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Confirmation Bias, Overconfidence, and Investment Performance: Evidence from Stock Message Boards

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Abstract

Using data from a new field experiment in South Korea, we study how information from virtual communities such as stock message boards influences investors' trading decisions and investment performance. Motivated by recent studies in psychology, we conjecture that investors would use message boards to seek information that confirms their prior beliefs. This confirmation bias would make them more overconfident and adversely affect their investment performance. An analysis of 502 investor responses from the largest message board operator in South Korea supports our conjecture. We find that investors exhibit confirmation bias when they process information from message boards. We also demonstrate that investors with stronger confirmation bias exhibit greater overconfidence. Those investors have higher expectations about their performance, trade more frequently, but obtain lower realized returns. Collectively, these results suggest that participation in virtual communities increases investors' propensity to commit investment mistakes and is likely to be detrimental to their investment performance.

JEL Codes: G11, G12

Keywords: Confirmation bias, overconfidence, investment decisions, Korean individual investors, virtual communities, stock message boards.

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ABSTRACT

Using data from a new field experiment in South Korea, we study how information from virtual communities such as stock message boards influences investors' trading decisions and investment performance. Motivated by recent studies in psychology, we conjecture that investors would use message boards to seek information that confirms their prior beliefs. This confirmation bias would make them more overconfident and adversely affect their investment performance. An analysis of 502 investor responses from the largest message board operator in South Korea supports our conjecture. We find that investors exhibit confirmation bias when they process information from message boards. We also demonstrate that investors with stronger confirmation bias become more overconfident. Those investors have higher expectations about their performance, trade more frequently, but obtain lower realized returns. Collectively, these results suggest that participation in virtual communities increases investors' propensity to commit investment mistakes and is likely to be detrimental to their investment performance.

1. Introduction

Investors are increasingly flocking to virtual communities or message boards to seek, clarify, and exchange information. Businesses like Seekingalpha.com and leading business magazines (e.g., Fortune) are evaluating, synthesizing, and reporting comments made on message boards or blogs. Numerous online services (e.g., PredictWallStreet.com, Marketwatch.com, socialpicks.com, Stockpkr.com) have started to aggregate stock sentiments from these message boards and make the information available to online brokerages (e.g., TDAmeritrade) and other financial informediaries. In May 2010, Yahoo! Finance Message Boards recorded 41.4 million unique visitors (comScore Media Metrix 2010).

The non-trivial number of users of message boards and the increasing use of community sentiments raise the question of how investors use information from message boards to formulate their investment decisions. It is important to understand whether these message boards are beneficial or detrimental to investors' financial health. This research investigates how investors process message board information and analyzes the impact of their information gathering activities on their return expectations and investment performance.

Prior studies in accounting and finance suggest that virtual communities often provide more accurate information than analyst forecasts (Bagnoli et al 1999, Clarkson et al. 2006). Early evidences of Enron collapse from accounting tricks were first reported in message boards (Felton and Kim 2002). Some studies show that the volume of posts or the level of investor sentiments in virtual communities has a positive relation with market activity (e.g., trading volume or volatility) (Antweiler and Frank 2004, Bagnoli et al. 1999, Das and Chen 2007, Tumarkin and Whitelaw 2001). These findings indicate that message boards attract insiders and informed investors and information in virtual communities can have an impact on investor investment decisions and

trading activities. However, research explicating how this information influences their investment performance is still evolving.

The value of these message boards in information processing and decision-making can be explained using both economic and psychological perspectives. However, these two perspectives suggest different behaviors. From an economic perspective, one would expect that message boards have a beneficial effect, since they provide timely information at a much lower search cost (Birchler and Butler 2007). The economic principle suggests that individuals are rational in obtaining information (Birchler and Butler 2007). That is, they tend to seek information without any bias, objectively assess the relevance and veracity of each piece of information, and integrate the information in forming an investment strategy that may yield better investment performance. On the contrary, psychological studies indicate that virtual communities may not necessarily make investors more informed or lead to better investment performance. In particular, the behavioral finance literature shows that psychological biases, particularly in an uncertain and noisy environment, influence investors' information processing behavior (Kahneman and Riepe 1998, Barber and Odean 2001).

Our study extends this behavioral literature and develops several hypotheses motivated primarily by the psychology literature on confirmation bias. Our main goal is to examine whether psychological factors influence how individuals process information from virtual communities and whether such behavior in turn influences their investment expectations and actual performance. Our key conjecture is that investment-related virtual communities would not necessarily benefit investors because they are likely to seek information that aligns more closely with their prior beliefs, i.e., they would exhibit confirmation bias. Further, since the messages posted on virtual communities are likely to reinforce their prior beliefs, investors

would become overconfident and hence more prone to making investment mistakes such as excessive trading (Barber and Odean 2001, 2002, Graham et al. 2009). Such behavior would lead to less carefully considered investment decisions, and ultimately, lower returns on their investments.

To test these conjectures, we conducted a field experiment on investors participating in Naver.com, which is a popular message board community in South Korea. In this experiment we estimate investors' prior beliefs, information processing behavior, and expected and actual investment performance. To our knowledge, this is among the first studies to conduct an experiment of message board users at the time of information consumption.

Our empirical results indicate that contrary to the predictions of standard economic theory (e.g., Birchler and Butler 2007), investors process information from stock message boards inefficiently and exhibit confirmation bias. In particular, investors with stronger prior beliefs are more likely to accept confirming opinions from virtual communities. Further, we find that investors with stronger confirmation bias have higher expectations about their investment performance, but they engage in excessive trading and experience lower realized performance. A natural interpretation of this evidence is that confirmation bias makes investors overconfident and overly optimistic, which results in lower returns on stock investments. We also find that investors' perceived knowledge negatively moderates the confirmation bias such that investors with a higher level of perceived knowledge have less motivational needs to confirm their own opinions from others.

These findings contribute to the finance literature that investigates the economic value of information disseminators such as virtual communities. We demonstrate that message board participation may not necessarily improve individuals' financial well-being. Our study also

contributes to a better understanding of investors' behavioral biases in financial markets. While investors are known to demonstrate overconfidence and illusion of knowledge, our analysis takes a step further by showing that virtual investment-related communities contribute to these biases. Last, our paper makes significant contributions to the virtual community literature in information systems (IS). Prior IS literature has focused mainly on the motivations to participate (e.g., Wasko and Faraj 2005, Ma and Agarwal 2007), but has not investigated the performance impact of participation in virtual communities.

The rest of the paper is organized as follows. In the next section we discuss the related literature and outline the main testable hypotheses. In Section 3, we summarize our survey methods and data. We present our main empirical results in Section 4 and conclude in Section 5 with a brief discussion.

2. Related Literature and Hypothesis Development

2.1 Related Research

Our study is related to three distinct lines of research. First, our paper adds to a growing body of behavioral literature on virtual communities. It is well accepted that decision makers are often influenced by multiple psychological biases that distort their decision making and economic outcomes (Barber and Odean 2001, 2002, Kahneman and Riepe 1998, Raghunathan and Corfman 2006). In particular, Barber and Odean (2001) argue that the illusion of control (e.g., people believe that they can influence the outcome of chance events), the illusion of knowledge (e.g., when people have far more data, they believe that they are more knowledgeable than they really are), and self-attribution bias (e.g., people tend to attribute their success to their own abilities while attribute their failure to bad luck) drive investors to be overconfident.

Overconfident investors are known to trade more frequently and have negative abnormal returns amongst stock market traders, especially when they are less experienced yet successful (Odean 1998, Barber and Odean 2001). These studies provide valuable insights that help investigate the relation between overconfidence and investment performance. The current study extends this analysis to participants in virtual communities.

Second, our study is related to the research stream that explicates homophilous behavior. Homophily is defined as an individual's tendency to associate with others who have similar backgrounds or beliefs (McPherson et al. 2001, Gu et al. 2010). Brown et al. (2007) suggest that users' identity information may help to form a homophily of interests with virtual communities. They also argue that the virtual community itself may create homophily. Since virtual communities are formed based on a topic, activity, hobby, or ideology, the design encourages community members to form social interactions with people who share similar interests (Best and Krueger, 2006, Brown et al, 2007). Gu et al. (2010) suggest that homophilous behavior of investors can be explained based on cognitive dissonance theory whereby investors are motivated to reduce dissonances between their own opinions and opinions expressed in virtual communities.

This research is also related to the IS literature that investigates individual's motivation to participate in virtual communities (Bagozzi and Dholakia 2002, Butler 2001). Understanding this motivation helps reveal information processing behavior and the motivation for users to contribute in virtual communities. These studies suggest that social and economic benefits are major motivations to participate. Individuals perceive extrinsic (e.g., reciprocity, reputation) and intrinsic benefits (e.g., self-efficacy, enjoyment of helping others) from their participation. In particular, IS literature explains such motivations by using social capital and social exchange

theories (Wasko and Faraj, 2005, Ma and Agarwal 2007, Constant et al. 1996). However, current IS literature has not investigated how individuals process information from virtual communities and the impact of virtual communities on individual's decision process and resulting performance. Our study adds to the current body of this literature.

2.2 Main Testable Hypotheses

Our main testable hypotheses are motivated by the literature on confirmation bias and the recent evidence on individual investor behavior from the behavioral finance literature. The confirmation bias literature from psychology suggests that decision makers tend to put too much weight on evidence that confirms their prior views and too little weight on evidence that contradicts or invalidates their views (Shefrin 1999, Lord et al. 1979). Decision makers are often disposed to the confirmation bias and depreciate information that opposes their beliefs (Festinger 1957, McMillan and White 1993, Nickerson 1998, Raghunathan and Corfman 2006,). This indicates that, when decision makers process information, they often discount disconfirming evidences while selecting and emphasizing confirming evidences. The bias can be explained by the cognitive dissonance theory which suggests that individuals attempt to reduce cognitive dissonance by distorting information in favor of the chosen alternative (e.g., Russo et al. 1996, Festinger 1957, Frey 1986). The need for individuals to reduce cognitive dissonance leads to confirmation bias among investors in seeking information in message boards.

The behavioral finance literature has long argued that retail investors adhere excessively to previously formed beliefs in spite of new information (Lord et al. 1979, Ko and Hansch 2008). This behavior generates under-reaction to new information and reinforces prior beliefs. Such adherence becomes more substantial in online environments (Barber and Odean 2001, Konana

and Balasubramanian 2005). Online investors exhibit strong sentiments about their stock holdings (i.e., sentiments to either buy or sell) and trading decisions as they can access more data and information over the Internet (Barber and Odean 2001). A greater volume of information is known to increase the illusion of knowledge, whereby individuals' subjective assessment of the depth, relevance, or accuracy of their own knowledge exceeds the objective assessment of that knowledge by a disinterested expert (Barber and Odean 2001, Konana and Balasubramanian 2005). Thus, these investors are likely to have strong beliefs about their trading abilities and/or the market's future performance.

These above arguments indicate that online investors may be driven by their desire to reduce cognitive dissonance between their own opinion and the widespread opinions in virtual communities, where the magnitude of the dissonance may be determined by the strength of their beliefs. When investors with strong beliefs receive disconfirming messages from virtual communities, their cognitive dissonance is likely to become more severe. Thus, they would be more motivated to accept confirming information but exert more effort to scrutinize disconfirming messages to reduce the dissonance. We thus expect investors' confirmation bias to become more salient when they hold a stronger belief about their stock position. Therefore, we conjecture that:

H1: Investors with strong prior beliefs about a stock's future performance are more likely to show confirmation bias in processing information from the virtual communities.

By selectively screening out non-confirming evidence, confirmation bias is known to increase investor overconfidence that has been widely reported in financial literature (Burger

1989, Deci and Ryan 1987, Barber and Odean 2001). When investors seek information that confirms their prior beliefs, it is likely to enhance overconfidence (Barber and Odean 2001). The literature suggests that overconfident investors overestimate the precision of information or underestimate the volatility of random events in financial markets (David et al. 2007, Glaser and Weber 2007). Such investors' miscalibration is known to increase the differences of opinion among investors, which, in turn, leads to excessive trading (Varian 1989). The mis-calibration is estimated by asking for upper and lower bounds of 90% confidence intervals for the return on a stock in the future (Glaser et al. 2004, Hilton 2001).

The extant literature shows that overconfident investors' confidence intervals are very tight and this estimate is negatively related to trading frequency (Glaser and Weber 2007). Further, the literature demonstrates that overconfident investors' excessive trading leads to poor investment performance (Barber and Odean 2000, 2001, Konana and Balasubramanian 2005, Glaser et al. 2004). Although individual investors are motivated to trade when they expect to earn high stock returns to offset their trading costs, overconfident investors experience poor overall performance because they trade frequently and speculatively and have greater trading costs (Barber and Odean 2000).

In our research context, investors who confirm their beliefs using information from virtual communities are more likely to become overconfident. These investors would reinforce their decisions and would be disposed to overestimate the precision of their decisions or underestimate the variance of their information signals. Therefore, confirmation bias can drive investors to engage in excessive trading and has lower investment performance.

By screening out disconfirming evidence, confirmation bias can also lead to higher perceived competence. Recent studies in finance suggest that perceived competence is positively

related to investor trading frequency (Graham et al. 2009). Investors who feel more competent in their investment-related skills tend to trade with their own beliefs than investors who feel less competent. Therefore, these investors are more likely to make investment mistakes (e.g., excessive trading) and have lower returns on their investments. In the context of virtual communities, investors can easily find the confirming opinions that reinforce their prior beliefs. Consequently, they are likely to feel more competent, which reduces their investment performance due to excessive trading. More formally, our second hypothesis posits that:

H2: Investors who exhibit confirmation bias would trade excessively and experience lower investment performance.

We also posit that confirmation bias would be positively related to investor optimism. Optimism represents a decision maker's tendency to be overoptimistic about the future and the outcome of planned actions (Hilton 2001, Weinstein 1980). People often have unrealistic positive views about themselves or believe that their skills are better than others. For instance, optimistic managers in firms have positive performance estimates and believe that their firm's chance of success is greater than others in the same business category (David et al. 2007, Simon et al. 1997). The literature has reported that optimism is common in various contexts and has a strong impact on an individual's decision making (Weinstein 1980, Kahneman and Riepe 1998). In particular, finance literature suggests that individual investors often have optimistic views of their stock investment performance since they perceive to have made rational choice (Hilton 2001, Glaser et al. 2004, Glaser and Weber 2007). The optimism bias makes investors

overestimate their abilities and thus have unrealistic optimistic views about the future performance (Kahneman and Riepe 1998).

In virtual investment-related communities, investors may foster optimistic view about their stock investment performance. As discussed earlier, online investors driven by confirmation bias can reinforce their prior beliefs using information from virtual communities. Those investors may believe that they are better than others in investment-related tasks and develop unrealistic optimism about their investment abilities and performance. Therefore, investors who show biased information seeking behavior in virtual communities would have a higher level of expectation about their investment performance. Our third hypothesis formally states this conjecture:

H3: Investors who exhibit confirmation bias are likely to have higher expectations about their investment performance.

2.3 Moderating Effects and Auxiliary Hypotheses

We investigate three moderating factors that can influence investors' confirmation bias in virtual investment-related communities. Studies in information processing suggest that decision makers' ability and motivation determine how to process information (Petty and Cacioppo 1986). In our context, investors' investment-related knowledge and trading experience are related to their ability, and investment amounts are related to their motivation (Sussman and Siegal 2003). Thus, investors' knowledge, trading experience, and portfolio size would influence how they process information from message boards.

2.3.1. Perceived Knowledge

Specifically, we posit that the relation between investors' belief strength and confirmation bias in virtual communities can be moderated by the level of the investors' perceived knowledge. Perceived knowledge is defined as the knowledge which people believe they hold irrespective of what they actually know (Salmon 1986). When decision makers believe that they are more knowledgeable than others, the dissonance induced by disconfirming opinions in virtual communities becomes less significant as these investors can easily dismiss such opinions as uninformed. Hence, their motivation to seek confirmation from outside sources will decrease.

On the contrary, a low level of perceived knowledge could reduce decision makers' self-esteem and, thus, increase their motivation to seek confirming evidence. Self-esteem is a basic human need that reflects an individual's assessment of his or her own worth or competence (Branden 1969). When investors believe that they are less knowledgeable in understanding stock investment, it may become more difficult for them to dismiss disconfirming opinions. Subsequently, these investors may become more motivated to resolve the dissonance by seeking confirmatory evidence in virtual communities. Thus, we conjecture that, for the investors with a high level of perceived knowledge, the strength of beliefs about the stock would have less effect on confirmation bias in virtual communities. More formally, we posit that:

H4: The relation between an investor's strength of beliefs and confirmation bias would be stronger for investors with lower perceived investment-related knowledge.

2.3.2. Trading Experience

The relation between trading experience and the degree of overconfidence has been studied in the behavioral finance literature (Gervais and Odean 1999, Nicolosi et al. 2010). This literature suggests that investors are more likely to be overconfident when they are less experienced as they learn about their true ability through experience (Barber and Odean 2001). This implies that overconfidence would decrease with experience. There are some empirical findings indicating that psychological biases of investors indeed decrease with trading experience due to the learning effect (Coursey et al. 1987, Dhar and Zhu 2006). Inexperienced investors, therefore, are more likely to be overconfident in their investment decisions. As overconfident investors demonstrate higher self-esteem, they have less need to seek confirming evidence to support their prior belief.

However, other studies show that experts could be overconfident than non-experts (Heath and Tversky 1991, Knetsch and Sinden 1984, Camerer and Hogarth 1999, Glaser et al. 2003). They argue that learning can take a long time and may not be effective in reducing investors' behavioral biases. Glaser et al. (2003) show that professional traders are more overconfident than students in forecasting stock price movements. They also find in their experiments that experienced individuals are significantly more overconfident in most tasks than inexperienced people (Glaser et al. 2004). In our research context, these findings suggest that experienced investors may be overconfident and less motivated to resolve the discrepancy between their beliefs and disconfirming messages to reduce dissonance.

Overall, the extant research suggests that the relation between investors' beliefs and their confirmation bias in virtual communities could decrease or increase as their trading experience increases. It is, therefore, an empirical question to assess the relationship between trading

experience and the degree of confirmation bias. Thus, we propose a pair of competing hypotheses:

H5a: The relation between an investor's strength of beliefs and confirmation bias would be stronger for more experienced investors.

H5b: The relation between an investor's strength of beliefs and confirmation bias would be stronger for less experienced investors.

2.3.3. Investment Amount

In our last hypothesis, we examine whether confirmation bias is moderated by an investor's stake in a stock. The theory of cognitive dissonance suggests that the magnitude of dissonance increases when the issue under consideration has serious personal consequences (Festinger 1957). In our setting, this theory implies that investors who are more involved in a stock could show a higher level of confirmation bias. Those investors may be more motivated to seek confirmatory evidence to reduce dissonance.

Specifically, investors are likely to be more involved in a stock when they invest a substantial amount of money in the stock. When these investors have a strong belief and encounter disconfirming messages in virtual communities, they are more motivated to reject such disconfirming opinions and more motivated to seek and accept confirming opinions. We thus posit that:

H6: The relation between an investor's strength of beliefs and confirmation bias would be stronger for investors with higher investment amount in a stock.

To summarize, our fundamental conjecture is that investment performance is adversely affected by participation in stock message boards. Investment performance is influenced by trading frequency, both trading frequency and investment expectations are influenced by confirmation bias, and the severity of confirmation bias is influenced by the strength of an investor's beliefs about a stock. We further conjecture that the relation between strength of beliefs and confirmation bias would be moderated by perceived knowledge, online investing experience and investment amount. The constructs and theoretical arguments of these linkages are illustrated in Figure 1.

3. Data and Summary Statistics

In this section, we describe the data used to test the three main and the three auxiliary hypotheses.

3.1 Design of the Field Experiment

Our main data set comes from a field experiment on the participants of Naver stock message boards, which are operated by Naver.com (http://stock.naver.com). Naver is the largest online portal website in South Korea and it provides a wide range of services including financial news service, stock quotes, stock exchange rates, corporate press releases, reports and recommendations. Naver reports that its 1,992 stock message boards attract about 100,000 unique visitors per day. Overall, on any given day, Naver attracts about 600,000 visitors and 46 million page views.

With the help of Naver.com, we posted the link to our research experiment at the top of each Naver stock message board during the October 7, 2009 to October 21, 2009 period. To

facilitate participation and completion, we offered gifts (e.g, iPod Touch, iPod Nano, iPod Shuffle) with monetary values between $100 and $300, which were raffled among the participants who completed our field experiment. In total, twenty participants were given a reward. We also assured participants that the results would be reported only in aggregate and that their anonymity would be secured.

At the beginning of the experiment, participants were asked to complete an online questionnaire.[1] The questionnaire included investors' demographic information, information search behavior, investment patterns, perceived knowledge and perceived competence about stock investments. Participants were asked to answer questions specific to the stock related to the stock message board. For instance, if they participated in our experiment on the SAMSUNG Electronics message board, the questions would be related to SAMSUNG Electronics. The participants were asked to report their current opinion about the stock (e.g., strong sell, sell, hold, buy, and strong buy), their current investment amount in the stock, and their expected return of the stock one month following the date of participation in the experiment. Participants were allowed to join our experiment multiple times at different stock message boards, but they could only participate once on each stock message board.

The questionnaire was pre-tested with 24 employees of Naver who were also actual retail investors. They were asked to comment on the questions, to raise concerns related to the questionnaire, and to describe any ambiguities. To address the concerns of content validity, the questionnaire was also pretested with three academic researchers familiar with virtual investment-related communities. The survey questions were then modified according to the comments from researchers and Naver employees.

[1] The questionnaire is presented in Appendix B.

To measure investors' confirmation bias on message boards, we asked them to read five new messages posted on stock message boards. With the help of Naver, we created five new messages at the top of each message board.[2] The titles of two messages represented positive opinion about the stock, two messages represented negative opinion about the stock, and the last message represented a neutral opinion or no opinion about the stock. The messages were randomly selected from the database of Naver stock messages and the titles of messages were modified for clarity. These five new messages were randomly ordered at the top of the stock message boards and marked as newly posted messages. Since we used actual Naver stock message boards for our field experiment, we controlled for the number of replies, sentiments, rating values, posting date, etc. A screenshot of the experimental setup is provided in Figure 2.

For each of the five new messages, we asked participants to answer the following questions: (1) which opinion appears to have the most widespread support, (2) which opinion appears to be most strongly backed by news about the stock, and (3) which opinion appears to have the most convincing argument. Participants were asked to click on one of the five new messages for each of the above questions.

Investors driven by confirmation bias are more likely to click on messages consistent with their prior beliefs. For instance, if an investor with a strong buy opinion about a stock exhibits confirmation bias, he would be more disposed to accept positive messages of the stock while rejecting negative messages. These investors may believe that positive messages among the new five messages have the most widespread support, are most strongly backed by news, and offer the most convincing argument. Overall, they are more likely to click on positive messages.

[2] We only provided the titles of new messages since it is difficult to control for participants' subjective judgment of message content. Investors could see the titles, but not the content of new messages.

Thus, using the message clicking behavior of investors, we are able to measure their confirmation bias.

3.2 Experimental Data

During the two-week experimental period, 651 participations clicked on the link to our experiment. Of these responses, we dropped 149 responses because of scattered and substantially incomplete data. We were left with 502 data points that are used in our empirical analysis. Table 1, Panel A provides the demographic attributes for these 502 participants.

We find that the survey participants are relatively young. About 61% of investors belong to the 25-35 years old age group. The majority of the participants (70%) have undergraduate degree or higher education level. The demographic data are similar to other research studies related to virtual communities (e.g., Nonnecke et al. 2006). The majority of the participants are male (87%), which is also consistent with evidence from past research which indicates that men dominate women in investment activities (e.g., Barber and Odean 2001). Examining the participants' income levels, we find that about 85% of the participants earn less than ₩100 million won per year ($82,000).

3.3 Main Variables

To test our hypotheses, we obtain measures of investors' strength of beliefs about a stock and their degree of confirmation bias:

- *Strength of Beliefs About a Stock:* This variable takes a value of 2 if an investor has a "strong sell" or "strong buy" opinion about a stock, 1 if he has a "sell" or "buy" opinion, and 0 if he has a "hold" opinion.

- *Confirmation Bias:* This variable takes a value of 1 if an investor clicks on positive (negative) messages when he holds a "strong buy" or "buy" (a "strong sell" or "sell" opinion), -1 if an investor clicks on negative (positive) messages when he holds a "strong buy" or "buy" (a "strong sell" or "sell" opinion), and 0 otherwise.

The first variable represents an investor's strength of beliefs about a stock and is a categorical variable. The second variable is also a categorical variable and measures the confirmation bias of an investor. Since participants were asked to click on the message titles for each of the three questions, the maximum value of confirmation bias is 3 while the minimum value is -3. A higher score indicates that an investor is more likely to exhibit the confirmation bias.

In addition to these two key variables, we obtain a measure of trading frequency of each investor, which is used as a mediating variable. Participants were asked to report their average weekly trading frequency. This self-reported measure is used to capture an investor's trading behavior.

Our set of moderating variables includes perceived knowledge, investment experience, and amount invested in a stock. An investor's perceived knowledge is measured based on responses to three items in the questionnaire: (1) I am well informed about the stock market, (2) I am familiar with the stocks I trade (e.g., their business, financial status), and (3) I am well informed about the major economic news that impacts the stock market. A seven-point Likert scale is used to collect these responses. To ensure the reliability and convergent validity of this scale, we use the Cronbach alpha measure and confirmatory factor analysis (CFA), respectively. We find that the scale has a Cronbach alpha of 0.81 for the sample while the CFA indicates that a

single factor solution can extract 72.79% of the item variance. Both Cronbach and CFA values meet the recommended threshold values.

Investors' online investing experience is measured as 1 if an investor's experience is less than 1 year, 2 if the experience is between 1 and 2 years, 3 if the experience is between 3 and 6 years, and 4 if the experience is greater than 6 years. Investors were also asked to report their average amount invested in each stock (in Korean Won). We use the standardized value (i.e., the mean is set to zero and the standard deviation is one) of this variable in our empirical analysis.

One of our key dependent variables is an investors' realized investment performance. We compute the realized stock return during the one month period following the participation date:

$$R_{i,t+1} = \frac{P_{i,t+1} - P_{i,t}}{P_{i,t}}$$

In the above equation, $R_{i,t+1}$ represents the actual return of an investor i who holds the stock from time t to t+1. $P_{i,t+1}$ is the stock price at the end of time period t+1 and $P_{i,t}$ is the stock price at the end of time period t. The time period t is the date on which investor i participated in our experiment and the time period t+1 refers to the one month period following the participation date. The prices of all stocks are obtained from the Naver stock price database. Our second key dependent variable $\widehat{R_{i,t+1}}$ is the expected stock return for the one month period following the participation date, as reported by the investor in the questionnaire.

3.4 Summary Statistics

Table 1, Panels B and C present the summary statistics for all dependent and independent variables. The majority of participants (77%) spend two hours or less per day on

stock message boards searching for information, but many investors (about 5%) spend more than 7 hours per day. About 48% of participants are passive participants with no postings, whereas about 52% of participants post their opinions more than once a week. These investors are not very experienced (about 70% have less than two years of experience) but they have reasonable sized portfolios and they trade moderately. Examining their trading frequency, we find that about 57% of participants trade at least once per week.

There is significant heterogeneity in the investors' beliefs about the future stock performance. The statistics presented in Panel B indicate that about 50% of the respondents have a hold opinion about their stock position, 32.90% of them have directional opinions (e.g., sell or buy), and 16.70% of them have strong directional opinions (e.g., strong sell or strong buy). Further, the evidence in Panel C indicates that the mean value of their expected one-month return is 28.43%, which indicates that most investors expect significant positive returns from their stock investment. These expectations are very optimistic in comparison to the performance of the overall market (Korea Composite Stock Price Index), which yielded only +3.49% during the study period. The mean value of investors' realized return, however, is -4.9%, which indicates that many participants experienced negative returns from their stock investments.

To get a first peek at investors' confirmation bias, we study their message clicking behavior. The evidence presented in Table 2 indicates that about 85% of participants are disposed to accepting confirming opinions from stock message boards. About 70% of investors who hold strong buy opinion click on confirming messages while roughly 60% of investors who hold strong sell opinion click on confirming messages. This evidence suggests that investors with buy opinions show stronger confirmation bias in processing information from message boards than those who hold sell opinions. We also find that investors are more likely to click confirming

messages if they have stronger beliefs. The rate of clicking confirming messages rises from 44% (71.32%) to 60% (78.26%) as investors' opinions change from sell (buy) to strong sell (strong buy).

4. Empirical Results

In this section, we summarize our empirical framework and report the results from our main analysis.

4.1 Estimation Framework: Systems of Equations

We estimate several systems of equations to test our key hypotheses. To begin, we examine whether investors' prior beliefs influence their degree of confirmation bias, which subsequently influences their trading frequency and realized stock performance. The first system of equations is specified as follows:

Realized Performance System of Equations:

(1a)

$$\begin{aligned}\text{ConfirmationBias}_{i,t} = {} & \alpha_1 \text{StrengthOfBelief}_{i,t} + \alpha_2 \text{Knowledge}_{i,t} * \text{StrengthOfBelief}_{i,t} \\ & + \alpha_3 \text{Experience}_{i,t} * \text{StrengthOfBelief}_{i,t} + \alpha_4 \text{Amount}_{i,t} * \text{StrengthOfBelief}_{i,t} \\ & + \alpha_5 \text{Knowledge}_{i,t} + \alpha_6 \text{Experience}_{i,t} + \alpha_7 \text{Amount}_{i,t} + \varepsilon_{i,t};\end{aligned}$$

(1b)

$$\text{TradingFrequency}_{i,t} = \beta_1 \text{ConfirmationBias}_{i,t} + \delta_{i,t};$$

(1c)

$$\begin{aligned}R_{i,t+1} = {} & \gamma_1 \text{TradingFrequency}_{i,t} + \gamma_2 \text{Age}_{i,t} + \gamma_3 \text{Sex}_{i,t} + \gamma_4 \text{Eduation}_{i,t} + \\ & \gamma_5 \text{Income}_{i,t} + \delta_{i,t}.\end{aligned}$$

In this set of equations, i = 1, 2, …, N are the investors who participated in our experiment, t denotes each investor's participation date, and t+1 represents the period one month following the participation date. In equation (1a), $ConfirmationBias_{i,t}$ captures the confirmation bias of investor i at time t and $StrengthOfBelief_{i,t}$ denotes the strength of beliefs of investor i at time t. We also include three interaction terms with $StrengthOfBelief_{i,t}$ to estimate the moderating effects of perceived knowledge ($Knoweldge_{i,t}$), trading experience ($Experience_{i,t}$), and investment amount ($Amount_{i,t}$).

In equation (1b), $TradingFrequency_{i,t}$ captures the trading frequency of investor i at time t. In equation (1c), $R_{i,t+1}$ represents the actual realized stock return of investor i during the time period t+1. Drawing on the previous literature (e.g., Graham et al. 2009), we consider four control variables that may influence investors' performance, including investor's age ($Age_{i,t}$), gender ($Sex_{i,t}$), level of education ($Eduation_{i,t}$), and income ($Income_{i,t}$).

Next, we investigate whether confirmation bias affects performance through the overconfidence channel. One of our key conjectures is that investors reinforce their prior beliefs in virtual communities and they become more overconfident or feel more competent. Increased overconfidence subsequently induces investors to trade excessively and lowers their performance levels.

To test this conjecture, we include both overconfidence and competence measures in our empirical model. We estimate overconfidence using a mis-calibration measure that is based on an investor's estimates of the upper and lower bounds of 90% confidence intervals for the return and value of a stock in the future (Glaser et al. 2004, Hilton 2001). And we measure investors' perceived competence based on their responses to three items in the questionnaire: (1) I am comfortable with my ability to understand investment products, alternatives and opportunities, (2)

I am competent in my ability to invest successfully, and (3) I am skillful in investment activities (e.g., stock picking, position, volume) [3].

To examine the relation between confirmation bias and overconfidence/competence (see Figure 3), we estimate the following system of equations:

Trading Frequency System of Equations:

(2a)

$$\text{Miscalibration}_{i,t} = \alpha_1 \text{ConfirmationBias}_{i,t} + \delta_{i,t}$$

(2b)

$$\text{Competence}_{i,t} = \beta_1 \text{ConfirmationBias}_{i,t} + \delta_{i,t}$$

(2c)

$$\text{TradingFrequency}_{i,t} = \gamma_1 \text{Miscalibration}_{i,t} + \gamma_2 \text{Competence}_{i,t} + \gamma_2 \text{Age}_{i,t} + \gamma_3 \text{Sex}_{i,t} + \gamma 4\text{Eduationi,t} + \gamma 5\text{Incomei,t} + \delta \text{i,t}$$

The $\text{Miscalibration}_{i,t}$ variable in equation (2a) is the difference between an investor's upper and lower bounds of the 90% confidence interval for the stock return during the one month period following the participation date. Motivated by Glaser and Weber (2007), we use this measure as a proxy for the degree of investor overconfidence. The $\text{Competence}_{i,t}$ variable in equation (2b) is motivated by Graham et al. (2009). It captures the degree of perceived competence of an investor in his abilities or skill related to stock investing. In equation (2c), we incorporate these two measures to investigate how overconfidence and competence influence investor trading behavior.

[3] A seven-point Likert scale is used to collect the responses.

Last, using a similar structure, we use the following system of equations to examine how confirmation bias affects an investor's expectations about future stock return:

Expected Return System of Equations:

(3a)

Confirmation bias equation: same as equation (1a);

(3b)

$$\widehat{R_{i,t+1}} = \beta_1 \text{ConfirmationBias}_{i,t} + \beta_2 \text{Age}_{i,t} + \beta_3 \text{Sex}_{i,t} + \beta_4 \text{Eduation}_{i,t} + \beta_5 \text{Income}_{i,t} + \delta_{i,t}.$$

In equation (3b), $\widehat{R_{i,t+1}}$ is the expected stock return of investor i for time period t+1. Since we only replace the actual return with expected return as the new final dependent variable, other variables in the specification remain the same as in the actual return system of equations (see system of equations (1)).

We estimate these systems of equations by constructing path analysis models. The path analysis estimation framework is identical to the system of equations models commonly used in econometric analysis. It highlights the causal relation among variables, where a variable can serve as both a dependent variable in one relation and an independent variable in another relation.[4] Further, a path analysis model shows direct, indirect and total effects of all variables, while a system of equations model mainly focuses on the direct effects. Appendix A provides additional details about the path analysis estimation framework.

[4] The results from path analysis models are usually presented graphically to illustrate the causal relation among variables.

4.2 Path Analysis Estimation Results: Tests of the Main Hypotheses

We begin our formal empirical analysis by estimating the first system of equations that examines the link between confirmation bias and realized performance. The estimation results are presented in Table 3. When we estimate the model without any moderating or control variables, we find that an investor's strength of belief has a significant impact on the degree of confirmation bias (see Column (1)). Further, confirmation bias positively affects trading frequency, while trading frequency adversely affects realized performance (see Columns (2) and (3)). Both these effects are statistically significant and are consistent with our first two hypotheses (H1 and H2).

Next, we consider the impact of various moderating variables, including perceived knowledge, online investing experience, and investment amount in a stock. We include the moderating variables in equation (1a) and also add various control variables such as gender, age, education level, and income to equation (1c). The estimates reported in Columns (4)-(6) indicate that the coefficient estimates of our key independent variables remain qualitatively similar as we add the moderating and control variables into the system of equations.

Specifically, we find that the path from the strength of beliefs to confirmation bias is positive at the 10% significance level (coefficient estimate = 0.260). This evidence is consistent with our first hypothesis, which posits that investors with stronger beliefs exhibit stronger biases in processing information from virtual communities. These investors are more likely to seek and accept confirming evidences from stock message boards and ignore opinions that contradict with their beliefs.

We also find that the path from confirmation bias to trading frequency is positive at the 1% significance level (coefficient = 0.185), while the path from trading frequency to realized

return is negative and statistically significant (coefficient = -0.079). This evidence supports our second hypothesis (H2) and indicates that investors with stronger confirmation bias are likely to trade more frequently, which has a detrimental effect on performance. The result is consistent with the view that confirming opinions reinforce investors' prior beliefs, which makes them more overconfident and induces them to trade excessively. This behavior in turn leads to lower investment performance.

The effect of confirmation bias on realized performance is economically significant. We observe a considerable shift in realized return as an investor's confirmation bias changes. When an investor's confirmation bias increases by one standard deviation, the realized stock return decreases from its mean value of -4.92% to -5.42%. This evidence indicates that the average investment loss of an investor increases from ₩494,108.37 ($407.04) to ₩544,322.63 ($448.41) when his confirmation bias increases by one standard deviation. Thus, participation in virtual communities can make investors considerably worse-off because it amplifies their information processing biases.

The model fit statistics in Table 3 indicate that our system of equations model is well-specified. Our model explains 7.54% of variance in confirmation bias, 3.40% of variance in trading frequency, and 7.70% of variance in realized performance. Further, the χ^2/df (Marsh and Hocevar 1985) of the model is 3.24, where a small value represents better model fit. Also, the root mean square error of approximation (RMSEA) is less than 0.08, suggesting a reasonable fit of the model in relation to the degrees of freedom (Browne and Cudeck 1993). Other model fit indices also suggest a reasonable fit (>0.90).

To investigate whether the decline in performance can be attributed to an increase in investor overconfidence and/or perceived competence, we estimate the second system of

equations. The results reported in Table 4 are consistent with our conjecture that confirmation bias increases both investor overconfidence as well as perceived competence, which leads to increased levels of trading. The evidence reported in Columns (1) and (4) of Table 4 indicates that the path from confirmation bias to mis-calibration is negative and statistically significant at the 10% level (coefficient = -0.109). This finding indicates that confirmation bias makes investors overconfident and consequently their confidence intervals become tighter. We also find that confirmation bias has a positive and significant impact on perceived competence (coefficient = 0.263), which indicates that investors who confirm their prior beliefs using information from virtual communities have higher levels of perceived competence in their investment abilities.

The estimates from the trading frequency equation reported in Column (6) show that the path from mis-calibration to trading frequency is significantly negative (coefficient = -0.237), while the path from competence to trading frequency is significantly positive (coefficient = 0.254). This finding indicates that both overconfidence and perceived competence affects trading frequency, although the effect of competence is marginally higher. The evidence is consistent with recent studies which demonstrate that trading frequency is explained more by competence effect than due to mis-calibration (e.g., Graham et al. 2009).

Examining the goodness of fits for the models with mis-calibration and competence measures, we observe that the model explains 1.20% of variance in mis-calibration, 6.90% of variance in competence, and 14.40% of variance in trading frequency. The χ^2/df of the model is 3.16 and the root mean square error of approximation (RMSEA) is 0.067. All model fit statistics point to a reasonable model fit.

In the next set of tests, we gather support for the third hypothesis. Specifically, we estimate the expected return system of equations (see equation set (3)) and report the results in

Table 5. The estimates in Column (2) of this table indicate that the path from confirmation bias to expected return is positive and significant at the 1% level (coefficient estimate = 0.115). Thus, consistent with our third hypothesis (H3), confirmation bias increases investors' expectation of investment performance. Investors who exhibit stronger biases in processing information from virtual communities have more distorted expectations about their investment performance.

Again, the model fit statistics suggest a reasonable overall model fit. Specifically, we find that 8.53% of variance in expected returns can be explained by the model. The χ^2/df of the model is 3.41 and the root mean square error of approximation (RMSEA) is 0.069.

The impact of confirmation bias on the investment expectation is economically large. The coefficient estimates reported in Table 5 indicate that when an investor's confirmation bias increases by one standard deviation, their stock return expectation increases from its mean of 28.43% to 32.01%. In monetary terms, this evidence indicates that when an investor's confirmation bias increases by one standard deviation, the investor expects that his investment gain on average will increase from ₩2,852,170.25 (= $2,349.59) to ₩3,214,717.24 (= $2,648.26).

4.3 Path Analysis Estimation Results: Tests of Auxiliary Hypotheses

Next, we test our hypotheses related to the effects of moderating variables. Specifically, we assess the influence of moderating variables on confirmation bias. The interaction term estimates reported in Column (4) of Table 3 show that perceived knowledge has a significantly negative moderating impact on the strength of belief-confirmation bias relation (coefficient estimate = -0.158). This evidence supports our fourth hypothesis (H4) and indicates that while investors with stronger beliefs about a stock are more disposed to seek confirming evidences

from message boards, the extent of this behavior depends on the level of their perceived knowledge. The strong belief about a stock has a greater impact on confirmation bias among investors with a low level of perceived knowledge. In contrast, investors with a higher level of perceived knowledge have less motivational need to confirm their own opinions using the opinions of other investors.

We also find that online investing experience and investment amount do not significantly affect the strength of belief-confirmation bias relation. The path from online investing experience to confirmation bias is negative, while the path from investment amount to confirmation bias is positive, but both interaction term estimates are statistically insignificant. Thus, our results do not support Hypotheses 5 and 6.

4.4 Path Analysis Estimation Results: Tests of Direct Effects

We now consider several alternative models to seek additional insights into the effect of confirmation bias on investment performance. We first investigate whether strength of beliefs has a direct impact on trading frequency. If investors with strong beliefs trade excessively regardless of their participation on message boards, strength of beliefs will have a strong direct impact on trading frequency. To examine this possibility, we add $\text{StrengthOfBelief}_{i,t}$ into the trading frequency equation and re-estimate the trading frequency system of equations (see system of equations (2)).

The estimates reported in Columns (1) and (2) of Table 6 indicate that coefficient of $\text{StrengthOfBelief}_{i,t}$ in the equation (2a) is statistically insignificant. This evidence indicates that investors who have stronger beliefs about the stock do not necessarily engage in excessive trading. An investor's strength of beliefs has an effect on trading frequency only through the

confirmation bias channel. Overall, these results support our view that investors' biased processing of information from message boards plays an important role in positively influencing their trading activities.[5]

We also investigate whether strength of beliefs has a direct impact on realized performance. It is possible that investors with stronger beliefs about their investment decisions make other mistakes and experience lower investment performance. Those investors are not necessarily influenced by the information on virtual communities and do not trade excessively. To test this possibility, we exclude the trading frequency equation from the first system of equation and add $\text{StrengthOfBelief}_{i,t}$ into the realized return equation to obtain the following system of equations:

(4a)

Confirmation bias equation: same as equation (1a);

(4b)

$$R_{i,t+1} = \beta_1 \text{ConfirmationBias}_{i,t} + \beta_2 \text{StrengthOfBelief}_{i,t} + \beta_3 \text{Age}_{i,t} + \beta_4 \text{Sex}_{i,t} + \beta_5 \text{Eduation}_{i,t} + \beta_6 \text{Income}_{i,t} + \delta_{i,t.}$$

The estimation results reported in Columns (3) and (4) of Table 6 indicate that $\text{StrengthOfBelief}_{i,t}$ does not have a statistically significant coefficient estimate. Further, the goodness of fit statistics of this new model (Chi-square/df = 3.12, RMSEA = 0.065 and CFI = 0.965) are not significantly different from the original model. Thus, investors who have stronger beliefs about a stock do not necessarily realize lower returns from their stock investments. This

[5] We also find that the goodness of fits of this new model (Chi-square/df = 3.27, RMSEA = 0.067 and CFI = 0.963) does not differ significantly from the original models.

evidence is consistent with our conjecture that information from message boards hurts investors' financial performance because they process the information in a biased manner.

4.5 Another Overconfidence Proxy

To further examine the confirmation bias-overconfidence relation, we consider an alternative proxy of overconfidence. Our choice of the proxy is motivated by Barber and Odean (2001), who describe overconfident investors as those who have elevated trading and poor performance. Specifically, following Goetzmann and Kumar (2008), the overconfidence proxy is set to 1 if an investor's trading frequency is greater than its sample median and his performance is below the sample median. We use this proxy of overconfidence as the final dependent variable and estimate the following system of equations:

(5a)

Confirmation bias equation: same as equation (1a);

(5b)

$$\begin{aligned}&\text{ProxyOverconfidence}_{i,t+1}\\&= \beta_1 \text{ConfirmationBias}_{i,t} + \beta_2 \text{Age}_{i,t} + \beta_3 \text{Sex}_{i,t} + \beta_4 \text{Eduation}_{i,t}\\&+ \beta_5 \text{Income}_{i,t} + \delta_{i,t.}\end{aligned}$$

The estimates in Columns (5) and (6) or Table 6 indicate that confirmation bias has a significant impact on investor overconfidence (coefficient estimate = 0.111). This finding is consistent with our previous finding that investors with biased information processing behavior in virtual communities are likely to trade more actively and realize worse performance due to their overconfidence.

4.5 Discussion

Taken together, our empirical results provide strong support to our main hypotheses. The strength of investors' beliefs influences their degree of overconfidence and perceived competence, which subsequently affects investors' trading frequency and realized performance. Investors with strong beliefs exhibit stronger confirmation bias and experience a larger adverse impact on investment performance. These empirical findings provide interesting new insights into the behavior of investors on stock message boards.

Our study also has several limitations. For example, we do not observe the antecedents of investor beliefs. Such beliefs are potentially influenced by environmental factors such as stock market movements, firms' announcements, news reports and other information sources. Future studies may develop a better understanding on how individuals form their beliefs on individual stocks.

Further, our experiment provides new messages on top of each message board and focus on how investors evaluate these messages. Prior studies on confirmation bias however reveal that confirmation bias not only influences individuals' interpretation and evaluation of information but also their information search process. Future studies are needed to develop a better understanding on the influence of confirmation bias on both the information search process and information processing behavior.

Third, our study is a cross-sectional experiment by analyzing investors with different degrees of confirmation bias. We do not observe how investors' confirmation bias changes over time and how such changes influence their investment expectation and actual performance. Obtaining longitudinal data on individual behavior in virtual communities and their investment

performance will provide a more comprehensive understanding on the impact of confirmation bias in virtual communities.

Finally, we conjecture that confirmation bias in virtual communities leads to illusion of knowledge, which in turn leads to greater overconfidence. As people reinforce their prior beliefs from virtual communities, they believe that they are more knowledgeable than they really are. This illusion of knowledge ultimately makes them overconfident (Barber and Odean 2001). However, the studies in psychology and finance literature posit that confirmation bias could directly lead to overconfidence (Daniel et al. 1998, Barber and Odean 2001). Future research could identify other psychological biases among message board participants and provide a more comprehensive understanding of decision makers' information processing behavior.

5. Summary and Conclusions

Virtual communities have attracted millions of retail investors and have aroused interests among financial executives and academic researchers. Economic theory suggests that virtual communities could be beneficial to investors as they provide more information with much lower costs (Antweiler and Frank 2004, Tumarkin and Whitelaw 2001). Our results, however, suggest that participation in virtual communities could adversely affect retail investors because they are likely to exhibit biases in processing information gathered from these settings. In particular, investors use the gathered information to confirm their prior beliefs. This confirmation bias strengthens their prior beliefs and makes them optimistic as well as overconfident. Subsequently, confirmation bias induces investors to form higher expectations about their stock investments, but those investors experience lower actual performance.

This analysis takes a first step to understand how investors' information processing behavior influences their trading frequency, investment performance, and expectations. Investors are known to demonstrate behavior biases in making investment decisions. However, little is known what contributes to such behavior biases. In this analysis, we show that an important contributing factor is the manner in which investors process information from external sources.

While our study focuses on investors' information processing behavior on message boards our finding may be generalized to other contexts where decision makers with prior beliefs process new information before making decisions. For example, when a consumer who has a strong preference about a particular brand visits online Word-Of-Mouth networks (e.g., consumers' review websites), she is more likely to accept the opinions that are consistent with her prior belief (Duan et al. 2009). Thus, she may make purchase decisions based on her biased beliefs, and overlook or underweight different opinions that are related to her purchase decisions. Also, a project manager within organizations may participate in internal knowledge management networks or project management networks where her team members discuss a project's directions or decisions. However, if a project manager has a strong belief toward a particular way of the project, she will be disposed to seek and accept opinions that are aligned with her own opinions. Such behavior may lead to a project's failure. Our model thus provides a foundation that can be extended to other contexts.

This study also informs the behavioral finance literature. While investor behavior biases such as overconfidence have been widely observed in financial markets, less is known about the fundamental factors that generate those biases. Our analysis reveals that confirmation bias in investors' interpretation of information could be a key factor that drives investor overconfidence.

In addition, our results could provide guidance to online investors and financial infomediaries. Confirmation bias suggests that individuals become selective in information acquisitions according to their prior beliefs. To be unbiased in information acquisition and processing, investors should expose themselves to both confirming and disconfirming information, objectively assess the relevance and veracity of new information, and integrate all the information before making a decision. Message board operators can help investors by presenting both confirming and disconfirming opinions and warning participants that the selective information seeking may yield undesirable results.

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Table 1: Summary Statistics

This table reports the summary statistics for all variables obtained from the field experiment. The experimental link was posted at the top of each Naver stock message board during the October 7, 2009 to October 21, 2009 period. All data are self-reported. Panel A reports the self-reported demographic attributes of 502 investors who responded to our survey. Panel B reports statistics for various measures of investment behavior. In this panel, current opinion is set to -2 for investors with a strong sell opinion, -for investors with a sell opinion, 0 for investors with a hold or neutral opinion, 1 for investors with a buy opinion, and 2 for investors with a strong buy opinion about a stock. Strength of beliefs about a stock is set to 2 for investors with a strong sell or strong buy opinion, 1 for those with a sell or a buy opinion, and 0 for those with a hold or a neutral opinion. Confirmation bias is set to 1 for investors who selected positive (negative) messages in the experiment when they have strong buy or buy opinion (strong sell or sell opinion), set to -1 for investors who selected negative (positive) messages in the experiment when they have strong buy or buy opinion (strong sell or sell opinion), and 0 otherwise. Investors were asked to click on one of the messages provided by researchers based on the following three questions: (1) which opinion appears to have the most widespread support, (2) which opinion appears to be most strongly backed by news about the stock, and (3) which opinion appears to have the most convincing argument. We sum the scores from these three questions. The total investment amount is the self-reported total current investment amount in Korea won. The frequency of trading represents an investor's average weekly trading frequency. The number of stocks is the total number of stocks in an investor's portfolio. 10,000 Korean Won is equivalent to 8.39 US dollars.

Panel A: Demographic Characteristics

Characteristic	Category	Sample (%)
Gender	Female	12.97%
	Male	87.03%
Age	< 25 years	14.88%
	25 to 35 years	61.22%
	36 to 50 years	23.69%
	51 to 65 years	0.21%
	> 65 years	0.00%
Education	High school	14.01%
	2-year college	16.77%
	4-year college	62.85%
	Master's degree	5.73%
	PhD degree	0.64%
Income	< 15 million won	29.30%
	15 to 50 million won	25.90%
	50 to 100 million won	32.70%
	100 to 200 million won	10.40%
	>200 million won	1.80%

Panel B: Investment Behavior

Characteristic	Category	Sample (%)
Time Spent on Message Boards Per Day	< 1 hour	44.49%
	1 to 2 hours	32.06%
	3 to 6 hours	17.64%
	7 to 10 hours	4.81%
	> 10 hours	1.00%
Number of Postings	0	48.06%
	1 to5	38.24%
	6 to10	6.75%
	11 to20	4.50%
	>20	2.45%
Current Opinion	Strong Sell	3.00%
	Sell	5.20%
	Hold	50.40%
	Buy	27.70%
	Strong Buy	13.70%
Strength of Beliefs	1	50.40%
	2	32.90%
	3	16.70%
Confirmation Bias	-3	5.20%
	-2	4.20%
	-1	10.80%
	0	17.90%
	1	24.10%
	2	13.30%
	3	21.50%
Investment Amount	< 5 million won	36.53%
	5~10 million won	22.94%
	10 ~ 50 million won	33.53%
	50~100 million won	3.59%
	> 100 million won	2.99%
Online Investment Experience	< 1 year	35.80%
	1~2 years	34.00%
	3~6 years	22.00%
	7~10 years	4.60%
	>10 years	3.60%
Trading Frequency	< 1	43.49%
	1~2	25.45%
	3~6	14.43%
	7~10	8.42%
	> 10	8.22%
Number of Stocks in the Portfolio	1	20.70%
	2-3	41.40%
	4-6	22.50%
	7-10	11.00%
	> 10	4.40%

Panel C reports the statistics for other investor responses. In this panel, expected return is the self-reported expected return on a stock one month after the participation date. Actual return is the actual stock return during the one month period following the participation date. The 90% confidence interval is calculated as the upper value of expected stock return minus the lower value of expected stock return, and this interval is divided by the standard deviations within the confidence interval. Investors are asked to report the upper and lower bounds of 90% confidence interval for a stock return over next one month. The minimum rate of expected returns was measured by asking investors to report the following question: There is a 1-in-10 chance the actual return will be less than ( ) %. Maximum rate of expected returns was measured by asking investors to report the following question: There is a 1-in-10 chance the actual return will be less than ( ) %. Competence is investors' perceived competence based on the following three items: (1) I am comfortable with my ability to understand investment products, alternatives and opportunities, (2) I am competent in my ability to invest successfully, and (3) I am skillful in investment activities (e.g., stock picking, position, volume). A seven-point Likert scale is used to collect the responses. We sum the scores from the three questions. Perceived knowledge is based on investors' response to the following questions: (1) I am well informed about the stock market, (2) I am familiar with the stocks I trade (e.g., their business, financial status), and (3) I am well informed about the major economic news that impacts the stock market. A seven-point Likert scale is used to estimate the perceived knowledge about the stock investment. We sum the scores from the three questions. Ten thousand Korean Won is equivalent to 8.39 USD.

Panel C: Other Variables

Variables	Mean	S.D	Min	Max	25th Pctl	Median	75th Pctl
Expected Return	28.43%	47.16	-100%	500%	10%	15%	30%
Actual Return	-4.92%	0.29	-82.81%	82.31%	-13.15%	-5.67%	5.33%
Miscalibration	4.96%	4.57	0	26.41%	1.57%	3.77%	6.41%
Min. Expected Return	8.91%	30.32	-120%	400%	0%	5%	10%
Max. Expected Return	49.66%	94.51	-50%	1000%	10%	25%	50%
Perceived Knowledge	4.10	1.09	1	7	4	3.50	4.50
Perceived Competence	4.12	1.17	1	7	3.33	4	4.67

Table 2: Confirmation Bias Statistics

This table reports the clicking statistics of investors, conditional upon their strength of beliefs about their stock position. Strong sell, sell, buy and strong buy represent an investor's current opinion about a stock. It is set to -2 if investors have a strong sell opinion, -1 if they have a sell opinion, 1 if they have a buy opinion, and 2 if they have a strong buy opinion about the stock. Clicked disconfirming messages, clicked neutral messages, and clicked confirming messages reflect an investor's confirmation bias. It is set to 1 if investors select positive (negative) messages in the experiment when they have strong buy or buy opinion (strong sell or sell opinion), set to -1 if investors select negative (positive) messages in the experiment when they have strong buy or buy opinion (strong sell or sell opinion), and 0 otherwise. Investors were asked to click on one of the messages based on the following three questions: (1) which opinion appears to have the most widespread support, (2) which opinion appears to be most strongly backed by news about the stock, and (3) which opinion appears to have the most convincing argument. We estimated the percentage of clicks on disconfirming, neutral, and confirming messages when investors have strong sell, sell, buy and strong buy opinions, respectively.

	Strength of Beliefs			
Action	Strong Sell	Sell	Buy	Strong Buy
Clicked Disconfirming Messages	20.00%	36.00%	11.76%	10.14%
Clicked Neutral Messages	20.00%	20.00%	16.91%	11.59%
Clicked Confirming Messages	60.00%	44.00%	71.32%	78.26%

Table 3: Realized Performance System of Equations Estimates

This table reports the path analysis estimates for the realized performance system of equations reported in equation set (1). All variables have been previously defined in Table 1. The estimates in Columns (1)-(3) are from the system of equations without control variables, while the estimates in Columns (4)-(6) are from the system of equations with all variables. A lower value of χ^2/df and RMSEA below 0.08 represents a good fit of the overall model; NFI, RFI, TLC and CFI above 0.9 indicates a good fit of the model. The *t*-statistics of the coefficient estimates are reported in parentheses below the estimates. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

	Dependent Variable:					
Independent Variables	CBias (1)	TrdFreq (2)	RealPerf (3)	Cbias (4)	TrdFreq (5)	RealPerf (6)
Strength of Beliefs$_{i,t}$	0.234***			0.260*		
	(5.332)			(1.832)		
Strength of Beliefs$_{i,t}$ * *Knowledge*				-0.158*		
				(-1.663)		
Strength of Beliefs$_{i,t}$ * *Experience*				-0.050		
				(-0.378)		
Strength of Beliefs$_{i,t}$ * *Inv Amount*				-0.028		
				(-0.156)		
Knowledge				0.251**		
				(2.647)		
Experience				0.052		
				(0.502)		
Investment Amount				0.130		
				(1.170)		
Confirmation Bias$_{i,t}$		0.186***			0.185***	
		(4.348)			(4.309)	
Trading Frequency$_{i,t}$			-0.075*			-0.079*
			(-1.663)			(-1.750)
Age						0.030
						(0.587)
Gender						-0.021
						(-0.433)
Education						0.014
						(0.302)
Income						-0.050
						(-0.977)
Adjusted R^2	5.54%	3.40%	6.20%	7.54%	3.40%	7.70%
Number of Obs.	502	502	502	502	502	502
Model Fits						
Chi-square/df			4.97			3.24
RMSEA			0.089			0.067
Normed Fit Index			0.762			0.937
Relative Fit Index			0.207			0.906
Tucker-Lewis Coefficient			0.246			0.933
Comparative Fit Index			0.774			0.955

Table 4: Trading Frequency System of Equations Estimates

This table reports the path analysis estimates for the trading frequency system of equations reported in equation set (2). All variables have been previously defined in Table 1. The estimates in Columns (1)-(3) are from the system of equations without control variables, while the estimates in Columns (4)-(6) are from the system of equations with all variables. A lower value of χ^2/df and RMSEA below 0.08 represents a good fit of the overall model; NFI, RFI, TLC and CFI above 0.9 indicates a good fit of the model. The *t*-statistics of the coefficient estimates are reported in parentheses below the estimates. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

	Dependent Variable:					
Independent Variables	MisCal (1)	Comp (2)	TrdFreq (3)	MisCal (4)	Comp (5)	TrdFreq (6)
Confirmation Bias$_{i,t}$	-0.109*	0.263***		-0.109*	0.263***	
	(-1.926)	(5.900)		(-1.927)	(5.895)	
Miscalibration$_{i,t}$			-0.237***			-0.237***
			(-5.046)			(-4.721)
Competence$_{i,t}$			0.254***			0.254***
			(5.839)			(5.501)
Age						0.044
						(0.926)
Gender						0.063
						(1.432)
Education						-0.078*
						(-1.762)
Income						-0.108**
						(-.2.251)
Adjusted R^2	1.20%	6.90%	13.70%	1.20%	6.90%	14.40%
Number of Obs.	502	502	502	502	502	502
Model Fits						
Chi-square/df			4.38			3.16
RMSEA			0.082			0.067
Normed Fit Index			0.919			0.804
Relative Fit Index			0.594			0.607
Tucker-Lewis Coefficient			0.829			0.812
Comparative Fit Index			0.931			0.847

Table 5: Expected Return System of Equations Estimates

This table reports the path analysis estimates for the expected return system of equations reported in equation set (3). All variables have been previously defined in Table 1. A lower value of χ^2/df and RMSEA below 0.08 represents a good fit of the overall model; NFI, RFI, TLC and CFI above 0.9 indicates a good fit of the model. The *t*-statistics of the coefficient estimates are reported in parentheses below the estimates. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

	Dependent Variable:	
	ExpRet	ExpRet
Independent Variables	(1)	(2)
Confirmation Bias$_{i,t}$	0.116***	0.115**
	(2.516)	(2.526)
Age		0.024
		(0.316)
Gender		-0.028
		(0.601)
Education		0.016
		(-1.349)
Income		-0.033
		(-1.199)
Adjusted R^2	7.92%	8.53%
Number of Obs.	502	502
Model Fits		
Chi-square/df	9.65	3.41
RMSEA	0.131	0.069
Normed Fit Index	0.781	0.945
Relative Fit Index	0.315	0.913
Tucker-Lewis Coefficient	0.364	0.937
Comparative Fit Index	0.733	0.960

Table 6: Path Analysis Model Estimates to Test Direct Effects

This table reports the path analysis estimates for the system of equations (4) and (5). The estimates in Columns (1) and (2) are from a slightly modified form of system of equations (1). All variables have been previously defined in Table 1. A lower value of χ^2/df and RMSEA below 0.08 represents a good fit of the overall model; NFI, RFI, TLC and CFI above 0.9 indicates a good fit of the model. The *t*-statistics of the coefficient estimates are reported in parentheses below the estimates. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

	Dependent Variable:					
	Trading Frequency		Realized Performance		Overconfidence	
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Confirmation Bias$_{i,t}$	0.174***	0.175***	-0.149***	-0.149***	0.108**	0.111**
	(3.827)	(3.925)	(-3.241)	(-3.237)	(2.410)	(2.504)
Strength of Beliefs$_{i,t}$	0.078*	0.073	-0.055	-0.053		
	(1.741)	(1.656)	(-1.209)	(-1.176)		
Age		0.024		0.021		0.034
		(0.501)		(0.419)		(0.686)
Gender		0.072		-0.026		0.067
		(1.593)		(-0.556)		(1.463)
Education		-0.086*		0.016		-0.047
		(-1.859)		(0.345)		(-1.012)
Income		-0.115**		-0.033		-0.154**
		(3.163)		(-0.645)		(-3.086)
Adjusted R^2	4.20%	8.10%	11.44%	12.50%	7.32%	8.40%
Number of Obs.	502	502	502	502	502	502
Model Fits						
Chi-square/df	2.52	3.21	2.42	3.12	4.38	3.43
RMSEA	0.056	0.067	0.044	0.065	0.082	0.070
Normed Fit Index	0.984	0.948	0.965	0.950	0.885	0.945
Relative Fit Index	0.965	0.917	0.793	0.920	0.308	0.913
Tucker-Lewis Coefficient	0.979	0.941	0.926	0.944	0.336	0.937
Comparative Fit Index	0.990	0.963	0.988	0.965	0.894	0.960

Figure 1: The Main Conceptual Model

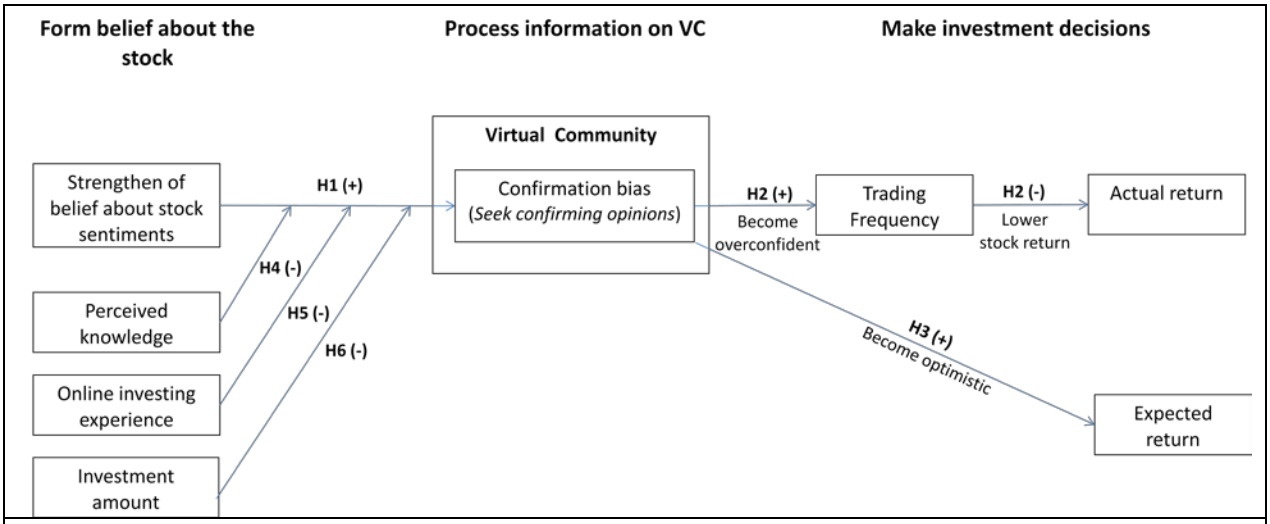
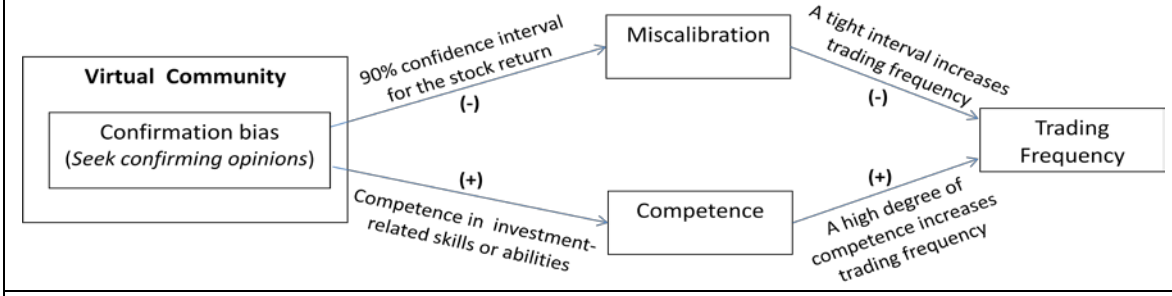


Figure 2: A Snapshot of Experiment on Naver Stock Message Boards

Figure 3: Conceptual Model for Overconfidence and Competence as Mediating Variables



Appendix A: Path Analysis Modeling

Path analysis is an extension of standard multiple regression models. A path analysis model is a diagram relating independent, mediating (or moderating), and dependent variables. Single arrows indicate causation between exogenous or mediating variables and the dependents. Arrows connect the error terms with their respective endogenous variables. Figure 4 provides a graphical illustration of the path analysis model used in our study.

The path analysis framework is similar to system of equations modeling in econometrics. In particular, the two-Stage least squares (2SLS) model is a path estimation procedure in which estimates are obtained in a non-recursive manner. There are no loops or reciprocal causal relation between two variables. It is a "causal modeling" framework, which allows us to test theoretical propositions about cause and effect without manipulating variables. This research approach is commonly used in many social science disciplines, including organizational behavior, information systems and marketing (Medsker et al. 1994, Gefen et al. 2000, Steenkamp and Baumgartner 2000).

The path estimates in a path analysis model can be obtained using the maximum likelihood estimation (MLE) or the ordinary least squares (OLS) procedure. A path coefficient is a standardized regression coefficient (or beta coefficient) that shows the direct effect of an independent variable on a dependent variable.

The most important reason for using a path analysis model instead of a traditional econometric model is that researchers can easily compare overall model fit to several alternative models as the path analysis provides more statistics about overall model fit, including likelihood ratio chi-square test, Normed Fit Index (NFI), Tucker Lewis Index or Non-normed Fit Index (NNFI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), etc. These statistics have different threshold values (e.g., the threshold for RMSEA is < 0.08; the threshold for NFI, CIF and other statistics is > 0.90). The path analysis model compares the default model proposed by researchers to the saturated model and an independent model. The saturated model is the model with all possible paths and the independent model

is a model with no path arrows. A path analysis can be used to test the fits of models against two or more alternative models. For example, researchers can compare the RMSEA, NFI, CIF or other statistics from two different models and identify the model with a better fit (Balasubramanian et al. 2003).

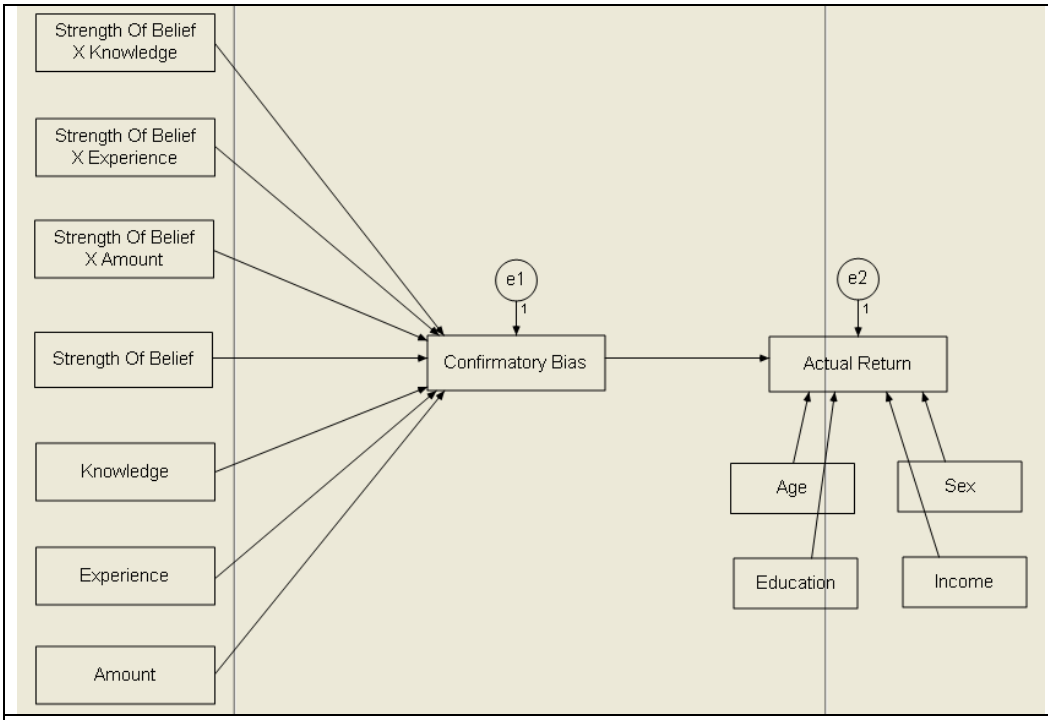


Figure 4. Estimation of a path analysis model using AMOS 7.0. (Actual return as the final dependent variable).

Appendix B: Survey Questions

Characteristics	Category
Demographic Questions	
Gender	Female Male
Age	< 25 years 25 to35 years 36 to50 years 51 to65 years > 65 years
Education	High school 2-year college 4-year college Master's degree PhD degree
Annual income level[1]	< 15 million won 15 to50 million won 50 to100 million won 100 to200 million won >200 million won
Questions related stock investment	
Online investing experience	< 1 year 1 to2 years 3 to6 years 7 to10 years >10 years
The number of stocks in your stock portfolio	1 2 to 3 4 to 6 7 to 10 >10
Frequency of trading per week	< 1 1 to 2 3 to 6 7 to 10 > 10
Perceived Knowledge (1) I am well informed about the stock market (2) I am familiar with the stocks I trade (e.g., their business, financial status) (3) I am well informed about the major economic news that impacts the stock market	**7-Point Likert Scale** Strongly Disagree Disagree Somewhat Disagree Neutral Somewhat agree Agree Strongly Agree
Perceived Competence (1) I am comfortable with my ability to understand investment products, alternatives and opportunities (2) I am competent in my ability to invest successfully (3) I am skillful in investment activities (e.g., stock picking, position, volume).	**7-Point Likert Scale** Strongly Disagree Disagree Somewhat Disagree Neutral Somewhat agree Agree Strongly Agree
Questions related to the stock message board[2]	
Time spent searching for information at stock message boards per day	< 1 hour

	1 to 2 hours 3 to 6 hours 7 to 10 hours > 10 hours
Number of postings at the stock message boards	0 1 to 5 6 to 10 11 to 20 >20
Questions specific to the stock[3]	
Your current investment opinion of the stock is	Strong sell Sell Hold Buy Strong buy
Are you currently holding the stock?	Yes No
What is your current investment amount in the stock?	< 5 million won 5 to10 million won 10 to 50 million won 50 to 100 million won > 100 million won
What overall rate of return do you expect to get on your stock over the next one month?	Your return: ( )%
There is a 1-in-10 chance the actual return will be less than ( )%	Min return: ( )%
There is a 1-in-10 chance the actual return will be greater than ( )%	Max return: ( )%
Questions about confirmation bias[4]	
(1) Which opinion appears to have the most widespread support (2) Which opinion appears to be most strongly backed by news about the stock (3) Which opinion appears to have the most convincing argument	Click one of the five new messages for each of the questions

1, 2: 10,000 Korean Won is equivalent to 8.39 US dollars. 3: If investors participated in our experiment on the SAMSUNG Electronics message board, the questions would be related to SAMSUNG Electronics. 4: We showed five new messages (two positive messages about the stock, two negative messages about the stock, and one neutral message about the stock). Then, investors were asked to click on one of the five new messages for each of the above three questions.