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

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ABSTRACT

Theoretically, investors are considered to be rational decision makers in regards to trading in stock markets, however, some empirical studies have statistically discredited this believe. Evidence shows that investors seem to act irrationally in the financial markets. This research, therefore, 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 Classifications: D91, G11, G12, G15, E22, G4

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); Modigliani and Miller (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 Kahneman (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 valuation and trading skills. Numerous empirical findings in the academic literature show 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 causes this positive relationship. This cognitive error is a form of heuristics that develop 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

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

2 See the literature review section.

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 induce 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 and Schmidt (2016); and Gasteren (2016).

Statman 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 irrational investment decisions. For example, 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 (1998b), 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. Gervais and Odean (2001) have developed a theory that overconfident investors tend to exaggerate their trading skills and ignore the fact that they are in a bull market. For instance, 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 investigate 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 take into account the influence of past stock market returns on investors overconfidence. In an empirical study, Statman et al. (2006) investigate the impact of overconfidence bias on trading volume in the US stock market. They have used market return to measure the degree of overconfidence, given that the level of overconfidence changes with market returns. Their results indicate 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 parallel with the Statman et al. (2006) findings.

1.2. Research Objective, Justification, and Contribution

There are certain objectives that will 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. In this study, we will investigate 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 follow Statman et al. (2006) and use turnover of stocks as a proxy for the level of overconfidence. Because overconfident investors believe in their abilities and will act based on the information they obtain, trading volume is affected. Therefore, if current trading volume can be explained by the past market return, it can be considered as evidence of overconfidence. Based on this lead-lag relationship, we will apply a market-wide Vector autoregression (VAR) model and impulse response function (IRF) 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 and Lee, 2006; Glaser and Weber, 2007). However, there have been hardly any such empirical studies on the Saudi stock market. Our aim is to fill that void by investigating the Saudi stock market with recent data of Tadawul. By testing the lead-lag relationship between returns and turnover, our empirical results confirm 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 specified in section 1. Section 2 delivers a theory review as well as summarizing related research findings. Section 3 presents the data and provides a discussion on the empirical model. Also, this section delivers 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 presents and analyzes the findings. Section 5, the last section, summarizes the main findings and discusses if 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 (Malkiel and Fama, 1970). 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 and Fama (1970, p. 56). 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 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.[3] 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 within a certain confidence interval, people usually are less accurate. In a similar study by Alpert and Raiffa (1982), participates 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 have provided guesses that contained fewer correct answers than nine out of ten. In a related study, De Bondt (1998) asked 46 stock market investors to predict stock prices and forecast risks in US stock market. The results confirm that there is a miscalibration in the stock market since investors were asked to place 90% confidence intervals on their predictions. In another word, they have found that the majority of investors failed to specify a range of expected future stock prices. Glaser et al. (2013) obtained similar findings for student and professional stock traders.

Some studies focus on the volatility estimates of investors. For example, Hilton (2001); and Andersen et al. (2004) asked investors to each provide confidence intervals for the return or price of a stock in the future. These studies conclude that investors tend to provide intervals that are too tight and therefore deviate from the possibilities of a correct guesses; they underestimate historical volatilities. Graham and Harvey (2015) found similar findings. They have asked Chief Financial Officers of US firms to provide quarterly confidence intervals for the market risk premium. They 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. See for example 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 skill and past failure to bad luck are likely to be overconfident. An investor who is overconfident will want to utilize his perceived superior ability to obtain large returns. In addition, overconfident investors underestimate the risks of their active investing, and so, on average, trade more than other investors do (Kyle and 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.[4] Investors in financial markets are no exception according to their argument. Gervais and Odean (2001) have formulated a model for determining how investors learn about their trading skills and in what way self-attribution bias leads to overconfidence. They begin 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 show 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, as a result of self-attribution bias, investors 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 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 have a stronger effect on investors' overconfidence level: past market returns, or past portfolio returns. They have found that both past market returns, and past portfolio returns affects investors' overconfidence, leading them to trade more. They further show that higher past portfolio returns cause investors to trade more, leading to higher risk taking. However, high past market returns are not associated with higher risk taking. According to

3 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.

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

them, high past portfolio returns make investors overconfident because of self-attribution bias. They 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 investor 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 people 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) examine an overconfidence hypothesis that indicates that if investors are overconfident, they will trade more aggressively after experiencing stock gains. They pointed out that successful past trading experience create 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) found several comprehensive results such as, past stock market gains lead investors to be overconfident and thus trade more actively.[5] 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 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 8 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, they have found that overconfident participants tended to trade more and, as a result, underperform 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 was to test the trading volume predictions of formal overconfidence models. They point 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).[6] Using Vector Autoregression and IRFs, 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.

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 and Manias, 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 et al. (1998) (DHS) model as it demonstrates the relationship between overconfidence, volatility and bubbles. It starts when *investor X* receive 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 overconfidence in creating bubbles begins when investors overvalue stocks prices, overconfidently thinking that other investors would pay higher in the future and therefore generating profits, for instance similar to *investor X*. According to Michailova and Schmidt (2011), they have designed an experiment on 60 subjects (German participants) by which they had to participate in a simulated stock market with virtual money. However, at the end of the experiment, each participant were payed the exact amount earned in the simulation in cash. The purpose of their experiment was to closely test if overconfidence leads to bubbles in stock markets. They have found that the majority of participants were overconfident and that led to the formation of a bubble in the simulated stock market. The ramification of participants' overconfidence led to overall lower returns. This experiment was on a smaller scale, however, in any given real stock market, that potentially mean 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 have 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%, and 84%, 103.7% in the following 2 years of 2004 and 2005, respectively.

5 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.

6 See also, Lo and Wang (2000).

On February 25 of 2006, TASI had closed at its historical peak of 20,634.86 one day before the market collapse started. By the end of this year, TASI had lost about 65% 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 annual reports by Saudi Arabian monetary authority the loans granted for 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. As a result of this irrational behavior, the ramifications hit the Saudi average families the hardest at which those families found themselves in bitter situation of not being able to pay the loans back.

Several studies such as Alkhaldi (2015); Baamir (2008); and Lerner et al. (2017) have investigated the 2006 Saudi stock market crash, and found that the crash was caused by different factors, such as the lack of investor's knowledge and experience, the lack of transparency and market infrastructure, and the lack of regulator's experience. All of these factors together were the main cause of the crash. The lack of knowledge and experience might lead investors to a cognitive bias when they are making their investment decisions. Understanding investors' behavior in the stock market is very essential since it might help address the kind of problems we have in the market and the way we deal with them.

There is an apparent lack of empirical literature on investors' behavior in the Saudi stock market. That said, the overwhelming majority of research has taken a questionnaire-based approach. For instance, Alquraan et al. (2016) have randomly distributed 140 questionnaire. The main targeted population of the study was the Saudi individual investors in the year of 2015. The results suggested that Saudi investors tend to be overconfident when they make 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) have found that investors in the Saudi stock market appears to participate in a speculative behavior when making investment decisions. They conclude that overconfidence bias is among other behaviors that persist 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 return and market turnover (i.e., trading volume) using empirical model designed specifically to investigate overconfidence bias. This model, the market-wide security model, is based on Statman et al. (2006),[7] is formulated by estimating vector autoregression (VAR) and IRFs 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.

H_0: The current trading volume of transactions is not positively related to lagged market returns.

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 following gains achieved by the market.[8] The Vector autoregression (VARX) model is applied to examine whether investors will trade more aggressively after market gains, as predicted by the overconfidence hypothesis.[9]

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 following:

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

Where,

Yt: a (n*1) vector of endogenous variables[10] with t observations each.

Ak: The matrix that measures how trading proxy and returns react to their lags.

Bl: The matrix that measure how trading proxy and returns react to month (t-1) realizations of exogenous variables.

Xt: *a* (n*1) vector of exogenous variables[11] 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, Schwartz Criteria (SC), and Hannan Quinn[12]. In this paper, the SC leads to K=1 (Table 1) and L=1,[13] look at Table 1.

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

8 This hypothesis is also mentioned by Odean (1998) and Gervais and Odean (2001).

9 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).

10 Returns and trading proxy (turnover and volume).

11 Dispersion and volatility.

12 $AIC = log\left|\sum\right| + \frac{2K}{T}$ $SC = log\left|\sum\right| + \frac{K}{T}\log(T)$,
$HQ = log\left|\sum\right| + \frac{2K}{T}\log(\log(T))$

13 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.

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. AIC: Akaike Information Criteria, SC: Schwartz Criteria, HQ: Hannan quinn

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

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

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

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 (ADF) and Phillips Perron (PP) tests that have been applied to the data.

3.1.2. Definition of variables

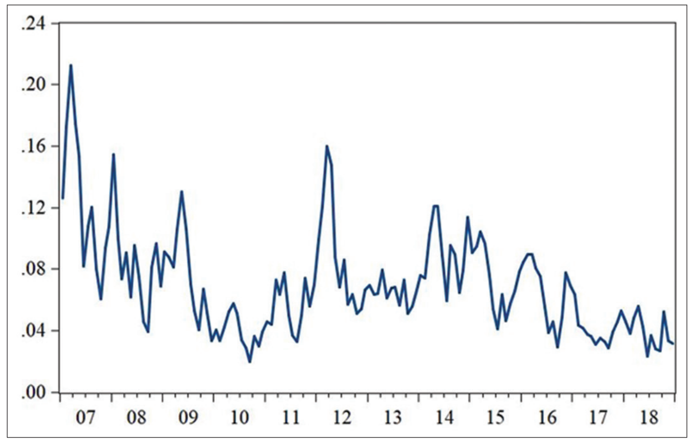
• *Mturn*: The monthly market turnover (shares traded)

According to earlier literature, 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 will be used because it is a relative measure which 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) provide thorough calculation formulas for both share turnover and value-weighted turnover. Suppose Vi represents the number of shares traded monthly for individual stock i, and Si is the outstanding shares of the stock i. Hence, the individual turnover is calculated by, $Ti = \frac{Vi}{Si}$. The weight wi 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:

$$t_{vw} = \sum_{i=1}^{n} wi * Ti$$ [14]

14 Where $wi = \frac{\textit{The capitalization of the security}}{\textit{Sum of capitalization for all securities in the market}}$ and $Capitalization = Pi * Si$ (Pi, is initial price per share, and Si, is shares outstanding for each security).

Figure 1: Monthly market turnover of the Saudi stock market (Tadawul all share index)



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.

Perhaps it is noticeable that Figure 1 indicates that the series may be accompanied with a trend. Therefore, the ADF unit root test was applied, and the test reject the null hypothesis of existence of a unit root at 1% confidence level. The results suggest 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 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.

$$\textit{Total stock returns, Mret} = \frac{(P_1 - P_0) + D}{P_0}$$ [15]

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.

15 Where, P_0=Initial stock price, P_1=Ending stock Prices, and D=dividends.

Figure 2: Monthly market return of the Saudi stock market (Tadawul all share index)

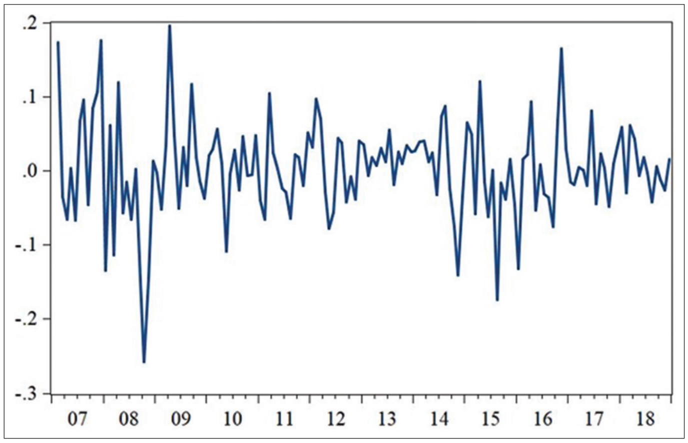
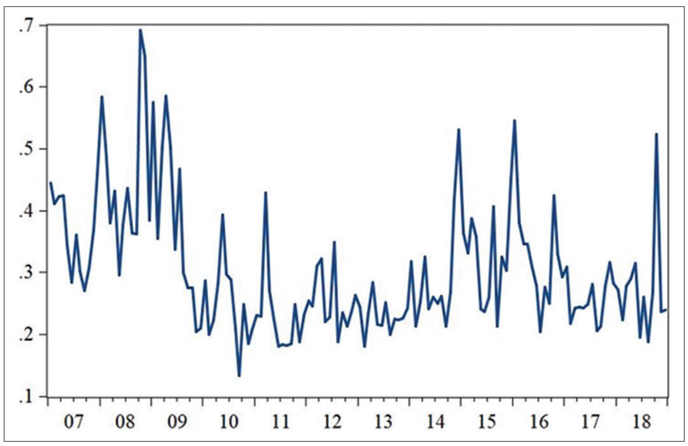


Figure 3: Monthly market volatility of the Saudi stock market (Tadawul all share index)



- *Msig*: The monthly temporal volatility of market return based on daily market returns within the month.[16]

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

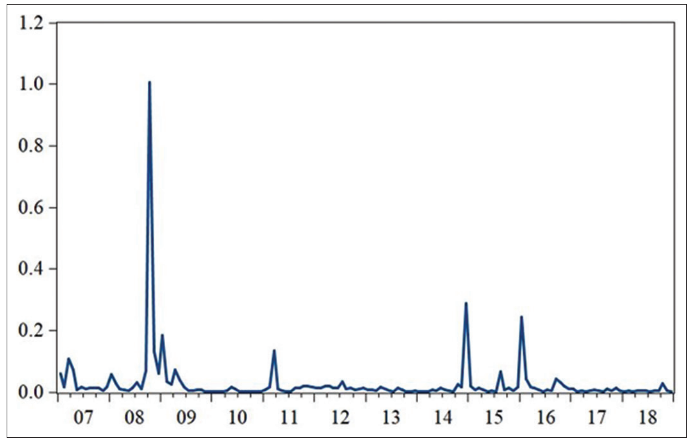
$$Msig_t^2 = \sum_{t=1}^{T} r_t^2 + 2\sum_{t=1}^{T} r_t r_{t+1}$$

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. Figure 3 shows that market return volatility of the Saudi stock market ($Msig^2$) is somewhat stable, however, 2008 witnessed a high volatility, most likely due to the global financial crisis. This elevated jump in volatility in 2008 can also be attributed to the fact that the Saudi stock market have gone through a crash in 2006 that might have temporarily caused investors sentiment in Saudi stock market to lean towards conservatism.

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

16 We have followed French et al. (1987) conditions of volatility calculation.

Figure 4: Monthly security volatility of the Saudi stock market (Tadawul all share index)



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.

$$Disp_t = \sqrt{\sum_{t=1}^{N} Wi(r_t - \bar{r})^2}$$ [17]

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

By looking at the cross sectional volatility of firms in TASI shown in Figure 4, we can observe that the crisis in 2008 had an impact of the behavior of stock trading that led to high fluctuations and volatility.

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 have excluded all traded funds such as REITs (Real Estate Investment Trust) because such funds do not have the same characterization of stocks. In addition, we have also excluded stocks that have been listed in late of 2018 because of the short observations in those stocks. After eliminating those stocks, there are 172 stocks under study. Tadawul is continually developing and as a result, each year, a considerable number of companies are listed; therefore, the number of shares traded increases noticeably. However, we took that into account by applying Statman et al. (2006) methods of offsetting the inevitable growth of shares traded over time. The data sample period is from

17 where, $\bar{r} = \frac{1}{N}\sum_{t=1}^{N} r_t$

January 2007 to December 2018. The data collected is a monthly based, however, daily data is needed to calculate monthly volatility. The data consists 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

There is a fairly large number of observations in this study at which n = 143. We believe, in such study, it is important to have an adequate number of observations as it provide 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.[18] We believe that the reason TASI recorded a low volatility could be 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*) records an average of 30% of the collective individual stocks in TASI.

18 See Statman et al. (2006), Chen and Zhang (2011) and Zoe (2016).

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 ADF test on all the variables.[19] The results show that at 1% confidence level, all variables are stationary at its level. We also ran the PP test to confirm that all variables are stationary in spite of running another unit root test.[20] The PP test results show that all variables are stationary at its level.

19 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.

20 The PP unit root (1988) statistics are computed as:

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

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

Where, $t_{\hat{\alpha}} = s^{-1}(\hat{\alpha} - 1)\left(\sum_{t=1}^{T} x_{t-1}^2\right)^{1/2}$, and $s^2 = T^{-1}\sum_{t=1}^{T} \hat{u}_t^2$

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

Table 2: Descriptive statistics

Full period 2007-2018			
Observations: 143			
Market returns (*Mret*)		**Market volatility (*Msig*²)**	
Mean	0.0030	Mean	0.0264
Standard deviation	0.0667	Standard deviation	0.0913
Minimun	−0.2575	Minimum	0.0006
Maximum	0.1959	Maximum	1.0060
Market turnover (*Mturn*)		**Dispersion (*Disp*)**	
Mean	0.0695	Mean	0.3029
Standard deviation	0.0334	Standard deviation	0.1037
Minimun	0.0198	Minimun	0.1340
Maximum	0.2124	Maximum	0.6923

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

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

Table 4: Market VAR estimation results (2007-2018)

	Constant	*Mret (t-1)*	*Mturn (t-1)*	*Mret (t-2)*	*Mturn (t-2)*	*Msig2 (t-1)*	*Disp (t-1)*
Mret	0.004400	0.061948	0.258487	−0.048566	−0.273192	−0.130787	0.008085
	(0.02014)	(0.09640)	(0.36980)	(0.09394)	(0.30684)	(0.08124)	(0.07655)
Mturn	0.018690***	0.066930**	0.717416***	−0.003085	−0.002681	0.041684*	−0.004950
	(0.00563)	(0.02696)	(0.10344)	(0.02628)	(0.08583)	(0.02272)	(0.02141)

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

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

4.2. Market-wide VAR Estimation and IRF

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).

Table 4 shows the result of testing our hypothesis using VAR estimation by incorporating the full sample (2007 to 2018). This study is interested in the second row of Table 4 as it shows the results of our hypotheses. 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 have noticed the existence of serial correlation at lag 1, to solve this problem, we proceed to use lag 2 for all endogenous variables as the selection of lag 2 seems to remove serial correlation problem as proposed by Foscolo (2012).[21] 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. Also, the results indicate that market volatility at lag 1 has a positive and statistically significant coefficient of 0.042 in explaining market turnover. In other words, 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 results on the US stock market (Statman et al., 2006; Odean, 1998a; Gervais and Odean, 2001), Hong Kong stock market (Chen and Zhang, 2011), and French stock market (Siwar, 2011). However, the degree of overconfidence understandably varies between countries.[22] 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. In addition, the estimated VAR is stable (stationary) as all roots lie inside the unit circle as can be seen in Figure 6 (Appendix). For more diagnostic tests such as heteroscedasticity and normality test, see Tables 7 and 8 in appendix.

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 result confirms the overconfidence hypothesis in the Saudi stock market. The null hypothesis "*Mret* does not Granger Cause *Mturn*" produced a P = 0.0155, therefore, it is rejected at 5% significant interval. This means that past market return (*Mret*) has a positive impact on current market turnover (*Mturn*), i.e., trading volume. However, this relationship does not hold in the opposite way. The P > 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 return and current market turnover.

4.2.2. Market IRF

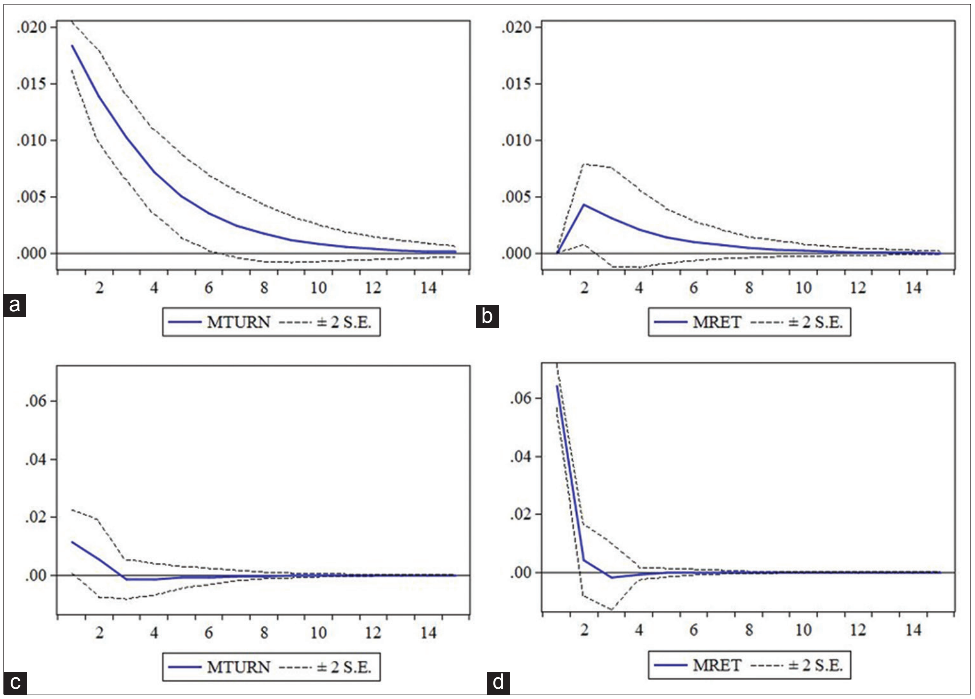
IRF uses all the VAR coefficient estimates to check the impact of one standard deviation shock from the residual. Figure 5 shows the four possible IRF graphs using the VAR estimation results in Table 4.

Figure 5a and b plot the response of market turnover (*Mturn*) to a one standard deviation shock in market turnover (*Mturn*) and market return (*Mret*), respectively. For instance, Figure 5a 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 5b, 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 2nd month's market turnover. 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, in that it is an evidence that market return impacts investors' overconfidence, leading them to trade more. Figure 5b 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

21 Foscolo suggested that serial autocorrelation rapidly declines at higher lags. The serial correlation test results will be displayed in Tables 9 and 10 (Appendix).

22 It could be a result of different time series or different estimation models.

Figure 5: Impulse response function. Response to Cholesky on SD (d.f. adjustrd) innovations±2 SE. (a) Response of MTURN to MTURN, (b) Response of MTURN to MRET, (c) Response of MRET to MTURN, (d) Response of MRET to MRET



compared to Saudi. This phenomena of a positive relationship between higher experience and overconfidence behavior in financial markets is supported by Heath and Tversky (1991); Frascara (1999); Kirchler and Maciejovsky (2002)[23].

Figure 5c and d plot the response of market return (*Mret*) to a one standard deviation shock in market turnover (*Mturn*) and market return (*Mret*), respectively. For instance, Figure 5c shows that market return response to a one standard deviation shock to market turnover is weak, and exists only from 1 month to 3 months. In the 3rd 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 3rd month. In other words, positive lagged market returns leads Saudi investors to trade more and as a result, this leads to negative overall current market returns. Figure 5d 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) – positive returns tend to follow gains in a short time horizon. Table 6 (Appendix) shows a more detailed results on the Impulse Response Function.

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. Also, it 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*)[24]. 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, to test for overconfidence bias. The results obtained from the VAR model, confirm 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 show that past market returns and market turnover (volume) are positive related. The results reveal that investors tend to trade more when they get positive returns in the previous month, i.e. they exhibit overconfidence bias. The objectives of the study are met using

23 In addition, Glaser et al. (2013) 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.

24 See chapter 3 (page 18) for further elaboration on the variables.

appropriate estimation model (VAR model). At a fundamental level, this study aimed to test for overconfidence bias in the Saudi stock market. This objective was achieved using the brilliant example of Statman et al. (2006) as the primary foundation to build up the hypothesis and model of this study.

5.2. Limitation of the Study and Recommendations for Future Research

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 collect stock market data past 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. Also, a longer sample size would allow for more insight 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 by using Statman et al. 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. For example, see Hilton (2001); and De Bondt (1998). Another way, time consuming but effective, is to collect data using a questionnaire such as in Zaiane and Abaoud (2010); and Huisman et al. (2012). Also, as mentioned earlier, the data is 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, shorting the sample period is ideal in this case.

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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 7: Normality test results

Component	Skewness	Chi-square	df	Prob.
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-square**	**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

Figure 6: Stability test

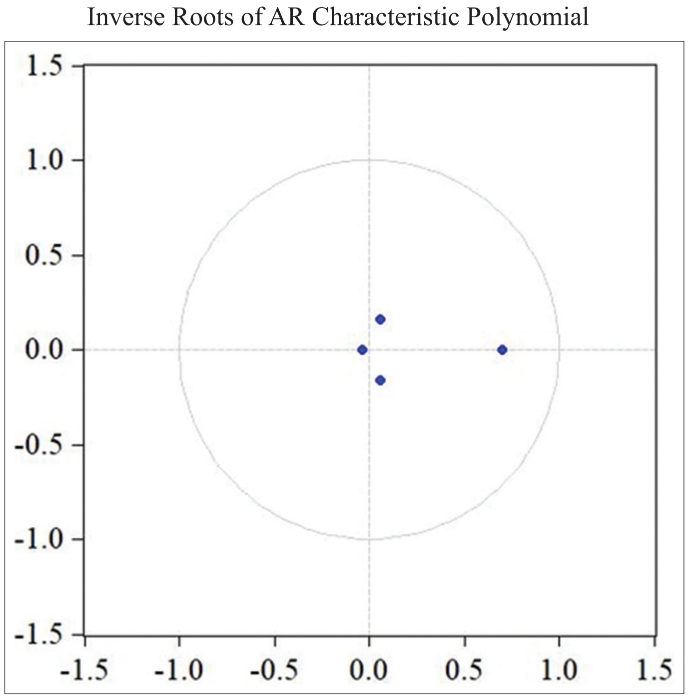

Table 8: Heteroscedasticity test (includes cross terms)

Joint test	Chi-square	df	Prob.		
	138.2060	81	0.0001		
Individual components					
Dependent	R-squared	F(27,113)	Prob.	Chi-square (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

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