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Behavioral trading strategies and investor sentiment: Empirical research in Tehran Stock Exchange (TSE)

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In this study, we analyze contrarian and momentum strategies in periods associated with optimism or pessimism, and we compare them to the normal market sentiment condition. We evaluate the sentiment using the Arms adjusted index. Then, using the vector autoregressive test, we analyze the relationships among sentiment, stock returns, excess returns, and volatility. The results show that the formation of a short-term portfolio in one- and three-month periods of optimism and pessimism do not create additional returns and results in losses. In addition, the outcomes indicate that combining normal market sentiment with behavioral finance strategies increases performances, with more significant results seen using contrarian strategies compared to momentum strategies.

Keywords: *contrarian and momentum strategies; Arms index; optimism and pessimism sentiments*

JEL classification: G02

Introduction

Investment strategies based on behavioral finance theories are established regarding two contrasting hypotheses: over-reaction and under-reaction. Positive (negative) over-reaction leads to an unexpected dramatic over-valuation (under- valuation) in stock prices. De Bondt and Thaler (1985) show that loser portfolios, which have poor performance due to over-reactivity, have better performance using future winner portfolios. Previous studies have assessed the contrarian strategy's success due to over-reaction in global financial markets (Lakonishok, Shleifer, & Vishny, 1994; Mugwagwa, Ramiah, & Moosa, 2015). However, in the under-reaction hypothesis, all the available information on the stock price is not reflected when the market is inefficient; therefore, the disclosure of information is delayed as well as the pertaining effects. Jegadeesh and Titman (1993) challenge the hypothesis of market efficiency confirming low reactivity. The authors test the momentum strategy, buying a winner portfolio and selling a loser portfolio to display that the momentum strategy can yield a significant excess return. Other studies report that the momentum strategy is successful in various financial markets (Anusakumar, Ali, & Wooi, 2012; Griffin, Ji, & Martin, 2003; Herberger & Kohlert, 2015;

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Moskowitz & Grinblatt, 1999).

Recent studies in behavioral finance are theorizing the role of investors' sentiment on financial markets. Baker and Wurgler (2006, 2007) are attempted to create a sentiment composite index and test the effect of that on stock markets. They found that increasing the investors' sentiment lead to decreasing future return of stocks. In addition, Tetlock (2007) considered the influence of "media sentiment index" on financial markets, but could not explain the effect of that on volatility and asset price. According to the research, the influence of sentiment can be observed on compression, which caused by transactions' volume in pessimistic status. However, various types of research have been done in this field, but the relationship between investors' sentiment and performance of investing strategies are not explained clearly yet. The main question of this research is "What is the role of the investors' sentiment on the performance of winner and loser portfolio during the portfolio formation?" Antoniou, Doukas, and Subrahmanyam (2013) with the following of Hong and Stein (1999) argued that momentum relates to sentiment significantly. They found that loser portfolio in underpricing condition has better performance in pessimistic than on optimistic states and vice versa for the winner portfolio. Momentum phenomenon has significant influence in optimistic states. Their research shows that the momentum strategy is profitable in the months when sentiment is in the average level. The results indicate that decreasing the momentum profit happens just after an optimistic period, although Daniel, Hirshleifer, and Subrahmanyam (1998), evaluate the momentum profit without considering the sentiment in long term periods, conversely.

The major purpose of this research is to explain the role of sentiment in the development of trading strategies based on momentum and contrarian. We aim to test the profitability of momentum and contrarian strategies in different sentiment states. In this paper, a few our hypotheses based on empirical results of previous studies (Brown & Cliff, 2004; De Bondt & Thaler, 1985; Hachicha & Bouri, 2008; Hong & Stein, 1999; Jegadeesh & Titman, 1993; Mugwagwa et al., 2015; Wang, Keswani, & Taylor, 2006). Therefore, the research hypotheses are as follows:

Hypothesis 1: the relationship between the sentiment and stock returns, excess returns, and volatility are positive and significant.

Hypothesis 2: Winner portfolio in short-term and loser portfolio in long-term have positive and significant returns.

In addition, based on the results of some researchers (Antoniou et al., 2013; Christiana, Septiana, & Mamduch, 2016; Cooper, Gutierrez, & Hameed, 2004; Luxianto, 2010; Ma, 2014), the following hypothesis is assumed;

Hypothesis 3: Optimism (pessimism) sentiment in portfolio formation period has a significant and positive effect on the future return of winner (loser) portfolios.

Finally, based on our experiences in TSE the following hypothesis has been added.

Hypothesis 4: Normal sentiment in portfolio formation period has a positive and significant effect on the future return of winner (loser) portfolios.

We test portfolio formation strategies regarding the sentiment index as a factor affecting portfolio formation. We test these strategies after studying loser and winner portfolios in periods of optimism and pessimism compared to normal conditions. First, we create a measure to evaluate trading behaviors. By using the Arms (1989) trading behavior index and converting it to a 0 to 100 measure, we develop an application framework for optimism, pessimism, and normality. Based on this measure, we classify the states of the investors' sentiments into optimistic (over-purchase), pessimistic (over-sale), or normal behavior. Subsequently, considering momentum and contrarian strategies, we test their success in different behavioral situations using the OLS test.

The results show that pessimism and optimism, as well as momentum and contrarian investment strategies, not only do not yield positive returns, but they also often yield negative returns. We also find, in agreement with other studies (Qiu & Welch, 2004; Wang et al., 2006), stationarity in sentiment index. The stationarity sentiment in TSE challenges its market efficiency, like in other markets. Therefore, we illustrate optimism in the period of investigation. This study presents our results on the selection of momentum and contrarian strategies in different sentiment states, providing a decision-making framework and strategy measurement methods for the selection of an optimal market strategy. This study has a more close resemblance to Antoniou et al. (2013) findings, which indicates that exceed return of momentum can be achieved when the sentiments are in normal and optimistic status. However, momentum and contrarian strategies do not reach to exceed return in pessimistic status. Our results are useful and beneficial in contribution of strategies. A wide range of investors and portfolio manager can apply our trading strategies method, as it is conceptually easy to use, clearly defined, simply measured, and allows for a timely selection of the optimal portfolio strategy.

This paper proceeds as follows: in the next section, we describe some related studies on financial behavioral trading strategies, such as momentum and contrarian strategies. This section shows the role of sentiment indices in various financial markets. Then, the data pertaining to the results of behavioral portfolio strategies, optimism and pessimism sentiments, stock returns, and volatility are gathered and presented. After that, the basic grounds for the examinations and inferences are presented. Consequently, the results are explicated and conclusions are drawn.

Literature Review

A brief introduction to Tehran Stock Exchange (TSE)

We focus on Iran for the following reasons. Iran ranks 26th globally in terms of GDP.[1] As Foster and Kharazi (2008) point out, "Tehran Stock Exchange is still developing". They believe that Iran's large domestic market, strategic geographical location, and its large population of over 80 million people (up to dated), which makes making it second only to Turkey in the Middle East, are the main reasons that provided a suitable country for investment. Tehran Stock Exchange is an emerging market. The lifting of sanctions after the international agreement on the nuclear program of Iran reached in Vienna on 14 July 2015 caused a boost and provides investment opportunities in petrochemical, mining, and banking sectors of TSE. The average annualized return of the Tehran Stock Exchange Index was about 37% from 2008-2014. Companies are listed on the first and second board in TSE. The average free-float ratio and volume turnover ratio of the whole market are 19% and 22% respectively. 62% of stock's transactions are done by institutional investors[2]. Iran's population median of 27.8 years. After the renew government's privatization policies since 2008, Tehran Stock Exchange plays an important role in the economy. Some researchers have been done about the investors' sentiment in Iran. Fayyazi and Maharlouei (2015) and Mansouri, Tehrani, and Ansari (2012) found that stock returns are influenced by investors' sentiment. According to regional advantages and emerging market specifications from local and global aspects, sentiment has an important and useful role in the performance of momentum and contrarian strategies. Most of the phenomena in financial behavioral studies such as sentiment can be beneficial for the countries like Iran.

The role of sentiment in financial markets

The efficient market theory makes investors rational and does not consider the role of sentiment during the given time period, while it exists intuitively. The basic assumption of traditional portfolio selection models is that investors are not influenced by sentiments. Recent studies reject these assumptions, showing

[1] Retrieved from www.databank.worldbank.org
[2] Data is selected from Tehran stock exchange (see www.tse.ir)

that sentiments significantly affect stock returns (Baker & Wurgler, 2006, 2007; Barberis, Shleifer, & Vishny, 1998; Brown & Cliff, 2004; Neal & Wheatley, 1998; Wang et al., 2006; Yang & Copeland, 2014). Barberis et al. (1998) presents sentiment model using under- and over-reaction for an abstract model of investors' behavior. Arik (2011) measures individual investors' sentiments in 2010 and 2011, finding that 55% were optimistic in that period. Shefrin (2008) considers sentiments as being influenced by beliefs and priorities

The behavioral financial theory focuses on emotional traders instead of rational traders. Therefore, the sentiment of investors plays an important role in the markets. If investors' sentiments are disregarded, it can mislead them. The roles of sentiments in recent behavioral financial studies are investigated. We divide the results into four groups. The first group finds that if the positive sentiments increase the return of stocks will enhance. On the other hand, when the negative sentiments increase, the returns of stocks will decrease. In other words, the investor sentiment has a direct effect on stock return (Antoniou et al., 2013; Ma, 2014; Yang & Copeland, 2014). The second group believes that the investor sentiments play an inverse role in markets. Sentiments' enhancement will lead to a decrease of future stock return (Baker & Wurgler, 2007). The third group shows that not only sentiments do not affect on stock return and volatility but also it will be influenced by them (Barberis et al., 1998; Brown & Cliff, 2004; Hachicha & Bouri, 2008; Kaniel, Saar, & Titman, 2008; Wang et al., 2006).The fourth group, in contrast to all studies, Derrien and Kecskés (2009) demonstrate that investor sentiment does not seem to matter very much for aggregate equity issuance activity.

A study on the role of investor sentiment in the British stock market reveals that the bullish sentiment leads to excess returns, and, conversely, bearish behavior leads to a decrease in excess market returns (Yang & Copeland, 2014). At the first and second lag, there is no Granger causality between sentiments, a change in sentiments, or excess market returns; however, there is Granger causality between excess returns and sentiments in a lag of 6 and 12 months and a change in sentiments and excess stock returns. Antoniou et al. (2013) evaluate profitability of momentum strategies find that when sentiment is optimistic, the 6-month momentum strategy creates significant profits, equal to an average monthly return of 2.00% and, when investor sentiment is pessimistic, momentum profits decrease dramatically to an insignificant monthly average of 0.34 (Antoniou et al., 2013). Therefore, the momentum strategy during recession does not make a profit, and it has an inverse effect on declining markets. Momentum in a growth period has a significant and positive profitability (approximately 2% on average), but it has an inverse effect on declining markets (Antoniou et al., 2013).

Baker and Wurgler (2007) show that when the market sentiment is high, the market return is low. In optimistic markets, the monthly average return is about -0.41%. When the market sentiment is very low, the average return is about 2.75%. Using the portfolio weight index, high sentiments yield an average return of about 0.34% while the return of low sentiments is 1.18%. This difference is explained by the equal stock's weight in small companies. Baker, Wurgler, and Yuan (2012) show that optimism correlates with lower future stock returns. The authors also conclude that markets in Canada, France, Germany, Japan, the United Kingdom, and the United States respect the statistical and economical return forecast for market efficiency. Schmeling (2009) finds a correlation between Granger causality[3], consumer sentiment, and stock returns. He shows that sentiment affects return and return affects sentiment. The author's conclusions, in agreement with Baker and Wurgler (2007), indicate that optimism tends to reduce future returns. Feldman (2010) explicates how to utilize sentiment indices to find bubbles and financial crises in financial markets. The bearish sentiment

[3] Granger causality is a statistical concept of causality based on a prediction. According to Granger causality, if a signal A1 Granger causes a signal A2, then past values of A1 should contain information that helps predict A2 above and beyond the information contained in past values of A2 alone (Granger, 1969).

might not be as strong as the investor's gaining profit. Shu and Chang (2015) explain that the extreme optimism of hopeful investors is the underlying reason for over-valuation of the stock; consequently, upon disappearance of the positive sentiment, the bubble disappears and stock prices decline dramatically. Supporting the significance of sentiment studies as learning behavior errors creates opportunities for excess returns. Their results show that there is a strong correlation between a shift in the investors' sentiment at the individual level and newspapers, while there are no significant changes at the market macro-level. Further, Fisher and Statman (2000) report a negative relationship between investors' sentiments and future stock returns. Waggle and Agrrawal (2015) illustrate that low (high) returns are usually the result of high (low) levels of extreme positive sentiment, illustrating the contrarian effect of sentiment.

Brown and Cliff (2005) show, using a sentiment direct measurement measure, a positive and significant relationship between sentiment and the over-valuation of assets during a period of optimism. Between 1962 and 2000, the sentiment index had a positive skewness to the right. In the first group, the samples have positive skewness to the right (0.428), and the samples in the second group have a negative skewness (-0.171). They use the B coefficient as a sentiment index with long-term negative returns, showing high arbitrage restrictions in advanced markets. In the same study, the sentiment index distribution is normal. Therefore, when investors are optimistic, market values are higher than the intrinsic values. Wang et al. (2006) show that there is little evidence that sentiments affect returns. The ARMS index has a two-way Granger causality relationship with price volatility. Wang et al. (2006) find that the Arms index can predict volatility, but it is a poor tool to forecast returns. Their results show that the criteria of sentiments are usable as causal variables. The results are consistent with those of Brown and Cliff (2004), which show that return is affected by sentiments. Hachicha and Bouri (2008) find that Granger sentiments cause efficiency in Tunisia, but the authors describe sentiments as an unstable phenomenon, as their results were positive in terms of field of activity, size, and the ratio of B/M but negative for stock liquidity. The authors also show that Granger sentiments cause instability. Their study contradicts the results obtained by (Barberis, Shleifer, & Wurgler, 2005), who suggest that sentiments cause volatility and increasingly help predict volatility. Kaniel et al. (2008) conclude that volatility is a temporary and normal phenomenon

Derrien and Kecskés (2009) demonstrate that the proxies for sentiment explain roughly 10 percentage points of the time-series variation of equity issuance beyond the roughly 40% explained by fundamentals. They conclude that investor sentiment does not seem to matter very much for aggregate equity issuance activity. Berger and Turtle (2012) studied the association between transparency and sentiments in stock companies, finding that the stock performance of transparent companies, unlike opaque ones, has a loose association with the sentiment.

The sentiment indices

What are investors' sentiments? Various definitions exist about sentiments. Practically, it can be defined as an individual feeling which is excessively optimistic or pessimistic about a situation. Empirical studies often disagree on investors' sentiment measure. Previous researchers have used two types of sentiment measurements thus far. The first type is the direct measure in the form of attitude questionnaires. The second group consists of indices that aim to quantitatively measure investors' or the market's sentiment. These indicators measure market behavior using the quantitative financial models of the investors. Baker and Wurgler (2006) provide a sentiment-measuring model that examines the effect of investors' sentiments on stock return's cross-sectional data. They conducted their study using several financial parameters and show how sentiments are associated with the stock returns of companies that are small and young with high volatility and critical, unpredictable profit but no financial experience or stock growth. Tetlock (2007) investigates the interactions between media content and stock market activity. He constructs a simple measure of media sentiment index and finds that the low market returns lead to high media pessimism.

Arms (1989) was among the first to measure trade behavior with a forecast index to predict short-term directions. Some researcher use Arms Index to predict the return and volatility of stock markets (Blair, Poon, & Taylor, 2001; Christensen & Prabhala, 1998; Fleming, 1998; Poon & Granger, 2003). Because of this fact that Arms index is a market broad technical indicator and be represented in bullish and bearish condition, traders use it as a sentiment index (Brown & Cliff, 2005; Hachicha & Bouri, 2008; Wang et al., 2006). Arms index is calculated by dividing two ratios. The first ratio is the result of dividing the transaction volume of the shares with a price increase and the transaction volume of the shares with a price decrease. The second ratio is the result of the number of shares with a price increase and the number of shares with a price decrease. Then, the outcomes of these two ratios are divided. If the result is lower than 1, the trading volume in rising shares is higher than the falling shares, which means the stock's market prices increase significantly. If the result is higher than 1, the falling shares are higher than the rising shares, and the market is likely to decline. The index decreases while the order pressure increases in optimistic status. It will be increased by descending the order pressure during the pessimistic status.

Behavioral portfolio strategies

Prior studies have demonstrated the profitability of behavioral finance strategies under up and down market states (Christiana et al., 2016; Cooper et al., 2004; Daniel et al., 1998; De Chassart & Firer, 2001; Hong & Stein, 1999; Luxianto, 2010; Ma, 2014), optimism and pessimism (Brown & Cliff, 2004) and market dynamics (Asem & Tian, 2011; Galariotis, Holmes, Kallinterakis, & Ma, 2014; Lin, Ko, Feng, & Yang, 2016). Daniel et al. (1998) report that the formation of a momentum portfolio in the up- market state and its sales in the down market state are profitable. Hong and Stein (1999) state that the profitability of the momentum strategies is realized during the transition of the market state from up to up since wealth creation increases when risk aversion decreases in the market. Cooper et al. (2004), hereafter CGH, and Lin et al. (2016) prove the foregoing hypothesis to be true in other markets. According to CGH, The average monthly momentum profit following positive market returns is 0.93%, whereas the average profit following negative market returns is −0.37%. Galariotis et al. (2014) state that their findings do not have any significant impact on the performance of momentum portfolios predicted by CGH. They further elaborate that "splitting up and down market does not add significant explanatory power to that obtained by CGH approach." Luxianto (2010) has tested momentum and contrarian strategies in bearish and bullish conditions of the Indonesian capital market. He found that when the market is bearish, the momentum strategy is ineffective, though the strategy is effective in the bullish state. This result shows that in bearish market conditions, the contrarian strategy is more effective. Chung, Hung, and Yeh (2012) examine sentiments in expansion and recession states, concluding that there is a relationship between economic states and sentiments. In the economic expansion state, sentiment has the ability to predict the economic situation, though it could not predict it in a recession. Ma (2014) evaluates the performance of market winners and losers by evaluating up and down phases. He provides a model for strategy momentum and market conditions. The author indicates that under both the up-up phase and the down-down phase, winners have positive returns and losers have negative or zero returns; therefore, the contrarian strategy is inappropriate. Under the up-down phase, both the losers' and winners' returns are negative, while in down-up phases, both losers and winners have positive returns.

Anusakumar et al. (2012) show that in 13 Asian countries between 2000 and 2011, the winner portfolio and momentum strategy created positive returns for all patterns. Nine out of thirteen countries in Asia showed a statistically significant difference. The same study showed that the loser portfolio had positive returns only in six countries. Bangladesh with 1.9%, South Korea with 1.13%, and Hong Kong with 1% had the maximum performance of the momentum strategy. Have reviewed the use of momentum and contrarian strategies in the Tehran Stock Exchange (TSE) from 1997 to 2000, and evidence for the short-term market anomaly has not been found. They found no evidence for the use of contrarian strategies; however, the 3–12 month period using the momentum strategy were higher than previous periods. Moreover, they show that the TSE is a developing market with the potential to attract foreign investments in the post-sanction era.

De Bondt and Thaler (1985) show that loser stocks in the past 3 to 5 years outperform winners by 25% over the next 3 years. By a direct extension this view, the author's suggesting that contrarian strategies and show that the loser portfolios over the past 3 to 5 years outperform winner portfolios in the next 3 years. Jegadeesh and Titman (1993) show that winner portfolio over the past 6 months outperforms losers by 1% per month during the next six to twelve months. They construct overlapping portfolios, find that evidence of significant return reversals in the 4 to 5 years after the portfolio formation date. The phenomenon of price contrarian is documented in several studies (Lakonishok et al., 1994; Mugwagwa et al., 2015). Several empirical studies document that momentum strategy is proper for short horizon (3-12 months), but contrarian strategy will be efficient for long horizon. Furthermore, some behavioral theories suggest that reversals occur due to investors' behavioral biases in forecasting stock characteristic and future growth (Barberis et al., 1998; Daniel et al., 1998; De Bondt & Thaler, 1985; Hong & Stein, 1999), compensation for risk and reflect investors' rational response to a delay in the taxes payment when making their portfolio decision.

Research Methods

Data

The statistical population consists of all the companies listed on the TSE in Iran, and the samples are collected from the most liquid stock companies[4] (N = 77) in various industries between April 2008 and March 2014.[5] First of all, capital gain and dividends of individual stocks each month is calculated. The annual standard deviation is used as the volatility for each stock. Following Jegadeesh and Titman (1993) method of constructing winner and loser portfolios, we select portfolios by sorting stocks with the highest returns to the lowest, classifying the top 20% (16 of the top shares in a formation period of one to three months) and bottom 20% (16 of the bottom shares in a formation period of one to three months) of stocks as winner and loser portfolios, respectively. Following Baker and Wurgler (2006) method, we define stocks with greater annual standard deviations during the previous year as high-risk stocks and those with smaller annual standard deviations during the previous year as low-risk stocks. Then, we order the shares from the highest to the lowest volatility, classifying the first half as high risk and the bottom half as low risk in accordance with Baker and Wurgler (2006) approach. Finally, portfolio rate of return, being an equally weighted average of individual stocks of the portfolio, is obtained. The excess rate of return is calculated by subtracting the monthly portfolio rate of return from the monthly risk-free rate of return[6]. The portfolio is to be formed in a 1- and 3-month periods and evaluated after 1-, 3-, 6-, and 12-month periods in a rolling form method, which will be repeated 72 times over a period of 6 years and evaluated 1, 3, 6, and 12 months after formation of each portfolio. The costs of trading and short selling are not included in this research. We use the Arms trading in-

[4] Trading cessation and low Turnover ratio is common in TSE. Portfolio formation is rollover and repetitive monthly. From the sample rule selection, a stock will be selected if it trades in 150 days of average 250 trading days.

[5] Farvardin 1387 and Esfand 1392 (Iranian calendar)

[6] Rate of free-risk return is calculated with respect to maximum of governmental bond rate and short term deposit rate. In this research, the average value for rate of free-risk return is considered to be 2.1%, and the average inflation rate is considered to be 1.9%.

dex (ARMS) to measure the sentiment proxies. In emerging markets such as those in Iran, many indices are based on financial tools, like the fear index, the put-call ratio (PCR), and Baker's index, and are not available or not applicable for use. Therefore, models based on these tools are not used to gauge sentiments. We calculate the Arms sentiment index as follows:

$$AD_t = \frac{ADV_t}{DEC_t} \quad (1)$$

$$VOLU_t = \frac{ADVOL_t}{DECVOL_t} \quad (2)$$

$$ARMS_t = \frac{AD_t}{VOLU_t} \quad (3)$$

where ADV_t is the number of companies with a price increase over the period of the study t and DEC_t is the number of companies with a price decrease over the same period. AD_t is then the ratio between ADV_t and DEC_t. In addition, $ADVOL_t$ is the trading volume of companies with a price increase over the period of the study t, while $DEVCOL_t$ is the trading volume of companies with a price decrease over the same period. $ARMS_t$ is then the ratio between $ADVOL_t$ and $DEVCOL_t$. The Arms sentiment index is obtained by dividing AD_t by $VOLU_t$. We use the Wilder Jr (1986) adjustment to normalize the Arms index, obtaining 0 as the lower limit and 100 as the upper limit. This normalization allows for a clear representation of the sentiments and for a more concise formula, which is presented in Equation 4.

$$ARMS_t \text{ adj} = 100 - \frac{100}{1 + ARMS_t} \quad (4)$$

We classify the investors' sentiment conditions as optimistic (over-bought), pessimistic (over-sold), or normal. "Over-sold" is the condition under which the asset price decreases and falls lower than the fundamentalists' price (Brown & Cliff, 2004). This condition referred to as pessimism in our study, and it is usually caused by the over-reactivity of investors who sell undervalued stocks. For this study, we define over-sale reaction as the situation in which the market-adjusted sentiment index score is higher than 60. "Over-bought" is the condition in which one or more asset prices increase sharply to surpass the real value of the transaction. This generally occurs with low reactivity and expensive asset purchases. This situation is referred to as unrealistic optimism in psychology, and it results in a dramatic increase in stock prices. In our study, we define market-adjusted sentiment index scores lower than 40 as excessive purchase reactions and sales opportunities[7].

Methods

We commence by examining the bilateral relationship between sentiment (SENT), stock returns (RET), excess returns (ER), and volatility (VOL) based on the Granger causality test and using the VAR model in order to evaluate the effectiveness of behavioral models in developing investment strategies.[8] The Granger causality test is based on the assumption that the prediction of variables, such as SENT and VOL, exclusively relies on the time-series data related to the variables. First, we test the unit root hypothesis using the ADF unit root test and prepare results for the two models, i.e., the model with the constant state and the model with both the constant state and the trend. after that, for determining the optimal lag(s) in the VAR model we make use of Akaike information, Schwarz information, Hannan–Quinn information, and the likelihood ratio criteria. We select 1 lag for all variables except for the excess return, which is 0. To predict the variables, we specify the following VAR model:

$$\begin{aligned} RET_t &= a_0 + \sum_{k=1}^{1} \beta_{11l} RET_{t-k} + \sum_{k=1}^{1} \beta_{21l} SEN_{t-k} + \epsilon_{1t} \\ SEN_t &= a_0 + \sum_{k=1}^{1} \beta_{12l} RET_{t-k} + \sum_{k=1}^{1} \beta_{22l} SEN_{t-k} + \epsilon_{2t} \end{aligned} \quad (5)$$

[7] Arms adjusted index is measured on a daily basis. For instance, any day for which index is below 40 is considered as optimistic, and any day for which index exceeds 60 is considered as a pessimistic one. Then, overall count of optimistic days within a month yields the optimism percentage.

[8] We followed (Anusakumar et al., 2012; Baker et al., 2012; Brown & Cliff, 2004) in testing the assumption that market sentiment causes returns, excess returns, and volatility using the VAR model.

$$\begin{aligned} ER_t &= a_0+\sum_{k=1}^{l}\beta_{11l}ER_{t-k}+\sum_{k=1}^{l}\beta_{21l}SEN_{t-k}+\epsilon_{1t} \\ SEN_t &= a_0+\sum_{k=1}^{l}\beta_{12l}ER_{t-k}+\sum_{k=1}^{l}\beta_{22l}SEN_{t-k}+\epsilon_{2t} \end{aligned} \quad (6)$$

$$\begin{aligned} VOL_t &= a_0+\sum_{k=1}^{l}\beta_{11l}VOL_{t-k}+\sum_{k=1}^{l}\beta_{21l}SEN_{t-k}+\epsilon_{1t} \\ SEN_t &= a_0+\sum_{k=1}^{l}\beta_{12l}VOL_{t-k}+\sum_{k=1}^{l}\beta_{22l}SEN_{t-k}+\epsilon_{2t} \end{aligned} \quad (7)$$

where l is the optimal lag, t is the time, β_1 and β_2 are the vector regression coefficients, and ϵ_{1t} and ϵ_{2t} are unexplained errors. In this study, we investigate whether momentum or contrarian strategies are more suitable in conditions of optimism and pessimism compared to normal conditions. We specify the following models to test the effects of sentiments on behavioral portfolio strategies and on the performance of these strategies:

$$RET_i = ai_0+\beta_1 RET_{i0}+\beta_2 OP_i+ \beta_3 PES_i+\epsilon_i \quad (8)$$

$$RET_i = ai_0+\beta_1 RET_{i0}+\beta_4 NORM_i+\epsilon_i \quad (9)$$

where RET_i indicates the returns during portfolio evaluation and RET_{i0} indicates the returns during portfolio formation. OP_i, PES_i, and $NORM_i$ stand for optimistic, pessimistic, and normal conditions, respectively, during portfolio formation. ϵ_i represents the unexplained errors. The models are run both for winner and loser portfolios. Since, the sum of optimism, pessimism, and normal states percentages during a month is100%, in order to control for the co-linearity effects, we address to the normal state effects within a different model. We determine Equations 8 and 9 using the OLS estimator.

The coefficient β_1 is expected to be positive and statistically significant with a momentum strategy and negative and statistically significant with a contrarian strategy. Within a momentum strategy, in which price continuation is postulated, we expect the winner portfolio outperform in the next period. Accordingly, β_1 is expected to be positive. However, due to price reversal assumption in the context of contrarian strategy negative is expected. The coefficients of optimism, pessimism, and normality, β_2, β_3, and β_4, respectively, are also expected to be statistically significant. The sign of β_2, β_3, and β_4 is a matter of empirics. According to the results of previous studies (Antoniou et al., 2013; Christiana et al., 2016; Cooper et al., 2004; Luxianto, 2010; Ma, 2014), we expect the optimism (pessimism) beta coefficient for winner (loser) portfolios to be positive (negative) and significant. In other words, optimism coefficient should be positive and significant for winner portfolio and pessimism coefficient should be negative and significant for loser portfolio. We also expect that coefficient has a positive and significant result for winner and loser portfolios. The sign of β_2, β_3, and β_4 is a matter of empirics. Because of the cross-sectional data, heteroscedasticity variance is likely to occur in terms of errors. To control the variance and to achieve consistent estimates, we use the White method.

Results and Discussions

Descriptive statistics

Arms adjusted index in a 1446 trading days illustrates the percentage of optimism, pessimism and normal states are 54%, 20%, and 26%, respectively. Descriptive statistics for research variables are presented in Table 1. Mean, median and standard deviation are displayed in panel A. Mean and standard deviation of Arms adjusted index is 36.6 and 8.99, respectively. A confidence interval for the mean of Arms adjusted index with 5% sig. is 34.59 and 38.13. As this analysis, the statistics of other variables have been shown in Table 1.

We check the sentiment index's normality using the Anderson–Darling test (Ryan & Joiner, 2001) as shown in panel B of Table 1. The index is abnormal (p-value = 0.032). The Anderson–Darling statistic is nearly 0.821, where the normal statistic is 0.641. The distribution of the adjusted sentiment index is skewed to the left with a negative coefficient of skewness equal to -0.402, indicating that the market sentiment tended to be optimistic between 2008 and 2014 in accordance with previous reports (Arik, 2011), in which the optimism ratio was shown to be 55±3%.

Table 1. Data Description

Panel A. Mean and standard deviations

Variable	Minimum	Mean	Median	Maximum	Standard Deviation Mean	Median	Confidence Interval for Mean*		Confidence Interval for Median*		Confidence Interval for StDev*	
ARMS	0.06	0.59	0.57	1.65	0.24	0.53	0.52	0.65	0.52	0.64	0.20	0.28
$ARMS_t$ adj	5.90	36.01	36.60	62.30	8.99	33.09	34.59	38.13	34.59	39.09	7.72	10.76
RET	-0.14	0.04	0.03	0.27	0.07	0.02	0.00	0.06	0.00	0.05	0.06	0.09
ER	-0.15	0.02	0.02	0.25	74.00	0.00	-0.01	0.03	-0.01	0.03	0.06	0.08
VOL	0.06	0.13	0.11	0.29	0.04	0.11	0.10	0.13	0.1	0.13	0.03	0.05

Panel B. Anderson–Darling test

Variable	Skewness	a-square	p-value
ARMS	1.37	1.37	0.005
$ARMS_t$ adj	-0.40	0.82	0.032
RET	0.82	0.09	0.027
ER	765.00	86.00	26.000
VOL	1.25	1.38	0.005

Note: This table is based on monthly data from 77 firms between April 2008 and March 2014. ARMS = ARMS trading index, ARMS adj = adjusted trading index, RET = stock returns, ER = excess return, VOL = stock volatility, a-square = Anderson–Darling normality statistic. *indicates confidence at 95%.

Table 2. ADF[9] Unit Root Test Results

Variable	Model with Constant			Model with Constant and Trend		
	t-statistic	Optimal Lag	Critical Value	t-statistic	Optimal Lag	Critical Value
VOL	-5.049	0	-2.903	-5.250	0	-3.474
OPT	-5.956	0	-2.903	-5.922	0	-3.474
PES	-5.940	0	-2.903	-6.123	0	-3.474
NORM	-7.003	0	-2.903	-7.133	0	-3.474
ER	-5.439	1	-2.903	-5.644	1	-3.474

Note: This table is based on monthly data from 77 firms between April 2008 and March 2014. ARMS = ARMS trading index, ARMS adj = adjusted trading index, RET = stock returns, ER = excess return, VOL = stock volatility, OPT = optimism sentiment, PES = pessimism sentiment, NORM = normal sentiment. To save space, we do not report the estimated values.

Causality between sentiment, returns, excess returns, and volatility

To test the mutual relationship between sentiment, returns, excess returns, and volatility, we estimate VAR models using Equations 5, 6, and 7. In Table 3, a comparison of the test statistic value with the critical value (5%) shows that the unit root hypothesis for all the variables is rejected. Based on these results, the VAR model at the level of each variable can be estimated. Our findings also show that the time-series data are not random; therefore, as the unit root hypothesis is rejected, market non-efficiency is confirmed.

Table 3 presents the Wald statistic and the p-value for Equations 5, 6, and 7 for estimated VAR models. The results indicate that optimism is a Granger causality for returns and excess returns with a Wald statistic and p-value of 0.018 and 0.017, respectively. While the high sentiment of optimism shows to have an influence on the market return as in Wang et al. (2006), there no link between neither pessimism nor normality and returns/excess returns. The later finding is consistent with previous studies (Brown & Cliff, 2004; Hachicha & Bouri, 2008; Yang & Copeland, 2014). The Wald statistic for Granger causality indicates a unilateral causality both from stock returns and excess returns to pessimism. Furthermore, Investors' sentiments in states of optimism and pessimism do not affect volatility, which is consistent with the results of Wang et al. (2006).

Based on hypothesis 1, the relationship between the sentiment and stock returns, excess returns, and volatility should be positive and significant. Our main results can be summarized as follows. Granger causality shows that optimism is the cause of stock returns and that stock returns affect pessimism. Moreover, volatility is a causal variable that affects normal

[9] Augmented Dickey-Fuller test

Table 3. Granger Causality between Sentiment, Stock Returns, Excess Returns, and Volatility

Independent Variable	Dependent Variable OPT	PES	NORM	RET	VOL	ER
OPT				10.122	0.501	10.150
				(0.018)	(0.479)	(0.017)
PES				0.640	7.304	0.640
				(0.424)	(0.121)	(0.424)
NORM				0.001	2.822	0.000
				(0.980)	(0.244)	(0.999)
RET	1.262	2.922	1.541			
	(0.738)	(0.087)	(0.215)			
VOL	1.401	2.697	7.137			
	(0.237)	(0.610)	(0.028)			
ER	1.269	2.911	1.472			
	(0.736)	(0.088)	(0.225)			

Note: This table is based on monthly data from 77 firms between April 2008 and March 2014. The table represents the Wald statistic, and the Number in parentheses represents its p-value. RET = stock returns, ER = excess return, VOL = stock volatility, OPT = optimism sentiment, PES = pessimism sentiment, NORM = normal sentiment, respectively. Where, Wald statistic is significant and p-value is less than significance level, granger causality is not rejected. Accordingly, the influence of independent variable on dependent one is accepted. For instance, in case of the relationship between VOL and NORM, p-value is 0.028 which is less than significance level. Therefore, null hypothesis of granger causality is rejected meaning that VOL is a cause for NORM. For simplicity, we do not report the estimated values of the VAR model's coefficients. The significance level is 10%.

sentiments, as previously reported by Baker and Wurgler (2007). Furthermore, we find that excess market returns cause pessimism. Sentiment index is able to forecast returns for optimistic period (Baker & Wurgler, 2007; Baker et al., 2012; Brown & Cliff, 2004; De Long, Shleifer, Summers, & Waldmann, 1990; Fisher & Statman, 2000; Yang & Copeland, 2014), and it can identify entry and exit times to the market. However, we observed no effect of pessimism on returns or excess returns. Furthermore, the casualty test results show that volatility is affected by the normal sentiment but is not affected by optimism or pessimism.

Strategy test results

We measure the efficiency of investment strategies and evaluate them during the periods of 1, 3, 6, and 12 months. The results and their significance of β_1, β_2, β_3, and β_4 for the OLS are summarized in Tables 4. Moreover, Table 5 displays the significance of overall coefficients statistics. We calculate the significance of the coefficients in OLS models for 1-month and 3-months formation periods (Table 5). In Table 5, among the 64 tests, 34 coefficients are significant, in the OLS model. Based on hypothesis 2, β_1 is expected to be positive and significant for the momentum strategy, and it is expected to be negative and significant for the contrarian strategy. Based on hypothesis 3 and 4, the coefficients of optimism, pessimism, and normality, β_2, β_3, and β_4, respectively, are also expected to be significant and support previous researchers findings.

As Table 4, significance test of β_1 in regression equation 6 implies positive and significant β_1 in 6 cases out of 32 cases. Maximum number of significance was obtained in a winner and high-risk portfolios (hereafter, WH portfolios). Let J be portfolio formation period and K portfolio evaluation period, we observed a positive significant β_1 for WH portfolios in (J = 1, K = 1,6) and (J = 3, K = 6). Our findings confirm that momentum strategy succeeds in achieving returns in 1 and 6-month intervals after portfolio formation. Similarly, β_1 is positive and significant for the loser and high-risk portfolios in (J = 3, K = 12).Our results show that the momentum strategy is significant for the portfolio formed for 1 month, which is evaluated after 1- and 6-month periods. Furthermore, our results show that the momentum strategy is significant for the portfolio formed for 3 months, which is evaluated after a 12-month period. Our results are in line with existing empirical evidence, regarding the efficiency of momentum and contrarian strategies in achieving returns in short-term and long-term, respectively. Using the contrarian strategy for lower-risk portfolios is successful after 6 months following a 1-month

Table 4. Significance of β_1, β_2, β_3, and β_4 in OLS Tests for Strategy Analysis after 1 Month and 3 Months

Coefficient	Portfolio Strategy	Formation Period							
		J = 1				J = 3			
		Evaluation Period							
		K = 1	K = 3	K = 6	K = 12	K = 1	K = 3	K = 6	K = 12
Panel A. Optimism and pessimism sentiments									
β_1	**Winner and Higher Risk**	0.223	0.039	0.093	-0.02	0.066	-0.22	0.141	0.038
		[0.025]	[0.356]	[0.004]	[0.270]	[0.668]	[0.827]	[0.033]	[0.527]
	Winner and Lower Risk	0.059	0.3	0.088	0.018	0.056	0.055	0.087	-0.003
		[0.579]	[0.571]	[0.019]	[0.570]	[0.710]	[0.622]	[0.311]	[0.970]
	Loser and Higher Risk	0.346	0.015	0.081	-0.111	0.285	0.065	0.067	-0.111
		[0.100]	[0.929]	[0.489]	[0.020]	[0.231]	[0.703]	[0.407]	[0.047]
	Loser and Lower Risk	0.639	0.078	0.12	-0.043	0.315	0.057	0.138	0.035
		[0.018]	[0.602]	[0.171]	[0.398]	[0.195]	[0.710]	[0.100]	[0.551]
β_2	**Winner and Higher Risk**	-0.094	-0.076	-0.126	-0.025	-0.053	-0.048	-0.202	-0.091
		[0.381]	[0.179]	[0.001]	[0.380]	[0.694]	[0.511]	[0.005]	[0.007]
	Winner and Lower Risk	0.004	-0.029	-0.129	-0.058	-0.053	-0.048	-0.202	-0.091
		[0.964]	[0.562]	[0.000]	[0.021]	[0.650]	[0.554]	[0.002]	[0.022]
	Loser and Higher Risk	-0.021	-0.065	-0.129	-0.041	-0.282	-0.121	-0.242	-0.059
		[0.841]	[0.278]	[0.001]	[0.042]	[0.083]	[0.232]	[0.000]	[0.084]
	Loser and Lower Risk	-0.003	-0.096	-0.132	-0.043	-0.265	-0.193	-0.237	-0.048
		[0.977]	[0.156]	[0.000]	[0.035]	[0.126]	[0.029]	[0.000]	[0.190]
β_3	**Winner and Higher Risk**	0.005	-0.024	0.038	0.041	-2.8	-0.184	-0.159	-0.095
		[0.967]	[0.772]	[0.456]	[0.204]	[0.125]	[0.149]	[0.056]	[0.445]
	Winner and Lower Risk	0.127	0.073	-0.015	0.007	-0.166	-0.125	-0.219	-0.037
		[0.170]	[0.382]	[0.773]	[0.812]	[0.296]	[0.242]	[0.038]	[0.464]
	Loser and Higher Risk	0.021	-0.058	-0.037	-0.009	-0.452	-0.167	-0.175	0.058
		[0.764]	[0.203]	[0.069]	[0.315]	[0.005]	[0.174]	[0.070]	[0.255]
	Loser and Lower Risk	-0.096	-0.187	-0.139	-0.033	-0.392	-0.283	-0.166	0.056
		[0.508]	[0.046]	[0.007]	[0.178]	[0.037]	[0.024]	[0.054]	[0.300]
Panel B. Normal Sentiments									
β_1	**Winner and Higher Risk**	0.600	0.163	0.083	0.095	0.106	0.004	0.149	0.037
		[0.068]	[0.594]	[0.789]	[0.829]	[0.500]	[0.969]	[0.015]	[0.534]
	Winner and Lower Risk	0.038	0.009	0.062	0.000	0.087	0.079	0.093	-0.110
		[0.717]	[0.848]	[0.096]	[0.990]	[0.549]	[0.488]	[0.234]	[0.886]
	Loser and Higher Risk	0.299	-0.039	-0.002	-0.127	0.398	0.096	0.019	-0.201
		[0.141]	[0.799]	[0.989]	[0.013]	[0.046]	[0.544]	[0.819]	[0.000]
	Loser and Lower Risk	0.681	0.134	0.125	-0.050	0.392	0.113	0.089	-0.034
		[0.014]	[0.396]	[0.157]	[0.333]	[0.087]	[0.441]	[0.274]	[0.520]
β_4	**Winner and Higher Risk**	0.469	0.249	0.704	1.136	0.108	0.083	0.169	0.085
		[0.326]	[0.594]	[0.139]	[0.005]	[0.447]	[0.366]	[0.010]	[0.017]
	Winner and Lower Risk	0.041	0.002	0.093	0.036	0.080	0.065	0.206	0.081
		[0.630]	[0.972]	[0.017]	[0.164]	[0.513]	[0.443]	[0.003]	[0.039]
	Loser and Higher Risk	0.056	0.101	0.071	-0.001	0.326	0.133	0.221	0.025
		[0.491]	[0.056]	[0.025]	[0.946]	[0.026]	[0.174]	[0.000]	[0.497]
	Loser and Lower Risk	0.031	0.120	0.134	0.041	0.030	0.216	0.217	0.021
		[0.776]	[0.079]	[0.000]	[0.036]	[0.075]	[0.020]	[0.000]	[0.589]

Note: The figure in the square brackets represents the p-value, and the other figure represents the beta coefficients. The β_1 coefficientis expected to be positive and significant for the winner portfolio, and it is expected to be negative and significant for the loser portfolio. The coefficients of optimism, pessimism, and normality, β_2, β_3, and β_4, respectively,are also expected to be significant. Where, J = portfolio formation period and k = portfolio evaluation period. The significance level is 10%.

formation period. In addition, the contrarian strategy for lower-risk portfolios is successful 1 and 6 months later after evaluation following a 3-month formation period. Our study reconfirms effectiveness of momentum strategy in short-term, regarding previous researchers on TSE such as Foster and Kharazi (2008) and Mansouri et al. (2012). However, in the case of contrarian strategies effectiveness in long-term (J = 3, K = 12), our results do not support Foster and Kharazi (2008) in this regard.

Based on Hypothesis 3, optimism (pessi-

Table 5. OLS Regression Coefficients

Portfolio	Sentiment	Formation Period J = 1				J = 3			
		Evaluation Period K = 1	K = 3	K = 6	K = 12	K = 1	K = 3	K = 6	K = 12
Winner and Higher Risk	**Optimism and Pessimism**	0.050	0.562	0.014	0.045	0.33	0.418	0.001	0.940
Winner and Lower Risk		0.550	0.421	0.002	0.0027	0.62	0.497	0.002	0.060
Loser and Higher Risk		0.340	0.549	0.041	0.034	0.02	0.428	0.004	0.000
Loser and Lower Risk		0.020	0.075	0.003	0.318	0.05	0.048	0.002	0.065
Winner and Higher Risk	**Normal**	0.230	0.792	0.279	0.017	0.58	0.674	0.001	0.099
Winner and Lower Risk		0.810	0.982	0.021	0.352	0.63	0.480	0.000	0.098
Loser and Higher Risk		0.150	0.08	0.065	0.053	0.01	0.275	0.002	0.004
Loser and Lower Risk		0.010	0.084	0.001	0.185	0.02	0.031	0.001	0.753

Note: The figures represent the p-values for the overall test. Where, J = portfolio formation period and k = portfolio evaluation period. The significance level is 10%.

mism) sentiment in portfolio formation period should be significant and positive effect on the future return of winner (loser) portfolios. Our findings show β_2 and β_3 were negative and significant in 16 and 10 cases out of 32 cases, respectively. Our results indicate that optimism has no positive and significant effect on returns of winner portfolio, but it has a positive and significant effect on returns of loser portfolio in periods (J = 1, K = 6, 12) and (J = 3, K = 3). In addition, results (in Table 4) show that pessimism has a negative and significant effect on returns of winner portfolio in periods (J = 3, K = 6). Therefore, contrarian and momentum strategies are not successful in periods of optimism or pessimism. Our results, consistent with the results of a previous report by Antoniou et al. (2013), Daniel et al. (1998), and Luxianto (2010) indicate that using the momentum strategy in a period of recession does not lead to profit; further, its use is counterproductive and has a dangerous effect on declining markets. Moreover, the β_1 coefficient of the sentiment index in the momentum strategy shows long-term negative returns, as previously reported (Brown & Cliff, 2004). This confirms that optimism correlates with low returns for high-risk portfolios, as already observed (Baker & Wurgler, 2007).

In according to hypothesis 4, normal sentiment in portfolio formation period should be positive and significant effect on the future return of winner (loser) portfolios. A noteworthy result in Table 4 regarding β_4 is its positive and significant status in 16 out of 32 cases of equation run, establishing positive effect of normal sentiment on return. In other cases it was insignificant. β_4 is found to be positive and significant in loser portfolio and winner portfolio merely in 10 and 6 cases respectively meaning insufficient evidence of aforementioned strategies effect on achieving returns, which does not support Antoniou et al. (2013), Daniel et al. (1998), Luxianto (2010), and Ma (2014) in this regard. Our analysis of significance for normal sentiment conditions using the β_4 coefficient shows that the use of contrarian and momentum strategies in normal conditions leads to an increase in returns during the following periods. This indicates that combining the normal market sentiment with behavioral financial strategies leads to an increase in returns; however, more significant results are seen using contrarian strategies compared to using momentum strategies. Our results are inconsistent with those of previous studies (Antoniou et al., 2013; Anusakumar et al., 2012; Herberger & Kohlert, 2015). Previously, the momentum strategy was declared an appropriate method for use during periods of optimism; however, we find that contrarian strategies have a more significant beta compared to momentum strategies under normal market circumstances.

Finally, we conclude that the momentum and contrarian strategies in both optimistic and pessimistic states lead to the selection of portfolios that are not profitable and that actually result in losses. Our results are not consistent with the research Antoniou et al. (2013), Daniel et al. (1998), Luxianto (2010), and Ma (2014) and beta coefficients of sentiment are more positive and significant in normal sentiment. We could not statistically and strongly confirm the hypothesis 3, but hypothesis 4 is statistically confirmed in most cases.

Conclusions

Selecting a portfolio strategy based on market sentiment indicators is one of the most important aspects of investing in stock markets. In this paper, we calculate the ARMS-adjusted index and then examine its Granger causality considering market returns, excess returns, and volatility. In classifying winner and loser portfolios based on high- and low-risk criteria in various sentiment states, we analyze portfolio return sensitivity during selected evaluation periods. Our results indicate that optimism affects both stock market returns and excess returns. Furthermore, the causality test shows that although volatility is affected by normal sentiment, it is not affected by optimism or pessimism. Further, the sentiments in the TSE did not comply with random walk behavior. Winner and high-risk portfolios are economically positive and statistically significant in short-term.

According to our empirical analysis, returns in winner and loser portfolios do not show significant nor positive sensitivity to optimistic or pessimistic market sentiments. The formation of winner and loser portfolios does not yield significantly positive returns during optimism or pessimism. However, we find that returns in winner and loser portfolios are significantly positive under normal sentiment status. The evidence suggests that investors should consider the role of market sentiment in stock pricing, and regulators should consider market sentiment to prevent economic shock. As a result, we recommend to portfolio managers and investors to use momentum and contrarian strategies when sentiment is normal. Further researches can be developed based on new indices of sentiment and in other markets.

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