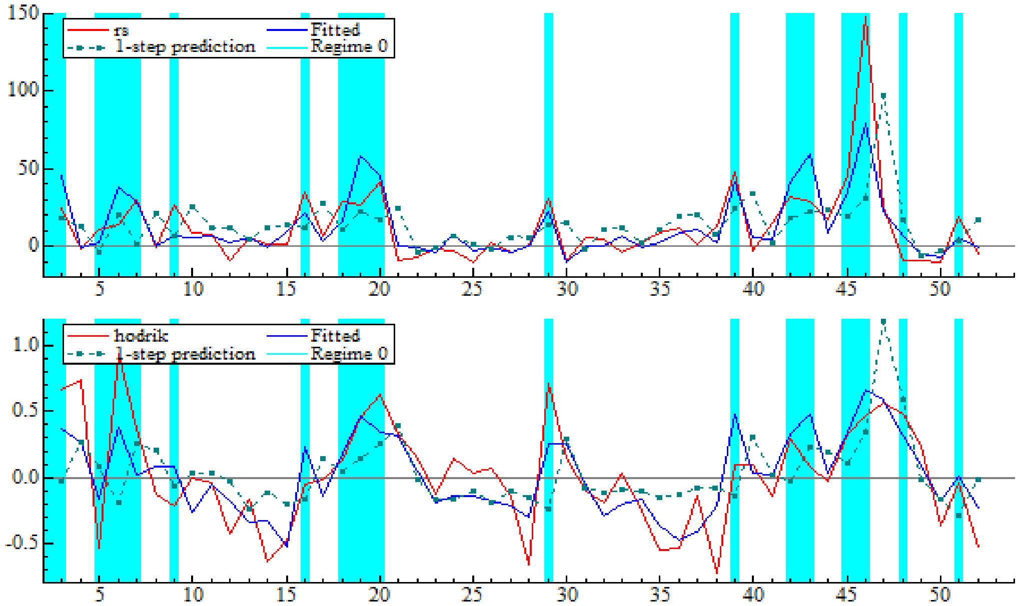

Figure 2. Regime Figures

Source: Research finding.

As shown in Figure 2, both performance and sentiment results are adequately explained. The red lines depict the statistical data of stock returns and investor sentiment, while the blue line depicts the estimated results. The red line is well explained by the blue line based on the estimates.

Regime 0 may be advantageous for the Iranian economy. A thriving stock market can facilitate the transmission of funds for the country's production. In addition, it has the potential to reduce inflation by accumulating liquid assets. Altering the market's direction from a prosperous period to a recession or bear market could have severe repercussions for the economy. According to Table 6 and Figure 2 for regime 0, whenever the stock market has a positive trend with a high rate of return and a positive trend in trading volume lags, policymakers should take action. To maintain positive returns on the stock market and to put the Tehran Stock Exchange more effectively at the disposal of Iran's economy, economists must implement policies to prevent the entrance of financially illiterate and sentimentally vulnerable individuals into financial matters. A finding such as this may be more beneficial to investors than to Iranian economic policymakers (and perhaps professional investors maximize profits by playing on investors' sentiments).

9. Conclusion

The capital markets of developed economies are highly efficient. This form of market is widely acknowledged as one of the most important economic drivers. In addition to providing financial assistance to manufacturing firms, this is advantageous for investors. The Iranian economy has always aimed for sustainable economic growth. Despite the increase in liquidity, it has always been difficult to provide production companies with liquidity. It has been argued for a long time that Iran’s economy lacks an efficient capital market. Several studies of foreign stock markets indicate that human and emotive behaviors play a significant role in the performance of the stock market. The optimism regarding the American housing market is one of the most significant recent events in the global economy that has captured the attention of economic scientists. This incident caused the 2008-2009 global recession. Several studies on the Iranian economy have utilized the same theory that emotive behaviors influence the economy and stock market. The majority of these studies have employed linear methods, and the asymmetric effects of investor sentiments have received little attention. This study seeks to fill a research void. In addition, the findings of this study apply to policy development. Literature and empirical studies on sentimental behavior and the stock market indicate that if investors are optimistic, stock returns will rise. If these sentiments are pessimistic, the stock market will be negatively impacted. Most studies investigating the effects of investors' sentiments on the stock market have considered two approaches. In the first approach, the linear relationship between investors' sentiments and stock market returns is considered. In the second one, the non-linear relationship between the stock market and investors' sentiments is investigated. In this approach, the return of the stock market is always a dependent variable and investors' feelings explain it. Meanwhile, according to the research literature, macro variables and the stock market can play a very important role in the changes in investors' sentiments. These cases show that there is a dynamic relationship between investors' sentiments and stock market returns.

In other words, as investors' sentiments play a significant role in explaining stock market returns, stock market business cycles can also be important in the changes in investors' sentiments and investors' sentimental cycles. These cases show that the mentioned methods in investigating investors' sentiments and stock market returns need to provide reinsurance that can determine the dynamics of the relationship between these two variables, and separate the cycles of sentiments (optimism and pessimism) and the stock market (bull and bear) to provide the results by reality. This study has used the new econometric approach of Markov Switching, which can solve the aforementioned gaps. The nonlinear MS-VAR method was utilized to test the hypothesis that the stock market is sensitive to variations in sentiment. To investigate the relationship between the two variables, trading volume lags were calculated as a proxy for investor sentiment using the Hodrick-Prescott filter method. The optimal interval for estimating the model was then determined using the Akaike information criterion. The MSIH(2)-VAR(2) model of estimation provides the same regime function of coefficients, variance, and width. The estimation results show that investor sentiment has a negative (nonsignificant) influence on stock market returns in regime 0. In contrast, the coefficients of stock return indicate that a rise in stock return is associated with a rise in investor optimism. Due to the significance of the yield coefficients and the nonsignificance of the sentiment coefficients, it can be concluded that economic prosperity boosts traders' optimism. Therefore, a causal relationship can be established between bullish sentiment and bullish markets. In regime 1, the bull market regime, sentiments have a negative effect on stock market returns. The stock market has stagnated due to investors' pessimism, and this effect is quite significant. In contrast, estimation results suggest that the stock market has little effect on sentiment in the first regime. This analysis demonstrates the causal relationship between pessimistic sentiments and the bear market.

This analysis indicates the causality of pessimistic sentiments towards the bear market. The results show that pessimism in Iran's economy has a strong negative impact on the Tehran Stock Exchange market. As a result, it seems necessary to create platforms to reduce their pessimism by educating investors and introducing them to fundamental analysis, and taking effective measures to make the stock market more efficient.

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