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UNIVERSITY OF CALIFORNIA SAN DIEGO

Essays on Social Finance

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy

in

Management

by

Youngjae Choi

Committee in charge:

Professor Joseph Engelberg, Chair
Professor James Andreoni
Professor Snehal Banerjee
Professor Christopher Parsons
Professor Yuval Rottenstreich
Professor Charles Sprenger

2020

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The dissertation of Youngjae Choi is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California San Diego

2020

DEDICATION

This dissertation is dedicated to my wife Dongeun, my daughter Lena, and my parents whose unyielding support, love, and encouragement have inspired me to pursue and complete this research.

I also dedicate this dissertation to my advisors Joey, Chris, and Yuval who have patiently guided me every step of the way as I prepared for this dissertation.

Last but not least, I dedicate this work to God for the strength and spiritual support he has provided me throughout my Ph.D. program.

EPIGRAPH

The time has come to move beyond behavioral finance to social finance, which studies the structure of social interactions, how financial ideas spread and evolve, and how social processes affect financial outcomes.

— David Hirshleifer

We need to incorporate the contagion of narratives into economic theory. Otherwise, we remain blind to a very real, very palpable, very important mechanism for economic change, as well as a crucial element for economic forecasting. If we do not understand the epidemics of popular narratives, we do not fully understand changes in the economy and in economic behavior.

— Robert Shiller

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ACKNOWLEDGEMENTS

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I am indebted to Professor Chris Parsons and Professor Yuval Rottenstreich for their immeasurable support. I remember the day Yuval stayed up until 3am to help me revise my experimental design the night before the lab schedule. I remember the day Chris met with me at Peet's Coffee helping me add the final touches on my job market presentation. It has been my honor to be able to receive invaluable advice from them and without a doubt, my paper would not have been finished without them. I will certainly miss the countless discussions we had together with Joey.

I am deeply grateful to my dissertation committee members, Professor James Andreoni, Professor Snehal Banerjee, and Professor Charles Sprenger for their great advice on my work. Beyond the one-on-one meetings to receive direct advice on my work, I was inspired by their lectures and seminars.

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Finally, I would like to thank my family who is the driving force behind the pursuit of my

career. I would not be here without their dedication and trust.

VITA

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ABSTRACT OF THE DISSERTATION

Essays on Social Finance

by

Youngjae Choi

Doctor of Philosophy in Management

University of California San Diego, 2020

Professor Joseph Engelberg, Chair

This dissertation investigates the impact of social interaction in the financial market. The focus of this defense is on understanding 1) how investment information is transmitted from one investor to another and 2) how social interaction between investors change their trading strategies. The first chapter of this dissertation finds that conversational norms shape the diffusion of investment information. The results in the second chapter show that investors are more likely to drastically adjust their investment strategies when other investor's current buying (selling) strategies and past performance are consistent.

Chapter 1

When Losers Talk: Conversations, Social Norms, and Information Diffusion

Conversations are vessels through which information travels. To understand how investment information spreads via person-to-person conversations, I observe paired investors in a well-controlled experiment. While self-enhancement bias suggests that investors may be more likely to discuss their performance when they have positive returns, I find the reverse: in conversations, investors with positive returns appear less likely to talk about their investment outcome. Experimental transcripts highlight conversational norms as a key mechanism. For example, though sharing information about one's positive performance may feel good, it may have a negative effect on the listener, and making one's counterpart feel bad is often inappropriate. Thus, in the experiment, investors with positive returns are reluctant to discuss their performance if they do not know their counterpart's return, or if they learn it is negative. These results show that conversational norms shape the diffusion of investment information.

1.1 Introduction

Over the past four decades, the field of behavioral finance has examined the impact of psychological factors on financial decision making. Much of this research concerns cognitive biases measured at the individual level, such as overconfidence and loss aversion. However, less is known about how the psychology of interactions influences financial and economic decisions. This conceptual gap is important because many choices, such as buying a stock, opening a bank account, or refinancing a mortgage, often arise from conversations with others (Shiller and Pound 1989). Consequently, a role for psychology concerning interpersonal dynamics, rather than cognitive processing at the individual level, seems important for financial decision-making. This sentiment is embodied in Hirshleifer's call to arms that, "The time has come to move beyond behavioral finance to social finance, which studies the structure of social interactions, how financial ideas spread and evolve, and how social processes affect financial outcomes."

Accordingly, in this paper, I take seriously the idea that in addition to the role played by individual psychology, the "structure of social interactions" represents an additional, and indispensable, determinant of how investment ideas spread. More specifically, when considering the process by which information travels from person A to person B, there are three relevant psychological processes: that of person A, that of person B, and that of the A-B pair. I argue that the latter – the specific way individuals relate to each another – has first order implications for both the rate and type of information that can flow between them.

To better understand how investment information is spread through social interactions, I collect experimental data on conversations between investors. My main hypothesis is that because social norms shape financial conversations, they influence the financial information that is transmitted. In other words, how something is said affects what is said.

Consistent with this claim, I find that investors are less likely to disclose their investment outcome when it is positive than when it is negative. This result would be surprising if we only consider individual processes, such as self-enhancing biases, but it accords well with norms in conversations. Though sharing information about one's positive performance may feel good, it may have a negative effect on the listener, and making one's counterpart feel bad is often inappropriate. When this effect is strong, positive signals may be less rather than more likely to diffuse, and accordingly, alter the predicted dynamics for trading and asset prices.

In my experiment, each participant chooses a stock, then receives a return based on this choice, and finally may discuss his or her investment outcome with another participant. To give a feel for how such conversations may evolve, below is an excerpt of an interaction occurring in the lab. Hereafter, I refer to investors with negative returns as "losers" and those with positive returns as "winners."

Loser (-10%)	Hello!
Winner (+5%)	Hi! What was your strategy?
Loser (-10%)	My strategy was to pick a stock that seemed relatively the same throughout the year without a lot of changes
Winner (+5%)	Yeah same! Also I looked at the y axis because the numbers varied
Loser (-10%)	but, the stock that I chose ended up being the worst one :(
Winner (+5%)	Rip

The above conversation illustrates a few patterns that will generalize across my sample. For example, only the loser disclosed his/her outcome, while the winner did not. To reiterate, this is perhaps surprising because the notion of self-enhancement suggests that winners will be more interested in disclosing their outcome (Bali et al. 2019; Han et al. 2019; Heimer and Simon 2015; Huang et al. 2019). Second, the winner behaved differently than he/she thought he/she would behave. Immediately before this conversation occurred, the winner was asked, "The return of the stock you picked in Round 1 is not released to anyone else. How likely are you to talk about your return in Round 1 with another participant in this lab?" He/she then responded, "Very likely." Yet when the scenario played out, the winner did not disclose his/her return, after hearing that his/her randomly assigned partner lost 10%.

In this conversation, Loser 2 volunteered his poor performance and, upon hearing this, Loser 1 followed suit. Indeed, as I discuss below, provided one party discloses her result, the second party's chance of also disclosing is higher when they have similar performance. Across all the conversations I analyze, the results are as follows:

1) Winners Ask: Winners are significantly more likely to ask about their partners' investment outcome before disclosing their own.

2) Losers Volunteer: When investors do not know their counterpart's investment outcome and have not been asked about their own outcome, losers are significantly more likely to disclose this information.

3) Similarity Facilitates: Having learned their partner's outcome, losers are significantly more likely to disclose their outcome to fellow losers. Likewise, winners are significantly more likely to disclose their outcome to fellow winners.

4) Losers Talk More: Given the above, by the end of a conversation, losers are significantly more likely to have disclosed their outcome.

5) People Mispredict: When I survey investors prior to their conversing with other investors, winners believe they are relatively likely to disclose their outcome, and losers believe they are relatively unlikely to do so. Thus, it appears that investors do not anticipate the norms that will govern their ensuing conversations.

These findings can largely be explained via two social psychological considerations. First, people prefer to get along during social interactions, and it is typically appropriate not to threaten a counterpart's face (Goffman 1967; Brown and Levinson 1987). Just as they do not want to be embarrassed while interacting with others, people are often careful not to hurt a counterpart's feelings. The observation that winners ask, and do not volunteer, seems to reflect this consideration. Second, people more readily get along with those who are similar to them. The tendency to associate with others that are similar, known as homophily (McPherson et al. 2001; Lazarsfeld and Merton 1954; Laumann 1966; Verbrugge 1977), is reflected in the observation that similarity facilitates.

My experiment is designed to capture a common type of conversation among investors: a short, dyadic engagement involving anonymous peers. Of course, this sort of interaction is not the only kind of conversation one might consider. In other settings, such as with friends, or in one-to-many communication, different social considerations may apply. Moreover, norms governing what is appropriate are also expected to vary across contexts. While the precise findings I present may not apply across settings, the main observation – that conversational norms shape the diffusion of investment information – is, I believe both general and novel in the finance and economics literature.

My work complements existing evidence that social interactions have a meaningful impact on investment decisions (Bailey et al. 2018; Hong et al. 2005; Hvide and Ostberg 2015), returns (Bali et al. 2019), market participation (Hong et al. 2004; Kaustia and Knupfer 2012) and anomalies (Heimer 2016). These papers infer that people have interacted based on measures like shared workplaces (Hvide and Ostberg 2015) or population density (Bali et al 2019). In essence, they show that the opportunity to interact (by being together) facilitates information flow. Critically, I consider not just the opportunity to interact, but the dynamics that prevail during interactions. Because of conversational norms, the opportunity to interact is not sufficient for information flow since, as the results here show, winners may not volunteer.

The remainder of the paper is organized as follows. Section 2 describes the data and experimental design. Section 3 discusses the results of the experiment and the social mechanisms associated with the results. Section 4 discusses some broader implications of my results for various financial market phenomena and the real effects of conversations. Section 5 concludes.

1.2 Data and Experimental Design

I conducted my experiment in the behavioral lab at the University of California at San Diego Rady School of Management. A total of 810 participants were recruited over two years, from 2017 to 2018; 47% were female and 28% had investment experience. Further demographic information is presented in Table 1.1. The experiment was conducted using z-Tree (Fischbacher (2007)), software which is widely-used for conducting lab studies in economics and finance. Each experimental session lasted about 15 minutes. Participants received class credits as compensation.

Table 1.1: Demographic information

		N	%
Gender	Male	422	52.10
	Female	381	47.04
	Other	7	0.86
Ethnicity	White	146	18.02
	Hispanic or Latino	99	12.22
	Black or African American	7	0.86
	Native American	3	0.37
	Asian	511	63.09
	Other	44	5.43
Native Language	English	460	56.79
	Other	350	43.21
Investment Experience	Yes	233	28.77
	No	577	71.23
Major	Engineering or Physics	131	16.17
	Natural Sciences	84	10.37
	Social Sciences	108	13.33
	Economics or MGMT	290	35.80
	Literature or Art or History	8	0.99
	Other	189	23.33
Age	Above 27	27	3.33
	26-27	27	3.33
	24-25	80	9.88
	22-23	351	43.33
	20-21	306	37.78
	Below 20	19	2.35
Total		**810**	

1. If you were given a chance to do so, how likely are you to talk about your **experience or strategy** of choosing a stock in round 1 with another participant in this lab?
2. If you were given a chance to do so, how likely are you to talk with another participant in this lab about your **choice** in round 1?
3. If you were given a chance to do so, how likely are you to **strategize** with someone else in this lab before choosing your next stock in round 2?
4. The return of the stock you picked in round 1 is not released to anyone else. How likely are you to talk about your **return** in round 1 with another participant in this lab?

In answering questions 5A and 5B, please suppose that in real life you invested $100 in the stock you chose in round 1, and you received the same return as in round 1.

5A. How likely would you be to talk about your **choice or return** with a friend?

5B. If you could send a message to your friend, what would it be? Please write your message in the following box.
(You may leave the box empty if you do not wish to send any message.)

6. How comfortable are you with your **return being released** to others in this lab?

Figure 1.1: Survey Questions

The experiment consisted of three stages and two rounds. In the investment decision stage, participants were asked to make an investment choice. Specifically, they were shown graphs with historical price information for four different stocks, and they were asked to choose one stock that they thought would give them the maximum return in the year following the last date on the graphs.

Academics have been skeptical of the practicability of technical analysis, but it is a widely used method and has even been accepted and adopted by professional investors (Coval 2005; Schwager 1995). Additionally, evidence from the data (i.e., 40% of the participants talked about their strategies) shows that the participants too believe that graphs were informative.

To facilitate an even distribution of choices, the four graphs did not show any clear patterns, and the stocks were selected when the stock market was relatively stable (the year 2013). Table 1.2 results confirm the random assignment of the samples as well as outline the even distribution of characteristics between winners and losers. Numbers in Column (1) and (2) present the averages and the standard errors of the corresponding variables. Numbers in column (3) present the F-test results. Covariate balance is tested only if the sample size of the variable

Table 1.2: Covariates Balance

		Investors with a positive return: Winners (N=377) (1)	Investors with a negative return: Losers (N=430) (2)	P-Value of Test: (1) = (2) (3)	N
Gender	(=1 if male)	0.4 (0.098)	0.4 (0.12)	0.72	803
Ethnicity	(=1 if Asian)	0.41 (0.023)	0.43 (0.017)	0.64	810
	(=1 if White)	0.30 (0.030)	0.34 (0.033)	0.60	
	(=1 if Black)	0.02 (0.13)	0.02 (0.12)	0.20	
Native Language	(=1 if English Speaker)	0.72 (0.023)	0.75 (0.018)	0.53	810
Investment Experience	(=1 if investor has experience)	0.31 (0.10)	0.28 (0.096)	0.12	810
Major	(=1 if Econ or MGMT major)	0.34 (0.17)	0.36 (0.14)	0.48	810
Age		22.35 (2.15)	23.11 (2.32)	0.37	810

sample size is greater than 5% of the entire sample, which is 40.5. For example, gender of 'other' is less than 40.5 (i.e., 7) and therefore the covariate balance test is omitted. The variable ethnicity is not a binary choice so multiple covariates are tested for its balance. To avoid deception (Bonetti 1998; Hertwig and Ortmann 2008), the stocks used were real stocks from the New York Stock Exchange. After each participant selected his or her own stock, they learned the actual return of both their chosen stock and each of the other stocks.

Next, in the chatting stage, participants are put into pairs to discuss for 3 minutes. During this time, I chose to look at the most common type of conversation (i.e., dyadic conversations and text messaging) among investors (Independent 2012; newswiretoday 2010). To ensure that participants felt comfortable and were not pressured to talk about the experiment, the instructions stated that they could discuss anything they desired, including the weather or school. Overall, most people engaged in the discussion. About 80% chatted about the experiment, but many participants also mentioned other topics.

After the chatting stage, participants were asked to answer a few more survey questions, and then Round 2 began. In this round, participants saw new graphs for each of the four stocks. These new graphs showed price information for an additional year. Participants were again asked to choose a stock they believed would do best in the subsequent year. Though the focus of my study is to observe what information people transmit about their initial return, I created an investment decision stage in Round 2 so that participants would feel like the investment process was continuous. However, this dummy round played no other role in the analysis, and the results are omitted from the paper. The experiment concluded after a few demographic survey questions. The full experimental materials are provided in the appendix 1b.

1.3 Results and Social Mechanisms

This section provides the results of the text analyses and survey questions. The chatting stage lasted 3 minutes, and participants were paired with a randomly assigned partner in the lab to talk about any topic. On average, each participant typed 37 words, with a standard deviation of 19 words. The maximum was 165 words. A few pairs failed to complete their conversation within 3 minutes, and these incomplete conversations are excluded from the analysis. The word cloud in Figure 1.2 visually presents the most common words used in the chat boxes. Stop words (e.g., the, a, in) are not included in the word cloud.

I generated dummy variables to analyze the chat box contents. The dummies represent four different types of investment information I identified in the conversations: (1) return, (2) choice, (3) performance, and (4) strategy. These four types of information are decreasing in their directness moving from (1) to (4). For example, sharing one's return is clearly the most direct way to disclose information. However, because every participant was informed about the returns of all available stocks, disclosing one's choice of investment is also fairly direct. I define sharing one's performance (group 3) as talking about one's return or choice somewhat vaguely.

Figure 1.2: Word cloud

For example, if a participant says, "I did well" or "I didn't choose the right one", a receiver of this message can rule out a few options but is still unsure what exactly the partner chose. Therefore, "performance" is indirect investment information. Finally, I categorize "strategy" as indirect investment information as well because sharing one's strategy for choosing a stock is not directly revealing one's choice and outcome. I coded the talk dummy variables manually by reading through each chat box.

1.3.1 Winners Ask

Winners are significantly more likely to ask about their partner's outcome before releasing their own. The percentage of people asking for the partner's outcome before releasing their own (hereafter, "who asks first" percentage) was, on average, 7% higher for winners than losers (significant at the 5% level). This subsection shows a sample figure.

I estimate a univariate logistic regression to test the statistical significance of the difference

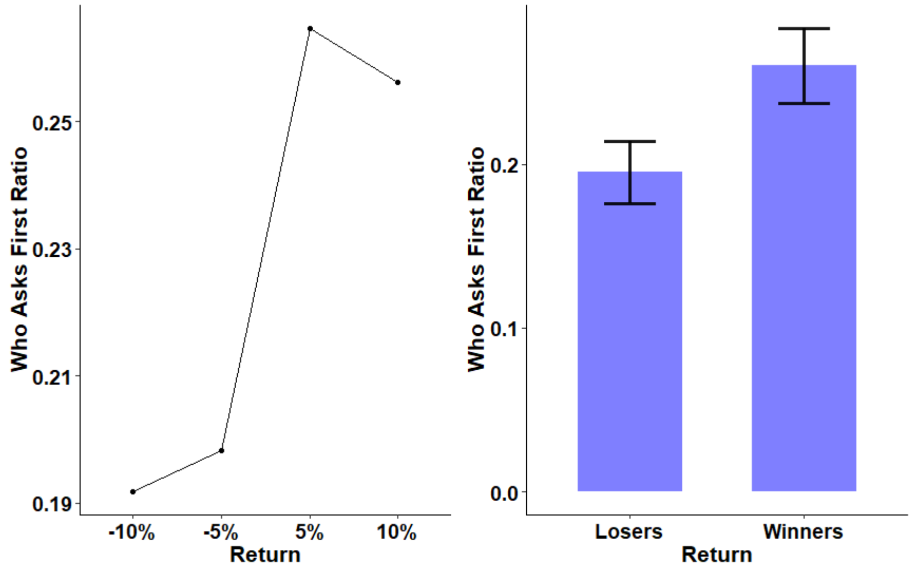

Figure 1.3: Percentage of People Asking before Releasing their Outcome

in who asks first ratio between winners and losers.

$$logit(Y_i) = ln(\frac{\pi}{1-\pi}) = \alpha + \beta_1 Pret_i + \varepsilon_i \tag{1.1}$$

The dependent variable Yi in the regression formula is a dummy variable that takes a value 1 when the participant asked before disclosing their own outcome and 0 otherwise. The independent variable Preti is a dummy variable used to compare winners $(Pret_i = 1)$ and losers $(Pret_i = 0)$. Finally, π is the probability of the event, which, in this case is talking about outcome. The first row of Table 1.3 describes the result of this regression. I find that who asks first ratio of winners is significantly greater than that of losers. The rest of the results in Table 1.3 will be discussed below.

One potential explanation for this result is that, in general, people prefer to get along during interactions. They do so by cooperating and by maintaining each other's face (Brown and Levinson 1987; Goffman 1967); that is, individuals avoid being embarrassed or humiliated while interacting with others and also try not to hurt other peoples' feelings. Consequently, winners

Table 1.3: Univariate logistic regressions

	Coefficient	T-stats	P-value
Who Asks First	0.186	2.206	0.027**
Voluntary talk	-0.273	-2.657	0.008***
Talk	-0.168	-2.318	0.020**

tend to ask for other's outcomes before releasing their own in order to minimize the awkwardness that might come by divulging their win to a counterpart who has lost. The following dialogue demonstrates how one winner navigated this issue:

Loser (-5%)	Hey
Winner (+10%)	Yo
Loser (-5%)	How is it going
Winner (+10%)	Pretty well. how'd your choices go?
Loser (-5%)	Not as well as I thought
Winner (+10%)	Lol Did you go in with any strategy?
Loser (-5%)	I thought I was choosing one with a positive gain and ended up being negative
Loser (-5%)	Nope
Winner (+10%)	How bad?
Loser (-5%)	-5%
Winner (+10%)	Meh haha
Loser (-5%)	What about u

Winner (+10%)	10% +
Loser (-5%)	Niceeeeee
Winner (+10%)	Try choosing a stock that doesn't seem to volatile
Loser (-5%)	you must be an economist ;)
Loser (-5%)	ohhh yeah that's where I went wrong
Loser (-5%)	choose the one with the most volatility
Winner (+10%)	Big jumps between high and low usually signify a very risky stock

Interestingly, the winner in this dialogue does not disclose his outcome initially; rather, he asks his partner three times before being asked about his own investment outcome. A similar approach arises in the next dialogue.

Winner (+10%)	Hello. How did you do on the stock return thing?
Loser (-10%)	hi. Not the great
Winner (+10%)	which on did you choose?
Loser (-10%)	the weather seems gloomy today. The last one.
Winner (+10%)	I agree. It does. But it does look like it's going to get better.
Winner (+10%)	The sky looks blue over the ocean, so I'm optimistic.
Loser (-10%)	must be a sign that finals will soon come, but they will also soon pass
Winner (+10%)	That's very poetic.

Here, the winner hesitates to share his investment outcome voluntarily. Instead, he asks for his interlocutor's outcome. Moreover, he avoids disclosing his own outcome after hearing about his losing partner's results.

Although my study is limited by the fact that I paired two strangers to talk to each other, I predict that this pattern - winners asking first rather than voluntarily disclosing investment information – may persist and perhaps even be accentuated among friends. Tice et al. (1995) provide evidence that modesty is stronger between friends than strangers, because friends are expected to maintain a longer relationship.

1.3.2 Losers Volunteer

The first section explored the question of which party inquiries about the other's outcome, before disclosing their own. This section turns to the question of who is more likely to voluntarily talk about their outcome. Guided by the same logic, I predicted that winners, who are weary of awkward interactions with losers, are less likely to voluntarily talk about their own outcomes. This prediction is borne out in the data.

In this analysis I make a distinction between voluntarily sharing one's own information and being pressured to do so or in response to a question. For example, suppose person A initiates a conversation about her investment return. She asks Person B how his investment is going. Person B, who doesn't feel comfortable sharing his investment experience may nevertheless share this information because he feels pressured to do so.

Accordingly, I categorize conversations in terms of the parties' revealed willingness to talk. I similarly categorize revealed willingness to "not talk." As described in Figure 1.4, I define "voluntarily talking without being asked or heard" to be the highest degree of willingness to talk and term it "Talk, Not Asked, Not Heard" (hereafter, "voluntary talk")'. It is strictly greater than any other category as there is no pressure to talk about one's information. I define "talking without being asked, after hearing partner's information" to be the second level of willingness. Talking without hearing, but after being asked, is the third level of willingness. Because some may feel hearing their partner's information may apply as much pressure as being asked directly, I say the second level of willingness is weakly greater than the third. Finally, I define "talking after being asked and after hearing one's partner's information" as the least willing to talk about his/her information because this person experiences double pressure by hearing both their partner's information and by being asked to release their own information. The categories in the "Not Talk" groups are ordered according to the same logic.

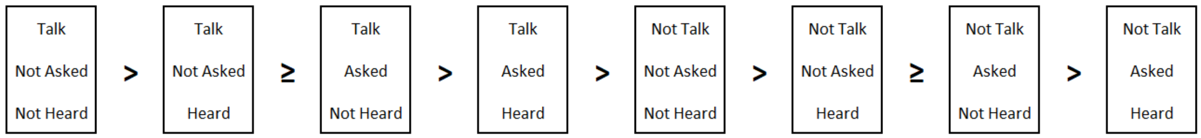

Figure 1.4: Willingness to talk categorization

The results indicate that losers are significantly more likely to talk voluntarily than winners. In other words, losers were very willing to talk about their outcome before being asked or hearing about their partner's return or choice. Even though the line graph is not a smooth downward slope, the difference between winners and losers remains apparent. The logistic regression results shown in Figure 1.5 and Table 1.3 confirm that the difference in voluntary talk ratio between winners and losers is statistically significant at a 1% level.

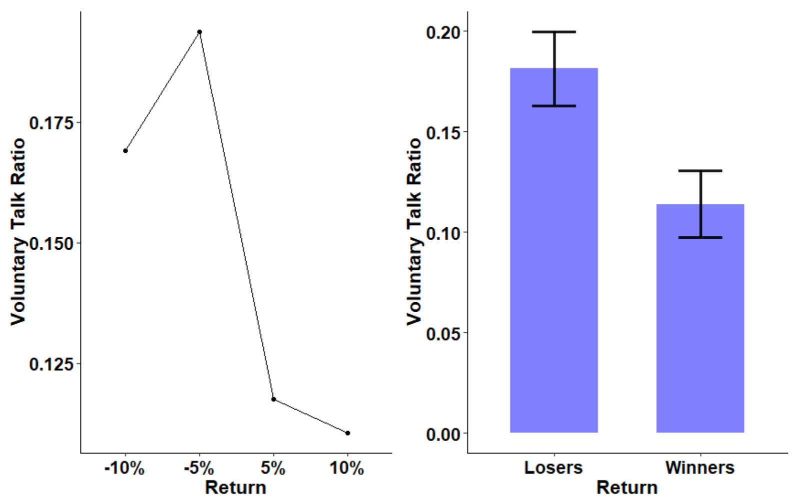

Figure 1.5: Voluntary Talk Percentage for Losers and Winners

1.3.3 Similarity Facilitates

In Sections 1.3.1 and 1.3.2, I argued that winners are likely to ask about their partner's outcome before revealing their own outcome. They are less likely to voluntarily disclose their outcome because they want to circumnavigate the awkwardness of sharing their success in front of the less fortunate. Based on these results, I predicted that in a dyadic conversation, when an

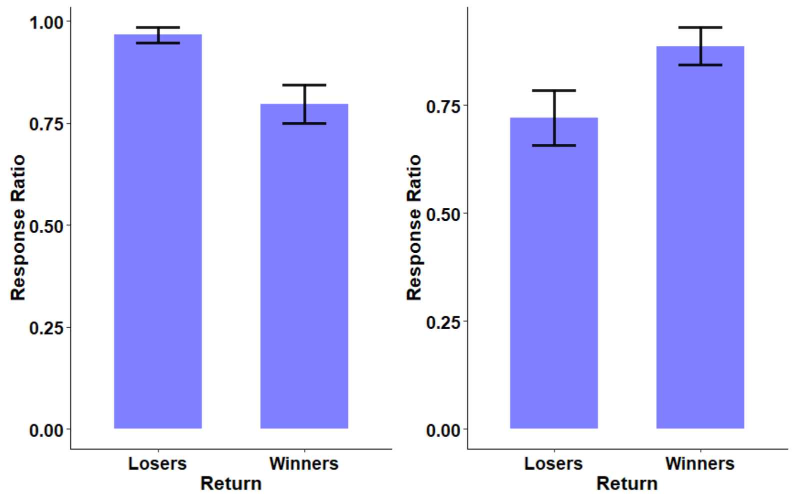

Figure 1.6: Response Percentage after Learning Partner's Outcome

investor realizes that their interlocutor achieved an outcome opposite to their own, they would want to avoid the awkwardness of sharing their outcome. Said another way, I predict that losers (winners) will feel comfortable disclosing their outcome when they learn their partner is also a loser (winner). If so, then conversations would give rise to a phenomenon known as homophily (McPherson et al. 2001), which is embodied in the idiom "Birds of a feather flock together." People's similarities can be categorized in various ways, such as gender, ethnicity, organizational role, and age group. In the context of my study, similarity among investors can be defined based on their return: losers and winners.

The data indeed indicate that similarity of returns facilitates discussion. As Figure 1.6 shows, winners were significantly more likely to disclose their outcome after learning of their partner's winner status. Likewise, losers were significantly more likely to reveal their outcome after learning that they were interacting with another loser.

1.3.4 Losers Talk More

Taken together, the results from Sections 1.3.1 through 1.3.3 lead to the overall conclusion that losers are significantly more likely to converse about their outcomes. The line graph in Figure

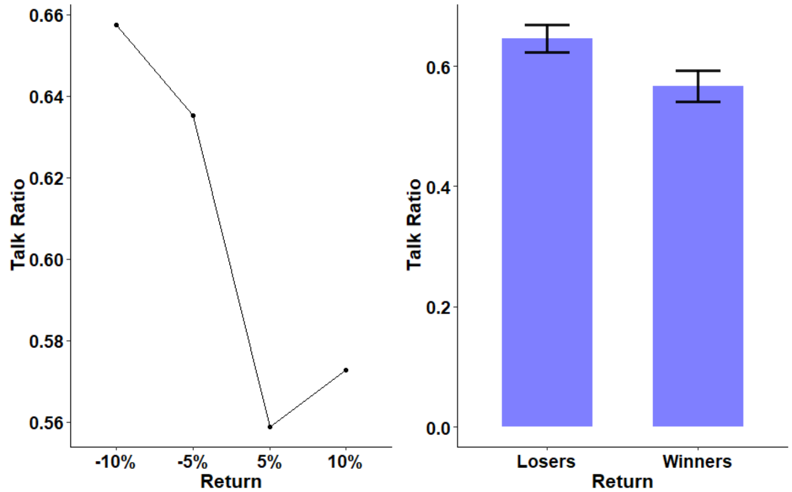

Figure 1.7: Talk Percentage of Losers and Winners

1.7 indicates that the propensity to talk about the outcome decreases as an individual's return increases. As shown in the bar chart of Figure 1.7, it was not the winners, but rather the losers, who talked about their outcomes more. The logistic regression result shown in Table 3 confirms that the talk ratio of losers is significantly greater than that of winners.

To further analyze whether individual characteristics affect the talk ratio, voluntarily talk ratio, and asking before releasing ratio, I run an extended multiple logistic regression controlling for demographic information.

$$logit(Y_i) = ln(\frac{\pi}{1-\pi}) = \alpha + \beta_1 Pret_i + \beta_2 X_i' + \varepsilon_i \tag{1.2}$$

X_i in equation (1.2) represents the demographic controls. Y_is are the talk ratio, voluntary talk ratio, and who asks first ratio respectively. Table 4 describes the results of the multiple logistic regressions. Besides the significant differences I find between losers and winners in various aspects (i.e., talk ratio, voluntary talk ratio, who asks first ratio), I find a few interesting results among the demographic variables. As the participants aged, they tended to talk more about their investment outcome. The talk ratio seems to consistently increase as the participants aged. Non-native English speakers disclosed their outcome significantly less (at 10% level of significance) than the native English speakers did. Compared with the White participants, significantly fewer Black and Hispanic participants voluntarily talked about their outcome. Despite a relatively small sample size, one possible explanation is that different cultural backgrounds may also affect conversational norms in way that could potentially alter the dynamics of the information diffusion. However, no demographic control showed a consistent pattern across the different dependent variables.

1.3.5 People Mispredict

The results from Section 1.3.1 through 1.3.4 run counter to the notion of self-enhancement bias. This is surprising because the outcome-based social transmission literature (Bali et al. 2019; Han et al. 2019; Heimer and Simon 2015; Huang et al. 2019) predicts winners are more likely to disclose their outcomes. Interestingly, my survey data show that individuals share this prediction about themselves. As Figure 1.8 demonstrates, winners tend to predict a higher propensity to disclose their outcome. The logistic regression tables and bar charts comparing winners and losers in Appendix 1b. consistently show that winners have a significantly higher self-prediction to share their investment information with others than losers do.

The third question in the survey stage asked participants whether they would like to strategize with others. The negative slope depicted in Figure 1.8 suggests that losers thought they would like to talk with winners, who might be seen as more knowledgeable and more likely to suggest improved investment strategies. However, there is again a discrepancy between people's forecasts and that they end up doing during the chats.

Figure 1.9 illustrates the discrepancy between the survey results and the text analyses. Specifically, the red bars in the first bar chart represent the proportion of investors who said they don't want to discuss their investment information with others in the survey, but end up disclosing their direct investment information in the chatting stage. The first bar chart in Figure 1.9, shows

Table 1.4: Logistic Regression with Demographic Controls

		Who asks first	Voluntary Talk	Talk
Losers vs Winners	**Winners**	**0.198***** [2.303]	**-0.298***** [-2.819]	**-0.177***** [-2.383]
Gender	Female	-0.147 [-0.768]	-0.134 [-0.589]	-0.049 [-0.296]
	Other	-14.566 [-0.027]	1.000 [1.121]	1.666 [1.477]
Ethnicity	Hispanic or Latino	0.055 [0.173]	-0.818*** [-2.048]	-0.331 [-1.187]
	Black or African American	-0.403 [-0.362]	0.432 [0.490]	-1.540** [-1.782]
	Native American	-14.696 [-0.018]	-13.353 [-0.026]	-0.396 [-0.307]
	Asian	0.070 [0.298]	-0.407 [-1.614]	-0.199 [-0.952]
	Other	0.427 [1.078]	-0.714 [-1.362]	-0.070 [-0.190]
Native Language	Other	-0.201 [-1.073]	-0.174 [-0.780]	-0.284** [-1.784]
Investment Experience	No	-0.138 [-0.693]	-0.216 [-0.950]	0.093 [0.531]
Major	Natural Sciences	-0.029 [-0.083]	0.566 [1.472]	0.044 [0.151]
	Social Sciences	0.467 [1.481]	0.221 [0.580]	0.399 [1.402]
	Economics or MGMT	-0.001 [-0.004]	0.155 [0.497]	0.368 [1.626]
	Literature or Art or History	-0.556 [-0.499]	0.588 [0.631]	-1.109 [-1.367]
	Other	0.112 [0.395]	-0.256 [-0.725]	0.284 [1.170]
Age	20 – 21	0.332 [0.510]	0.473 [0.597]	0.680 [1.392]
	22 – 23	0.195 [0.299]	0.637 [0.808]	0.738 [1.514]
	24 – 25	0.426 [0.612]	0.453 [0.535]	0.943** [1.766]
	26 – 27	0.903 [1.171]	0.689 [0.718]	1.411*** [2.132]
	Above 27	0.554 [0.703]	1.034 [1.118]	1.241** [1.912]
	Constant	-1.429** [-2.005]	-1.813 [-2.147]	-0.306 [-0.559]
	Obs	810	810	810
	Pseudo R^2	0.025	0.04	0.027

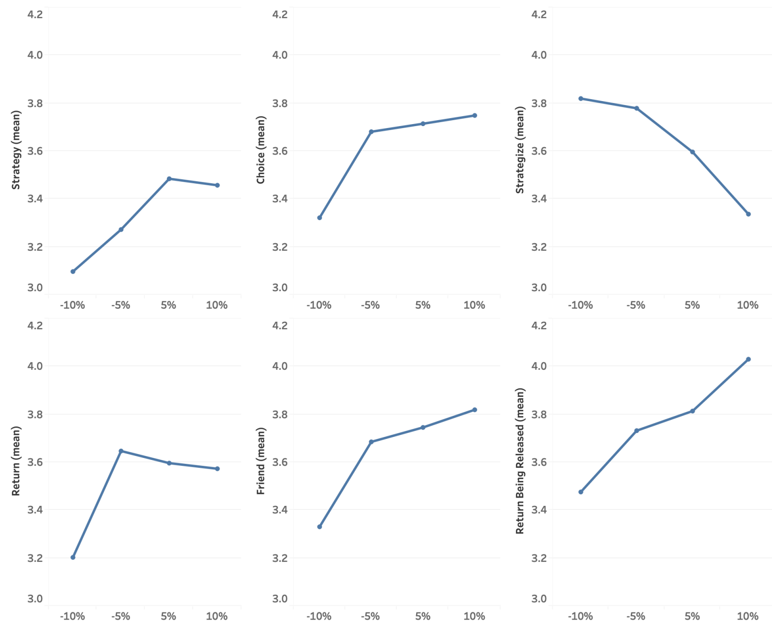

Figure 1.8: Survey Results

that many people who predicted that they would not share their investment information (colored in red) ended up doing so. The next bar chart reveals an even greater discrepancy between participants' predictions of their behavior and their ensuing behavior. On average, 40% of the people who said they would disclose their investment information (colored in red) ended up not doing so.

These discrepancies fit with a large social psychological literature (Nisbett and Ross 1991) which shows that in making predictions about their own behavior, people place insufficient weight on situational factors– they place too much weight on their preferences and disposition. That is, people find it challenging to predict their own behavior in future situations; they do not make adequate allowance for the constraining force of situational factors such as conversational norms. The divergence between participants' survey responses, anticipating their coming chats, and their subsequent chat experience may suggest that investors will also fail to anticipate the situational factors that shape their and others' information disclosure.

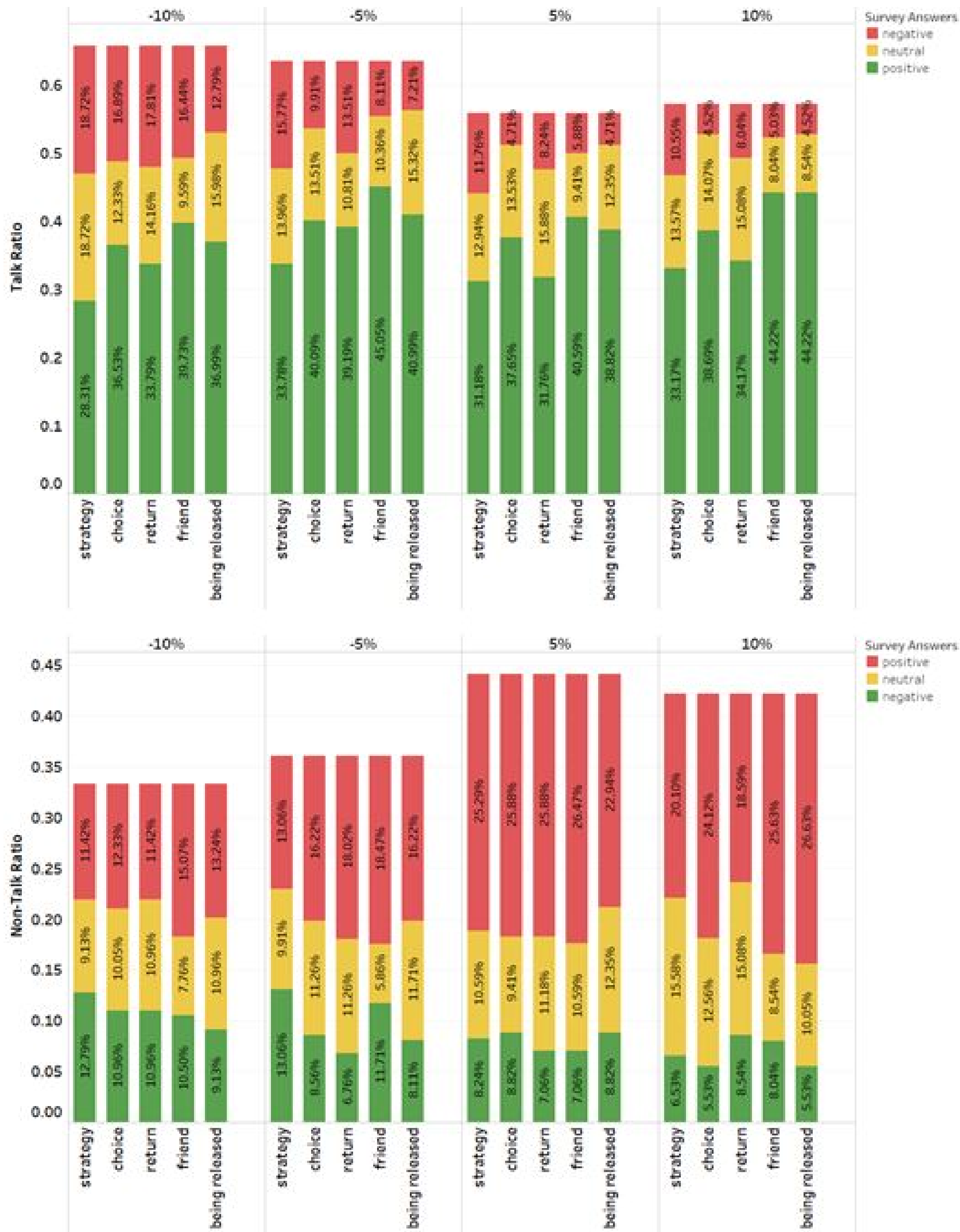

Figure 1.9: Talk Ratio and Not Talk Ratio. This figure illustrates the discrepancy between the survey results and the text analyses.

1.4 Discussion and Implications of the study

In this section, I discuss the implications of the study results for various financial market phenomena such as bubbles and crashes, runs, governance, and agglomeration. More broadly, I explore how conversational norms may impact financial information diffusion and lead to numerous real effects in financial markets.

Bubbles and Crashes. A bubble is a spike in valuation unconnected to fundamentals (i.e., overvaluation). Shiller (2012) defines a bubble as a "social epidemic whose contagion is mediated by price movements." He points out that word-of-mouth plays a crucial role in forming bubbles. My finding that investors with similar outcomes are relatively likely to converse with each other is relevant to this phenomenon. Bubbles often involve widely held assets such as stocks and real estate. When an asset is widely held, investors may place a high probability on similarity with their interlocutors ("housing prices are down, I'm in the red. She lives here and is probably in the red too.") They may thus feel more comfortable sharing their investment performance. In sum, conversations given a high probability of homophily may provide fuel for bubbles, because they will facilitate information flow that is impeded in more typical settings. This observation may partly explain the larger magnitude and greater length for real estate bubbles than stock market bubbles (Ikromov and Yavas 2012). Housing price changes are likely to similarly impact people who are in close contact, while individual stock prices changes will not.

Runs. Coordinated withdrawals from banks, or other financial institutions, can occur for two reasons. First, they may stem from investors' fear of future liquidity shocks (Bernardo and Welch 2004; Calbo 2012). Second, runs can result from self-fulfilling beliefs (Diamond and Dybvig 1983; Postlewaite and Vives 1987). Importantly, in the second channel, the simple belief that other investors are likely to withdraw their funds creates an incentive to make withdrawals. What roles do conversations play, and what motivates investors to share their self-fulfilling beliefs, losses, and emotion (e.g., panic)? Kelly et al. (2000) provide supporting evidence on how conversations contribute to bank runs. They find that the most important factor in market panics is place of origin. More specifically, they find that one specific group of people – residents of the same county in Ireland who immigrated to New York – tended to close their accounts during the market panics of 1854 and 1857. These observations are consistent with the idea that conversations given a high probability of homophily facilitate information flow that is impeded in more typical settings. In particular, potential deposit losers who were not at risk of threatening a counterpart's face might voluntarily share their outcomes, beliefs, and emotions with others. Moreover, losers may have felt comfortable sharing their bank run experience with others who came from the same county in Ireland, lived together in New York, and anticipated the same losses. Sudden, dramatic events such as market crashes and bank runs will give rise to conversations, and understanding the impact of conversational norms can help us understand whether these conversations will or will not lead to information disclosure.

Governance. Corporate governance plays two primary roles: 1) mitigating agency problems (John and Senbet 1998); and 2) helping the CEO make better decisions such as giving advice (Adams and Ferreria 2007; Williamson 2007). The latter is inherently based on conversations. Anything that shuts down conversations, therefore, also shuts down the potential for giving advice. Adams and Ferreria (2007) claim that in their model, active conversations and information transfer between CEOs and board members are the key roles of corporate governance, so it is optimal to form management-friendly boards.

The various types of conversational norms within firms could also have real effects. For example, explaining a model of corporate boards' decision-making processes, Malenko (2014) argues that open-ballot voting is the optimal voting policy because it encourages directors to communicate more before the voting stage. She claims that boards of directors experience pressure to achieve conformity, so having more conversations in the decision-making stage can lead to greater conformity in the voting stage, thereby positively affecting the decision-making process. In this context, a conversational norm is the pressure to conform, presumably arising from the general desire to get along during social interactions and not threaten others' face. An analysis of audio-taped conversations among board members and senior managers provides evidence supporting this argument (Samra-Fredericks 2000).

Agglomeration. Conversational norms and dynamics are not necessarily limited to the transmission of financial information (e.g., stocks, real estate) among individual investors. Urban agglomeration and industrial clusters owe their existence, at least primarily, to the transmission of information. Information is transmitted among workers partly through conversations. Benartzi (2001) and Hvide and Ostberg (2015) find that employees, on average, hold much of company stock (e.g, one third of the large retirement savings and one quarter of discretionary contributions), and equity investment decisions are similar across co-workers. From the perspective of homophily, a common set of experiences, perhaps investment performance can be the starting point for such conversations.

Aoki (2000) observes that venture capitalists in Silicon Valley not only are located in a compact area but are also in very close proximity and frequently converse casually. He argues that venture capitalists play a crucial role as information mediators among other venture capitalists and clusters of entrepreneurial firms, generating competition among entrepreneurial firms and contributing to the development of innovative product systems. From the perspective of homophily, I hypothesize that information transfer among venture capitalists and clusters of entrepreneurial firms can significantly increase if they share similarities such as ethnicity, friendship, and educational background (McPherson et al. 2001).

1.5 Conclusion

By analyzing dyadic conversations in a controlled environment, I find that it is not winners, but rather losers, who are more likely share their investment experiences with others. This result arises from both winners and losers trying to avoid the awkwardness of conversing about winning in the presence of someone who has lost: (1) winners (losers) are more (less) likely to ask about their interlocutor's outcome before revealing their own and (2) winners (losers) are more likely to disclose their investment results with other winners (losers). Taken together, the results suggest that the social psychology surrounding conversational norms impacts the diffusion of investment information.

The key takeaway from my study is that, although information is often diffused through conversations, conversations are about more than just information exchange. In particular, social norms, and the attendant emotions that arise when attempting to respect them, has a first order impact on the types of information which may spread through person-to-person conversations. This study reveals that even in the simplest conversational setting (i.e., a one-to-one conversation), social mechanisms, such as maintaining each other's face and homophily, are in play.

This study is the first to illustrate how aspects of conversations can fundamentally change the dynamics of information transfer. The analysis of conversations between individual investors and their impact on the financial market can be extended in various directions. First, although one-on-one conversations may be the major form of daily conversation, various other types, such as one-to-many conversations (e.g., group chatting on social networks and social media postings) are also worthy of study. Second, we do not yet know much about how the aforementioned individual behavioral biases are developed, transferred, amplified, or reduced through social interactions and conversations. Heimer (2016) finds a positive association between social interaction and the disposition effect. Likewise, further study might clarify how the psychology of interactions and conversational norms impacts other individual biases identified in the existing literature.

Finally, conversations contain verbal language, non-verbal language, norms, and pragmatic rules. Combining this with the observation that different language use may lead to different decision making (Chen 2013), conversations might be more powerful in some moments than in others. Because the way which information is transmitted from one person to another has implications for what information spreads, the study of conversations, social norms, and information diffusion is crucial for a full understanding of the impact of social interaction processes on financial markets, and for moving beyond behavioral finance to social finance.

Chapter 2

Social Interaction and Individual Investors' Investment Decisions

I experimentally investigate how investors perceive and interpret the information they receive from others and adjust to their investment trading decisions. The lab experiment and survey results show that investors are more likely to drastically adjust their investment strategies when they know that other investors' current buying or selling strategies and past performance are consistent. This result indicates the performance of other investors affects an investor's future trading decisions, not because investors update their beliefs about the other investors' level of sophistication based on their past performance, but instead because they learn about the financial market from other investors' performance, and extrapolate the received information into the future trading decisions.

2.1 Introduction

Investors continuously interact with each other through various channels. As recent literature in finance has indicated, social interactions can have a meaningful impact on investment decisions. We have learned that investors' decisions concerning the financial market are affected by their neighbors (Hong et al. 2005), co-workers (Hvide and Ostberg 2015), and friends (Kaustia and Knupfer 2012), even if they live geographically far away from one another (Bailey et al. 2018). The same patterns have been observed among institutional investors (Hong et al. 2004).

Despite the importance of understanding the role of social interaction in the financial market (Hirshleifer 2015; Shiller 2017), the lack of social interaction data has made it challenging to further investigate the effects of social interaction in the financial market. For example, we have limited insight on how financial information is transmitted from person to person and we do not know precisely how the circumstances under which this information is transmitted impacts another person's investment decisions.

Choi (2020) found that investors often discuss their performance (i.e. return) in conjunction with their individual strategies. The focus of this paper is to understand how investors perceive and apply the strategies of other investors based on their past performance. The effectiveness of performance-based peer effect is still under debate in the field of behavioral economics (Bandiera 2009; Falk et al. 2006; Guryan et al. 2009). Finance literature has suggested some evidence that investors are affected by their performance of their counterparts (Ouimet 2019; Pomorski 2006; Han et al. 2020), but the mechanism behind such evidence has not been studied extensively.

I conducted lab experiments and survey studies to first investigate the existence of the performance-based peer effect and then study the mechanism behind this result. In the first lab experiment, investors were given a chance to discuss their investment experience with another participant. I measured the likelihood of investors changing their investments based on their counterpart's return, and surveyed participants on whether their decisions were influenced by their conversations with other investors. I found that when making a decision to purchase a new stock, investors are more likely to mimic another investor's strategies and investment decisions if the counterpart's return is higher. This result is consistent with the existing literature (Han et al. 2020).

The remaining question is to understand why investors' response (i.e. purchase more stocks) corresponds with knowledge of their counterparts' higher returns and current strategy. One potential explanation would be that investors are updating their beliefs about other investors based on their recent performance (Pomorski 2006). Investors might change their trading decisions because they believe that other investors with higher return are more sophisticated investors and they find the information to be more trustworthy. An alternative explanation would be that investors are learning about the stocks and the financial market from other investors' performance. Given this assumption, the results of the experiment above may be supporting evidence of the existing extrapolative models in the financial market (Barberis 2018; Glaeser et al. 2017).

I conducted surveys on Mturk (Litman et al. 201717) to investigate the effect of social interaction, especially on the sell side, and to better understand the mechanism behind the phenomenon of performance-based peer effect. In the first survey, I aimed to understand the main effects of two different independent variables: buy or sell recommendations and past performance. In addition, I asked a few more questions to understand investors' expectations of their counterparts' trading behaviors, given their knowledge of those counterparts' past performance. The results of the survey indicate that investors are significantly more likely to adjust their trading strategy when another investor recommends them to buy as opposed to sell. Furthermore, investors are equally likely to make changes to their trading strategy regardless of the success of other investors' past performance. In general, a given investor expects other investors to sell following a negative return and buy following a positive return.

In the next survey, I sought to observe the interaction effect between the two independent variables. I asked subjects to imagine a case in which they conducted enough research to purchase one stock with 50% of their assets. I then presented them with four different scenarios and asked them to buy or sell up to 100% of the same stock. One of the four scenarios is illustrated below:

"You had a chance to talk with Bob about your investment. Bob is your close friend. Bob tells you that he made a 10% positive return (profit) from investing in the same stock you just purchased (i.e., stock A) and he believes that stock A's earnings next quarter will be a lot better than the market expectation (i.e., outperform the market expectation by 10%). He tells you that he plans to buy more of stock A tomorrow. As a result of this conversation with Bob, do you think you will purchase more or sell shares of stock A tomorrow?"

Participants were given three more scenarios with variations on Bob's return (i.e., 10% positive return or 10% negative return), his market expectation, and strategy (e.g., Bob plans to buy more of stock A or sell stock A). From here on, each pairing of the other investor's performance and strategy will be referred to as PB, NB, PS, and NS, where PB stands for obtaining positive return and plans to buy more, NB stands for obtaining negative return and plans to sell, PS stands for obtaining positive return and plans to sell, and NS stands for obtaining negative return and plans to sell, respectively.

The result of this survey shows a significant interaction effect. That is, investors were more likely to buy or sell significant amounts of stock A in response to information provided by the other investor when the other investor's return on stock A corresponded with the investor's current investment strategy. On average, investors purchased 252% more when their counterpart revealed himself to be PB as opposed to NB. Conversely, investors, on average, sold 39% more when their opponent revealed himself to be NS as opposed to NB. The results from this survey shows that social interactions have impact on investors, especially when they hear that other investors' current buying (selling) strategies and past performance are consistent.

In my final survey, I made one variation to the previous conditions. That is, I adjusted Bob's level of sophistication. For this trial, Bob is described as the smartest friend of the investor.

From this trial, I found that overall, investors were more responsive to the recommendation of the other investor, but there is no evidence of change in relationship between the response to PB and NB as well as the response to PS and NS under this fixed level of sophistication condition.

To supplement the results of the experiment and surveys, I present an anecdotal example from Warren Buffett. In early 2020, Warren Buffet announced that Berkshire Hathaway would sell all of its airline industry stock positions after experiencing enormous amounts of unrealized loss. The market's reaction to the airline industry stocks following Warren Buffet's announcement demonstrates a real world replication of the results of this study. More details of this anecdotal example are provided in section 4.

In conjunction, investors appear to find the same information to be more informative and make greater changes in their trading decisions when the other investor's current buying (selling) strategies and past performance are consistent. This indicates that investors do not assess or learn about the other investor's level of sophistication from their past performance, but rather, they learn about stock A and tend to late other investor's past returns into the future.

This paper complements existing evidence of models with investors' extrapolative beliefs (De Long et al. 1990; Anufriev and Hommes 2012; Adam et al. 2014; Barberis et al. 2015). Recent papers in behavioral finance suggest that understanding the social interaction mechanism would be the key to understanding how bubbles and crashes are formed (Shiller 2019). This paper suggests that extrapolation can occur via social interaction as investors use other investors' past performance to predict future return of the market.

The remainder of the paper is organized as follows: section 2 describes the data and experimental design; section 3 discusses the results of the experiment and the social mechanisms associated with the results; section 4 discusses anecdotal evidence of my results; section 5 sums up this paper.

2.2 Data and Experimental Design

2.2.1 Experimental design

The experiment of this study was conducted in the behavioral lab at the University of California at San Diego, Rady School of Management. A total of 370 participants were recruited over two years, from 2017 to 2018; 48% were female and 32% had investment experience. Further demographic information is presented in Appendix 1a. The experiment was conducted using z-Tree (Fischbacher (2007)), the software which is widely-used for conducting lab studies in economics and finance. Each experimental session lasted about 15 minutes. Participants received class credits as compensation. The experiments were designed with two rounds and three stages.

In the first round, participants were given information about four stocks and were asked to choose the stock they expected to offer the maximum return. Based on their choice, each participant was given one of the four possible returns (-10%, -5%, +5%, and +10%). Participants were asked to answer a few survey questions about their willingness to share their investment experience with other people; then, they entered the chatting stage, in which they were paired with another participant to talk freely about any topic for three minutes. After the chatting stage, participants were asked a few more survey questions to conclude the first round. The second round was the same, except 1) there was no additional stage and 2) participants were asked the concluding survey questions right after making their investment decision and right before receiving their return. In the survey stage, participants were asked whether their second-round investment decision was affected by their conversation with another participant in round one.

Participants were asked the following three questions:

1) When you were given time to chat in the chat box previously in this lab, did the other person say anything about his return in round 1? If yes, did the other person's return affect your decision in round 2?

2) When you were given time to chat in the chat box previously in this lab, did the other

person say anything about his choice in round 1? If yes, did the other person's choice affect your decision in round 2?

3) When you were given time to chat in the chat box previously in this lab, did the other person say anything about his strategy in round 1? If yes, did the other person's strategy affect your decision in round 2?

The survey results of round two are shown in Figure 1. The experiment concluded after participants answered a few demographic survey questions. The full experimental materials are provided in Appendix 1b.

2.2.2 Survey design

The first survey was conducted on Mturk, and 391 participants were recruited, 42% of whom were female and 47% of whom had previous investment experience. The age of the participants ranged from 19 to 77 years. To collect high-quality data, I chose participants who had a 99% approval rate and had participated in at least 1,000 prior surveys. Also, a screening question was asked at the beginning of the survey. This survey was designed to learn how investors perceive information obtained from other investors. Participants were asked how much they would change their trading decisions based on other investors' strategies or performances. They were also asked to predict how other investors' trading decisions would change after learning of those investors' past returns. The full survey questions are provided in Appendix 1c.

The second and third surveys were distributed concurrently on Mturk. Participants were randomly assigned to one of the two surveys, 191 people to the second survey and 195 people to the third survey. The same screening question and restrictions were applied to ensure the high quality of the data. The second and third surveys aimed to observe the interaction effect between investors' actions and their counterparts' performances and strategies. The difference between the surveys was the counterpart's role. I presented the counterpart as the participant's close friend in the second survey and as the participant's smartest friend in the third survey.

Participants in both surveys were asked to answer questions about four different scenarios. Each scenario presented a combination of two pieces of information about the other investor (i.e. past return and current strategy). The other investor has a +10% return or a -10% return and recommends buying more of stock A or selling stock A. For example, one scenario presented the counterpart as an investor with a +10% return who recommends selling stock A. The full survey questions are provided in Appendix 1d.

2.3 Results

2.3.1 Experimental results

This section provides results of the experiment. This experiment aimed to verify the existence of performance-based peer effect. After interacting in randomly assigned pairs in the chatting stage, participants were asked to choose the stock they believed would give them the highest return. Participants were asked how much they were influenced from the other investor with whom they interacted with in the chat box.

The results in Figure 2.1 show that investors are more affected by other investors' returns, choices, or strategies when their counterparts' returns are higher. In other words, investors are more likely to mimic another investor's strategies and investment decisions if the counterpart's return is higher.

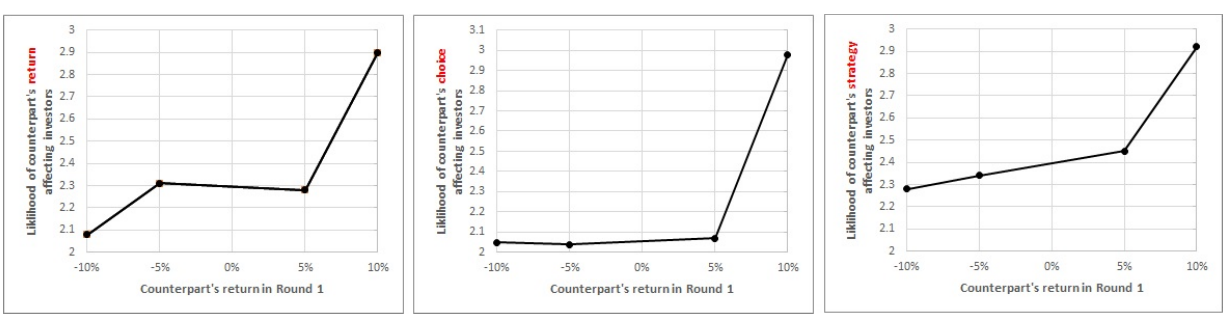

Figure 2.1: Investors' investment (purchase) decision after interacting with a peer

2.3.2 Survey results

The existing literature provides two potential explanations for the results in Figure 2.1. One explanation would be that investors update their beliefs about another investor's investment ability based on their counterpart's past returns. In this interpretation, investors would follow the advice of peers they consider competent, regardless of whether that advice is to buy or sell. Another explanation could be that investors use their peers' returns less as indicators of competence, than of the market's overall trends. In order to explore the mechanism behind the observed performance-based peer effect, I conducted further surveys, looking at the impact of peer performance information on both buy and sell side decisions.

The first survey sought to compare the mean difference between investors' response when they learn of their counterpart's strategy to buy or sell and their response when they learn of their counterpart's performance (i.e., positive or negative). In addition, investors were asked to present their expectation of other investors' trading behavior after learning of those investors' performance.

As shown in figure 2.2, the results from the first set of questions show that investors are significantly more likely to change their trading strategy when they hear that another investor intends to buy. Note that the vertical axis on the graph represents the magnitude of the change in investment in response to the counterpart's recommendation. For example, the first bar implies that investors, on average, sold 23 shares of stock in response to their counterpart's recommendation.

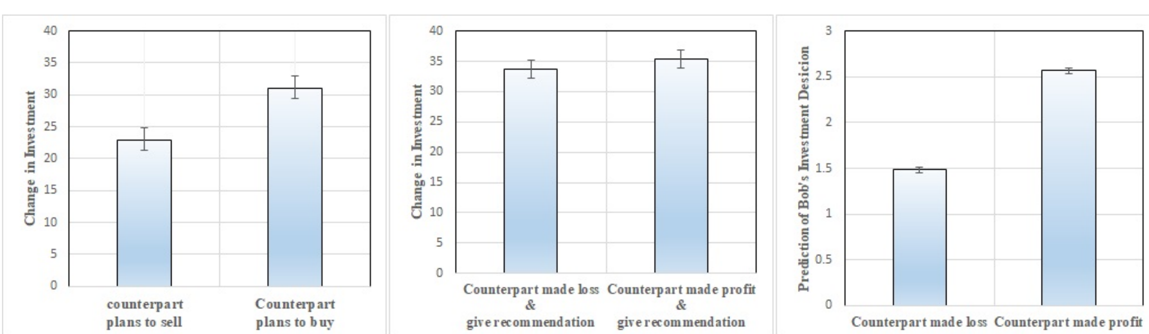

Figure 2.2: Mean comparison of the first survey results

Table 2.1: Statistical analyses for the first survey results

		Mean	Std. Error	*t-stat*	*p-value*
Investment	Bob plans to sell	-22.739	2.070		
	Bob plans to buy	31.033	1.599		
Change in investment	Bob plans to sell	22.739	2.070	3.176	0.001***
	Bob plans to buy	31.033	1.599		
Change in investment	Bob made loss	33.642	1.513	0.837	0.201
	Bob made profit	35.394	1.453		
Prediction of Bob's investment decisions	Bob made loss	1.486	0.029	-24.655	0.000***
	Bob made profit	2.568	0.033		

In contrast, investors are equally likely to make changes to their trading decisions based on their counterparts' past performance, regardless of whether that performance was positive or negative. No significant difference is observed between the gains case and the loss case, with investors responding that they would adjust their trading strategy by nearly 35% in both cases.

The answers for the last set of questions were recorded as the categorical values, where 1, 2, and 3 represent 'sell', 'hold', and 'buy more', respectively. The results show that, in general, investors expect other investors to sell or hold following a loss and either hold or buy more following a profit. These results indicate that investors expect others not to engage in the disposition effect. More details of the statistical comparison are described in table 2.1

The second survey aimed to observe the interaction effect that occurs when investors are asked to consider their peers' strategies and past performance together. Subjects were given two pieces of information at a time (e.g., bob made a profit and he plans to sell). The first graph in figure 2.3 represents the average change to their trading positions that investors made in response to each scenario.

The second graph represents the magnitude of the changes in investors' positions in each scenario (e.g., when the counterpart recommends to sell and the investor decides to sell accordingly, such response is recorded as a positive number). Investors, on average, purchased

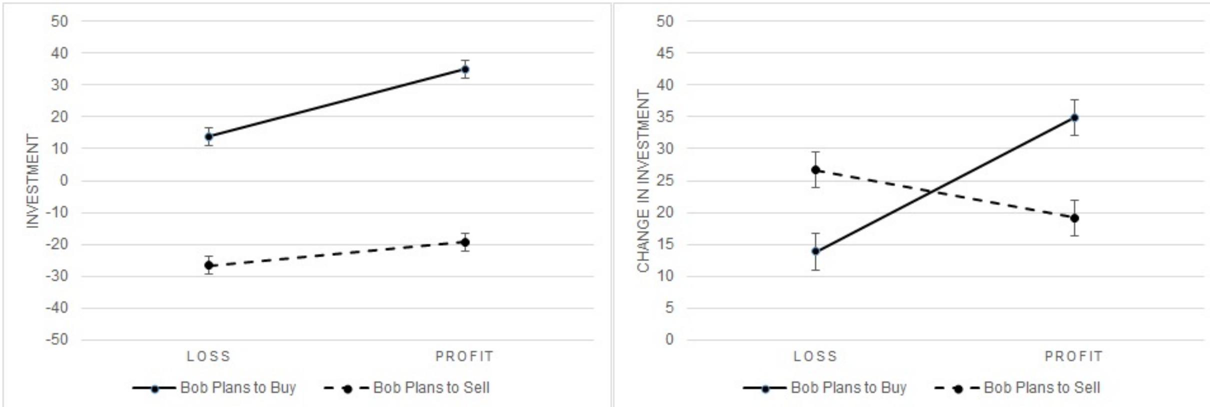

Figure 2.3: Survey 2 results

252% more when their counterpart revealed himself to be PB as opposed to NB (35% vs 14% increases, respectively). On the other hand, when the other investor recommends to sell, investors sold 39% more when the peer was NS compared to PS (27% vs 19% increase, respectively).

2-way Analysis of Variance test results in table 2.2 shows that the interaction effect between two independent variables (i.e., the counterpart's past return and current strategy) is statistically significant. Another noticeable result from the ANOVA test is that investors changed their trading decisions significantly more to match their peer's when that peer had seen positive returns. This indicates that the other investors' past returns constitute a considerable portion of the interaction effect. However, the main effect of the other investors' past return appears to depend on their recommendation.

Table 2.2: Test of interaction Effects

Parameters	*Df*	*Sum SQ*	*F-value*	*P-value*	
Close friend					
Counterpart's past return	1	9167.02	5.939	0.015	**
Counterpart's recommendation	1	402.05	0.260	0.610	
Counterpart's past return x Counterpart's recommendation	1	39405.05	25.527	0.000	***
Smart friend					
Counterpart's past return	1	724.52	0.413	0.521	
Counterpart's recommendation	1	2315.31	1.319	0.251	
Counterpart's past return x Counterpart's recommendation	1	47089.01	26.832	0.000	***

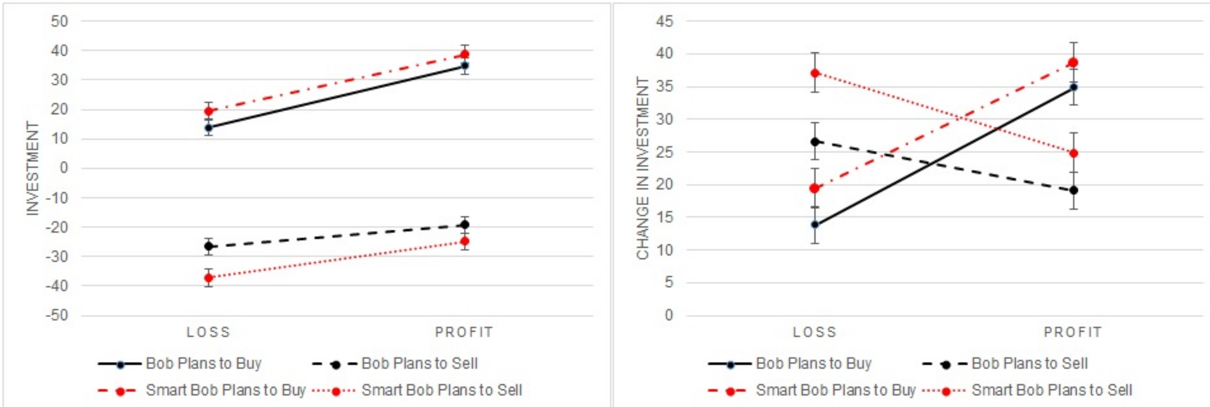

Figure 2.4: Comparison of investors' change in investment when Bob is investors' smartest friend vs. Bob is investors' close friend

The third survey sought to observe the interaction effect under one new condition. I presented Bob as the investors' smartest friend, rather than just a close friend of theirs. As shown in figure 2.4, the magnitude of investors' response have increased overall, but the overall interaction effect persisted under the new condition. This result indicates that investors appear to learn about the stock A from perceive the other investors and extrapolate the received information into the future trading decisions. More specifically, when the other investors reveal themselves as losers and they recommends to sell, investors are more likely to respond to the sell recommendation as opposed to when the winners recommends the same strategy.

2.4 Empirical Evidence from an Anecdotal Example

This section provides supplementary empirical evidence to support my experimental results. The recent stock market crash caused by the COVID-19 pandemic generated huge losses for many investors. In early 2020, Warren Buffet, who is regarded as one of the most successful investors of all time, announced that Berkshire Hathaway would sell all of its airline industry stock position. It was surprising news for many investors because, at the time of his announcement, Berkshire Hathaway had experienced huge unrealised losses.

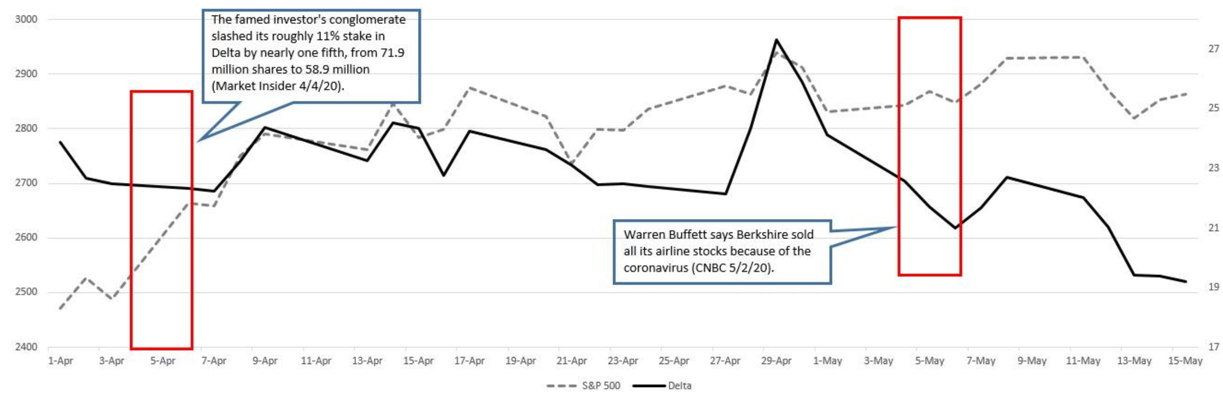

Figure 2.5: Stock price movement of Delta airline (Solid line) and SP 500 (dotted line) around the period of Warren Buffet's airline stocks sale announcement

On April 3rd, 2020, after the market closure, Berkshire sold 13 million Delta shares without providing any reasons for their sale. The next day, Delta fell by 0.71% while the SP 500 bounced back by 7%. About a month later, at the Berkshire Hathaway annual shareholders meeting on May 2nd, Buffett said Berkshire Hathaway sold the entirety of its equity position in the U.S. airline industry because he and Berkshire Hathaway were not convinced about the airline sector's outlook. During the following 3 trading days, Delta Airline plunged -13.5% while the SP 500 went up by 0.63%. The market's reaction to the airline industry stocks following Buffet's announcement demonstrates a real world replication of the results of this study. Given his losses, Buffett could be interpreted as the "loser" in the context of my study, and the market's strong reaction to his advice validates my experimental findings.

2.5 Conclusion

This paper provides a new perspective on how investors perceive new information via social interaction and alter their trading decisions based on a counterpart's past performance and current investment strategy. I find that investors are more likely to drastically adjust their investment strategies when they hear that other investor's current buying or selling strategies and past performance are consistent. This result suggests that investors extrapolate based on the other investors' past performance.

A natural step for a future study would be to investigate what investors do with the stocks they purchased or sold from the other investor's recommendation. For example, we can study if the magnitude of disposition effect changes for the stocks that investors purchased through their friend's recommendation.

Understanding how investors perceive and interpret new information via social interaction has implications for how financial information is transmitted from one investor to another and what kind of financial information is more effectively delivered between investors. As Shiller (2019) pointed out, understanding epidemics of popular narratives between investors will help us further understand changes in the economy, economic behavior, and financial market. This understanding will become even more important as the introduction of new social network channels have enabled us to talk with others beyond the boundaries of geographical distance.

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