Portfolio selection and investors, optimism and pessimism sentiment: empirical study in the Iran capital market

MEHRANI, Kiarash*†', RAHNAMAY-ROODPOSHTI, Fereydoon', NEKOMARAM, Hashem' and SAEEDI, Ali''

'*Department of financial management, Science and research Branch, Islamic Azad University, Tehran, Iran*
'' *Faculty Member, Department of Management, North-Tehran Branch, Islamic Azad University, Tehran, Iran*

Received January 29, 2015; Accepted June 12, 2015

Abstract

We investigate the link between behavioural investment strategies with optimism or pessimism market sentiment and compared them to the normal state. The proposed methods, thanks to its simplicity, can be applied to a wide range of investors. First, we evaluated the sentiment using Arms adjusted index. Since we observed no unit root for sentiments stationary, we confirmed the stock market inefficiency. Then, using the vector auto regression test, we analysed the relationships between sentiment, stock returns, and volatility. Ultimately, we tested contrarian and momentum portfolio strategies in conditions of optimism, pessimism, and normal behaviour based on the short-term Probit and ordinary least squares model coefficients. The results showed that the formation of a short-term portfolio in one and three-month periods of optimism and pessimism did not create an additional return and resulted in losses. Also, the outcomes indicate that the combination of normal market sentiment with behavioural finance strategies increases performances, with more significance results in the contrarian strategies compared with the momentum strategies. In terms of strategy effectiveness, portfolio formation based on momentum approach provides an efficient output in short term, while the contrarian performance is instead not efficient enough.

Contrarian and momentum strategy, Arms index, optimism and pessimism sentiment.

Citation: Mehrani, Kiarash, Rahnamay-Roodposhti, Fereydoon, Nekomaram, Hashem and Saeedi, Ali. Portfolio selection and investors, optimism and pessimism sentiment: empirical study in the Iran capital market. ECORFAN Journal-Mexico 2015, 6-15: 1289-1304

* Correspondence to Author (email: mehrani@pardisiau.ac.ir)
† Researcher contributing first author.

December 2015 Vol.6 No.15 1289-1304

Introduction

This study attempts to link between financial behavioural portfolio strategies and sentiment Indies. We tested portfolio formation strategies with due consideration of the sentiment index as a factor affecting portfolio formation. Investment strategies based on behavioural finance theories are established on the basis of two contrasting hypotheses, the over and low-reactive hypotheses. Overreaction results in poorly-performing loser stocks undergoing a low valuation. Bondt and Thaler (1985) Showed that loser portfolios, which had poor performance in the past due to over-reactivity, have better performance in future winner portfolios. The contrarian strategy triggers reverse in the prices. Previous studies assessed the contrarian strategy successfulness because of over-reaction in global financial markets (Mugwagwa, Ramiah, & Moosa, 2015).On the other hand, in the underreaction hypothesis, all the available information in the stock price is not reflected when the market does not work; therefore, the disclosure of information is delayed as well as the pertaining effects. Jegadeesh and Titman (1993, 2001) challenged the hypothesis of market efficiency confirming low reactivity. The author tested the momentum strategy, buying from a winner portfolio and selling loser portfolio, showing that this second strategy can yield a significant excess return. Other studies report that contrarian strategy is successful in various financial markets (Herberger & Kohlert, 2015), (Anusakumar, Ali, & Wooi, 2012).

Briefly, we aimed to test the effectiveness of momentum and contrarian strategies in different sentimental conditions. We tested these strategies after studying loser and winner portfolio in terms optimism and pessimism compared to normal conditions. First, we created a scale to measure trading behaviours.

On the basis of this scale, we classified the states of the investors' sentiments into optimism (over purchase), pessimistic (over sale) and normal behaviour. In the next step, we examined the relationship between this scale and stock returns, excess returns, and volatility to evaluate the effectiveness of the behavioural models in investment strategies. Then, considering investment strategies of momentum and contrarian, we tested the success of these strategies in different behavioural situations using the OLS test and probit model.

The present study measured the Stock Exchange investors' sentiments with sentiment index indirectly in Iran for the first time. Using Richard Arms (1989) trading behaviour index (trading index) and converting it to a 0 to 100 scale, we developed an application framework for optimism, pessimism, and normality. In emerging markets such as Iran, many indexes based on financial tools like the fear index, Put-Call-Ratio (PCR) and Baker's index are not available or not applicable enough. Therefore, models based on these tools are not used to gauge sentiments (Baker & Wurgler, 2006).

Portfolio selection model based on our method can be applied to a wide range of investors, as it is conceptually easy, clearly defined, simply measurable, and allows a timely selection of the optimal portfolio strategy. The final results showed that pessimism and optimism as well as momentum and contrarian investment strategies, not only do not yield positive returns, but also in most cases they yield negative returns. We also found, in agreement with other studies (Qiu & Welch, 2004), (Wang, Keswani, & Taylor, 2006) stationary of sentiment index. The stationary in market sentiment in Iran challenges its efficiency like other markets. Therefore, we illustrated optimism in the period of investigation.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

This study presents our result on the selection of momentum and contrarian strategies in different sentimental states, providing a decision-making framework and strategy measurement methods for the selection of an optimal market strategy.

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

Literature and research questions

Evidence of Behavioural portfolio strategies

Investment strategies based on behavioural finance theories are established on the basis of two contrasting hypotheses, the over and low-reactive hypotheses. Overreaction results in poorly-performing loser stocks undergoing a low valuation. Bondt and Thaler (1985) showed that loser portfolios, which had poor performance in the past due to over-reactivity, have better performance in future winner portfolios. The contrarian strategy triggers reverse in the prices. Previous studies assessed the contrarian strategy successfulness because of over-reaction in global financial markets (Lakonishok, Shleifer, & Vishny, 1994), (Mugwagwa et al., 2015).

On the other hand, in the underreaction hypothesis, all the available information in the stock price is not reflected when the market does not work; therefore, the disclosure of information is delayed as well as the pertaining effects. Jegadeesh and Titman (1993), Jegadeesh and Titman (2001) challenged the hypothesis of market efficiency confirming low reactivity. The author tested the momentum strategy, buying from a winner portfolio and selling loser portfolio, showing that this second strategy can yield a significant excess return. Other studies report that contrarian strategy is successful in various financial markets (Moskowitz & Grinblatt, 1999), (Griffin, Ji, & Martin, 2003), (Herberger & Kohlert, 2015), (Anusakumar et al., 2012).

Foster and Kharazi (2008) have reviewed Momentum and contrarian strategies in Iran stock market during 1997-2000, and evidence for short-term anomaly have not been found. They found no evidence for contrarian; however, the 3-12 month periods of momentum strategy were higher than the previous periods.

Kaniel, Saar, and Titman (2008) Concluded that volatility is a temporary and normal phenomenon. Chung, Hung, and Yeh (2012) Examined sentiments in expansion and recession states concluding that there is a relationship between economic state and sentiments. In economic expansion state, sentiment had the ability to predict the economic situation, while it could not predict in recession. Berger and Turtle (2012) studied the association between transparency and sentiments in stock companies, finding that the stock performance of transparent companies, unlike the opaque one, have a loose association with sentiment levels.

Anusakumar et al. (2012) showed in thirteen Asian countries in 2000 and 2011 indicated that the winner portfolio and momentum strategy has created positive returns for all pattern.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

December 2015 Vol.6 No.15 1289-1304

9 out of 13 countries in Asia showed a statistically significant difference. The same study showed that 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 momentum.

Luxianto (2010) tested momentum and contrarian strategies in the bearish and bullish condition in Indonesian capital market. He finds that that when market bearish, the momentum strategy ineffective performance while this strategy is effective in the bullish state. This result showed that in bearish market condition, contrarian strategy will be more effective.

Ma (2014) evaluated the performance of market winners and losers using evaluation of recession and expansion phases. They provide a model for the strategy momentum and market conditions. The author indicated that under both expansion- expansion phase and recession-recession phase, winners have positive returns and losers have negative or zero returns; therefore, the momentum strategy is inappropriate. Under expansion- recession phase, both losers and winners returns are negative while in expansion-recession phases both losers and winners have positive returns. Coelho (2015) indicates that sentiment impacts stock returns with complex arbitrage in the Swiss stock exchange.

Evidence of Sentiment role in financial markets

The basic assumption of traditional portfolio selection models is that investors are not influenced by sentiments.

Previous studies rejected these assumptions, showing that sentiments significantly affect stock returns (Barberis, Shleifer, & Vishny, 1998), (Neal & Wheatley, 1998), (Baker & Wurgler, 2006), (Baker & Wurgler, 2007), (Brown & Cliff, 2004), (Wang et al., 2006), (Yang & Copeland, 2014).

Empirical studies often disagree on investors' sentiment scales. Previous researchers did use two types of sentiment measurements so far. The first types are direct scale in the form of attitude questionnaires and qualitative. The second group consists of indexes that aim to quantitatively measure the investors' or market's sentimental behaviour. These indicators measure the market behaviour with quantitative financial models of the investors. Richard Arms (1989) was among the first ones to measure trade behaviour with a forecast index to predict short-term directions. This index is calculated by dividing two ratios. The first ratio is the result of dividing transactions volume of the shares with a price increase to transactions volume of the shares with a price decrease. The second ratio is the result of the numbers of the shares with a price increase to the shares with a price decrease. Then the outcomes of these two ratios are divided. If the result is lowered than 1, the trading volume in raising shares is higher than the falling shares which mean the market prices of the stock increases significantly. If the result is higher than 1, falling shares are higher than the raising shares and the market is likely to decline.

Support the significance of sentiment studies as learning behaviour errors creates opportunities for excess returns. Their results show, 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 simultaneously.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

Barberis et al. (1998) presented an investor sentiment model using under- and over-reaction for an abstract model of investors' behaviour. Neal and Wheatley (1998) designed a sentiment index on the basis of market ratios. De Long, Shleifer, Summers, and Waldmann (1990) pointed out that investors' behaviour during growth leads to an increase in purchases and stock prices, leading to a decrease of future expected returns through price pressure.

Shefrin (2008) considered sentiments being influenced by beliefs and priorities. Fisher and Statman (2000) reported a negative relationship between investors' sentiments and future stock returns.

Waggle and Agrrawal (2015) illustrated that low (high) returns are usually the result of high (low) levels of extreme positive sentiment; therefore, it illustrated contrarian effect of sentiment.

Baker and Wurgler (2006) provided sentiments measuring model examining the effect of investors' sentiments on the stock return cross-sectional data. They conducted their study by several financial parameters like the closed-end fund discount (CEFD), log turnover (TURN), the number of IPOs (NIPO), first-day return of IPOs (RIPO), dividend premium (PDND), and equity share in new issues (S) to coin sentiment index. The authors showed how sentiments are associated with stock returns of companies that are small, young, with high volatility, critical, with unpredictable profit, and no financial experience or stocks growth.

Baker and Wurgler (2007) showed that when the market sentiment is high, the market return is low. In optimistic markets, the monthly average return is of 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) showed that optimism correlates with lower future stock returns. The authors also concluded that market in Canada, France, Germany, Japan, the United Kingdom, and the United States do respect the statistical and economical return forecast as for market efficiency.

Schmeling (2009) found that there is the correlation Granger causality relationship between consumer sentiment and stock returns. Schmeling (2009) showed that sentiment effects on return and return effects on sentiment too. Granger causality is a statistical concept of causality that is based on the 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). The author's conclusions, in agreement with Baker and Wurgler (2007), indicate that optimism tends to reduce future returns.

Feldman (2010) explicated how to utilize sentiment indices as to find bubbles and financial crisis in financial markets. The bearish sentiment might not be that much strong as the investors gain profit (Feldman, 2010).

Brown and Cliff (2005) showed, using a sentiment direct measurement scale, a positive and significant relationship between sentiment and over-valuation of assets during the period of optimism. In the period from 1962 to 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 also had a negative skewness (-0.171).

December 2015 Vol.6 No.15 1289-1304

They used the B coefficient as the sentiment index with long-term negative returns, showing high arbitrage restrictions in advanced markets. Also, in the same study, the sentiment index distribution is normal. This shows that when investors are optimistic, market values are higher than the intrinsic values.

Shu and Chang (2015) extreme optimism of hopeful investors is the underlying reason for overvaluation of the stock; consequently, upon disappearance of the positive sentiment the bubble is gone and stock prices have declined dramatically which probably results in a fall down.

Wang et al. (2006) showed that there is little evidence that sentiments Granger cause returns. At the same time, sentiment granger cause returns and likelihood ratio (LR) for both surface and interrupts. Arms index has a two-way Granger causality relationship with price volatility. The authors found 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, but they are the effect variables. The results are consistent with those of Brown and Cliff (2004), showing that return is the casualty of sentiments. Hachicha and Bouri (2008) found that sentiments Granger causes efficiency in Tunisia, but the authors described sentiments as an unstable phenomenon as the results were positive in terms of field of activity, size, and the ratio of B/M and negative as for stock liquidity.

The authors also showed that sentiments Granger caused instability. Their study was in contrast to the results obtained by (Barberis, Shleifer, & Wurgler, 2005). Their results suggested that sentiments caused volatility and increasingly helps predict volatility.

A study on the role of investor sentiment in the British stock market revealed that bullish sentiment led to excess returns, and conversely, bearish behaviour led to a decrease in market excess returns (Yang & Copeland, 2014). At the first and second lag, there is no Granger causality between sentiments, change in sentiments, and market excess return; however, there is Granger causality between excess return and sentiments in the lag of the period six and twelve, and change in sentiments and excess stock return. When investors are optimistic, the six-month momentum strategy has significant profit and on the average has an efficiency of 1.64%. When investors are pessimistic, the momentum strategy increasingly loses its significance and drop to 0.56%.Therefore, the momentum strategy during a recession does not make a profit and it has an inverse effect on declining markets (Antoniou, Doukas, & Subrahmanyam, 2010). Momentum in a growth period has a significant and positive profitability that is about 1.8% on average but it has an inverse effect on declining markets (Antoniou et al., 2010). Arik (2011) measures individual investors' sentiment for the years 2010 and 2011, finding that 55% were optimistic in that period.

Data and Methodology

Data

The statistical population consisted of all companies listed on TSE (Tehran Stock Exchange) in Iran and the samples were collected from the most liquid stock companies (N =77) in various industries over the period 2008-2013[1].

1 We collect all data set from TSE (Tehran Stock Exchange) database and CBI (central bank of Iran).

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

Variable

In this study, we investigated whether momentum and contrarian strategies were more suitable in conditions of optimism and pessimism compared to normal conditions.

In this line, we calculated the efficiency of each portfolio as the average of the monthly stock returns. We also calculated the monthly rate of returns and excess rate of returns of the portfolio which consisted of 77 public stock companies.

The excess return was calculated by the subtracting monthly rate of return from the monthly risk-free rate of return. The one-year standard deviation was used as the annual volatility index for each stock.
The cost of trading and short selling was not included in this research.

Proxy for sentiment

We use the Arms trading index (ARMS) to measure sentiments proxy. We calculated the Arms sentiment index as follows:

$$\mathrm{AD_t} = \frac{\mathrm{ADV_t}}{\mathrm{DEC_t}} \tag{1}$$

$$\mathrm{VOLU_t} = \frac{\mathrm{ADVOL_t}}{\mathrm{DECVOL_t}} \tag{2}$$

$$\mathrm{ARMS_t} = \frac{\mathrm{AD_t}}{\mathrm{VOLU_t}} \tag{3}$$

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. $ADVOL_{tis}$ the trading volume of companies with price increase the period of the study t, while $DECVOL_{tis}$ the trading volume of companies with a price decrease over the period of the study. $VOLU_{tis}$ then the ratio between $ADVOL_{tand}$ $DECVOL_t$. Arms sentiments index is obtained by dividing AD_t by$VOLU_t$. We used Wilder (1986) adjustment to normalize the Arms index, obtaining 0 as the lower limit and 100 the upper one.

This normalization allows to have a clear presentation for sentiments and to provide more concise formula as follows:

$$\mathrm{ARMS_t\ adj} = 100 - \frac{100}{1+\mathrm{ARMS_t}} \tag{4}$$

We classified investors' sentiments conditions as optimism (over purchase), pessimistic (over-sale), or normal state. Over sale in the market is the condition under which asset price decreases and falls lower than the real value of the transaction (Keene [2013]).

This condition referred to as scepticism in our study, is usually caused by over-reactivity of stockholders who sell their stocks under value. For this study, we defined over-sale reaction as a situation with the market adjusted sentiment index higher than 60. Over-purchased is the condition under which one or more assets prices increase sharply to surpass the real value of the transaction. This generally happens with low reactivity and expensive assets purchases. This situation is referred to as unrealistic optimism in psychology which results in dramatic increase in the stock prices.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

Descriptive statistics

In our study, we defined market adjusted sentiment index lower than 40 as excessive purchases reaction and sales opportunities. We checked the sentiment indexes normality using Anderson-Darling model (Ryan & Joiner, 2001), finding the index to be abnormal (P-value =0.032). The Anderson-darling statistic is nearly 0.821, where the normal range was 0.641.The distribution of the adjusted sentiment indexes is skewed to the left with a negative coefficient of skewness equal to -0.402, indicating that market sentiment tended to be optimistic between 2008 and 2013, in accordance with previous reports (Arik, 2011), where the optimism ratio was 55±3%.

	Mean	Standard Deviation	Skewness	A-square	P-Value
$ARMS_t$	0.594	0.238	1.373	1.37	0.005
$ARMS_t$ adj	36.01	8.99	-.402	.82	0.032
RET	0.038	0.074	0.816	.085	0.027
ER	0028	0074	0765	086	0026
VOL	0.126	.0426	1.25	1.38	.005

Table 1 Data description

Note: These figures are based on data from 77 firms. ARMS, ARMS adj, RET,ER and VOL stand for of ARMS Trading index, adjusted Trading index, pessimism, stock return , excess return and volatility, respectively.

Research design

We commence by examining the bilateral relationship between sentiment (SENT) and stock returns (RET), excess returns (ER), and volatility (VOL) on the base Granger causality test and using the VAR model, in order to evaluate the effectiveness of behavioural models in developing investment strategies[2].

2 We followed previous studies Brown and Cliff [2004], Baker et al. [2012] Anusakumar et al. [2012], Yang and Copeland [2014] and tested the assumption that market sentiment Granger causes return, excess returns, and volatility using the VAR model.

Granger causality test was based on the assumption that information to predict variables such as SENT and VOL exclusively lies in the time-series data related to these variables. To do so, we specified the following VAR model:

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

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

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

Where, l is the optimal lag(s), t is time, β_1 and β_2are the vector regression coefficients and ϵ_1t and ϵ_2tare unexplained errors. Akaike's information criterion, Schwarz Information Criterion, Hannan-Quinn Information Criterion, likelihood ratio, Final Prediction Error was used to determine the optimal number of lag(s) in the VAR model.

Following Baker and Wurgler (2006) we look further to see whether momentum and contrarian strategies were more suitable in conditions of optimism and pessimism compared with normal conditions.

Also, we asked whether these strategies in case of hard to difficult or easy to arbitrage portfolio formation performed better in a short-term period in different sentiment conditions.

Following Jegadeesh and Titman (1993) to construct the winner and loser portfolios, we selected portfolios sorting stocks going from the highest returns to the lowest, classifying the top 25% (16 top shares and in each formation period of one to three months) and bottom 25% (16 of the bottom shares and in each formation period of one to three months) stocks as winner and loser portfolios. Then, we ordered the shares from highest to lowest volatility, classifying the first half as high risk and the bottom half as low-risk portfolios.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

The portfolio will be formed in a 1 month and a 3 month periods and will be evaluated after 3 months, 6 months, and 12 months periods. The method is in rolling form. That is the portfolio formation process which will be repeated for 72 times in a period of 6 years and will be evaluated in different periods of 1, 3, 6, and 12 months after the formation.

We specify following models to test the effects of sentiments on behavioural portfolios strategies and performance of strategies:

$$\mathrm{RET_i} = \mathrm{a_{i0}} + \beta_1 \mathrm{RET_{i0}} + \beta_2 \mathrm{OP_i} + \beta_3 \mathrm{PES_i} + \varepsilon_i \quad (8)$$

$$\mathrm{RET_i} = \mathrm{a_{i0}} + \beta_1 \mathrm{RET_{i0}} + \beta_4 \mathrm{NORM_i} + \varepsilon_i \quad (9)$$

Where, RET_iindicates the returns during portfolio evaluation, RET_i0 indicates the returns in the portfolio formation time, while OP_i, PES_iand NORM_ (i) stand for of optimism, pessimism, and normal condition during portfolio formation, and ε_ (i) is unexplained errors.

We estimated equations 8 and 9 using ordinary least squares estimator.

We also considered the dependent variable (RET_i), as a dummy variable; If RET_iwas positive in the evaluation time, the value of this variable would be equal to 1 and if negative to 0.For this case, we used Probit model. The β_1 the coefficient was expected to be positive and statistically significant with a momentum strategy and negative and significant in for contrarian strategy. The coefficients of optimism, pessimism and normality, β_2, β_3 and β_4are also expected to be positive and significant. Because of the cross-sectional data, he variance heteroscedasticity is likely to occur in terms errors. In order to control it and also to achieve consistent estimates, we used a robust estimator. In the present study, we corrected the coefficient variance using the White method.

Empirical analysis

Effect of sentiment on sample portfolio returns, excess return, and volatility

To test the mutual Relationship between sentiment and returns, excess return, and volatility, we estimated VAR models by equations No. 5, 6 and 7. To estimate VAR models by equations No. 5, 6 and 7, firstly we tested unit root hypothesis using ADF unit root test and prepared the results for the two models i.e. the model with constant state and the model with both constant state and trend in table 2. We selected the optimal lag(s) using Schwartz criteria. We selected 1 lag for all variables except for excess return for which 0.

Comparison of the test statistic value with the critical value (5%) showed that the unit root hypothesis for all variables was rejected. Based on these results, we could estimate the VAR model at the level of the variables.

Our findings also showed that the time series were not random walks, therefore; the market non-efficiency was confirmed as the unit root hypothesis was rejected.

Variable	model with constant			model with constant and trend		
	test statistic	Optimal lag	critical value	test statistic	Optimal lag	critical value
VOL	-	0	-	-	0	-
OPT	-	0	-	-	0	-
PES	-	0	-	-	0	-
NOR	-	0	-	-	0	-
ER	-	1	-	-	1	-

Table 2 ADF Unit root test results

Note: OPT, PES, NORM, RET, ER and VOL stand for of optimism, pessimism, normal Sentiment, stock returns, excess returns, and volatility, respectively. To save the space we did not report estimated values of VAR model's coefficients.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

We presented the Wald statistics and its p-value for each equation in VAR models No. 5, 6 and 7 in table 2. The result indicated Optimism is Granger causality for returns and excess returns (Wald statistic with p-value 0.018 and 0.017, respectively). We found no influence of pessimism on returns and excess return being influenced by pessimism.

The Wald statistics for granger causality from the stock returns and excess returns to pessimism were equal to 2.922 and 2.911 with p-value 0.087 and 0.088 respectively, which indicated a unilateral relationship.

Moreover, our results showed that there are not any interactions between pessimism and normality with returns and excess returns, in agreement with previous studies (Brown & Cliff, 2004), (Hachicha & Bouri, 2008), (Yang & Copeland, 2014). These results indicated that the periods of high optimism can influence market returns.

These results are in line with the findings obtained by Wang et al. (2006) for a period of pessimism and in contrast with a period of optimism.

The Granger causality test results indicated that investors' Sentiment in the states of optimism and pessimism did not affect volatility. Our results are consistent with previous studies (Wang et al., 2006). It suggested that the criteria of sentiment were causal variable when predicting volatility in spite of the results obtained by Hachicha and Bouri (2008) which stated criteria as effect variable. The results indicated that optimism affects both stock returns and excess returns (Brown & Cliff, 2004), (Hachicha & Bouri, 2008), (Yang & Copeland, 2014). However, we observed no effect of pessimism on returns and excess returns.

Furthermore, the casualty test results showed that volatility affect normal sentiment and it is not affected by optimism and pessimism.

	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)			

Table 3 Granger causality between sentiment (optimism, Pessimism, normal) and stock returns, excess return and volatility

Note: the figure in the bracket is Wald statistic and the figure in the parentheses its p-value. OPT, PES, NORM, RET, ER and VOL stand for of optimism, pessimism, normal Sentiment, stock returns, excess returns, and volatility, respectively. We did not report estimated values of VAR model's coefficients to be concise.

Momentum and contrarian Strategies results in different sentimental

We measured the efficiency of investment strategies and evaluated them during one, three, six or twelve-month period after their formation. Our results showed that the contrarian and momentum strategies were not successful in periods of optimism and pessimism. In order to be able to confirm this result, we matched the outcomes of Probit and OLS.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

The summary of the coefficients' significant results of β_1, β_2, β_3 and β_4 for probit and OLS test are summarized in table 4, 5. Table 4 present the results of the strategies coefficients and sentiments.

The β_1 the coefficient was expected to be positive and significant for a momentum strategy and it was expected to be negative and significant for contrarian strategy. The coefficients of optimism, pessimism and normality, β_2, β_3, and β_4 were also expected to be positive and significant too. In table 5, the Strategies' beta and sentiments' beta statistically have been indicated.

Our results showed that the momentum strategy was significant for the one-month formed portfolio which was evaluated after one and six month periods. Furthermore, our results showed that the momentum strategy was significant for the three-month formed portfolio which was evaluated after twelve month periods.

The Result of the study indicates that momentum and contrarian strategies led to the selection of portfolios which were not profitable and resulted in losses.

Our analysis of significance for normal sentiment conditions β_4 coefficient showed that the use of contrarian and momentum strategies in normal conditions led to an increase in return during the following periods. This indicates that combining the market normal sentiment with behavioural financial strategies leads to an increase in returns; however there were more significant results in the contrarian strategies in comparison with momentum strategies.

Our results, together with previous reports Antoniou et al. (2010), indicate that the momentum strategy in the period of recession does not lead to profit but also is counterproductive and it has a dangerous effect on declining markets.

Moreover, the β coefficient of sentiments indexes in momentum strategies showed to have long-term negative returns as previously reported (Brown & Cliff, 2004).

This confirms that optimism correlates with low future returns for high-risk portfolios, as already observed (Baker & Wurgler, 2007).

The contrarian strategy for lower risk portfolio in one-month formation period was successful six months later.

The contrarian strategy for lower risk portfolio in three-month formation period was successful one and six months later when they were evaluated.

Our results are consistent with what were previously studied (Antoniou et al., 2010), (Herberger & Kohlert, 2015), (Anusakumar et al., 2012).

Previously, momentum strategy has been found appropriate for periods of optimism, but we found out that contrarian strategies have more significant beta compared to momentum strategies under normal circumstances of the market.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

		OLS				PROBIT			
coefficient	portfolio strategy	evaluation period							
		1	3	6	12	1	3	6	12
Panel A. Optimism and pessimism sentiments									
β_1	Momentum and Higher risk	0.223	0.039	0.093	-0.020	2.166	0.786	1.615	0.737
		[0.025]	[0.356]	[0.004]	[0.270]	[0.058]	[0.499]	[0.293]	[0.795]
	Momentum and Lower risk	0.059	0.300	0.088	0.018	0.489	1.690	-1.365	-7.050
		[0.579]	[0.571]	[0.019]	[0.570]	[0.681]	[0.347]	[0.292]	[0.049]
	Reverse and Higher risk	0.346	0.015	0.081	-0.111	2.093	-1.245	4.388	-0.793
		[0.100]	[0.929]	[0.489]	[0.020]	[0.389]	[0.629]	[0.157]	[0.293]
	Reverse and Lower risk	0.639	0.078	0.120	-0.043	6.586	1.917	8.450	1.595
		[0.018]	[0.602]	[0.171]	[0.398]	[0.041]	[0.555]	[0.106]	[0.740]
β_2	Momentum and Higher risk	-0.094	-0.076	-0.126	-0.025	-1.730	-1.600	-4.081	-10.480
		[0.381]	[0.179]	[0.001]	[0.380]	[0.228]	[0.030]	[0.503]	[0.140]
	Momentum and Lower risk	0.004	-0.029	-0.129	-0.058	-0.454	-6.980	-1.770	-3.940
		[0.964]	[0.562]	[0.000]	[0.021]	[0.755]	[0.005]	[0.315]	[0.219]
	Reverse and Higher risk	-0.021	-0.065	-0.129	-0.041	-0.463	-0.868	-4.267	-0.222
		[0.841]	[0.278]	[0.001]	[0.042]	[0.724]	[0.539]	[0.011]	[0.425]
	Reverse and Lower risk	-0.003	-0.096	-0.132	-0.043	-1.536	-0.911	-6.418	-2.636
		[0.977]	[0.156]	[0.000]	[0.035]	[0.532]	[0.539]	[0.053]	[0.432]
β_3	Momentum and Higher risk	0.005	-0.024	0.038	0.041	-0.539	-0.199	0.204	-9.910
		[0.967]	[0.772]	[0.456]	[0.204]	[0.753]	[0.917]	[0.939]	[0.041]
	Momentum and Lower risk	0.127	0.073	-0.015	0.007	2.776	-1.517	-5.160	-0.047
		[0.170]	[0.382]	[0.773]	[0.812]	[0.111]	[0.449]	[0.063]	[0.991]
	Reverse and Higher risk	0.021	-0.058	-0.037	-0.009	0.797	-0.920	-1.015	-0.229
		[0.764]	[0.203]	[0.069]	[0.315]	[0.289]	[0.333]	[0.317]	[0.128]
	Reverse and Lower risk	-0.096	-0.187	-0.139	-0.033	-0.785	-1.961	-8.860	-3.100
		[0.508]	[0.046]	[0.007]	[0.178]	[0.692]	[0.294]	[0.022]	[0.412]
Panel B. Normal Sentiments									
β_1	Momentum and Higher risk	0.600	0.163	0.083	0.095	1.940	0.365	0.583	0.474
		[0.068]	[0.594]	[0.789]	[0.829]	[0.153]	[0.668]	[0.814]	[0.863]
	Momentum and Lower risk	0.038	0.009	0.062	0.000	-0.082	-1.415	1.139	-7.365
		[0.717]	[0.848]	[0.096]	[0.990]	[0.942]	[0.261]	[0.501]	[0.028]
	Reverse and Higher risk	0.299	-0.039	-0.002	-0.127	1.600	-2.338	1.743	-4.180
		[0.141]	[0.799]	[0.989]	[0.013]	[0.495]	[0.300]	[0.515]	[0.327]
	Reverse and Lower risk	0.681	0.134	0.125	-0.050	6.236	2.639	10.831	2.041
		[0.014]	[0.396]	[0.157]	[0.333]	[0.034]	[0.417]	[0.049]	[0.698]
β_4	Momentum and Higher risk	0.469	0.249	0.704	1.136	1.360	2.810	0.813	10.400
		[0.326]	[0.594]	[0.139]	[0.005]	[0.341]	[0.120]	[0.602]	[0.006]
	Momentum and Lower risk	0.041	0.002	0.093	0.036	-0.532	1.694	6.538	3.453
		[0.630]	[0.972]	[0.017]	[0.164]	[0.698]	[0.321]	[0.007]	[0.262]
	Reverse and Higher risk	0.056	0.101	0.071	-0.001	-0.376	1.888	1.444	0.630
		[0.491]	[0.056]	[0.025]	[0.946]	[0.658]	[0.058]	[0.139]	[0.612]
	Reverse and Lower risk	0.031	0.120	0.134	0.041	1.297	1.184	6.422	2.660
		[0.776]	[0.079]	[0.000]	[0.036]	[0.430]	[0.402]	[0.038]	[0.420]

Panel B. Normal Sentiments									
β_1	Momentum and Higher risk	0.600	0.163	0.083	0.095	1.940	0.365	0.583	0.474
		[0.068]	[0.594]	[0.789]	[0.829]	[0.153]	[0.668]	[0.814]	[0.863]
	Momentum and Lower risk	0.038	0.009	0.062	0.000	-0.082	-1.415	1.139	-7.365
		[0.717]	[0.848]	[0.096]	[0.990]	[0.942]	[0.261]	[0.501]	[0.028]
	Reverse and Higher risk	0.299	-0.039	-0.002	-0.127	1.600	-2.338	1.743	-4.180
		[0.141]	[0.799]	[0.989]	[0.013]	[0.495]	[0.300]	[0.515]	[0.327]
	Reverse and Lower risk	0.681	0.134	0.125	-0.050	6.236	2.639	10.831	2.041
		[0.014]	[0.396]	[0.157]	[0.333]	[0.034]	[0.417]	[0.049]	[0.698]
β_4	Momentum and Higher risk	0.469	0.249	0.704	1.136	1.360	2.810	0.813	10.400
		[0.326]	[0.594]	[0.139]	[0.005]	[0.341]	[0.120]	[0.602]	[0.006]
	Momentum and Lower risk	0.041	0.002	0.093	0.036	-0.532	1.694	6.538	3.453
		[0.630]	[0.972]	[0.017]	[0.164]	[0.698]	[0.321]	[0.007]	[0.262]
	Reverse and Higher risk	0.056	0.101	0.071	-0.001	-0.376	1.888	1.444	0.630
		[0.491]	[0.056]	[0.025]	[0.946]	[0.658]	[0.058]	[0.139]	[0.612]
	Reverse and Lower risk	0.031	0.120	0.134	0.041	1.297	1.184	6.422	2.660
		[0.776]	[0.079]	[0.000]	[0.036]	[0.430]	[0.402]	[0.038]	[0.420]

Table 4 Coefficients significance results of β_1, β_2, β_3, β_4 and for probit and OLS test of strategies analysis in a 1-month period

Note: The figures in the square brackets are P-value and the other is beta coefficients.

		OLS				PROBIT			
coefficient	portfolio strategy	evaluation period							
		1	3	6	12	1	3	6	12
Panel A. Optimism and pessimism sentiments									
β_1	Momentum and Higher risk	0.066	-0.220	0.141	0.038	-0.118	-1.480	3.966	8.196
		[0.668]	[0.827]	[0.033]	[0.527]	[0.965]	[0.565]	[0.174]	[0.019]
	Momentum and Lower risk	0.056	0.055	0.087	-0.003	2.757	0.391	4.079	-17.870
		[0.710]	[0.622]	[0.311]	[0.970]	[0.337]	[0.901]	[0.389]	[0.043]
	Reverse and Higher risk	0.285	0.065	0.067	-0.111	-0.195	0.724	4.374	-2.440
		[0.231]	[0.703]	[0.407]	[0.047]	[0.954]	[0.828]	[0.251]	[0.702]
	Reverse and Lower risk	0.315	0.057	0.138	0.035	-0.572	0.443	3.461	0.450
		[0.195]	[0.710]	[0.100]	[0.551]	[0.867]	[0.898]	[0.352]	[0.919]
β_2	Momentum and Higher risk	-0.053	-0.048	-0.202	-0.091	1.432	-1.920	-9.665	-31.280
		[0.694]	[0.511]	[0.005]	[0.007]	[0.681]	[0.376]	[0.036]	[0.028]
	Momentum and Lower risk	-0.053	-0.048	-0.202	-0.091	1.432	-1.920	-9.665	-31.280
		[0.650]	[0.554]	[0.002]	[0.022]	[0.485]	[0.406]	[0.005]	[0.002]
	Reverse and Higher risk	-0.282	-0.121	-0.242	-0.059	-3.163	-0.736	-8.259	-5.104
		[0.083]	[0.232]	[0.000]	[0.084]	[0.143]	[0.730]	[0.006]	[0.162]
	Reverse and Lower risk	-0.265	-0.193	-0.237	-0.048	-2.790	-2.844	-8.620	-3.552
		[0.126]	[0.029]	[0.000]	[0.190]	[0.194]	[0.185]	[0.013]	[0.217]
β_3	Momentum and Higher risk	-2.800	-0.184	-0.159	-0.095	-3.505	-2.416	-7.424	-6.858
		[0.125]	[0.149]	[0.056]	[0.445]	[0.166]	[0.376]	[0.109]	[0.057]
	Momentum and Lower risk	-0.166	-0.125	-0.219	-0.037	-1.870	-3.653	-9.073	-23.041
		[0.296]	[0.242]	[0.038]	[0.464]	[0.437]	[0.171]	[0.038]	[0.012]
	Reverse and Higher risk	-0.452	-0.167	-0.175	0.058	-6.439	-2.984	-8.714	3.138
		[0.005]	[0.174]	[0.070]	[0.255]	[0.013]	[0.253]	[0.021]	[0.589]
	Reverse and Lower risk	-0.392	-0.283	-0.166	0.056	-5.249	-4.436	-9.087	1.067
		[0.037]	[0.024]	[0.054]	[0.300]	[0.052]	[0.119]	[0.045]	[0.773]

		Panel B. Normal Sentiments							
β_3	Momentum and Higher risk	0.106	0.004	0.149	0.037	0.370	-1.237	3.930	7.906
		[0.500]	[0.969]	[0.015]	[0.534]	[0.886]	[0.620]	[0.190]	[0.032]
	Momentum and Lower risk	0.087	0.079	0.093	-0.110	3.633	0.902	3.976	-13.376
		[0.549]	[0.488]	[0.234]	[0.886]	[0.188]	[0.768]	[0.407]	[0.050]
	Reverse and Higher risk	0.398	0.096	0.019	-0.201	1.984	2.227	4.762	-6.748
		[0.046]	[0.544]	[0.819]	[0.000]	[0.494]	[0.456]	[0.147]	[0.187]
	Reverse and Lower risk	0.392	0.113	0.089	-0.034	924.000	1.505	3.826	-2.450
		[0.087]	[0.441]	[0.274]	[0.520]	[0.764]	[0.636]	[0.252]	[0.548]
β_4	Momentum and Higher risk	0.108	0.083	0.169	0.085	1.525	1.318	7.197	5.865
		[0.447]	[0.366]	[0.010]	[0.017]	[0.469]	[0.552]	[0.050]	[0.029]
	Momentum and Lower risk	0.080	0.065	0.206	0.081	-0.639	2.270	9.497	23.552
		[0.513]	[0.443]	[0.003]	[0.039]	[0.750]	[0.320]	[0.008]	[0.000]
	Reverse and Higher risk	0.326	0.133	0.221	0.025	3.904	1.357	8.391	3.097
		[0.026]	[0.174]	[0.000]	[0.497]	[0.061]	[0.513]	[0.006]	[0.450]
	Reverse and Lower risk	0.030	0.216	0.217	0.021	3.384	3.300	8.748	2.618
		[0.075]	[0.020]	[0.000]	[0.589]	[0.105]	[0.123]	[0.015]	[0.399]

Table 5 Coefficients significance results of β_1, β_2, β_3, β_4 and for probit and OLS test of strategies analysis in a 3-month period

Note: The figures in the square brackets are P-value and the other is beta coefficients.

We calculated the significant of the coefficients of the probit model and OLS for the one month and three month formation periods (Table 6). Results of table 6 show that the total significance of coefficients at the level of 10% generally for guidelines in periods of 6 and 12 months based on OLS model is acceptable. In probit model, the total significance of coefficients is acceptable generally for guidelines in periods of 12 months. In table 6 reports the simultaneous significance of all coefficients with likelihood ratio statistics.

Although in binary regression models, the standard of goodness of fit was of secondary importance to the expected signs of the regression coefficients, but we used for further investigation the likelihood ratio statistic for testing the significance of all the regression coefficients.

We set the significance level to 10% for Probit model test of all coefficients.

Among the 64 probit tests, only 10 coefficients were significant, while in the OLS model the majority of the coefficients were instead significant.

			OLS				PROBIT			
			evaluation period							
Formation period	**Portfolio**	**Sentiment**	**1**	**3**	**6**	**12**	**1**	**3**	**6**	**12**
One Month	Momentum and high volatility	Optimism and pessimism	*0.05*	0.562	*0.014*	*0.045*	*0.06*	0.29	0.499	0.795
	Momentum and low volatility		0.55	0.421	*0.002*	*0.0027*	0.68	0.29	0.347	*0.049*
	Reverse and low volatility		0.34	0.549	*0.041*	*0.034*	0.39	0.63	0.157	0.293
	Reverse and high volatility		*0.02*	*0.075*	*0.003*	0.318	*0.04*	0.56	0.106	0.74
	Momentum and high volatility	Normal	0.23	0.792	0.279	*0.017*	0.15	0.67	0.814	0.863
	Momentum and low volatility		0.81	0.982	*0.021*	0.352	0.94	0.26	0.501	*0.028*
	Reverse and low volatility		0.15	*0.08*	0.065	0.053	0.5	0.36	0.515	0.327
	Reverse and high volatility		*0.01*	0.084	*0.001*	0.185	*0.03*	0.42	*0.049*	0.698
Three Months	Momentum and high volatility	Optimism and pessimism	0.33	0.418	*0.001*	0.94	0.97	0.57	0.174	*0.019*
	Momentum and low volatility		0.62	0.497	*0.002*	*0.06*	0.33	0.9	0.389	*0.043*
	Reverse and low volatility		*0.02*	0.428	*0.004*	*0*	0.95	0.83	0.251	0.702
	Reverse and high volatility		*0.05*	*0.048*	*0.002*	*0.065*	0.87	0.9	0.352	0.919
	Momentum and high volatility	Normal	0.58	0.674	*0.001*	*0.039*	0.87	0.62	0.19	*0.032*
	Momentum and low Volatility		0.63	0.48	*0*	*0.038*	0.19	0.77	0.407	*0.05*
	Reverse and low volatility		*0.01*	0.275	*0.002*	*0.004*	0.49	0.46	0.147	0.187
	Reverse and high volatility		*0.02*	*0.031*	*0.001*	0.753	0.76	0.64	0.252	0.548

Table 6 Results of likelihood ratio statistic (LR) for general test of probit model and OLS regression coefficients

Note: The figures are p-value for the overall test. The significance level is %10 in this research.

Conclusion

Results of Granger causality show that optimism is the cause of stock return and that stock return affects pessimism. Moreover, volatility is a causal variable which affects normal sentiments similar to what previously reported by Baker and Wurgler (2007). Furthermore, we found that market excess returns Granger cause pessimism.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

December 2015 Vol.6 No.15 1289-1304

Sentiment indices are able to forecast returns for following months (Fisher & Statman, 2000), (Baker & Wurgler, 2007), (Baker et al., 2012), (Brown & Cliff, 2004), (Yang & Copeland, 2014), (De Long et al., 1990) and it can identify entry and exit time to the market.

The present study provides an exploratory framework for investment strategies in Tehran stock market.

Our results show that combining market normal sentiments with behavioural financial strategies leads to increase in returns, in particular with contrarian strategies.

From the perspective of strategic effectiveness, portfolio formation based on momentum approach provides appropriate returns in the short-term, but the contrarian strategy lacks the required efficiency. According to the results, it is strongly recommended to make use of the strategies evaluated in our study in normal conditions. We propose that investors do not constitute portfolio within the range of more than 60 and less than 40 of the sentiment index and they shall always be sensitive to the sentiment index. We recommend that models for investment pricing and evaluation should also consider the role of investors' behaviours since these influence stock pricing. Moreover, regulators should also be sensitive towards sentiments indices as to prevent and avoid economic shock.

References

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2010). Investor sentiment and price momentum. SSRN eLibrary.

Anusakumar, S. V., Ali, R., & Wooi, H. C. (2012). Momentum and Investor Sentiment: Evidence from Asian Stock Markets. Paper presented at the Seventh Annual Conference on Asia-Pacific Financial Markets, South Korea.

Arik, A. (2011). Modeling Market Sentiment and Conditional Distribution of Stock Index Returns under GARCH Process. THE CLAREMONT GRADUATE UNIVERSITY.

Arms, R. W. (1989). The Arms Index (TRIN): An introduction to the volume analysis of stock and bond markets: Irwin Professional Pub.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The Journal of Finance, 61(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market: National Bureau of Economic Research Cambridge, Mass., USA.

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. Journal of Financial Economics, 104(2), 272-287.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of financial economics, 49(3), 307-343.

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. Journal of Financial Economics, 75(2), 283-317.

Berger, D., & Turtle, H. (2012). Cross-sectional performance and investor sentiment in a multiple risk factor model. Journal of Banking & Finance, 36(4), 1107-1121.

Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? The Journal of finance, 40(3), 793-805.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. Journal of Empirical Finance, 11(1), 1-27.

Brown, G. W., & Cliff, M. T. (2005). Investor Sentiment and Asset Valuation*. The Journal of Business, 78(2), 405-440.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

Chung, S.-L., Hung, C.-H., & Yeh, C.-Y. (2012). When does investor sentiment predict stock returns? Journal of Empirical Finance, 19(2), 217-240.

Coelho, F. J. M. (2015). The impact of investor sentiment in the Swiss stock market.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of political Economy, 703-738.

Feldman, T. (2010). A more predictive index of market sentiment. Journal of Behavioral Finance, 11(4), 211-223.

Fisher, K. L., & Statman, M. (2000). Cognitive biases in market forecasts. The Journal of Portfolio Management, 27(1), 72-81.

Foster, K. R., & Kharazi, A. (2008). Contrarian and momentum returns on Iran's Tehran Stock Exchange. Journal of International Financial Markets, Institutions and Money, 18(1), 16-30.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society, 424-438.

Griffin, J. M., Ji, X., & Martin, J. S. (2003). Momentum investing and business cycle risk: Evidence from pole to pole. The Journal of Finance, 58(6), 2515-2547.

Hachicha, N., & Bouri, A. (2008). Behavioral beta and asset valuation models. International Research Journal of Finance and Economics, 16, 175-192.

Herberger, T., & Kohlert, D. (2015). Trading in Turbulent Markets Does Momentum Work?

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of finance, 48(1), 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. The Journal of Finance, 56(2), 699-720.

Kaniel, R., Saar, G., & Titman, S. (2008). Individual investor trading and stock returns. The Journal of Finance, 63(1), 273-310.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. The journal of finance, 49(5), 1541-1578.

Luxianto, R. (2010). Comparison in Measuring Effectiveness of Momentum and Contrarian Trading Strategy in Indonesian Stock Exchange. Available at SSRN 1680228.

Ma, L. (2014). A Model of Momentum and Market States: Theory and Evidence. Available at SSRN 2517168.

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum? The Journal of Finance, 54(4), 1249-1290.

Mugwagwa, T., Ramiah, V., & Moosa, I. (2015). The Profitability of Option-Based Contrarian Strategies: An Empirical Analysis. International Review of Finance, 15(1), 1-26.

Neal, R., & Wheatley, S. M. (1998). Do measures of investor sentiment predict returns? Journal of Financial and Quantitative Analysis, 33(04), 523-547.

Qiu, L., & Welch, I. (2004). Investor sentiment measures.

Ryan, B. F., & Joiner, B. L. (2001). Minitab handbook: Duxbury Press.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. Journal of Empirical Finance, 16(3), 394-408.

Shefrin, H. (2008). A behavioral approach to asset pricing: Academic Press.

Shu, H.-C., & Chang, J.-H. (2015). Investor Sentiment and Financial Market Volatility. Journal of Behavioral Finance, 16(3), 206-219.

Waggle, D., & Agrrawal, P. (2015). Investor Sentiment and Short-Term Returns for Size-Adjusted Value and Growth Portfolios. Journal of Behavioral Finance, 16(1), 81-93.

Wang, Y.-H., Keswani, A., & Taylor, S. J. (2006). The relationships between sentiment, returns and volatility. International Journal of Forecasting, 22(1), 109-123.

Yang, Y., & Copeland, L. (2014). The Effects of Sentiment on Market Return and Volatility and The Cross-Sectional Risk Premium of Sentiment-affected Volatility.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682