WP/19/07

SAMA Working Paper:

An Empirical Analysis of Behavioral Finance in the Saudi Stock Market:

Evidence of Overconfidence Behavior

November 2019

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Abstract

Theoretically, investors are considered to be rational decision makers in regard to trading in stock markets, however, some empirical studies have statistically discredited this believe. Evidence shows that typically, investors act irrationally in the financial markets. Therefore, this research aims to empirically investigate investor's irrational behavior, specifically, overconfidence behavior in the Saudi stock market, Tadawul. The data under investigation is from 2007 to 2018, monthly based. According to previous research, positive past market returns influence the level of investors' overconfidence leading to higher trading turnover in stock markets. To test for overconfidence behavior, a market-wide Vector autoregression (VAR) model is designed to investigate the lead-lag relationship between market returns and market turnover. The results obtained in this research suggest that investors in the Saudi stock market are overconfident.

Keywords: Behavioral Finance, overconfidence bias, stock market, VAR

JEL Classification Code: D91, G11, G12, G15, E22, G4.

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1 Introduction

1.1 Background

"People in standard finance are rational. People in behavioral finance are normal."

- *Meir Statman*

Many of the theories in both finance and economics, such as in Sharpe (1964), Miller and Modigliani (1958), and Malkiel and Fama (1970), share a common assumption that investors act rationally and analyze all available information before making investment decisions. However, more recent studies, such as Kahnemen (1979), Hirshleifer and Shumway (2003), and Statman et al. (2006) pointed out that investors are far from rational. These studies argue that investors cannot conform to the "rational" assumptions of the standard finance theories. Perhaps most notably, it has been pinpointed by Statman et al. (2006) that investors are not the "calculative utility maximizing machines" as assumed by the traditional theories in finance. More precisely, people are influenced by their sentiments or emotions and are more likely to make cognitive errors when making investment decisions. For instance, they may be overconfident about their abilities, overreact, or follow the crowd blindly.

Overconfidence bias is one of many examples of the cognitive errors affecting investor decision making.[1] This bias, among others, influences investors' stock

[1] Other observable biases are herding behavior, disposition effect, self-attribution bias, anchoring bias, etc (Thaler, 2005).

valuation and trading skills. Numerous empirical findings in the academic literature have shown a positive relationship between trading activity and past stock market returns.[2] Specifically, past stock gains influence investors to trade more. Researchers have pointed out that overconfidence bias cause this positive relationship. This cognitive error is a form of heuristics that develops from the brain's tendency to make mental shortcuts rather than engaging in longer analytical processing. There are various studies in the literature of economics and finance that provide evidence of overconfidence bias in stock markets. For example, this is best explained in both Daniel et al. (1998) theoretically, and Statman et al. (2006), empirically. They have concluded that subsequent to positive stock returns, there will be an increase in trading (volume) in the stock market. That is because gains from past returns have the effect of increasing the confidence of investors, by which it induces them to trade more. The ramification of such behavior could lead to a bubble in stock market, according to Shiller (2002), Scheinkman and Xiong (2003), Michailova (2010), and Gasteren (2016).

Statmen et al. (2006) described overconfidence bias as an exaggerated estimation by an investor of his or her likelihood to experience positive events. This bias has a negative effect on investors' overall portfolio returns. According to Trinugroho and Sembel (2011), overconfidence increases the likelihood of making

[2] See the literature review section.

irrational investment decisions. For example, it is stated in their research that overconfidence can lead investors to buy a stock at a high price, overconfidently thinking its price might go up further, or sell at a low price, overconfidently thinking the stock is worth less now than it was at the purchase date. This is best described by Odean (1998), who has designed a behavioral model to understand overconfident investors. In his model, he assumes that overconfident investors believe they have above average accuracy in their security valuations, and as a result, trade too much and, thereby, lower their wealth or expected utility. Gevias and Odean (2001) have developed a theory on overconfidence behavior by which investors tend to exaggerate their trading skills and ignore the fact that they are in a bull market. For instance, they argue that during a bull market, stocks tend to perform well, and generate profits, but overconfident investors tend to attribute the realized profit to their own skills. They disregard the fact that the realized gains where most likely due to the current state of the market, which is bullish.

Several studies that investigated overconfidence bias in stock markets consider trading volumes as a proxy for investor overconfidence, such as in Shefrin and Statman (1985), Statman et al. (2006), Goetzmann and Massa (2003), and Ranguelova (2001). These studies took into account the influence of past stock market returns on investors' overconfidence. In an empirical study, Statman et al. (2006) investigated the impact of overconfidence bias on trading volume in the US stock market. They used market returns to measure the degree of overconfidence, given that the level of overconfidence changes with market returns. Their results showed a significantly positive relationship between market turnover and past (lagged) market returns. This also indicates the presence of overconfidence bias in the US stock market. In another related study about the German stock market, Glaser and Weber (2007) found that investors tend to trade more when they are overconfident, which is consistent with the Statman et al. (2006) findings.

1.2 Research Objective, Justification and Contribution

There are certain objectives that form the basis of this research. The aim is to meet these objectives using empirical models like those of previous studies. Earlier studies have confirmed the presence of overconfidence bias in many countries. This study investigates whether this bias is manifested in the Saudi stock market (Tadawul). In addition, we will evaluate, from the obtained results, how strong the level of overconfidence is and go further to investigate the reasons behind it. Considering data availability, we followed Statman et al. (2006) and used turnover of stocks as a proxy for the level of overconfidence. Trading volume (turnover) is affected because overconfident investors believe in their abilities and act based on the information they obtain. Therefore, if past market returns can explain the current changes in trading volume, it can be considered as evidence of overconfidence. Based on this lead-lag relationship, this study uses a market-wide Vector autoregression (VAR) model and Impulse Response Function analysis to examine the existence of overconfidence bias in Tadawul.

Several studies have found evidence of a relationship between current trading volume and lagged returns in the stock markets of developed countries (Statman et al., 2006; Chuang & Lee, 2006; Glaser & Weber, 2007). However, there have been hardly any such empirical studies on the Saudi stock market. This study aims to fill this void in the existing literature by investigating the Saudi stock market with recent data of Tadawul. By testing the lead-lag relationship between returns and turnover, our empirical results confirmed the existence of overconfidence bias in the Saudi stock market.

1.3 Research Structure

In this study, there will be five sections organized as follows. Section 1 introduces and covers a concise background of the study. To give more context to the study, the objectives, justifications and the contribution are also included in Section 1. Section 2 delivers a theory review, as well as summarizes related research findings. Section 3 presents the data and provides a discussion on the empirical model. It also covers details on the dependent and independent variables, for instance, the formulas used in calculating the variables. Section 4 is the empirical section of the study. It discusses and analyzes the findings. The last section, Section 5, lays out a summary of the main findings and discusses whether the objectives are met.

2 Literature Review

One of the basic assumptions in classical Finance, and perhaps the most controversial, is that of rational agents and efficient markets. The Efficient Market Hypothesis, developed by Eugene Fama in the 1960s, has become one of the fundamental theories of market behavior[3]. Fama defined an efficient market as *"a market where there are large numbers of rational profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants"* (Malkiel & Fama, 1970, p. 56). According to their research paper, an efficient financial market should have no speculation because all traders would have the same information as one another and could not therefore rationally expect to profit from speculative trading. However, this fundamental concept of market efficiency is highly unlikely to occur in the real world.

In the late 1980s, several empirical papers found that investors in financial markets exhibited irrational behavior that could not be explained by classic economic theory. Therefore, the assumptions of the Efficient Market Hypothesis were questioned, especially its assumption of agents rationality. Several prominent studies in psychology showed that people are not always rational when they make

[3] See, Malkiel and Fama (1970).

decisions. In a Nobel Prize winning research on prospect theory, Kahneman and Tversky (1979) argued that people value gains and losses differently and base decisions more on the prospect of gains than on the possibility of losses.[4] Applying cognitive psychology to evaluate the effect of investors' behavior in financial markets led to the development of behavioral finance. Unlike classical finance, behavioral finance assumes that people exhibit subjective reasoning, which leads to more realistic empirical models. Overconfidence bias is one of many cognitive errors or biases discussed in behavioral finance.

In the behavioral psychology literature, such as in Yates (1990) and Campbell et al. (2004), people who presume themselves to have more abilities than they actually retain, and who make decisions based on that presumption, are described as being overconfident. Glaser and Waber (2007) presented three manifestations of overconfidence: miscalibration, underestimation of volatility, and the 'above average' effect. The following is a concise elaboration on these forms of overconfidence.

According to Glaser and Waber (2007), miscalibration is the difference between the accuracy and the probability assigned in any decision making process. For instance, when asked to make a forecast without being precise but estimating

[4] For example, if a person were given two equal choices, one expressed in terms of possible gains and the other in possible losses, people would choose the former even when they achieve the same economic result i.e. The Prospect Theory.

within a certain confidence interval, people usually are less accurate. In a similar study by Alpert and Raiffa (1982), participants were presented with a sequence of ten difficult questions, such as “What is the length of the Nile river?”. They were, then, asked to provide a low guess and a high guess that they thought would be the correct answer with a probability of 90%. If participants were well calibrated, nine out of ten of them would provide upper and lower guesses that actually contained the correct answer. As expected, participants were, in general, not well calibrated since they provided guesses that contained fewer correct answers than nine out of ten. In a related study, DeBondt (1998) asked 46 stock market investors to predict stock prices and forecast risks in US stock market. The results confirmed that there was a miscalibration in the stock market since investors were asked to place 90 percent confidence intervals on their predictions. In another word, DeBondt have found that the majority of investors failed to specify a range of expected future stock prices. Glaser et al. (2010) obtained similar findings for student and professional stock traders.

Some studies have focused on the volatility estimates of investors. For example, Hilton (2001) and Andersen et al. (2004) asked investors to provide confidence intervals for the return or price of a stock in the future. These studies concluded that investors tend to provide intervals that are too tight and therefore deviate from the possibilities of a correct guesses; such studies underestimated historical volatilities. In addition, Graham and Harvey (2015) found similar findings. They asked Chief Financial Officers of US firms to provide quarterly confidence intervals for the market risk premium. In their research, Graham and Harvey (2015) tended to underestimate historical volatilities.

A third form of overconfidence is the belief that one is better than the average person is. This is called the 'above average' effect. Numerous studies have confirmed the existence of this effect, such as Dunning (2005), Beer and Hughes (2010), Sharot (2011) and Chamorro-Premuzic and Furnham (2014). Many researchers have concluded that the above average effect is nearly universal. For instance, when a sample of U.S. students (22 years of age) were asked to evaluate their own driving safety, 93% judged themselves to be in the top 30% of the group (Svenson, 1981). Glaser and Weber (2007) found that more than half of stock market traders think their investment skills are above average, which leads them to trade more. Investors who attribute past success to their skills and past failure to bad luck are likely to be overconfident. An investor who is overconfident will want to utilize his/her perceived superior ability to obtain large returns. Furthermore, overconfident investors underestimate the risks of their active investment, and so, on average, trade more than other investors do (Kyle & Wang, 1997; Odean, 1998b).

2.1 Stock Market Returns and Overconfidence Bias

The correlation between stock market returns and overconfidence has been under the scope for many years. Miller and Ross (1975) finds that people attribute their success to their own ability, and attribute their failures to external factors.[5] Investors in financial markets are no exception according to their argument. Gervais and Odean (2001) formulated a model for determining how investors learn about their trading skills and in what way self-attribution bias leads to overconfidence. They began by assuming that investors do not know the range of their trading skills and they learn about it through experience. They pointed out that each investor's overconfidence level depends on past successes and failures in stock market trading. They also showed that greater overconfidence leads to higher trading volume. The authors also argue that their model could apply to the changing stock market states. For instance, investors during a bull market have more opportunities to make successful investments and gain profits. Accordingly, investors with self-attribution bias will become overconfident and trade more in a bull market, ignoring the fact that their success is more likely to have resulted from the bull market than from their own ability. Based on that, it could be expected that overconfidence bias among

[5] Scientifically, this behavior is called Self-Attribution Bias. See for more details, Feather and Simon (1971) and Hoffmann and Post (2014).

investors is higher and trading volume is greater, when there is an overall stock market gain.

Glaser and Weber (2007) investigated the effect of stock returns on individual investors in the German stock market from 1997 to 2001. More specifically, they considered which type of stock returns had a stronger effect on investors' overconfidence level: past market returns or past portfolio returns. They found that both past market returns and past portfolio returns affect investors' overconfidence, leading them to trade more. In their study, Glaser and Weber (2007) showed that higher past portfolio returns make investors trade more, leading to higher risk taking. However, high past market returns are not associated with higher risk taking. According to them, high past portfolio returns make investors overconfident because of self-attribution bias. Investors feel overconfident in the sense that they think themselves to be better investors than others. On the other hand, high past market returns could potentially make investors overconfident in the sense that they underestimate the volatility of stock returns. As a result, prediction intervals would be too tight that ultimately may result in misevaluation of the stocks.

2.2 Overconfidence Bias and Trading Volume

When analyzing investors' behavior using stock brokerage data, trading frequency is commonly used as a proxy for overconfidence. Barber and Odean (2000, 2001) and Odean (1999) found that U.S. individual investors trade excessively, expose themselves to a high level of risk, and make poor investment decisions. Investors with superior information and better trading skills will utilize this ability by trading often to capture high returns. Therefore, people with actual high ability and those who believe they have high ability will both trade excessively. It is generally assumed that there are few truly highly investors compared to the number of overconfident ones. Therefore, the trading frequency proxy is often believed to represent the behavior of overconfident investors on average. Similarly, Gervais and Odean (2001) examined an overconfidence hypothesis that proposes if investors are overconfident, they will trade more aggressively after experiencing stock gains. They pointed out that successful past trading experience creates overconfidence in investors' original price trend predictions. Such trading gains would then induce investors to buy or sell more in the following periods, and to do so more aggressively.

In a related study, Chuang and Lee (2006) reported several comprehensive results such as, past stock market gains lead investors to be overconfident and thus trade more actively.[6] Furthermore, a positive relationship between investor's overconfidence and stock market volatility was confirmed in their model. Additionally, overconfidence leads investors to underreact to risks associated with

[6] The reason behind more active trading is that during stock market gains (bull market), investors are more likely to make right forecasts about future stock returns. Then, investors become overconfident because of self-attribution bias.

investments, causing them to trade more in riskier stocks and as a result, lower their returns. These results are parallel to an experiment conducted by Yeoh and Wood (2011) in which participants were engaged in an eight weeks trading competition using London Stock Exchange share prices. Simulating a real-life investment experience, participants were given freedom to trade at any time. Using miscalibration as a measure of overconfidence, Yeoh and Wood (2011) revealed that overconfident participants tended to trade more and, as a result, underperformed in the experiment.

In a prominent empirical study, Statman et al. (2006) examined the New York Stock Exchange from 1962 to 2002. The focal point in their research was to test the trading volume predictions of formal overconfidence models. They pointed out that when examining long-term stock market trading activity, one must account for the fact that the number of shares for a typical stock has increased noticeably over the last four decades. Therefore, to offset the secular increase in number of shares, they measured trading activity with turnover (shares traded divided by outstanding shares).[7] Using Vector Autoregression and Impulse Response Functions, they were able to show that there is a statistically significant tendency for market trading activity to increase in the months following positive market returns after accounting for volatility associations.

[7] See also, Lo and Wang (2000).

2.3 Overconfidence Bias and Stock Market Bubble

Ultimately, stock market bubbles are infamous for its destructive impact on investments and the economy as a whole. In financial economics, a bubble is referred to as the systematic deviation from the asset's fundamental value (Kindleberger, 1978). Even more specifically, a stock market bubble occurs when the asset's trading price exceeds the discount value of the expected future cash flows (Gasteren, 2016). Historically, bubbles have been observed in many cases, such as the Dutch Tulip Mania in 1634, Black Monday in the 1920s, the Dot Com bubble, the recent subprime crisis in 2008 and The Saudi stock market crash in 2006. It is fair to say that the main causes of a bubble in stock markets are investors' irrational behaviors. Perhaps, this is best explained by the Daniel, Hirshleifer and Subrahmanyam (DHS) model as it demonstrates the relationship between overconfidence, volatility and bubbles. It starts when *investor X* receives some private information at time *t*, he/she tends to overreact to this piece of information and value stocks much higher than its actual price. At time *t+1*, this private information reaches the public, consequently other investors will eventually correct the initial overreaction until the stock reaches its rational expected value at *t+k*. This is what is considered a short run (harmless) bubble according to Daniel et al. (1998). However, in the long run when more investors are involved, the bubble could do a lot of damage in the stock market where instead of stocks prices going back to its rational expected value, it plummets sharply.

The role of overconfidence in creating bubbles begins when investors overvalue stocks prices, overconfidently thinking that other investors would pay higher in the future and thus generating profits, for instance similar to *investor X*. Michailova and Schmidt (2011) designed an experiment on 60 subjects (German participants) who were asked to participate in a simulated stock market with virtual money. At the end of the experiment, each participant was paid the exact amount earned in the simulation in cash. The purpose of their experiment was to closely test if overconfidence contributes to the creation of bubbles in stock markets. Their findings demonstrated that the majority of participants were overconfident which led to the formation of a bubble in the simulated stock market, and the ramification of participants' overconfidence led to overall lower returns. This experiment, however, was on a smaller scale as in any given real stock market, this potentially means that many people could lose substantial amount of money and as a result, the general confidence becomes weak in the stock market and the economy as a whole.

2.4 The Saudi Stock Market Crash of 2006 and Investors' Behavior

The Saudi Stock Exchange (Tadawul) is considered to be relatively new since it was established not that long ago in 1985. Throughout these 34 years, the Saudi stock market has not experienced anything like the 2006 crash. By the end of 2003, the

Tadawul All Share Index (TASI), which is the Saudi Stock Market Index, recorded a growth in its value by approximately 76 percent, and 84 percent, 103.7 percent in the following two years of 2004 and 2005, respectively. On February 25th of 2006, TASI closed at its historical peak of 20,634.86 one day before the market collapse. By the end of that year, TASI lost about 65 percent of its value. Unfortunately, the observed pattern was that more than half of the Saudi investors, at that time, borrowed money to invest or liquidated their assets to finance their investments. According to Saudi Arabian Monetary Authority (SAMA) annual reports, the loans granted to Saudi citizens reached a gross balance of US$ 13.4 billion (SAR 50.5 billion) at the end of 2002, however the gross loan balance reached US$48 billion (SAR180 billion) at the end of 2005.

Several Studies, such as Baamir (2008), Alkhaldi (2015) and Lerner et al. (2017) investigated the 2006 Saudi stock market crash and found that the crash was caused by different factors such as lack of investor's knowledge and experience. The lack of knowledge and experience might lead investors to a cognitive bias when they were making their investment decisions. Thus, understanding investors' behavior in the stock market is very essential since it might help in identifying and addressing the problems existing in the market.

There is an apparent lack of empirical literature on investors' behavior in the Saudi stock market. A great deal of the existing research has used a questionnaire-based approach. For instance, Alquraan, Alqisie and Shorafa (2016) randomly distributed 140 questionnaires in their study. The main targeted population of the study was the Saudi individual investors in the year of 2015. The results suggested that Saudi investors tended to be overconfident when they made their investment decisions, which means Saudi investors have a tendency to overestimate their own knowledge, abilities, and judgements. In an attempt to examine investors' stock portfolios in the Saudi stock market, Alsedrah and Ahmed (2018) found that investors in the Saudi stock market appeared to participate in a speculative behavior when making investment decisions. They concluded that overconfidence bias was one of the behaviors that persisted in the Saudi stock market.

3 Empirical Framework and Data Collection

3.1 Model Specification

In this study, overconfidence bias is tested in the Saudi stock market (Tadawul) by closely examining the interactions between market returns and market turnover (i.e. trading volume) using empirical model designed specifically to investigate overconfidence bias. This model, the market-wide security model which is based on Statman et al. (2006)[8] is formulated by estimating vector autoregression (VAR) and Impulse Response Functions (IRF) analysis using aggregate stock market data. Ultimately, empirical tests based on these estimates are critical in studying the interactions between lagged market returns and trading volume, which are used to test for overconfidence.

$\boldsymbol{H_0}$ **:** The current trading volume of transactions is not positively related to lagged market returns.

$\boldsymbol{H_1}$ **:** The current trading volume of transactions is positively related to lagged market returns.

This hypothesis is justified by the fact that following a bull market, the overconfidence of investors leads them to trade more aggressively due to self-attribution bias. Of this fact, this study assumes an increase in transaction volume

[8] Also, Chen and Zhang (2011), Zaiane (2013), Metwally and Darwish (2015) My et al. (2016), and Zia and Hashmi (2016).

following gains achieved by the market.[9] The Vector autoregression (VARX) model is applied to examine whether investors will trade more aggressively after market gains, as predicted by the overconfidence hypothesis.[10]

3.1.1 The Model: The Estimation of VAR to Test for Overconfidence Behavior

Vector autoregressive model (VARX) is constructed to investigate whether there are lead-lag relationships among variables. Unlike the univariate time-series model, the standard VAR model estimates several equations simultaneously without specifying which variables are exogenous or endogenous. In this study, a Vector autoregression (VARX) model is used as it is considered appropriate to test such relationship while introducing exogenous variables based on previous literature. The basic Vector autoregression (VARX) model is specified as follows:

$$Y_t = a + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_{t-l} + e_t$$

Where,

- Y_t: a (n*1) vector of endogenous variables[11] with t observations each.
- A_k: the matrix that measures how trading proxy and returns react to their lags.

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[9] This hypothesis is also mentioned by Odean (1998) and Gervais and Odean (2001).

[10] The VARX model is different from VAR in that it allows the use of control variables (exogenous variables in which their values are calculated outside the model).

[11] Returns and trading proxy (turnover and volume).

– B_l: the matrix that measures how trading proxy and returns react to month (t-1) realizations of exogenous variables.

– X_t: a (n*1) vector of exogenous variables[12] with t observations each.

– K and L: numbers of endogenous and exogenous observations respectively. K and L are chosen based on the Akaike Information Criteria (AIC), Schwartz Criteria (SC), and Hannan Quinn (HQ)[13]. In this paper, the SC leads to K=1 (See table 1) and L=1,[14] look at table 1.

– e_t: a (n*1) residual vector. It captures the contemporaneous correlation between endogenous variables.

Table 1: Lag structure criteria for endogenous variables in market-wide VARX model

Lag	LL	LR	FPE	AIC	SC	HQ
0	500.7258	NA	1.80e-06	-7.553065	-7.421376	-7.499554
1	566.5567	126.6367*	7.00e-07*	-8.497049*	-8.277568*	-8.407864*
2	567.5626	1.904173	7.32e-07	-8.451337	-8.144064	-8.326478
3	571.5948	7.510420	7.32e-07	-8.451829	-8.056763	-8.291296
4	572.4306	1.531179	7.69e-07	-8.403520	-7.920662	-8.207313
5	573.7617	2.398097	8.01e-07	-8.362774	-7.792124	-8.130894
6	577.7007	6.975882	8.02e-07	-8.361842	-7.703400	-8.094288
7	580.9740	5.697061	8.12e-07	-8.350748	-7.604513	-8.047519
8	582.0740	1.881022	8.50e-07	-8.306474	-7.472447	-7.967572

Value with star (*) is chosen by specific criterion.

[12] Dispersion and volatility.

[13] $AIC = log|\hat{\Sigma}| + \frac{2K}{T}$, $SC = log|\hat{\Sigma}| + \frac{K}{T}\log(T)$, $HQ = log|\hat{\Sigma}| + \frac{2K}{T}\log(\log(T))$

[14] As for the exogenous variables' lag selection, the appropriate lag is chosen after running VARX model in respect to different lag, starting from lag 1 to lag 5. The smallest AIC number associated from running VARX model is chosen.

Fundamentally, the model is constructed to investigate the lead-lag relationship between market return and trading volume, which is specified as follows:

$$\begin{bmatrix}\mathrm{Mturn}_t\\ \mathrm{Mret}_t\end{bmatrix} = \begin{bmatrix}\alpha_{\mathrm{Mturn}}\\ \alpha_{\mathrm{Mret}}\end{bmatrix} + \sum_{k=1}^{1} \mathrm{A}_k \begin{bmatrix}\mathrm{Mturn}_{t-k}\\ \mathrm{Mret}_{t-k}\end{bmatrix} + \sum_{l=0}^{1} \mathrm{B}_l \begin{bmatrix}Msig_{t-1}^2\\ \mathrm{Disp}_{t-l}\end{bmatrix} + \begin{bmatrix}\mathrm{e}_{\mathrm{Mturn},t}\\ \mathrm{e}_{\mathrm{Mret},t}\end{bmatrix}$$

The market turnover series is required to be stationary to ensure the model estimation is non-biased and valid. The variables are stationary at their level according to the Augmented Dickey Fuller and Phillips Perron tests that have been applied to the data.

3.1.2 Definition of Variables

– *Mturn*: The monthly market turnover (shares traded)

According to previous research, trading volume (in shares) and the turnover ratio are both commonly used indicators to measure trading activities. This paper takes into account the historically growing trend of trading volume in the sample period. Following Statman et al. (2006), the turnover ratio is used because it is a relative measure that eliminates the influence of growth. The turnover ratio has to be estimated for each stock, using the data of trading volume (in shares) for each individual stock. Lo and Wang (2000) provided thorough calculation formulas for both share turnover and value-weighted turnover. Suppose V_i represents the number of shares traded monthly for individual stock *i*, and S_i is the outstanding shares of the stock i. Hence, the individual turnover is calculated by, $\mathrm{T}i = \frac{Vi}{Si}$. The weight w_i for each stock is different with its own market value divided by the total market capitalization. By applying different weights to the turnover ratio for each stock, the market turnover is expressed as follows:

$$t_{vw} = \sum_{i=1}^{n} \mathrm{w}i * \mathrm{T}i$$ [15]

The calculation of each stock during the whole sample period was repeated to obtain a market turnover time series. Figure 1 is the plotted graph of monthly market turnover.

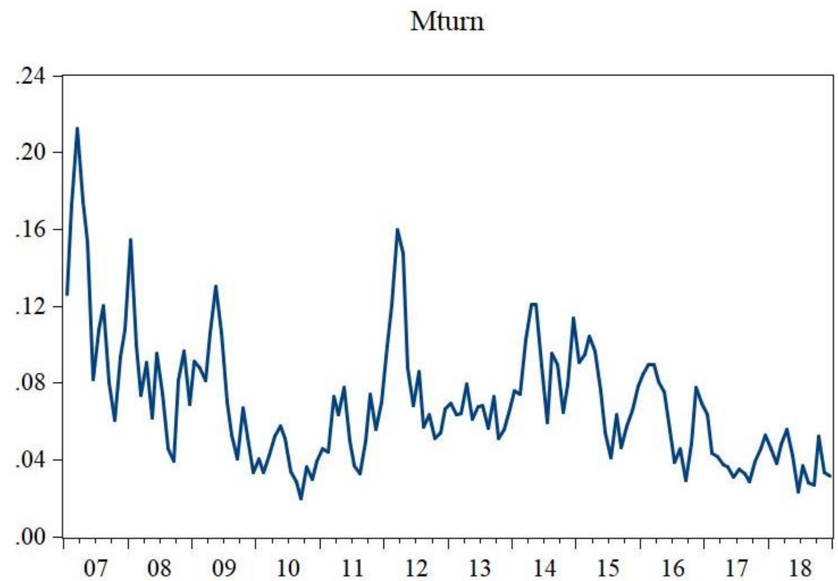

Figure 1: Monthly market turnover of the Saudi Stock Market (TASI)

Perhaps, it is noticeable that Figure 1 indicates that the series may be accompanied with a trend. Therefore, the Augmented Dickey-Fuller (ADF) unit root

[15] Where, $\mathrm{w}i = \frac{\text{The capitalization of the security}}{\text{Sum of capitalization for all securities in the market}}$ and $Capitalization = Pi * Si$ (**Pi**, is initial price per share, and **Si**, is shares outstanding for each security).

test was applied, and the test rejected the null hypothesis of existence of a unit root at 1% confidence level. The results revealed market turnover is stationary at its level. A stationary turnover time-series is desired as it eliminates bias in coefficient estimates of the VAR model. The results of the unit root tests will be presented in details in section 4.

– *Mret: The monthly stock market return*

One way of calculating market returns is directly through raw data on TASI. For monthly market returns, the process involves calculating returns for all stocks within the index for each month.

$$Total\ Stock\ Returns, Mret = \frac{(P_1 - P_0) + D}{P_0}$$ [16]

The market return series, *mret* is therefore generated by repeating the process for all months during the sample period. Furthermore, market return passes the stationary test (ADF unit root test) at 1% significance level. Figure 2 shows the fluctuations of market return based on TASI. As can be seen, the recent global financial crises of 2008 affected market returns fluctuations by large margins.

[16] Where, $P_0 = Initial\ stock\ price$, $P_1 = Ending\ stock\ Prices$, and $D = dividends$.

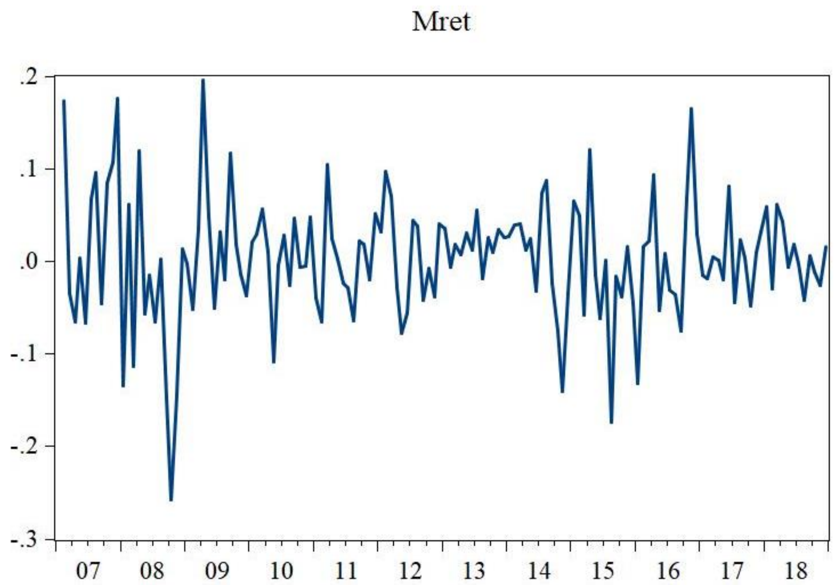

Figure 2: Monthly market return of the Saudi Stock Market (TASI)

- *Msig: The monthly temporal volatility of market return based on daily market returns within the month.*[17]

In addition to *Mturn* and *Mret*, market volatility (*Msig*) is employed as the first control variable.

$$Msig_t^2 = \sum_{t=1}^{T} r_t^2 + 2\sum_{t=1}^{T} r_t r_{t+1}$$

Following the Statman et al. (2006) specification of the monthly volatility, using the formula provided by French et al. (1987), which is computed by adding squared daily returns with twice the sum of the products of adjacent returns. Assuming that r_t is day t's return and **T** is the number of trading days in month **t**.

[17] This research follows French et al. (1987) conditions of volatility calculation.

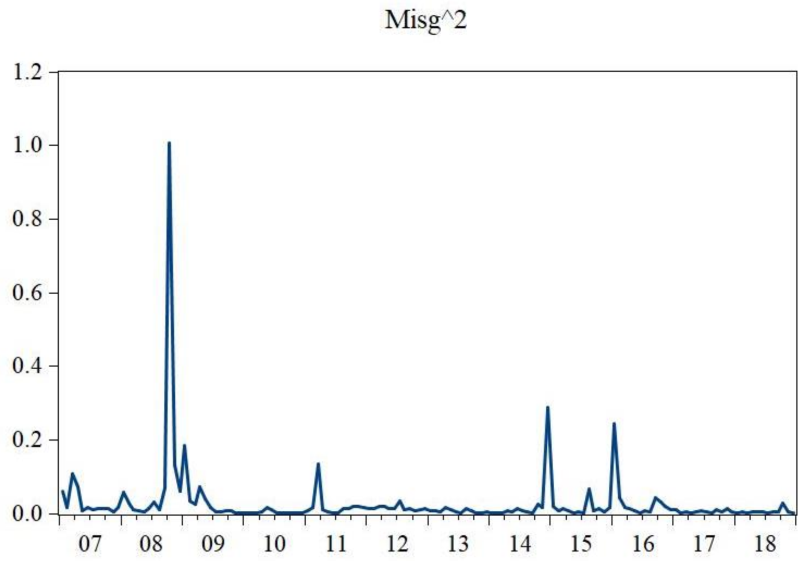

Figure 3: Monthly market volatility of the Saudi Stock Market (TASI)

Figure 3 shows that the Saudi investors were affected by the global financial crisis in 2008, leading to a very high volatility. The impact of this volatility may have been the reason for the sharp declines in market returns in 2008, see Figure 2.

– *Disp: Cross-sectional standard deviation of returns for all stocks in month t.*

The second control variable dispersion (*Disp*) is introduced, following Campbell and Lettau (1999). In order to capture the individual risk for individual firms, dispersion variable is employed, which is the cross-sectional volatility of individual firms within TASI on monthly basis. The reason the return dispersion is used as a control variable is to account for any potential trading activity associated with portfolio rebalancing. For instance, large deviations between the individual stock returns within an investment portfolio might lead investors to initiate a trading activity in order to maintain their incepted portfolio weights associated with an investment strategy.

$$Disp_t = \sqrt{\sum_{t=1}^{N} Wi(r_t - \bar{r})^2} \quad ^{18}$$

First, squared deviation from mean return for each stock is computed and following is the multiplication of market-capitalization weights to generate *disp* series.

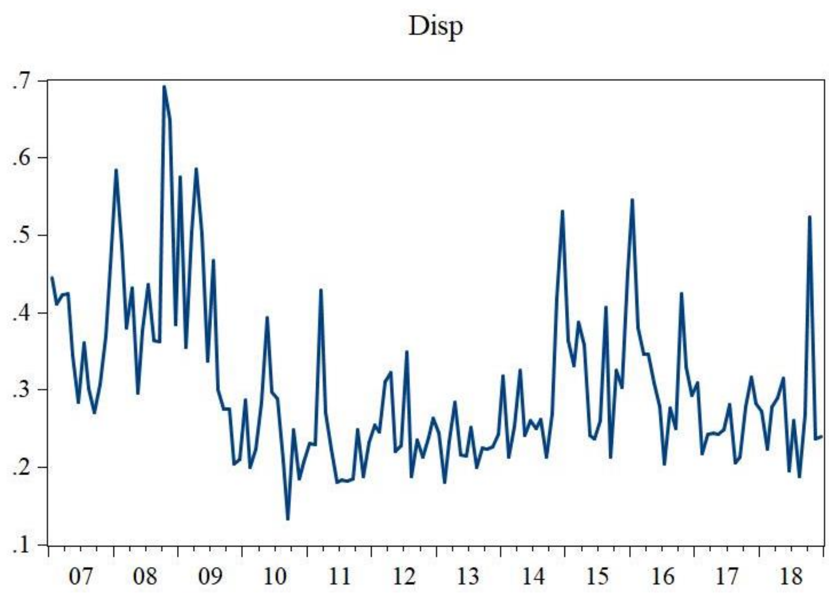

Figure 4: Monthly market volatility of the Saudi Stock Market (TASI)

By looking at the cross sectional volatility of firms in TASI, we can observe that the crisis in 2008 had an impact on the behavior of trading that led to high fluctuations and volatility.

[18] where $\bar{r} = \frac{1}{N} \sum_{t=1}^{N} r_t$.

3.2 Data

The data of the Saudi stock market in this paper were collected from Bloomberg's database. The TASI is a free float market capitalization-weighted index of more than 190 stocks. For consistency, we excluded all traded funds, such as REITs (Real Estate Investment Trust) because such securities do not have the same characterization of stocks. In addition, this study excludes stocks that had been listed in late of 2018 because of the short observations of these stocks. After eliminating such stocks, there were 172 stocks under investigation. Tadawul has been continually developing and as a result, each year, a considerable number of companies are listed; therefore, the number of shares traded increases noticeably. However, this was considered in the study by applying Statman et al. (2006) methods of offsetting the inevitable growth of shares traded over time. The data sample period is from January 2007 to December 2018. The data collected is a monthly based, however, daily data is needed to calculate monthly volatility. The data consist of approximately 400,000 daily observations of price, trading volume and market capitalization for each stock listed in the TASI.

4 Empirical Results

4.1 Descriptive Statistics and Unit Root Tests

Table 2: Descriptive Statistics

Full Period 2007 – 2018

Observations: 143			
Market returns (*Mret*)		**Market volatility (*Msig²*)**	
Mean	0.0030	Mean	0.0264
Std. Dev.	0.0667	Std. Dev.	0.0913
Minimum	-0.2575	Minimum	0.0006
Maximum	0.1959	Maximum	1.0060
Market turnover (*Mturn*)		**Dispersion (*Disp*)**	
Mean	0.0695	Mean	0.3029
Std. Dev.	0.0334	Std. Dev.	0.1037
Minimum	0.0198	Minimum	0.1340
Maximum	0.2124	Maximum	0.6923

There is a fairly large number of observations in this study at which N = 143. We believe, in this study that it is important to have an adequate number of observations as it provides an estimation that is more precise. By looking at Table 2, the results show that the average market return $(Mret)$ is 0.3% across all stocks in TASI over the full sample period. The turnover $(Mturn)$ averaged about 7% across TASI. However, the Descriptive Statistics show an unusual outcome for market volatility ($Msig^2$) as it averaged about 2.6% which is considered to be low compared to other stock markets, such as 16% in the US, 15% in Japan, 15% in Germany and 7% in Hong Kong.[19] We believe that the reason TASI recorded a low volatility could be

[19] See Statman et al. (2006), Chen and Zhang (2011) and Zoe (2016)

due to the fact that investors are being cautious after the devastating 2006 bubble. This may have led investors to implement a safe investment strategy, such as buy and hold. The dispersion *(Disp)* recorded an average of 30% of the collective individual stocks in TASI.

Table 3: Unit Root Tests

	Augmented Dickey Fuller (ADF)		Phillips Perron (PP)	
	Level Data		Level Data	
	Constant	Trend	Constant	Trend
Mret	-10.73	-10.69	-10.73	-10.69
Mturn	-4.01	-4.40	-3.52	-4.18
Msig^2	-10.14	-10.31	-10.23	-10.35
Disp	-6.00	-6.31	-6.07	-6.46

Note: The ADF 5% critical values for constant = -2.88, and for trend= -3.44. For the PP constant = -2.88, and for trend = -3.44.

Intuitively stationarity implies that the statistical properties of a time series variables do not change over time. In a time series model, it is essential for the variables to be stationary in order to have a valid assumption. As can be seen in Table 3, we ran the Augmented Dickey Fuller (ADF) test on all the variables.[20] The results show that at 1% confidence level, all variables are stationary at its level. This

[20] After processing the data, the following ADF test (1981) is used:

$$\Delta y_t = \alpha_0 + \gamma_t + \beta y_{t-1} + \sum_{j=1}^{k} \phi_j y_{t-j} + \varepsilon_t$$

The theory of unit root test underlies consideration of the serial correlation problem. The null hypothesis of the ADF test is $\gamma = 0$ versus the alternative hypothesis $\gamma \neq 0$. Failing to reject the null hypothesis means that the series under investigation is not stationary, and a unit root exists.

study ran the Phillips Perron (PP) test to confirm that all variables are stationary in spite of running another unit root test.[21] The PP test results show that all variables are stationary at its level.

4.2 Market-wide VAR Estimation and Impulse Response Function

4.2.1 Market VAR Estimation

Table 4 summarizes the estimation results of the market VARX system that contains endogenous variables: market turnover, *Mturn*, and market return, *Mret*. Furthermore, the control variables are market volatility, *Misg*^{2}, and dispersion, *Disp*. The following paragraphs discuss the main results obtained from VARX model that was designed to test overconfidence behavior in the Saudi stock according to Statman et al. (2006), the overconfidence hypothesis is verified when lagged market returns are associated with increased market turnover (trading volume).

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[21] The PP unit root (1988) statistics are computed as:

$$Z_\alpha = T(\hat{\alpha}-1) - \frac{1}{2}\left(\widehat{\lambda^2} - \delta^2\right)\left(\frac{1}{T^2}\sum_{t=1}^{T} x_{t-1}^2\right)^{-1}$$

$$Z_t = \frac{\delta}{\hat{\lambda}} t_{\hat{\alpha}=1} - \frac{1}{2}\left(\widehat{\lambda^2} - \delta^2\right)\left(\frac{\widehat{\lambda^2}}{T^2}\sum_{t=1}^{T} x_{t-1}^2\right)^{-1/2}$$

Where,

$$t_{\hat{\alpha}} = s^{-1}(\hat{\alpha}-1)\left(\textstyle\sum_{t=1}^{T} x_{t-1}^2\right)^{1/2}, \text{ and } s^2 = T^{-1}\textstyle\sum_{t=1}^{T} \widehat{u_t^2}$$

and $\hat{\lambda}^2$ are estimators of the short and long run variances of u_t. The null hypothesis of the PP test proposes that there is a unit root. Failing to reject the null hypothesis means that the series under investigation is not stationary.

Table 4: Market VAR Estimation Results (2007-2018)

	Constant	*Mret (t-1)*	*Mturn (t-1)*	*Mret (t-2)*	*Mturn (t-2)*	*Msig^2 (t-1)*	*Disp (t-1)*
Mret	0.004400 (0.02014)	0.061948 (0.09640)	0.258487 (0.36980)	-0.048566 (0.09394)	-0.273192 (0.30684)	-0.130787 (0.08124)	0.008085 (0.07655)
Mturn	0.018690*** (0.00563)	0.066930** (0.02696)	0.717416*** (0.10344)	-0.003085 (0.02628)	-0.002681 (0.08583)	0.041684* (0.02272)	-0.004950 (0.02141)

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4 shows the results of testing this study's hypothesis using VAR estimation by incorporating the full sample (2007 to 2018). This study is interested in the in the interactions between lagged market returns and market turnover. Looking at market turnover (*Mturn*) with market return (*Mret*) at lag 1, the result shows a statistically significant coefficient, with the estimated parameter of 0.067. However, we noticed the existence of serial correlation at lag 1. To solve this problem, we proceeded to use lag 2 for all endogenous variables as the selection of lag 2 seemed to remove serial correlation problem as proposed by Foscolo (2012).[22] This suggests that current market turnover depends on the first lagged market return. From this observation, the overconfidence hypothesis of our model is verified and confirmed in the Saudi stock market, Tadawul. In other words, positive past market returns make investors overconfident leading them to trade more. Besides, the results

[22] Foscolo suggested that serial autocorrelation rapidly declines at higher lags. The serial correlation test results will be displayed in the Appendix.

indicate that market volatility at lag 1 has a positive and statistically significant coefficient of 0.042 in explaining market turnover. That is, when volatility is high, Saudi investors tend to trade more in the subsequent period. We believe the reason behind it is that when there is volatility in TASI, Saudi investors might anticipate that the market is reacting to positive news while in reality that is not the case as in many cases, volatility is caused by noisy traders. These results are consistent with Statman et al. (2006).

The results in table 4 are similar to the results that have been observed in the US stock market (Statman et al., 2006; Odean, 1998a; Gervais and Odean, 2001), Hong Kong stock market (Chen & Zhang, 2011), and French stock market (Siwar, 2011). However, the degree of overconfidence understandably varies between countries.[23] For instance, the coefficient of the market return lag 1 with current market turnover in the United States (Statman et al., 2006), is 0.816, in Hong Kong the coefficient is 0.3330, and in France, the coefficient is significant at 0.540, compared with this study's equivalent results, in which Saudi Arabia has a significant coefficient of 0.082.

Table 5: Granger causality test (*Mret* and *Mturn*)

Null Hypothesis:	Observations	F-statistics	Prob.
Mret does not Granger Cause *Mturn*	142	6.00551	0.0155
Mturn does not Granger Cause *Mret*	142	0.25745	0.6127

[23] It could be a result of different time series or different estimation models.

Based on estimates of the VAR model, this study is interested to know whether market return (*Mret*) Granger-causes market turnover (*Mturn*). Market return is said to Granger-cause market turnover if past values of market return are useful for predicting market turnover. For instance, failure to reject the null hypothesis is failure to reject the hypothesis that *Mret* (*Mturn*) does not Granger-cause *Mturn* (*Mret*). Table 5 shows that the Granger causality test results confirm the overconfidence hypothesis in the Saudi stock market. The null hypothesis "*Mret* does not Granger- cause *Mturn*" produced a p-value of 0.0155, therefore, it is rejected at 5% significant interval. This means that past market returns (*Mret*) have a positive impact on current market turnover (*Mturn*), i.e., trading volume. Nevertheles, this relationship does not hold in the opposite way. The p-value is greater than 10% when the dependent variable is market return. Thus, the null hypothesis cannot be rejected. As a result, the influence of past trading volume on the current market return is not realized in the Granger causality test. To sum up, this study found a unidirectional granger causality running from lagged market returns and current market turnover.

4.2.2 Market Impulse Response Function

Impulse response function uses all the VAR coefficient estimates to check the impact of one standard deviation shock from the residual. Figure 5 shows the four possible impulse-response function graphs using the VAR estimation results in Table 4.

Figure 5: Impulse Response Function

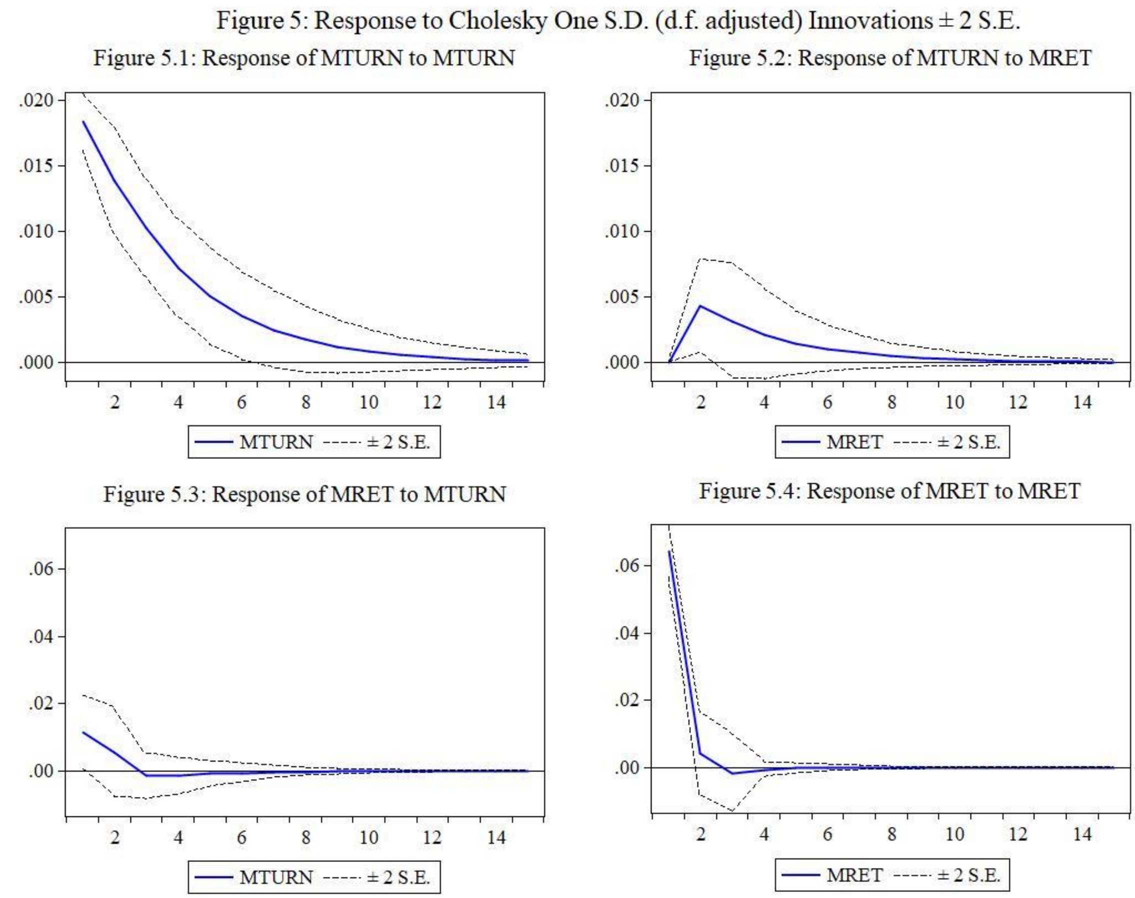

Figure 5.1 and 5.2 plot the response of market turnover (*Mturn*) to a one standard deviation shock in market turnover (*Mturn*) and market returns (*Mret*), respectively. For instance, Figure 5.1 shows that a one standard deviation shock to market turnover results in a positive response of 1.8% in the next month's turnover. This verifies the serial dependence of market turnover, by which the positive effect of a one standard deviation shock to market turnover persists at period one (the effect

starts to slowly decline after period one). In Figure 5.2, the first and second period impulse-responses imply that a one standard deviation shock to market return is followed by 0.4% increases in the market turnover of the second month. The accumulated response over the first 10 months is a 1.0% increase in market turnover compared to average levels. This is a key finding, as it is an evidence that market return impacts investors' overconfidence, leading them to trade more. Figure 5.2 accords with VAR estimation and Granger-causality test results. However, it shows a relatively weak response of market turnover to market return starting the following month by 0.4% in the Saudi stock market compared to the large and persistent response in the US stock market of approximately 7%, according to Statman et al. (2006). The results suggest that investors in the US show a higher level of overconfidence compared to Saudi investors. This could be a result of the higher experience level of investors in the US compared to Saudi peers. This phenomena of a positive relationship between higher experience and overconfidence behavior in financial markets is supported by Heath and Tversky (1991), Frascara (1999) and Kirchler and Maciejovsky (2002)[24].

Figure 5.3 and 5.4 plot the response of market return (*Mret*) to a one standard deviation shock in market turnover (*Mturn*) and market return (*Mret*), respectively.

[24] In addition, Glaser et al. (2003) has a similar result because in their experiments professional traders have a higher degree of overconfidence than students in the two tasks examined, namely trend recognition and forecasting of stock price movements.

For instance, Figure 5.3 shows that market return response to a one standard deviation shock to market turnover is weak, and is present only from 1 month to 3 months. In the third month and afterwards, the impact of the shock starts to move to the negative range. That means that a one-unit shock of market turnover will negatively affect returns by -0.2% in the third month. In other words, positive lagged market returns lead Saudi investors to trade more, resulting in negative overall current market returns. Figure 5.4 indicates that the first period impulse-response with a one standard deviation shock to market return results in a 6.4% increase in the next month's return. However, the impact of the shock declines after 2 months and starts to disappear after 3 months. This behavior of market returns can be explained by the Momentum Theory (Rouwenhorst, 1998), which suggests that positive returns tend to follow gains in a short time horizon.

5 Conclusion

This section summarizes the main empirical findings obtained in Section 4. Furthermore, there will be a brief discussion whether the objectives of this research are achieved as well as addressing the limitations of this research. In addition, suggestions and recommendations for future research will be highlighted in this chapter.

5.1 Summary of the Study

This paper focuses on the most common behavior observed in financial stock markets that is overconfidence bias. This bias is confirmed to have an effect on investor's decision making in many advanced countries, such as the United States, France, Japan, and Germany. In addition, this is observed on a stronger level in developing countries, such as Taiwan, Hong Kong, Hungary, Tunisia, and Egypt. The method used to obtain the results of this study was by collecting Saudi stock market (Tadawul) data from 2007 to 2018 using Bloomberg database. After processing the data, four variables, in total, were formed (*Mret, Mturn,* $Msig^2$, *Disp*)[25]. Subsequently, a VAR model was estimated to test for overconfidence behavior in the Saudi stock market. The focal point after running the model is to analyze the relationship between lagged market return and current market turnover

[25] See chapter 3 (page 18) for further elaboration on the variables.

and to test for overconfidence bias. The results obtained from the VAR model, confirmed the existence of overconfidence behavior in the Saudi stock market. As predicted, the level of overconfidence in Saudi is somewhat lower to those of other developed countries. A Granger causality test was also conducted as a robustness check for VAR results. The outcome of the Granger causality test matches the VAR estimation results fairly well. That is, both results showed that past market returns and market turnover (volume) are positively related. The results revealed that investors tend to trade more when they get positive returns in the previous month, i.e., they exhibited overconfidence bias. This study aimed to test for overconfidence bias in the Saudi stock market. This objective has been met using appropriate estimation model (VAR model) and the brilliant example of Statman et al. (2006) as the primary foundation to build up the hypothesis and model of this study.

5.2 Limitations and Recommendations of the Study

The results confirm that investors in the Saudi stock market (Tadawul) exhibit overconfidence behavior in their decision-making. The most substantial limitation of this study is being unable to collect stock market data before 2007. This would have been beneficial in terms of studying the Saudi investor’s behavior before and after the global financial crisis of 2008 and the local market crash of 2006. Moreover, a longer sample size would allow for more insights into past stock market behavior and comparison of changes in behavior with recent data.

This study investigated the lead-lag relationship between market returns and market turnover, using Statman et al. (2006) estimation models on a monthly basis. However, there are more ways to test for overconfidence behavior. Most obvious and most difficult is by conducting experiments[26]. Another limitation, it is time consuming but effective to collect data using a questionnaire, such as in Zaiane and Abaoud (2010) and Huisman et al. (2012). Also, as mentioned earlier, the data were collected and then calculated on a monthly basis. As Statman et al. (2006) suggested, a daily-based data might introduce more insight into investor's behavior. Given the fact that there is no research on the Saudi stock market (at the time of conducting this research) that contains daily observations, it would be interesting for future studies to take that into consideration. One concern of using daily observations is that it will produce an extremely large dataset. Therefore, shortening the sample period is ideal in this case.

[26] See Hilton (2001) and DeBondt (1998).

Reference:

Alkhaldi, B. A. (2015). The saudi capital market: The crash of 2006 and lessons to be learned. *International Journal of Business, Economics and Law*, *8*(4), 135-146.

Alpert, M., & Raiffa, H. (1982). A progress report on the training of probability assessors.

Alquraan, T., Alqisie, A., & Al Shorafa, A. (2016). Do behavioral finance factors influence stock investment decisions of individual investors? (Evidences from Saudi Stock Market). American International Journal.

Alsedrah, I., & Ahmed, N. (2018). Behavioral Finance And Speculative Behavior Of Investors: Evidence From Saudi Stock Market. The 8th International Economics & Business Management Conference. Doi: Https://Dx.Doi.Org/10.15405/Epsbs.2018.07.02.65

Andersen, B. L., Farrar, W. B., Golden-Kreutz, D. M., Glaser, R., Emery, C. F., Crespin, T. R., ... & Carson III, W. E. (2004). Psychological, behavioral, and immune changes after a psychological intervention: a clinical trial. Journal of clinical oncology: official journal of the American Society of Clinical Oncology, 22(17), 3570.

Baamir, A. Y. (2008). Issues of transparency and disclosure in the Saudi Stock Market. Arab Law Quarterly, 63-87.

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. The journal of Finance, 55(2), 773-806.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. The quarterly journal of economics, 116(1), 261-292.

Barber, B., Odean, T., & Zhu, N. (2006). Do noise traders move markets?.

Beer, J. S., & Hughes, B. L. (2010). Neural systems of social comparison and the “above-average” effect. Neuroimage, 49(3), 2671-2679.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. The Journal of Finance, 56(1), 1-43.

Campbell, W. K., Goodie, A. S., & Foster, J. D. (2004). Narcissism, confidence, and risk attitude. Journal of behavioral decision making, 17(4), 297-311.

Cekauskas, K., Liatukas, V., Verlaine, M., & Putniņš, T. (2011). Behavioural Biases of the Disposition Effect and Overconfidence and their Impact on the Estonian Stock Market.

Chamorro-Premuzic, T., & Furnham, A. (2014). Personality and intellectual competence. Psychology Press.

Chen, Z., and Zhang, S. (2011). Overconfidence and Turnover (Master dissertation). Retrieved from: https://lup.lub.lu.se/student-papers/search/publication/2152932

Chuang, W. I., & Lee, B. S. (2006). An empirical evaluation of the overconfidence hypothesis. Journal of Banking & Finance, 30(9), 2489-2515.

Chui, P. M. (2001). An experimental study of the disposition effect: Evidence from Macau. The journal of psychology and financial Markets, 2(4), 216-222.

Coval, J. D., & Shumway, T. (2005). Do behavioral biases affect prices?. The Journal of Finance, 60(1), 1-34.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. The Journal of Finance, 53(6), 1839-1885.

De Bondt, W. F. (1998). A portrait of the individual investor. European economic review, 42(3-5), 831-844.

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. Handbooks in operations research and management science, 9, 385-410.

Dhar, R., & Zhu, N. (2002). Up close and personal: An individual level analysis of the disposition effect.

Dunning, D. (2005). Self-insight: Roadblocks and detours on the path to knowing thyself. New York: Psychology Press.

Feather, N. T., & Simon, J. G. (1971). Attribution of responsibility and valence of outcome in relation to initial confidence and success and failure of self and other. Journal of Personality and Social Psychology, 18(2), 173.

Foscolo, E. (2012). Analysis of Financial Time Series with EViews.

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. Journal of financial Economics, 19(1), 3-29.

Gasteren, L. V. (2016). The effect of overconfidence on stock market bubbles, velocity and volatility.

Gervais, S., & Odean, T. (2001). Learning to be overconfident. The Review of financial studies, 14(1), 1-27.

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. The Geneva Risk and Insurance Review, 32(1), 1-36.

Goetzmann, W. N., & Massa, M. (2003). Disposition matters: Volume, volatility and price impact of a behavioral bias (No. w9499). National Bureau of Economic Research.

Goo, Y. J., Chen, D. H., Chang, S. H. S., & Yeh, C. F. (2010). A study of the disposition effect for individual investors in the Taiwan stock market. Emerging Markets Finance and Trade, 46(1), 108-119.

Graham, J. R., & Harvey, C. R. (2015). The Equity Risk Premium in 2015.

Hilton, D. J. (2001). The psychology of financial decision-making: Applications to trading, dealing, and investment analysis. The Journal of Psychology and Financial Markets, 2(1), 37-53.

Hirshleifer, D., & Luo, G. Y. (2001). On the survival of overconfident traders in a competitive securities market. Journal of Financial Markets, 4(1), 73-84.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. The Journal of Finance, 58(3), 1009-1032.

Hoffmann, A. O., & Post, T. (2014). Self-attribution bias in consumer financial decision-making: How investment returns affect individuals' belief in skill. Journal of Behavioral and Experimental Economics, 52, 23-28.

Huisman, R., van der Sar, N. L., & Zwinkels, R. C. (2012). A new measurement method of investor overconfidence. Economics Letters, 114(1), 69-71.

Joo, I., & Ormos, M. Disposition effect: do hungarian investors keep their mistakes?. European Financial Systems 2012, 85.

Kahneman, D. (1979). Prospect theory: An analysis of decisions under risk. Econometrica, 47, 278.

Kahneman, D., & Tversky, A. (1979). On the interpretation of intuitive probability: A reply to Jonathan Cohen.

Kindleberger, C. P., & Manias, P. (1978). Crashes: a history of financial crises.

Kyle, A. S., & Wang, F. A. (1997). Speculation duopoly with agreement to disagree: Can overconfidence survive the market test?. The Journal of Finance, 52(5), 2073-2090.

Lerner, J. O. S. H., Leamon, A., & Dew, S. T. E. V. E. (2017). The CMA and the Saudi stock market crash of 2006. BELLA Research Group, Saudi Capital Market Authority (CMA).

Lo, A. W., & Wang, J. (2000). Trading volume: definitions, data analysis, and implications of portfolio theory. The Review of Financial Studies, 13(2), 257-300.

Locke, P. R., & Mann, S. C. (2005). Professional trader discipline and trade disposition. Journal of Financial economics, 76(2), 401-444.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The journal of Finance, 25(2), 383-417.

Metwally, A. H., & Darwish, O. (2015). Evidence of the overconfidence bias in the Egyptian stock market in different market states. The Business & Management Review, 6(4), 178.

Michailova, J. (2010). Overconfidence and bubbles in experimental asset markets.

Michailova, J., & Katter, J. K. (2014). Quantifying overconfidence in experimental finance. International Journal of Behavioural Accounting and Finance, 4(4), 351-367.

Miller, D. T., & Ross, M. (1975). Self-serving biases in the attribution of causality: Fact or fiction?. Psychological bulletin, 82(2), 213.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. The American economic review, 48(3), 261-297.

Mossin, J. (1966). Equilibrium in a capital asset market. Econometrica: Journal of the econometric society, 768-783.

Nofsinger, J. R. (2005). Social mood and financial economics. The Journal of Behavioral Finance, 6(3), 144-160.

Odean, T. (1998). Are investors reluctant to realize their losses?. The Journal of finance, 53(5), 1775-1798.

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. The journal of finance, 53(6), 1887-1934.

Odean, T. (1999). Do investors trade too much?. American economic review, 89(5), 1279-1298.

Ranguelova, E. (2001). Disposition effect and firm size: New evidence on individual investor trading activity.

Scheinkman, J. A., & Xiong, W. (2003). Overconfidence and speculative bubbles. Journal of political Economy, 111(6), 1183-1220.

Sharot, T. (2011). The optimism bias. Current biology, 21(23), R941-R945.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance, 19, 42-425.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. The Journal of finance, 40(3), 777-790.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. The Journal of finance, 40(3), 777-790.

Shiller, R. J. (2002). Bubbles, human judgment, and expert opinion. Financial Analysts Journal, 58(3), 18-26.

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. The Review of Financial Studies, 19(4), 1531-1565.

Svenson, O. (1981). Are we all less risky and more skillful than our fellow drivers?. Acta psychologica, 47(2), 143-148.

Tehrani, R., & Gharehkoolchian, N. (2012). Factors affecting the disposition effect in Tehran stock market. International Business Research, 5(3), 40.

Thaler, R. H. (Ed.). (2005). Advances in behavioral finance (Vol. 2). Princeton University Press.

Trinugroho, I., & Sembel, R. (2011). Overconfidence and excessive trading behavior: An experimental study. International Journal of Business and Management, 6(7).

Weber, M and Camerer, CF. 1998. The disposition effect in securities trading: an experimental analysis. Journal of Economic Behaviour & Organization, 33: 167–84.

Yates, J. F. (1990). Judgment and decision making. Prentice-Hall, Inc.

Yeoh, L. Y., & Wood, A. (2011). Overconfidence, competence and trading activity. Working paper. Retrieved 10 January, 2012, from http://www. cass. city. ac. uk/__data/assets/pdf_file/0006/79152/Wood. pdf.

Zaiane, S. (2013). Investor overconfidence: An examination of individual traders on the Tunisian stock market. Advances in Management and Applied Economics, 3(5), 41.

Zaiane, Salma, and Ezzeddine Abaoub. "Investors overconfidence: A survey on the Tunisian stock market." Journal of Accounting in Emerging Economies (2010).

Zia, L., & Hashmi, S. (2016). Disposition Effect and Overconfidence in Pakistani Stock Market.

Appendix:

Table 6: Impulse Response Function Results

Response of MTURN:			Response of MRET:		
Period	MTURN	MRET	Period	MTURN	MRET
1	0.018343	0.000000	1	0.01144	0.064572
	(-0.00109)	(0.00000)		(-0.00548)	(-0.00385)
2	0.013925	0.004322	2	0.00545	0.004
	(-0.00204)	(-0.00176)		(-0.00657)	(-0.00623)
3	0.01027	0.003169	3	-0.00163	-0.001771
	(-0.00188)	(-0.00218)		(-0.00344)	(-0.00574)
4	0.007205	0.002131	4	-0.001515	-0.000666
	(-0.00188)	(-0.00172)		(-0.00273)	(-0.00113)
5	0.005045	0.001481	5	-0.000958	-0.00027
	(-0.00183)	(-0.00122)		(-0.00196)	(-0.00078)
6	0.003541	0.001041	6	-0.00065	-0.000184
	(-0.00168)	(-0.00087)		(-0.00135)	(-0.00049)
7	0.002486	0.000731	7	-0.000457	-0.000134
	(-0.00147)	(-0.00063)		(-0.00091)	(-0.00031)
8	0.001745	0.000514	8	-0.000321	-9.47E-05
	(-0.00124)	(-0.00047)		(-0.00062)	(-0.00021)
9	0.001225	0.000361	9	-0.000226	-6.64E-05
	(-0.00102)	(-0.00035)		(-0.00043)	(-0.00014)
10	0.00086	0.000253	10	-0.000158	-4.66E-05
	(-0.00082)	(-0.00026)		(-0.00030)	-9.80E-05
11	0.000604	0.000178	11	-0.000111	-3.27E-05
	(-0.00065)	(-0.0002)		(-0.00021)	-6.80E-05
12	0.000424	0.000125	12	-7.81E-05	-2.30E-05
	(-0.00051)	(-0.00015)		(-0.00014)	-4.70E-05
13	0.000298	8.76E-05	13	-5.48E-05	-1.61E-05
	(0.000298)	(-0.00011)		(-0.00010)	-3.30E-05
14	0.000209	6.15E-05	14	-3.85E-05	-1.13E-05
	(0.00030)	(-8.70E-05)		-7.00E-05	-2.30E-05
15	0.000147	4.32E-05	15	-2.70E-05	-7.95E-06
	(-0.00023)	(-6.50E-05)		-5.00E-05	-1.60E-05

Cholesky Ordering: MRET MTURN, Standard Errors: Analytic

Table 8: Normality Test Results

Component	Skewness	Chi-sq	df	Prop.
1	-0.283495	1.888688	1	0.1693
2	0.704340	11.65822	1	0.0006
Joint	--	13.54690	2	0.0011
Component	Kurtosis	Chi-sq	df	Prob.
1	4.608130	15.19323	1	0.0001
2	3.623673	2.285184	1	0.1306
Joint	--	17.47842	2	0.0002
Component	Jarque-Bera		df	Prob.
1	17.08192		2	0.0002
2	13.94340		2	0.0009
Joint	31.02532		4	0.0000

Table 7: Heteroscedasticity Test (includes cross terms)

Joint test:

Chi-sq	df	Prob.
138.2060	81	0.0001

Individual components:

Dependent	R-squared	F(27,113)	Prob.	Chi-sq(27)	Prob.
res1*res1	0.299650	1.790661	0.0184	42.25061	0.0311
res2*res2	0.418221	3.008583	0.0000	58.96912	0.0004
res2*res1	0.268455	1.535838	0.0626	37.85217	0.0802

Figure 6: Stability Test

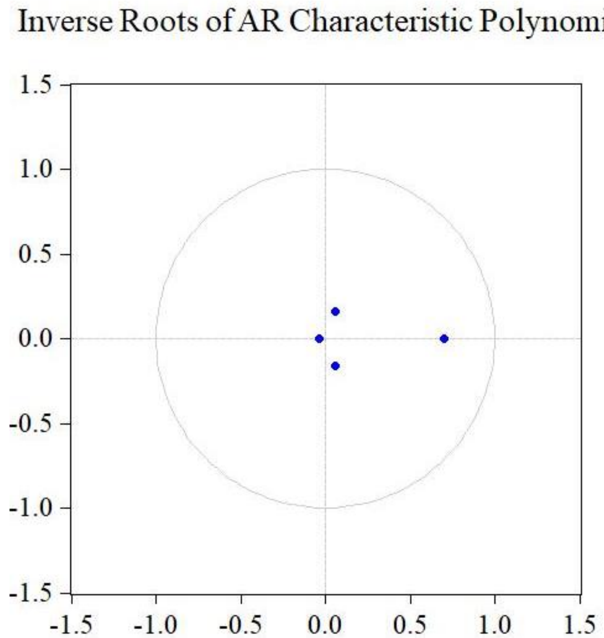

Table 9: Serial Correlation Test (endogenous variables at lag 1)

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	8.384069	4	0.0785	2.121108	(4, 268.0)	0.0785
2	2.085610	4	0.7200	0.521483	(4, 268.0)	0.7200
3	6.190617	4	0.1854	1.559780	(4, 268.0)	0.1854

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	8.384069	4	0.0785	2.121108	(4, 268.0)	0.0785
2	11.01181	8	0.2010	1.389466	(8, 264.0)	0.2011
3	18.79495	12	0.0936	1.592500	(12, 260.0)	0.0937

*Edgeworth expansion corrected likelihood ratio statistic.

Table 10: Serial Correlation Test (endogenous variables at lag 2)

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.238463	4	0.8717	0.309166	(4, 262.0)	0.8717
2	4.899923	4	0.2977	1.231762	(4, 262.0)	0.2977
3	10.20009	4	0.0372	2.590230	(4, 262.0)	0.0372

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.238463	4	0.8717	0.309166	(4, 262.0)	0.8717
2	7.652146	8	0.4682	0.959521	(8, 258.0)	0.4682
3	13.78147	12	0.3149	1.156788	(12, 254.0)	0.3150

*Edgeworth expansion corrected likelihood ratio statistic.