Social communication and FX retail trading

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Social Communication and FX Retail Trading

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Declaration

I hereby declare that the work presented in this thesis is my original work except where other references are cited. This thesis is an original work and has not been submitted as part of an application for another degree or qualification at any other Institute or University. The copyright of this thesis rests with the author and no quotation from it or information derived from it may be published without proper acknowledgement. I confirm that the following thesis does not exceed the word limit prescribed in the College regulations.

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Abstract

My thesis is motivated by the novel concept *social finance* in the survey paper "Behavioral Finance" (Hirshleifer, 2015). The author Hirshleifer calls for a new era of behavioral research in finance, so-called social finance. This stream of research aims to extend traditional behavioral finance literature by considering the impact of the structure of social interactions, the spread and evolution of financial ideas, and social processes on financial outcomes. These social elements in finance impact the information transmission in financial markets, the decision-making of individual investors, as well as the subsequent trading behavior and asset prices. In three studies, I investigate retail traders' (1) trading performance, (2) return synchronicity, and (3) survivorship in the foreign exchange (FX) market. I show that FX retail traders do not make money and do not possess skills. I also highlight the role of social communication in altering retail traders' return patters and market persistence. This set of studies empirically supports the social finance theory by presenting evidence that social communication impacts retail traders' behavior. This thesis adds to the limited literature, especially in the FX market, on retail trader behavior.

Dedication

I dedicate this thesis to my grandma

who encouraged me to pursue a much different passion:

from a future industrial designer

to a future financial economist.

Acknowledgement

I would like to express my sincere gratitude to my supervisor Professor Alex Preda who has always been so helpful and patient with my studies and research. I have been greatly benefited from his deep knowledge and attitudes towards academic research. I am most grateful for the pastoral care that he demonstrated throughout my Ph.D. studies which encouraged me as a researcher and as a person. I would also like to thank my second supervisor Dr. Andrew McFaull who supported me to the largest extent possible and provided me with very thoughtful assistance and mentoring. I thank Professor Christian Borch for hosting my academic visit at Copenhagen Business School which was one of the most valuable and precious experiences during my Ph.D. studies. I thank my Ph.D. program director Professor Jon Hindmarsh for his continued help since my first visit in London and meeting with my supervisor Alex in November 2015.

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Chapter 1: Introduction

In the introduction section, I summarize the motivation of the research, related literature, the dataset used in the research, and the content of three separate studies.

1.1 Motivation of My Research

Traditional wisdom argues that individual investors should not trade, given that they are assumed to be unskilled and cannot make money in the market. However, individual investors do trade in the market. This has drawn attention from academic researchers to investigate the reasons why they trade in the market. For example, the following questions have been raised in prior literature: “Retail traders should not trade. And yet they do. What is the secret? How do markets manage to keep them trading?” (Preda, 2017, p. 11); we “should see (electronic) finance in terms of groups rather than as noisy swarms of atomized participants” (Preda, 2017, p. 174). Additionally, individual investors are not identical to each other and they are different in many aspects. Some investors tend to talk to people when they invest in the market and make financial decisions, but others are less talkative and tend to listen to other people or just invest by themselves making independent decisions.

Is no deal better than a bad deal? People keep trading and losing money, but there are always many people trading in the market. Are they all gamblers seeking joyfulness rather than profitability? Do long-lived ‘gamblers’ on average lose more than those short-lived ones in the market? Furthermore, why do people stay in the market? They do not seem to care very much about their money since the majority of individual investors on average lose money during their entire survivorship in the market. Then what factors drive them to realize that they are losing money and therefore make the decision to quit?

The investigation in this research is based upon the emergence of social finance literature, emphasizing the importance of social interactions on the behavior of individual investors (Hirshleifer, 2015), the emergence of social trading platforms (STPs), and the increasing trend of investigation on individual investors.

1.1.1 The Emergence of Social Trading Platforms

Over the last decade, there has been an emergence of a new form of trading, incorporating social media with online trading platforms, where investors can communicate among other investors and share their ideas and experiences in trading activities (Cetina, 2003; Preda, 2017). This new form of trading is based upon social trading platforms (STPs), which emphasize the social interactions or social elements among individual investors. This new form of trading is more prevalent among individual investors than institutional investors. In addition, social trading platforms are focusing on the currency market, including both fiat currency trading and recently cryptocurrency trading. However, there has not been much research in terms of the impact of the market organization (STP) on the behavior of individual investors.

Social trading platforms not only draw the attention of academic researchers but also attract millions of investors to invest and to chat on such platforms. For example, eToro[1], which was founded in January 2007, has attracted more than 6 million people worldwide. ZuluTrade[2], which was also founded in 2007, has more than 500 million transactions per year. Ayondo[3], which was founded in 2008, has users from over 195 different countries and more than 117,695,068 real money transactions made as of July 2018. All these numbers indicate that the emergence of social trading platforms have been taken seriously by both the individual investors and by the financial market.

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[1] https://www.etoro.com/
[2] https://en.zulutrade.com/
[3] https://www.ayondo.com/en

1.1.2 The Increasing Trend of Studying Individual Investors

Given these numbers, it is not surprising that there is an increasing trend of investigation on individual investors over the last few decades and even the last century. This increasing trend can be seen from both the Google Books Ngram Viewer and the EconLit search engines. The Google Books Ngram Viewer search engine returns the frequencies of words or phrases that can be found by Google from the printed text sources in several languages, from the years ranging from 1500 to 2008. EconLit is a comprehensive database with a focus on economic literature dating back to 1969 provided by the American Economic Association (AEA). EconLit includes, among other sources, books, peer-reviewed journal articles, working papers, conference proceedings, and Ph.D. dissertations.

1.1.2.1 Google Books Ngram Viewer on Individual Investors

If I search the phrase 'individual investors' in Google Books Ngram Viewer, with a date range of from 1908 to 2008 and within English language resources, it will return the following figure, showing the significantly increasing trend of investigation on individual investors during the last century. In addition, the frequency curve reaches its peak from 2002 to 2003, which might be correlated with Shiller's investigation on the financial bubbles in his famous book *Irrational Exuberance* (2001).

Figure 1-1 Nagram Viewer Trend

1.1.2.2 EconLit on Individual Investors

Similarly, if I search in EconLit with any of the following phrases, individual investors, individual traders, retail traders, or retail investors, appearing in the abstracts of all the resources from 1980 to 2019, it will return 3,386 results, including 2,722 scholarly journals, 490 working papers, 91 books, and 83 dissertations. Additionally, within the 3,386 results, there are 29 records from 1980 to 1989, 267 records from 1990 to 1999, 1,212 records from 2000 to 2009, and 1,879 records from 2010 to 2019, showing a significantly increasing trend of investigation on individual investors during the last few decades among all kinds of academic resources.

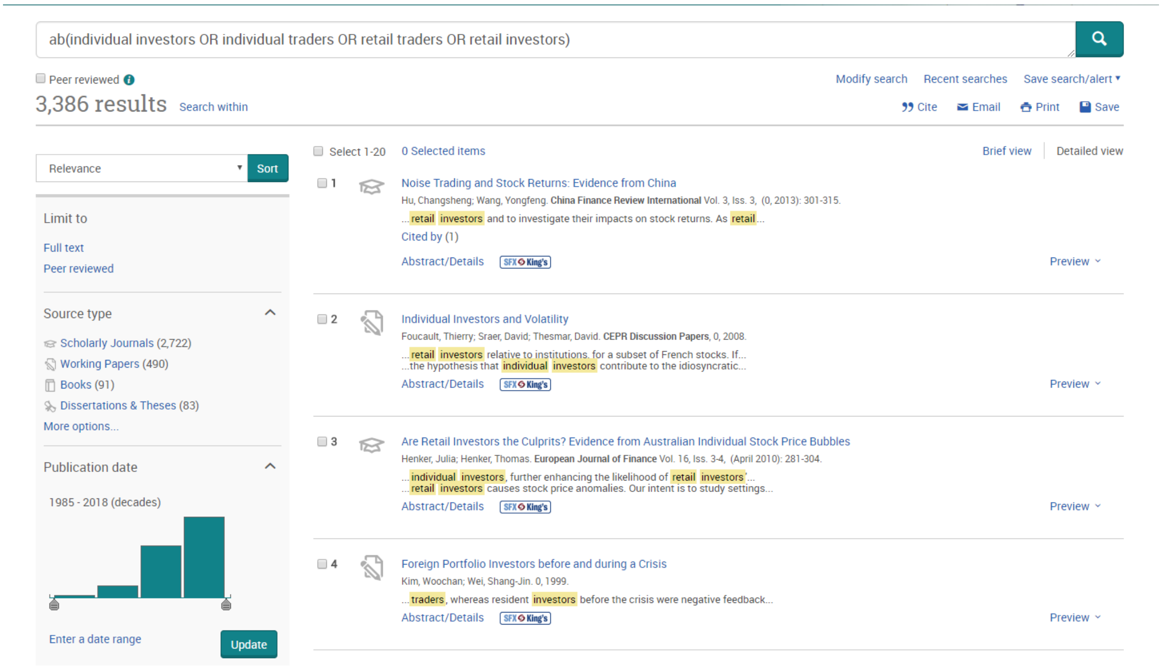

Figure 1-2 EconLit Research Trend

Overall, the significantly increasing trend of investigation on individual investors can be seen from both the general printed resources during the last century and the academic economic literature during the past few decades. This data indicates that individual investors not only make an impact on the financial market but also draw the attention of researchers for publication. My research is in line with this trend.

1.2 Related Literature

1.2.1 Social Media and Individual Behavior

There is ample evidence in domains other than finance showing that social media changes the behavior of individuals, affects life satisfaction, and even causes addiction-like symptoms and mental health issues (i.e. mental depression (Shensa et al., 2017)) in varieties of settings (Alkhalaf et al., 2018; Colucci, 2016; Kuss et al., 2013; Leung, 2014; O'Reilly et al., 2018; Turel et al., 2018; Turel & Gil-Or, 2018).

Although the usage of WhatsApp is not associated with the academic performance of students, the time spent on using WhatsApp proportionally relates to the symptoms of addiction (Alkhalaf et al., 2018). In addition, apart from the evidence that, to some extent, the negative association between social media addiction and wellbeing differs between women and men (Turel & Gil-Or, 2018). Adolescents themselves are reported to perceive social media as a threat to their wellbeing (O'Reilly et al., 2018). Furthermore, addiction-like symptoms and problematic behavior that are associated with the excessive or even compulsory usage of social media are prevalent among the general population in relation to human brain systems and processes. This addiction can be explained from a perspective of the morphology of the posterior subdivision of the insular cortex (Turel et al., 2018). It is estimated that more than 210 million people suffer from addictions to the internet and social media from all around the world (Longstreet & Brooks, 2017).

However, given the above-mentioned impact of social media on individual behavior, together with the effects of social media on information diffusion and on asset prices, as opposed to traditional news (Desmarchelier & Fang, 2016; Jiao et al., 2016), there is no evidence in finance literature showing whether participants in social interaction on online trading platforms get addicted to chatting. Specifically, I do not have evidence showing whether the usage of social media impacts the behavior of individual investors in relation to their survivorship in the financial market. Are they addicted to chatting on the social trading platforms and therefore stay longer in the market? It is possible that, in the domain of finance, people communicate and lose money in a similar way among individual investors given the presence of social media.

1.2.2 The Persistence of Individual Investors

It is documented that noise trading is prevalent and even dominant in the market (Baklaci et al., 2011; DeLong et al., 1988; Long, 1991; Menkhoff & Rockemann, 1994;

Peress & Schmidt, 2017; Preda, 2017). There is also evidence that social interactions are associated with behavioral biases (Gemayel & Preda, 2018a, 2018b; Heimer, 2016). It can be possible that individual investors and their peers communicate in the market and they stay longer in the market simply because they love trading, and they enjoy the joyfulness of chatting and being communicative (Preda, 2017). This exchange of information through chatting can impact the behavior of investors (Eren, 2007; Ozsoylev, 2004; Xia, 2008).

Why does this happen in the market? One reason might be that individual investors who persist in the market see the losses as the price of exchanging information with others. Therefore, it is possible that non-communicative investors who do not participate in the social interactions on social trading platforms lose money and make the decision to quit trading. This is because they do not see the losses as the price of exchanging information with others. In contrast, for the communicative investors who see the losses from their trading activities as the price of exchanging information in the market, they persist in the market. Therefore, they tend to stay in the market longer. The prediction is that these groups of individual investors who chat frequently in the market eventually change their behavior due to social communications, despite the fact they know that they are losing money.

Trading platforms can be organized in different ways: some of them integrate social media features, while some others do not. There are investors on social trading platforms who do not use such social media features. Traders who choose to communicate with peers might be impacted differently from traders who are not using social media features. Will this make a difference on their decision to persist in the market? How exactly does this participation in communication impact their survivorship? There is a need to examine the impact of communication on the survivorship of individual investors on social trading platforms in the currency market.

1.2.3 Social Interaction and Financial Decisions

There is a stream of literature which investigates the relationship between social interactions and investment biases, such as disposition effects (Heimer, 2016) and herding effects (Gemayel & Preda, 2018b); however, most of the studies are silent on how these impact the financial performance of individual investors (Gemayel & Preda, 2018a, 2018b; Heimer, 2014, 2016). Online communication is one particular form of social interactions; the evidence shows that online chats include some useful information in terms of decision-making for individual investors (Antweiler & Frank, 2004; Das & Chen, 2007).

A common feature of the above-mentioned literature is that it emphasizes the importance of social trading platforms (Gemayel & Preda, 2018a, 2018b; Heimer, 2016) and of the information system (IS) [4] (Abuelfadl et al., 2016), with the help of which individual investors make their financial decisions. The features of online trading platforms (including social interaction features) provide a channel for researchers to investigate how social interactions affect the investor behavior while being aware that the majority of individual investors on average lose money on such platforms (Preda, 2017).

For example, using a dataset from an investment-specific online social network of 5,693 foreign exchange retail traders with around 2.2 million trades from early 2009 to December 2010, prior studies have explored the effect of social interactions on disposition effect (investment bias), showing that the magnitude of a trader's disposition effect nearly doubles after gaining access to the social network (Heimer, 2016). By employing the dataset from the Consumer Expenditure Quarterly Interview Survey (CEQ) from 2000Q2 to 2010Q1, Heimer (2014) shows that social interactions are strongly associated with active portfolio management (more prevalent among active investors rather than passive

[4] For a detailed description, please see in the appendix in Abuelfadl et al. (2016).

investors). As acknowledged by the author, this study cannot identify the direction of causality in the association between communication and active portfolio management (Heimer, 2014). An additional implication is that social interactions seem to increase risk-taking which potentially leads to reductions in the financial welfare of traders (Heimer, 2014).

However, existing literature has not addressed a basic question, namely whether being communicative (with more social interactions among others) in the market is a good thing or a bad thing with respect to the financial performance of individual investors. In particular, existing literature does not treat individual investors separately in terms of individual investors' social characteristics. Therefore, there is a gap in the literature between the financial performance of individual investors and their diverse levels of communication in the market.

The second strand of literature aligns with the wider social sciences and natural sciences, and tries to uncover the impact of social interactions on the financial performance of individual investors from the perspective of human complex systems and social networks (Liu et al., 2016; Saavedra, Duch, et al., 2011; Saavedra, Hagerty, et al., 2011). The focus here is on understanding the complexity of human systems and the collective effect of human wisdom, rather than the outcomes of the financial decisions in the market (Altshuler et al., 2015; Pan et al., 2012).

These investigations show that the patterns and the content (e.g. word bundles, expressed emotions) of instant messages (IMs) that are sent and received by professional stock day traders at typical trading firms can be interpreted as an indication of the collective wisdom of individual investors among different types of platforms. This kind of communication potentially affects investors' performance (Liu et al., 2016; Saavedra, Duch, et al., 2011; Saavedra, Hagerty, et al., 2011).

Using a dataset of 66 individual stock day traders in a typical trading firm between September 2007 to February 2009 with over 1 million trades, of which 55% are profitable, Saavedra, Hagerty, et al. (2011) show that synchronous trading is positively associated with the probability of making money. The authors also find that the patterns of instant are closely associated with the level of synchronous trading. Additionally, using a dataset of 30 professional day traders with around 886,000 trading decisions and over 1.2 million instant messages from January 2007 to December 2008, Liu et al. (2016) finds that expressed online emotions are associated with the profitability of actual trades; traders who express little emotion or high levels of emotion make relatively unprofitable trades while traders who express moderate levels of emotion make relatively profitable trades. Using data from an online social trading platform (eToro), Pan et al. (2012) provide evidence that social trades (crowd wisdom) are more likely to outperform individual trades. However, social trades are not always optimal (Pan et al., 2012). These studies suggest that social influences play a significant role in individual investors' decision-making process, calling for a more accurate behavioral model (Pan et al., 2012).

Furthermore, using data from the same online social trading platform (eToro) of over 3 million individual investors with more than 40 million trades during 2011 to 2014, Altshuler et al. (2015) show an inverted U-shape of the average financial gains associated with the amount of information sources used for decision-making. This indicates that too little information is not sufficient, while too much information is detrimental in terms of financial performance. As mentioned earlier, while some studies show an association between social interactions and financial performance, the literature does not compare communicative and non-communicative individual investors in relation to their financial performance.

Analytical models are needed to accurately describe the influence of social interactions on the financial performance of individual investors. There is a need to address this question by distinguishing between communicative and non-communicative investors and using an analytical model to explore the relationship between communication in the market and the financial performance of individual investors.

1.2.4 The Wisdom of Crowds

Another strand of literature examines the collective effect of the wisdom of groups of people, namely the wisdom of crowds, which reflects the predictability in financial markets from analyzing the behavior or the information produced by a group of people (Azar & Lo, 2016; Chalmers et al., 2013; Karagozoglu & Fabozzi, 2017; Nofer & Hinz, 2014; Polzin et al., 2018). Using text analysis, research shows that both the articles and investors' comments posted on a popular US social media platform for investors can predict stock returns and earnings surprises (Chen et al., 2014).

In addition, social media, as a tool for reflecting the sentiment of investors, contains information on future asset prices. Using tweets from Twitter regarding the Federal Reserve as data, a tweet-based asset allocations strategy has a better performance than a number of benchmarks, including a buy and hold strategy on the market index (Azar & Lo, 2016).

Furthermore, in domains other than finance, such as in computer science and other social sciences, research shows that a complex human system, including social interactions between participants, has a significant impact on the processes of decision-making of individuals. This social structure turns out to influence the financial performance of investors in such a complex system (Altshuler et al., 2015; Liu et al., 2016; Pan et al., 2012; Saavedra, Duch, et al., 2011; Saavedra, Hagerty, et al., 2011).

There is an inverted-U shape, which shows the relationship between information and the financial performance of investors, who send and receive instant messages when they are making financial decisions, where financial performance increases as the information level goes up, but eventually reverses when there is too much information (Altshuler et al., 2015). Interestingly, the accuracy or efficiency of the wisdom of crowds increases when the crowd is more diverse in terms of their skills and abilities, and from the structure of the crowds (e.g., population size and social structure) (Economo et al., 2016; Hong & Page, 2001, 2004; Page, 2007). In terms of problem solving, a group with diverse agents sampled from an intelligent population outperforms a group with high ability agents, which indicates the trade-off between ability and diversity on the wisdom of crowds (Hong & Page, 2004).

Based on this information, it is apparent that social media significantly impacts the behavior of individual investors in both financial markets and other domains of everyday life. As individuals are impacted under various settings, it is worth considering how exactly this social feature influences the behavior of a group people and the associated outcome. Therefore, it is relevant to mention the wisdom of crowds literature for further discussion. However, from the literature on the wisdom of crowds in the financial market, there is not enough evidence on the dynamic of the wisdom of crowds over time or under different circumstances and on the reactions of the wisdom to external shocks (e.g., inclusion of social media). Moreover, there is not sufficient evidence showing which groups of people in the crowds are more impacted by the external shock (inclusion of social media) and how the wisdom changes when there are social interactions and when there are no social interactions among the individuals.

However, the impact of the inclusion of social media on the wisdom of crowds is not very clear in literature. This is because one can argue that the inclusion of social media improves the wisdom of crowds, as individual investors gain access to more sources of information, together with their investing activities online. Nevertheless, one can argue that the wisdom of crowds is negatively impacted by the inclusion of social media, as the additional information brought by this new function can be ambiguous to the individual investors, and they can also be distracted by the new form of information exchanging activities.

Similarly, it is also not clear who will be impacted more by the inclusion of the social media. It can be argued that those people who are very much involved with these social activities are more impacted by them since they use these features the most. In contrast, it can also be argued that the less involved investors are impacted more, since they do not fully understand what is going on in these chats, given their limited exposure to these activities. Eventually, the less involved investors get distracted by these activities rather than making use of them. Consequently, there is a need to see more investigation and more evidence.

How does the inclusion of social media impact the decision-making of individual behavior, and among different types of investors, who are the most impacted by social media in this context? There are social trading platforms and non-social trading platforms. There are investors on social trading platforms who do not use such social media features, even if they are available. Traders who choose to communicate with peers might be impacted differently from traders who are not using social media features. One goal of my thesis is to understand the differences between these two groups and to examine the effect of social media on each.

Will social communication make a difference on the decision-making of individual investors with respect to their participations in the social media features? How exactly does this inclusion of social media impact on individual investors in the market? There are investors who are actively using these social media features when they are investing, while there are also investors who are not actively using these social media features. Which groups of investors are more impacted by the inclusion of social media, with respect to their participation times in these online social activities?

Therefore, there is a need to examine the impact of the inclusion of social media on the wisdom of individual investors on the social trading platforms in the currency market. This is helpful to understand the behavior of retail traders on STPs.

1.3 A Novel Dataset for My Research

1.3.1 Dataset

I utilize a novel dataset from a social trading platform (STP), including the full trading records of 1,119,342 trader-day observations associated with 4,731 individual broker accounts registered on this online trading platform from the beginning of January 2009 to the end of June 2010. The trading profits and losses are aggregated on a daily basis for each broker account in US dollars which is excess of fee. In addition, open balances, money deposits and money withdrawals for each broker account are accounted in US dollars and presented in a daily frequency in the dataset. I note that the input (open balances, money deposits and money withdrawals) and the outcome (profits and losses) of their trading activities are daily aggregated with all the trading accounts.

This online social trading platform specially focuses on foreign exchange trading, and all the individual investors on this platform can participate in social interactions or communications with other individual investors. They can either participate in the online discussion or one-to-one messaging. The online forum feature includes three types of social activities, such as creating a discussion topic, posting a comment under a discussion topic, and liking a comment under a discussion topic. The one-to-one messaging is only among two-person pairs who are connected based upon approval of a friend request.

1.3.2 Social Communication

I identify communicative and non-communicative investors based upon their participation in the three types of social activities on the social trading platform. An investor can communicate among other investors by creating a discussion topic as a creator, posting a comment under a discussion topic as a commenter, and/or liking a post as a liker. If an investor participates in any of the above-mentioned three types of social activities during the sample period, I identify this investor as a communicative investor. Otherwise, if an investor does not participate in any of these activities during the sample period, I identify this investor as a non-communicative investor. An investor is either identified as a communicative investor or non-communicative investor.

It does not mean that communicative investors are only exposed to the social activities they participate. Communicative investors are able to observe other discussions and other social interactions participated by other communicative investors. They are potentially influenced by other investors. It is documented that in a complex human system the engagement with social activities impacts the behavior of individual investors, such as utilizing online information and decision making (Altshuler et al., 2015; Liu et al., 2016; Pan et al., 2012; Saavedra, Duch, et al., 2011; Saavedra, Hagerty, et al., 2011).

1.4 Summary of The Three Studies

I explore how a complex human system affects trader behavior and performance in relation to their social communication. I use a novel dataset from a social trading platform

(STP) (similar to the dataset used in Heimer (2016)) in the foreign exchange (FX) market. One innovative feature of this STP is that retail traders on this platform can create their Facebook-like profiles to connect with other traders. Traders can communicate amongst others through an online discussion forum or one-to-one messaging while trading. The title of the three studies are as follows.

[1] "Do FX Retail Traders Really Make Money?"

[2] "Social Communication and Return Synchronicity: Evidence from FX Retail Traders"

[3] "Does Social Communication Impact Investor Survival in the Market?"

This set of studies is motivated by a recent survey paper "Behavioral Finance" (Hirshleifer, 2015), where the author David Hirshleifer calls for a new area of study in finance, namely, social finance. As mentioned in Hirshleifer's paper, "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".

This call is important. In traditional behavioral studies, it is assumed that investors have systematic behavioral biases, such as prospect theory-based gain-loss utility, overconfidence, and over-extrapolation (Barberis, 2018). These biases are psychologically accurate (consistent with real world behavior), extending rational beliefs, and rational preferences. However, recent empirical facts suggest that social interactions, networks, and communications make a difference on the decision-making processes of investors. Some well-known behavioral biases can be impacted by social interactions. For instance, it is found that the disposition effect of traders (the tendency to sell wins and hold losses) doubles after accessing social networks (Heimer, 2016). Therefore, it is important to investigate how social communication impacts the various aspects of investor behavior, how social communication interacts with (e.g., amplifies or mitigates) the documented behavioral biases, and how the social communication-based trading environment deviates from a non-communicative trading environment in terms of impacting trading decisions.

My Ph.D. thesis consists of three studies regarding retail traders' behavior in the foreign exchange (FX) market. In particular, I look at three aspects of retail traders' behavior: (1) the trading performance of retail traders in the FX market; (2) the impact of social communication on the return synchronicity of traders; and (3) the impact of social communication on investor survival. In study [1], I investigate whether retail traders in the FX market make money or not, and whether they possess certain profitability skills. I use a comprehensive dataset from a social trading platform to address potential data limitation concerns in Abbey & Doukas (2015). I show that FX retail traders on average lose money instead of making money which is shown in Abbey & Doukas (2015). I find evidence that there is a negative association between trading activities and trading performance. The evidence is consistent with the overconfidence hypothesis which suggests that "trading is hazardous to traders' wealth" (Barber & Odean, 2000). "Do FX Retail Traders Really Make Money?" adds to the debates on the profitability of FX retail trading by empirically providing a more accurate estimation of FX retail traders' profitability and skills.

In study [2], I investigate the role of social communication in the return synchronicity of retail traders on a STP. I find that the retail traders' return synchronicity is positively impacted by the social communication on the STP, especially by the social activity leaders. I show that the participants in discussion groups exhibit significantly positive chat-level return synchronicity. However, I find little evidence that the chat-level return synchronicity of traders is attributed to chat-level characteristics, such as the number of participants, the number of comments, and the number of likes. Overall, the evidence implies that social communication online reduces the level of disagreement among retail traders. This evidence is consistent with the literature which suggests that social communication online alters retail traders' behavior (Heimer, 2016).

In study [3], I explore the effect of social communication on investor survivorship in the FX market. Previous studies have suggested the causal relationship between social communication and market entry decisions. Survivorship studies have highlighted the role of psychological and career-related factors in determining investors' decision to quit the market. I use a novel dataset covering 1.1 million observations for 4,731 traders over an 18-month period. I highlight the important role of social communication in influencing traders' decision to stay in the market. I show that traders who are actively engaged in communication are 17% to 30% less likely to quit trading. I also identify a positive Granger-causal relationship between social communication and retail traders' survival probability. My results are robust to alternative measures of social communication and different control variables. This study contributes to the survivorship literature by drawing attention to the role of social communication on traders' decision to persist in the market.

Overall, this set of studies adds to the literature on retail trader behavior and the role of social communication in the processes of information transmission and decision-making of individual traders. Specifically, study [1] enhances the accuracy of the estimation of FX retail traders' performance compared to prior literature. Study [2] highlights the importance of social communication in online trading and its impact on trading behavior and return patterns (i.e. synchronicity). Study [3] (to the best of my knowledge for the first time) documents the role of social communication on traders' survivorship.

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Chapter 2: Do FX Retail Traders Really Make Money?

Abstract

I investigate whether foreign exchange (FX) retail traders make money and possess skills. I extend the empirical findings in Abbey & Doukas (2015) by using a comprehensive dataset in FX retail trading to address potential data limitation concerns. I find that FX retail traders on average lose money contrasting Abbey & Doukas's (2015) view that these traders make money. Moreover, I show that retail traders' trading activities are negatively associated with trading performance. This evidence supports the overconfidence hypothesis in the context of FX retail trading. This is consistent with the insight in equity retail trading which shows that trading is hazardous to traders' wealth (e.g., Barber & Odean (2000)).

Keywords

Behavioral Finance, Currency Market, Individual Investors, Trading Performance

2.1 Introduction

Over the last decade, social trading platforms have gained in popularity among retail traders (Cetina, 2003; Gemayel & Preda, 2018b, 2018a; Preda, 2017). Essentially, one could argue that the rise of general social media (such as Facebook) has been quickly followed by the rise of social media exclusively dedicated to traders ("Facebook" for traders). These platforms provide unique opportunities for researchers to investigate the behavior of traders as an experimental setting.

These platforms are mostly focused on the foreign exchange (FX) market. FX retail trading has reached a large scale that cannot be neglected by researchers. Though retail trading is difficult to measure, evidence suggests that by 2001 it had grown to 10% of FX trading (King et al., 2012). By 2010, FX retail trading was estimated to reach 125 to 150 billion US dollars per day, which is about 8 to 10 percent of the global FX spot turnover (King & Rime, 2010).

One of the significant questions in the academic discussion in retail trading is regarding retail traders' performance. The evidence shows that retail traders in the equity market tend to be overconfident and trade excessively, which is harmful to their trading performance (Barber et al., 2004, 2009; Barber & Odean, 2000; Odean, 1999). For instance, Barber & Odean (2000) find a negative association between trading activities, proxied by turnover, and trading performance. They argue that trading is hazardous to traders' wealth as too much trading is associated with a significant amount of transaction costs.

In the currency market, Oberlechner & Osler (2012) show through their survey that currency traders are on average overconfident and their overconfidence does not vary with their experience. Evidence also shows that retail traders do not learn from their trading experience or past performance in terms of improving their future profitability (Ben-David et al., 2018; Hayley & Marsh, 2016). Furthermore, there is an extensive body of literature suggesting that retail currency traders on average lose money (Ben-David et al., 2018; Hayley & Marsh, 2016; Osler, 2012).

Another question regarding currency traders' performance is whether currency traders possess skills. For professional currency managers, prior research suggests that around 24% of professional currency managers can earn significantly positive abnormal returns under a four-factor model in the currency market (Pojarliev & Levich, 2008). However, there is no evidence showing that currency fund managers can persistently generate abnormal returns (Pojarliev & Levich, 2010). Evidence also shows that the majority of currency analysts possess little ability in terms of predicting the future (Marsh & Power, 1996).

In terms of retail currency traders, Abbey & Doukas (2015) (abbreviated as AD) apply a comprehensive framework to examine whether FX retail traders make money and possess skills. They find a similar proportion (around 25%) of traders who possess trading skills and earn significant positive alpha under a four-factor model (Pojarliev & Levich, 2008, 2010), even after accounting for transaction costs. They also find that trading activities (e.g., day trader, turnover, trades per day) are positively associated with trading performance. This evidence, however, seems to be inconsistent with the traditional theories regarding retail trading. For instance, Barber & Odean (2000) show that trading activities are negatively associated with profitability. This inconsistency is also acknowledged by the authors in AD.

To be specific, AD distinguish between two alternative hypotheses, namely, the calibration hypothesis and the overconfidence hypothesis. The calibration hypothesis states that retail traders are well-calibrated. This is because high-frequency traders receive timely feedback and they are able to use the feedback to improve their trading performance (Russo & Schoemaker, 1992; Skala, 2008). The prediction of the calibration hypothesis is that high-frequency traders (e.g., day traders, traders with high turnover, and traders with high trades per day) outperform low-frequency traders (e.g., non-day traders, traders with low turnover, and traders with low trades per day). In contrast, the overconfidence hypothesis states that retail traders are overconfident about their trading skills and cannot interpret their past trading activities correctly to improve their trading performance. In addition, too much trading brings a significant amount of transaction costs (Barber & Odean, 2000; Odean, 1999). The prediction of the overconfidence hypothesis is that high-frequency traders underperform low-frequency traders.

The empirical results in AD show that FX retail traders on average earn significant and positive returns, even after accounting for transaction costs. For instance, FX retail traders on average earn statistically significant 0.51 percent gross returns and statistically significant 0.17 percent net returns. In terms of traders' skills, the authors show that FX retail traders are able to earn positive abnormal returns under a four-factor model (Pojarliev & Levich, 2008, 2010). Specifically, 75% traders earn significant and positive abnormal returns before accounting for transaction costs and 25% traders earn significant and positive abnormal returns after accounting for transaction costs. In addition, they show a positive association between trading activities and performance. For example, they find that day traders trade more frequently than non-day traders and outperform non-day traders. Sorting on trading activities (i.e., trades per day, turnover), traders who trade more frequently outperform traders who trade less frequently. These results support the calibration hypothesis that FX retail traders are well-calibrated and can improve their trading performance through more trading activities. Overall, AD suggest that FX retail traders perform quite well, possess skills (75% in terms of gross returns and 25% in terms net returns), and make money from their frequent trading activities.

However, the evidence in literature regarding retail trading seems to be inconsistent with the conclusion in AD. Here are a number of reasons why the evidence is inconsistent with the existing literature. The first reason is regarding trading performance. The evidence regarding the notion that the majority of retail traders lose money is more pronounced in literature. In the currency market, the evidence suggests that on average retail FX traders lose money (Ben-David et al., 2018; Hayley & Marsh, 2016; Osler, 2012). For retail traders in the equity market, it is also well documented that retail traders on average loss money (Barber & Odean, 2000; Odean, 1999). However, the traders in AD’s sample on average appear to earn positive returns in terms of both gross returns and net returns (after accounting for transaction costs). For instance, the FX retail traders in AD’s sample on average earn 0.51 percent daily gross returns and 0.17 percent daily net returns. They conclude that FX retail traders on average earn positive returns.

The second reason is regarding the relationship between trading activities and performance. Though there is some evidence that a very small proportion of retail traders (e.g., 5%) can earn abnormal returns despite a high level of trading activities, these traders can achieve this superior performance due to potential private information (Dahlquist et al., 2016; Goetzmann & Kumar, 2008). Furthermore, it is well documented in Barber & Odean (2000) that traders trade too much due to their overconfidence, and trading frequency is negatively associated with trading performance. Therefore, there are not sufficient reasons to believe that this positive relationship between trading activities and trading performance exists among FX retail traders in general.

The third reason is regarding calibration skills. AD argue that retail currency traders exhibit calibration behavior, which leads to a good trading performance (e.g., about 75% of retail currency traders earn significantly positive alpha before accounting for transaction costs). However, the literature suggests that FX retail traders are most likely to be uninformed traders (Osler, 2012). They do not learn from past performance (Hayley & Marsh, 2016) or feedback (Ben-David et al., 2018) to improve their future returns. Specifically, Hayley & Marsh (2016) show that even experienced FX retail traders perform poorly. Ben-David et al. (2018) show that past performance does not predict future success, and FX retail traders attribute their past success to their trading skills and subsequently increase their risk taking. Increased risk taking does not necessarily result in improved trading performance. For example, Heimer & Simsek (2019) show that risk taking (e.g., the use of leverage) is negatively associated with trading performance. Therefore, I do not have good reasons to believe why an average retail trader should possess calibration skills.

The fourth reason is regarding the use of leverage. AD argue that the superior performance of FX retail traders is potentially due to the use of leverage. However, Heimer & Simsek (2019) show that the use of leverage is negatively associated with FX retail traders' performance. I acknowledge the fact that this negative association between the use of leverage and trading performance was unknown to the authors in AD at the time when they conducted their research. However, taken the evidence in AD and Heimer & Simsek (2019) together, it might be possible that the retail traders in AD's sample are skilled traders who can take advantage of the use of leverage to generate superior performance compared to novice traders.

In summary, the superior trading performance and skills found in AD seem to be a less common case in the literature on retail trading. After carefully examining the experimental setting in AD, I argue that the superior trading performance and skills of the

FX retail traders in AD might be associated with potential data limitation concerns. These concerns can result in a systematic overestimation of retail traders' performance and skills. There are a number of reasons why I conjecture that there might be data limitation concerns and a systematic overestimation of traders' performance in AD.

First, the dataset used in AD covers the period of the 2008 financial crisis (i.e. from March 2004 to September 2009). It can be argued that those retail traders who were still actively trading during the crisis might possess superior skills. Therefore, the results in AD might not reflect the real skills and profitability of an average trader in non-extreme market conditions. In my dataset, the sample period is from January 2009 to June 2010, which mitigates the concerns regarding extreme market conditions.

Second, the sample size in AD is relatively small, including 428 trading accounts. Given the 5.5-year sample period in AD, on average there are only about 78 trading accounts each year. In addition, the traders in AD on average stay around 82 days on the trading platform. In each three-month time interval, there are roughly about fewer than 20 trading accounts. Therefore, one can argue that, over a more than five-year sample period, 428 accounts on a trading platform is a relatively small sample provided the large scale of retail trading in the FX market (King et al., 2012; King & Rime, 2010; Osler, 2012). This might challenge the representativeness of the data. The fact that a small number of traders who were actively trading during the sample period is consistent with the argument that these traders might be skilled. In my dataset, the sample size is big enough for the purposes of the empirical analysis in this study.

Third, there might be a potential selection bias related to the dataset used in AD. Although the data sample in AD include all the FX trading accounts, it could still suffer from a potential sample selection bias. This is due to the setup of the trading platform where their sample is from. On AD's trading platform, traders can manage multiple accounts trading different asset portfolios, including forex, futures, stocks, and options. Though traders' assets have to be managed in different accounts, it is a concern that traders might strategically allocate their assets based upon their knowledge of trading and skills. Firstly, if some traders exclusively trade forex, this might indicate skills and profitability (included in AD's sample). Secondly, if some traders intensively trade assets other than forex and only have a few trades in their forex trading accounts, this might indicate a lower level of skills and profitability in trading FX (excluded in AD's sample – e.g., accounts with less than 10 roundtrip transections or less than 30-day daily observations). Thirdly, if some traders do not trade forex at all on this platform as they can easily access other assets (they would have done so if they traded on platforms without access to other assets), this might indicate a lowest level of skills of profitability in trading forex (excluded in AD's sample). Given these possibilities of the potential selection bias, traders' skills and profitability can be overestimated using the sample in Abbey & Doukas (2015).

Fourth, one limitation of the dataset in AD is regarding a potential survival bias, given the business model of the trading platform. The traders on the trading platform have to pay a monthly subscription fee. Therefore, it is mentioned in AD that the low age of the traders (i.e. 82 days) might be due to the fact that it is difficult to retain the traders who do not have a long history of superior performance. Consequently, the traders who survive on the platform are those who have a long history to make money. As a result, the limitation of the business model of the trading platform in AD might result in a systematic overestimation of the performance of FX retail traders. In my dataset, the average age of the traders is around 129 days, which is around 60% longer than that in AD. This can be due to the fact that traders on my platform do not need to pay a subscription fee.

Fifth, another limitation of the dataset in AD arises regarding the fact that the money in and out of traders' accounts (deposits and withdrawals) are not directly observable. They estimate the daily opening balance based on daily PnL (profits and losses). However, the daily opening balance can be underestimated without considering the deposits and withdrawals. This is because given the fact that the majority traders lose money in the FX market (Osler, 2012), they are more likely to put in additional money to keep the trading activities active. Therefore, if the money deposits are not considered, the open balance will be underestimated, resulting in an overestimation of the returns. This is another source of potential overestimation of the performance of the traders in AD.

Collectively, given the above-mentioned reasons, I argue that due to the data limitation concerns, there might be a systematic overestimation of the performance of FX retail traders in AD. If the traders selected in AD's sample are mostly skilled traders due to the data limitation, the results in their study can inaccurately attribute the superior performance in that particular dataset to the fact that FX retail traders are well-calibrated as opposed to be overconfident. Despite the data limitation concerns, I acknowledge that there are significant contributions of AD to the literature on retail trading, especially in the context of the FX market. The contributions concern both the theoretical framework regarding whether FX retail traders are on average well-calibrated or overconfident, and the empirical evidence regarding the profitability and skills of FX retail traders. I also acknowledge that the research design and empirical framework in AD are appropriate and valuable for identifying the trading performance and skills of FX retail traders. Specifically, AD use three sets of measures of FX retail traders' returns to assess their trading performance and skills. They use raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). These measures are applied both before and after accounting for transaction costs.

Therefore, I argue that it is important and necessary to revisit the research question: *do individual currency traders make money?* in Abbey & Doukas (2015), using a sample which mitigates the potential data limitation concerns and drawing upon insights from recent literature which might not be available to the authors in AD when they conducted their research (e.g., Ben-David et al., 2018; Hayley & Marsh, 2016; Heimer & Simsek, 2019). This would provide a more accurate and representative estimation of FX retail traders' skills and profitability.

Specifically, I use a novel dataset including 18 months of trading records from January 2009 to June 2010 for 3,269 retail traders with 1,119,342 observations on an online foreign exchange social trading platform (STP). I explore the trading performance of FX retail traders. I use raw returns and passive benchmark returns to identify traders' performance. I use the traditional four-factor model in the FX market to identify traders' skills (Abbey & Doukas, 2015; Pojarliev & Levich, 2008, 2010). I show evidence that FX retail traders on average lose money and high-frequency traders underperform low-frequency traders. My evidence is consistent with the overconfidence hypothesis that retail traders do not improve their trading performance through more frequent trading activities.

Although I revisit the research question in AD, there are a number of distinctions between my study and AD. First, I use a dataset which mitigates the concerns regarding the data limitation in AD. The results in principle should better address the question whether or not FX retail traders make money and possess skills. Second, I draw a different conclusion than that of AD, which makes better sense and is consistent with existing literature which shows retail traders do not make money. Third, my evidence supports a distinct hypothesis (overconfidence hypothesis), which shows a negative relationship between trading activities and performance, compared to that in AD (calibration hypothesis). Third, I use additional measures of trading activities (i.e. volume per day) and social communication (i.e. communicative traders) to further validate my results in this study.

This study contributes to the literature in several ways. First, I directly extend AD by examining FX retail traders' performance and skills, using a comprehensive dataset which mitigates the data limitation concerns. I show that retail traders on average lose money as opposed to that retail traders on average make money as shown in Abbey & Doukas (2015). Second, I contribute to the understanding of FX retail traders' trading skills and abilities. I show that 75% percent of FX retail traders significantly lose money and do not exhibit skills, as they earn a significant and negative alpha under a four-factor model in the currency market (in terms of both gross returns and net returns). Third, I find empirical evidence in the FX market that retail traders are overconfident and excessive trading activities reduce their trading performance. This result is consistent with the insights on equity retail trading (e.g., Barber & Odean (2000)).

Overall, I argue that by comparing the results between my study and those in AD, one can better understand retail traders' performance in the FX market. This study also sheds light on how potential data limitation concerns might influence the results and conclusions regarding retail traders' performance and skills. I suggest that the potential data limitation discussed in this study should be considered in the future research regarding the estimation of FX traders' profitability.

2.2 Literature Review

There is extent literature which investigates the skills and abilities of investors (including both professional investors and retail investors) for making money in financial markets. I make distinctions between professional investors and retail investors, in the sense that individual investors exhibit different patterns of decision-making processes compared with financial professionals (Preda, 2017).

For professional investors, prior research posits that around 24% of professional currency managers (in a sample of 34 individual currency fund managers) can earn significantly positive abnormal returns under a four-factor model in the currency market (Pojarliev & Levich, 2008), but there is no evidence showing that currency fund managers can persistently generate abnormal returns (Pojarliev & Levich, 2010). Evidence also shows that currency analysts rarely possess the ability to predict the future (Marsh & Power, 1996).

For retail investors, prior wisdom argues that, in the stock market, active trading individual investors underperform passive trading individual investors, which is explained by the transaction costs associated with the high level of trading (e.g., turnover) (Barber & Odean, 2000). In contrast, other studies present evidence that there are small subsets of highly active individual investors who can earn abnormal returns (Dahlquist et al., 2016; Goetzmann & Kumar, 2008). For example, in Sweden's Premium Pension System, there are 5.8% active and 0.6% highly active individual investors earning significantly higher returns, earning average returns of 6.86% and 12.57% per year respectively. This is compared with the rest of the 93.5% inactive individual investors, with average returns of 3.82% per year, in managing their account by allocating money from different funds in their pension accounts (Dahlquist et al., 2016). In addition, there is evidence that around 2% high-turnover and under-diversified individual investors' portfolios perform better than high-turnover and better-diversified portfolios in the stock market (Goetzmann & Kumar, 2008). This shows that active trading is not always bad, at lease for some investors, though the proportion of these investors is very small.

There are two theoretical frameworks regarding the skills of retail traders. One is the calibration view and the other is the overconfidence view. The calibration view is that retail traders are well-calibrated. This can be due to the fact that high-frequency traders receive timely feedback from their trading activities. In the meanwhile, retail traders incorporate the feedback into their trading strategies, which subsequently increases their trading performance (Russo & Schoemaker, 1992; Skala, 2008). One prediction of the calibration view is that high-frequency traders (e.g., day traders) have better trading performance than low-frequency traders (e.g., non-day traders). The overconfidence view is that retail traders are on average overconfident. They cannot interpret their past trading activities and performance correctly in order to improve their trading performance (Ben-David et al., 2018; Hayley & Marsh, 2016). Furthermore, excessive trading can introduce a significant amount of transaction costs, which reduce retail traders' performance (Barber & Odean, 2000; Odean, 1999). One prediction of the overconfidence view is that high-frequency traders have worse performance than low-frequency traders.

As for individual currency investors, who are the focus of this study, Abbey & Doukas (2015) use a four-factor model (Pojarliev & Levich, 2008) showing that individual currency investors can earn abnormal returns even after controlling for transaction costs. However, there are some data limitation concerns in AD. For instance, the sample is small (428 accounts between March 2004 to September 2009). In addition, the 428 accounts and associated trading activities are selected from individual traders who can trade forex, futures, stocks, and options on the trading platform, which involves potential selection biases. For example, exclusive currency traders can be skilled in FX trading, and this might be what explains the superior abnormal returns. Furthermore, the measures of returns might not be as accurate, since the measures of returns in AD do not take the money deposits and withdrawals over time into consideration. This impacts the accuracy of the calculation of returns.

In summary, I argue that due to the data limitation concerns, the results in AD, which show that FX retail traders perform well and possess skills, can be related to a systematic overestimation. Therefore, it is necessary to address these data limitation concerns and further investigate whether an average FX retail trader makes money or not, and whether an average retail trader possess trading skills (earn significant and positive four-factor alpha).

2.3 Data

The dataset used in this research is from an online trading platform, specializing in the currency market, with a sample period from January 2009 to the end of June 2010 (18 months in total). The dataset makes it possible to observe the aggregated daily trading records of 3,269 individual investors with 1,119,342 trader-day observations. To be more specific, I am able to look at the daily trading profits and losses (PnL) excess of fee, deposits, withdrawals, and open balances (OB) of each investor during the entire sample period. All the money values of each account are reconciled in US dollars.

I apply the same data trimming method in AD to select a data sample for the analysis in this study. Specifically, I include traders who have no less than 10 roundtrip transactions and who have no less than 30 days' return observations (Abbey & Doukas, 2015). After the data trimming, I have 1,915 trading accounts, which include 1,558 day traders and 357 non-day traders. Day traders are defined as traders who on average hold their positions for less than 1,440 minutes. Non-day traders are defined as traders who on average hold their positions for more than 1,440 minutes. This classification of day traders and non-day traders is from Abbey & Doukas (2015).

2.4 Empirical Strategies

In order to make my results directly comparable to those in AD, I adopt the same methods to estimate the trading performance. However, my estimation of the traders' returns is supposed to be more accurate than that in AD. This is because my data overcomes the potential data limitation in AD in the sense that I directly observe the opening balances for each trader in each day. As discussed, the estimation of the open balances in AD is biased due to the fact that they do not directly observe the money deposits and withdrawals.

2.4.1 Return Performance

The daily financial performance of traders is calculated as the return of the daily available funds to invest in the market. I measure traders' returns in two terms. One is in the net return term and the other is in the gross return term. In other words, the daily net return (Net_Return) of individual investors equals the daily profits and losses (PnL) (excess of transaction fees) divided by the open balance (OB) which is the funds available to invest on that day. The calculation of the net return measure is in Equation (1).

$$Net\_Return_{i,t} = \frac{PnL_{i,t}}{OB_{i,t}} \qquad \text{Equation (1)}$$

In the FX market, the transaction fee is at the minimum level (Abbey & Doukas, 2015; Heimer, 2016). The only transaction fee is from the bid-ask spread, approximately from 2 to 3 pips (one pip equals one percent of 0.01) (Abbey & Doukas, 2015; Heimer, 2016). In AD, the transaction fee is estimated as 3 pips per contract (10,000 units), which is \$3 dollars per contract. I adopt the same method to estimate the transaction fee ($TC_{i,t}$) and add it back to the daily profits and losses to represent how much money a trader would make without the transaction fee. Then I calculate the gross return based on the before-transaction-fee daily profits and losses. The calculation of the gross return measure is in Equation (2).

$$Gross\_Return_{i,t} = \frac{PnL_{i,t} + TC_{i,t}}{OB_{i,t}} \qquad \text{Equation (2)}$$

Then, based on these two measures, I calculate the equal-weighted portfolio returns of traders in a daily frequency as in AD in order to understand whether on average traders make money or not.

2.4.2 A Passive Benchmark Model

The passive benchmark model used in this study is based on AD and Pojarliev & Levich (2008, 2010). Specifically, the passive benchmark used is the Deutsch Bank Currency return Index (DBCR). This index is an investable index that includes a basket of currencies, which can be used by passive currency traders. The passive benchmark returns are calculated in both gross returns and net returns.

$$Benchmark\_Return_{i,t} = Gross/Net\_Return_{i,t} - Benchmark_{\ t} \qquad \text{Equation (3)}$$

2.4.3 Four-Factor Alpha

I employ the four-factor model (Abbey & Doukas, 2015; Pojarliev & Levich, 2008; Pojarliev & Levich, 2010) in currency markets, in order to identify abnormal returns which cannot be explained by the four factors in the existing factor model. The alpha in the four-factor model represents traders' skills.

$$R_t = \alpha + \Sigma_i \beta_i F_{i,t} + \varepsilon_t \qquad \text{Equation (4)}$$

In the above model, R_t represents the excess return generated by individual investors in the time period t, which is defined as the raw return (gross return or net return) less the risk-free rate return. α in the model is the intercept of the regression and it quantifies the skills and abilities of individual investors. β_i measures the sensitivity of excess returns associated with different factors F_i. ε_t is the random error term of the factor model in time period t.

In terms of the four factors in the model, they are carry factor (Carry), momentum factor (Mom), value factor (Value) and volatility factor (Vol). All four of the factors mentioned above are considered as proxies of different types of trading strategies used by currency traders (Pojarliev & Levich, 2008). As used in prior literature (Abbey & Doukas, 2015), the proxies for the four factors are constructed by the Deutsche Bank's DBIQ database as follows: the Deutsche Bank (DB) G10 Currency Harvest Index (USD) as the proxy for the carry trading strategy, the DB FX Momentum (USD) as the proxy for trend-following trading strategy, the DB FX Purchasing Power Parity (PPP) (USD), and the 60-day volatility calculated based on the Deutsche Bank (DB) G10 Currency Harvest Index (USD) as the proxy for the volatility trading strategy. In order to adapt the proxies for the factors to individual investors, I use the Deutsche Bank (DB) Currency Carry USD Index instead of the Deutsche Bank (DB) G10 Currency Harvest Index (USD). This is because individual currency traders trade more currencies than the G10 currencies, which better reflect the trading activities of individual investors. I select all of the four factors above with USD as the base currency, since the profits and losses (PnL) in my dataset is in US dollars.

As for the risk-free rate of return, I use the overnight USD London Interbank Offered Rate (LIBOR) instead of the one-month USD London Interbank Offered Rate (LIBOR) (Abbey & Doukas, 2015), since the returns in this study are calculated on a daily frequency. All the proxies for the four factors and the proxy for the risk-free rate of return are from Bloomberg.

2.5 Results

This section discusses the results and implications of the empirical framework on retail traders' performance and skills. The main tables (Table 2-1 to Table 2-7) include raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). In Appendix 2-1, I report a detailed description of the four-factor model results which are not reported in the main tables.

Table 2-1 shows the summary statistics of the dataset used in this research. There are 1,915 traders in total, including 1,558 day traders, and 357 non-day traders (Panel A). This sample is much bigger than that in AD which includes 428 accounts in total with 263 day traders, and 165 non-day traders. Panel B reports the summary statistics for the full sample. Panel C reports the summary statistics for day traders, and Panel C reports the summary statistics for non-day traders. In addition, Panel E reports the difference in means between day traders and non-day traders.

The variables reported in the table include leverage, trade size ($), price per contract, trades per day, transaction costs (%), and age (days). I first calculate the mean values of each variable for each account and then take an average across different accounts. Leverage is defined as the average leverage used by a trader in a day. Trade size ($) is defined as the dollar value of all trades for each trader in a day. Price per contract is defined as the dollar value of each contract (one contract equals 10,000 units). Trades per day is defined as the number of trades for each trader in a day. Transaction costs (%) is estimated as 3 pips ($3) per contract for each roundtrip transaction divided by the amount of capital (margin-adjusted) needed to open a position (Abbey & Doukas, 2015). Age is defined as the number of days between the first observation of the trading account and the last trade in the dataset.

As shown in the statistics, an average trader in this dataset closes 3.82 trades per day with a trade size of 40,226.86 US dollars. This average trader's age is 131.49 days during the sample period. The summary statistics are similar to those in AD. For instance, in AD the mean age of the traders is 81.92 days, the mean trades per day is 3.31, and the transactions costs (%) is 0.89. However, the average trade size in AD ($ 457,161.40) is much bigger (more than 10 times) than that in my dataset ($ 40,226.86), which is consistent with the previous discussion that the traders in AD might be the skilled traders who tend to have a larger trade size. Therefore, the analysis using my dataset would lead to a better estimation of FX retail traders' trading skills.

In addition, in terms of the comparison between day traders and non-day traders, the results are consistent with those in AD. Specifically, day traders tend to have a higher level of trades per day, but a lower age. I also describe the leverage used by day traders and non-day traders, which is not shown in AD. Day traders appear to use more leverage than non-day traders.

[Insert Table 2-1]

Table 2-2 reports the main results of this study. By comparing the results in this table and those in AD, I can have a clear idea of how my results and implications differ from those in AD. All three performance measures (raw returns, passive benchmark returns, and the four-factor alpha) for the full sample suggest that FX retail traders on average lose money, no matter when I examine their gross returns or net returns (Panel A). However, in AD the traders appear to earn positive raw returns, passive benchmark returns, and even positive four-factor alpha, which is not consistent with the view that the majority of retail traders lose money in the FX market (Osler, 2012). My results are consistent with the literature which finds that FX retail traders perform poorly (e.g., Hayley & Marsh, 2016).

In terms of gross returns, I show that only the top performers (25%) earn positive and significant raw returns, passive benchmark returns, and four-factor alpha. However, in AD, all of the top three quartiles of traders (75%) earn significant trading returns using these three performance measures. This is consistent with the discussion that the traders in AD's sample might be the skilled traders. For the worst performers (25%), the results in my study are consistent with those in AD, indicating that the worst performers significantly lose money in the FX market. Therefore, there might be up to a 50% overestimation of FX traders' skills in AD when evaluating the gross returns. This is because I show that the middle performers (50%) (traders excluding the 25% top performers and 25% worst performers) significantly lose money, however, AD show that they significantly make money.

In terms of the net returns, I show that only the top performers (25%) earn significantly positive returns. However, AD show that 50% traders earn significant and positive raw returns and passive benchmark returns. Both my results and those in AD show that only the top 25% performers in the FX earn significantly positive four-factor alpha, indicating that these traders are skilled traders. Therefore, the results in AD might exhibit up to a 25% overestimation of traders' skills when using raw returns and passive benchmark returns after accounting for transaction costs (net returns).

Overall, by comparing the results with those in AD, I show that the potential overestimation of FX retail traders' trading skills can be as large as 25% to 50% in terms of the proportion of winning traders among all the traders. These results are consistent with the discussion that due to the potential limitation of the dataset used in AD, there might be a systematic overestimation of retail traders' performance. The evidence in here further validates the necessity of this research, which tries to provide a more accurate examination of whether retail traders in the FX market really make money and possess skills. This evidence adds to the literature on FX retail trading.

[Insert Table 2-2]

Table 2-3 shows the trading performance of day traders and non-day traders. As discussed, day traders trade more frequently than non-day traders both in my study and in AD. Specifically, in my study day traders on average close 4.1 trades per day, while non-day traders close 2.6 trades per day. The difference in the means is 1.5 trades per day with a t-value of 4.34. In AD, the day traders on average close 3.68 trades per day, and non-day traders close 3.08 trades per day. The difference in means is 0.60 with a t-value of 2.03.

However, in terms of the trading performance, my results show that day traders (frequent traders) underperform non-day traders (less frequent traders). The results are consistent with the evidence in Barber & Odean (2000) which shows that frequent traders lose more money than less frequent traders. This is because excessive trading is associated with significant transaction costs. In the contrary, the results in AD show that day traders outperform non-day traders. This evidence is consistent with the argument that the traders in AD's sample might be the skilled traders who possess the timing ability to buy and sell frequently and in the meanwhile earn positive returns.

[Insert Table 2-3]

Table 2-4 shows that the trading performance of FX retail traders is negatively associated with turnover. Specifically, traders with the highest turnover (Q4) earn the lowest returns, while the traders with the lowest turnover (Q1) earn the highest returns. High-frequency traders significantly lose more money than low-frequency traders. This relationship exists both in terms of gross returns and net returns. These results are consistent with those in Barber & Odean (2000) which show that high-frequency traders lose more money compared to low-frequency traders. In this table, I provide empirical evidence in the context of FX retail trading, which supports the overconfidence hypothesis of retail traders. In comparison, in AD the authors find that high-frequency traders outperform low-frequency traders in terms of gross returns. However, after accounting for transaction costs, this relationship is not significant.

[Insert Table 2-4]

Table 2-5 shows the results of traders' performance with sorts on trades per day. The results show that high-frequency traders (traders with more trades per day) underperform low-frequency traders (traders with fewer trades per day). The evidence is consistent with the results in Table 2-4.

[Insert Table 2-5]

In addition, to further validate the results in my study, I examine the trading performance with sorts on trading volume (units) per day. The results are reported in Table 2-6. The results show that traders who trade a higher volume underperform traders who trade a lower volume. The results are consistent with the view that traders who are overconfident perform poorly. The results are consistent with those in the previous tables, which support the overconfidence hypothesis of FX retail traders.

[Insert Table 2-6]

2.6 Robustness Tests

Since my dataset is from a social trading platform, I also test whether the trading performance significantly differs between traders who participate in the online social communication (communicative traders) and traders who do not participate in the online social communication (non-communicative traders). The online social communication includes three forms of activities, such as creating a discussion topic, posting a comment under a discussion topic, or liking a comment under a discussion topic.

I test whether the trading performance differs between communicative traders and non-communicative traders. If the trading performance is not significantly different between communicative and non-communicative traders, this helps to mitigate concerns over the impact of the social communication features on the results of this study. The results show that social communication is not significantly associated with the trading performance of FX retail traders. This evidence supports the robustness of the results in this study.

[Insert Table 2-7]

2.7 Conclusion

In this study, I revisit the research question: *do individual currency traders make money?* in Abbey & Doukas (2015). I use a comprehensive dataset which mitigates the potential data limitation concerns in Abbey & Doukas (2015). I show that FX retail traders do not make money and high-frequency traders underperform low-frequency traders. The evidence supports the overconfidence hypothesis that retail traders are on average overconfident and they lose more money from more frequent trading activities. The evidence is consistent with the insights in the retail trading literature (e.g., Barber & Odean (2000)).

This study closely follows Abbey & Doukas (2015), but it makes a number of distinctions from AD. First, the dataset used in this study mitigates the potential data limitation and produces an empirically more accurate estimation of FX retail traders' performance and skills. Second, this study concludes that FX retail traders do not make money as opposed to make money which is shown in AD. Third, my evidence empirically supports the overconfidence hypothesis of FX retail traders and identifies a negative association between trading activities and trading performance. Third, I include an additional trading activity measure (trading volume per day), and examine the potential impact of social communication (i.e. communicative traders) on the results to further validate the conclusion in this study.

Overall, this study adds to the literature on the performance of retail traders in the context of the foreign exchange market. It presents evidence that FX retail traders on average do not make money and are overconfident.

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Table 2-1 Summary Statistics

Panel A: Summary Data for Accounts						
		All Traders		Day Traders		Non-Day Traders
Accounts		1,915		1,558		357
Panel B: All Traders (1,915)						
Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl	Obs.
Leverage	45.83	88.94	6.54	17.36	43.76	1,875.00
Trade_Size ($)	40,226.86	274,539.20	3,536.97	11,461.02	25,050.82	1,915.00
Price_per_Contract	12,478.16	1,929.98	11,455.00	12,579.51	13,645.67	1,915.00
Trades_per_Day	3.82	5.92	0.92	2.12	4.65	1,915.00
Transaction_Costs (%)	0.81	1.64	0.11	0.29	0.79	1,875.00
Age (days)	131.49	98.96	58.00	102.00	172.00	1,915.00
Panel C: Day Traders (1,558)						
Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl	Obs.
Leverage	49.54	88.94	8.23	20.65	50.65	1,525.00
Trade_Size ($)	34,917.69	230,272.86	3,665.64	11,645.85	24,925.53	1,558.00
Price_per_Contract	12,535.24	1,881.43	11,516.25	12,651.73	13,704.64	1,558.00
Trades_per_Day	4.10	6.01	1.03	2.38	5.03	1,558.00
Transaction_Costs (%)	0.87	1.64	0.13	0.36	0.88	1,525.00
Age (days)	129.36	98.88	56.00	99.50	171.00	1,558.00
Panel D: Non-Day Traders (357)						
Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl	Obs.
Leverage	29.66	87.28	3.39	7.48	18.47	350.00
Trade_Size ($)	63,396.86	415,517.68	3,110.54	9,792.07	25,466.63	357.00
Price_per_Contract	12,229.07	2,113.81	11,254.34	12,411.12	13,390.42	357.00
Trades_per_Day	2.60	5.38	0.48	1.23	3.16	357.00
Transaction_Costs (%)	0.53	1.60	0.06	0.14	0.33	350.00
Age (days)	140.78	98.92	68.00	113.00	182.00	357.00
Panel E: Difference between Day traders and Non-day Traders						
		Difference in Means	t-stat	Sig.		
Leverage		19.87	3.78	***		
Trade_Size ($)		-28479.2	-1.77	*		
Price_per_Contract		306.2	2.71	***		
Trades_per_Day		1.50	4.34	***		
Transaction_Costs (%)		0.34	3.53	***		
Age (days)		-11.42	-1.97	**		

This table reports the summary statistics of the data sample used in this study. Panel A reports the numbers of day traders and non-day traders. Panel B reports the summary statistics of all traders. Panel C and D report the statistics of day traders and non-day traders respectively. The variables include leverage, trade size ($), price per contract, trades per day, transaction costs (%), and age (days). Leverage is calculated as the average leverage used by a trader in a day. Trade size ($) is calculated as the dollar value of all trades in a day. Price per contract is calculated as the dollar value of each contract (one contract equals 10,000 units). Trades per day is calculated as the number of trades in a day. Transaction costs (%) is calculated as 3 pips ($3) per contract for each roundtrip transaction divided by the amount of capital (margin-adjusted) needed to open a position (Abbey & Doukas, 2015). Age is calculated as the number of days between the first observation of the trading account and the last trade in the dataset. Panel E reports the differences in the variables between day traders and non-day traders.

Table 2-2 Trading Performance for all Traders

	Gross Returns									**Net Returns**								
	Raw Returns			Passive benchmark			Four-factor alpha			Raw Returns			Passive benchmark			Four-factor alpha		
Panel A: Trading Performance for the Full Sample																		
Full	-0.24%	-9.56	***	-0.23%	-9.52	***	-0.38%	-10.64	***	-0.52%	-14.77	***	-0.49%	-14.59	***	-0.77%	-15.82	***
Panel B: Trading Performance with Sorts on Performance																		
Q4 (Top Performers)	0.37%	9.50	***	0.36%	9.20	***	0.46%	8.52	***	0.13%	2.15	**	0.17%	3.87	***	0.18%	2.78	***
Q3	-0.06%	-1.57		-0.05%	-1.55		-0.12%	-2.55	**	-0.20%	-5.40	***	-0.19%	-5.06	***	-0.34%	-6.57	***
Q2	-0.36%	-8.23	***	-0.34%	-7.86	***	-0.55%	-9.22	***	-0.63%	-11.11	***	-0.62%	-10.86	***	-0.96%	-12.38	***
Q1 (Worst Performers)	-1.13%	-12.48	***	-1.14%	-12.57	***	-1.71%	-13.47	***	-1.66%	-14.25	***	-1.62%	-14.02	***	-2.41%	-15.32	***
Panel C: Difference in Means between Q4 and Q1																		
Diff	1.50%	15.22	***	1.50%	15.19	***	2.17%	14.38	***	1.79%	13.78	***	1.79%	14.60	***	2.55%	15.44	***

This table reports the results of the trading performance of all traders in the sample. The trading performance is calculated in gross returns and net returns (accounting for transaction costs). Transaction costs are calculated as 3 pips ($3) per contract. Return measures are raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). The mean values, t-statistics, and significant levels are reported. Panel A reports the results for the full sample. Panel B reports the results of an equal-weighted portfolio for each quartile of the traders with sorts on performance. The rank of traders is based on the four-factor alpha t-statistics. Top performers (Q4) (worst performers (Q1)) are with the highest (lowest) four-factor alpha t-statistics. Panel C reports the difference in means between Q4 and Q1.

Table 2-3 Trading Performance for Day Traders and Non-Day Traders

	Gross Returns									**Net Returns**								
	Raw Returns			Passive benchmark			Four-factor alpha			Raw Returns			Passive benchmark			Four-factor alpha		
Panel A: Results for Day/Non-Day Traders																		
Day	-0.34%	-11.50	***	-0.34%	-11.32	***	-0.54%	-14.07	***	-0.71%	-13.25	***	-0.65%	-17.20	***	-1.01%	-22.06	***
Non-Day	-0.01%	-0.35		-0.01%	-0.46		-0.06%	-1.65	*	-0.10%	-2.93	***	-0.10%	-2.90	***	-0.22%	-4.38	***
Panel B: Difference in Means between Day Trades and Non-Day Traders																		
Diff.	-0.33%	-8.60	***	-0.33%	-8.42	***	-0.48%	-9.85	***	-0.61%	-9.52	***	-0.55%	-10.78	***	-0.80%	-12.36	***

This table reports the results of the trading performance of day traders and non-day traders. The trading performance is calculated in gross returns and net returns (accounting for transaction costs). Transaction costs are calculated as 3 pips ($3) per contract. Return measures are raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). The mean values, t-statistics, and significant levels are reported. Panel A reports the results for day traders and non-day traders. Panel B reports the difference in means between day traders and non-day traders.

Table 2-4 Full Sample Trader Performance on Turnover

	Gross Returns									Net Returns								
	Raw Returns			Passive benchmark			Four-factor alpha			Raw Returns			Passive benchmark			Four-factor alpha		
Panel A: Trading Performance with Sorts on Turnover																		
Q4 (Highest Turnover)	-0.72%	-10.88	***	-0.72%	-10.86	***	-1.10%	-12.58	***	-1.13%	-13.23	***	-1.07%	-14.01	***	-1.62%	-16.54	***
Q3	-0.37%	-9.59	***	-0.37%	-9.75	***	-0.59%	-11.59	***	-0.58%	-12.24	***	-0.58%	-12.06	***	-0.90%	-14.62	***
Q2	-0.16%	-5.30	***	-0.14%	-4.84	***	-0.26%	-6.20	***	-0.28%	-7.84	***	-0.26%	-7.33	***	-0.45%	-8.75	***
Q1 (Lowest Turnover)	0.00%	0.03		0.00%	-0.02		-0.05%	-0.72		-0.36%	-6.52	***	-0.35%	-6.36	***	-0.58%	-7.04	***
Panel B: Difference in Means between Q4 and Q1																		
Diff	-0.72%	-8.92	***	-0.72%	-8.89	***	-1.06%	-9.47	***	-0.77%	-7.47	***	-0.71%	-7.51	***	-1.03%	-8.24	***

This table reports the results of the trading performance of all traders with sorts on turnover. The trading performance are calculated in gross returns and net returns (accounting for transaction costs). Transaction costs are calculated as 3 pips ($3) per contract. Returns measures are raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). The mean values, t-statistics, and significant levels are reported. Panel A reports the results of an equal-weighted portfolio for each quartile of the traders with sorts on turnover. The rank of traders is based on turnover. Highest Turnover (Q4) (Lowest Turnover (Q1)) are traders with the highest (lowest) turnover. Panel B reports the difference in means between Q4 and Q1.

Table 2-5 Full Sample Trader Performance on Trades Per Day

	Gross Returns									**Net Returns**								
	Raw Returns			Passive benchmark			Four-factor alpha			Raw Returns			Passive benchmark			Four-factor alpha		
Panel A: Trading Performance with Sorts on Trades Per Day																		
Q4 (Highest)	-0.68%	-8.88	***	-0.68%	-8.96	***	-1.09%	-10.50	***	-0.94%	-11.59	***	-0.94%	-11.54	***	-1.48%	-13.80	***
Q3	-0.43%	-7.62	***	-0.43%	-7.57	***	-0.68%	-8.44	***	-0.80%	-12.43	***	-0.79%	-12.21	***	-1.23%	-13.80	***
Q2	-0.11%	-1.95	*	-0.11%	-1.89	*	-0.21%	-2.55	**	-0.41%	-5.43	***	-0.36%	-5.43	***	-0.57%	-6.21	***
Q1 (Lowest)	-0.07%	-3.60	***	-0.07%	-3.53	***	-0.11%	-4.10	***	-0.26%	-8.15	***	-0.25%	-7.89	***	-0.39%	-8.71	***
Panel B: Difference in Means between Q4 and Q1																		
Diff	-0.61%	-7.76	***	-0.62%	-7.87	***	-0.98%	-9.34	***	-0.68%	-7.78	***	-0.69%	-7.94	***	-1.09%	-10.06	***

This table reports the results of the trading performance of all traders with sorts on trades per day. The trading performance are calculated in gross returns and net returns (accounting for transaction costs). Transaction costs are calculated as 3 pips ($3) per contract. Returns measures are raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). The mean values, t-statistics, and significant levels are reported. Panel A reports the results of an equal-weighted portfolio for each quartile of the traders with sorts on trades per day. The rank of traders is based on trades per day. Highest trades per day (Q4) (lowest trades per day (Q1)) are traders with the highest (lowest) trades per day. Panel B reports the difference in means between Q4 and Q1.

Table 2-6 Full Sample Trader Performance on Trading Volume Per Day

	Gross Returns									**Net Returns**								
	Raw Returns			Passive benchmark			Four-factor alpha			Raw Returns			Passive benchmark			Four-factor alpha		
Panel A: Trading Performance with Sorts on Trading Volume Per Day																		
Q4 (Highest)	-0.36%	-5.98	***	-0.37%	-6.19	***	-0.63%	-7.54	***	-0.78%	-11.01	***	-0.74%	-12.37	***	-1.18%	-14.65	***
Q3	-0.48%	-8.43	***	-0.48%	-8.29	***	-0.76%	-9.67	***	-0.89%	-11.74	***	-0.85%	-11.37	***	-1.29%	-13.09	***
Q2	-0.25%	-4.78	***	-0.25%	-4.84	***	-0.42%	-5.61	***	-0.56%	-7.94	***	-0.56%	-7.83	***	-0.89%	-8.56	***
Q1 (Lowest)	-0.11%	-4.50	***	-0.10%	-4.22	***	-0.16%	-4.71	***	-0.24%	-7.33	***	-0.23%	-7.01	***	-0.37%	-7.90	***
Panel B: Difference in Means between Q4 and Q1																		
Diff	-0.25%	-3.88	***	-0.27%	-4.18	***	-0.48%	-5.41	***	-0.54%	-6.87	***	-0.51%	-7.48	***	-0.81%	-9.12	***

This table reports the results of the trading performance of all traders with sorts on trading volume per day. The trading performance are calculated in gross returns and net returns (accounting for transaction costs). Transaction costs are calculated as 3 pips ($3) per contract. Returns measures are raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). The mean values, t-statistics, and significant levels are reported. Panel A reports the results of an equal-weighted portfolio for each quartile of the traders with sorts on trading volume per day. The rank of traders is based on trading volume per day. Highest trading volume per day (Q4) (lowest trading volume per day (Q1)) are traders with the highest (lowest) trading volume per day. Panel B reports the difference in means between Q4 and Q1.

Table 2-7 Full Sample Trader Performance on Social Communication

	Gross Returns									Net Returns								
	Raw Returns			Passive benchmark			Four-factor alpha			Raw Returns			Passive benchmark			Four-factor alpha		
Panel A: Trading Performance for Communicative Traders and Non-Communicative Traders																		
Communicative	-0.31%	-7.03	***	-0.31%	-6.96	***	-0.50%	-8.14	***	-0.51%	-9.77	***	-0.50%	-9.58	***	-0.80%	-11.25	***
Non-Communicative	-0.27%	-10.30	***	-0.27%	-10.19	***	-0.44%	-12.78	***	-0.61%	-11.75	***	-0.55%	-15.96	***	-0.87%	-20.16	***
Panel B: Difference in Means between Communicative Traders and Non-Communicative Traders																		
Diff.	-0.03%	-0.67		-0.03%	-0.67		-0.05%	-0.83		0.10%	1.36		0.05%	0.80		0.09%	1.10	

This table reports the results of the trading performance of communicative traders and non-communicative traders. The trading performance are calculated in gross returns and net returns (accounting for transaction costs). Transaction costs are calculated as 3 pips ($3) per contract. Returns measures are raw returns, passive benchmark returns, and risk-adjusted returns (four-factor alpha). The mean values, t-statistics, and significant levels are reported. Panel A reports the results for communicative traders and non-communicative traders. Panel B reports the difference in means between communicative traders and non-communicative traders.

Appendix 2-1 Four-Factor Model Results

Table 2-8 Full Sample Trading Performance Test

	Gross Returns						**Net Returns**					
	(1)	(2)	(3)	(4)	(5)	(6) Diff	(7)	(8)	(9)	(10)	(11)	(12) Diff
Factor	Full	Q4 (Top)	Q3	Q2	Q1 (Worst)	Q4-Q1	Full	Q4 (Top)	Q3	Q2	Q1 (Worst)	Q4-Q1
carry	-0.06966	0.05153	-0.13516*	-0.11023	-0.14901	0.20054	-0.12611*	0.05383	-0.10183	-0.20457**	-0.29362	0.32326
	[-1.51]	[0.72]	[-1.95]	[-1.43]	[-0.96]	[1.12]	[-1.82]	[0.53]	[-1.51]	[-2.04]	[-1.44]	[1.55]
value	-0.03167	-0.06404	-0.03538	0.06912	-0.12879	0.06475	0.16420	-0.13316	-0.04559	0.24873	0.71880	-0.80690
	[-0.40]	[-0.53]	[-0.33]	[0.52]	[-0.44]	[0.19]	[0.90]	[-0.89]	[-0.35]	[1.22]	[1.12]	[-1.33]
mom	-0.01155	-0.02619	0.09801	0.08221	-0.20837	0.18218	0.14459	0.08597	0.03810	0.21623*	0.24305	-0.16703
	[-0.15]	[-0.37]	[1.31]	[0.93]	[-0.68]	[0.54]	[1.53]	[0.90]	[0.49]	[1.85]	[0.77]	[-0.52]
vol	-0.03436	0.01908	-0.01240	-0.04857	-0.12921	0.14829	-0.03129	0.03290	-0.02823	-0.05881	-0.09477	0.13264
	[-1.55]	[0.87]	[-0.58]	[-1.65]	[-1.58]	[1.62]	[-1.23]	[1.08]	[-1.21]	[-1.43]	[-1.18]	[1.59]
Const	-0.00382***	0.00462***	-0.00121**	-0.00551***	-0.01706***	0.02168***	-0.00768***	0.00177***	-0.00336***	-0.00962***	-0.02414***	0.02547***
	[-10.64]	[8.52]	[-2.55]	[-9.22]	[-13.47]	[14.38]	[-15.82]	[2.78]	[-6.57]	[-12.38]	[-15.32]	[15.44]
Obs	1,905	379	389	379	379	379	1,738	389	381	381	379	389
R^2	0.003	0.004	0.034	0.016	0.016	0.013	0.009	0.010	0.014	0.040	0.027	0.028

This table reports the full results of the four-factor model on trading performance. The results are reported for the full sample (column (1) and column (7)) and an equal-weighted portfolio for each quartile of the traders with sorts on trading performance. The rank of traders is based on trading performance. Top performers (Q4) (worst performers (Q1)) are with the highest (lowest) four-factor alpha t-statistics. It also reports the difference in means between Q4 and Q1. Robust t-statistics are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 2-9 Trading Performance Test on Day/Non-Day Traders

	Gross Returns			Net Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Factor	Day	Non-Day	Diff	Day	Non-Day	Diff
carry	-0.11610*	0.03589	-0.14722**	-0.17134**	-0.02738	-0.15401
	[-1.89]	[0.82]	[-2.06]	[-2.42]	[-0.47]	[-1.64]
value	0.02215	-0.12042	0.13838	0.11755	0.07934	0.04058
	[0.26]	[-1.49]	[1.20]	[0.97]	[0.61]	[0.23]
mom	0.03749	0.00176	0.03807	0.11973	0.12873	-0.01750
	[0.57]	[0.04]	[0.51]	[1.53]	[1.29]	[-0.13]
vol	-0.03852*	-0.01568	-0.02322	-0.04934**	-0.02468	-0.02657
	[-1.95]	[-0.91]	[-0.94]	[-2.33]	[-0.72]	[-0.67]
Const	-0.00541***	-0.00058*	-0.00484***	-0.01014***	-0.00219***	-0.00795***
	[-14.07]	[-1.65]	[-9.85]	[-22.06]	[-4.38]	[-12.36]
Obs	389	379	389	389	379	389
R^2	0.024	0.018	0.022	0.050	0.017	0.010

This table reports the full results of the four-factor model on trading performance for day traders and non-day traders. The results are reported for an equal-weighted portfolio for day traders and non-day traders. It also reports the difference in means between day traders and non-day traders. Robust t-statistics are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 2-10 Trading Performance Test on Turnover

	Gross Returns						Net Returns					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Factor	Full	Q4 (High)	Q3	Q2	Q1 (Low)	Diff Q4-Q1	Full	Q4 (High)	Q3	Q2	Q1 (Low)	Diff Q4-Q1
carry	-0.06490	-0.21462*	-0.13211	-0.00425	0.00282	-0.21207	-0.15827***	-0.17672	-0.21075*	-0.01376	-0.19388*	-0.02495
	[-1.60]	[-1.81]	[-1.38]	[-0.07]	[0.04]	[-1.40]	[-2.70]	[-1.42]	[-1.88]	[-0.22]	[-1.65]	[-0.15]
value	-0.01410	0.21300	-0.00312	-0.12218	-0.12109	0.33359	0.18923*	0.16041	0.11123	0.00803	0.10802	0.05873
	[-0.23]	[1.12]	[-0.02]	[-1.50]	[-0.88]	[1.33]	[1.85]	[0.77]	[0.70]	[0.06]	[0.41]	[0.19]
mom	0.02095	0.12069	0.05406	0.02669	-0.08290	0.20826	0.18212**	0.12848	0.13208	0.03546	0.10056	-0.00874
	[0.48]	[0.97]	[0.59]	[0.41]	[-0.79]	[1.18]	[2.46]	[0.91]	[1.18]	[0.54]	[0.64]	[-0.04]
vol	-0.02571*	-0.11048***	0.00372	0.00007	-0.02265	-0.08640*	-0.05898**	-0.10223**	-0.01574	-0.00113	-0.04516	-0.06255
	[-1.88]	[-2.59]	[0.15]	[0.00]	[-0.80]	[-1.75]	[-2.51]	[-2.21]	[-0.65]	[-0.06]	[-1.15]	[-1.02]
Const	-0.00365***	-0.01100***	-0.00591***	-0.00256***	-0.00046	-0.01056***	-0.00874***	-0.01617***	-0.00901***	-0.00450***	-0.00578***	-0.01032***
	[-12.69]	[-12.58]	[-11.59]	[-6.20]	[-0.72]	[-9.47]	[-20.49]	[-16.54]	[-14.62]	[-8.75]	[-7.04]	[-8.24]
Obs	1,908	388	379	381	381	387	1,909	389	379	381	381	389
R^2	0.004	0.027	0.024	0.011	0.007	0.021	0.018	0.019	0.042	0.001	0.019	0.003

This table reports the full results of the four-factor model on trading performance with sorts on turnover. The results are reported for the full sample (column (1) and column (7)) and an equal-weighted portfolio for each quartile of the traders with sorts on turnover. The rank of traders is based on turnover. Highest turnover (Q4) (lowest turnover (Q1)) are traders with the highest (lowest) turnover. It also reports the difference in means between Q4 and Q1. Robust t-statistics are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 2-11 Trading Performance Test on Trades Per Day

	Gross Returns						Net Returns					
	(1)	(2)	(3)	(4)	(5)	(6) Diff	(7)	(8)	(9)	(10)	(11)	(12) Diff
Factor	Full	Q4 (High)	Q3	Q2	Q1 (Low)	Q4-Q1	Full	Q4 (High)	Q3	Q2	Q1 (Low)	Q4-Q1
carry	-0.12550**	-0.24942*	-0.05276	-0.17508	-0.02164	-0.22793*	-0.19122***	-0.25128*	-0.22782**	-0.24818	-0.03522	-0.21607
	[-2.26]	[-1.86]	[-0.53]	[-1.37]	[-0.62]	[-1.66]	[-2.96]	[-1.71]	[-2.15]	[-1.63]	[-0.62]	[-1.39]
value	0.03893	0.11289	0.05275	0.01213	-0.01689	0.12951	0.15711	0.36346	0.43827*	-0.22727	0.05715	0.30632
	[0.41]	[0.45]	[0.28]	[0.07]	[-0.30]	[0.52]	[1.13]	[1.04]	[1.67]	[-0.86]	[0.49]	[1.02]
mom	0.03531	0.05763	-0.00609	0.09417	-0.00520	0.06340	0.16799**	0.16984	0.29699**	0.22953	-0.02282	0.19266
	[0.48]	[0.39]	[-0.03]	[0.57]	[-0.13]	[0.40]	[2.26]	[0.99]	[2.48]	[1.32]	[-0.33]	[1.08]
vol	-0.04520**	-0.12764***	-0.00624	-0.04071	-0.00403	-0.12360***	-0.05224***	-0.14180***	-0.03707	-0.01106	-0.01790	-0.12390**
	[-2.28]	[-3.20]	[-0.13]	[-1.10]	[-0.28]	[-3.18]	[-2.73]	[-3.19]	[-1.11]	[-0.31]	[-0.79]	[-2.58]
Const	-0.00522***	-0.01093***	-0.00683***	-0.00207**	-0.00112***	-0.00980***	-0.00916***	-0.01484***	-0.01226***	-0.00566***	-0.00394***	-0.01091***
	[-12.84]	[-10.50]	[-8.44]	[-2.55]	[-4.10]	[-9.34]	[-20.27]	[-13.80]	[-13.80]	[-6.21]	[-8.71]	[-10.06]
Obs	1,526	378	381	388	379	378	1,528	379	381	389	379	379
R^2	0.007	0.022	0.001	0.015	0.002	0.020	0.021	0.033	0.055	0.052	0.004	0.027

This table reports the full results of the four-factor model on trading performance with sorts on trades per day. The results are reported for the full sample (column (1) and column (7)) and an equal-weighted portfolio for each quartile of the traders with sorts on trades per day. The rank of traders is based on trades per day. Highest trades per day (Q4) (lowest trades per day (Q1)) are traders with the highest (lowest) trades per day. It also reports the difference in means between Q4 and Q1. Robust t-statistics are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 2-12 Trading Performance Test on Volume Per Day

	Gross Returns						Net Returns					
	(1)	(2)	(3)	(4)	(5)	(6) Diff	(7)	(8)	(9)	(10)	(11)	(12) Diff
Factor	Full	Q4 (High)	Q3	Q2	Q1 (Low)	Q4-Q1	Full	Q4 (High)	Q3	Q2	Q1 (Low)	Q4-Q1
carry	-0.10297**	-0.04908	-0.10452	-0.28414***	0.02047	-0.06599	-0.16327***	-0.05924	-0.17225	-0.43808***	0.00784	-0.08225
	[-1.99]	[-0.42]	[-0.82]	[-3.07]	[0.51]	[-0.54]	[-2.61]	[-0.52]	[-1.08]	[-3.79]	[0.13]	[-0.64]
value	0.02830	0.07578	0.11266	-0.01097	-0.06190	0.13911	0.14769	0.03169	-0.02400	0.54182	0.04381	-0.00843
	[0.34]	[0.41]	[0.64]	[-0.06]	[-0.89]	[0.73]	[1.03]	[0.15]	[-0.10]	[1.30]	[0.44]	[-0.04]
mom	0.03976	0.12425	0.04257	-0.07533	0.06386*	0.06392	0.13304*	0.09331	0.21701	0.13558	0.08038	-0.00045
	[0.65]	[1.09]	[0.31]	[-0.49]	[1.72]	[0.55]	[1.72]	[0.76]	[1.24]	[0.71]	[1.13]	[-0.00]
vol	-0.04173**	-0.08639**	-0.03525	-0.06402*	0.01846	-0.10367***	-0.04602**	-0.09744***	0.01968	-0.10215**	-0.00486	-0.09499**
	[-2.39]	[-2.26]	[-1.02]	[-1.65]	[1.26]	[-2.67]	[-2.29]	[-2.65]	[0.49]	[-2.23]	[-0.17]	[-2.37]
Const	-0.00491***	-0.00629***	-0.00755***	-0.00419***	-0.00157***	-0.00477***	-0.00931***	-0.01180***	-0.01287***	-0.00887***	-0.00367***	-0.00813***
	[-13.74]	[-7.54]	[-9.67]	[-5.61]	[-4.71]	[-5.41]	[-21.22]	[-14.65]	[-13.09]	[-8.56]	[-7.90]	[-9.12]
Obs	1,528	389	379	381	379	389	1,528	389	379	381	379	389
R^2	0.007	0.018	0.006	0.024	0.015	0.018	0.016	0.022	0.027	0.061	0.005	0.014

This table reports the full results of the four-factor model on trading performance with sorts on trading volume per day. The results are reported for the full sample (column (1) and column (7)) and an equal-weighted portfolio for each quartile of the traders with sorts on trading volume per day. The rank of traders is based on trading volume per day. Highest trading volume per day (Q4) (lowest trading volume per day (Q1)) are traders with the highest (lowest) trading volume per day. It also reports the difference in means between Q4 and Q1. Robust t-statistics are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 2-13 Trading Performance Test on Social Communication

	Gross Returns			Net Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Factor	Communicative	Non-Communicative	Diff	Communicative	Non-Communicative	Diff
carry	0.01837	-0.11252**	0.12949*	-0.03778	-0.16120**	0.12066
	[0.24]	[-2.02]	[1.66]	[-0.45]	[-2.41]	[1.22]
value	-0.05825	0.01068	-0.07362	-0.10243	0.15440	-0.26771
	[-0.45]	[0.13]	[-0.52]	[-0.77]	[1.35]	[-1.52]
mom	0.01495	0.03488	-0.02249	0.08690	0.11201	-0.03060
	[0.20]	[0.58]	[-0.28]	[0.97]	[1.58]	[-0.28]
vol	0.02843	-0.04829***	0.07422**	0.01653	-0.06531***	0.07645**
	[0.84]	[-2.82]	[2.27]	[0.52]	[-3.17]	[2.05]
Const	-0.00502***	-0.00441***	-0.00054	-0.00798***	-0.00866***	0.00085
	[-8.14]	[-12.78]	[-0.83]	[-11.25]	[-20.16]	[1.10]
Obs	381	389	381	381	389	381
R^2	0.003	0.033	0.018	0.010	0.058	0.019

This table reports the full results of the four-factor model on trading performance for communicative traders and non-communicative traders. The results are reported for an equal-weighted portfolio for communicative traders and non-communicative traders. It also reports the difference in means between communicative traders and non-communicative traders. Robust t-statistics are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Chapter 3: Social Communication and Return Synchronicity: Evidence from FX Retail Traders

Abstract

This paper studies the role of social communication in the return synchronicity of retail traders on a social trading platform (STP). I show that the synchronicity of retail traders' returns is positively impacted by the social communication online, especially by the social activity leaders. In addition, I find that discussion participants in each online discussion topic exhibit significantly positive chat-level return synchronicity. However, I find little evidence that the chat-level return synchronicity of traders in discussion groups can be attributed to chat-level characteristics, such as the number of participants, the number of comments, and the number of likes. Overall, the evidence implies that social communication online reduces the level of disagreement among retail traders, through the information content of the online discussions. This is reflected in the fact that when there is more social communication online, there is a higher level of return synchronicity among traders. The evidence is consistent with the notion that social communication online alters retail traders' behavioral changes (Heimer, 2016).

Keywords

Return Synchronicity, Information Environment, Disagreement, Behavioral Finance, Retail Traders, the FX Market

3.1 Introduction

Disagreement has been an important concept in finance (Fama & French, 2007; Hong & Stein, 2007; Sadka & Scherbina, 2007). Traditionalists argue that disagreement generates trading activities and affects asset prices in financial marks (Hong & Stein, 2007). Regarding trading activities, Hong & Stein (2007) introduce the concept of "disagreement models" to refer to models which speak directly to the joint behavior of stock prices and trading volume. In terms of asset prices, disagreement among investors is associated with a positive risk premium (Carlin et al., 2014). In the currency market, MacDonald & Marsh (1996) show that disagreements among foreign exchange forecasters are key variables in terms of determining the market trading volume. If there is no disagreement among traders, they should not trade.

Such disagreement in the market can be related to various factors, for example, information environment (Crawford et al., 2012; Piotroski & Roulstone, 2004). Piotroski & Roulstone (2004) find that analyst forecasts provide industry-specific and market-specific information, resulting in a higher level of stock return synchronicity. In contrast, insider trading activities produce firm-specific information, which is associated with a lower level of stock return synchronicity. The evidence indicates that the information environment impacts the level of return synchronicity in the stock market. In the currency market, MacDonald & Marsh (1996) find that the idiosyncratic interpretation of widely available information among foreign exchange forecasters is associated with economically different forecast accuracy. When there is less disagreement among traders, they tend to have a higher level of similarity in terms of their trading activities as they perceive the market conditions in a similar way. This similarity in their trading activities is reflected in the similarity of their subsequent returns, resulting in a higher level of return synchronicity.

However, the existing literature regarding return synchronicity mainly focuses on the stock market. This paper investigates a different level and a different type of financial market: the platform level (the trading activities of traders within a trading platform) and the foreign exchange (FX) market. After the 2008 financial crisis, there has been an increase in the development and usage of Social Trading Platforms (STPs) which integrate social media features into trading activities (Cetina, 2003; Gemayel & Preda, 2018a, 2018b). Specifically, individual traders on STPs can organize their trading activities and, at the same time, communicate amongst others. There are typically two social communication features on STPs: the online discussion forum feature and the one-to-one messaging feature. The online discussion forum feature is significant. Under this online discussion forum, traders create online discussion topics, post comments under discussions, and like posted comments. The contents of the online discussion forum are viewable by all traders on the platform. This social communication feature potentially influences the decision-making of the traders on the STP and their subsequent trading activities and return patterns (Heimer, 2016; Hirshleifer, 2015). The one-to-one messaging feature is among connected two-person pairs based upon approval of friend requests. This feature is supposed to be less influential on the entire trading community on the STP compared to the online discussion forum feature, as other traders cannot see what has been discussed between two connected traders. However, given the social communication features, there are two puzzles: (1) why are these social communication features combined with trading, and (2) what are the influences of these features on retail traders' trading activities and the patterns of returns?

One significant difference between traditional trading platforms and social trading platform arises in the information environment surrounding traders on the platforms. The information environment refers to the platform-level information environment on a trading platform and is defined as the variation in information asymmetry among traders on the platform, informativeness of widely available information, and private information gathering and sharing (Armstrong et al., 2012; Beyer et al., 2010; Frankel & Li, 2004). The information environment of STPs can be different from traditional trading platforms. This is because traders on traditional platforms do not communicate with others and they make independent decisions. On STPs, traders communicate with others. Traders share their trading activities, interpretation of widely available information, and potential private information. One trader's interpretation of widely available information can be different when they communicate with others compared to when this trader does not communicate. Therefore, traders' decision-making can be impacted through their communication with others (Hirshleifer, 2015). However, it is not known in literature whether and how the differences in the information environment impacts the level of disagreement among traders on a social trading platform.

I study how platform-level disagreement (proxied by return synchronicity) is related to the information environment (proxied by social communication) on one STP. If there is less disagreement among traders, I would expect a higher level of return synchronicity among traders as they tend to have a higher level of similarity in their trading activities and subsequent returns. If there is social communication online, I would expect an improved information environment as the information transmission process is more transparent, accessible, and equitable among traders. This is because the information environment surrounding traders has a higher level of transparency and a lower level of opacity which reduces the information asymmetry among traders. Therefore, the information environment improves through the social communication among traders on the STP. However, an improved information environment does not necessarily indicate a higher level of the quality of information which is available to traders. Instead, it means a higher level of transparency and a lower level of information asymmetry among traders on the STP, which leads to the changes in the disagreement among traders.

I address the research question: *does social communication impact the return synchronicity of retail traders?* The question concerns whether social communication produces or reduces platform-level disagreement among retail traders. If there is a lower level of disagreement among retail traders, they should have similar trading activities and thus similar returns, at least in the direction of their returns (i.e. positive/negative). Therefore, a lower level of disagreement among retail traders should be associated with a higher level of co-movements in their returns (measured by return synchronicity). In contrast, if there is a higher level of disagreement among retail traders, they should have more diverse trading activities and thus different returns, resulting in a lower level of return synchronicity. Consequently, the return synchronicity of retail traders reflects the extent to which retail traders disagree with others.

To understand the real effect of social communication on the return synchronicity of retail traders, I pay close attention to the discussions they have on a particular social trading platform. I present a number of detailed examples of the online discussion contents. These examples help to identify the potential mechanisms through which social communication impacts the level of disagreement among traders, which is associated with the level of synchronized trading activities and thus the level of return synchronicity of retail traders.

STPs enable retail traders to conduct their trading activities and, at the same time, communicate among others. The communication feature is an essential channel which allows information exchange between one trader and another. In terms of how this communication feature impacts the entire trading community on the STP, the discussion forum feature would be particularly important to serve as a space for information exchange. This is because the forum feature is distinct from the one-to-one messaging in the sense that the discussion contents are visible to all the traders on the STP.

On the one hand, the transparency of the information (discussion contents) would suggest a better platform-level information environment, compared to an opaque information environment (without this online discussion forum feature). Supposing there is only a one-to-one messaging feature available, the other traders would not know what information has been exchanged (what has been discussed) by a closely connected two-person group. However, the online discussion forum feature, in contrast, would allow an instant transmission of information to the entire trading community on the STP as soon as the discussion contents are posted in the forum. Even though the amount of time it takes for this information to reach each trader differs, this forum provides a powerful setting for traders to instantly exchange information and disclose this information to others.

On the other hand, the contents of the online discussion forum also help traders to establish consensus with others. Traders can discuss their understanding of the current market situation and their subsequent trading activities, expectations, and proposed reactions to different future states of the market. As seen in Appendix 3-1, under the discussion topic "USD/CAD trade" (id: 19), a trader (commenter id: 92) mentioned "looks like a dead dog bounce that will be short lived. I tend to agree with Darren on this one" at 02APR2009:19:03:48. This indicates that the level of disagreement among traders decreases after their discussion on this topic, as it is mentioned "I tend to agree." It is possible that this discussion impacts other traders who see it in a similar way in terms of the consensus reached between the discussion participants.

Another example can be seen under the discussion topic "New No-Hedge CFTC rules should create additional volatility" (id: 130), where the discussion initiator (creator id: 234) shared a particular piece of information, "FYI, today is the day CFTC rules came into effect banning hedging. We may see additional volatility from this." This discussion topic would also facilitate the understanding of the market condition for the traders on the STP. One reason can be that a trader (commenter id:188; name: Max) responded that "If there is any volatility today it's going to be influenced by any news that comes out and the fact that it's option expiration so equity markets will be more volatile." This indicates that the trader Max is to some extent influenced by the discussion initiator, as Max makes his predictions according to the information provided. As a consequence, it is possible that other traders who see this discussion might be influenced in a similar way to Max. Thus, there would be more consensus among traders based upon the discussion of this topic. Even if there might be traders who view this discussion and disagree with Max's interpretation, these traders might also exhibit a higher level of similarity in their subsequent behavior based upon their disagreement.

Taken together, the online discussion forum feature allows for a transparent information exchange environment and provides a virtual space to produce a lower level of disagreement (a higher level of consensus) among traders. In other words, the online discussion forum feature reduces the level of disagreement among traders on the STP through a transparent information environment. A lower level of disagreement leads to a higher level of synchronized trading activities. Consequently, the return synchronicity is expected to be higher and positively associated with the online social communication. Therefore, I hypothesize that ***social communication positively impacts the return synchronicity of retail traders (H1)***.

This paper examines the impact of social communication (information environment) on retail traders' return synchronicity (disagreement) within a social trading platform. Using a panel VAR model, a Granger causality identification, and impulse response functions (IRFs), I identify a causal link between social communication and return synchronicity. Specifically, social communication improves the online information environment (platform-level) and increases the return synchronicity of traders on the STP, indicating that social communication reduces the disagreement among traders.

Return synchronicity of individual stocks has been investigated by an extensive body of literature (e.g., Piotroski & Roulstone, 2004; Chan & Hameed, 2006; Crawford, Roulstone, & So, 2012; Ye, 2012). The return synchronicity in the stock market reflects important information about the information environment of the market (e.g., Piotroski & Roulstone, 2004). For example, Piotroski & Roulstone (2004) show that analyst forecasts are associated with industry-specific and market-specific information, which brings a higher level of stock return synchronicity. While insider trading activities are associated with firm-specific information, resulting in a lower level of stock return synchronicity. The evidence indicates that the differences in the information environment is closely related to return synchronicity in the stock market (Piotroski & Roulstone, 2004).

However, the information environment is not only important in the stock market. It also matters in other types of organizations of trading (e.g., social trading platforms). On social trading platforms, traders can communicate among others through online discussion forums while trading. The online discussion forum feature allows for a transparent information exchange environment and provides a virtual space for traders to establish consensus with others. This is because the content of the online discussion forum is viewable by all the registered traders on the STP. Specifically, traders can raise questions in the discussion forum and other traders can help to solve their questions. Also, traders can share updates on the market conditions or regulations to help each other to understand or predict the market movements. By clarifying the discussion questions and exchanging information, traders would have a lower level of disagreement among others, which therefore influences their trading activities and the patterns of returns. Some examples of the discussion topics are provided in Appendix 3-1.

Nevertheless, from a micro level, there is a lack of evidence in literature in terms of how social communication impacts the individual traders and, through which mechanisms, it impacts the traders' trading activities and the patterns of returns. I address this issue by hypothesizing that social communication reduces the level of disagreement among retail traders. This would suggest that social communication increases the return synchronicity of traders.

I use a novel dataset, which contains the full trading records of 3,426 traders over an 18-month period, to investigate the return synchronicity of these traders in relation to their social communication on the trading platform. This is possible due to the fact that the dataset is from a new form of organization of trading: Social Trading Platforms (Cetina, 2003; Gemayel & Preda, 2018a, 2018b; Heimer, 2016), where individual traders can establish their trading positions and, at the same time, communicate with others on the platforms (e.g., online discussion forum). Therefore, I establish a link between traders' return synchronicity and their social communication activities, thanks to the unique setups of the STP.

I construct two measures of return synchronicity of individual traders on the STP based upon the synchronicity measure used in the stock market (Morck et al., 2000). The two measures are the *platform-level return synchronicity* f_{jt} and the *trader-level return* *synchronicity* g_{it}. The *platform-level return synchronicity* f_{jt} captures the level of return co-movements (up or down) of all the traders on the STP. The *trader-level return synchronicity* g_{it} captures the level of co-movements of each individual trader's return with the entire platform's return movements (up or down). Specifically, the *platform-level return synchronicity* can be interpreted as the extent to which the returns of all traders are synchronized on the platform in a particular day. The *trader-level return synchronicity* can be interpreted as the extent to which an individual trader's return is synchronized with the co-movements of all the traders' returns on the platform.

The two measures are designed to capture the return synchronicity (co-movements) of individual traders on the STP, namely, the return co-movements among all the traders on the STP (*platform-level return synchronicity*) and the return co-movements between an individual trader and all the traders on the STP (*trader-level return synchronicity*). The synchronicity of returns reflects the level of disagreement among traders on the STP. Given the constructions of the two measures, I investigate the relationship between social communication and the platform-level/trader-level return synchronicity on the STP. If the two levels of return synchronicity are positively (negatively) impacted by social communication, it evidences the fact that social communication decreases (increases) the disagreement among individual traders. In addition, the relationship between social communication and return synchronicity also indicates behavioral changes among retail traders on the STP. Specifically, traders can be influenced by others in terms of how synchronized their trading activities are.

I use a panel VAR framework to examine the impact of social communication on the above-discussed two levels of return synchronicity. Using a panel VAR framework, together with Granger causality tests, and impulse response functions (IRFs), I show that both the platform-level return synchronicity and the trader-level return synchronicity are positively impacted by the social communication online. I also show that social communication leaders (traders who create discussion topics on the discussion forum) positively impact the platform-level return synchronicity, indicating that social communication leaders are influential on the platform-level return patterns.

In addition, I construct a chat-level return synchronicity measure, using the average pairwise return correlation among chat participants in each online discussion, to examine (1) whether chat participants in each online discussion exhibit synchronized returns, and (2) whether this chat-level return synchronicity can be explained by chat-level characteristics (i.e. the number of participants, the number of comments, and the number of likes). I measure the chat-level return synchronicity as the average pairwise return correlation among each discussion group, including traders who create the discussion topic, post a comment, and like a comment under each discussion topic.

I show that chat participants exhibit significantly positive chat-level return synchronicity, indicating that these participants have obtained consensus through their discussions. This consensus (reduced disagreement) results in significantly positive return correlations among chat participants. Furthermore, I find evidence that this positive chat-level return synchronicity is more significant in market-related chat topics (e.g., question-related topics and market-related topics). However, I find little evidence that the chat-level return synchronicity can be explained by the chat-level characteristics (i.e. the number of participants, the number of comments, and the number of likes). This suggests that the return synchronicity is attributed to the information content of the online discussions instead of the chat-level characteristics.

Overall, the evidence suggests that the return synchronicity of retail traders on the STP is positively impacted by the social communication online. In addition, the evidence shows that social communication leaders are influential on the platform-level return synchronicity. Chat participants exhibit synchronized returns, especially in market-related discussion topics. These results indicate that social communication reduces the disagreement among individual traders, through the information content of the online discussions. The results are consistent with the literature which suggests that social communication plays a role in retail traders' trading behavior (Cetina, 2003; Gemayel & Preda, 2018a, 2018b; Heimer, 2016; Hirshleifer, 2015; Preda, 2017). In addition, my results are confirmed by additional robustness tests.

The remainder of the paper proceeds as the following. Section 3.2 discusses the related literature. Section 3.3 describes the data. Section 3.4 introduces the methodology. Section 3.5, 3.6, 3.7, and 3.8 present the empirical results of the impact of social communication on the platform-level, the platform-level (social leader), the trader-level, and the chat-level return synchronicity, respectively. Section 3.9 performs additional robustness tests. Section 3.10 concludes the paper.

3.2 Literature Review

3.2.1 Stock Market Return Synchronicity

A large body of literature has documented the presence of stock market return synchronicity both in developed markets and emerging markets (Chan & Hameed, 2006; Crawford et al., 2012; Piotroski & Roulstone, 2004; Ye, 2012). The synchronicity of stock market returns is more prevalent in emerging markets (Chan & Hameed, 2006; He et al., 2013; Khanna & Thomas, 2009; Martens & Poon, 2001; Morck et al., 2000), which can be particularly well explained by higher fundamental correlations and lower property rights

(Morck et al., 2000). Morck et al. (2000) argue that strong property rights are related to increased informed arbitrage.

However, the existing evidence on return synchronicity largely focuses on stock markets, which examines (1) the extent to which individual stock returns can be explained by market- and industry-level stock returns, and (2) what factors influence the synchronicity (e.g., Piotroski & Roulstone, 2004). One factor influencing the stock market return synchronicity is the analyst coverage, which produces firm-specific, industry- and market-level information and changes the information environment of the market (Crawford et al., 2012; Piotroski & Roulstone, 2004).

However, little evidence is seen in literature about the return synchronicity of individual traders in the market. This might be due to the fact that individual traders' trading activities are not typically observable or accessible to researchers. I exploit a powerful setting on the STP to examine individual traders' return synchronicity. In addition, little is known about why individual traders should synchronize their trading activities and, as a consequence, increase the synchronicity of their trading returns. One possibility for return synchronicity is that traders establish consensus through information exchange (i.e. social communication), which improves the information environment of the traders' community and thus decreases the disagreement among traders. This paper examines the impact of social communication (information environment) on the return synchronicity of traders (disagreement).

3.2.2 The Emergence of Social Trading Platforms

Two questions are central to investigate the relationship between social communication and return synchronicity. First, how do individual investors exchange essential information so that they can have synchronized trading activities and thus synchronized trading returns? Second, how are individual traders connected, and under which specific type of trading environment can individual traders synchronize their trading activities and returns?

These questions can be further explored thanks to the emergence of a specific type of organization of trading (STPs) that arose after the 2008 financial crisis (Cetina, 2003; Gemayel & Preda, 2018a, 2018b). STPs are trading platforms with integrated social networks, where retail traders are able to communicate within the platform among other traders through a number of ways. They can join online discussions and they can send one-to-one messages with connected traders based upon the approval of an electronic friend invitation. As a consequence, the traders on such STPs are, by construct, naturally connected through the online communication features. The social networks embedded on such STPs are supposed to improve the information environment of retail traders by allowing transparent information exchange. Therefore, an improved information environment through communication can reduce the disagreement among traders and allow them to have synchronized trading and returns.

Therefore, trading synchronicity and return synchronicity might be possible on such STPs given the above-discussed feature (i.e. communication feature). This is because social communication potentially reduces the disagreement among traders, which allows traders to have synchronized trading activities and synchronized returns. Consequently, I hypothesize that the platform-level return synchronicity is impacted by social communication on the trading platform. This paper uses return synchronicity as a proxy of the disagreement among traders. A higher (lower) level of return synchronicity indicates a lower (higher) level of disagreement among traders.

3.2.3 The Social Media Influence on Financial Markets

The impact of social media on investor behavior is not new in literature. Prior literature shows a causal impact of media in financial markets both on trading activities (Engelberg & Parsons, 2011) and stock market returns (Huberman & Regev, 2001). Evidence shows that by linking US cities' media coverage and local trading actives, media coverage significantly impacts local trading (Engelberg & Parsons, 2011). A *New York Times* article significantly influenced a biotechnology company's stock prices by influencing the public attention and enthusiasm (Huberman & Regev, 2001). Apart from the influence of traditional media on financial markets, new forms of social media (e.g., Facebook and Twitter) also alter the trading activities of individual investors and stock prices (Azar & Lo, 2016; Heimer et al., 2015; Kuss et al., 2013).

In addition, social activities are influential to individual investors' financial decisions (Guiso & Jappelli, 2005; Hong et al., 2004). For example, social interactions increase the probabilities of individuals to invest in the stock market (Hong et al., 2004), whose decisions can be partially due to the increase of awareness of the existence of potential investing opportunities and instruments through social interactions (Guiso & Jappelli, 2005).

STPs allow both the features of social media and online social interactions (through communication). To be specific, each trader on the STP can have their own homepage (like on Facebook) to be connected with other traders (Heimer, 2016). They can also participate in online discussion forums to enjoy social interactions with other traders through communication. Therefore, the social communication feature is expected to be associated with changes in the behavior of traders (Hirshleifer, 2015).

3.2.4 Retail Traders in the FX Market

Retail traders' trading activities and trading behavior have drawn much attention in recent years, particularly in the foreign exchange (FX) market. One reason is that retail traders' trading behavior in the FX market exhibits similar properties compared to retail traders in the equity market. For instance, Heimer (2016) finds that FX retail traders exhibit similar behavior in the disposition effect compared to equity retail traders. To be specific, the disposition effect is found to double after access to the social communication feature among FX retail traders on the STP (Heimer, 2016).

Another reason is that the FX market is the largest financial market in the world, which allows retail traders to trade with the largest possible liquidity (Hayley & Marsh, 2016; Heimer, 2016). Retail traders have easy access to the FX market through brokers with access to leverage trading (Heimer & Simsek, 2019). These retail traders are sometimes trading through online trading platforms, which are good settings as natural experiments to observe individual traders' trading behavior. Furthermore, there are social trading platforms, which are dedicated to retails traders. As such, researchers are able to investigate retail traders' trading behavior in relation to their social activities in the FX market.

To summarize, given the above-discussed literature, I hypothesize that the usage of the social communication feature on STPs, which allows individual traders to communicate amongst others, has a substantial impact on the return synchronicity of individual traders. This is because social communication improves the information environment on the STP and reduces the disagreement among traders. However, there is very little evidence in the literature which investigates individual traders' return synchronicity. Retail traders may synchronize their trading activities for potentially better financial decisions and better financial performance (Saavedra, Hagerty, & Uzzi, 2011; Saavedra, Duch, & Uzzi, 2011). Nevertheless, Saavedra et al. (2011) focus on the association between trading synchronicity and financial performance, showing that more synchronization of trading activities among traders is associated with less likelihood to lose money. In addition, they find that instant messaging patterns are closely associated with trading synchronicity. However, it is not yet clear whether social communication impacts the return synchronicity of traders. Therefore, this paper studies the impact of social communication on retail traders' return synchronicity in the FX market. Social communication is related to the information environment on the STP and return synchronicity is an indication of the level of disagreement among traders.

This paper has several contributions to literature. First, this paper contributes to the literature on return synchronicity. To be specific, prior studies mostly focus on the return synchronicity of individual stocks in the equity market (Crawford et al., 2012; Khanna & Thomas, 2009; Piotroski & Roulstone, 2004), whereas this paper focuses on the return synchronicity of individual traders. The return synchronicity of retail traders reflects information on trader-level decision-making processes, as opposed to the collective information in a stock's returns formed by numerous investors trading one stock. This paper highlights the importance of retail traders' return synchronicity in reflecting the level of disagreement among traders on a platform level. A higher level of return synchronicity is related to a lower level of disagreement among traders.

Second, this paper contributes to the literature on retail traders in the FX market. There is a very limited range of literature focusing on retail traders' behavior in the FX market (Abbey & Doukas, 2015; Hayley & Marsh, 2016; Heimer, 2016). This paper adds to this strand of literature by presenting evidence on the return synchronicity of retail traders in the FX market, in relation to the social communication online. This evidence helps to better understand the return patters of individual traders.

Third, this paper contributes to the research regarding the relationship between social communication and behavioral changes (Heimer, 2016). Return synchronicity of retail traders reflects information about the synchronicity of their trading activities and the information available to traders. Specifically, the platform-level return synchronicity would be positively related to social communication online, if traders tend to have synchronized trading activities given the presence of social communication online. This prediction is confirmed by this paper.

3.3 Data

I use a novel dataset to explore the relationship between social communication and return synchronicity. The dataset is from a Social Trading Platform from early 2009 to mid-2010 (18 months), which records all the trading activities (1.1 million observations) made by all the traders (4,731 traders) on the platform. Therefore, there should be no concerns regarding potential sample selection bias, which appears to be an issue for some other studies using self-reported trading records.

This STP focuses on FX trading, where users can trade different currency pairs and communicate at the same time. One of the key features of the STP is the social communication feature. The social communication feature is that traders can join two types of social communications online: one is the online forum discussion and the other is the one-to-one messaging feature (Heimer, 2016). In this paper, I focus the online forum discussion of the social communication feature which is viewable to all the traders online. The online forum discussion is supposed to be more influential to the trading activities of all traders on the STP, in terms of providing platform-wide information. The platform-wide influence of the social communication feature is related to the platform-level return synchronicity which is the focus of this paper. In the online discussion forum, traders can enjoy three types of social participation activities: creating a discussion topic, posting a comment under a discussion topic, or liking a comment.

For the purposes of the empirical analysis of this study, I perform a slight data trimming. I select traders who start their trading activities within the sample period to make sure that I am able to observe their trading behavior since she/he joins the STP. I select traders with at least two days of active trading (with closed trades). After this data trimming, my sample includes 3,426 traders, among whom 699 (20.4%) traders are actively involved with the online discussion forum feature, and 2,727 (79.6%) traders are not involved with this feature, however, they can view the discussions of other traders' in the discussion forum.

3.4 Methodology

I employ a panel VAR model as my baseline model. Combining Granger causality tests and impulse response functions (IRFs), I explore the impact of social communication on the return synchronicity of retail traders. The main variable of interest (dependent variable) is the return synchronicity. I measure it in two ways as follows: the platform-level return synchronicity (f_{jt}) and the trader-level return synchronicity (g_{it}).

By adapting the stock return synchronicity measure in Morck, Yeung & Yu (2000), this paper constructs a platform-level return synchronicity measure and a trader-level return synchronicity measure. The platform-level return synchronicity captures the level of co-movements (up or down) of traders' returns across the platform in a given day. The trader-level return synchronicity captures the extent to which a trader's return co-moves with the majority traders' returns (winning or losing) across the platform in a given day.

To be specific, the platform-level return synchronicity is measured as $f_{jt} = \frac{\max[n_{jt}^{up}, n_{jt}^{down}]}{n_{jt}^{up} + n_{jt}^{down}}$. f_{jt} is the platform-level (platform j) return synchronicity in day t. n_{jt}^{up} is the total number of traders with a positive return in day t. n_{jt}^{down} is the total number of traders with a negative return in day t. The platform-level return synchronicity (f_{jt}) represents the proportion of traders who end up with a similar pattern of returns (either winning or losing), capturing how synchronized the returns are for the traders on a particular day. A higher platform-level return synchronicity indicates a higher proportion of traders who end up with winning/losing, implying potentially similar trading activities of these traders.

The second step is to construct a trader-level return synchronicity measure for each trader in a given day. The trader-level return synchronicity measure is given by $g_{it} = D_{it} \times f_{it} = D_{it} \times \frac{\max[n_{jt}^{up}, n_{jt}^{down}]}{n_{jt}^{up} + n_{jt}^{down}}$. g_{it} represents the return synchronicity of trader i in day t. D_{it} is a dummy variable indicating the profitability of trading for trader i in day t (1 if same with the market movement direction (up or down), -1 if opposite to the market movement, and 0 if not trading). f_{jt} represents the platform-level (platform j) return synchronicity in day t (n_{jt}^{up} is the total number of traders in day t with positive returns, and n_{jt}^{down} is the total number of traders with negative returns). This trader-level measure captures the level of co-movements of a trader's return in comparison to the return pattern (winning or losing) of the majority of the traders in a given day. A higher level of trader-level return synchronicity indicates a trader's return co-moves with the majority traders' returns, implying potentially similar trading activities of this trader to the majority traders.

Apart from the return synchronicity measures, other variables used in the panel VAR model include social_times, dollar_PnL, leverage, intraday_vol, and maxdd. *Social_times* denotes the number of times of social communication in the online discussion forum feature (creating a discussion topic, posting a comment, or liking a comment) during any given day for each trader. *Dollar_PnL* denotes the dollar value of profits or losses for each trader in any given day. *Leverage* denotes the average leverage that a trader uses in a trading day. *Intraday_vol* and *maxdd* denote intraday volatility and maximum drawdown. Table 3-1 presents the summary statistics for the variables used in the paper.

[Insert Table 3-1]

In addition, for all the panel VAR models used in this paper, I apply the Helmert transformation to remove panel-specific fixed effects (Abrigo & Love, 2016; Arellano & Bover, 1995), which minimizes the data loss for unbalanced panels.

3.5 Social Communication and Platform-level Return Synchronicity

In this section, I examine whether social communication impacts the platform-level return synchronicity. If social communication positively (negatively) impacts the platform-level return synchronicity, it indicates social communication reduces (increases) the disagreement among retail traders.

I use a panel VAR model to identify the impact of *social_times* on the platform-level synchronicity (dependent variable f_{jt}). The key variable of interest in this section is the platform-level return synchronicity (f_{jt}), which measures the return synchronicity of the entire platform. A larger (smaller) platform-level return synchronicity (f_{jt}) indicates that more (less) traders are synchronized in terms of their returns. Since this measure is the platform-level return synchronicity, it is identical for every single trader in any given day in the panel VAR framework. The results show that the platform-level return synchronicity significantly increases after social activities. The results are significant and can be seen in the panel VAR model, and the Granger causality tests.

The panel VAR model includes variables for each investor in any given day: platform-level return synchronicity (f_{it}), social_times, dollarPnL, maxdd, intravol, and leverage. To use the panel VAR model, I have to make sure that all the variables used in the model are stationary. Therefore, I perform unit root tests (Fisher type – Dfuller test) for all the variables. The results of the unit root tests indicate that all variables used in the panel VAR system are stationary.

Then, I perform a model selection to identify the optimal orders for the variables to appear in the model. I use the first three orders in the panel VAR model with the first four lags of all variables as instruments to identify the optimal lag order for the variables of the model specification. Based on the MAIC and the MQIC criteria, the preferred lag order is two (Table 3-2).

[Insert Table 3-2]

3.5.1 Panel VAR Results

The panel VAR model is specified as in the model selection section, where the variables are with two lags maximum and with the first four orders as instruments. The results of the panel VAR model suggest that the *social_times* (with 1 lag or 2 lags) is significantly positively associated with the platform-level return synchronicity. The results (Table 3-3) show that social communication online is positively associated with the platform-level return synchronicity. The evidence may indicate a positive impact of social communication on the return synchronicity. However, I have to further perform a Granger causality test to identify the causality between social communication and the platform-level return synchronicity.

[Insert Table 3-3]

3.5.2 Granger Causality Results

The results (Table 3-4) of the Granger causality tests show that social communication Granger causes the return synchronicity. The evidence shows that the social communication online increases the platform-level return synchronicity, indicating that social communication reduces the disagreement among traders on the STP.

[Insert Table 3-4]

Overall, the evidence from panel VAR identification and Granger causality tests implies that social communication reduces the disagreement among traders, leading to a higher level of synchronized trading activities which is reflected in a higher level of return synchronicity.

3.5.3 Impulse Response Functions

Furthermore, I estimate the impulse response functions (IRFs) to investigate the sensitivity of the platform-level return synchronicity to social communication. The IRFs capture the response of one variable (response) in the panel VAR system to a one standard deviation shock of another variable (impulse).

Therefore, the variables of interest in here are the return synchronicity (response) and social communication (impulse). Specifically, I am interested in the response of the platform-level return synchronicity (mkt_sych) to a one standard deviation shock in social communication (social_times).

[Insert Figure 3-1]

As shown in Figure 3-1, there is not a clear pattern of the response of the platform-level returns synchronicity to a one standard deviation shock in social communication. This may indicate that the response of the platform-level return synchronicity might be sensitive to different types of social communication activities. For example, there are social communication activities initiated by different people who are of different influence or popularity on the STP.

Therefore, it makes sense to further investigate the impact of a decomposition of social communication initiated by different types of communicative traders (creators, commenters, and likers). In the next section, I investigate the impact of social communication of different traders on the platform-level return synchronicity, which sheds light on the influence of communicative traders on the STP.

3.6 Social Communication Leaders and the Platform-level Return Synchronicity

The evidence shows that the social communication increases the platform-level return synchronicity, indicating that social communication reduces the disagreement among traders. However, the online discussions are associated with different groups of people: creators who initiate a discussion topic, commenters who post a comment under a discussion topic, and likers who like a post. It can be the case that these people have different degrees of influence on the platform-level return synchronicity, if other traders pay different levels of attention to different groups of people. Those chat initiators' (creators) social activities might be in a sense more influential for people on the STP. In this section I define social communication leaders as those who lead the discussions, namely, creators and commenters (excluding likers).

I note here that a chat initiator can also be a commenter and/or a liker. However, one trader enters each of the categories (creator, commenter, and liker) as long as she/he participates at any point in creating, commenting, or liking. As most chat creators are also engaged in chat commenting (as can be seen in Appendix 3-1), the two categories *creator* and *commenter* are overlapping to a large extent. Therefore, I expect these two categories to exhibit similar influences on the platform-level return synchronicity. I expect the category *liker* to exhibit the weakest influence on the platform-level return synchronicity, as it is intuitive that people are less influential if they tend to like other people's opinions as opposed to offering their own opinions.

In this section, I examine whether different groups of people (creators, commenters, and likers) have different levels of influence on the platform-level return synchronicity. I show that the social activity participants in different categories (initiator, commenter, liker) all positively influence the platform-level return synchronicity. To be specific, the social communication leaders (chat initiators/creators) significantly increase the platform-level return synchronicity, indicating that social communication leaders (creators) matter in terms of reducing the disagreement among retail traders on the platform. However, likers exhibit the least influence in terms of significance level. These results indicate that social communication participants impact the platform-level return synchronicity to different extents.

3.6.1 The panel VAR model

To investigate how the levels of influence on the platform-level return synchronicity differ from different groups of people (creators, commenters, and likers), I use a panel VAR model to identify the impact of *social_times* on the *platform-level return synchronicity* (dependent variable f_{it}). To do this, I choose a subsample of chat initiators (who create discussion topics on the STP) to perform the model (with observations of the chat initiators only). Similarly, I also perform the same tests among subsamples of chat commenters and chat likers.

The panel VAR model specification used is the same as discussed in the previous section, with two lags of each variable and with the first four lags of the variables as instruments. The results are reported in Table 3-5 and associated with categories of creators

(Panel A), commenters (Panel B), and likers (C). The results show that the coefficients (Panel A and Panel B) are positive and significant for both the first-order social_times (L.social_times) and the second-order social_times (L2.social_times) for both chat creators and commenters. As expected, the magnitudes of the coefficients and significance levels are quite similar for these two categories (creator and commenter). The evidence indicates that the social activities of social communication leaders' (creator/commenter) are significantly associated with the platform-level return synchronicity.

However, the results (Panel C) for the category *liker* are either not significant (L.social_times) or not very significant (L2.social_communication) (at the significance level of 10%). The results suggest that the social communication of likers is not significantly associated with the platform-level return synchronicity, indicating that likers' social activities exhibit a much lower association with the platform-level return synchronicity compared to the other social communication leaders (creator/commenter).

[Insert Table 3-5]

3.6.2 Granger Causality Test

Then, I perform Granger causality tests to examine whether *social_times* Granger causes an increase in the platform-level return synchronicity for the three categories of social communication participants (creator, commenter, and liker). The results of the Granger causality tests are reported in Table 3-6. The three panels (Panel A, B, and C) represent the results for the categories of creator, commenter, and liker, respectively.

[Insert Table 3-6]

Consistent with the findings in the panel VAR identifications (Table 3-5), the results suggest that the social communication (social_times) for both creators and commenters Granger causes the platform-level return synchronicity at a significance level of 1%. In contrast, the social communication of likes does not Granger cause the platform-level return synchronicity. Overall, the evidence shows that the platform-level return synchronicity is positively affected by the social activities of social communication leaders (creator/commenter), as opposed to likers. This suggests that social communication leaders impact the pattern of returns on the STP, particularly, the platform-level return synchronicity.

3.6.3 The Impulse Response Functions

I further estimate the impulse response functions (IRFs) for different groups of chat participants: creators, commenters, and likers. The results are reported in Figure 3-2, Figure 3-3, and Figure 3-4, respectively. Interestingly, the impulse response functions show that the platform-level return synchronicity only significantly responses to the one standard deviation shock of the social communication of chat initiators (creators). This might indicate that creators are to some extent more influential than commentors which cannot be captured by the panel VAR model and the Granger causality tests.

[Insert Figure 3-2]

[Insert Figure 3-3]

[Insert Figure 3-4]

As shown in Figure 3-2, for chat creators, a one standard deviation increase in *social_times* significantly increases the platform-level return synchronicity in the first one to two days after the social communication. However, this relationship is not significant in Figure 3-3 and Figure 3-4, suggesting that this relationship is more pronounced among creators, as opposed to commenters and likers. This also clarifies why the pattern in Figure 3-1 for all the chat participants without differentiating categories is not clear.

Overall, the results indicate that the influence of social communication initiated by chat creators is stronger than those by chat commenters and likers, in terms of the platform-level return synchronicity. Together with the results from panel VAR identifications and Granger causality tests, I conclude that the social communication leaders, chat creators in particular, exhibit the strongest influence on the platform-level return synchronicity, compared to other chat participants.

3.7 Social Communication and the Trader-level Return Synchronicity

In this section, I investigate whether/how the trader-level return synchronicity (g_{it}) is influenced by social communication using a panel VAR framework, which allows me to specify the short-term impact of social communication on trader-level return synchronicity. The trader-level return synchronicity (g_{it}) captures the extent to which an individual trader's return co-moves with the returns of the rest of the traders on the platform. Therefore, this measure (g_{it}) implies the level of disagreement between individual traders and other traders on the STP.

A higher trader-level return synchronicity (g_{it}) indicates a higher level of similarity in the return co-movements between a particular trader's return and the rest of the returns (of other traders), suggesting that this trader does not perform much differently from the majority of the traders in terms of his/her return. Meanwhile, it also implies that this trader's disagreement with the rest of the traders is low, which is reflected in their return patterns (high return co-movements/high trader-level return synchronicity).

I show that social communication positively impacts the trader-level return synchronicity. The results suggest that retail traders' returns are influenced by social communication online and social communication increases the level of synchronicity between a trader's return and the rest of the traders' returns on the platform. This evidence indicates that, for each trader, social communication online reduces his/her disagreement with other traders, resulting in her/his return being more synchronized with the others' returns. The results are consistent with the evidence regarding the platform-level return synchronicity, suggesting that social communication reduces the disagreement among traders on the STP.

To be specific, I employ a panel VAR framework to examine the impact of social communication on the trader-level return synchronicity, including the following variables for each investor in each given day: trader-level return synchronicity (g_{it}), social_times, dollarPnL, maxdd, leverage, and intravol. To begin with, I perform unit root tests (Fisher type – Dfuller tests) for each of the variables. The unit root tests indicate that all variables used in the panel VAR system are stationary.

Then, I perform a model selection to identify the optimal orders of the variables. I use the first three orders of the variables in the panel VAR model, with the first four lags of all variables as instruments, to identify the optimal lag orders for the variables for the model specification. Based on the MBIC and the MQIC criteria, the preferred lag order is one (Table 3-7).

[Insert Table 3-7]

3.7.1 Panel VAR Model

Therefore, I use the specified lag order (one) with the first four lags of all variables as instruments for the panel VAR model. The results suggest that *social_times* is positively associated with the trader-level return synchronicity, meaning that social communication online is positively associated with the extent to which each retail traders' returns co-move with the returns of the rest of the traders on the STP (Table 3-8). This result suggests that the level of disagreement among traders is negatively associated with social communication.

[Insert Table 3-8]

3.7.2 Granger Causality Test

In addition, I perform Granger causality tests to identify the causal effect between the social communication and the trader-level return synchronicity. The Granger causality test is used to identify the causal relationship between the variables used in the panel VAR framework. The results (Table 3-9) show that the social communication online (social_times) Granger causes the trader-level return synchronicity after the occurrence of their online social participations. The impact is significant and positive, which means that if a trader participates in any form of social communication online (e.g., creating a discussion topic, posting a comment, or liking a post), this trader's return is more likely to co-move with the returns of the other traders on the platform. These results suggest that social communication reduces the disagreement among traders on the STP, which is consistent with the findings associated with the platform-level return synchronicity.

[Insert Table 3-9]

3.7.3 Impulse Response Functions

I estimate the impulse response functions (IRFs) to visualize the dynamics of the platform-level return synchronicity given a one standard deviation shock in social communication. The IRFs are plotted in Figure 3-5. The results of the Impulse Response Functions further confirm the results and implications of the above-discussed evidence. Specifically, a one standard deviation change in *social_times* causes a dramatic increase in the trader-level return synchronicity in the first one to two days after the social communication.

[Insert Figure 3-5]

Overall, the positive relationship between social communication and the trader-level return synchronicity suggests that social communication increases the extent to which one trader's return co-moves with the returns of other traders. These results indicate that social communication online reduces the disagreement of among traders on the STP.

3.8 Analysis of Chat-level Return Synchronicity

This section presents an analysis of the chat-level return synchronicity, which examines (1) the chat-level return synchronicity, measured by the average pairwise correlation of the returns of chat participants, and (2) whether the chat group participants' chat-level return synchronicity is explained by chat-level characteristics (e.g., the numbers of participants, comments, and likes). I show that the chat-level return synchronicity is significantly positive, suggesting that chat participants have synchronized returns. This finding, from a micro level (i.e. chat level), further supports the argument that social communication reduces the disagreement among traders on the STP. In addition, I do not find significant evidence that the chat-level return synchronicity can be explained by chat-level characteristics (e.g., the numbers of participants, comments, and likes). This suggests that the chat-level return synchronicity is attributed to the information content of the online discussions instead of the chat-level characteristics.

3.8.1 The Chat-level Return Synchronicity

I define the chat group as the group involving people in each particular discussion, including chat participants (1) who create the topic, (2) who comment on the topic, and (3) who like the comments. Then, I look at the returns of each chat group of participants over an eight-week period of time. Specifically, I measure the chat-level return synchronicity as the average pairwise correlation of the returns of each group. I show that the chat-level return synchronicity is significant and positive. The figure (Figure 3-6) shows the distribution of the chat-level return synchronicity (the pairwise return correlation) of different chat groups over an eight-week period.

[Insert Figure 3-6]

The following table reports the chat-level synchronicity (Table 3-10). The chat-level return synchronicity (the average return correlation of different discussion groups) is significantly positive, with a mean value 0.05 and a t-value 4.77, indicating that on average the participants in chats tend to have synchronized returns. These results suggest that at the chat level, the participants in different chats can synchronize with each other in terms of their returns, indicating that they have reached consensus (reduced disagreement) through social communication. These findings provide evidence from a micro level (i.e. chat level) that social communication reduces the disagreement among traders on the STP.

[Insert Table 3-10]

Furthermore, I analyze the chat groups by categories. The categories are associated with each chat topic when the chat initiator creates the discussion topics. There are eight categories of discussion topics, including "ECONOMIC", "FEED_ITEM", "MARKET", "NEWS REPORT", "POLL", "POSITION", "QUESTION", and "TECHNICAL". For chats under different categories, the significance levels of chat-level synchronicity are different. For instance, chats under the category of "Question" are associated with the most significant influence on chat-level synchronicity. Chats about "FEED_ITEM" and "Market" are also associated with a significantly positive effect on the chat-level return synchronicity, though less significant than the "Question" category.

In particular, the "Question" category online communication offers unique opportunities for traders to discuss their questions, which as a consequence reduces the level of the disagreement among traders by clarifying their questions. The results indicate that traders tend to have synchronized returns after participating "Question" related discussions. This may imply that traders are more likely to trade in the same direction, achieve similar returns, and exhibit return synchronicity. This is consistent with the finding that social communication reduces the disagreement among retail traders.

Overall, the evidence shows that there is a chat-level return synchronicity among chat participants, providing micro-level evidence that social activities increase the return synchronicity. In addition, different topics of online discussions have different influences on the return synchronicity of retail traders, suggesting that the return synchronicity is from the reduced disagreement among traders. In addition, discussions on “Question” related topics produce the most significant impact on the chat-level of return synchronicity. The results are consistent with the finding that online communication is associated with positive return synchronicity on the STP.

3.8.2 The Determinants of the Chat-level Return Synchronicity

The evidence regarding the chat-level return synchronicity so far suggests that social communication participants influence the chat-level synchronicity by providing chat-wide consensus which is scopic/market-wide to all traders on the STP. In this section, I investigate the determinants of the chat-level return synchronicity. A chat can be characterized by its information content and other observable characteristics (the numbers of participants, comments, and likes). The information content of a chat refers to its relevance to traders’ decision-making and behavioral changes. I use chat-group characteristics (N_participants, N_comments, N_likes) to explain the chat-level return synchronicity so that I can understand whether it depends on the chat characteristics. If these observable characteristics cannot explain the chat-level synchronicity, it implies that the synchronicity is due to the information content of the chats which causes the subsequence return patters.

[Insert Table 3-11]

The results are reported in Table 3-11. It reports the results of the OLS regression. The dependent variable is the chat-level return synchronicity (average pairwise correlation of the returns of participants in each chat). The independent variables are chat-level characteristics, including the number of participants of the chat (N_participants), the number of comments of the chat (N_comments), and the number of likes received by the chat (N_likes).

The results are not significant, suggesting that the chat-level return synchronicity cannot be explained by chat-level characteristics (e.g., the numbers of participants, comments, and likes). In addition, I have shown that the chat-level return synchronicity is related to different discussion categories (e.g., the "Question" category). This evidence indicates that these categories have different levels of relevance in terms of determining traders' decision-making. Taken together, the evidence indicates that the chat-level return synchronicity is attributed to the information content of the discussions, instead of other observable chat-level characteristics. Therefore, it suggests that the impact of social communication on the return synchronicity is attributed to the information content of the discussions initiated by the communicative traders on the STP. These results are consistent with the argument that social communication online changes the information environment of the STP, as the information content of the chats impacts traders' subsequence return patters. If there is no information in the chats, there should not be subsequence patterns in traders' returns.

3.9 Robustness Tests

I perform several robustness tests which further validate the results in this paper. First, I present evidence in the previous sections that the chat-level return synchronicity (the correlation of the average pairwise returns of social communication participants in different chat groups) cannot be explained by chat-level characteristics over an eight-week period, such as the number of participants, the number of comments, and the number of likes. I also examine the identifications over alternative time lengths, such as 1-week, 2-week, 3-week, 4-week, and 12-week. The results are consistent with the finding that the chat-level return synchronicity cannot be explained by chat-level characteristics.

[Insert Table 3-12]

The results using alternative time periods are reported in Table 3-12. As shown in the table, the chat-level characteristics cannot explain the chat-level synchronicity, indicating that it is the information content of the online discussions which matters in terms of influencing the return synchronicity of traders on the online trading platform.

Second, I include additional variables in the panel VAR framework (at both the platform-level and the trader-level) to mitigate concerns over whether investor sentiment expressed in the discussion contents may influence the results. Specifically, I include two variables (polarity and subjectivity) in the panel VAR model, which measure how positive the sentiment is in each discussion comment (polarity), and how subjective (as opposed to objective) the statement is in each discussion comment (subjectively). The measure of polarity is from -1 (negative sentiment) to 1 (positive sentiment)), and the measure of subjectivity is from 0 (objective) to 1 (subjective). The two variables are constructed using the *TextBlob* package in Python, which is a commonly used technique to process text information (e.g., Twitter sentiment analysis) (Micu et al., 2017; Munjal et al., 2018). Each sentence in the online discussion is given two scores: polarity and subjectivity, using the dictionary-based *TextBlob* package in Python. The package analyzes the words used in the discussion content and automatically assign scores for each discussion comment. Then I take an average of the scores for each day to represent the daily sentiment out of all the discussion content on the STP. The results are consistent with the conclusion that social communication increases the return synchronicity of traders.

[Insert Table 3-13]

[Insert Table 3-14]

The model selection procedure suggests that for both the platform-level and trader-level panel VAR models, the optimal lag orders are three. Therefore, I include the first three lags of each variables in the model and the first four lags of all variables as instruments. The results of the panel VAR model and the Granger causality tests are reported in Table 3-13 and Table 3-14. As shown in Table 3-13, social communication positively impacts the return synchronicity of traders at both the platform-level and the trader-level, after controlling the investor sentiment in the discussion contents. In addition, as shown in Table 3-14, the Granger causality tests show that social communication Granger causes both the platform-level return synchronicity and the trader-level return synchronicity, after controlling the investor sentiment in the discussion contents. Taken together, the results show that after controlling the investor sentiment in the discussion contents, social communication increases the return synchronicity of traders.

Third, to eliminate concerns regarding the influence of the FX market events on the results, I include day-fixed effects into the trader-level synchronicity tests which are the main tests in this paper. Though in the previous discussion I already include day-level trader sentiment measures (polarity and subjectivity) which to some extent capture the market situation as trader sentiment is expected to be correlated with market events, it still makes sense to control for day-fixed effects to precisely eliminated related concerns. Thus, I control for day-fixed effects to the trader-level synchronicity tests and present the results in Table 3-15 and Table 3-16. The results remain robust to controlling for day-fixed effects.

[Insert Table 3-15]

[Insert Table 3-16]

Fourth, I examine whether the main results presented in this paper are sensitive to standard error clustering. The standard error clustering method used in this paper is robust standard error clustering. I present in here the trader-level return synchronicity tests with standard errors clustered at trader level. The results are presented in Table 3-17 and Table 3-18. As shown in the results, the conclusion does not change, and the significance level does not decline after clustering standard errors at trader level. Specifically, social communication positively impacts and Granger causes trader-level return synchronicity.

[Insert Table 3-17]

[Insert Table 3-18]

Overall, my results are robust to alternative tests, indicating that social communication increases the return synchronicity of traders on the STP. The evidence implies that social communication reduces the disagreement among traders on the STP, through the information content of the online discussions.

3.10 Conclusion

This paper investigates the relationship between social communication and the return synchronicity of traders on a Social Trading Platform (STP). Using two measures of return synchronicity: the platform-level and the trader-level return synchronicity, I show that social communication significantly increases both the platform-level and the trader-level return synchronicity. The evidence implies that social communication online reduces the disagreement among traders on the STP.

In addition, the platform-level return synchronicity is positively impacted by the social communication leaders, especially the chat creators. In contrast, chat likers exhibit the lowest level of influence on the platform-level return synchronicity compared to chat creators and chat commenters. These results indicate that different categories of social communication participants exhibit different levels of influence on impacting the platform-level return synchronicity on the STP. This suggests that social communication participants (creators, commenters, and likers) influence the disagreement among traders at different magnitudes.

In terms of online discussion groups, I show that participants in different chat groups exhibit significantly positive chat-level return synchronicity, measured by the average pairwise correlation of returns. Moreover, the significance of the chat-level return synchronicity is relevant to the categories of discussion topics. For example, discussions asking a "Question" are associated with the largest degrees of significance in terms of the chat-level return synchronicity, indicating that the social communication under such categories provides chat-group-level consensus among traders by clarifying the questions. However, I find little evidence that the chat-level return synchronicity can be explained by chat-level characteristics, such as the number of participants, the number of comments, and the number of likes. Taken together, the evidence suggests that the chat-level return synchronicity is attributed to the information content of the online discussions, instead of the chat-level characteristics.

Overall, I show that the three levels of return synchronicity (platform-level, trader-level, and chat-level) are positively influenced by the social communication on the STP. The evidence suggests that social communication online reduces the disagreement among retail traders on the STP, through the information content of the online discussions.

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Appendix 3-1 Examples of Online Discussion Topics

Obs	Id	Category	Creator	Topic	Comments	Commenter	Create Time	Post Time
43	19	QUESTION	38	USD/CAD trade	5 minute chart buy got exhausted about 20 mins ago. this was a short term play on cad from 1.23500 to 1.24000	38	02APR2009: 17:05:14	02APR2009: 17:42:59
44	19	QUESTION	38	USD/CAD trade	Seems to me that the previous trend is fading right now. So I'd go long for the next few hours and go back short around 1.2450	3	02APR2009: 17:05:14	02APR2009: 17:45:04
45	19	QUESTION	38	USD/CAD trade	looks like a dead dog bounce that will be short lived. I tend to agree with Darren on this one.	92	02APR2009: 17:05:14	02APR2009: 19:03:48
46	19	QUESTION	38	USD/CAD trade	yeah i made a few trades very short term for scalps	38	02APR2009: 17:05:14	02APR2009: 19:08:38
232	130	QUESTION	234	New No-Hedge CFTC rules should create additional volatility	FYI, today is the day CFTC rules came into effect banning hedging. We may see additional volatility from this.	234	15MAY2009: 14:13:02	15MAY2009: 14:13:02
233	130	QUESTION	234	New No-Hedge CFTC rules should create additional volatility	If there is any volatility today it's going to be influenced by any news that comes out and the fact that it's option expiration so equity markets will be more volatile.	188	15MAY2009: 14:13:02	15MAY2009: 14:20:25
234	130	QUESTION	234	New No-Hedge CFTC rules should create additional volatility	Hi Max, I agree... as always these have an effect on volatility as well.	234	15MAY2009: 14:13:02	15MAY2009: 14:41:52
235	130	QUESTION	234	New No-Hedge CFTC rules should create additional volatility	Thanks Barak, great info.	234	15MAY2009: 14:13:02	15MAY2009: 23:24:36

240	134	QUESTION	234	Wow, love this EUR/USD range - Short now	Shorted again target 1.3537	234	19MAY2009: 14:27:17	19MAY2009: 14:27:17
241	134	QUESTION	234	Wow, love this EUR/USD range - Short now	Experiencing short term bounce off support but I believe we will find weakness ahead. Holding my short position.	234	19MAY2009: 14:27:17	19MAY2009: 16:19:19
242	134	QUESTION	234	Wow, love this EUR/USD range - Short now	Still holding my short. Looks like double top formation on the EUR/USD, will short more lots if we see break of support at 1.3557	234	19MAY2009: 14:27:17	19MAY2009: 21:18:00
243	134	QUESTION	234	Wow, love this EUR/USD range - Short now	I agree, however I closed a couple trades negative in case we flag this and move higher. Noticing a possible flag formation.	234	19MAY2009: 14:27:17	20MAY2009: 05:11:00
244	134	QUESTION	234	Wow, love this EUR/USD range - Short now	I was tracking on the H1 and h4, but ouch. :) Flag got me. I'm still in for a nice loss, holding my position.	234	19MAY2009: 14:27:17	20MAY2009: 11:56:54
245	134	QUESTION	234	Wow, love this EUR/USD range - Short now	Yes I stopped out as well.. Yet took it again from a better price when it stopped on a fibo 61.8 level and couldn't close a candle above that level. Hence it may have a risky potential to fibo 50 or 38.2..	8	19MAY2009: 14:27:17	20MAY2009: 21:15:49
246	134	QUESTION	234	Wow, love this EUR/USD range - Short now	yeah, interesting waves, I'm assuming this is due to US dollar weakening.	234	19MAY2009: 14:27:17	20MAY2009: 23:18:33
247	134	QUESTION	234	Wow, love this EUR/USD range - Short now	i want to short if it ever goes to 1.3970 (I have a limit sell)	38	19MAY2009: 14:27:17	21MAY2009: 21:55:37

435	254	QUESTION	428	NZD/USD Long trade today.	It just broke a support point and its heading downwards. The predictive algorithms are signaling a reversal with adaptive rsi saying the same thing. MACD and OSMA divergences signals bearish movements. The 5 min, 15min, 30min, 1hr, 4hr, and daily charts all say down.	3	02JUL2009:2 1:19:39	02JUL2009:2 1:38:01
436	254	QUESTION	428	NZD/USD Long trade today.	CMDT signaled short at 0.6450	3	02JUL2009:2 1:19:39	02JUL2009:2 1:40:43
437	254	QUESTION	428	NZD/USD Long trade today.	Bullish reversal signal from the OSMA and MACD	3	02JUL2009:2 1:19:39	02JUL2009:2 2:18:22
438	254	QUESTION	428	NZD/USD Long trade today.	Agree with David Thimm, fundamentally, NZD/USD is at support level and I am expecting a rebound at this current level. Waiting for this pair to go above 1.6550		02JUL2009:2 1:19:39	03JUL2009:0 5:40:32

This table presents three examples of the online discussion topics. Observation id (Obs), discussion id (Id), discussion category (Category), creator id (Creator), discussion topic (Topic), discussion content (Comments), commenter id (Commenter), discussion topic creation time (Create Time), and discussion comments posted time (Post Time) are reported in the table. The discussion content is reported exactly as shown in the online discussion forum (including typos).

Table 3-1 Summary Statistics

Panel A: Full Sample (3,426 traders)								
variables	obs	mean	sd	min	p25	p50	p75	max
mkt_sych	538,810	0.570	0.075	0.000	0.522	0.547	0.589	1.000
synchronicity	538,810	0.115	0.228	0.000	0.000	0.000	0.000	1.000
social_times	538,810	0.007	0.179	0.000	0.000	0.000	0.000	33.000
dollarpnl	537,484	-7.687	2,439.555	-909,997.200	0.000	0.000	0.000	429,394.700
maxdd	517,482	0.483	0.472	0.000	0.109	0.410	0.861	12.153
leverage	538,810	19.949	264.708	-990.000	0.000	0.000	0.000	9,997.000
intravol	534,807	0.001	0.024	0.000	0.000	0.000	0.000	5.966
Panel B: Communicative Traders (699 traders)								
variables	obs	mean	sd	min	p25	p50	p75	max
mkt_sych	124,594	0.570	0.075	0.000	0.523	0.547	0.589	1.000
synchronicity	124,594	0.129	0.237	0.000	0.000	0.000	0.000	1.000
social_times	124,594	0.032	0.370	0.000	0.000	0.000	0.000	33.000
dollarpnl	124,445	-0.633	2,281.319	-250,483.000	0.000	0.000	0.000	388,947.500
maxdd	119,630	0.486	0.358	0.000	0.129	0.440	0.856	1.206
leverage	124,594	12.925	204.356	-750.000	0.000	0.000	0.000	9,828.000
intravol	123,889	0.000	0.017	0.000	0.000	0.000	0.000	2.585
Panel C: Non-communicative Traders (2,727 traders)								
variables	obs	mean	sd	min	p25	p50	p75	max
mkt_sych	414,216	0.570	0.075	0.000	0.522	0.547	0.589	1.000
synchronicity	414,216	0.111	0.225	0.000	0.000	0.000	0.000	1.000
social_times	414,216	0.000	0.000	0.000	0.000	0.000	0.000	0.000
dollarpnl	413,039	-9.812	2,485.254	-909,997.200	0.000	0.000	0.000	429,394.700
maxdd	397,852	0.482	0.501	0.000	0.103	0.401	0.863	12.153
leverage	414,216	22.062	280.297	-990.000	0.000	0.000	0.000	9,997.000
intravol	410,918	0.001	0.026	0.000	0.000	0.000	0.000	5.966

This table reports the summary statistics for the traders on the STP. Panel A includes all the traders in the sample. Panel B includes communicative traders who participate in the online discussion activities (creating a discussion topic, posting a comment, or liking a post) at least once. Panel C includes traders who are not actively involved with the online discussion activities. All the variables are at a daily level, including the platform-level return synchronicity (mkt_sych), the trader-level return synchronicity (synchronicity), social participation times (social_times), dollar profits and losses (dollarpnl), maximum drawdown (maxdd), leverage (leverage), and intraday volatility (intravol).

Table 3-2 Model Selection (Platform-level)

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	-1.623	551.373	1.19E-60	-702.897	335.373	21.703
2	-0.257	234.079	5.01E-19	-602.101	90.079	-119.035
3	0.686	219.078	4.19E-28	-199.012	147.078	42.521

This table reports the results of the model selection for the panel VAR model. The criteria reported include the model overall CD, J statistics, the corresponding p-value of the J statistics, MBIC, MAIC, and MQIC.

Table 3-3 Social Communication and Platform-level Return Synchronicity

VARIABLES	(1) mkt_sych	(2) social_times	(3) dollarpnl	(4) maxdd	(5) leverage	(6) intravol
L.mkt_sych	0.144***	-0.073***	3,476.164***	-0.007***	-26.104	-0.000
	[0.000]	[0.000]	[0.001]	[0.000]	[0.260]	[0.572]
L2.mkt_sych	0.015*	-0.001	-416.602	-0.002	1.570	-0.000
	[0.082]	[0.979]	[0.790]	[0.140]	[0.950]	[0.794]
L.social_times	**0.001****	0.104***	-116.007	0.001***	5.170***	-0.000
	[0.034]	[0.000]	[0.120]	[0.004]	[0.009]	[0.451]
L2.social_times	**0.002*****	0.071***	64.382	0.000	-0.085	-0.000
	[0.004]	[0.000]	[0.468]	[0.430]	[0.965]	[0.155]
L.dollarpnl	-0.000	-0.000	0.050	-0.000	0.000	0.000
	[0.344]	[0.854]	[0.591]	[0.258]	[0.890]	[0.834]
L2.dollarpnl	0.000**	0.000	0.007	0.000	0.000	0.000
	[0.023]	[0.320]	[0.826]	[0.579]	[0.605]	[0.683]
L.maxdd	0.071***	-0.212***	115,374.941***	0.909***	-2,545.263***	0.005***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L2.maxdd	-0.046**	0.128**	-115,691.478***	0.073***	2,535.548***	-0.004***
	[0.031]	[0.011]	[0.000]	[0.009]	[0.000]	[0.000]
L.leverage	-0.000*	0.000	-1.125	0.000***	0.435***	0.000
	[0.059]	[0.511]	[0.141]	[0.000]	[0.000]	[0.417]
L2.leverage	0.000***	-0.000***	0.637	-0.000	0.214***	0.000
	[0.000]	[0.003]	[0.279]	[0.167]	[0.000]	[0.430]
L.intravol	11.669**	-9.518**	2110851.990**	-0.809**	-10,640.444	0.248***
	[0.026]	[0.027]	[0.028]	[0.022]	[0.231]	[0.002]
L2.intravol	-1.292	0.159	84,708.534	0.342*	-30,798.368*	-0.038
	[0.207]	[0.751]	[0.414]	[0.091]	[0.069]	[0.303]
Observations	110,595	110,595	110,595	110,595	110,595	110,595

This table reports the results of the panel VAR model. The dependent variables in each column (from (1) to (6)) are the platform-level return synchronicity (mkt_sych), social participation times (social_times), dollar profits and losses (dollarpnl), maximum drawdown (maxdd), leverage (leverage), and intraday volatility (intravol), respectively. The explanatory variables are the first two orders of these variables. L. indicates the first order of the variable. L2. indicates the second order of the variable. P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3-4 Granger Causality Test (Platform-level)

Dependent Variable	Explanatory Variable	chi2	Prob	Sig.
mkt_sych	**social_times**	**13.158**	**0.001**	*******
	dollarpnl	5.249	0.072	*
	maxdd	29.323	0.000	***
	leverage	25.604	0.000	***
	intravol	5.807	0.055	*
social_times	mkt_sych	13.184	0.001	***
	dollarpnl	1.094	0.579	
	maxdd	54.452	0.000	***
	leverage	14.922	0.001	***
	intravol	5.006	0.082	*
dollarpnl	mkt_sych	20.353	0.000	***
	social_times	2.940	0.230	
	maxdd	18.377	0.000	***
	leverage	2.183	0.336	
	intravol	7.175	0.028	**
maxdd	mkt_sych	21.816	0.000	***
	social_times	8.715	0.013	**
	dollarpnl	1.627	0.443	
	leverage	21.072	0.000	***
	intravol	7.417	0.025	**
leverage	mkt_sych	1.515	0.469	
	social_times	6.854	0.032	**
	dollarpnl	0.282	0.868	
	maxdd	17.679	0.000	***
	intravol	5.840	0.054	*
intravol	mkt_sych	0.392	0.822	
	social_times	2.906	0.234	
	dollarpnl	0.222	0.895	
	maxdd	36.809	0.000	***
	leverage	5.118	0.077	*

This table presents the results of Granger causality tests. Chi-squares (chi2), p-values (Prob) and significance levels (Sig.) are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 3-5 Social Communication Leader and Platform-level Return Synchronicity (Creator, Commenter, and Liker)

	Dependent Variables											
	mkt_sych	social_times	dollarpnl	maxdd	leverage	intravol	mkt_sych	social_times	dollarpnl	maxdd	leverage	intravol
	Panel A: Creators						*Panel B: Commenters*					
L.mkt_sych	0.141***	-0.077*	-129.489	-0.007***	41.624**	0.000	0.146***	-0.084***	5,424.827***	-0.007***	-38.921	0.000
	[0.000]	[0.066]	[0.117]	[0.000]	[0.015]	[0.992]	[0.000]	[0.000]	[0.001]	[0.000]	[0.185]	[0.833]
L2.mkt_sych	0.010**	-0.060	307.835***	-0.001	-31.533*	0.002**	0.019**	-0.005	-198.141	-0.002	18.347	0.000
	[0.020]	[0.144]	[0.002]	[0.511]	[0.096]	[0.027]	[0.037]	[0.826]	[0.938]	[0.182]	[0.627]	[0.833]
L.social_times	**0.001****	0.108***	6.257	0.001**	2.994***	0.000	**0.001****	0.105***	-244.014**	0.001***	7.354***	-0.000
	[0.045]	[0.000]	[0.239]	[0.017]	[0.010]	[0.613]	**[0.032]**	[0.000]	[0.028]	[0.001]	[0.002]	[0.730]
L2.social_times	**0.002*****	0.074***	-10.321	-0.000	1.398	-0.000*	**0.002*****	0.072***	36.476	0.000	-0.033	-0.000
	[0.009]	[0.000]	[0.227]	[0.938]	[0.257]	[0.096]	[0.005]	[0.000]	[0.769]	[0.326]	[0.987]	[0.150]
L.dollarpnl	-0.000	-0.000	0.122	-0.000	-0.006	0.000	-0.000	-0.000	0.110	-0.000	-0.001	0.000
	[0.235]	[0.200]	[0.140]	[0.374]	[0.490]	[0.245]	[0.845]	[0.719]	[0.315]	[0.149]	[0.789]	[0.782]
L2.dollarpnl	0.000	0.000	0.024	-0.000*	-0.001	-0.000	0.000**	0.000	0.010	0.000	0.000	0.000
	[0.838]	[0.797]	[0.645]	[0.082]	[0.801]	[0.484]	[0.036]	[0.281]	[0.779]	[0.431]	[0.943]	[0.911]
L.maxdd	-0.059**	0.293	-4,364.915*	1.009***	-752.951**	-0.014	0.111***	-0.248***	202,818.724***	0.851***	-3,697.656***	0.004***
	[0.035]	[0.386]	[0.085]	[0.000]	[0.021]	[0.197]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
L2.maxdd	0.088***	-0.452	4,391.039*	-0.026**	733.908**	0.016	-0.087***	0.156***	-203,530.442***	0.131***	3,690.405***	-0.003**
	[0.001]	[0.177]	[0.081]	[0.037]	[0.023]	[0.151]	[0.003]	[0.006]	[0.000]	[0.000]	[0.000]	[0.014]
L.leverage	-0.000	-0.000*	0.201*	0.000***	0.489***	0.000***	-0.000**	0.000	-3.257**	0.000***	0.487***	0.000
	[0.449]	[0.073]	[0.063]	[0.001]	[0.000]	[0.004]	[0.014]	[0.202]	[0.030]	[0.000]	[0.000]	[0.472]
L2.leverage	0.000***	0.000	-0.270***	-0.000	0.183**	-0.000***	0.000***	-0.000***	1.199	-0.000	0.193***	0.000
	[0.000]	[0.118]	[0.005]	[0.238]	[0.016]	[0.003]	[0.000]	[0.006]	[0.339]	[0.152]	[0.002]	[0.200]
L.intravol	0.374	2.648	-28,453.014	-0.083	4,991.735	0.013	11.463**	-10.364**	3298445.665**	-0.755**	-33,334.774**	0.251***
	[0.664]	[0.594]	[0.423]	[0.636]	[0.319]	[0.905]	[0.012]	[0.012]	[0.013]	[0.012]	[0.031]	[0.002]
L2.intravol	0.255	1.171	15,085.428	-0.039	-4,847.180	0.015	-0.926	0.122	220,911.115	0.145	-22,236.793	-0.054
	[0.118]	[0.230]	[0.455]	[0.265]	[0.292]	[0.756]	[0.263]	[0.772]	[0.226]	[0.172]	[0.138]	[0.215]
Observations	53,524	53,524	53,524	53,524	53,524	53,524	97,418	97,418	97,418	97,418	97,418	97,418

This table shows the results of the panel VAR model. The dependent variables in each column are the platform-level return synchronicity (mkt_sych), social participation times (social_times), dollar profits and losses (dollarpnl), maximum drawdown (maxdd), leverage (leverage), and intraday volatility (intravol), respectively. Panel A, Panel B, and Panel C are associated with creators, commenters, and likers, respectively. The explanatory variables are the first two orders of these variables. L. indicates the first order of the variable. L2. indicates the second order of the variable. P-values are reported in the brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3-5 Social Communication Leader and Platform-level Return Synchronicity (Creator, Commenter, and Liker) *(Continued)*

	Dependent Variables					
	mkt_sych	**social_times**	**dollarpnl**	**maxdd**	**leverage**	**intravol**
			Panel C: Likers			
L.mkt_sych	0.127***	-0.243***	-266.680**	-0.006**	-63.939	-0.001
	[0.000]	[0.000]	[0.024]	[0.016]	[0.252]	[0.141]
L2.mkt_sych	0.023***	-0.069	-259.204**	-0.004*	14.505	0.000
	[0.007]	[0.220]	[0.017]	[0.090]	[0.718]	[0.692]
L.social_times	**0.000**	0.095***	2.289	0.000*	-1.117	-0.000
	[0.699]	[0.000]	[0.720]	[0.091]	[0.247]	[0.184]
L2.social_times	**0.001***	0.067***	6.569	-0.000	-0.663	-0.000
	[0.071]	[0.001]	[0.411]	[0.707]	[0.686]	[0.751]
L.dollarpnl	0.000***	-0.000	0.031	-0.000	-0.001	-0.000
	[0.005]	[0.388]	[0.445]	[0.683]	[0.580]	[0.645]
L2.dollarpnl	-0.000	-0.000	0.038	-0.000	0.001**	0.000
	[0.542]	[0.458]	[0.290]	[0.813]	[0.036]	[0.128]
L.maxdd	0.009	-0.310*	-1,601.537	0.994***	-297.023	0.000
	[0.687]	[0.050]	[0.436]	[0.000]	[0.371]	[0.934]
L2.maxdd	0.019	0.183	1,527.119	-0.011	265.323	-0.000
	[0.387]	[0.231]	[0.455]	[0.553]	[0.426]	[0.977]
L.leverage	-0.000	-0.000	0.029	0.000	0.388***	0.000
	[0.301]	[0.321]	[0.443]	[0.154]	[0.000]	[0.187]
L2.leverage	0.000***	0.000	0.005	-0.000	0.201***	-0.000
	[0.000]	[0.660]	[0.870]	[0.165]	[0.007]	[0.555]
L.intravol	-3.609	-11.341	-28,726.763	0.116	-13,269.194	0.116
	[0.390]	[0.399]	[0.399]	[0.394]	[0.405]	[0.589]
L2.intravol	0.297	0.853	8,060.766	-0.115	-3,862.378	0.025
	[0.867]	[0.882]	[0.478]	[0.746]	[0.875]	[0.819]
Observations	34,326	34,326	34,326	34,326	34,326	34,326

Table 3-6 Granger Causality Test (Platform-level) for Creators, Commenters, and Likers

		Panel A: Creators			***Panel B: Commenters***			***Panel C: Likers***		
Dependent Variables	Independent Variables	chi2	Prob	Sig.	chi2	Prob	Sig.	chi2	Prob	Sig.
mkt_sych	**social_times**	**11.426**	**0.003**	***	**13.299**	**0.001**	***	**3.436**	**0.179**	
	dollarpnl	1.415	0.493		4.609	0.100	*	8.169	0.017	**
	maxdd	70.162	0.000	***	37.711	0.000	***	41.697	0.000	***
	leverage	26.027	0.000	***	19.719	0.000	***	20.805	0.000	***
	intravol	3.173	0.205		7.419	0.024	**	1.055	0.590	
social_times	mkt_sych	4.611	0.100	*	13.241	0.001	***	19.677	0.000	***
	dollarpnl	1.647	0.439		1.422	0.491		1.458	0.482	
	maxdd	41.521	0.000	***	55.550	0.000	***	28.521	0.000	***
	leverage	3.461	0.177		9.872	0.007	***	1.154	0.562	
	intravol	2.143	0.343		6.330	0.042	**	1.013	0.603	
dollarpnl	mkt_sych	13.780	0.001	***	17.291	0.000	***	7.981	0.018	**
	social_times	2.848	0.241		4.874	0.087	*	0.867	0.648	
	maxdd	3.426	0.180		20.063	0.000	***	1.626	0.444	
	leverage	7.793	0.020	**	5.545	0.063	*	1.949	0.377	
	intravol	1.114	0.573		9.448	0.009	***	0.714	0.700	
maxdd	mkt_sych	12.953	0.002	***	21.036	0.000	***	6.675	0.036	**
	social_times	5.749	0.056	*	11.821	0.003	***	2.873	0.238	
	dollarpnl	4.925	0.085	*	2.763	0.251		0.255	0.880	
	leverage	11.065	0.004	***	29.719	0.000	***	2.510	0.285	
	intravol	1.816	0.403		8.355	0.015	**	1.026	0.599	
leverage	mkt_sych	11.925	0.003	***	2.946	0.229		6.705	0.035	**
	social_times	7.272	0.026	**	9.481	0.009	***	1.400	0.497	
	dollarpnl	0.503	0.778		0.074	0.964		4.553	0.103	
	maxdd	5.694	0.058	*	19.585	0.000	***	6.988	0.030	**
	intravol	1.994	0.369		8.270	0.016	**	0.853	0.653	
intravol	mkt_sych	5.080	0.079	*	0.095	0.953		2.464	0.292	
	social_times	2.904	0.234		2.350	0.309		1.946	0.378	
	dollarpnl	1.689	0.430		0.094	0.954		2.375	0.305	
	maxdd	23.571	0.000	***	32.593	0.000	***	4.538	0.103	
	leverage	10.081	0.006	***	7.821	0.020	**	1.981	0.371	

This table presents the results of Granger causality tests. Panel A, Panel B, and Panel C are associated with creators, commenters, and likers, respectively. Chi-squares (chi2), p-values (Prob) and significance levels (Sig.) are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 3-7 Model Selection (Trader-level)

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	-0.191	576.216	4.89E-65	-678.054	360.216	46.546
2	-0.554	406.880	3.23E-48	-429.300	262.880	53.766
3	0.789	281.144	9.31E-40	-136.946	209.144	104.587

This table shows the results of the model selection for the panel VAR model. The criteria reported include the model overall CD, J statistics, the corresponding p-value of the J statistics, MBIC, MAIC, and MQIC.

Table 3-8 Social Communication and Trader-level Return Synchronicity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	synchronicity	social_times	dollarpnl	maxdd	leverage	intravol
L.synchronicity	0.357***	-0.020	11,685.298*	0.001	-131.027	0.002**
	[0.000]	[0.744]	[0.099]	[0.708]	[0.154]	[0.011]
L.social_times	0.068***	0.196***	-18,799.124***	0.013***	217.919***	-0.002***
	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.001]
L.dollarpnl	0.000	-0.000	0.094	-0.000	0.000	0.000
	[0.633]	[0.445]	[0.397]	[0.288]	[0.988]	[0.523]
L.maxdd	-0.002	-0.174**	19,965.006**	0.977***	-202.275*	0.003***
	[0.951]	[0.046]	[0.034]	[0.000]	[0.095]	[0.003]
L.leverage	0.000***	-0.000***	0.185	0.000*	0.450***	0.000**
	[0.007]	[0.000]	[0.799]	[0.056]	[0.000]	[0.010]
L.intravol	24.219	51.364	-6294539.326	3.225	82,844.899	-0.639
	[0.151]	[0.150]	[0.150]	[0.149]	[0.149]	[0.167]
Observations	110,599	110,599	110,599	110,599	110,599	110,599

This table shows the results of the panel VAR model. The dependent variables in each column (from (1) to (6)) are the trader-level return synchronicity (synchronicity), social participation times (social_times), dollar profits and losses (dollarpnl), maximum drawdown (maxdd), leverage (leverage), and intraday volatility (intravol), respectively. The explanatory variables are the lag of these variables. P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3-9 Granger Causality Test (Trader-level)

Dependent Variable	Explanatory Variable	chi2	Prob	Sig.
synchronicity	social_times	14.620	0.000	***
	dollarpnl	0.228	0.633	
	maxdd	0.004	0.951	
	leverage	7.327	0.007	***
	intravol	2.058	0.151	
social_times	synchronicity	0.107	0.744	
	dollarpnl	0.582	0.445	
	maxdd	3.976	0.046	**
	leverage	14.352	0.000	***
	intravol	2.075	0.150	
dollarpnl	synchronicity	2.724	0.099	*
	social_times	11.671	0.001	***
	maxdd	4.512	0.034	**
	leverage	0.065	0.799	
	intravol	2.075	0.150	
maxdd	synchronicity	0.141	0.708	
	social_times	12.313	0.000	***
	dollarpnl	1.128	0.288	
	leverage	3.657	0.056	*
	intravol	2.079	0.149	
leverage	synchronicity	2.034	0.154	
	social_times	11.733	0.001	***
	dollarpnl	0.000	0.988	
	maxdd	2.780	0.095	*
	intravol	2.079	0.149	
intravol	synchronicity	6.426	0.011	**
	social_times	11.777	0.001	***
	dollarpnl	0.408	0.523	
	maxdd	8.978	0.003	***
	leverage	6.590	0.010	**

This table reports the results of Granger causality tests. Chi-squares (chi2), p-values (Prob) and significance levels (Sig.) are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 3-10 The Chat-level Return Synchronicity (8-week)

Panel A: Full Sample (Analysis Variable: pairwise_corr)

	N	Std	Mean	t Value	P1	P10	P25	P50	P75	P90	P99
	639	0.24	0.05	4.77	-0.68	-0.18	-0.05	0.02	0.13	0.29	0.96

Panel B: Category groups (Analysis Variable: pairwise_corr)

Category	N	Std	Mean	t Value	P1	P10	P25	P50	P75	P90	P99
ECONOMIC	3	0.12	-0.06	-0.83	-0.18	-0.18	-0.18	-0.06	0.06	0.06	0.06
FEED_ITE	2	0.09	0.22	3.45	0.16	0.16	0.16	0.22	0.29	0.29	0.29
MARKET_C	70	0.21	0.06	2.20	-0.46	-0.18	-0.03	0.03	0.10	0.29	0.86
NEWSREPO	3	0.17	0.16	1.63	-0.03	-0.03	-0.03	0.21	0.31	0.31	0.31
POLL	47	0.32	0.03	0.74	-0.99	-0.34	-0.05	0.02	0.11	0.39	1.00
POSITION	76	0.32	0.00	0.12	-0.68	-0.29	-0.17	-0.00	0.14	0.36	1.00
QUESTION	374	0.21	0.05	4.67	-0.44	-0.15	-0.05	0.02	0.12	0.27	0.96
TECHNICA	64	0.28	0.06	1.60	-1.00	-0.15	-0.04	0.05	0.18	0.32	0.87

This table reports the chat-level return synchronicity (pairwise_corr). Panel A reports the chat-level return synchronicity for the full sample. Panel B reports the chat-level return synchronicity for chats under different categories, including ECONOMIC, FEED_ITE, MARKET_C, NEWSREPO, POLL, POSITION, QUESTION, and TECHNICA.

Table 3-11 Determinants of The Chat level Return Synchronicity

Variable	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.05499	0.01565	3.51	0.0005
N_participants	0.00054099	0.00329	0.16	0.8694
N_comments	-0.00183	0.00260	-0.70	0.4816
N_likes	-0.00197	0.00746	-0.26	0.7918

This table shows the OLS regression results of the determinants of the chat-level return synchronicity. The dependent variable is the chat-level return synchronicity. The explanatory variables include the number of participants (N_participants), the number of comments (N_comments), and the number of likes (N_likes).

Table 3-12 Determinants of The Chat level Return Synchronicity (1,2,3,4,12-week)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Panel A:1-week				
Intercept	0.02588	0.02966	0.87	0.3833
N_participants	0.00268	0.00636	0.42	0.6732
N_comments	-0.00317	0.00398	-0.80	0.4269
N_likes	0.00843	0.01173	0.72	0.4730
Panel B: 2-week				
Intercept	0.06967	0.02283	3.05	0.0024
N_participants	-0.00060555	0.00488	-0.12	0.9012
N_comments	-0.00394	0.00324	-1.22	0.2241
N_likes	0.00647	0.00959	0.67	0.5004
Panel C: 3-week				
Intercept	0.05631	0.02109	2.67	0.0078
N_participants	-0.00169	0.00454	-0.37	0.7108
N_comments	-0.00149	0.00320	-0.47	0.6416
N_likes	0.00226	0.00919	0.25	0.8056
Panel D: 4-week				
Intercept	0.05688	0.01995	2.85	0.0045
N_participants	-0.00155	0.00420	-0.37	0.7116
N_comments	-0.00069131	0.00311	-0.22	0.8241
N_likes	-0.00343	0.00898	-0.38	0.7022
Panel E: 12-week				
Intercept	0.07109	0.01409	5.05	<.0001
N_participants	-0.00046968	0.00293	-0.16	0.8728
N_comments	-0.00166	0.00243	-0.69	0.4928
N_likes	-0.00367	0.00693	-0.53	0.5969

The dependent variable is the chat-level return synchronicity. The explanatory variables include the number of participants (N_participants), the number of comments (N_comments), and the number of likes (N_likes).

Table 3-13 The Panel VAR Results (Including Trader Sentiment Measures)

Panel A: Platform-level

VARIABLES	(1) mkt_sych	(2) social_times	(3) dollarpnl	(4) maxdd	(5) leverage	(6) intravol	(7) polarity	(8) subjectivity
L.mkt_sych	0.163***	-0.015	406.745	-0.005***	-13.160	-0.000	0.083***	-0.304***
	[0.000]	[0.608]	[0.597]	[0.007]	[0.372]	[0.631]	[0.000]	[0.000]
L2.mkt_sych	0.055***	0.003	-1,033.931*	-0.004**	45.781***	-0.001	-0.042***	0.143***
	[0.000]	[0.893]	[0.093]	[0.020]	[0.000]	[0.433]	[0.000]	[0.000]
L3.mkt_sych	-0.062***	0.066***	-6,374.902***	0.001	-141.279***	-0.001*	-0.004	-0.134***
	[0.000]	[0.002]	[0.000]	[0.554]	[0.000]	[0.081]	[0.660]	[0.000]
L.social_times	**0.002*** **	0.081***	-17.620	0.000	-0.655	-0.000	0.002	0.002
	[0.003]	[0.000]	[0.796]	[0.325]	[0.411]	[0.396]	[0.166]	[0.131]
L2.social_times	**0.003*** **	0.058***	124.772**	0.000	-0.520	-0.000	0.000	0.000
	[0.000]	[0.000]	[0.040]	[0.845]	[0.521]	[0.173]	[0.742]	[0.708]
L3.social_times	**0.003*** **	0.052***	20.866	-0.000	-1.148	-0.000*	-0.000	0.001
	[0.000]	[0.000]	[0.741]	[0.834]	[0.156]	[0.090]	[0.765]	[0.580]
L.dollarpnl	0.000*	-0.000	0.217***	0.000	-0.001	0.000**	-0.000**	0.000
	[0.092]	[0.222]	[0.002]	[0.883]	[0.215]	[0.042]	[0.023]	[0.824]
L2.dollarpnl	-0.000**	0.000***	-0.128**	-0.000	-0.001*	-0.000**	0.000***	-0.000**
	[0.043]	[0.000]	[0.023]	[0.421]	[0.071]	[0.022]	[0.006]	[0.024]
L3.dollarpnl	0.000	-0.000**	0.155**	0.000*	0.002***	0.000***	-0.000**	0.000*
	[0.162]	[0.028]	[0.026]	[0.095]	[0.004]	[0.003]	[0.044]	[0.061]
L.maxdd	0.175***	-0.740***	151,037.608***	1.040***	-1,523.606***	-0.002	-0.005	0.463***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.183]	[0.743]	[0.000]
L2.maxdd	-0.418***	1.538***	-288,229.550***	-0.096*	2,761.047***	0.016***	-0.061***	-0.893***
	[0.000]	[0.000]	[0.000]	[0.060]	[0.000]	[0.000]	[0.001]	[0.000]
L3.maxdd	0.271***	-0.877***	137,255.958***	0.040	-1,288.305***	-0.013***	0.101***	0.608***
	[0.000]	[0.000]	[0.000]	[0.122]	[0.000]	[0.000]	[0.000]	[0.000]
L.leverage	-0.000***	0.000**	-1.639***	0.000***	0.580***	0.000	0.000*	0.000
	[0.000]	[0.027]	[0.002]	[0.009]	[0.000]	[0.679]	[0.070]	[0.167]
L2.leverage	0.000	-0.000	0.470	0.000	0.011	0.000	0.000	-0.000
	[0.143]	[0.405]	[0.474]	[0.849]	[0.861]	[0.924]	[0.251]	[0.194]

L3.leverage	0.000***	-0.000***	1.442*	0.000	0.069	-0.000	-0.000**	0.000***
	[0.000]	[0.001]	[0.067]	[0.200]	[0.344]	[0.729]	[0.012]	[0.000]
L.intravol	-0.761**	-0.029	-41,886.997	0.031	4,343.834	0.154**	-1.042	-1.557**
	[0.010]	[0.971]	[0.527]	[0.395]	[0.299]	[0.050]	[0.263]	[0.020]
L2.intravol	1.643**	-3.136**	238,964.492	0.048	11,458.895**	0.172**	-1.765**	4.124**
	[0.036]	[0.045]	[0.101]	[0.252]	[0.023]	[0.014]	[0.041]	[0.035]
L3.intravol	1.095**	4.541***	-963,582.922***	-0.547***	-139.090	-0.069	3.280***	4.054**
	[0.018]	[0.005]	[0.005]	[0.005]	[0.890]	[0.279]	[0.004]	[0.012]
L.polarity	-0.030***	0.000	-1,489.504***	0.000	3.155	0.001**	0.045***	-0.088***
	[0.000]	[0.979]	[0.002]	[0.632]	[0.737]	[0.045]	[0.000]	[0.000]
L2.polarity	0.001	-0.022*	2,487.206***	-0.000	31.747***	-0.000	-0.090***	-0.108***
	[0.841]	[0.062]	[0.000]	[0.709]	[0.000]	[0.972]	[0.000]	[0.000]
L3.polarity	0.006***	0.007	-263.661	-0.001	-40.716***	-0.000	0.079***	-0.034***
	[0.007]	[0.581]	[0.537]	[0.491]	[0.000]	[0.835]	[0.000]	[0.000]
L.subjectivity	-0.000	-0.032***	1,329.949***	-0.002***	36.749***	-0.000	-0.101***	0.036***
	[0.991]	[0.001]	[0.000]	[0.003]	[0.000]	[0.271]	[0.000]	[0.000]
L2.subjectivity	0.030***	0.002	-1,232.859***	-0.002**	-42.921***	-0.000	-0.025***	-0.050***
	[0.000]	[0.848]	[0.001]	[0.024]	[0.000]	[0.950]	[0.000]	[0.000]
L3.subjectivity	-0.022***	-0.007	-1,016.319**	-0.001	2.210	-0.000	-0.023***	0.021***
	[0.000]	[0.467]	[0.011]	[0.235]	[0.794]	[0.239]	[0.000]	[0.000]
Observations	96,835	96,835	96,835	96,835	96,835	96,835	96,835	96,835

Panel B: Trader-level

	(9) synchronicity	(10) social_times	(11) dollarpnl	(12) maxdd	(13) leverage	(14) intravol	(15) polarity	(16) subjectivity
L.social_times	**0.008*****	0.080***	-5.059	0.000	-0.313	-0.000	0.002	0.001
	[0.007]	[0.000]	[0.953]	[0.440]	[0.810]	[0.310]	[0.119]	[0.614]
L2.social_times	**0.006****	0.056***	4.759	-0.000	1.027	-0.000	0.001	-0.001
	[0.016]	[0.001]	[0.946]	[0.778]	[0.402]	[0.521]	[0.383]	[0.295]
L3.social_times	**0.008*****	0.044***	-63.468	-0.000	0.666	-0.000*	0.001	-0.000
	[0.004]	[0.001]	[0.434]	[0.702]	[0.630]	[0.083]	[0.396]	[0.817]
L.dollarpnl	0.000	-0.000*	0.230***	-0.000	-0.000	0.000*	-0.000**	-0.000
	[0.325]	[0.089]	[0.005]	[0.637]	[0.719]	[0.050]	[0.016]	[0.301]
L2.dollarpnl	-0.000	0.000**	-0.108*	-0.000	-0.000	-0.000**	0.000	-0.000

	[0.644]	[0.019]	[0.060]	[0.518]	[0.881]	[0.047]	[0.101]	[0.201]
L3.dollarpnl	0.000	-0.000	0.070	0.000	0.001	0.000**	-0.000	0.000
	[0.186]	[0.484]	[0.253]	[0.482]	[0.102]	[0.029]	[0.451]	[0.537]
L.maxdd	0.312***	-0.876***	145,162.714***	1.027***	-1,406.917***	-0.001	0.006	0.266***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.323]	[0.726]	[0.000]
L2.maxdd	-0.338***	1.515***	-268,031.799***	-0.076	2,584.435***	0.011***	0.115***	-0.431***
	[0.000]	[0.000]	[0.000]	[0.140]	[0.000]	[0.000]	[0.000]	[0.000]
L3.maxdd	0.203***	-0.698***	123,479.800***	0.035	-1,236.634***	-0.009***	-0.024	0.321***
	[0.000]	[0.000]	[0.000]	[0.198]	[0.000]	[0.000]	[0.168]	[0.000]
L.leverage	0.000	0.000	-2.539***	0.000**	0.565***	0.000	0.000	0.000
	[0.257]	[0.317]	[0.001]	[0.023]	[0.000]	[0.278]	[0.192]	[0.816]
L2.leverage	-0.000	-0.000	1.787	0.000	0.027	-0.000	-0.000	-0.000
	[0.979]	[0.451]	[0.246]	[0.143]	[0.711]	[0.433]	[0.478]	[0.625]
L3.leverage	0.000	-0.000	0.348	-0.000	0.026	0.000	-0.000	0.000
	[0.160]	[0.304]	[0.812]	[0.637]	[0.748]	[0.270]	[0.271]	[0.222]
L.intravol	-4.660*	3.855*	-352,622.452*	-0.116*	-15,626.946*	-0.147	2.679*	-0.367
	[0.079]	[0.071]	[0.062]	[0.075]	[0.082]	[0.251]	[0.071]	[0.699]
L2.intravol	29.392***	-14.770***	1520171.121***	0.352***	50,187.539***	0.592***	-8.866***	17.317***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L3.intravol	-2.515***	14.965***	-2319462.604***	-0.993***	-11,522.380***	-0.290***	6.419***	8.107***
	[0.010]	[0.000]	[0.000]	[0.001]	[0.000]	[0.005]	[0.000]	[0.004]
L.polarity	0.084***	-0.014	304.592	-0.000	44.080**	0.002**	0.020***	-0.059***
	[0.000]	[0.299]	[0.807]	[0.927]	[0.020]	[0.011]	[0.001]	[0.000]
L2.polarity	0.013	-0.012	1,274.599	-0.000	18.487	0.000	-0.087***	-0.128***
	[0.309]	[0.386]	[0.211]	[0.644]	[0.399]	[0.849]	[0.000]	[0.000]
L3.polarity	-0.035***	-0.000	10.326	-0.000	-13.444	-0.000	0.046***	-0.003
	[0.005]	[0.976]	[0.992]	[0.724]	[0.480]	[0.687]	[0.000]	[0.780]
L.subjectivity	0.009	0.014	-1,769.771*	-0.001	-39.830*	-0.002***	0.035***	-0.027***
	[0.551]	[0.285]	[0.093]	[0.379]	[0.080]	[0.000]	[0.000]	[0.007]
L2.subjectivity	0.037***	0.004	355.809	-0.000	-1.264	-0.000	0.072***	-0.033***
	[0.001]	[0.730]	[0.623]	[0.767]	[0.948]	[0.984]	[0.000]	[0.000]
L3.subjectivity	0.046***	0.025*	-2,076.561**	-0.000	-38.479*	-0.001**	0.087***	-0.017*
	[0.001]	[0.059]	[0.040]	[0.922]	[0.095]	[0.037]	[0.000]	[0.068]
L.synchronicity	0.410***	0.080***	-4,174.953***	0.006***	15.288	0.000	0.025***	0.036***

	[0.000]	[0.000]	[0.000]	[0.000]	[0.478]	[0.474]	[0.000]	[0.000]
L2.synchronicity	-0.063***	-0.014	1,706.523*	-0.001	-76.806***	-0.001**	0.036***	0.043***
	[0.000]	[0.248]	[0.083]	[0.576]	[0.002]	[0.013]	[0.000]	[0.000]
L3.synchronicity	0.049***	0.003	2,092.470*	0.001	-1.472	0.000	0.004	-0.020**
	[0.000]	[0.780]	[0.084]	[0.176]	[0.930]	[0.183]	[0.330]	[0.017]
Observations	96,835	96,835	96,835	96,835	96,835	96,835	96,835	96,835

The table reports the results of the panel VAR model with trader sentiment measures included. Pane A reports the results of the platform-level synchronicity tests. Pane B reports the results of the trader-level synchronicity tests. The dependent variables in each column (from (1) to (6)) are the trader-level return synchronicity (synchronicity), social participation times (social_times), dollar profits and losses (dollarpnl), maximum drawdown (maxdd), leverage (leverage), and intraday volatility (intravol), respectively. The added variables are (7) polarity and (8) subjectivity, representing how positive and subject the comments are, respectively. The explanatory variables are the lag of these variables. P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3-14 Granger Causality Tests

Panel A: Platform-level					**Panel B: Trader-level**				
Dependent Variables	Explanatory Variables	Chi-2	Prob	Sig	Dependent Variables	Explanatory Variables	Chi-2	Prob	Sig
mkt_sych	social_times	35.730	0.000	***	synchronicity	social_times	22.522	0.000	***
	dollarpnl	9.727	0.021	**		dollarpnl	2.471	0.481	
	maxdd	167.921	0.000	***		maxdd	166.434	0.000	***
	leverage	55.361	0.000	***		leverage	9.955	0.019	**
	intravol	15.024	0.002	***		intravol	14.233	0.003	***
	polarity	145.934	0.000	***		polarity	70.231	0.000	***
	subjectivity	310.395	0.000	***		subjectivity	24.873	0.000	***
social_times	mkt_sych	15.859	0.001	***	social_times	synchronicity	56.441	0.000	***
	dollarpnl	24.658	0.000	***		dollarpnl	9.527	0.023	**
	maxdd	142.736	0.000	***		maxdd	71.419	0.000	***
	leverage	21.251	0.000	***		leverage	7.543	0.056	*
	intravol	11.478	0.009	***		intravol	20.335	0.000	***
	polarity	4.293	0.232			polarity	2.051	0.562	
	subjectivity	12.043	0.007	***		subjectivity	3.587	0.310	
dollarpnl	mkt_sych	109.632	0.000	***	dollarpnl	synchronicity	27.462	0.000	***
	social_times	4.484	0.214			social_times	0.617	0.892	
	maxdd	124.441	0.000	***		maxdd	69.220	0.000	***
	leverage	13.321	0.004	***		leverage	13.393	0.004	***
	intravol	9.353	0.025	**		intravol	20.263	0.000	***
	polarity	45.335	0.000	***		polarity	2.001	0.572	
	subjectivity	47.207	0.000	***		subjectivity	5.370	0.147	
maxdd	mkt_sych	14.914	0.002	***	maxdd	synchronicity	38.894	0.000	***
	social_times	1.081	0.782			social_times	0.739	0.864	
	dollarpnl	2.867	0.413			dollarpnl	0.899	0.826	
	leverage	15.760	0.001	***		leverage	11.765	0.008	***
	intravol	10.854	0.013	**		intravol	19.846	0.000	***
	polarity	0.852	0.837			polarity	0.337	0.953	
	subjectivity	13.205	0.004	***		subjectivity	0.880	0.830	
leverage	mkt_sych	135.216	0.000	***	leverage	synchronicity	11.065	0.011	**
	social_times	3.175	0.365			social_times	1.069	0.785	
	dollarpnl	13.609	0.003	***		dollarpnl	3.201	0.362	
	maxdd	134.457	0.000	***		maxdd	66.723	0.000	***
	intravol	15.119	0.002	***		intravol	20.598	0.000	***
	polarity	42.824	0.000	***		polarity	6.790	0.079	*
	subjectivity	64.031	0.000	***		subjectivity	3.777	0.287	
intravol	mkt_sych	3.417	0.332		intravol	synchronicity	6.357	0.095	*
	social_times	6.221	0.101			social_times	4.178	0.243	
	dollarpnl	18.749	0.000	***		dollarpnl	11.972	0.007	***
	maxdd	80.728	0.000	***		maxdd	35.120	0.000	***
	leverage	0.447	0.930			leverage	2.378	0.498	
	polarity	4.627	0.201			polarity	7.549	0.056	*
	subjectivity	2.504	0.475			subjectivity	16.930	0.001	***
polarity	mkt_sych	206.092	0.000	***	polarity	synchronicity	133.832	0.000	***
	social_times	2.151	0.542			social_times	4.216	0.239	
	dollarpnl	17.048	0.001	***		dollarpnl	8.452	0.038	**
	maxdd	111.164	0.000	***		maxdd	237.658	0.000	***
	leverage	10.725	0.013	**		leverage	7.374	0.061	*
	intravol	16.531	0.001	***		intravol	20.501	0.000	***
	subjectivity	423.629	0.000	***		subjectivity	336.924	0.000	***
subjectivity	mkt_sych	1643.097	0.000	***	subjectivity	synchronicity	128.450	0.000	***
	social_times	2.980	0.395			social_times	1.378	0.711	
	dollarpnl	8.233	0.041	**		dollarpnl	2.822	0.420	
	maxdd	832.194	0.000	***		maxdd	248.743	0.000	***
	leverage	21.129	0.000	***		leverage	2.177	0.536	
	intravol	13.887	0.003	***		intravol	18.756	0.000	***

polarity	572.270	0.000	***	polarity	302.811	0.000	***

This table shows the results of the Granger Causality tests with including the trader sentiment measures. Pane A reports the results of the platform-level synchronicity tests. Pane B reports the results of the trader-level synchronicity tests. *mkt_sych* represents the platform-level synchronicity measure. *synchronicity* represents the trader-level synchronicity measure. Chi-squares (chi2), p-values (Prob) and significance levels (Sig.) are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 3-15 Controlling for Day-fixed Effects (Trader-level)

VARIABLES	(1) synchronicity	(2) social_times	(3) dollarpnl	(4) maxdd	(5) leverage	(6) intravol
L.synchronicity	0.383***	0.020***	-22.905	0.007***	20.676**	0.002***
	[0.000]	[0.000]	[0.699]	[0.000]	[0.013]	[0.000]
L.social_times	**0.007*** **	0.127***	-11.315	0.000	-0.056	-0.000
	[0.000]	[0.000]	[0.345]	[0.114]	[0.936]	[0.270]
L.dollarpnl	0.000	-0.000	0.081	0.000	0.000	-0.000
	[0.449]	[0.426]	[0.135]	[0.600]	[0.384]	[0.763]
L.maxdd	-0.002	-0.023***	-321.637	0.969***	69.718**	0.006***
	[0.855]	[0.004]	[0.128]	[0.000]	[0.049]	[0.001]
L.leverage	0.000***	-0.000***	-0.050	0.000**	0.495***	0.000**
	[0.000]	[0.000]	[0.133]	[0.013]	[0.000]	[0.017]
L.intravol	0.045***	0.001	-45.208	0.057***	-4.086	0.038***
	[0.004]	[0.945]	[0.188]	[0.008]	[0.920]	[0.004]
Observations	499,013	499,013	499,013	499,013	499,013	499,013

This table shows the results of the panel VAR model with day-fixed effects. The dependent variables in each column (from (1) to (6)) are the trader-level return synchronicity (synchronicity), social participation times (social_times), dollar profits and losses (dollarpnl), maximum drawdown (maxdd), leverage (leverage), and intraday volatility (intravol), respectively. The explanatory variables are the lag of these variables. P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3-16 Granger Causality Test (Trader-level Controlling for Day-fixed Effects)

Dependent Variable	Explanatory Variable	Chi2	Prob	Sig.
synchronicity	**social_times**	**13.240**	**0.000**	***
	dollarpnl	0.574	0.449	
	maxdd	0.033	0.855	
	leverage	123.867	0.000	***
	intravol	8.445	0.004	***
social_times	synchronicity	58.163	0.000	***
	dollarpnl	0.635	0.426	
	maxdd	8.353	0.004	***
	leverage	66.726	0.000	***
	intravol	0.005	0.945	
dollarpnl	synchronicity	0.149	0.699	
	social_times	0.891	0.345	
	maxdd	2.319	0.128	
	leverage	2.259	0.133	
	intravol	1.733	0.188	
maxdd	synchronicity	17.137	0.000	***
	social_times	2.494	0.114	
	dollarpnl	0.275	0.600	
	leverage	6.117	0.013	**
	intravol	7.074	0.008	***
leverage	synchronicity	6.127	0.013	**
	social_times	0.006	0.936	
	dollarpnl	0.757	0.384	
	maxdd	3.869	0.049	**
	intravol	0.010	0.920	
intravol	synchronicity	22.476	0.000	***
	social_times	1.215	0.270	
	dollarpnl	0.091	0.763	
	maxdd	10.902	0.001	***
	leverage	5.684	0.017	**

This table reports the results of Granger causality tests. Chi-squares (Chi2), p-values (Prob) and significance levels (Sig.) are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 3-17 Clustering Standard Errors at Trader Level

VARIABLES	(1) synchronicity	(2) social_times	(3) dollarpnl	(4) maxdd	(5) leverage	(6) intravol
L.synchronicity	0.499***	0.017*	125.802	0.011***	-49.797**	-0.001**
	[0.000]	[0.069]	[0.135]	[0.000]	[0.016]	[0.037]
L.social_times	**0.014*** **	0.127***	-5.500	0.000	-2.871**	-0.000**
	[0.000]	[0.003]	[0.669]	[0.131]	[0.040]	[0.015]
L.dollarpnl	0.000	-0.000	0.081	0.000	0.000	-0.000
	[0.311]	[0.409]	[0.151]	[0.708]	[0.301]	[0.627]
L.maxdd	0.326***	-0.034*	205.976	0.983***	-165.761***	-0.005***
	[0.000]	[0.082]	[0.200]	[0.000]	[0.002]	[0.001]
L.leverage	0.000***	-0.000***	-0.031**	0.000**	0.486***	-0.000*
	[0.000]	[0.000]	[0.046]	[0.015]	[0.000]	[0.082]
L.intravol	0.079***	0.000	-18.785	0.059***	-14.282	0.038**
	[0.001]	[0.985]	[0.539]	[0.007]	[0.732]	[0.011]
Observations	499,013	499,013	499,013	499,013	499,013	499,013

This table shows the results of the panel VAR model with standard errors clustered at trader level. The dependent variables in each column (from (1) to (6)) are the trader-level return synchronicity (synchronicity), social participation times (social_times), dollar profits and losses (dollarpnl), maximum drawdown (maxdd), leverage (leverage), and intraday volatility (intravol), respectively. The explanatory variables are the lag of these variables. P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3-18 Granger Causality Test (Clustering Standard Errors at Trader Level)

Dependent Variable	Explanatory Variable	Chi2	Prob	Sig.
synchronicity	social_times	25.019	0.000	***
	dollarpnl	1.027	0.311	
	maxdd	24.355	0.000	***
	leverage	36.729	0.000	***
	intravol	11.666	0.001	***
social_times	synchronicity	3.296	0.069	*
	dollarpnl	0.683	0.409	
	maxdd	3.027	0.082	*
	leverage	17.767	0.000	***
	intravol	0.000	0.985	
dollarpnl	synchronicity	2.237	0.135	
	social_times	0.183	0.669	
	maxdd	1.640	0.200	
	leverage	3.995	0.046	**
	intravol	0.377	0.539	
maxdd	synchronicity	16.429	0.000	***
	social_times	2.282	0.131	
	dollarpnl	0.140	0.708	
	leverage	5.879	0.015	**
	intravol	7.155	0.007	***
leverage	synchronicity	5.795	0.016	**
	social_times	4.222	0.040	**
	dollarpnl	1.072	0.301	
	maxdd	10.020	0.002	***
	intravol	0.117	0.732	
intravol	synchronicity	4.331	0.037	**
	social_times	5.921	0.015	**
	dollarpnl	0.237	0.627	
	maxdd	11.667	0.001	***
	leverage	3.023	0.082	*

This table reports the results of Granger causality tests. Chi-squares (Chi2), p-values (Prob) and significance levels (Sig.) are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

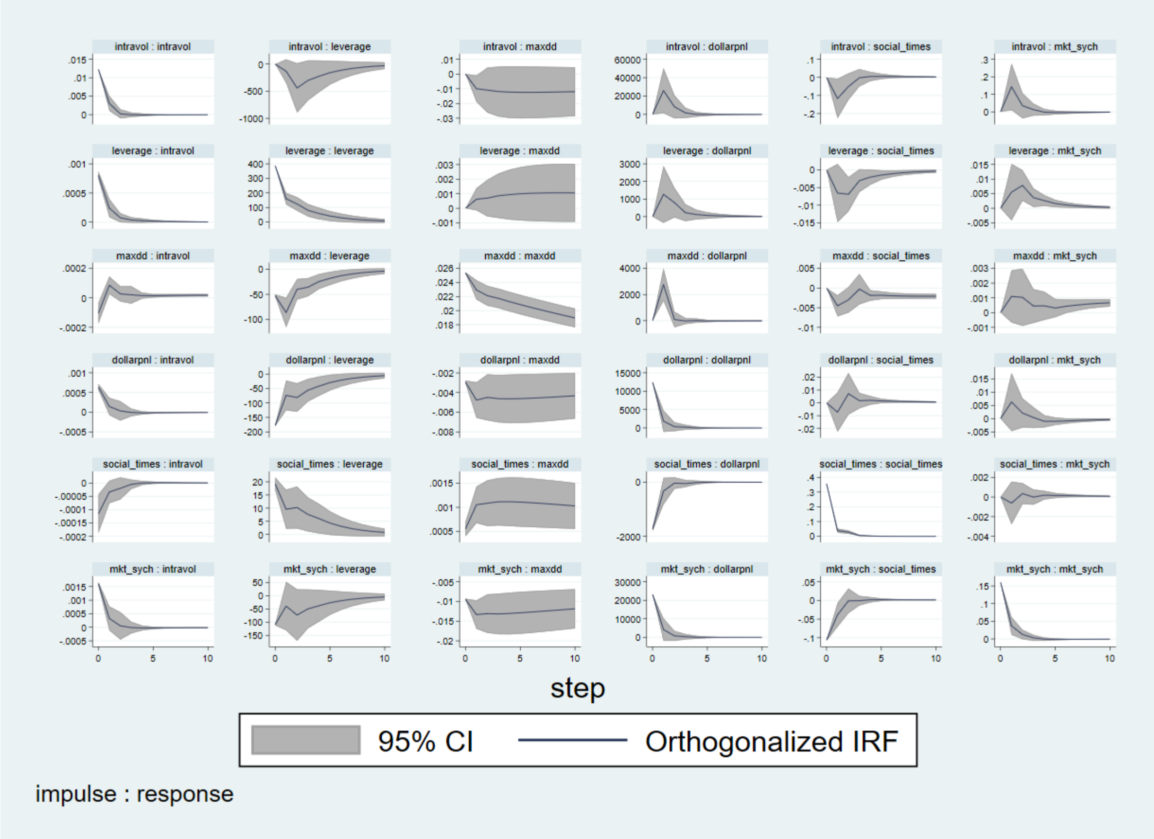

Figure 3-1 Social Communication and Return Synchronicity (Platform-level)

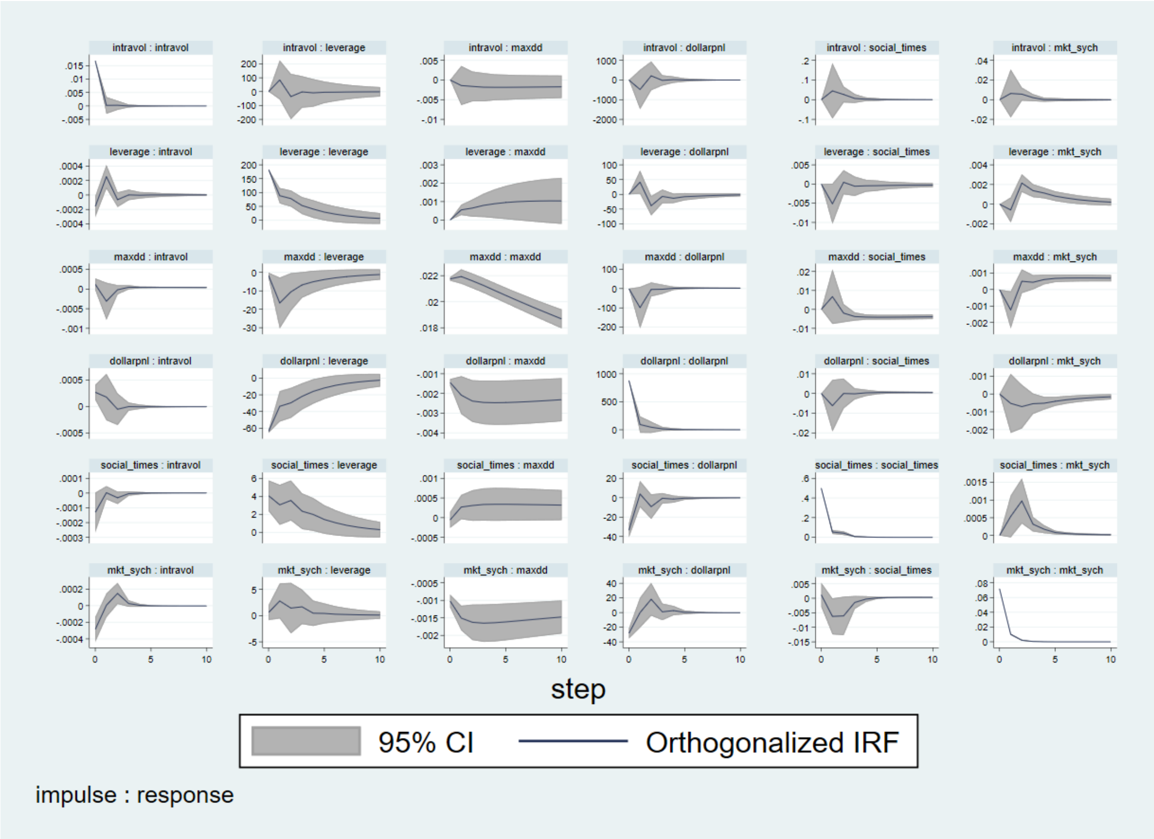

Figure 3-2 Social Communication and Platform-level Return Synchronicity (Creator)

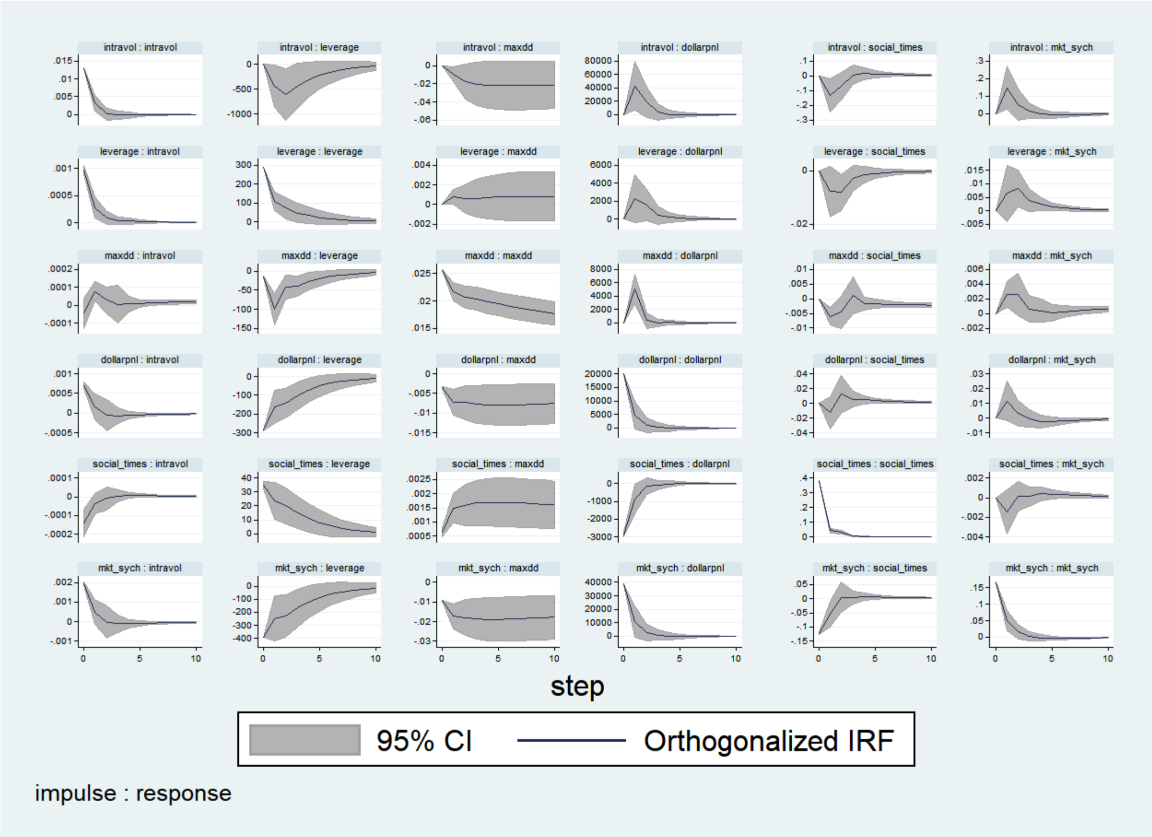

Figure 3-3 Social Communication and Platform-level Return Synchronicity (Commenter)

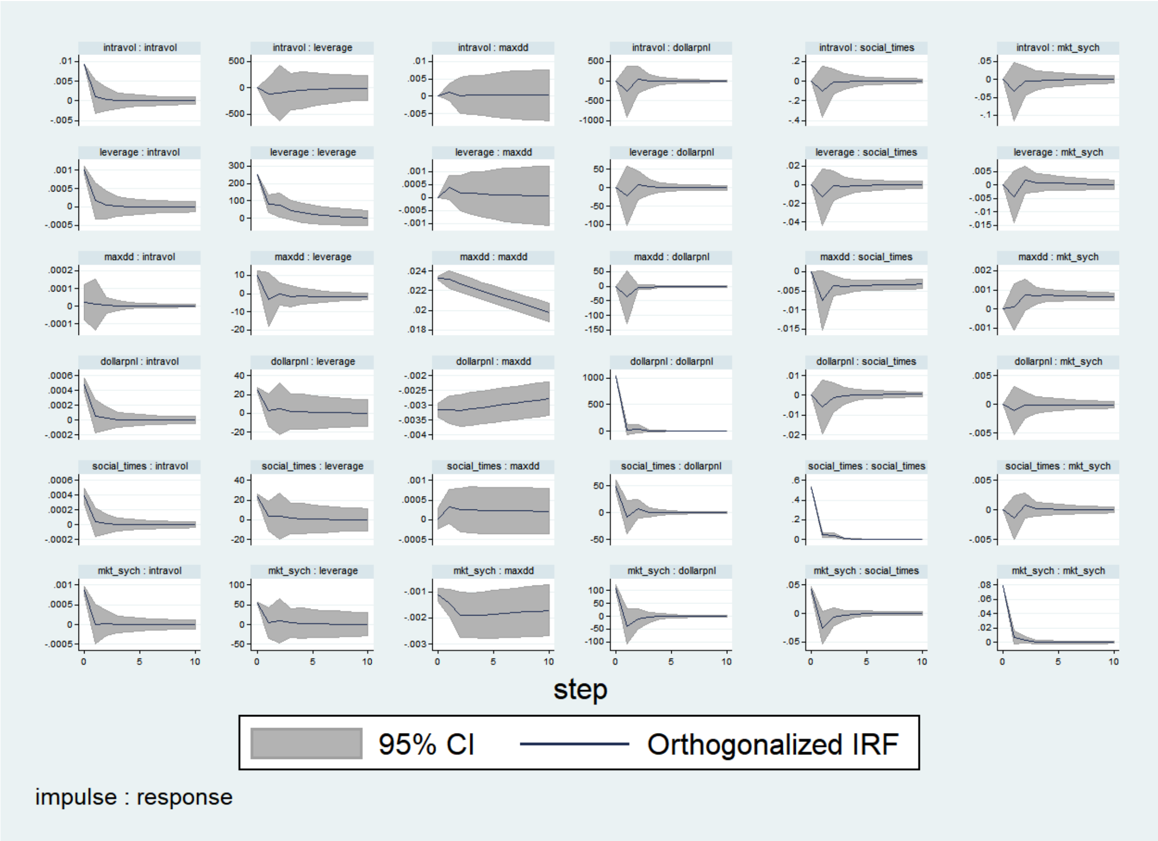

Figure 3-4 Social Communication and Platform-level Return Synchronicity (Liker)

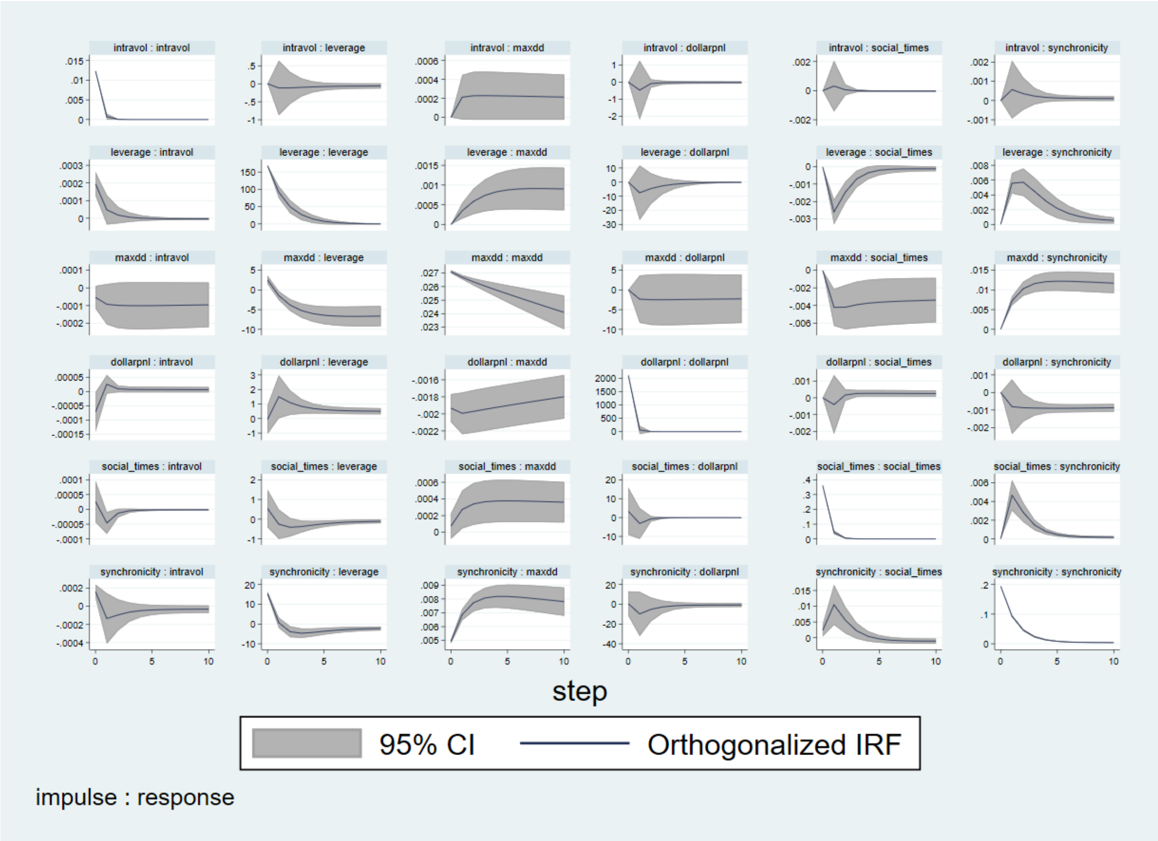

Figure 3-5 Impulse Response Functions (IRFs) (Trader-level)

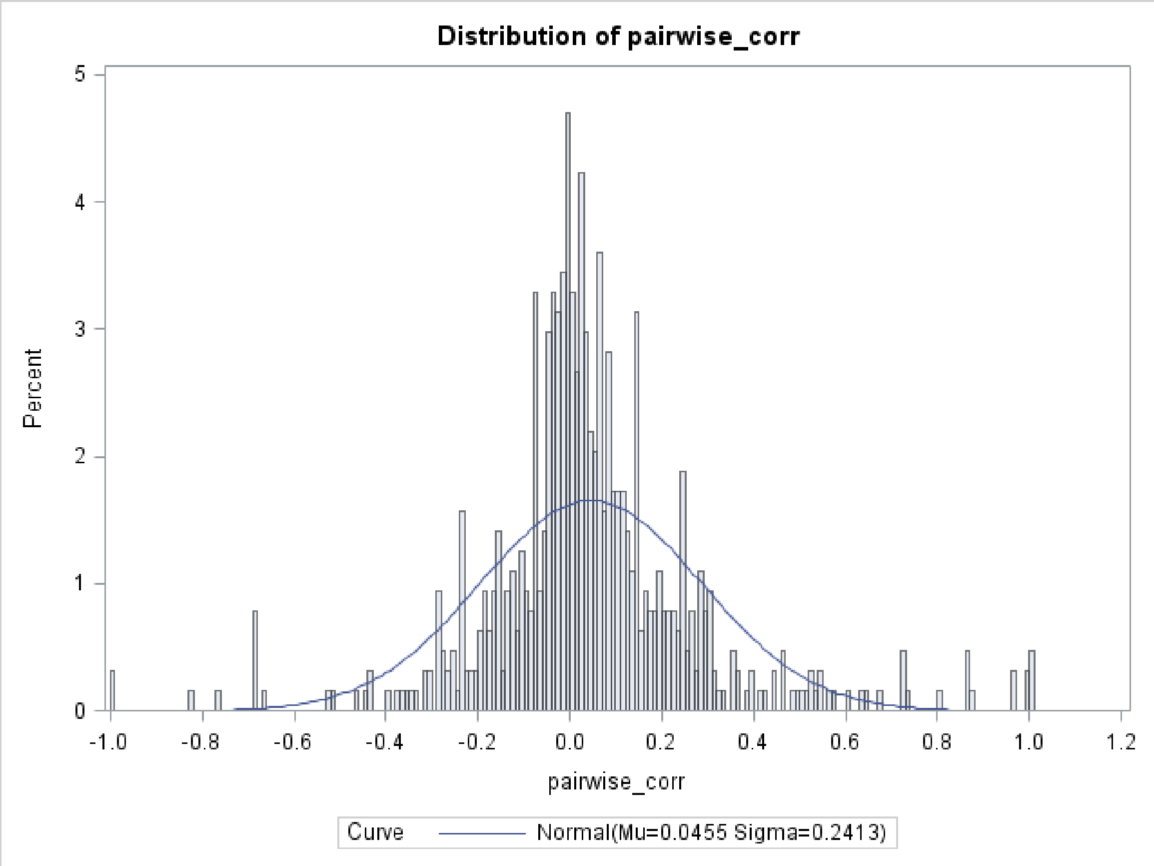

Figure 3-6 The Distribution of the Chat-level Return Synchronicity

Chapter 4: Does Social Communication Impact Investor Survival in the Market?

Abstract

This paper analyzes the effect of social communication on investor survivorship in the foreign exchange market. Previous studies on social communication have emphasized its causal role with respect to market entry, while survivorship studies have overwhelmingly highlighted the role played by psychological and career-related factors in the investors' decision to quit the market or not. Using a novel dataset covering 1.1 million observations for 4,731 traders over an 18-month period, I reveal the important role of social communication in influencing traders' decisions to stay in the foreign exchange market. I find that traders who actively use communication tend to be 17% to 30% less likely to quit trading. My results also identify a positive Granger-causal relationship between social communication and the probability of survival. My results are robust to alternative measures of social communication and different sets of control variables. I contribute to the survivorship literature by drawing attention to the role played by social communication with respect to the decision to stay in the market.

Keywords

Behavioral Finance, Individual Investors, Social Trading Platforms, Survival Analysis, Social Finance

4.1 Introduction

It is documented in finance literature that social communication alters investors' trading behavior and decision-making process (Han, Hirshleifer, and Walden, 2018; Heimer, 2016). It is documented that traders can be influenced by the social communication in terms of stock market participation (Guiso & Jappelli, 2005; Hong et al., 2004) and investing strategies (Han & Hirshleifer, 2012; Heimer, 2014). It is also intuitive that traders can be influenced by the conversations they have with others while trading, especially when they are discussing their ongoing trading activities and decisions. The consequences of the social communication on traders not only include the decision to participate and to adapt their trading strategies, but also include the decision to continue (survive) or to cease (quit) their trading activities.

However, the decision to continue trading (survival) in relation to social communication is underexplored in the literature. The investigation of the survival of traders has a distinct value for understanding the dynamics of a trader's trading lifetime decision-making processes, apart from the decision to participate (at the beginning of a trading life) and to choose their trading strategies (in middle of a trading life). It is the decision to quit trading (at the end of a trading life), which finally adds to the full description of the characteristics of a trader's trading life.

It is not known to the academic community what traders talk about and how the various aspects of their trading activities are influenced by the conversations they have while making their trading decisions (let alone examining the impact of social communication on traders' behavior). However, in a special setting (social trading platform), I am able to observe what traders talk about while trading and how their behavior is subsequently altered by such social communication. I observe that traders are keen to talk about the future (see a more detailed discussion in 4.3 Hypothesis Development). For example, *"Today is looking very sketchy, I'm going to hold a long aud/jpy averaged about 77.90 and call it a week."*, *"What do yu think the EURUSD pair is going to do in the next 5 hours?"*, and *"Maybe MyFXtrade will have a real-time graph of these numbers in the future we can use."*

Intuitively, these discussions anchor traders' expectations regarding the future. Traders should therefore be more curious to check out their expectations in the future, compared to instances where they do not have any expectations at all. Consequently, traders should have the incentives to continue to stay (survive) in the market (as oppose to exit the market) after having such conversations regarding the future of the market. Therefore, in this paper, I examine whether social communication impacts the survival of traders.

Empirical studies have documented that social communication plays a role in the retail investors' decision to start trading in equity and foreign exchange markets (e.g., Changwony, Campbell, and Tabner 2015; Chen and Roscoe 2017; Brown, Ivkovic, Smith, and Weisbrenner 2008; Kaustia and Knupfer 2012). Face-to-face communication in one's local community and social networks plays a causal role with respect to one's decision to take up trading. This leads to the question whether social communication within trading communities plays a role with respect to market survival as well. This question has been much less investigated, although it is especially relevant since technological evolutions have led to integrating communication with real-time trading.

This integration changes the way transactions are organized, in the sense that it becomes possible to obtain real-time information about fellow traders' decisions, swap opinions, and interpret market information jointly. Investigating the impact of such changes on market survival also has relevance with respect to debates about whether communication on social media can predict prices in equity markets and FX movements (e.g., Lachanski and Pav 2017; Reed 2016; Ozturk and Ciftci 2014). Recently, studies have developed theoretical models in order to describe information transmission in the market through network communication, capturing the impact on the behavior of investors and the implications on asset prices (Han & Yang, 2013; Han, Hirshleifer, & Walden, 2018; Ozsoylev, 2004; Xia, 2008). Therefore, understanding the broader impact of social communication integrated with trading should take the question of market survival into account.

I address here the question whether communication impacts the survival of retail traders by analyzing data from such integrated trading systems, also known as social trading platforms (STPs). STPs have grown in popularity over the past decade; they include at least two significant features. First, they allow participating traders to observe each other in real time, including trading activities, performance, and ranking (the so-called scopic system feature, see detailed descriptions in (Gemayel & Preda, 2018a; Gemayel & Preda, 2018b; Heimer, 2016; Knorr Cetina, 2003)). Second, traders on STPs are able to communicate with others instantly when trading online by participating in online forum discussions or individual messaging (communication feature). I focus in this paper on the communication feature of STPs.

Using a novel dataset from a foreign exchange STP, I investigate the question of whether traders who use communication features stay longer in the market. The dataset includes a total of 1,119,342 observations associated with 4,731 individual traders' trading accounts across an 18-month period. This makes it possible to compare traders based upon their specific communication activities on this STP. In my sample (see details in the data section) of 3,426 active traders there are 699 (20.4%) traders who actively use the communication features of the trading platform, including creating discussion topics, posting messages within the discussion groups, and liking the posts of others. I refer to these traders as "communicative traders". First, I present evidence of survivorship within my dataset by utilizing Kaplan-Meier estimates to identify whether making use of these features (as a creator/commenter/liker of discussions) plays a role with respect to an individual trader's decision to quit or to stay active in the market. Then I perform a Cox hazard proportional model to quantify the effect of social communication usage on the decision to quit trading of individual traders. Finally, I employ a panel VAR framework and Granger causality tests to identify the causal relationship between use of communication and individual traders' survivorship. Across the same time period, communicative traders appear to stay longer compared with non-communicative ones. Communication appears to lead to an increased survival probability in the market.

I seek to stimulate a new area of debate within the survivorship literature relating to trading behavior, which has so far been dominated by the question of whether experience improves trading performance over time and can diminish known behavioral biases. I believe the discussion needs to be widened in order to recognize that there are additional factors shaping survivorship within financial markets. One of these factors is real time communication as intrinsic to how trading is organized. My findings also draw attention to the assumption of homogeneity of motives in financial trading, motives which might be impacted by how trading is organized. My results are also relevant with respect to recent investigations about social communication and market participation: while previous studies show that communication plays a central role with respect to market entry, I show that it plays a role with respect to market persistence as well. Overall, I call for a more fine-grained investigation of the role of communication in trading.

4.2 Literature Review

4.2.1 Social Communication and Market Participation

While there is an extensive body of empirical literature on the financial performance of retail traders and investors and its determinants (e.g., Chen, Chen, & Huang, 2014; Frankel, 2003; Gao & Oler, 2012; Kyle & Xiong, 2001; Mahani & Bernhardt, 2007; Spurgin & Tamarkin, 2005; Whaley, 2013; Zheng, 1999; Barber, Lee, Liu, & Odean, 2008; Gemayel & Preda, 2018a; Gemayel & Preda, 2018b; Hayley & Marsh, 2016; Heimer, 2016; Preda, 2017; Renani, Mohammadi, & Moeeni, 2014), the role of communication in relation to market participation has been much less explored. Existing studies point repeatedly to the role communication plays with respect to market entry. Communication with acquaintances impacts the retail traders' decision to enter the equities market, while communication with neighbors does not (Changwony, Campbell, & Tabner 2015). Communities that are more sociable—that is, communicate more—have a higher degree of market participation, and that communication plays a causal role in this (Brown, Ivkovic, & Weisbrenner 2008). If social communication is causally relevant for the decision to enter the market, to what extent is it causally relevant for the decision to stay in the market too? Studies linking social communication to market entry have focused on face-to-face communication; trading platforms, however, integrate communication with trading and offer participants the possibility of communicating with each other in real time while trading.

Social communication thus becomes intrinsic to the organization of trading. It has been long recognized that the ways in which trading is organized impact the behavior of market actors (O'Hara, 1999). The organization of trading includes not only the speed and rhythm of price and volume information, but also the information market actors have about each other and the information they exchange with each other. The integration of social communication with trading platforms through Social Trading Platforms (STPs) changes both. STPs provide participants with a scopic system -- that is, with the possibility of observing each other's transactions in real time, and of observing hierarchies of "trade leaders". Less successful traders can entrust such "trade leaders" with managing their portfolios, following a hedge fund model. Traders who do not wish to trade themselves can build portfolios of "trade leaders" and switch investments across such portfolios. In addition to this, STPs provide participants with the possibility of communicating with each other in real time, by initiating discussions, contributing to discussions, or signaling agreement to the opinions of others (e.g., liking a discussion post). The impact of this communication has not been studied in depth. A limited number of studies show that this real-time information that traders obtain about each other impacts herding behavior and the traders' disposition effect (Gemayel & Preda, 2018a; Gemayel & Preda, 2018b; Heimer, 2016).

4.2.2 Market Persistence and Retail Traders

If communication causally affects market entry, as studies show, to what extent does it causally impact market persistence? The traditional argument is that irrational (an admittedly vague term) traders won't survive in the market (Friedman, 1953) as they do not make money. However, individual investors, for a variety of reasons, might be reluctant to quit. Two categories of factors are usually seen as impacting persistence in the market: psychological and career-related ones, respectively. Misperceptions, overconfidence, and myopic loss aversion, among others, belong to the former category. Past immediate successes and experience belong to the latter. Behavioral finance argues that noise traders can eventually dominate the market, given their misperceptions on return variances (De Long et al., 1990). Plus, overconfident traders persist in the long-run steady-state equilibrium because they can perhaps better exploit the mispricing caused by either liquidity traders or noise traders, compared with rational traders (Hirshleifer & Luo, 2001). Similarly, professional currency dealers who are overconfident are not driven out of the market due to their losses, given that they overestimate their success and underestimate uncertainty (Oberlechner & Osler, 2012). In addition, non-professional traders are found to exhibit lower myopic loss aversion (MLA) behavior compared with professional traders (Haigh & List, 2005), which potentially contributes to the persistence of individual investors while losing money.

The existence in the market of traders deemed as not conforming to a benchmark model of rationality (and labelled with a variety of names) is important, since they impact the behavior of asset prices (Baklaci, Olgun, & Can, 2011; Coury & Sciubba, 2012; Coval & Shumway, 2005; Kogan, Ross, Wang, & Westerfield, 2006; Kogan, Ross, Wang, & Westerfield, 2017). At the same time, the behavior of individual investors, including the decision to keep trading or to quit, depends on features such as their past returns, most recent day success, overall career success rate, and the experience of investors (Ben-David, Birru, & Prokopenya, 2018; Boyd & Kurov, 2012; Hayley & Marsh, 2016; Nolte, 2012).

In addition to the psychological and career-related factors discussed above, there may be additional ones, such as communication integrated into the organization of trading. Since social communication impacts market entry, it is reasonable to ask if it impacts market survival as well. Because traders have the possibility of communicating with each other in real time (i.e., while trading), I could assume that this kind of communication is more readily available and frequent in electronic trading than face-to-face communication with neighbors, acquaintances, and the traders' wider social circle. The integration of communication into the organization of trading provides an opportunity to examine it in direct rapport with the transactions executed by traders and with their decisions to stay in or quit the market.

4.2.3 Contribution of the Paper

I contribute to studies of retail traders in the following ways. First, I contribute to the survivorship literature by identifying a causal relationship between social communication and survivorship. I thus add a further aspect to the known (psychological and career-related) factors impacting survivorship.

Second, I speak to the literature on social interactions and investor behavior (e.g., Hong et al., 2004; Guiso & Jappelli, 2005). Particularly, I contribute to this strand of literature in the context of social interactions through social media by extending the understanding of the impact of social media on investor behavior (Tetlock, 2007; Gu, Konana, Raghunathan & Chen, 2014; Barber & Odean, 2001). In addition, I contribute to the understanding of the implications of social media information on investing, discussed under the banner of Facebook finance (e.g., Heimer & Simon, 2012) and Twitter finance (e.g., Bollen, Mao, & Zeng, 2011; Zhang, Fuehres, & Gloor, 2011). I call for future research on various STPs, besides investigating platforms such as Facebook and Twitter.

Third, I contribute to the literature on retail traders in the FX market (Heimer & Simsek, 2019; Heimer, 2016; Ben-David et al., 2018), which is relatively small compared to the literature on retail investors in the equity market. This lack of literature may be due to the inaccessibility to account-level data in the foreign exchange market. The data used in prior literature, problematically, only comes from a single broker (e.g., Ben-David et al., 2018) instead of a wide range of brokers (e.g., Heimer & Simsek 2019). My dataset overcomes this challenge as it includes all traders and associated trading records during the sample period without potential selection bias or self-reporting issues on trading activities.

Broadly speaking, I also contribute to the literature on retail investors in financial markets. As Heimer (2016) shows by using data from a large discount brokerage used in

Barber and Odean (2000), the behavior of retail investors in the FX market is quite similar to that in the equity market.

4.3 Hypothesis Development

One reason why social communication can increase the survival of traders is that traders discuss about events in the future, which forms traders' expectation about the future and increases traders' willingness to stay in the market. This reason can be seen in the content of the online discussion forum. When I read through the content of the online discussion forum, one significant feature is that people are keen to talk about events in the future, share their predictions about the future, and discuss trading strategies based upon their perception of different states of the market in the future.

I have collected three examples of the online discussion topics and presented the discussion content in Appendix 4-1. The discussion content is reported exactly as shown in the online discussion forum (including typos/miscapitalization of letters), except that the name of the platform is replaced with MyFXtrade for the purposes of anonymity. In addition, for each record of the online discussion, it includes observation ID (Obs), discussion ID (Id), discussion category (Category), creator ID (Creator), discussion topic (Topic), discussion content (Comments), commenter ID (Commenter), discussion topic creation time (Create Time), and discussion comments posted time (Post Time).

For example (discussion ID: 463), the user (creator ID: 2420) shared about her/his understanding about the market condition (Market_C) by creating a discussion topic "Friday FUNdaMENTALS", saying that "*Today is looking very sketchy, I'm going to hold a long aud/jpy averaged about 77.90 and call it a week. Overall a good week for me, coming very close to personal goal. We seem to be consolidating the dollar and direction may be changing in the future (read: october).*" This comment was posted at

“25SEP2009:16:00:41” and predicted a future change in the market condition (in October). I would expect that this user is more likely to continue her/his stay in the market (until October) compared to users who do not have any expectation about the future market conditions at all, and/or who are not aware of any information to check the future realization/failure of a past prediction about the market. In addition, users who are actively engaged in this online forum discussion feature could also be potentially influenced by the online discussion content in a similar way – to see what is going to happen in October. Therefore, the survival probability of traders can be prolonged by such discussion topics forming/influencing future expectations of traders.

Similarly, under the discussion topic “Social Indicator Pattern” (discussion ID: 477), one of the participants (commenter ID: 498) mentioned in her/his post that “*Maybe MyFXtrade will have a real-time graph of these numbers in the future we can use.*” This particular comment about a potential technological change on the STP in the future may increase traders’ curiosity to try out or at least to observe the use of a potential money-winning technique of trading. This may also expand the likelihood of survival of the discussion participants and other traders who may read this discussion topic.

Another example can be seen under the discussion topic “EURUSD pair” (discussion ID 647). In this interaction, one user (name: Michael, commenter ID: 2479) asked a specific question in the discussion forum “*What do yu think the EURUSD pair is going to do in the next 5 hours?*” The other user (commenter ID: 3366) obviously missed the specified time interval of the required response time (5 hours). This is because the question was posted at “05NOV2009:02:50:48”, while the response was posted at “05NOV2009:19:28:07” – more than 5 hours since the posting of the question. However, the user (commenter ID: 3366) kindly shared her/his experience of sticking to trading plans which “*took 3 years”*. This comment may alter other traders’ expectation about how long they should continue to trade to be sufficiently trained to be a trader who is able to stick to her/his trading plans. Though not directly affecting the trading decision of the trader who posted the question, she/he generously offered some additional advice regarding trading strategies in the hope that the advice can be converted to some transferable skills for the discussion initiator "*in the future*". This may lead traders to use or at least try these advised strategies in the future, which may extend their trading life regardless of the success of these strategies. In addition, it is intuitive that the chat initiator is expected to be more directly impacted by the response than other viewers of this discussion, as the advice is particularly provided to the chat initiator. However, the viewers can actually alter their trading behavior as much as the chat initiator if they wish to do so as the discussion forum is equally accessible to all traders.

Overall, I can see from the discussion content that traders may be affected in terms of changing their future expectations about market/platform, altering their perception of their own trading skills, and trying out new trading strategies. These influences can be eventually translated into an increased survival probability of traders in the short term or a prolonged trading period in the long term. Therefore, I hypothesize that ***social communication increases the survival of traders on the STP.***

4.4 Data and Descriptive Statistics

4.4.1 Data

I utilize a novel dataset (unbalanced panel) from a social trading platform, including 18 months of detailed trading records (1,119,342 observations) from January 2009 to June 2010 for 4,731 individual trading accounts on an online foreign exchange (FX) social trading platform (STP). In particular, there are two communication features on the STP, namely, online discussions and one-to-one messaging.

In this study, I focus on the usage of online discussions; the one-to-one messages are not visible to the entire trader community, while online discussions are visible to anyone, including those who do not participate in them. This allows us to compare the survival of those who actively participate in online discussions vs. those who do not. The other communication feature (i.e. one-to-one messaging) is examined in 4.7 Alternative Analysis in this paper.

For the purposes of investigating the trading behavior of each trader, I restrict the sample with several conditions. I select the sample with traders who started their trading within the observation period. This includes traders whose first observation date is after 1st January 2009 as otherwise the estimation of survival function will not accurately capture the actual survivorship of traders. I also select accounts with at least two observations between the first observation and the last observation with closed trades during the observation period. After the data trimming, there are 3,426 traders (3,426 trading accounts) in the sample.

For the traders in the sample, there are 699 (20.4%) traders who used the online forum discussion feature at least once (creating a discussion topic, posting a message under a discussion topic, or liking a post). There are 2,727 (79.6%) traders who did not use the online forum discussion feature during their entire trading period on the STP. For each trader's account, I observe records of daily aggregated trading activities for a total of 381 trading days (545 calendar days). Trading profits and losses (Pnl) are aggregated at daily frequency and daily profits and losses are accounted as US dollar value (excess of fee). Open balances, deposits (money in) and withdrawals (money out) are available for each individual broker account on each trading day.

4.4.2 Identification of Communicative Traders

I identify communicative traders based upon their participation in discussions throughout the sample period. There are 1,455 discussions in total, where any user on the platform can create a discussion topic (creator), post a message under a discussion topic (commenter) or like a post (liker). I call users communicative if they create, comment upon, or like discussion threads or contributions thereto, or a combination of any of them. Traders can actively involve with more than one social activity on the platform. A trader can create discussion topics, comment on other traders' discussions, and like other traders' posts. Those traders who are not involved in any of the above-mentioned activities are identified as non-communicative. It is important to note that non-communicative traders can observe what is posted and discussed by communicative traders on the platform. After identifying all the communicative traders and the non-communicative traders, I match these users with their daily trading activities associated with their broker accounts.

There are 1,455 discussions used for identifying creators, 4,240 posts used for identifying commenters and 869 likes used for identifying likers. On average, there are around 3 comments per discussion topic and around 0.2 likes per comment.

In order to investigate the influence of social communication on market survival, I group participants according to their usage of social media on the STP. In the context of this paper, usage refers to the frequency of individual traders participating in discussions on the trading platform, including creating a discussion topic, posting a comment under a discussion topic, and liking a particular post. By counting the number of activities that each individual trader participates in, I am able to distinguish different levels of communication associated with each individual trader.

4.4.2.1 Performance Measure

Similar to Heimer & Simsek (2019) and Ben-David et al. (2018), to control for traders' performance in my analysis I measure traders' daily performance (Eq. 1) with account balances (opening balances (OB), closing balances (CB)) excluding the net changes in deposits. I use the absolute value of OB as denominator for that there are a small proportion of situations where OB is negative. This measure is used for the calculating of both traders' active trading days, when the closed volume of trades is not zero, and non-active trading days when the closed volume of trades is zero (the daily return measure equals zero).

$$Return_{i,t} = \frac{CB_{i,t} - OB_{i,t} - Net\ Changes\ in\ Deposits}{|OB_{i,t}|} \quad (1)$$

4.4.2.2 Descriptive Statistics

Summary statistics on account-level variables are reported in Table 4-1. I define active trading days as days during which the number of closed trades is non-zero. I define a trader as quitting trading if I do not observe an active trade of this trader during the entire one month prior to the end of the sample period (Hayley & Marsh, 2016). The one-month cut-off is reasonable and robust as shown in Hayley & Marsh (2016), for the reason that most active traders trade quite often the average length (4 days) between two active trading days, which is far less than one month. In my sample, the mean survival days for a trader is 81.49 days and the mean active trading days for a trader is 29.02 days, which implies on average there is an active trading day for a trader about every 3 days. Therefore, the one-month cut-off is sufficient to decide if a trader quits trading. The variables include average return (the average return during the sample period for each trader), recent return (return for the most recent active trading day that closed trades during that day is non-zero), recent success (dummy variable equals 1 if the most recent observed active trading day is with profits), career success (the total number of win trades divided by the total number of closed trades), total dollar PnL (the total dollar PnL for the period), total closed trades (the total number of trades closed), survival days (the number of days between the first observation of a trader till the last observation with closed trades during that day), active days (days with non-zero closed trades), quit trade (dummy variable equals 1 if the trader quits trading), participation times (the cumulative online forum participation times, any of creating a discussion topic, posting a comment or liking a post), message (dummy variable equals 1 if the trader successfully send, receive or read a message amongst other traders), and age (the trader's age as of the first observation), for each trader's account for the entire sample period.

[Table 4-1]

I also report detailed statistics with a separation between communicative and non-communicative traders in Table 4-2. The two groups of traders begin their trading activities at a similar age. Communicative traders on average participate 8 times in online forum discussions during the entire sample period. Communicative traders' survival days and active trading days both exceed those of non-communicative traders.

[Table 4-2]

4.5 Preliminary Evidence and Intuition

4.5.1 Survival Analysis

I employ survival analysis to investigate whether communicability plays a role in terms of the traders' decision to quit trading. The occurrence of the event (also known as failure) in the context of this paper is defined as the decision to quit trading for the individual traders.

4.5.2 Survival Function

$$S(t) = P_r\{T \geq t\} = 1 - F(t) = \int_t^{\infty} f(x)\, \mathrm{d}x \tag{2}$$

The survival function $S(t)$ (Eq. 2) gives the probability of being active until an event happens (the status before an event happens is defined as being active), where $f(x)$ denotes the probability density function (PDF) of a continuous random variable with t representing the waiting time until an event occurs, and $F(t)$ denotes the cumulative distribution function (CDF).

4.5.3 Kaplan-Meier Estimator of Survival Function

$$\hat{S}(t) = \prod_{t_i \leq t} (1 - \frac{d_i}{n_i}) \tag{3}$$

I use the Kaplan-Meier estimator (Eq. 3) (see also in Heimer (2016) and Hayley & Marsh (2016)) to estimate the survival function $S(t)$, where $\hat{S}(t)$ is the estimator of the survivor function $S(t)$, d_i is the number of events occur at time t_i, and n_i is the number of observations survive at time t_i. The event in the context of my analysis refers to the decision to quit trading.

4.5.4 Hazard Function

$$\lambda(t) = \frac{f(t)}{S(t)} \tag{4}$$

The hazard rate $\lambda(t)$ (Eq. 4) represents the conditional probability of the occurrence of the event, given that this event has not occurred before the duration time t. The calculation of hazard rate is as follows (Eq. 5), where d_i is the number of events occur at time t_i and n_i is the number of observations that survive at time t_i.

$$\lambda(t_i) = \frac{d_i}{n_i} \tag{5}$$

To conduct the survival analysis, I have to reconstruct the sample in the dataset based on my knowledge on whether the individual traders quit trading or not by the end of the sample period, and whether they start trading before the sample period or they start trading after the sample period starts. To this end, I apply the method used by Hayley & Marsh (2016). Specifically, I identify an individual trader who survives in the market if this trader has at least one trading record in the last month of the sample period; otherwise, I identify this trader to quit trading before the sample period ends. As mentioned earlier, I only consider traders who started their trading in my sample period. I do this to make sure that my sample for the survival analysis captures the beginning date of trading and the decision to quit trading of the individual traders.

4.5.5 Survival Analysis of Individual Traders

Figure 4-1 shows the Kaplan-Meier estimates of the survival function for the full sample of 3,426 individual traders. The horizontal axis indicates how many days a trader persists in the market from the first trade to the last trade during the sample period. The vertical axis represents the probability of survival for the individual traders on the platform during the sample period. For example, at the very beginning (day 0) of the trading activity for each individual trader, the survival probability equals 1, meaning that all the traders are starting their first trades at this point. However, after 350 days, around only 20% of individual traders are still willing to trade. I can compare the survival probability and the hazard rates at different points of duration time. As is shown in Figure 4-1, the probability of survival decreases as survival days go up for individual traders.

[Figure 4-1]

Similarly, the hazard rate plotted in Figure 4-2 estimates represent the probability of the decision to quit trading among the surviving traders at different points in time. The hazard rate changes at different points in time. However, the hazard rate does not say much about the survival of traders with respect to social communication. I need to investigate this through further survival analysis among different groups of traders.

[Figure 4-2]

I also conduct a survival analysis to identify the impact of communication on the survivorship of individual traders. In Figure 4-3, I compare the survival curves for users and non-users of social media on the platform. The survival curve for users of social media is always above the survival curve for non-users, indicating that the former ones have higher survival rates at any points of duration time during the sample period.

[Figure 3-3]

4.5.6 A Cox Proportional Hazard Rate Model

In this section, I employ the Cox Hazard Proportional Model to quantify the effects of using online forum discussion on the decision to quit. I use a Cox proportional hazard rate model (Eq. 6) to identify the factors which affect the survival chances of individual traders, where the $h_0(t)$ is the unspecified baseline hazard:

$$h(t|x) = h_0(t) \exp\,(a + b_0\text{Social} + b_1\text{Day(t)Success} + b_2\text{CareerSuccess} + \text{Controls}) \qquad (6)$$

The results presented in Table 4-3 show that social media participation significantly increases the survival probability of individual traders. Panel A includes the regressions with two main variables, recent success and career success where the recent success is defined as the success of most recent active trading day of each trader (1 if profiting, 0 if losing) and the career success is defined as the proportion of the total number of win trades out of the total number of closed trades. The control variables in panel A include Year/Month dummy, logged total trading volume, and total number of trades. The results of panel A are broadly consistent with Hayley & Marsh (2016)[5], indicating that recent

[5] While a direct comparison to Hayley and Marsh (2016) is not possible as the significance level is not reported in their paper, my results are broadly consistent with theirs in that the hazard ratios in Panel A tend

success and career success can potentially increase (hazard ratio < 1) the survival chances of individual traders.

[Table 4-3]

However, the main variables of interest in this analysis are presented in Panel B to Panel D. I perform the Cox hazard proportion model in panel A again, when I include different measures of social communication. To be specific, the variable *Social Times* (Panel B) represents the total number of online forum participation times (including creating a topic, posting a comment, and liking a post) of a trader. The variable *Social* (Panel C) that takes the value of 1 for communicative traders and 0 otherwise. The variable *First Day Social* (Panel D) is defined as a dummy variable indicating that a trader participates in online discussion forum during the first day of their online trading (equals to 1; 0 otherwise).

The results are presented in panel B to panel D. I find that, in columns (4) to (12), the hazard ratios associated with online communication are all significantly smaller than 1 (except column (6)), suggesting that social communication is significantly associated with the survival chances of individual traders.

The panel D shows that the hazard ratios associated with communicative traders (measured by *First Day Social*) are 0.711, 0.749, and 0.642, indicating on average communicate trades are 30% less likely to quick trading compared to non-communicative traders at any point of time during their trading life. Similarly, the hazard ratio estimation, which captures the economic magnitude of the impact of social communication on survival,

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to be smaller than 1 (except the hazard ratios in regression (2) for recent success and in regression (3) for career success where the two hazard ratios are insignificant). I report hazard ratios in the results (instead of coefficients). I do not cluster standard errors to be compared to Hayley and Marsh (2016).

is on average 0.832 for panel B, suggesting communicative traders are 17% less likely to quit trading at any point of time compared to non-communicative traders. However, I do not interpret the economic magnitudes in Panel B for two reasons. First, this measure of social communication (*Social Times*) can be related to reverse causality concerns and the estimation can be biased (see a detailed discussion in below). Second, the incremental *Social Times* is in social communication times, which captures the impact of one additional social communication time on survive. I am more interested in the impact of being a communicative trader on survival (as seen in Panel C and Panel D). Overall, the evidence suggests that a communicative trader is by 17% to 30% less likely to quit trading compared to a non-communicative trader at any point of time of their trading life.

4.5.7 Reverse Causality

After defining the social communication variables, it is obvious that these measures of social communication can be related to survival days (reverse causality issues may arise). In Panel B, it can be the case that traders are more likely to participate in online discussion forum for more times as they survive longer in the market. To mitigate the concerns regarding reverse causality, I construct two other measures of social communication (Social/First Day Social), which are related to survival days to different extents compared to the total social participation times (Social Times). Then, I compare the changes in the estimated hazard rations and significance levels from the results to understand how significant the potential reverse causality issue is in the Cox model identifications.

In particular, the variable *Social,* which indicates whether a trader is communicative or not, should be associated with a lower degree of reverse causality concern compared to social times. While it is true that traders can participate more times as they stay longer on the STP, it is less intuitive why I should believe that traders are more likely to initiate their first online participation (to be identified as a communicative trader) in a later stage of their trading life (compared to in an early stage). This is because if a trader tends to be communicative, she/he may participate in the discussion at any time during their trading life.

Therefore, the level of reverse causality concern arising from the *Social* measure should be lower than the *Social Times* measure. This argument is also evidenced in the data. The average number of survival days of non-communicative traders is 76 days. The average number of days before initiating the first online participation (the number of days between a trader's first day on the STP and the first online social communication) is 34 days. Non-communicative traders on average have sufficient time to initiate their first social participation. These results indicate the reverse causality issue is less likely to be pronounced for the Social-Survival-Day relationship.

The variable *First Day Social* is supposed to exhibit a lower level of reverse causality compared to *Social Times* and *Social*. The *First Day Social* denotes that a trader is defined as a communicative trader since the first day on the STP. This means these traders do not even wait to stay on the STP to participate in the online discussion, but rather they decide to participate at the beginning of their trading life. These *First Day Social* traders take around 21% out of all the communicative traders (approximately the lowest quintile of the number of days before initiating the first online participation among communicative traders). Therefore, this measure should mitigate the reverse causality concerns to the largest extent possible among all the three social communication measures.

Overall, I do not see much variation among the significance levels in the Cox model identifications, as in Table 4-3 (Panel C to Panel D). The identifications appear to be all significant for the three social communication measures (apart from column (6)).

Especially in the columns (10) to (12), the hazard ratios associated with the *First Day Social* are all significant and consistently smaller than 1, suggesting that social communication positively impacts the survival of individual traders. Collectively, the evidence indicate that usage of online forum discussion increases the survival probability of individual traders.

4.6 The Main Empirical Test: A Panel VAR Analysis

This section addresses the question concerning the implicit causality between social communication and survivorship. More specifically, I examine if social media participation causes the increase of survivorship of communicative traders on STPs. I employ a panel VAR model to understand the underlying dynamics between social media participation and survivorship of traders, and use a Granger causality specification from panel VAR model to identify the causal relationship between these two key variables. Impulse response functions (IRFs) are used to further understand the persistence of impact from social interaction to traders' survivorship.

Furthermore, in this section, I include only communicative traders in the empirical analysis for two reasons. First, in the panel VAR framework I identify the impact of everyday social communications on traders' survival, where only communicative traders are actively engaged in the online discussion activities. Second, this also allows us to mitigate concerns regarding the disparity between communicative traders and non-communicative traders, by showing that within the communicate traders' community, the impact of social communication is still positively impacting the survival of traders.

4.6.1 The Panel VAR Framework

My dataset provides two types of timestamped social media participations including creating a discussion topic and posting a comment under a discussion topic. Though liking a post is not timestamped in this dataset, I believe that this activity would not significantly impact the results of this section, as it is expected that liking a post is, intuitively speaking, less communicative when compared with creating a discussion topic and posting a comment, respectively. Consequently, by accessing the time-series data of social media participations and online trading activities through a panel VAR model, I investigate whether social media participation influences traders' survivorship when other trade-related variables are controlled for.

In my analysis, individual trader's probability of survivorship can be constructed as a time-varying variable, which measures the residual probability of leaving the market in each given day. I assume that the arrival of traders' quitting decision follows the Poisson process. This is in line with the fact that the Cox proportional hazard model converges to Poisson regression when the baseline hazard is a constant. My approach allows us to model individual trader's survivorship that is independent of the survival of other traders, and that a trader's decision to exit the market is independent of the decisions of other traders. Specifically, I select communicative traders who both start and quit trading during the sample period (308 traders and 38,205 observations), so that I am able to accurately measure the survival days of these accounts in order to compute the survival probability of these traders and investigate the effects of online communication. Then, using the distribution of survival days of selected accounts to estimate the $lambda$ (λ) parameter in a Poisson process, the Cumulative Distribution Function (CDF) for Poisson process can then be calculated for each trading account in each day by the following function (Eq. 7), where k is the number of days that one trading account survives since its registration on the STP, and (1-CDF) is the survival probability (Prob) up to k. In this regard, the change of survival probability (Prob), which is denoted by diff_Prob (Eq. 8) from day k-1 to day k will represent the change in probability to keep staying in the market in any given day. When a trader leaves the market, the Prob of the day is assigned a value of zero.

$$F(k;\lambda) = \sum_{i=0}^{k} \left(\frac{\lambda^{i} e^{-\lambda}}{i!} \right) \tag{7}$$

$$diff\_Prob = F(k-1;\lambda) - F(k;\lambda) \tag{8}$$

Therefore, the panel VAR model specification which identifies the relationship between communication and survivorship will be as in Eq. 9, where $Y_{i,t}$ represents a six-variable vector {diff_Prob, social_times, dollarPnL, maxdd, leverage, intraVol}. Variable social_times represents the number of social media participation times for a trader in a given day, and the rest of the variables represent daily dollar profit and loss, maximum drawdown, average leverage and intraday volatility, respectively.

$$Y_{i,t} = Y_{i,t-1}A_1 + u_i + e_{i,t} \tag{9}$$

Dickey–Fuller tests suggest that these variables used in the model are stationary. In addition, I use Helmert transformation to remove panel-specific fixed effects (Abrigo & Love, 2016; Arellano & Bover, 1995), which minimize data loss for unbalanced panels. The estimated coefficients of the above-mentioned specifications are reported in Table 4-4. It shows that social_times interacts positively with ex post individual trader's survivorship in the market with a p-value of 0.00. These results suggest that social media participation is significantly associated with an individual trader's survivorship after controlling variables related to trading activities.

[Insert Table 4-4]

4.6.2 Granger Causality Test

Given the results from the panel VAR specification, I perform a Granger causality analysis to identify the causal relationship between communication participation times and traders' survivorship. Granger causality results are reported in Table 5. From Table 5 where diff_Prob is the dependent variable, I can see that social_times Granger-causes traders' survivorship with a p-value indicating significance at the 99% confidence level. It is important to note that controlling other explanatory variables relating trading activities, social_times still significantly Granger-causes diff_Prob. This highlights the importance of social communication in the formation of traders' decision to stay or quit the STP. My results echo the panel VAR estimation results that social communications influence traders' survivorship on the STP.

[Insert Table 4-5]

[Figure 4-4]

4.6.3 Impulse Response Functions

To further understand the persistence of the impact of social interaction on traders' survivorship, I generate the IRFs from the panel VAR system and report in Figure 4-4. The IRFs describe the response of one variable (response) in the panel VAR system to a one standard deviation shock of another variable (impulse). As it is shown in Figure 4-4, diff_Prob responses positively to innovations in social_times. The response of diff_Prob to shocks in social_times is a concave function with significance that last from 1 to 10 lags onward. In line with the findings from Granger causality, diff_Prob is responding only to shocks from social_times, after controlling other variables relating to online trading activities, which again highlights the special role of social communication in traders' decision about quitting or staying in the STP. The IRFs dynamics indicate the long-lasting impact of social interaction to traders' survivorship in the STP.

4.7 Alternative Analysis

I perform several additional tests by controlling for additional variables (e.g., online discussion sentiment, FX market factors, and one-to-one messaging) or alternative measures of communication (e.g., moving sum or average of the number of last 10/20/30 days' online communication) in the panel VAR model/Granger causality framework. I also examine the impact of social communication for a trader's first 6/9/12-month period since trading. The results are consistent with the previously discussed results and supportive to the conclusion, indicating that online communication impacts individual traders' survival by extending the probability of staying in the market, which ultimately increases the survival days of communicative traders.

4.7.1 Controlling for Discussion Sentiment

I include more control variables in the main panel VAR analysis in equation (9) to represent the text information from the online discussions. I employ a text analysis technique to extract two particular information from the online discussion texts. One is *polarity*, which is a measure of investor sentiment (ranging from -1 (negative sentiment) to 1 (positive sentiment)), and the other is *subjectivity* (ranging from 0 to 1), which is a measure of the degree whether one particular sentence in the online discussion is more subjective (closer to 1) or more objective (closer to 0). Each sentence in the online discussion is given two scores, namely, polarity and subjectivity, using the dictionary-based *textblob* package in Python. This package is widely used in online sentiment analysis (e.g., Twitter sentiment analysis) (Micu et al., 2017; Munjal et al., 2018).

As such, I add two sentiment measures (polarity and subjectivity) into the panel VAR model in equation (9). The results are presented in Table 4-6. The results show that adding sentiment measures does not change the results. I still see a positive association between social communication (social_times) and the incremental probability in survival (diff_prob). Interestingly, there is a positive relationship between discussion sentiment (polarity) and the incremental probability in survival (diff_prob), meaning that more positive sentiment is associated higher chances of survival. In addition, subjectivity measure is also positively associated the incremental probability in survival (diff_prob), meaning that higher level of subjectivity is associated with higher chances of survival.

[Insert Table 4-6]

In addition, I perform a Granger causality test associated with the panel VAR identification specified in Table 4-6. The results of the Granger causality test are reported in Table 4-7. The results show that after controlling the discussion sentiment in the online discussion text, social communication (social_times) still appear to Granger causes the incremental survival probability (diff_prob) at the 1% significance level.

[Insert Table 4-7]

Overall, this test (adding sentiment measures) mitigates the concerns that the content, especially the sentiment in the online discussions, may affect the survival of traders. However, the results show that after controlling the online discussion sentiment, social communication is still positively associated with the incremental survival probability of traders. The results show that after controlling the online discussion sentiment, social communication still Granger causes the survival probability of traders.

4.7.2 Controlling for FX Market Factors

I include FX market factors (Abbey & Doukas, 2015; Pojarliev & Levich, 2008, 2012) in the panel VAR model in equation (9) to mitigate concerns that survival probability can be related to market conditions. These factors include carry factor (Carry), momentum factor (Mom), value factor (Value) and volatility factor (Vol). The four factors are considered as proxies of different types of trading strategies used by currency traders (Pojarliev & Levich, 2008). As used in prior literature (e.g., Abbey & Doukas, 2015), the proxies for the four factors are from the Deutsche Bank’s DBIQ database, as follows: the Deutsche Bank (DB) Currency Carry USD Index as the proxy for carry trading strategy, the DB FX Momentum (USD) as the proxy for trend-following trading strategy, the DB FX Purchasing Power Parity (PPP) (USD), and the 60-day volatility calculated based on the Deutsche Bank (DB) G10 Currency Harvest Index (USD) as the proxy for the market volatility. The FX market factors used in the panel VAR model are the natural log of the returns of these market factor indexes (Abbey & Doukas, 2015; Pojarliev & Levich, 2008, 2012).

The results are presented in Table 4-8. The evidence shows that survival probability is still positively associated with social communication (social_times), after controlling the sentiment in the discussion text and controlling the FX market factors. These results indicate that higher social communication participations are positively associated with higher chances of survival.

[Insert Table 4-8]

In addition, the results (Table 4-9) of the Granger causality test, associated with the panel VAR model in Table 4-8, show that, after controlling both the online discussion sentiment and the FX market factors, social communication still Granger causes the increase in survival probability of traders.

[Insert Table 4-9]

Overall, the results indicate that the relationship that social communication increases survival probability of traders is robust to controlling both online discussion sentiment and FX market factors.

4.7.3 Controlling for One-to-One Messaging

As mentioned in previous sections, the online communication features include online discussion forum and one-to-one messaging. The main focus of this paper is to examine the impact of online discussion forum feature, which is more transparent and impactful to the entire trading community on the STP as opposed to the one-to-one messaging feature which only involves the bilateral participants. In addition, for the online discussion forum feature, I am able to observe the full text information of the online discussions. However, I am not able to observe the contents of the one-to-one messaging feature. Therefore, in previous sections, I examine the impact of online discussion forum on investor survival. One concern might be that one-to-one messaging may also have some influence on the survival probability of traders. In this section, I include three measures of the one-to-one messaging feature, namely, the number of messages sent (n_sent), the number of messages received (n_received), and the number of messages read (n_read) by each trader in each day.

The results of the panel VAR model after controlling the one-to-one messaging feature are presented in Table 4-10. The results show that after controlling one-to-one messaging, the survival probability of traders is still positively associated with social communication (social_times). In addition, the other three one-to-one messaging measures (n_sent, n_received, and n_read) are also positively related to the survival probability of traders (diff_prob).

[Insert Table 4-10]

Furthermore, I perform a Granger causality test to examine the relationship between social communication and survival probability after controlling one-to-one messaging. The results of the Granger causality test are presented in Table 4-11. The results indicate that after controlling one-to-one messaging social communication still Granger causes the survival probability of traders. Interestingly, the one-to-one messaging feature also appears to Granger cause the incremental survival probability of traders. This may indicate that one-to-one messaging also increases the survival of traders.

[Insert Table 4-11]

Overall, the results indicate that after controlling one-to-one messaging feature, the causal relationship between social communication (social_times) and the incremental survival probability of traders (diff_prob) is still significant. The evidence further confirms that social communication increases the survival of traders.

4.7.4 Alternative Measures of Social Communication

In the baseline model of the panel VAR framework in equation (9), I use social participation times for each trader in each day (social_times) as a measure of the online social communication. In this section, I examine the baseline model using alternative measures of online social communication. These measures include moving sum/average of last 10-day social communication (movsum_10, movavg_10), moving sum/average of last 20-day social communication (movsum_20, movavg_20), and moving sum/average of last 30-day social communication (movsum_30, movavg_30).

The results of the baseline model with alternative measures of social communication are presented in Table 4-12. The results associated with different alternative measures are organized in different panels in this table, namely, Panel A (movsum_10), Panel B (movavg_10), Panel C (movsum_20), Panel D (movavg_20), Panel E (movsum_30), and Panel F (movavg_30), respectively. The results show that, using alternative measures of social communication, social communication is consistently and positively associated with the incremental survival probability (diff_prob) of traders.

[Insert Table 4-12]

In order to further examine the causal relationship between the alternative measures of social communication and investor survival, I perform Granger causality tests associated with the panel VAR models. The results of the Granger causality tests are presented in Table

4-13. The results indicate that different measures of social communication consistently Granger cause the incremental survival probability of traders.

[Insert Table 4-13]

Overall, the results suggest that social communication increases the survival of traders. The results are robust to alternative measures of social communication.

4.7.5 First 6/9/12-month Social Communication on Survival

In order to mitigate concerns regarding whether the impact of social communication on survival persists throughout a trader's trading life, I conduct the panel VAR analysis using observations of traders' first 6-month, 9-month, and 12-month periods since they start their online trading activities on the STP. The results of the panel VAR identifications and Granger causality tests are reported in Table 4-14 and Table 4-15 respectively.

[Insert Table 4-14]

The results show that social communication consistent impacts the survival of traders by increasing the incremental survival probability of traders after they participate in online communications. It appears that the impact of social communication persists throughout a trader's trading life for a 6-month/9-month/12-month period.

[Insert Table 4-15]

The results of Granger causality tests further confirm that social communication Granger-causes the survival probability of traders. Collectively, the evidence suggests that the impact of social communication persist throughout the sample period.

4.7.6 Clustering Standard Errors at Trader Level

In this section, I examine whether the main results are sensitive to the standard error clustering. The standard error clustering method adopted in this paper is robust standard error clustering. I perform the main tests (Table 4-4 and Table 4-5) again with standard errors clustered at trader level. The results are presented in Table 4-16 and Table 4-17. The results show that the conclusion is not sensitive to standard error clustering and the significance level does not decrease.

[Insert Table 4-16]

[Insert Table 4-17]

4.8 Discussion

Apart from the above-mentioned online discussion content related reasons for the increased survival, there might also be other reasons regarding the decision to continue to trade in the market. To be specific, this paper shows that social communication on online trading platforms appears to increase the survival probability of traders, potentially through altering traders' decision making or trading behavior. These behavioral changes and/or changes in decision making of traders may be linked to the online discussion in other forms, besides the contents of the discussions. Though this paper does not try to disentangle different explanations which may increase traders' survival, I provide three alternative explanations to complement the discussion content related explanation.

First, the reason could be behavioral and be linked to the utility function of prospect theory: when comparing each trading day alongside each other, social media users on average lose less per day than non-users, which could suggest differences in their level of loss sensitivity. If this explanation was valid, I would expect to see that social media users exhibiting lower levels of loss-aversion, as compared with non-users. Evidence from other investigations suggest that this is not the case, as Heimer (2016) found that after accessing social interactions online the disposition effect of traders in fact doubles, which indicates that traders are actually more loss-averse, after they start using social media features, rather than less so. Consequently, this explanation seems not to hold.

Second, communicative traders may consider a proportion of the losses in their investing activities as a transaction cost to access information from other traders. Therefore, they would be willing to part with more investment in the pursuit of being better informed. If this explanation was valid, I should see learning effects appearing over time. For instance, I would expect traders who notice that information does not pay off to quit trading. Nevertheless, I do not see this learning effect, given the fact that social media users are reluctant to quit and stay longer in the market. Additionally, information can be obtained simply by reading the online communication, without participating in it. Therefore, non-communicative traders should obtain, in principle, the same information as communicative traders, in which case there should be no differences between the control group and communicative traders. This, however, is not the case, as I identify significant differences in survival. The possibility of regarding losses as the cost of information does not hold either.

There is a third possible explanation. Communication participation times are Granger caused by trading situations, such as drawdown and leverage. This suggests that when traders want to make sense of the situation they are in and compare it against other traders' experiences, they search for cues by participating in discussion threads or by initiating them. This makes them stay longer in the market because they see perhaps that their situation is comparable with other traders', or because they receive suggestions which they want to test. In other words, communicative traders would resort to the experiences, opinions, or advice of their peers as possible solutions to their trading problems, more than non-communicative traders do. This search for solutions based in community opinions makes them stay longer in the market. This explanation is consistent with the results of the

IRFs, which show that social communication at t-1 significantly increase the participants' probability at time t of staying longer in the market. Testing this explanation, however, requires a topical investigation of discussion threads which, while important, is beyond the scope of this paper.

The limitation of this study is that I am not able to disentangle the alternative explanations, through which social communication increases the survival of traders. The three alternative explanations are simply not directly observable, which makes it challenging to verify these potential mechanisms. However, I believe that they deserve separate and detailed investigations for future research. In addition, to further investigate the content of the online social communication, I also call for an integration of linguistical research techniques to the research in finance. This is because the language the traders use may also impact the decision to continue to trade. For example, the time lengths indicated in the future-orientation worlds in (tomorrow vs. after a month) may have different impacts on traders. In addition, it is not yet clear that whether the language used to discuss about trading is similar to the language used in everyday conversation, in terms of forward-looking expressions. It can be the case that in everyday life, people tend to talk about the present. While on the STP, people talk about the future more than that in everyday conversation, as the objectives in trading are all in the future.

4.9 Conclusion

This study contributes to documenting the impact of communication on the survivorship of individual traders. My results indicate that communicability in the market plays a role in shaping the persistence of individual traders.

These findings have important policy implications when considering the role that social trading platforms (STPs) play in the wider market environment, simply because they are likely to be the primary gateways through which many retail traders access the markets. It is already widely documented that trading can be a perilous task, but it is particularly true in the foreign exchange market due to its reliance on leverage and the fact that positions need to be actively managed. This is because returns in the foreign exchange market are usually made by capitalizing on small price movements, while passive investment strategies, such as buy and hold, are not usually viable due to overnight fees. In other words, regulators may need to specifically consider the inclusion of non-market features on such platforms if the social features are encouraging retail traders to persist in the market.

In terms of why communicative traders persist in the market, I present evidence using three examples in the online discussion topics reasons, where traders update their expectations about the future market/platform conditions, understanding of their own trading skills, and knowledge of potential useful trading strategies. These updates regarding the future ultimately increase the likelihood of traders' survival. As mentioned previously, it is widely thought that most new traders start small, experiment through trial and error, then make a rational decision about whether to remain or exit the market based upon their past performance. However, I show that the usage of online communication alters the dynamic of the decision to quit.

Overall, I am confident to present evidence that communication in the market is consequential. In addition, I draw attention to the need for deeper investigations of the content of online social communication among traders. This may further uncover the real decision-making processes of traders and extend the understanding of trading behavior/behavioral changes on an individual level. I also call for future research about the impact of social communication on traders' financial performance**.** This is because it is not yet clear whether traders benefit from the online communication in improving their trading skills/strategies both in the short term and the long term, while these communications keep them to decide to continue to trade in the market.

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Appendix 4-1 Examples of Online Discussion Topics

Obs	Id	Category	Creator	Topic	Comments	Commenter	Create Time	Post Time
940	463	Market_C	2420	Friday FUNdaMENTALS	Today is looking very sketchy, I'm going to hold a long aud/jpy averaged about 77.90 and call it a week. Overall a good week for me, coming very close to personal goal. We seem to be consolidating the dollar and direction may be changing in the future (read: october).	2420	25SEP2009:16:00:41	25SEP2009:16:00:41
966	477	Market_C	498	Social Indicator Pattern	With the current number of traders the range on the short side has been between 30 to 40. On the long side the number has been right around 20 not changing much all week. Maybe MyFXtrade will have a real-time graph of these numbers in the future we can use. Being new to FX it just seemed interesting that the shorts were getting out of winning positions and adding to losing ones and wanted to pass it along.	498	02OCT2009:18:42:36	02OCT2009:20:31:17
967	477	Market_C	498	Social Indicator Pattern	Comming back to the social indicator, my broker has the same monitoring the positions of his clients. The have done research and it shows that it is a counter indicator, meaning that when quite a lot clients are short prices will goo up and vice versa. When MyFXtrade grows I think you the social indicator should be used as counter indicator as wel.	2627	02OCT2009:18:42:36	04OCT2009:15:07:27
968	477	Market_C	498	Social Indicator Pattern	I think the effect that you are seeing is people enter on the top and then exit at a support level, this is what typically happens, plus most traders also have specified their exit point. Then they wait for a pullback then enter again. Also many	234	02OCT2009:18:42:36	05OCT2009:00:24:32

					people follow their emotions (which are always wrong). :)			
969	477	Market_C	498	Social Indicator Pattern	Well, if anyone is getting stopped out on only a 100 pip movement they have their stops way too tight or their leverage way too high for a single trade (requiring a too squeezed stop). The typical stop should be around 350 pips (IMHO).	234	02OCT2009:18:42:36	05OCT2009:23:13:13
970	477	Market_C	498	Social Indicator Pattern	Hi Avi, Agreed, everyone has their opinion on how to trade the markets, what I am warning is that many many traders keep their stops way too tight and end up killing themselves out when really sometimes its just about waiting out the market for your trade to become whole.	234	02OCT2009:18:42:36	06OCT2009:15:07:17
971	477	Market_C	498	Social Indicator Pattern	It is interesting to note during this recent move to the upside in the Eur/Usd there is still a greater % of traders short.	2515	02OCT2009:18:42:36	07OCT2009:17:04:42
972	477	Market_C	498	Social Indicator Pattern	@ Lawrence, SL of 350 pips? On what lot size you think?	2741	02OCT2009:18:42:36	07OCT2009:17:11:25
1455	647	Question	2479	EURUSD pair	I'm stuck in a short trade. What do yu think the EURUSD pair is going to do in the next 5 hours?	2479	05NOV2009:02:50:48	05NOV2009:02:50:48
1456	647	Question	2479	EURUSD pair	Michael, it took me 3 years before I learned that I HAD to stick to my trading plans. If you took the short trade and had an initial stop loss in mind, you MUST stick to it, even if it stops you out. I blew up my account because I constantly moved my stop losses further and further away in HOPES of having it turn around and go back in profit. When you enter a trade, you must	3366	05NOV2009:02:50:48	05NOV2009:19:28:07

have a limit and a stop loss at the same time, otherwise, you will end up in the whole before you know it. I know this doesn't answer your question, but I hope this helps in the future.

This table presents three examples of the online discussion topics. Observation id (Obs), discussion id (Id), discussion category (Category), creator id (Creator), discussion topic (Topic), discussion content (Comments), commenter id (Commenter), discussion topic creation time (Create Time), and discussion comments posted time (Post Time) are reported in the table. The discussion content is reported exactly as shown in the online discussion forum (including typos), except that the name of the platform is replaced with MyFXtrade for the purposes of anonymity.

Table 4-1 Summary Statistics

Variables	N	Mean	Std Dev	1st	5th	10th	25th	Median	75th	90th	95th	99th
Average return	3,333	0.21	10.72	-1.29	-0.19	-0.09	-0.02	0.00	0.00	0.02	0.06	0.73
Recent return	2,661	0.14	26.24	-1.79	-0.96	-0.78	-0.28	-0.02	0.01	0.06	0.14	0.59
Recent success	3,426	0.30	0.46	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Career success	3,426	0.56	0.22	0.00	0.20	0.30	0.43	0.55	0.69	0.83	0.94	1.00
Total dollar PnL	3,426	-1,153.54	40,563.52	-36,113.76	-7,008.97	-3044.33	-687.21	-91.15	4.19	325.89	1,139.20	14,010.00
Total closed Trades	3,426	229.99	763.98	1.00	3.00	6.00	21.00	71.00	215.00	534.00	936.00	1,998.00
Survival days	3,371	81.49	90.67	2.00	2.00	5.00	15.00	48.00	117.00	212.00	277.00	392.00
Active days	3,426	29.02	35.21	1.00	1.00	2.00	6.00	16.00	39.00	73.00	97.00	166.00
Quit trade	3,371	0.44	0.50	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Participation times	3,426	1.64	11.24	0.00	0.00	0.00	0.00	0.00	0.00	2.00	5.00	34.00
Message	3,426	0.86	0.35	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Age	3,163	36.99	12.51	19.00	21.00	23.00	28.00	35.00	44.00	54.00	59.00	76.00

This table reports the account-level summary statistics for the observed 3,426 traders during the sample period. The variables include average return (the average return during the sample period), recent return (return for the most recently closed trades during one trading day), recent success (dummy variable equals 1 if the most recent observed active trading during that day is with profits), career success (the total number of win trades divided by the total number of closed trades), total dollar PnL (the total dollar PnL for the period), total closed trades (the total number of trades closed), survival days (the number of days between the first observation of a trader till the last observation with closed trades during that day), active days (days with non-zero closed trades), quit trade (dummy variable equals 1 if the trader quits trading), participation times (the cumulative online forum participation times, any of creating a discussion topic, posting a comment or liking a post), message (dummy variable equals 1 if the trader successfully send, receive or read a message amongst other traders), and age (the trader's age as of the first observation), for each trader's account for the entire sample period.

Table 4-2 Summary Statistics for Communicative and Non-Communicative Traders

Variable	N	Mean	Std Dev	1st	5th	10th	25th	Median	75th	90th	95th	99th
Panel A Communicative Traders												
Average return	693	-0.04	0.94	-0.83	-0.15	-0.06	-0.02	0.00	0.00	0.02	0.05	0.20
Recent return	547	-0.18	0.46	-1.30	-0.90	-0.69	-0.29	-0.02	0.01	0.05	0.14	0.74
Recent success	699	0.31	0.46	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Career success	699	0.55	0.20	0.00	0.21	0.33	0.43	0.55	0.69	0.79	0.89	1.00
Total dollar PnL	699	21.98	58,621.92	-47,459.91	-8,332.72	-2,835.37	-808.82	-124.02	2.44	477.20	1,847.55	25,529.17
Total closed Trades	699	302.03	888.80	1.00	5.00	9.00	35.00	109.00	280.00	707.00	1,114.00	3,241.00
Survival days	697	102.57	99.87	2.00	3.00	9.00	25.00	70.00	150.00	253.00	321.00	408.00
Active days	699	37.43	40.81	1.00	2.00	3.00	9.00	22.00	51.00	90.00	124.00	191.00
Quit trade	697	0.45	0.50	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Participation times	699	8.04	23.84	1.00	1.00	1.00	1.00	2.00	5.00	15.00	34.00	128.00
Message	699	0.96	0.20	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Age	634	37.67	13.58	19.00	22.00	24.00	28.00	35.00	44.00	53.00	59.00	94.00
Panel B Non-Communicative Traders												
Average return	2,640	0.28	12.03	-1.46	-0.20	-0.09	-0.03	0.00	0.00	0.02	0.06	1.21
Recent return	2,114	0.22	29.44	-1.92	-0.97	-0.80	-0.28	-0.02	0.01	0.07	0.14	0.51
Recent success	2,727	0.30	0.46	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Career success	2,727	0.56	0.22	0.00	0.20	0.30	0.42	0.55	0.70	0.84	0.96	1.00
Total dollar PnL	2,727	-1,454.85	34,451.90	-35,471.92	-6,867.06	-3,092.31	-647.47	-84.03	4.37	299.00	1,102.24	13,491.65
Total closed Trades	2,727	211.52	727.59	1.00	3.00	5.00	18.00	64.00	198.00	489.00	863.00	1,948.00
Survival days	2,674	76.00	87.30	2.00	2.00	4.00	13.00	42.00	109.00	199.00	260.00	388.00
Active days	2,727	26.87	33.29	1.00	1.00	2.00	5.00	15.00	36.00	69.00	91.00	161.00
Quit trade	2,674	0.44	0.50	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Participation times	2,727	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Message	2,727	0.83	0.37	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Age	2,529	36.81	12.23	19.00	21.00	23.00	28.00	35.00	44.00	54.00	59.00	72.00

This table reports summary statistics for communicative traders, who use online discussion forum, and non-communicative traders who do not use this feature on the STP.

Table 4-3 Cox Proportional Hazard Rate Model

	Panel A			Panel B			Panel C			Panel D		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
First Day Social	-	-	-				-	-	-	**0.711****	**0.749****	**0.642*****
										(0.14427)	**(0.14514)**	**(0.14436)**
Social	-	-	-				0.791***	0.833***	0.871**	-	-	-
							(0.06371)	(0.06398)	(0.06401)			
Social Times	-	-	-	0.992***	0.993***	0.997	-	-	-	-	-	-
				(0.00285)	(0.06694)	(0.00240)						
Recent Success	0.681***	1.015	0.547***	0.668***	1.026	0.575***	0.684***	1.026	0.550***	0.668***	1.014	0.574***
	(0.06281)	(0.06348)	(0.06557)	(0.06569)	(0.06694)	(0.06750)	(0.06284)	(0.06369)	(0.06559)	(0.06571)	(0.06730)	(0.06749)
Career Success	0.832	0.852	1.573	1.039	1.012	1.663***	0.825	0.822	1.548***	1.029	1.000	1.681***
	(0.14506)	(0.14266)	(0.12533)	(0.14845)	(0.14662)	(0.12904)	(0.14479)	(0.14317)	(0.12532)	(0.14820)	(0.14578)	(0.12859)
Year/Month dummies	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

This table shows the results of the Cox proportional hazard rate regressions, following Hayley & Marsh (2016), where the hazard ratios (instead of the coefficients) and ta (in parentheses) are reported. There are three measures of social communication online. The variable First Day Social is defined as a dummy variable indicating that a trader participates in online discussion forum during the first day of their online trading (equals to 1; 0 otherwise). The social variable is a dummy variable (equals to 1 if a trader is a communicative trader and 0 if a trader is non-communicative. The variable social times represents the total number of online forum participation times (including creating a topic, posting a comment, and liking a post).The recent success is defined as a dummy variable, where it equals 1, if the most recent active trading day (with non-zero closed trades) is with a profit, and it equals 0, if the most recent active trading day is with a loss. The career success is defined as the proportion of total win trades divided by total closed trades during the sample period. Year/month dummies are controlled for some regressions, which is indicated with ‘Yes’ and ‘No’. Other control variables are logged total trading volume and total number of trades. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 4-4 Results of Panel VAR Model

VARIABLES	(1) diff_prob	(2) social_times	(3) dollarpnl	(4) maxdd	(5) leverage	(6) intravol
L.diff_prob	1.024***	0.223	350.584	0.024	-69.730	0.012
	[0.000]	[0.561]	[0.687]	[0.473]	[0.386]	[0.237]
L.social_times	**0.000*****	0.110***	-4.655	0.001*	-0.568	-0.000**
	[0.000]	[0.000]	[0.802]	[0.053]	[0.124]	[0.032]
L.dollarpnl	-0.000*	-0.000	0.003	-0.000	0.000	0.000
	[0.096]	[0.240]	[0.951]	[0.241]	[0.130]	[0.172]
L.maxdd	0.001***	-0.283***	87.473	0.986***	-16.220	-0.004
	[0.000]	[0.000]	[0.688]	[0.000]	[0.299]	[0.200]
L.leverage	0.000***	-0.000**	-0.003	0.000***	0.667***	0.000
	[0.000]	[0.018]	[0.856]	[0.000]	[0.000]	[0.432]
L.intravol	-0.000	-0.041	20.540	0.009	-83.922	0.122
	[0.395]	[0.391]	[0.150]	[0.110]	[0.286]	[0.221]
Observations	38,205	38,205	38,205	38,205	38,205	38,205

This table reports the main results of the panel VAR model, where diff_Prob represents the probability of surviving in the market. For the measuring social media participation times, diff_total denotes the first difference of the cumulative participation times till a given day (t), which is equal to the participation times in day (t). Other control variables include daily dollar PnL, first difference of maximum drawdown, average leverage and intraday volatility. P-values are reported in the parentheses. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 4-5 Granger Causality

Dependent Variables	Explanatory Variables	Chi2	Prob	Significance
diff_prob	**social_times**	**28.001**	**0.000**	*****
	dollarpnl	2.776	0.096	*
	maxdd	164.825	0.000	***
	leverage	27.603	0.000	***
	intravol	0.723	0.395	
social_times	diff_prob	0.338	0.561	
	dollarpnl	1.380	0.240	
	maxdd	15.299	0.000	***
	leverage	5.613	0.018	**
	intravol	0.735	0.391	
dollarpnl	diff_prob	0.162	0.687	
	social_times	0.063	0.802	
	maxdd	0.161	0.688	
	leverage	0.033	0.856	
	intravol	2.077	0.150	
maxdd	diff_prob	0.516	0.473	
	social_times	3.749	0.053	*
	dollarpnl	1.375	0.241	
	leverage	18.172	0.000	***
	intravol	2.549	0.110	
leverage	diff_prob	0.753	0.386	
	social_times	2.370	0.124	
	dollarpnl	2.289	0.130	
	maxdd	1.080	0.299	
	intravol	1.140	0.286	
intravol	diff_prob	1.399	0.237	
	social_times	4.582	0.032	**
	dollarpnl	1.869	0.172	
	maxdd	1.640	0.200	
	leverage	0.616	0.432	

This table presents the results of Granger causality tests. Chi-square, p-value and significance level are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 4-6 Controlling for Discussion Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**diff_prob**	**social_times**	**dollarpnl**	**maxdd**	**leverage**	**intravol**	**polarity**	**subjectivity**
L.diff_prob	1.025***	0.175	424.192	0.034	-14.641	0.008	-0.114	-0.470***
	[0.000]	[0.627]	[0.620]	[0.331]	[0.835]	[0.384]	[0.247]	[0.000]
L.social_times	**0.000*** **	0.125***	-5.137	0.001**	-0.488	-0.000**	0.005***	0.005***
	[0.000]	[0.000]	[0.797]	[0.044]	[0.288]	[0.028]	[0.002]	[0.002]
L.dollarpnl	-0.000	-0.000	0.004	-0.000	0.000	0.000	-0.000	-0.000**
	[0.150]	[0.204]	[0.936]	[0.234]	[0.151]	[0.185]	[0.802]	[0.039]
L.maxdd	0.001***	-0.264***	56.696	0.983***	-13.901	-0.003	0.042***	0.231***
	[0.000]	[0.000]	[0.774]	[0.000]	[0.297]	[0.202]	[0.000]	[0.000]
L.leverage	0.000***	-0.000**	-0.005	0.000***	0.666***	0.000	0.000	0.000***
	[0.000]	[0.013]	[0.773]	[0.000]	[0.000]	[0.397]	[0.521]	[0.004]
L.intravol	-0.000	-0.042	20.709	0.009*	-83.945	0.121	-0.019	-0.021
	[0.462]	[0.348]	[0.285]	[0.087]	[0.285]	[0.222]	[0.572]	[0.302]
L.polarity	**0.000***	0.038	-115.216	-0.003	9.919	0.000	-0.017**	-0.135***
	[0.095]	[0.238]	[0.293]	[0.141]	[0.232]	[0.802]	[0.022]	[0.000]
L.subjectivity	**0.001*** **	-0.181**	117.228	0.010**	2.472	-0.007	0.026	0.211***
	[0.000]	[0.047]	[0.644]	[0.042]	[0.898]	[0.108]	[0.122]	[0.000]
Observations	36,636	36,636	36,636	36,636	36,636	36,636	36,636	36,636

The table represents the panel VAR model results with discussion sentiment in the online discussion text controlled. The online discussion measures include polarity, which measures the sentiment (positive/negative) of the online discussions, and subjectivity, which measures how subjective/objective of the online discussions. The two measures are associated each comment under discussion topics. The other variables include survival measure (diff_prob), social_times, dollar PnL, maximum drawdown, leverage, and intro-day volatility.

P-values are in the brackets.

*** p<0.01, ** p<0.05, * p<0.1

Table 4-7 Granger Causality Test After Controlling Discussion Sentiment

Dependent Variables	Explanatory Variables	Chi-2	P-value	Significance
diff_prob				
	social_times	**41.112**	**0.000**	*******
	dollarpnl	2.075	0.150	
	maxdd	174.342	0.000	***
	leverage	25.472	0.000	***
	intravol	0.541	0.462	
	polarity	**2.786**	**0.095**	*****
	subjectivity	**64.934**	**0.000**	*******
social_times				
	diff_prob	0.237	0.627	
	dollarpnl	1.612	0.204	
	maxdd	20.810	0.000	***
	leverage	6.131	0.013	**
	intravol	0.881	0.348	
	polarity	1.390	0.238	
	subjectivity	3.939	0.047	**
dollarpnl				
	diff_prob	0.245	0.620	
	social_times	0.066	0.797	
	maxdd	0.082	0.774	
	leverage	0.084	0.773	
	intravol	1.142	0.285	
	polarity	1.106	0.293	
	subjectivity	0.213	0.644	
maxdd				
	diff_prob	0.945	0.331	
	social_times	4.062	0.044	**
	dollarpnl	1.416	0.234	
	leverage	17.232	0.000	***
	intravol	2.926	0.087	*
	polarity	2.164	0.141	
	subjectivity	4.135	0.042	**
leverage				
	diff_prob	0.044	0.835	
	social_times	1.130	0.288	
	dollarpnl	2.064	0.151	
	maxdd	1.088	0.297	
	intravol	1.141	0.285	
	polarity	1.427	0.232	
	subjectivity	0.017	0.898	
intravol				
	diff_prob	0.756	0.384	
	social_times	4.854	0.028	**
	dollarpnl	1.760	0.185	
	maxdd	1.626	0.202	

	leverage	0.718	0.397	
	polarity	0.063	0.802	
	subjectivity	2.589	0.108	
polarity				
	diff_prob	1.339	0.247	
	social_times	9.847	0.002	***
	dollarpnl	0.063	0.802	
	maxdd	12.663	0.000	***
	leverage	0.412	0.521	
	intravol	0.320	0.572	
	subjectivity	2.391	0.122	
subjectivity				
	diff_prob	15.652	0.000	***
	social_times	9.473	0.002	***
	dollarpnl	4.266	0.039	**
	maxdd	262.213	0.000	***
	leverage	8.102	0.004	***
	intravol	1.066	0.302	
	polarity	202.679	0.000	***

This table represents the Granger causality test results for the panel VAR model after controlling discussion sentiment. The variables include survival probability (diff_prob), social communication (social_times), dollar PnL, maximum drawdown, leverage, intra-day volatility, and two sentiment measures (polarity and subjectivity). Chi-square, P-values, and significance levels are reported in the table. *** p<0.01, ** p<0.05, * p<0.1

Table 4-8 Controlling for FX Market Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	**diff_prob**	**social_times**	**dollarpnl**	**maxdd**	**leverage**	**intravol**	**polarity**	**subjectivity**	**ln_ret_carry**	**ln_ret_value**	**ln_ret_mom**	**ln_ret_vol**
L.diff_prob	1.026***	-0.467	140.920	0.059	-45.697	-0.004	-0.430***	-0.710***	-0.026**	0.015***	-0.019**	-0.032
	[0.000]	[0.324]	[0.896]	[0.112]	[0.568]	[0.769]	[0.000]	[0.000]	[0.013]	[0.006]	[0.015]	[0.362]
L.social_times	**0.000*** **	0.155***	7.276	0.001**	0.448	-0.000***	0.000	-0.003**	-0.000	0.000	-0.000	0.000
	[0.000]	[0.000]	[0.830]	[0.045]	[0.406]	[0.005]	[0.742]	[0.045]	[0.100]	[0.340]	[0.281]	[0.430]
L.dollarpnl	-0.000	-0.000	-0.017	0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000
	[0.230]	[0.159]	[0.797]	[0.817]	[0.125]	[0.354]	[0.953]	[0.129]	[0.991]	[0.288]	[0.900]	[0.759]
L.maxdd	0.001***	-0.202***	44.681	0.970***	14.002	-0.005**	-0.115***	-0.053***	-0.009***	0.002***	0.004***	0.014***
	[0.000]	[0.000]	[0.897]	[0.000]	[0.305]	[0.017]	[0.000]	[0.000]	[0.000]	[0.004]	[0.000]	[0.002]
L.leverage	0.000***	-0.000**	0.002	0.000***	0.808***	0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	[0.000]	[0.038]	[0.943]	[0.000]	[0.000]	[0.431]	[0.179]	[0.169]	[0.413]	[0.920]	[0.408]	[0.748]
L.intravol	-0.000	0.008	13.014	0.008	-118.693	0.124	-0.008	-0.019	-0.005**	0.001	-0.004***	-0.001
	[0.498]	[0.288]	[0.745]	[0.119]	[0.230]	[0.230]	[0.815]	[0.475]	[0.018]	[0.408]	[0.004]	[0.894]
L.polarity	-0.000**	-0.032	-270.315	-0.002	3.190	0.001	-0.047***	-0.101***	0.001**	0.003***	0.000	-0.021***
	[0.016]	[0.256]	[0.133]	[0.391]	[0.751]	[0.148]	[0.000]	[0.000]	[0.022]	[0.000]	[0.460]	[0.000]
L.subjectivity	0.001***	0.008	194.524	0.003	41.093*	-0.010***	-0.098***	-0.078***	-0.003*	-0.007***	0.005***	-0.033***
	[0.000]	[0.929]	[0.671]	[0.656]	[0.094]	[0.007]	[0.000]	[0.000]	[0.076]	[0.000]	[0.002]	[0.000]
L.ln_ret_carry	**0.005*** **	0.005	73.707	-0.016	5.865	0.014	0.635***	1.508***	-0.070***	0.036***	0.013	-0.543***
	[0.000]	[0.996]	[0.974]	[0.732]	[0.965]	[0.502]	[0.000]	[0.000]	[0.000]	[0.000]	[0.150]	[0.000]
L.ln_ret_value	**-0.000**	0.560	2,652.269	-0.004	-375.721*	0.019	3.601***	1.595***	0.031**	-0.045***	0.065***	0.750***
	[0.784]	[0.506]	[0.683]	[0.947]	[0.052]	[0.265]	[0.000]	[0.000]	[0.030]	[0.000]	[0.000]	[0.000]
L.ln_ret_mom	**0.001**	0.213	-1,065.019	-0.039	74.557	-0.038*	1.637***	-1.116***	0.065***	-0.007	-0.014	0.236***
	[0.484]	[0.840]	[0.804]	[0.415]	[0.632]	[0.053]	[0.000]	[0.000]	[0.000]	[0.376]	[0.123]	[0.000]
L.ln_ret_vol	**0.001*** **	0.072	-1,521.724	0.028	-9.331	-0.003	0.252***	0.056	-0.048***	0.018***	-0.051***	-0.054***
	[0.001]	[0.564]	[0.151]	[0.101]	[0.862]	[0.603]	[0.000]	[0.108]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	20,466	20,466	20,466	20,466	20,466	20,466	20,466	20,466	20,466	20,466	20,466	20,466

The table represents the panel VAR model results with FX market factors controlled. The FX market factors include carry, value, monument, and volatility (Abbey & Doukas, 2015; Pojarliev & Levich, 2008; Pojarliev & Levich, 2010).The other variables include survival measure (diff_prob), social_times, dollar PnL, maximum drawdown, leverage, and intro-day volatility.
P-values are in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 4-9 Granger Causality Test After Controlling FX Market Factors

Dependent Variables	Explanatory Variables	Chi-2	P-value	Significance
diff_prob				
	social_times	**26.896**	**0.000**	***
	dollarpnl	1.440	0.230	
	maxdd	104.138	0.000	***
	leverage	20.032	0.000	***
	intravol	0.460	0.498	
	polarity	5.768	0.016	**
	subjectivity	42.041	0.000	***
	ln_ret_carry	29.444	0.000	***
	ln_ret_value	0.075	0.784	
	ln_ret_mom	0.491	0.484	
	ln_ret_vol	10.882	0.001	***
social_times				
	diff_prob	0.973	0.324	
	dollarpnl	1.987	0.159	
	maxdd	17.522	0.000	***
	leverage	4.306	0.038	**
	intravol	1.129	0.288	
	polarity	1.291	0.256	
	subjectivity	0.008	0.929	
	ln_ret_carry	0.000	0.996	
	ln_ret_value	0.443	0.506	
	ln_ret_mom	0.041	0.840	
	ln_ret_vol	0.332	0.564	
dollarpnl				
	diff_prob	0.017	0.896	
	social_times	0.046	0.830	
	maxdd	0.017	0.897	
	leverage	0.005	0.943	
	intravol	0.106	0.745	
	polarity	2.263	0.133	
	subjectivity	0.180	0.671	
	ln_ret_carry	0.001	0.974	
	ln_ret_value	0.167	0.683	
	ln_ret_mom	0.062	0.804	
	ln_ret_vol	2.060	0.151	
maxdd				
	diff_prob	2.520	0.112	
	social_times	4.011	0.045	**
	dollarpnl	0.054	0.817	
	leverage	14.428	0.000	***
	intravol	2.437	0.119	
	polarity	0.735	0.391	
	subjectivity	0.199	0.656	
	ln_ret_carry	0.117	0.732	
	ln_ret_value	0.004	0.947	

	ln_ret_mom	0.663	0.415	
	ln_ret_vol	2.690	0.101	
leverage				
	diff_prob	0.325	0.568	
	social_times	0.689	0.406	
	dollarpnl	2.349	0.125	
	maxdd	1.051	0.305	
	intravol	1.440	0.230	
	polarity	0.101	0.751	
	subjectivity	2.810	0.094	*
	ln_ret_carry	0.002	0.965	
	ln_ret_value	3.780	0.052	*
	ln_ret_mom	0.229	0.632	
	ln_ret_vol	0.030	0.862	
intravol				
	diff_prob	0.086	0.769	
	social_times	7.739	0.005	***
	dollarpnl	0.860	0.354	
	maxdd	5.678	0.017	**
	leverage	0.621	0.431	
	polarity	2.091	0.148	
	subjectivity	7.299	0.007	***
	ln_ret_carry	0.451	0.502	
	ln_ret_value	1.243	0.265	
	ln_ret_mom	3.746	0.053	*
	ln_ret_vol	0.270	0.603	
polarity				
	diff_prob	13.825	0.000	***
	social_times	0.108	0.742	
	dollarpnl	0.003	0.953	
	maxdd	62.658	0.000	***
	leverage	1.809	0.179	
	intravol	0.055	0.815	
	subjectivity	23.163	0.000	***
	ln_ret_carry	13.662	0.000	***
	ln_ret_value	545.041	0.000	***
	ln_ret_mom	80.743	0.000	***
	ln_ret_vol	67.871	0.000	***
subjectivity				
	diff_prob	36.615	0.000	***
	social_times	4.000	0.045	**
	dollarpnl	2.306	0.129	
	maxdd	13.725	0.000	***
	leverage	1.889	0.169	
	intravol	0.511	0.475	
	polarity	146.018	0.000	***
	ln_ret_carry	92.528	0.000	***
	ln_ret_value	78.288	0.000	***
	ln_ret_mom	51.270	0.000	***
	ln_ret_vol	2.589	0.108	

ln_ret_carry				
	diff_prob	6.111	0.013	**
	social_times	2.699	0.100	
	dollarpnl	0.000	0.991	
	maxdd	52.784	0.000	***
	leverage	0.669	0.413	
	intravol	5.560	0.018	**
	polarity	5.285	0.022	**
	subjectivity	3.153	0.076	*
	ln_ret_value	4.682	0.030	**
	ln_ret_mom	31.074	0.000	***
	ln_ret_vol	162.598	0.000	***
ln_ret_value				
	diff_prob	7.419	0.006	***
	social_times	0.912	0.340	
	dollarpnl	1.128	0.288	
	maxdd	8.379	0.004	***
	leverage	0.010	0.920	
	intravol	0.684	0.408	
	polarity	131.201	0.000	***
	subjectivity	43.993	0.000	***
	ln_ret_carry	24.788	0.000	***
	ln_ret_mom	0.785	0.376	
	ln_ret_vol	102.925	0.000	***
ln_ret_mom				
	diff_prob	5.870	0.015	**
	social_times	1.162	0.281	
	dollarpnl	0.016	0.900	
	maxdd	14.893	0.000	***
	leverage	0.685	0.408	
	intravol	8.328	0.004	***
	polarity	0.545	0.460	
	subjectivity	9.219	0.002	***
	ln_ret_carry	2.068	0.150	
	ln_ret_value	35.663	0.000	***
	ln_ret_vol	335.604	0.000	***
ln_ret_vol				
	diff_prob	0.832	0.362	
	social_times	0.622	0.430	
	dollarpnl	0.094	0.759	
	maxdd	10.004	0.002	***
	leverage	0.103	0.748	
	intravol	0.018	0.894	
	polarity	158.949	0.000	***
	subjectivity	24.384	0.000	***
	ln_ret_carry	105.220	0.000	***
	ln_ret_value	290.798	0.000	***
	ln_ret_mom	32.458	0.000	***

This table represents the Granger causality test results for the panel VAR model after controlling both discussion sentiment and FX market factors. The variables in this identification include survival probability (diff_prob), social communication (social_times), dollar PnL, maximum drawdown, leverage, and intro-day volatility, two sentiment measures (polarity and subjectivity), and FX market factors (the natural log of the returns of the carry, value, momentum, and volatility indexes). Chi-square, P-values, and significance levels are reported in the table. *** p<0.01, ** p<0.05, * p<0.1

Table 4-10 Controlling for One-to-one Messaging

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	diff_prob	social_times	dollarpnl	maxdd	leverage	intravol	n_sent	n_received	n_read
L.diff_prob	1.024***	0.136	378.602	0.021	-68.662	0.013	-0.232	1.995***	1.439***
	[0.000]	[0.724]	[0.651]	[0.524]	[0.398]	[0.223]	[0.949]	[0.000]	[0.000]
L.social_times	**0.000*** **	0.103***	-3.361	0.000	-0.516*	-0.000**	0.142**	0.047***	0.053***
	[0.000]	[0.000]	[0.832]	[0.203]	[0.059]	[0.030]	[0.012]	[0.001]	[0.000]
L.dollarpnl	-0.000	-0.000	0.003	-0.000	0.000	0.000	0.000	-0.000	-0.000
	[0.134]	[0.251]	[0.951]	[0.242]	[0.132]	[0.192]	[0.184]	[0.733]	[0.651]
L.maxdd	0.001***	-0.252***	80.342	0.987***	-16.599	-0.004	3.476***	-0.531***	-0.487***
	[0.000]	[0.000]	[0.693]	[0.000]	[0.305]	[0.193]	[0.000]	[0.000]	[0.000]
L.leverage	0.000***	-0.000**	-0.004	0.000***	0.667***	0.000	0.000***	-0.000***	-0.000***
	[0.000]	[0.035]	[0.832]	[0.000]	[0.000]	[0.441]	[0.000]	[0.000]	[0.000]
L.intravol	-0.000	-0.038	18.235	0.009	-84.004	0.121	0.762	0.558	0.392
	[0.408]	[0.382]	[0.196]	[0.109]	[0.285]	[0.222]	[0.282]	[0.175]	[0.186]
L.n_sent	**0.000***	0.003	-0.460	0.000	0.067*	-0.000	0.043	0.011***	0.009***
	[0.067]	[0.131]	[0.702]	[0.269]	[0.088]	[0.249]	[0.297]	[0.000]	[0.000]
L.n_received	**0.000*** **	-0.004	-20.390	0.000	0.513	0.000	0.061**	0.045***	0.014
	[0.004]	[0.301]	[0.218]	[0.244]	[0.353]	[0.851]	[0.032]	[0.000]	[0.108]
L.n_read	**0.000*** **	0.053***	11.464	0.001	-1.278	-0.000	0.274***	0.096***	0.122***
	[0.000]	[0.000]	[0.880]	[0.198]	[0.182]	[0.108]	[0.000]	[0.000]	[0.000]
Observations	38,205	38,205	38,205	38,205	38,205	38,205	38,205	38,205	38,205

P-values are in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4-11 Granger Causality Test after Controlling One-to-one Messaging

Dependent Variables	Explanatory Variables	Chi-2	P-value	Significance
diff_prob				
	social_times	**19.386**	**0.000**	*******
	dollarpnl	2.244	0.134	
	maxdd	164.136	0.000	***
	leverage	28.287	0.000	***
	intravol	0.685	0.408	
	n_sent	**3.350**	**0.067**	*****
	n_received	**8.285**	**0.004**	*******
	n_read	**17.029**	**0.000**	*******
social_times				
	diff_prob	0.125	0.724	
	dollarpnl	1.316	0.251	
	maxdd	12.125	0.000	***
	leverage	4.469	0.035	**
	intravol	0.764	0.382	
	n_sent	2.286	0.131	
	n_received	1.070	0.301	
	n_read	14.336	0.000	***
dollarpnl				
	diff_prob	0.205	0.651	
	social_times	0.045	0.832	
	maxdd	0.156	0.693	
	leverage	0.045	0.832	
	intravol	1.672	0.196	
	n_sent	0.146	0.702	
	n_received	1.517	0.218	
	n_read	0.023	0.880	
maxdd				
	diff_prob	0.406	0.524	
	social_times	1.618	0.203	
	dollarpnl	1.369	0.242	
	leverage	18.427	0.000	***
	intravol	2.575	0.109	
	n_sent	1.223	0.269	
	n_received	1.360	0.244	
	n_read	1.657	0.198	
leverage				
	diff_prob	0.713	0.398	
	social_times	3.562	0.059	*
	dollarpnl	2.267	0.132	
	maxdd	1.053	0.305	
	intravol	1.143	0.285	
	n_sent	2.905	0.088	*
	n_received	0.862	0.353	
	n_read	1.782	0.182	
intravol				
	diff_prob	1.487	0.223	
	social_times	4.736	0.030	**
	dollarpnl	1.701	0.192	
	maxdd	1.696	0.193	
	leverage	0.594	0.441	
	n_sent	1.329	0.249	
	n_received	0.035	0.851	
	n_read	2.581	0.108	

n_sent				
	diff_prob	0.004	0.949	
	social_times	6.248	0.012	**
	dollarpnl	1.761	0.184	
	maxdd	15.041	0.000	***
	leverage	13.397	0.000	***
	intravol	1.159	0.282	
	n_received	4.593	0.032	**
	n_read	21.072	0.000	***
n_received				
	diff_prob	31.373	0.000	***
	social_times	10.522	0.001	***
	dollarpnl	0.117	0.733	
	maxdd	53.214	0.000	***
	leverage	13.536	0.000	***
	intravol	1.841	0.175	
	n_sent	45.454	0.000	***
	n_read	12.624	0.000	***
n_read				
	diff_prob	31.129	0.000	***
	social_times	14.768	0.000	***
	dollarpnl	0.205	0.651	
	maxdd	85.714	0.000	***
	leverage	16.029	0.000	***
	intravol	1.745	0.186	
	n_sent	24.581	0.000	***
	n_received	2.578	0.108	

This table represents the Granger causality test results for the panel VAR model after controlling one-to-one messaging. The variables in this identification include survival probability (diff_prob), social communication (social_times), dollar PnL, maximum drawdown, leverage, and intro-day volatility, and three measures of one-to-one messaging (the number of message sent, received, and read by each trader each day). Chi-square, P-values, and significance levels are reported in the table. *** p<0.01, ** p<0.05, * p<0.1

Table 4-12 Alternative Measures of Social Communication

	Panel A						Panel B					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	diff_prob	movsum_10	dollarpnl	maxdd	leverage	intravol	diff_prob	movavg_10	dollarpnl	maxdd	leverage	intravol
L.diff_prob	1.024***	1.420**	281.779	0.007	-59.849	0.014	1.024***	0.142**	281.779	0.007	-59.849	0.014
	[0.000]	[0.014]	[0.754]	[0.837]	[0.464]	[0.197]	[0.000]	[0.014]	[0.754]	[0.837]	[0.464]	[0.197]
L.dollarpnl	-0.000	0.000	0.016	-0.000	0.000	0.000	-0.000	0.000	0.016	-0.000	0.000	0.000
	[0.107]	[0.571]	[0.775]	[0.201]	[0.171]	[0.176]	[0.107]	[0.571]	[0.775]	[0.201]	[0.171]	[0.176]
L.maxdd	0.001***	-0.208***	104.462	0.991***	-18.600	-0.004	0.001***	-0.021***	104.462	0.991***	-18.600	-0.004
	[0.000]	[0.009]	[0.651]	[0.000]	[0.263]	[0.179]	[0.000]	[0.009]	[0.651]	[0.000]	[0.263]	[0.179]
L.leverage	0.000***	-0.000	-0.008	0.000***	0.675***	0.000	0.000***	-0.000	-0.008	0.000***	0.675***	0.000
	[0.000]	[0.268]	[0.728]	[0.001]	[0.000]	[0.382]	[0.000]	[0.268]	[0.728]	[0.001]	[0.000]	[0.382]
L.intravol	-0.000	-0.068	19.420	0.007	-56.943	0.122	-0.000	-0.007	19.420	0.007	-56.943	0.122
	[0.362]	[0.288]	[0.126]	[0.150]	[0.425]	[0.221]	[0.362]	[0.288]	[0.126]	[0.150]	[0.425]	[0.221]
L.movsum_10	**0.000*** **	1.011***	-0.434	0.000	-0.023	-0.000**						
	[0.001]	[0.000]	[0.692]	[0.441]	[0.371]	[0.016]						
L.movavg_10							**0.000*** **	1.011***	-4.341	0.000	-0.226	-0.000**
L.movsum_20												
L.movavg_20												
L.movsum_30												
L.movavg_30												
Observations	35,823	35,823	35,823	35,823	35,823	35,823	35,823	35,823	35,823	35,823	35,823	35,823

This table represents the results of the panel VAR model using alternative measures of social communication. The variables included in the identification are survival probability (diff_prob), dollar PnL, maximum drawdown, leverage, and intro-day volatility, and measures of social communication, including moving sum of the last-

10/20/30-day social times (movsum_10, movsum_20, and movsum_30, respectively) and moving average of the last-10/20/30-day social times (movavg_10, movavg_20, and movavg_30, respectively). P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 4-12 Alternative Measures of Social Communication (Continued)

	Panel C						Panel D					
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
VARIABLES	diff_prob	movsum_20	dollarpnl	maxdd	leverage	intravol	diff_prob	movavg_20	dollarpnl	maxdd	leverage	intravol
L.diff_prob	1.023***	1.514***	189.472	-0.009	-153.512*	0.016	1.023***	0.076***	189.472	-0.009	-153.512*	0.016
	[0.000]	[0.010]	[0.842]	[0.784]	[0.050]	[0.183]	[0.000]	[0.010]	[0.842]	[0.784]	[0.050]	[0.183]
L.dollarpnl	-0.000	0.000	0.085**	-0.000	0.000	0.000	-0.000	0.000	0.085**	-0.000	0.000	0.000
	[0.192]	[0.360]	[0.013]	[0.163]	[0.218]	[0.235]	[0.192]	[0.360]	[0.013]	[0.163]	[0.218]	[0.235]
L.maxdd	0.001***	-0.241***	123.033	0.997***	-12.209	-0.005	0.001***	-0.012***	123.033	0.997***	-12.209	-0.005
	[0.000]	[0.008]	[0.634]	[0.000]	[0.381]	[0.202]	[0.000]	[0.008]	[0.634]	[0.000]	[0.381]	[0.202]
L.leverage	0.000***	-0.000	-0.016	0.000***	0.466***	0.000	0.000***	-0.000	-0.016	0.000***	0.466***	0.000
	[0.006]	[0.985]	[0.749]	[0.008]	[0.006]	[0.370]	[0.006]	[0.985]	[0.749]	[0.008]	[0.006]	[0.370]
L.intravol	-0.000	-0.068	20.386	0.006	-15.238	0.119	-0.000	-0.003	20.386	0.006	-15.238	0.119
	[0.344]	[0.291]	[0.168]	[0.203]	[0.799]	[0.228]	[0.344]	[0.291]	[0.168]	[0.203]	[0.799]	[0.228]
L.movsum_10												
L.movavg_10												
L.movsum_20	**0.000*** **	1.011***	-0.489	0.000	0.002	-0.000**						
	[0.001]	[0.000]	[0.609]	[0.347]	[0.875]	[0.018]						
L.movavg_20							**0.000*** **	1.011***	-9.773	0.000	0.045	-0.000**
							[0.001]	[0.000]	[0.609]	[0.347]	[0.875]	[0.018]
L.movsum_3 0												
L.movavg_30												
Observations	33,026	33,026	33,026	33,026	33,026	33,026	33,026	33,026	33,026	33,026	33,026	33,026

Table 4-12 Alternative Measures of Social Communication (Continued)

	Panel E						Panel F					
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
VARIABLES	diff_prob	movsum_30	dollarpnl	maxdd	leverage	intravol	diff_prob	movavg_30	dollarpnl	maxdd	leverage	intravol
L.diff_prob	1.023***	1.513**	578.638	-0.030	-189.538**	0.015	1.023***	0.050**	578.638	-0.030	-189.538**	0.015
	[0.000]	[0.012]	[0.366]	[0.365]	[0.014]	[0.268]	[0.000]	[0.012]	[0.366]	[0.365]	[0.014]	[0.268]
L.dollarpnl	-0.000	0.000	0.017	-0.000	0.000	0.000	-0.000	0.000	0.017	-0.000	0.000	0.000
	[0.207]	[0.137]	[0.824]	[0.144]	[0.315]	[0.172]	[0.207]	[0.137]	[0.824]	[0.144]	[0.315]	[0.172]
L.maxdd	0.002***	-0.241**	7.006	1.005***	-20.858	-0.004	0.002***	-0.008**	7.006	1.005***	-20.858	-0.004
	[0.000]	[0.019]	[0.957]	[0.000]	[0.103]	[0.372]	[0.000]	[0.019]	[0.957]	[0.000]	[0.103]	[0.372]
L.leverage	0.000**	0.000	-0.031	0.000**	0.293**	0.000	0.000**	0.000	-0.031	0.000**	0.293**	0.000
	[0.010]	[0.735]	[0.806]	[0.022]	[0.013]	[0.341]	[0.010]	[0.735]	[0.806]	[0.022]	[0.013]	[0.341]
L.intravol	-0.000	-0.035	20.463	0.005	16.178	0.090	-0.000	-0.001	20.463	0.005	16.178	0.090
	[0.327]	[0.348]	[0.461]	[0.316]	[0.760]	[0.347]	[0.327]	[0.348]	[0.461]	[0.316]	[0.760]	[0.347]
L.movsum_10												
L.movavg_10												
L.movsum_20												
L.movavg_20												
L.movsum_30	**0.000*** **	1.011***	-0.113	0.000	0.003	-0.000*						
	[0.002]	[0.000]	[0.491]	[0.338]	[0.837]	[0.054]						
L.movavg_30							**0.000*** **	1.011***	-3.392	0.000	0.082	-0.000*
							[0.002]	[0.000]	[0.491]	[0.338]	[0.837]	[0.054]
Observations	30,415	30,415	30,415	30,415	30,415	30,415	30,415	30,415	30,415	30,415	30,415	30,415

Table 4-13 Granger Causality Test with Alternative Measures of Social Communication

Panel A					**Panel B**				
Dependent Variables	Explanatory Variables	chi2	Prob	Sig.	Dependent Variables	Explanatory Variables	chi2	Prob	Sig.
diff_prob	movsum_10	11.413	0.001	***	diff_prob	movavg_10	11.413	0.001	***
	dollarpnl	2.595	0.107			dollarpnl	2.595	0.107	
	maxdd	162.325	0.000	***		maxdd	162.325	0.000	***
	leverage	16.605	0.000	***		leverage	16.605	0.000	***
	intravol	0.831	0.362			intravol	0.831	0.362	
movsum_10	diff_prob	6.051	0.014	**	movavg_10	diff_prob	6.051	0.014	**
	dollarpnl	0.321	0.571			dollarpnl	0.321	0.571	
	maxdd	6.790	0.009	***		maxdd	6.790	0.009	***
	leverage	1.226	0.268			leverage	1.226	0.268	
	intravol	1.129	0.288			intravol	1.129	0.288	
dollarpnl	diff_prob	0.098	0.754		dollarpnl	diff_prob	0.098	0.754	
	movsum_10	0.157	0.692			movavg_10	0.157	0.692	
	maxdd	0.205	0.651			maxdd	0.205	0.651	
	leverage	0.121	0.728			leverage	0.121	0.728	
	intravol	2.337	0.126			intravol	2.337	0.126	
maxdd	diff_prob	0.042	0.837		maxdd	diff_prob	0.042	0.837	
	movsum_10	0.593	0.441			movavg_10	0.593	0.441	
	dollarpnl	1.637	0.201			dollarpnl	1.637	0.201	
	leverage	10.702	0.001	***		leverage	10.702	0.001	***
	intravol	2.067	0.150			intravol	2.067	0.150	
leverage	diff_prob	0.537	0.464		leverage	diff_prob	0.537	0.464	
	movsum_10	0.799	0.371			movavg_10	0.799	0.371	
	dollarpnl	1.876	0.171			dollarpnl	1.876	0.171	
	maxdd	1.255	0.263			maxdd	1.255	0.263	
	intravol	0.636	0.425			intravol	0.636	0.425	
intravol	diff_prob	1.662	0.197		intravol	diff_prob	1.662	0.197	
	movsum_10	5.830	0.016	**		movavg_10	5.830	0.016	**
	dollarpnl	1.829	0.176			dollarpnl	1.829	0.176	
	maxdd	1.802	0.179			maxdd	1.802	0.179	
	leverage	0.765	0.382			leverage	0.765	0.382	

This table represents the results of the Granger causality tests with alternative measures of social communication. The variables include survival probability (diff_prob), dollar PnL, maximum drawdown, leverage, and intro-day volatility, and measures of social communication, including moving sum of the last-10/20/30-day social times (movsum_10, movsum_20, and movsum_30, respectively) and moving average of the last-10/20/30-day social times (movavg_10, movavg_20, and movavg_30, respectively). Chi-2, P-values, and significance levels (Sig.) are reported in the table.

Table 4-13 Granger Causality Test with Alternative Measures of Social Communication (Continued)

Panel C					**Panel D**				
Dependent Variables	Explanatory Variables	chi2	Prob	Sig.	Dependent Variables	Explanatory Variables	chi2	Prob	Sig.
diff_prob	movsum_20	10.200	0.001	***	diff_prob	movavg_20	10.200	0.001	***
	dollarpnl	1.702	0.192			dollarpnl	1.702	0.192	
	maxdd	158.966	0.000	***		maxdd	158.966	0.000	***
	leverage	7.627	0.006	***		leverage	7.627	0.006	***
	intravol	0.894	0.344			intravol	0.894	0.344	
movsum_20	diff_prob	6.658	0.010	***	movavg_20	diff_prob	6.658	0.010	***
	dollarpnl	0.837	0.360			dollarpnl	0.837	0.360	
	maxdd	7.072	0.008	***		maxdd	7.072	0.008	***
	leverage	0.000	0.985			leverage	0.000	0.985	
	intravol	1.116	0.291			intravol	1.116	0.291	
dollarpnl	diff_prob	0.040	0.842		dollarpnl	diff_prob	0.040	0.842	
	movsum_20	0.262	0.609			movavg_20	0.262	0.609	
	maxdd	0.227	0.634			maxdd	0.227	0.634	
	leverage	0.102	0.749			leverage	0.102	0.749	
	intravol	1.898	0.168			intravol	1.898	0.168	
maxdd	diff_prob	0.075	0.784		maxdd	diff_prob	0.075	0.784	
	movsum_20	0.883	0.347			movavg_20	0.883	0.347	
	dollarpnl	1.947	0.163			dollarpnl	1.947	0.163	
	leverage	7.051	0.008	***		leverage	7.051	0.008	***
	intravol	1.623	0.203			intravol	1.623	0.203	
leverage	diff_prob	3.840	0.050	*	leverage	diff_prob	3.840	0.050	*
	movsum_20	0.025	0.875			movavg_20	0.025	0.875	
	dollarpnl	1.518	0.218			dollarpnl	1.518	0.218	
	maxdd	0.767	0.381			maxdd	0.767	0.381	
	intravol	0.065	0.799			intravol	0.065	0.799	
intravol	diff_prob	1.769	0.183		intravol	diff_prob	1.769	0.183	
	movsum_20	5.550	0.018	**		movavg_20	5.550	0.018	**
	dollarpnl	1.408	0.235			dollarpnl	1.408	0.235	
	maxdd	1.627	0.202			maxdd	1.627	0.202	
	leverage	0.802	0.370			leverage	0.802	0.370	

Table 4-13 Granger Causality Test with Alternative Measures of Social Communication (Continued)

Panel E					Panel F				
Dependent Variables	Explanatory Variables	chi2	Prob	Sig.	Dependent Variables	Explanatory Variables	chi2	Prob	Sig.
diff_prob	movsum_30	9.840	0.002	***	diff_prob	movavg_30	9.840	0.002	***
	dollarpnl	1.589	0.207			dollarpnl	1.589	0.207	
	maxdd	154.405	0.000	***		maxdd	154.405	0.000	***
	leverage	6.606	0.010	**		leverage	6.606	0.010	**
	intravol	0.962	0.327			intravol	0.962	0.327	
movsum_30	diff_prob	6.337	0.012	**	movavg_30	diff_prob	6.337	0.012	**
	dollarpnl	2.210	0.137			dollarpnl	2.210	0.137	
	maxdd	5.508	0.019	**		maxdd	5.508	0.019	**
	leverage	0.114	0.735			leverage	0.114	0.735	
	intravol	0.881	0.348			intravol	0.881	0.348	
dollarpnl	diff_prob	0.817	0.366		dollarpnl	diff_prob	0.817	0.366	
	movsum_30	0.474	0.491			movavg_30	0.474	0.491	
	maxdd	0.003	0.957			maxdd	0.003	0.957	
	leverage	0.060	0.806			leverage	0.060	0.806	
	intravol	0.543	0.461			intravol	0.543	0.461	
maxdd	diff_prob	0.822	0.365		maxdd	diff_prob	0.822	0.365	
	movsum_30	0.918	0.338			movavg_30	0.918	0.338	
	dollarpnl	2.138	0.144			dollarpnl	2.138	0.144	
	leverage	5.235	0.022	**		leverage	5.235	0.022	**
	intravol	1.003	0.316			intravol	1.003	0.316	
leverage	diff_prob	5.996	0.014	**	leverage	diff_prob	5.996	0.014	**
	movsum_30	0.042	0.837			movavg_30	0.042	0.837	
	dollarpnl	1.011	0.315			dollarpnl	1.011	0.315	
	maxdd	2.653	0.103			maxdd	2.653	0.103	
	intravol	0.093	0.760			intravol	0.093	0.760	
intravol	diff_prob	1.227	0.268		intravol	diff_prob	1.227	0.268	
	movsum_30	3.709	0.054	*		movavg_30	3.709	0.054	*
	dollarpnl	1.864	0.172			dollarpnl	1.864	0.172	
	maxdd	0.796	0.372			maxdd	0.796	0.372	
	leverage	0.906	0.341			leverage	0.906	0.341	

Table 4-14 The Impact of Social Communication on Survival in a 6/9/12-Month Period

Panel A: 6-month Period						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	diff_prob	social_times	dollarpnl	maxdd	leverage	intravol
L.diff_prob	1.048***	0.478	455.128	0.028	-35.544	-0.000
	[0.000]	[0.246]	[0.633]	[0.521]	[0.688]	[0.981]
L.social_times	**0.000*** **	0.147***	-7.906	0.001*	-0.800	-0.000**
	[0.000]	[0.000]	[0.810]	[0.083]	[0.264]	[0.019]
L.dollarpnl	-0.000*	-0.000	0.003	-0.000	0.000	0.000
	[0.078]	[0.161]	[0.951]	[0.243]	[0.142]	[0.177]
L.maxdd	0.004***	0.038	115.320	0.985***	-11.121	-0.003
	[0.000]	[0.549]	[0.676]	[0.000]	[0.564]	[0.110]
L.leverage	0.000***	0.000	-0.002	0.000***	0.669***	0.000
	[0.000]	[0.217]	[0.912]	[0.000]	[0.000]	[0.509]
L.intravol	-0.000	-0.065	18.794	0.017*	-161.553	0.287
	[0.295]	[0.512]	[0.615]	[0.079]	[0.305]	[0.151]
Observations	30,998	30,998	30,998	30,998	30,998	30,998
Panel B: 9-month Period						
	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	diff_prob	social_times	dollarpnl	maxdd	leverage	intravol
L.diff_prob	1.025***	0.042	352.929	0.028	-66.176	0.005
	[0.000]	[0.914]	[0.689]	[0.415]	[0.414]	[0.596]
L.social_times	**0.000*** **	0.069**	-4.334	0.001**	-0.633	-0.000
	[0.000]	[0.021]	[0.830]	[0.035]	[0.127]	[0.268]
L.dollarpnl	-0.000*	-0.000	0.003	-0.000	0.000	0.000
	[0.085]	[0.158]	[0.951]	[0.248]	[0.128]	[0.246]
L.maxdd	0.001***	0.042	101.942	0.983***	-17.691	-0.002
	[0.000]	[0.590]	[0.668]	[0.000]	[0.291]	[0.576]
L.leverage	0.000***	0.000	-0.003	0.000***	0.667***	0.000
	[0.000]	[0.379]	[0.883]	[0.000]	[0.000]	[0.283]
L.intravol	-0.000	-0.031	21.976	0.008	-75.926	0.137
	[0.413]	[0.563]	[0.190]	[0.163]	[0.385]	[0.241]
Observations	35,359	35,359	35,359	35,359	35,359	35,359
Panel C: 12-month Period						
	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	diff_prob	social_times	dollarpnl	maxdd	leverage	intravol
L.diff_prob	1.024***	0.228	354.355	0.024	-73.396	0.011
	[0.000]	[0.553]	[0.685]	[0.467]	[0.364]	[0.282]
L.social_times	**0.000*** **	0.103***	-4.550	0.001*	-0.565	-0.000**
	[0.000]	[0.000]	[0.809]	[0.054]	[0.129]	[0.047]
L.dollarpnl	-0.000*	-0.000	0.003	-0.000	0.000	0.000
	[0.093]	[0.223]	[0.951]	[0.242]	[0.133]	[0.193]
L.maxdd	0.001***	-0.227***	89.159	0.985***	-14.542	-0.003
	[0.000]	[0.002]	[0.690]	[0.000]	[0.362]	[0.344]
L.leverage	0.000***	-0.000*	-0.003	0.000***	0.667***	0.000
	[0.000]	[0.065]	[0.861]	[0.000]	[0.000]	[0.392]
L.intravol	-0.000	-0.039	20.735	0.009	-83.767	0.122
	[0.399]	[0.416]	[0.153]	[0.112]	[0.288]	[0.222]

Observations	37,490	37,490	37,490	37,490	37,490	37,490

This table presents the results of the panel VAR model with different sample selections. The identifications in different panels (Panel A, B, and C) include observations of traders within their first 6-month/9-month/12-month trading periods, respectively, after they start trading on the STP. P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 4-15 Granger Causality Tests for 6/9/12-month Period

Dependent Variables	Explanatory Variables	chi2	Prob	Sig.	chi2	Prob	Sig.	chi2	Prob	Sig.
		Panel A: 6-month			***Panel B: 9-month***			***Panel C: 12-month***		
diff_prob	**social_times**	**59.912**	**0.000**	*******	**28.142**	**0.000**	*******	**27.606**	**0.000**	*******
	dollarpnl	3.110	0.078	*	2.963	0.085	*	2.825	0.093	*
	maxdd	659.498	0.000	***	201.233	0.000	***	170.204	0.000	***
	leverage	42.812	0.000	***	30.797	0.000	***	28.380	0.000	***
	intravol	1.095	0.295		0.670	0.413		0.710	0.399	
social_times	diff_prob	1.344	0.246		0.012	0.914		0.352	0.553	
	dollarpnl	1.964	0.161		1.994	0.158		1.484	0.223	
	maxdd	0.359	0.549		0.290	0.590		9.310	0.002	***
	leverage	1.521	0.217		0.775	0.379		3.413	0.065	*
	intravol	0.430	0.512		0.335	0.563		0.663	0.416	
dollarpnl	diff_prob	0.228	0.633		0.160	0.689		0.164	0.685	
	social_times	0.058	0.810		0.046	0.830		0.059	0.809	
	maxdd	0.175	0.676		0.185	0.668		0.159	0.690	
	leverage	0.012	0.912		0.022	0.883		0.031	0.861	
	intravol	0.253	0.615		1.715	0.190		2.042	0.153	
maxdd	diff_prob	0.413	0.521		0.663	0.415		0.528	0.467	
	social_times	3.001	0.083	*	4.450	0.035	**	3.710	0.054	*
	dollarpnl	1.361	0.243		1.335	0.248		1.369	0.242	
	leverage	17.313	0.000	***	17.646	0.000	***	18.072	0.000	***
	intravol	3.087	0.079	*	1.950	0.163		2.531	0.112	
leverage	diff_prob	0.162	0.688		0.666	0.414		0.824	0.364	
	social_times	1.248	0.264		2.326	0.127		2.306	0.129	
	dollarpnl	2.156	0.142		2.321	0.128		2.259	0.133	
	maxdd	0.333	0.564		1.114	0.291		0.832	0.362	
	intravol	1.051	0.305		0.756	0.385		1.131	0.288	
intravol	diff_prob	0.001	0.981		0.281	0.596		1.157	0.282	
	social_times	5.463	0.019	**	1.229	0.268		3.928	0.047	**
	dollarpnl	1.820	0.177		1.349	0.246		1.692	0.193	
	maxdd	2.556	0.110		0.313	0.576		0.897	0.344	
	leverage	0.435	0.509		1.153	0.283		0.732	0.392	

This table presents the results of the Granger causality tests. The identifications in different panels (Panel A, B, and C) are associated with the panel VAR specifications for traders' first 6-month/9-month/12-month trading periods, respectively. P-values are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 4-16 Clustering Standard Errors at Trader Level

VARIABLES	(1) diff_prob	(2) social_times	(3) dollarpnl	(4) maxdd	(5) leverage	(6) intravol
L.diff_prob	1.024***	0.223	350.584	0.024	-69.730	0.012
	[0.000]	[0.817]	[0.499]	[0.503]	[0.600]	[0.315]
L.social_times	0.000***	0.110	-4.655	0.001	-0.568	-0.000*
	[0.007]	[0.114]	[0.807]	[0.149]	[0.339]	[0.074]
L.dollarpnl	-0.000	-0.000	0.003	-0.000	0.000	0.000
	[0.266]	[0.277]	[0.794]	[0.294]	[0.248]	[0.322]
L.maxdd	0.001***	-0.283*	87.473	0.986***	-16.220	-0.004**
	[0.000]	[0.053]	[0.466]	[0.000]	[0.470]	[0.042]
L.leverage	0.000*	-0.000	-0.003	0.000***	0.667***	0.000
	[0.067]	[0.232]	[0.705]	[0.001]	[0.000]	[0.455]
L.intravol	-0.000	-0.041	20.540**	0.009	-83.922	0.122
	[0.405]	[0.347]	[0.015]	[0.101]	[0.276]	[0.180]
Observations	38,205	38,205	38,205	38,205	38,205	38,205

This table reports the main results of the panel VAR model with standard errors clustered at trader level, where diff_Prob represents the probability of surviving in the market. For the measuring social media participation times, diff_total denotes the first difference of the cumulative participation times till a given day (t), which is equal to the participation times in day (t). Other control variables include daily dollar PnL, first difference of maximum drawdown, average leverage and intraday volatility. P-values are reported in the parentheses. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 4-17 Granger Causality Test (Clustering Standard Errors at Trader-level)

Dependent Variables	Explanatory Variables	Chi-2	Prob	Significance
diff_prob	**social_times**	**7.155**	**0.007**	***
	dollarpnl	1.237	0.266	
	maxdd	13.686	0.000	***
	leverage	3.361	0.067	*
	intravol	0.692	0.405	
social_times	diff_prob	0.054	0.817	
	dollarpnl	1.182	0.277	
	maxdd	3.749	0.053	*
	leverage	1.426	0.232	
	intravol	0.885	0.347	
dollarpnl	diff_prob	0.456	0.499	
	social_times	0.060	0.807	
	maxdd	0.531	0.466	
	leverage	0.143	0.705	
	intravol	5.891	0.015	**
maxdd	diff_prob	0.449	0.503	
	social_times	2.078	0.149	
	dollarpnl	1.100	0.294	
	leverage	11.259	0.001	***
	intravol	2.683	0.101	
leverage	diff_prob	0.275	0.600	
	social_times	0.913	0.339	
	dollarpnl	1.333	0.248	
	maxdd	0.522	0.470	
	intravol	1.186	0.276	
intravol	diff_prob	1.010	0.315	
	social_times	3.192	0.074	*
	dollarpnl	0.981	0.322	
	maxdd	4.117	0.042	**
	leverage	0.558	0.455	

This table presents the results of Granger causality tests. Chi-square, p-value and significance level are reported. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

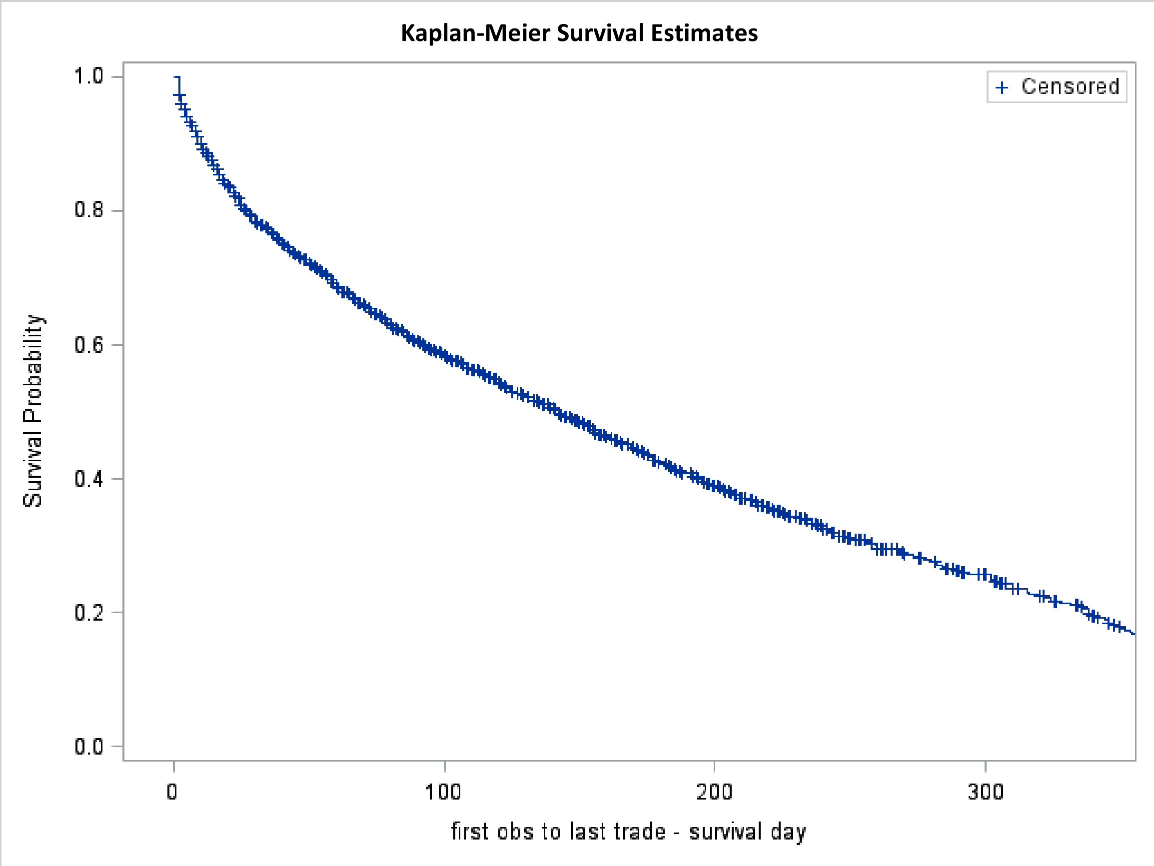


Figure 4-1 Survival Curve for The Full Sample

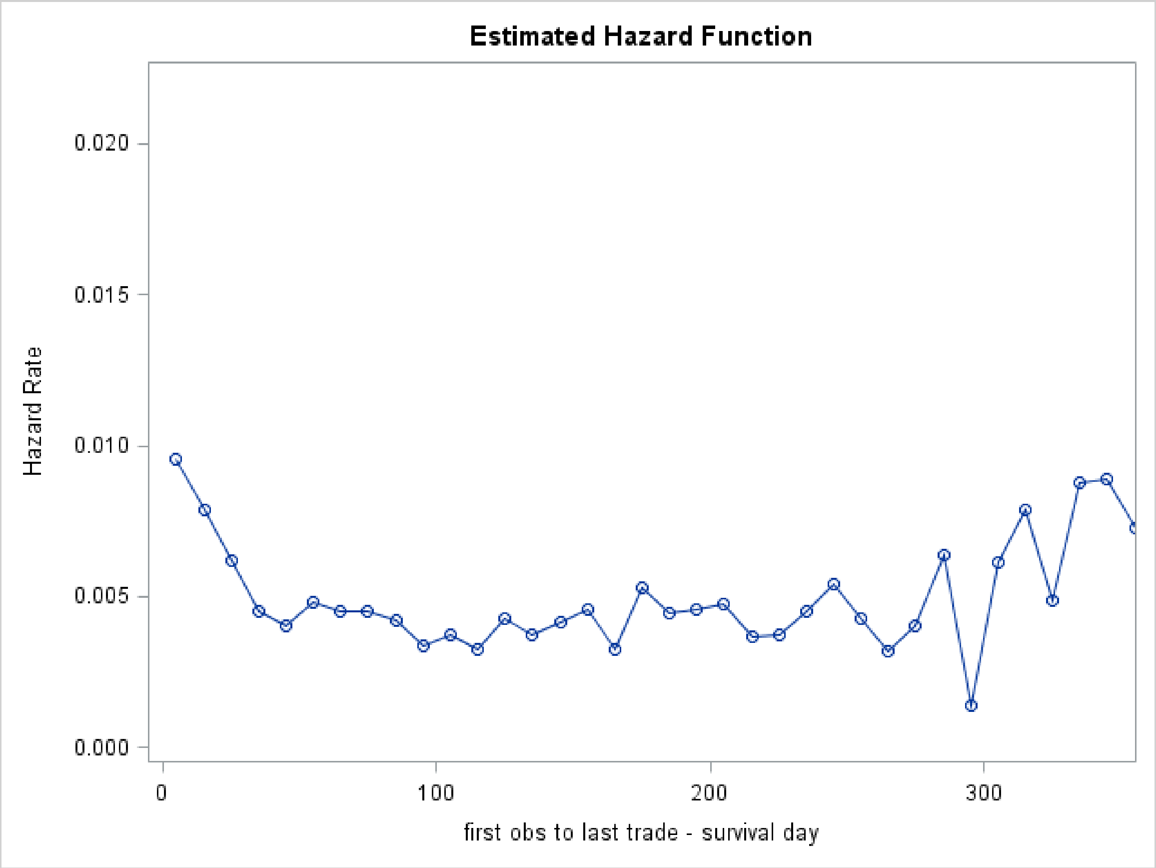
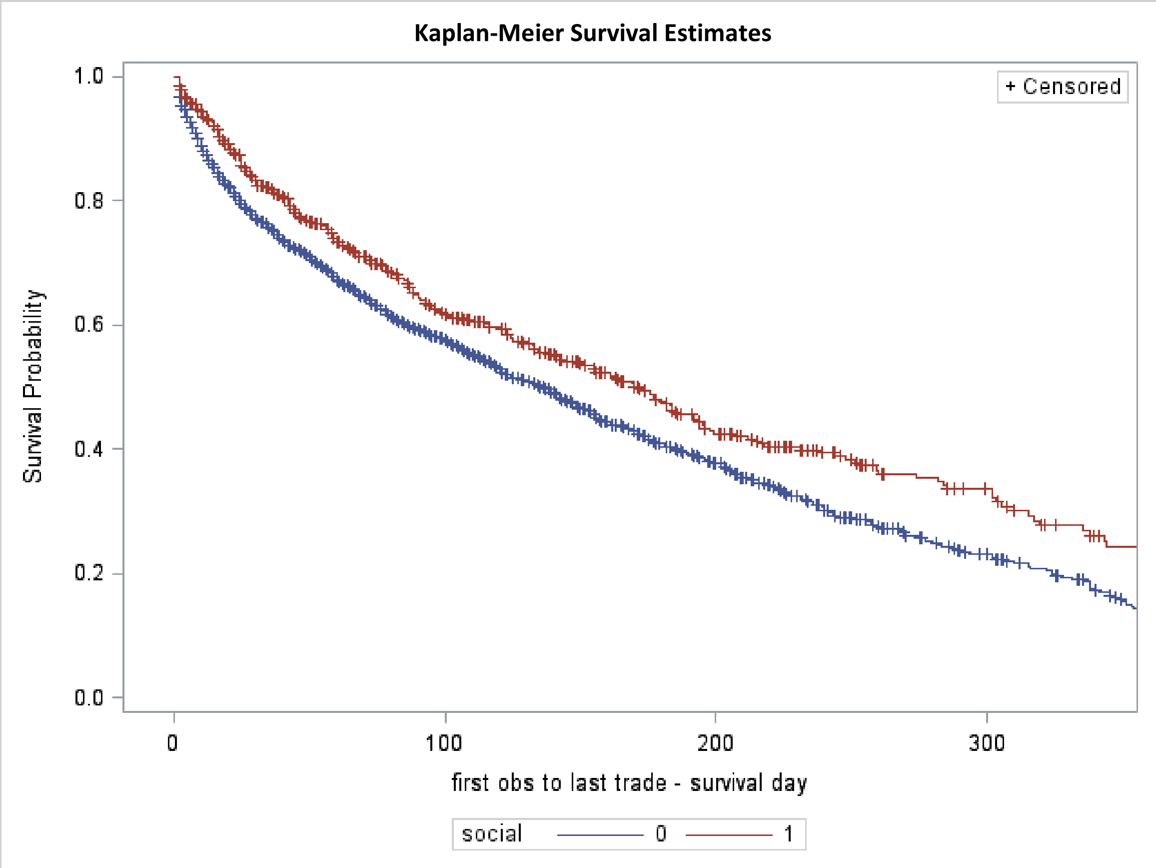


Figure 4-2 Hazard Function for The Full Sample



Note: social is a dummy variable equals one when a trader is communicative.

Figure 4-3 Survival Curves for Users and Non-users of Social Media

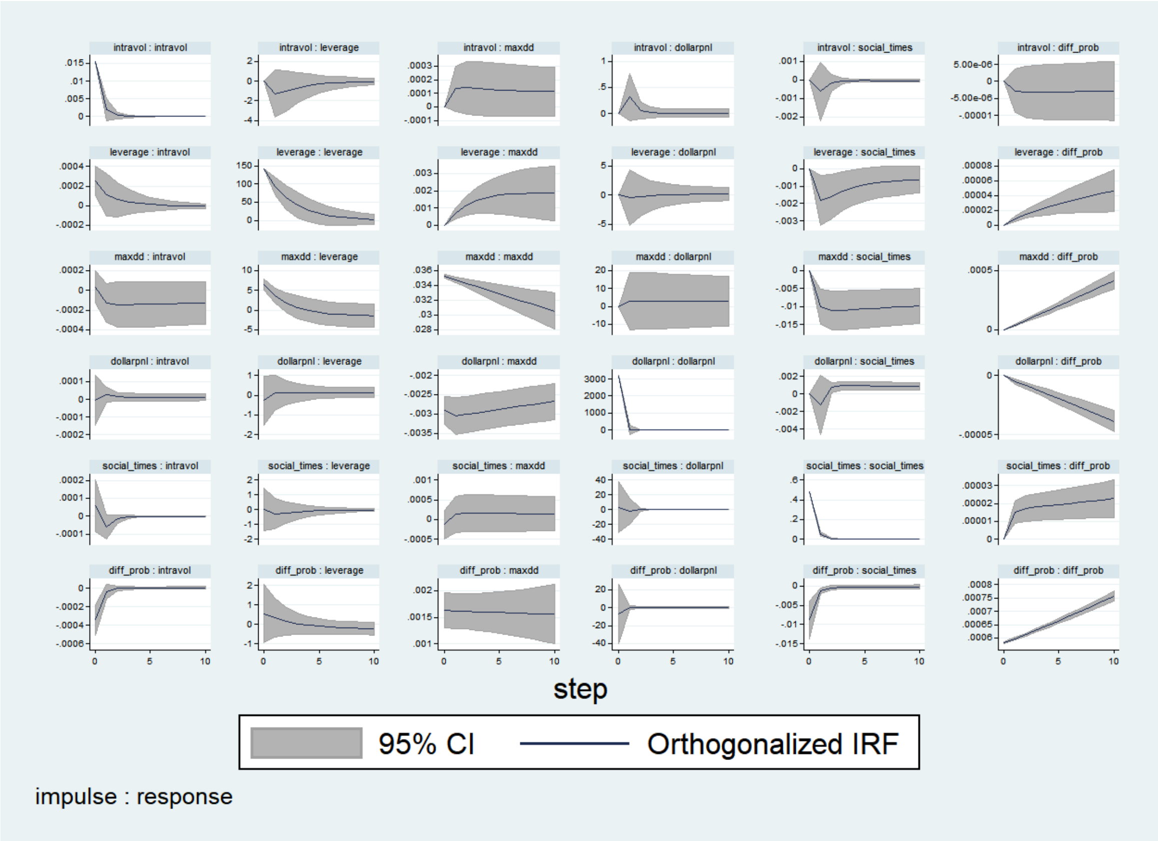


Figure 4-4 Impulse Response Functions (social_times)

Chapter 5: Conclusion and Future Research

My thesis is motivated by the novel concept *social finance* in the survey paper "Behavioral Finance" (Hirshleifer, 2015). In three studies, I investigate retail traders' (1) trading performance, (2) return synchronicity, and (3) survivorship on a social trading platform (STP) in the foreign exchange (FX) market. I use a novel dataset from a STP, similar to the dataset used in Heimer (2016), including more than 1 million trader-day observations and over 3,000 traders during an 18-month sample period. An interesting setup of this STP is that traders can create their Facebook-like profiles and communicate with each other while trading through the online discussion forum feature and/or the one-to-one messaging feature. Therefore, these features allow me to investigate the potential behavioral changes of the traders in relation to their social communication.

In the first study, I examine the trading performance of FX retail traders on the STP. I follow previous literature and use three measures to examine retail traders' profitability and skills: raw returns, passive benchmark returns, and abnormal returns under a four-factor model in the FX market (Abbey & Doukas, 2015; Pojarliev & Levich, 2008, 2010). I find evidence that FX retail traders on average lose money. My evidence is consistent with the literature which suggests that FX retail traders on average lose money and do not possess skills (Ben-David et al., 2018; Hayley & Marsh, 2016; Osler, 2012). I also find that high-frequency traders underperform low-frequency traders. This is aligned with the overconfidence hypothesis which suggests that retail traders lose more money through frequent trading activities. This evidence is consistent with the insight from retail trading in the stock market that "trading is hazardous to traders' wealth" (Barber & Odean, 2000). Although I revisit the research question in Abbey & Doukas (2015), there are a number of differences between my study and their research. Firstly, I employ a dataset which mitigates the potential data limitation concerns in their paper. Therefore, my results should better address the research question of whether or not FX retail traders make money and possess skills. Secondly, I show that FX retail traders do not make money, which is different from the conclusion in Abbey & Doukas (2015) that FX retail traders make money and possess skills. Third, my evidence supports the overconfidence hypothesis in the FX market and rejects the calibration hypothesis by showing that FX retail traders do not improve their performance through trading. Fourth, I apply an additional measure (volume per day) to further validate my results and I consider the potential influence of social communication on the results. This study relates to several streams of literature. First, this study directly extends Abbey & Doukas (2015) by addressing potential data limitation concerns and presenting new evidence on FX retail traders' profitability and skills. Second, this study contributes to the literature on retail trading in the context of the FX market. Third, this study finds evidence that retail traders lose more money through more trading activities, which is consistent with insights on retail trading in the equity market (e.g., Barber & Odean (2000)).

In the second study, I investigate the impact of social communication on retail traders' return synchronicity within a social trading platform. I construct two measures of return synchronicity of individual traders on the STP: the platform-level return synchronicity and the trader-level return synchronicity. Employing a panel VAR model, Granger causality tests, and impulse response functions (IRFs), I document a causal relationship between social communication and return synchronicity. To be specific, social communication increases the return synchronicity of traders on the STP, indicating that social communication reduces the disagreement among traders. I show that social communication online positively impacts both the platform-level and trader-level return synchronicity. Social communication leaders positively impact the platform-level return synchronicity. I also construct a chat-level return synchronicity measure to examine whether chat participants in online discussions exhibit synchronized returns. I show that chat participants exhibit significantly positive chat-level return synchronicity, which cannot be explained by chat-level characteristics (the number of participants, the number of comments, and the number of likes). Moreover, I find evidence that this positive chat-level return synchronicity is more pronounced in market-related chat topics. This evidence implies that the return synchronicity of traders on the STP is attributed to the information content of the online discussions instead of the observable chat-level characteristics. Overall, the evidence is consistent with literature which suggests that social communication alters retail traders' behavior (Cetina, 2003; Gemayel & Preda, 2018a, 2018b; Heimer, 2016; Hirshleifer, 2015; Preda, 2017).

In the third study, I explore whether social communication impacts the survival of retail traders in the FX market. I utilize a dataset on a STP where traders can communicate with each other while trading. The communication activities of the trading platform include creating discussion topics, posting comments, and liking the posts of others. These traders are referred to as "communicative". First, I study traders' survivorship utilizing Kaplan-Meier estimates to examine whether making use of communication features impacts a trader's decision to quit the market. Second, I employ a Cox hazard proportional model to identify the effect of social communication on traders' survival probabilities. Third, I use a panel VAR model, Granger causality identifications, and impulse response functions (IRFs) to identify the causal link between social communication and individual traders' survivorship. Communicative traders appear to stay longer on the STP compared to non-communicative ones. Communication appears to result in an increase in the survival probability of individual traders. My results relate to the literature on the market participation of individual investors. Previous studies show that communication impacts investors' decision on market entry (Hong et al., 2004). I show that communication also impacts investors' decision on market persistence. Overall, I call for a comprehensive investigation of the role of communication in trading, which stimulates a new area of debate within the behavioral finance literature relating to trading behavior (Hirshleifer, 2015).

In summary, this set of studies contributes to the literature on individual investor behavior. This stream of literature assumes that market participants exhibit systematic behavioral biases (e.g., overconfidence, over-extrapolation, and gain-or-loss utility based on prospect theory) (Barberis, 2018). Though these well-documented behavioral biases are psychologically more accurate than rational models, the social finance theory further suggests that the interactions among investors can also impact the information transmission processes, decision-making processes, and the subsequent trading behavior and asset prices. I show that FX retail traders do not make money and they are on average overconfident. This is consistent with insights on retail trading in the equity market which suggest that trading is hazardous to traders' wealth (Barber & Odean, 2000). My research empirically supports the social finance theory by providing evidence that social communication plays a role in a FX retail trader's return pattern (i.e. synchronicity) and decision to quit trading. This evidence adds to the very limited literature, especially in the FX market, on the role of social interaction/communication in altering a retail trader's behavior.

These results have regulatory implications. FX retail traders on average lose money on social trading platforms and communicative traders ultimately stay longer. They potentially lose a significant amount of money over time. Consideration should be given by regulators and policy makers in terms of small investor protection in the context of social trading. This consideration does not seem to be in place at the moment.

The limitation of this research may arise from the representativeness of the dataset and the demographic characteristics of the traders. A similar dataset from the same STP with a slightly longer (6 months) sample period is shown to be representative as a number of properties of the traders on the STP are similar to those retail traders in the equity market (e.g., disposition effects) (Heimer, 2016). One can still argue that, with the development of STPs, traders' behavior might change over time, and younger generations might interact with social media features differently compared to older generations and exhibit different trading behavior. Another argument is that the evidence found on retail traders' behavior might be partially associated with the demographic information of these traders, such as gender, education, income level, early life experience, etc. I argue that these factors are worth considering and might be possible when larger datasets are accessible and more comprehensive individual-level information is available.

For future research, it is worth investigating the impact of social communication on other trading behavior as well as judgement and decision-making. Recent literature has investigated the behavioral changes of traders (e.g., the disposition effect) in relation to social communication. However, the mechanisms associated with such behavioral changes (e.g., amplified biases) largely remain unknown (Heimer, 2016). Specifically, these behavioral changes are potentially due to the distorted beliefs of traders that arise from social communication. For instance, traders may believe that they are more likely to make money when they receive confirmation and/or reach agreements with other traders. These beliefs, however, are not necessarily correct. Though traders' beliefs are not directly observable, novel measures and/or proxies of traders' beliefs should be explored to enrich the understanding of the mechanisms between social communication and retail traders' behavioral changes.

Another direction of future research is related to "wisdom of crowds" literature. This thesis does not directly speak to this strand of literature as it does not examine the relationship between crowd-level characteristics and associated outcomes. For example, the diversity of crowds might be associated with the efficiency of crowd-level decision-making outcomes (Economo et al., 2016; Hong & Page, 2001, 2004; Page, 2007). However, the evidence in this thesis demonstrates that social communication on the STP alters the behavior of retail traders. This might serve as a potential mechanism in terms of investigating the impact of the social structure of crowds on their wisdom. To be specific, the wisdom of crowds within socially connected structures might be different from that within socially isolated structures (Saavedra, Duch, et al., 2011; Saavedra, Hagerty, et al., 2011). This is because social communication potentially serves as a channel to alter the decision-making processes among the crowds, which might subsequently change the wisdom (outcome) of the crowds. This idea might be done through the comparison between traders' behavior on STPs where traders are socially connected and non-STPs where traders are not socially connected. It might also be done by comparing traders' behavior between different types of STPs where the social connection structures are different. Such comparisons would shed light on how social structures among traders might change the wisdom of crowds.

In addition, qualitative studies regarding the discussion contents on STPs are worth exploring; and psychological and sociological research which directly observes the behavioral changes of traders would add to the theories and potential mechanisms in this new area of debate within social finance. The discussion contents might, to some extent, reflect the decision-making process of traders, but it might also be insufficient to describe a whole picture of how traders are influenced by social communication. This is because the discussion contents might only reflect a small piece of information of a complex decision-making process. As a result, it calls for psychological and sociological research which provides experimental settings to directly study the changes in traders' cognition, perception, attitude, emotion, as well as judgement and decision-making (Borch & Lange, 2017; Hansen, 2020a, 2020b). This information is reflected in the reactions of traders, the emotions they exhibit, the language they use, and the decisions they make. It might be useful to talk to traders when they make their trading decisions in relation to the social communication they receive. This would help researchers to understand how traders perceive social communication and how the subsequent decisions are made.

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