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BEHAVIORAL FINANCE AND SPECULATIVE BEHAVIOR OF INVESTORS: EVIDENCE FROM SAUDI STOCK MARKET

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Abstract

This study examines the profile of individual stock traders in Saudi stock market and attempts to determine the behavioral finance factors affecting the speculative behavior of investors as well as to discover the strongest predictors. Using questionnaire survey method, 130 individual traders in Saudi stock market were identified for this study. The survey is carried out in the biggest brokerage firms in Dammam, Riyadh, and Jeddah. It appears that more than 50% of the individual stock traders are in the age group of between 30-39 years and most of them are inexperienced traders. The results from the Partial Least Square method show that anchoring, confirmation, representativeness and overconfidence heuristics have a significant relationship with speculative behavior. Anchoring appears to be the main predictor of speculative behavior, followed by confirmation, representativeness, and overconfidence. In contrast, availability, loss aversion, and regret aversion does not play a significant role in the speculative behavior of individual traders. The behavior factors introduced in this study explain 34% of individuals' speculative behavior. The findings provide important implications to Capital Market Authority in Saudi to develop appropriate programs and strategies to help market participants to make better and wiser buying decisions that can aggregate to increase market efficiency rather than just to speculate on the price movement of the stock market.

Keywords: Behavioral finance, heuristic, PLS-SEM, stock market, Saudi Arabia, speculative behavior.

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1. Introduction

Online trading facilitates the participation of individuals to trade directly in the stock market. The explosion of financial information, the lack of skill together with uncertainty, makes average individuals overwhelmed. To simplify the trading decision, individuals rely on simple mental shortcuts called heuristics that usually drive a bias decision and subsequently irrational behavior. The similar bias behavior affects individual trader's portfolios and the market.

Individual decisions in the stock market are influenced by two categories of behavioral finance (BF) factors, which are heuristics and framing factors. When trading in the stock market, an individual might form certain beliefs or preferences. Hence, they are typically subjected to several judgment biases due to heuristics, which are defined as "*simple rules to reduce the complex task of assessing probabilities and predicting values to simpler judgment operations*" (Tversky & Kahneman, 1974). Heuristics are useful, especially when one wants to make fast, effortless and satisfactory decisions within a limited time. However, a trial-and-error decision process might result in biased decision outcomes, especially in the stock market (Brabazon, 2000; Tversky & Kahneman, 1974). Heuristics could lead to bias buying decisions, which is observed as irrational speculative behavior. There are two consequences of irrational speculative behavior. On the personal level, individuals continue to lose money (Barber & Odean, 2013). On the market level, irrational speculative causes stock prices to deviate from their fundamental values (Rietz, 2005), leading to market inefficiency (Shleifer, 2000), which Al Ashikh (2012) found to be the case in the Saudi Arabian Stock Market (SSM). Practitioners in SSM noticed that many stock prices of companies near to bankruptcy continued to increase in price while those companies that have been announced to be performing well recorded a decrease in prices.

On the other hand, framing factors which differ from the heuristic factors trigger individuals to respond differently based on the context in which a choice is framed. Stock market inefficiency could create bubbles, which led to a sharp correction in the prices and market crash causing individuals to lose money and confidence in the stock market. This was the case of the SSM in the years 2006, 2009, 2011, 2014, 2015 and 2016. This circle of negative consequences at both personal and market levels may continue unless the roots of the problem are investigated. In lieu of the characteristics of traders in SSM, this study attempts to answer the following research questions:

i. What is the profile of individual speculating in the Saudi stock market (SSM)?
ii. What are the behavioral finance (BF) factors that influence the speculative buying behavior of the traders in the Saudi stock market?
iii. Determine to what extent individuals' speculative behavior were due to BF factors?

Specifically, the objectives of the study are to examine the profile of individual stock traders that speculate in the Saudi stock market (SSM) and determine the behavioral finance factors that affect the speculative behavior of the investors. The rest of this article is arranged as follows: Section 2 reviews previous literature related to the study and proposes the theoretical framework. Data and research methodology are then described in the next section. Finally, the results, implications, and future research are discussed.

2. Literature review

2.1. Speculative Buying Behavior

Typically, stock trading decision consists of three dimensions: buy, sell and hold. However, the buying behavior dimension of individual traders is the focus of this research for two reasons; first, traders are net buyers (Barber & Odean, 2011); and second, measuring stock buying decisions can provide more accurate results than measuring the decision-making in general. Pride and Ferrel (2014) defined stock buying decision as "*the process and actions of traders involved in buying and trading stocks to achieve rates of return that exceed inflation and create wealth in the long run*." Such stock buying decision can be observed through speculative behavior (Schabacker, 1997). Speculative behavior is "*the process of buying and selling stocks to create capital gains, resulting in a process of movements in stock prices which are generally not justifiable based on any economic and financial principles and cannot be sustained*" (Islam & Watanapalachaikul, 2004).

Speculative behavior can either be constructive or destructive. Constructive speculative requires a high level of skill and intelligent analysis of the stock market and speculative exist in developed stock markets. The second speculative is destructive speculative, which is the most common speculative, especially among individuals in frontier markets like the SSM. Destructive speculative involves little evaluation of company fundamentals or intelligent prediction of trends (Islam & Watanapalachaikul, 2004). In the frontier market, traders usually use intuition, heuristics, rumors, and advice from others to make trading decisions. Psychologically and emotionally, speculative is more exciting than investment and therefore are more preferred by individual traders (Stäheli & Savoth, 2013). Investor speculative behavior can be explained by heuristic and framing factors. Theoretically, these factors are best explained under behavioral finance which conflicts with the pure finance that argued investors are rational. Heuristic factors are sub-divided into the following items:

2.2. Overconfident

Overconfidence is "*unjustified faith in one's intuitive, reasoning, judgments and cognitive ability to make an optimal decision*" (Pompian, 2012). Barber and Odean (2001) looked at account data for over 35,000 households from a large discount brokerage and analyzed the common stock investments of men and women between February 1991 and January 1997. The researchers found that both gender decisions were influenced by overconfidence. However, the men were more overconfident than women, therefore trading 45% more than the women. The main consequences of speculating were the drop in men annual return by 2.65 percentage points. On the other hand, women who traded less frequently due to less overconfidence reduced their returns by only 1.72 percentage points. Thus, the relationship between overconfidence and trading behavior is positive for men. Chuang and Soo Lee (2006) analyzed the data of listed companies on the New York Stock Exchange and American Stock Exchange between January 1963 and December 2001 and found a number of facts. First, overconfident investors underreact to public information while overreacting to private information. Second, the bullish market increases the investors' overconfidence and as a consequence, they trade more frequently during the next trading sessions. Thus, the overconfident investors" speculation behavior contributes to excessive volatility in the market. The study also indicates a positive relationship between overconfidence and speculation. A different study by

Statman, Thorley, and Vorkink (2006) found that positive portfolio returns increased overconfidence, and thus investors decided to trade more. Negative portfolio returns, on the other hand, decreased overconfidence, leading investors to trade less. In addition, the researchers found that high trading volume is an indication of speculation. Based on previous studies overconfidence motivates speculation behavior. Thus, the study hypothesized that

H1: Overconfident positively influence speculative-buying behavior.

2.3. Representativeness

Representativeness heuristics is "*the tendency of decision makers to view events as a representative of some specific class that is to see patterns where they perhaps do not exist*" (Thomaidis, 2004). Traders in the stock market most likely assume that recent past returns are representative of what they can expect in the future (De Bondt, 1992). The influence of representativeness on decision making can be explained through two concepts: stereotype events and the law of small numbers. Stereotype events mean that investors usually tend to categorize companies based on certain characteristics (e.g. a growth company or big company) then draw a conclusion about the company's risk and return by comparing it to other similar companies (Pompian, 2012). The law of small numbers means that based on a few random observations drawn from a population, a person will consider those observations as highly representative of the characteristics of the population (Tversky & Kahneman, 1971). De Bondt (1992) found that stock market analysts 48 made biased judgments regarding recent increases in stock price. They believed that recent trends would probably continue. The practical implication of representativeness heuristic is the tendency of traders to be more optimistic about recent winners and more pessimistic about recent losers. However, De Bondt and Thaler (1985) found that stocks that were losing in the previous three years performed much better in the subsequent three years than the winners in the last three years. Lakonishok, Shleifer, & Vishny Vishny (1994) found that misperception of the good characteristics of a company (e.g. high-quality products, high expected growth, and intensive media coverage) can be perceived as characteristics of a great buy option. Dhar and Kumar (2001) investigated the price trends of stocks bought by more than 40,000 households at a discount brokerage in the US over a 5-year period. They found that investors prefer to buy stocks that have recently enjoyed some positive abnormal returns, consistent with the thinking that the past price trend is representative of the future price trend. In another study, Goetzmann and Peles (1997) revealed that investors rely heavily on past performance when evaluating their fund purchase decisions.

Thus, the study hypothesized based on previous studies that:

H2: Representativeness positively influences speculative-buying behavior.

2.4. Confirmation

Confirmation heuristic is "*the process of seeking confirmation to what we believe in rather than disconfirmation*" One study conducted in South Korea analyzed responses from 502 investors and found that investors used message boards to search for information that confirmed their prior beliefs. In addition, those investors who exhibit high confirmation bias tend to exhibit high overconfidence, which affects their decision making and consequently, their investment performance (Park, Konana, Gu, Kumar & Raghunathan, 2010). Rabin and Schrag (1999) also documented the influence of the confirmation heuristic on individuals" behavior. The study indicated that people tend to believe false hypotheses, despite receiving a tremendous amount of information that contradicts such beliefs. Kosnik (2008) tested for the existence of the confirmation heuristic in different tax policy situations and found that the confirmation heuristic not only exists strongly but also affects decision-making. Unfortunately, there is a lack of studies on the relationship between the confirmation heuristic and speculation behavior. When individuals want to make fast speculation decisions, they rely on their beliefs (confirmation heuristics). Thus, the study hypothesized that:

H3: Confirmation positively influences speculation-buying behavior.

2.5. Anchoring and adjustment

Anchoring and adjustment are "*a strategy used to estimate an unknown value by starting from an initial point suggested by the formulation of the problem, then adjusting from it to reach a final value, which is usually biased toward the initial value*" (Tversky& Kahneman, 1974). Investors" decisions are influenced by anchoring when they are focused on a particular point, like the historical stable price (e.g. $10) and then estimate the next price using anchoring. Galinsky and Mussweiler, (2001) explored the influence of the first offer on buyer and seller behavior. Based on experiments, the researchers found that first offers influence the final negotiation decision, as they serve as a benchmark price (anchor) based on which the final price is estimated. They also demonstrate that whether they are the buyer or the seller, the party who makes the first offer obtains a better outcome. Zielonka (2004) carried out an experiment involving financial analysts and found out that certain historical peaks and lows in a security's price can serve as mental anchors in technical analysis. This means that anchoring and adjustment can influence the judgment and the speculating behavior of an individual. Thus, the study hypothesized that:

H4: Anchoring positively influenced speculative- buying behavior.

2.6. Availability

Availability heuristics is "*the people's ability to estimate the probability or frequency of a certain event based on life experience, where intense, large events are faster to be recalled than small, less intense events*". There is a lack of studies that relate availability heuristics to speculation buying behavior in the stock market. Rioux and Russo (1988) examined the influence of the availability heuristic on professional decisions. They found that the availability heuristic influences the buying behavior of professional managers. In a different study, Barber and Odean (2006) found that an individual's decision to buy a stock is influenced mainly by the attention. High trading volume and the highest gains appearing in the daily news motivate buying behavior due to the availability heuristic. Traders may find it difficult to search for potential stocks to buy among hundreds of companies in one sector. Therefore, availability heuristic helps to simplify the process of choosing and buying a stock. However, when the market just witnesses sharp correction, the attention will be to the recent negative events, which mean availability heuristics negatively influence speculative buying behavior. Thus, the study hypothesized that:

H5: Availability negatively influences speculative-buying behavior.

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2.7. Loss Aversion

Loss aversion is part of framing factors. Kahneman (2013) describes loss aversion as "*the possible loss looms twice as large as the possible gain*." Loss aversion causes people to avoid the pain of loss more so than seeking gain. Every day, we are faced with mixed options like the opportunity to gain and the risk of losing. For example, losing -$50,000 is two times more painful emotionally than the joy of gaining $50,000. Therefore, individuals tend to hold losing stock too long to avoid the emotional pain of loss and sell a winning one too soon to realize a gain (Shefrin & Statman, 1985). Kahneman & Tversky, (1979) and Mehra (1985) confirmed the influence of loss aversion on individual's trading decisions. In a different study, research by Benartzi and Thaler (1995) introduced the concept of myopia, where individuals evaluate their portfolios too frequently exhibit more loss aversion. Thus, the study hypothesized that:

H6: Loss aversion positively influences speculative-buying behavior.

2.8. Regret aversion

Regret aversion is part of framing factors. Pompian (2012) defined regret aversion as "*a cognitive phenomenon that often arises in investors, causing them to hold onto losing positions too long to avoid admitting errors and realizing losses*". Individuals who regret averse try to avoid two types of error, namely the error of commission, where a decision turns out to be wrong and error of omission, where no decision was made, thus an opportunity is lost. Regret is stronger for omission than for commission (Seiler, Seiler, Traub, & Harrison, 2008). Shefrin and Statman (1984) found that people prefer to buy stocks from well-known companies that pay dividends in order to avoid regret in case the stock value drops. Krähmer and Stone (2005) regret aversion lead to excess conservatism or a tendency to make up for missed opportunities. The data in this research collected when the SSM witness a sharp correction. Thus, the influence of regret on speculative buying behavior is said to be negative when market witness a sharp correction and therefore this study hypothesized the relationship as follows:

H7: Regret aversion negatively influences speculative- buying behavior.

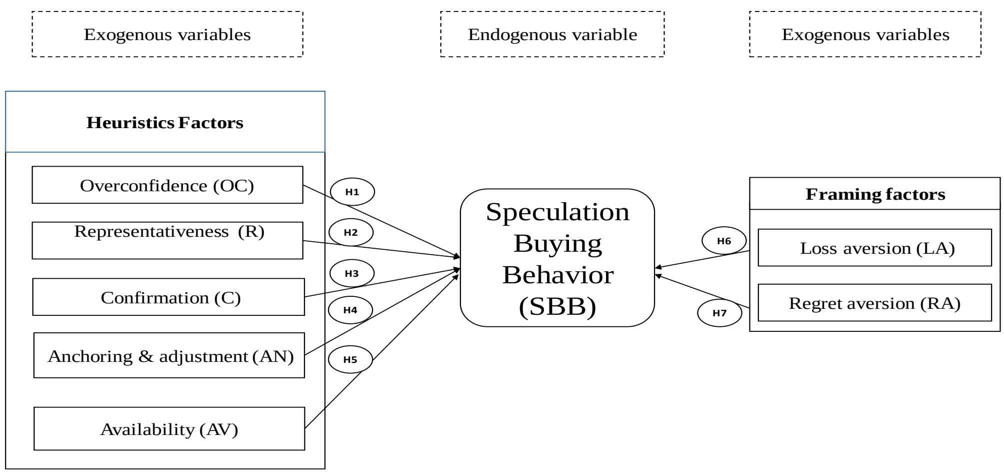

Figure 01. The proposed theoretical framework of the study

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3. Research Method

A total of 591 surveys were distributed in the largest brokerage firms in Dammam, Riyadh and Jeddah city using self-administrated survey. Out of which only 296 (54%) of the questionnaire could be used for the study. However, only 130 respondents who categorized themselves as speculators were used in this study. The survey consists of four sections. Section A was labeled as Demographic Profile. Section B was labeled as Traders' Information. Section C was labeled as Stock Trading Behavior cover both heuristics and framing factors. Lastly, Section D measured speculative behavior. The final survey was conducted in August 2014 for three months. The data collected during a sharp correction in the SSM. This study followed one-stage cluster sampling as suggested by Daniel (2011). In this study, all elements (traders) in each cluster (brokerage firms) were included. The respondents to the survey were individual traders who trade on the trading floors of the largest eleven-brokerage firms in Saudi Arabia. The survey ensured that the respondents entering the trading floor were speculators using screening question in the survey.

Partial Least Squares Structural Equation Modeling (PLS-SEM) 2.0 technique is used to analyze the proposed model and test hypotheses statements since it can predict key target construct and identifying driving construct. Furthermore, PLS is capable of handling complex structure model with small sample size (Hair, Hult, Ringle, & Sarstedt, 2013). The study followed two-stage model validation recommended by Hair et al. (2013). In the first stage, the measurement model evaluated for the reliability and validity. In the second stage, the structural model examined for its predictive capabilities and the relationship between the constructs.

4. Findings and Discussion of the Study

4.1. Demographic Profile of Individual Stock Traders

This section addresses the first objective in the study, that is, to examine the profile of individual stock traders that speculate in the Saudi stock market (SSM). Table 1 displays the demographic profile of the respondents. All respondents are male traders, and 43.1% of them fall under the age group category of 30-39 years old. In term of education level, 30.8% are high school, while 30.8% of respondents have a bachelor degree. Majority of respondents (67.7 %) are married, and about 57.8% of them worked in the private sector, followed by 31.3% respondents who are in the government sector.

Table 01. Demographic Profile of Respondents

Demographic	Respondents (N=130)	Percentage (%)
Gender		
Male	130	100%
Female	0	0%
Age		
Below 20	4	3.1%
20 – 29	34	26.2%
30 – 39	56	43.1%
40 – 49	28	21.5%
50 &Above	8	6.2%

Academic Qualifications		
High school & below	40	30.8%
Diploma	34	26.2%
Bachelor degree	40	30.8%
Post Graduate	14	10.8%
Other	2	1.5%
Marital Status		
Married	88	67.7%
Single	42	32.3 %
Employment status		
Government sector	48	31.3%
Private sector	72	57.8%
Business owner	6	7.5%
Retired	4	2.7%
Student	0	0%
Others	0	0%

4.2. Individual Traders' information

Table 2 provides information about the individual traders. It is revealed that 53.2% of respondents had less than five years trading experience, about 40% had 5 to 10 years of trading experience, and 7.2% have more than ten years trading experience. Half of the respondents (53.8%) had an average size portfolio of less than SR100, 000. About 37% of respondents cited wrong advice from friend or experts as the main factor affecting their buying decisions, followed by 23.1% who claimed to have insufficient trading research and analysis and 16.9% indicated lack of knowledge and skill about stock analysis.

About 36.9% reported that their biggest loss during their years of trading exceeded 20% of portfolio value. However, 76.9% of respondents were still optimistic about the SSM, and about 60.8 % of the respondents said that they are willing to increase their investments in the coming year. Regarding the tools used by individuals to make trading decisions, most of the respondents rely on advice (36.9%), followed by technical analysis (26.2%) as the main tool to make a stock trading decision.

Respondents equally reported fundamental analysis (18.5%) and intuition (18.5%) used in their decision making. Lastly, most respondents (76.6%) did not know about the existence of behavioral finance (BF).

Table 02. Individual Traders' Information

Years of trading experience	Respondents (N=130)	Percentage (%)
Less than five years	70	53.8 %
5 to 10 years	52	40.%
More than 10 years	8	6.2%
The average size of respondent's portfolio		
Less than SR 100,000	70	53.8%
SR 100,000 - 500,000	36	27.7%
SR 500,001 to 1000,000	16	12.3%
SR 1000,000 and above	8	6.2%
The main factor that negatively affects respondent's investments in the stock market		

Wrong advice from friend/market expert	48	36.9%
Bad market performance	16	12.3%
Insufficient research and analysis before making a decision	30	23.1%
Insufficient knowledge and skill about stock analysis	22	16.9%
My wrong decision	14	10.8%
Other factor	0	0%
The biggest loss in respondent's portfolio values as a percentage		
less than 5%	16	12.3%
5%-10%	26	20%
11%-20%	40	30.8%
More than 20%	48	36.9%
Market sentiments of respondents for the next year		
Optimistic	100	76.9%
Pessimistic	30	23.1%
Is respondent willing to increase his/her investments in the stock market next year?		
Yes	79	60.8%
No	51	39.2%
The tool used by traders to make a decision in the stock market		
Technical Analysis	34	26.2%
Fundamental Analysis	24	18.5%
Rumors	12	9.2%
Media	22	16.9%
Advice	48	36.9%
Intuition	24	18.5%
others	2	1.5%
Does respondent know about the existence of Behavioral Finance?		
Yes	30	23.1%
No	100	76.9%

Next to attain objective 2 and 3 of the study, the Partial Least Squares Structural Equation Modeling (PLS-SEM) 2.0 technique is used. Before estimating the model using this PLS method, the authors have to conduct internal consistency, convergent validity, and discriminant validity tests.

Internal consistency reliability was assessed using composite reliability (CR), where the different outer loadings of individual items are calculated (Hair et al., 2013). All the constructs in this study achieved the minimum required composite reliability (CR) value of 0.60 as recommended by Hair et al. (2013).

Next convergent validity is estimated since the scores obtained using two different instruments measuring the same concept are highly correlated (Bonds & Raacke, 2012). The outer loading of the indicator and Average Variance Extracted (AVE) used to check for convergent validity.

First, the outer loadings of individual items met and exceeded the minimum requirement of 0.50 recommended by Hair, Black, Babin, & Anderson (2009). Second, the results of AVE in Table 3 presents further support for convergent validity. The AVE, which includes the variance captured by the indicators

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related to measurement error exceeded the minimum requirement of 0.50. Overall, the construct presents sensible convergent validity of the measurement model introduced in this study.

Lastly, Discriminant validity is evaluated by comparing the correlation between constructs and the square root of $\sqrt{\text{AVE}}$ for a construct. There was no correlation between any two latent variables larger than or equal to the square root of the AVEs of the two latent variables confirming that the discriminant validity has been achieved (Hair et al., 2013). After deleting several items, the measurement model in this study displayed adequate measures required to examine the structure model. Table 3 summarizes the results of the measurement model.

Table 03. Results of Measurement Model

Construct	**Items**	**Convergent validity**			$\sqrt{\textbf{AVE}}$	**Discriminant Validity?**	**Collinearity**
		Factor Loadings	**Composite reliability**	**AVE**			**VIF**
Overconfidence heuristic	OC1 OC2 OC3 OC5	0.680 0.831 0.779 0.518	0.800	0.507	0.713	Yes	1.034
Representativeness heuristic	R1 R4 R6	0.765 0.819 0.542	0.757	0.517	0.719	Yes	1.027
Confirmation heuristic	C3_R C4_R	0.920 0.804	0.854	0.747	0.864	Yes	1.061
Anchoring heuristic	AN6	1	1	1	1.000	Yes	1.178
Availability heuristic	AV2 AV4	0.467 0.985	0.722	0.5952	0.772	Yes	1.168
Loss aversion	LA1 LA2	0.562 0.986	0.771	0.644	0.803	Yes	1.521
Regret aversion	RA1 RA2	0.924 0.560	0.726	0.584	0.765	Yes	1.537
Speculation behavior	BBS1 BBS3	0.897 0.692	0.787	0.558	0.801	Yes	NA

4.3. Structure Model

Once the measurement model is reliable and valid, we address the structure model. We follow the Structure model assessment procedure that consists of five steps. First, we assessed the model for collinearity. Collinearity "*refers to the correlation between two or more indicators in the proposed model*" (Hair et al., 2013). The results of the analysis in Table 3 indicate that variance inflation factor (VIF) of all constructs are all below five, implying no collinearity issue between the construct in the measurement model. Second, the path coefficients between the constructs assessed regarding sign, magnitude and significance (Hair et.al., 2009). Following the suggestion of Hair et al., (2013), the algorithm estimated to determine the significance level of loadings, weights, and path coefficients.

Third, Coefficient of Determination (R^2) was carried out. The R^2 value explains the variation for endogenous construct, which is due to the influence of exogenous constructs. The results indicate that 34.5% of individuals' speculative behavior can be explained by heuristics and framing factors introduced in the proposed model. Hair et al., (2013) stated R^2 value greater than 0.20 is considered high in behavioral research.

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Fourthly, the study conducted the effect size $f^2\ test.$ The effect size f^2 0.02, 0.15 and 0.35, represent small, medium and large effect respectively (Hair et al., 2013). The values of f^2 in this study indicate that loss aversion and regret aversion have no effect. However, all the remaining exogenous constructs have a small effect on the endogenous constructs.

The last step is the assessment of the predict the relevance of Q^2. The Stone-Geyser's Q^2 value is an indicator of the model's predicative relevance, which is obtained by using blindfolding procedure. A Q^2 value larger than zero indicates that the path model has predicts relevance (Hair et al., 2013). The value of the predictive relevance in this study is 0.186, which implies that the model has predictive relevance.

4.4. Results of the Estimated PLS Structural Model

Table 4 illustrates the estimated results of the PLS structural model. Overconfidence (β=0.242, p›0.01), Representativeness (β= 0.263, p›0.05), Confirmation (β= -0.277, p›0.01) and Anchoring (β=0.291, p›0.01) were statistically and significantly related to speculative buying behavior, therefore, supporting H1, H2, H3 and H4 in this study. While the results for availability, loss aversion, and regret aversion are insignificantly related to speculative buying behavior. Empirical results concur with the study of Scheinkman and Xiong (2003) who found that overconfidence encourages the speculative behavior. The authors argued that such speculative behavior is triggered when transaction costs are low, and the market is bullish. Furthermore, the findings of the study are also consistent with Barber and Odean (2001) findings, which found that men tend to be more overconfident than women and thus trade more frequently. Lakonishok et al., (1994) found that the good characteristics of a company such good past performance were perceived as a good stock to buy. Thus, representativeness was found to have a positive influence on speculative buying behavior. The three significant factors have a small effect f^2 on explaining the variation in speculative buying behavior. Closer looks on the findings unveil that anchoring is the strongest predictor of speculative buying behavior followed by confirmation, representativeness, and overconfidence.

Also, confirmation heuristics has a significant negative effect on speculative buying behavior. The results concur with studies of Kosnik (2008), Bashir, Javed, Meer and Naseern (2013) and Kahneman (2013). A reasonable explanation is that this study focuses on speculative buying behavior while those previous studies concentrate on judgment and decision making in general. Results of this study found anchoring to have a positive influence on speculative buying behavior. This concurs with findings by Galinsky and Mussweiler (2001) and Zielonka (2004).

Availability heuristic does not affect speculative buying behavior. The results contradicted with Barber and Odean, (2006) where they found that availability positively affects decision and judgment. However, previous studies use experiments to measure the relationship between availability and judgment whereas this study use self-administrated survey to investigate the influence on speculative behavior. Loss aversion results in this study contradict with Kahneman and Tversky, (1979) and Bashir et al., (2013) were both found loss aversion positively affect the trading decision when faced with loss or high risk but negative when faced with gain. Regret aversion in this study also contradicts with Krähmer and Stone (2005) who found that regret aversion positively affect the individual decision.

This section addresses the third objective in the study, which is to Quantify to what extent individuals' speculative behavior can be explained by BF factors. The heuristics and framing factors are

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found to be able to explain about 34.5 % of the variance in speculative buying behavior. The R² value which is greater than 0.20 considers high in behavioral research. (Hair et al., 2013). The findings provide theoretical and practical implications. Unlike previous studies that focused on judgment and decision making in general, this study specifically examined on the speculative buying behavior.

Thus, theoretically, this study adds to the growing body of behavioral finance literature. It also contributes to the evidence in support for the influence of anchoring, confirmation, representativeness and overconfidence heuristics on the speculative behavior of individuals, especially in Saudi Arabia context. Each significant factor introduced in this study can lead to several possible consequences for traders.

First, anchoring could lead traders to market or stock forecast that is too close to current levels.

Second, confirmation could lead to selection bias towards specific stocks, which creates an under-diversified portfolio.

Third, representativeness could lead to buying stocks based on company recent positive upward trend in the stock price. Lastly, overconfident could lead to under-diversified Portfolio and excessive trading that underestimate the risk (Pompian, 2012).

Since these four factors are the most important predictor of the speculative behavior of traders, practically the Capital Market Authority (CMA) needs to introduce a new program to create awareness about the impact of behavioral finance in general with a focus on anchoring, confirmation, representativeness, and overconfidence. Also, because speculating is more exciting than investment. It is advisable that speculators own two portfolios; one portfolio is to speculate while the second one is to invest in an index fund to avoid the behavioral errors during speculation, as a result achieving diversifications and average return in the long run. Understanding the role of psychology in trading decisions will help market participants to make better and wiser buying decisions that can aggregate to increase market efficiency, and reduce sharp market correction. Ultimately, CMA in Saudi Arabia will be able to achieve its main objective, which is creating an appropriate investment environment that boosts confidence and promoting the welfare of all market participants.

Table 04. Estimated Results of the PLS Structural Model

	Endogenous variable: Speculation buying behavior (BBS)				**R^2 value**		**Q^2 Value**	
					34%		0.186	
Exogenous -> Endogenous construct	**Path coefficients**	**Standard error**	**f^2 (Effect Size)**	**q^2 (Effect size)**	**T-value**	**p-value**	**Sig Level**	**Decision**
Overconfidence->BBS (H1)	0.242	0.087	0.071 (small)	0.034 (small)	2.779	0.006	1% ***	Supported
Representativeness->BBS (H2)	0.263	0.107	0.071 (small)	0.031 (small)	2.445	0.015	5% **	Supported
Confirmation ->BBS (H3)	-0.277	0.0989	0.103 (small)	0.049 (small)	2.804	0.005	1% ***	supported
Anchoring ->BBS (H4)	0.291	0.0746	0.112 (small)	-0.003 (none)	3.897	0.000	1% ***	Supported
Availability ->BBS (H5)	-.0.191	0.132	0.059 (small)	-0.030 (none)	1.446	0.150	NS	Not supported
Loss aversion ->BBS (H6)	0.103	0.102	0.010 (none)	0.004 (none)	1.010	0.314	NS	Not supported
Regret aversion ->BBS (H7)	-0.099	0.099	0.009 (none)	0.003 (none)	0.998	0.320	NS	Not supported

*** and ** denote significant at 1% and 5% level

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5. Conclusion

This study attempts to examine the profile of individual stock traders that speculate in the Saudi stock market (SSM) and determine the behavioral finance factors that affect the speculative behavior of the investors. Findings from questionnaire survey method used indicate that the majority of the individual stock traders are from the age group category of 30-39 years. In term of education level, 30.8% and 26.2% respondents are high schools and diploma holders respectively while 30.8% of respondents have a bachelor degree. Half the respondents have less than five years trading experience and only 40% said they have trading experience of between five to ten years. Generally, the individual stock traders do not seek expert financial advisors to trade in the SSM and are inexperienced traders. In addressing the second objective, the results from the Partial Least Square method show that anchoring, confirmation, representativeness and overconfidence heuristics have a significant relationship with speculative behavior. Anchoring appears to be the main predictor of speculative behavior, followed by confirmation, representativeness, and overconfidence. In contrast, availability, loss aversion, and regret aversion do not play a significant role in the speculative behavior of individual traders. The coefficients of determination indicated that 34.5 % of speculation behavior is explained by the influence of heuristics and framing factors Introduced in this study. The findings of the study provide important implication to Capital Market Authority to structure appropriate training and education program to ensure that individual stock traders are able to make better and wiser buying decisions.

Despite the valuable findings of this study, there are also limitations to be acknowledged. Findings cannot be generalized broadly to Saudi Arabia due to the scope of the study. Lastly, the survey used in this study was developed, pretested, pilot, tested and distributed in the Arabic language before being translated into English for analysis and reporting purposes, which could lead to interpretation bias. The future research related to this study could be expanded by (1) Conducting the study in other cities in Saudi Arabia, (2) including different heuristics in the model, and (3) replicating the study in a similar country like the United Arab Emirates.

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