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Do Risk Preferences Shape the Effect of Online Trading on Trading Frequency, Volume, and Portfolio Performance?

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Abstract

How do investors' risk preferences influence the relationships between investors' online channel use intensity and both their trading behaviors and performance? This study answers this important question even as investors are increasingly rely on the Internet for their trading activities. We leverage rare and unique micro-level historical dataset from more than 7,000 investor accounts over a 44-month period between 2010 and 2013 at a large brokerage firm in China. The dataset and analyses enable us to provide new insights into how investors' online channel use intensity and risk preferences jointly influence their trading behaviors and performance, even though some other aspects of financial markets have changed considerably over the years. The findings reveal that although online channel use intensity is associated with increased trading volume, trading frequency, and investment returns, these effects differ across investors with different risk preferences. We find that while online channel use intensity has strong positive effects on transaction frequency for both risk-seeking and risk-averse investors, it has a much lower effect on trading volume for risk-averse investors than for risk-seeking investors. We further find that risk-averse investors with higher online channel use intensity outperform investors with other risk preferences in terms of investment performance. This paper contributes to the emerging literature at the intersection of information systems and behavioral finance by revealing the moderating role of risk preferences in the relationships between investors' online trading channel use intensity and both their trading behaviors and outcomes. We discuss the implications for research and practice.

Keywords: *Chinese stock market, online trading, portfolio performance, return on investment, risk preferences, trading behavior.*

Introduction

The rise of the Internet in the last three decades has driven consumers worldwide to use online self-service channels to engage in financial activities, such as trading stocks [47]. Many financial service firms and stock-exchange platforms are increasingly offering online self-service channels that allow individual customers or investors (we use these terms interchangeably) to conduct self-directed research and investments, thereby allowing them to bypass intermediaries [9, 32, 39]. However, these online investment channels can be double-edged swords, exposing investors to both the *advantages* of autonomy and reduced costs [49] and the *risks* inherent in the illusion of control [6]. Despite the wisdom to consider both the potential *risks* and *returns* before making any investment [46], it remains unclear how individual investors' risk preferences shape the influence of online channel use on trading behaviors and portfolio performance.

From a practical perspective, firms were rarely required to consider and inform investors of their individual risk preferences before the 2008 financial crisis [90]. Policymakers called for tighter regulations after the crisis to better manage risks for both investors and the overall economy [64]. For instance, governments and regulatory institutions in Hong Kong and China required each financial firm to assess every investor's risk preference (i.e., risk-seeking, risk-neutral, or risk-averse) and inform them about the potential risks associated with their investments [20].

Although prior research explores the role of Internet self-service channels in affecting individuals' trading behaviors [47] and researchers recognize that personal risk preferences also affect individuals' trading behaviors, there has been limited understanding on how individual investors with different risk profiles differentially use online channels for their trading activities (e.g., trading frequency and volume) and how the intensity of such online channel use affects investors' performance outcomes (e.g., investment returns). Answering these questions is important from a practical perspective to develop prescriptions for investors and financial firms and from a theoretical perspective to understand the moderating effects of risk preferences in the relationships between investors' online channel use intensity and both their trading behaviors and performance. Some scholars question the role of online channels in fueling investments in risky assets that investors do not fully understand [47], while others blame the risk-seeking behavior of trading online without the financial knowledge needed to assess the risks involved [62]. Therefore, this study examines how online channel use intensity and personal risk preferences jointly affect trading behaviors and performance, leading to our core research question: *for investors with different risk preferences, how do their trading behaviors (i.e., trading frequency and trading volume) and performance vary with their online channel use intensity?*

To answer this question, we develop hypotheses considering the underlying mechanisms, such as information search, management costs, and transaction costs in online versus offline channels, and how investors process and act on information using different channels. We test our hypotheses using fine-grained longitudinal transaction data from more than 7,000 investors from a major Chinese brokerage firm for a period of 44 months (from Jan. 2010 to Aug. 2013). The China setting is also interesting because scholars have pointed to several differences between the Chinese financial market versus the financial markets in more developed economics. For example, Chinese financial market is more subject to government participation, in that all Chinese social pension accounts are managed by a government agency reducing the ability of individual investors to allocate their financial assets as they see fit [56]. Also, Chinese investors have generally lower levels of financial literacy which can potentially influence their financial well-being [98].

We leverage data on investors' online channel use intensity and risk preferences to examine how these two variables jointly influence trading frequency, volume, and performance. The results suggest that online channel use intensity is associated with higher trading frequency, larger trading volume, and better performance; however, these effects are not evenly distributed across investors with different risk preferences. We find that online channel use intensity has strong positive effects on transaction frequency for both risk-seeking and risk-averse investors, but a much weaker effect on trading volume for risk-averse investors than for risk-seeking investors. Interestingly, risk-averse investors with higher online channel use intensity outperform investors with other risk preferences in terms of investment performance. Even though online stock trading has been changing over the years, use of a historically relevant dataset provides generalizable findings to inform important insights that go beyond the specific context and time period of our study and enrich the ongoing academic discourse on the factors that determine individual investors' performance as they use online trading channels. [1] These findings also provide valuable implications for investors, financial service firms, and policymakers.

Theory Development and Hypotheses

The Internet and Investors

The Internet has changed investors' behaviors dramatically in many aspects. First, the Internet has made stock trading and portfolio management much easier and more convenient than ever before [54]. In particular, the Internet has reduced transaction costs because online investors do not need to go to the brick-and-mortar counters of a broker to trade stocks [49, 69, 87]. The Internet has also reduced portfolio management costs because online self-service trading channels grant investors more economical and easier ways to manage their portfolios online [60]. Second,

[1] We thank the anonymous AE for pointing to the value of historically relevant datasets for addressing fundamental questions.

the Internet enables investors to access a large amount of information online with much lower search costs. The information from the Internet includes not only relatively objective and explicit information (e.g., financial data on performance) but also relatively subjective information (e.g., social communication or social observational learning) [25]. The Internet and related technologies, such as instant messaging, online communities, and social media websites, also allow users to learn from others and share their investment ideas [19].[2]

However, some of these advantages also come with some risks. Because the Internet enabled access to far more data and trades without the need for intermediaries and financial advisors, it can potentially inflate online investors' overconfidence bias [7, 76]. Overconfidence describes a person's subjective confidence in her or his own judgments, which is typically greater than the objective accuracy of those judgments [74]. Overconfidence exists in online trading due to the increasing illusions of knowledge and illusion of control. In particular, the vast amount of information available on the Internet may foster the illusion of knowledge among investors [6]. Arguably, due to the easy access to vast quantities of investment data and their lack of professional training and experience in digesting investment-related data, online investors may be tempted to believe that the data themselves confer knowledge, thereby creating the illusion of knowledge.

Online self-serve investment technologies may also facilitate the illusion of control, which in turn bolsters overconfidence. In the investment context, active involvement is one of the key attributes fostering the illusion of control [51, 52]. Although active involvement is usually associated with improved performance in skill-based situations, in chance-based or partly chance-based situations in which the outcomes are at least partially driven by chance (e.g., investment),

[2] In our research context, these technologies were increasingly accessible by investors during our observational period. The most popular instant message software, Tencent QQ, was initially released in 1999, but it started to become widely used in the 2000s. Sina Weibo, one of the biggest social media platforms in China, was launched in 2009.

active involvement can result in inflated confidence beliefs [7, 51]. Thus, relative to offline investors, online investors are more likely to become overconfident when given more information on investment forecasts (illusion of knowledge) and behave as if their personal involvement can influence the outcomes of chance events (illusion of control) [7].

How does online trading influence investors' trading behaviors? We discuss two main mechanisms that explain changes in investors' trading behaviors (i.e., trading frequency and trading volume): (1) lower stock transaction and management costs and (2) reduced information search costs.

First, compared to offline investors, online investors generally incur lower transaction costs to trade stocks and obtain convenient access to their stock portfolios, which can potentially lead to higher trading frequency and trading volume. Lower transaction costs (e.g., avoiding physical travel to brokers' retail stores) could lead to higher trading frequency due to easy access to buying and selling stocks in a timely fashion. For example, Bogan [10] shows that the probability of engaging with the stock market is substantially higher for households with the Internet than for those without. Similarly, Choi et al. [21] study the impact of online trading channels on individuals' investments in 401(k) plans and find that trading frequency doubles after 18 months of Internet access. Moreover, online investors, relative to offline investors, are likely to trade in larger volume due to the convenience of online portfolio management, enabling investors to monitor their portfolios without extra effort. Such low management costs and easy access to online trading facilitate investors' involvement in stock trading since online investors place their orders without the support and involvement of an intermediate broker. Prior research suggests that active involvement is an important attribute fostering the illusion of control among online investors [81].

Investors may feel that such active involvement advances their chances of favorable outcomes prompting them to trade more [7].

Second, online trading with lower search costs and easier access to information in a timely manner may stimulate higher trading frequency. Arguably, lower search costs and more accurate and timely information related to the financial markets may benefit investors, particularly when they become better informed about the stocks and firms in which they invest. Therefore, accurate and timely information made available through online channels enables investors to adjust their stock portfolios more rapidly, leading to higher trading frequency compared to trading via offline channels with less timely information.

The above discussion collectively suggests that trading online, compared to trading offline, increases investors' trading frequency and trading volume. However, whether these effects apply evenly across investors with different risk preferences remains unknown based on our review of prior literature.[3] Thus, we examine whether the effects of online trading channel use intensity on trading frequency and volume are contingent on investors' risk preference.

How does online trading influence investors' performance? So far, we discussed the pros and cons associated with using online channels for trading behaviors, we now consider the likely impact on investment performance. On the positive side, online trading may enhance investors' performance due to lower transaction, management, and information search costs [53]. Online investors leverage these advantages to optimize their trading performance. Once they obtain information online for the stocks they are interested in, they can adjust their portfolios in a timely fashion with relatively little effort. For example, Barber et al. [5] show that timely portfolio rebalancing can help investors attain higher abnormal returns, yet this advantage may diminish if

[3] We summarize a list of selected studies on online trading in Appendix A.

a portfolio is rebalanced less frequently. Because of lower transaction and information search costs, trading through online channels (versus offline channels) allows for more frequent and timely portfolio rebalancing, thereby facilitating better investment outcomes.

On the negative side, intensive use of online channels can adversely affect investors' trading performance due to the overconfidence bias resulting from the illusions of knowledge and control. Compared to offline trading with limited information accessibility, online trading allows for better access to publicly available information and information transparency. Such information can enable investors to form initial beliefs about an investment target, and these initial beliefs play a vital role in their subsequent information search and processing. Specifically, when given extensive information regarding an investment target (e.g., a particular stock), investors tend to favor information that confirms or supports their prior beliefs [95]. As a result, relative to their offline counterparts, online investors' confidence (or beliefs) in the accuracy of their own price forecasts tends to increase dramatically, much more than the accuracy of their price forecasts [6, 73, 78]. At some point, with more information, the accuracy of investors' own forecasts may decline due to information overload [86]. Regrettably, people are more willing to bet on their own judgments when they feel skillful or knowledgeable [34], thereby often leading to suboptimal performance. Online social interaction can also increase investors' overconfidence in that when people are socially close to each other due to homophily, their investment strategies are likely to be confirmed and reinforced by similar counterparties through online social interaction. For instance, Pool, Stoffman and Yonker [80] find that socially associated fund managers have more similar portfolios and trades.

Taken together, the effects of online trading on individuals' trading behaviors and performance can be either positive or negative. Our main interest here, however, is not on the effects of online trading by itself; instead, we are interested in examining whether and how *individuals' risk preferences moderate the effects of online trading channel use intensity on their trading behaviors and performance.* We next review the concept of risk preference and discuss its contingent role for the effects of online trading.

The Role of Risk Preferences in Online Trading

Risk preferences. Investing in the financial market is an example of an individual behavior that involves trading off potential costs and benefits associated with some degree of risk and uncertainty. Prior work in psychology shows that stable personality and psychological traits may account for why individuals differ in their appetites for risk and their decisions to engage in such behaviors [18, 31, 63]. Following Mata, Frey, Richter, Schupp and Hertwig [63], we use the term "risk preference" to describe such a psychological trait that explains differences in individuals' appetites for risk.

Two aspects of risk preference are worth noting for our study. First, as with any psychological trait, risk preference shows a good degree of temporal stability, convergent validity, and predictive validity [63]. Second, risk preferences differ across individuals, and an individual's risk preference can span the continuum from risk-seeking to risk-neutral and then to risk-averse [85] based on his or her tendency to engage in behaviors that align with each category [35]. In the context of stock trading, when facing two stocks with similar expected returns, a risk-averse investor may prefer the stock with lower uncertainty. In contrast, risk-seeking implies acceptance of greater volatility and uncertainty in investments in exchange for higher anticipated returns. Risk-seeking investors prefer risk and are more likely to accept a lower probability of a higher payoff over a more certain but lower payoff. Sitting in the middle of the risk-averse and risk-seeking continuum, a risk-neutral investor is indifferent to risk as long as the final expected payoff is the same.

Importantly, we argue that investors' risk preferences moderate the effects of online trading channel use intensity on their trading behavior and performance for the following two reasons. First, by definition, risk-averse investors, risk-neutral investors, and risk-seeking investors are different in their appetites for risk [63], and they may behave differently when making investment decisions as they react to new information. Second, compared to traditional offline channels, the Internet provides investors with access to a richer pool of information, but lower search costs [6, 59, 60]. Using such online channels could nurture overconfidence making them trade more aggressively and less profitably [7]. Because overconfidence is more likely to occur among risk-seeking than risk-averse investors [75], we argue that investors' risk preferences may moderate the effects of online trading channel use intensity on trading behaviors and performance. Our premise is that although increased use of online channels may lead to lower transaction costs and better monitoring of stock portfolios, risk-averse investors, compared to the other types of investors, are less likely to suffer from overconfidence.

Risk preferences and trading behaviors. Investors make investment decisions based on their beliefs about the expected payoff of a particular stock. Going online increases trading frequency by allowing investors to update their beliefs more immediately and frequently and make quicker moves to buy or sell stocks based on their updated beliefs. Indeed, previous studies show that going online increases investors' trading frequency due to low transaction and information search costs [7, 21]. In terms of how the effect of online channel use intensity on trading frequency varies across investors with different risk preferences, we expect that compared with their risk-neutral peers, both risk-averse and risk-seeking investors are likely to exhibit increased trading frequency with increasing online trading channel use intensity [23]. According to the definition, risk-averse and risk-seeking individuals react to information regarding potential risk even when the final expected payoff is the same. Yet, unlike their risk-averse and risk-seeking counterparts, risk-neutral investors, whose decisions are less affected by the degree of uncertainty in a set of expected outcomes, may be less sensitive to information as long as the final expected payoff is the same.

Based on the above arguments, we expect that the increase in trading frequency stems from online trading channel use intensity is likely larger for risk-seeking and risk-averse investors compared to risk-neutral investors. Hence, we propose the following:

> *Hypothesis 1a (Risk-aversion, Online Intensity and Trading Frequency): Risk preferences moderate the relationship between online trading channel use intensity and trading frequency such that this relationship is stronger for <u>risk-averse</u> than risk-neutral investors.*

> *Hypothesis 1b (Risk-seeking, Online Intensity and Trading Frequency): Risk preferences moderate the relationship between online trading channel use intensity and trading frequency such that this relationship is stronger for <u>risk-seeking</u> than risk-neutral investors.*

Turning now to trading volume, we argue that the increase in trading volume derived from online trading channel use intensity is lower for risk-averse investors relative to their risk-neutral counterparts for the following reasons. To start with, holding or trading one stock at a large volume is considered riskier than diversifying one's portfolio or trading one stock at a small volume. It is likely that investors with different risk preferences have different inclinations to trade at a large volume at a time. For example, when public information online suggests that stock prices may fall, selling all of one's equity holdings could result in higher risk if the prediction does not turn out to be accurate. Under this circumstance, risk-averse investors may choose to sell their stocks gradually, resulting in a lower trading volume. In contrast, given their preference for higher payoffs with higher risk, risk-seeking investors are more likely to undertake a larger trading volume for each transaction even with higher risk.

Moreover, faster transactions, more convenient access, and easier monitoring in real time all facilitate the illusion of control via online channels [6]. This illusion of control may encourage impulsive investment decisions, thus leading to a larger trading volume with higher risks, which risk-seeking investors are willing to take. The above discussion suggests that considering investors' appetites for risk, risk-seeking investors are more likely to participate in impulsive purchases and make risky large transactions, risk-averse investors are less likely to participate in such impulsive purchases, and risk-neutral investors sit in the middle of these two groups. As such, we hypothesize the following:

> *Hypothesis 2a (Risk-aversion, Online Intensity and Trading Volume): Risk preferences moderate the relationship between online trading channel use intensity and trading volume such that this relationship is weaker for <u>risk-averse</u> than risk-neutral investors.*
>
> *Hypothesis 2b (Risk-seeking, Online Intensity and Trading Volume): Risk preferences moderate the relationship between online trading channel use intensity and trading volume such that this relationship is stronger for <u>risk-seeking</u> than risk-neutral investors.*

Risk preferences and investors' performance. We now discuss how investors' various risk preferences are associated with overconfidence bias and thus affect the link between online channel use intensity and trading performance differently. First, risk-seeking investors are more likely to develop overconfidence, thereby exacerbating the negative effect of online trading on trading performance. Psychology studies show a positive association between people's appetites for risk and overconfidence. Specifically, overconfidence in one's own abilities and a willingness to take risks might be common consequences of particular personality traits (e.g., narcissism) [13, 30, 50], emotional states, and dispositions (e.g., optimism) [70]. For example, Campbell et al. [16] show that narcissists have significantly inferior performance on general knowledge questions than non-narcissists due to narcissists' greater overconfidence and increased willingness to undertake risky initiatives. The above discussion suggests that individuals' risk preferences and their tendency for overconfidence are positively related.

Second, a low-risk tendency may attenuate the adverse effect of online trading on trading performance because risk-averse investors are less likely to become overconfident and engage in risky investment behaviors. A stream of research shows that overconfidence often leads to more risk-seeking behaviors [2]. Applying this logic to the investment context, risk-averse personal traits could inhibit risk-seeking behaviors from being stirred by overconfidence, rendering better investment performance. For example, Peón et al. [77] document evidence that a high level of overconfidence in credit managers correlates to riskier credit strategies, such as providing credit to low-quality clients at a lower price. In the context of stock trading, overconfident investors, compared to those who are not overconfident, may hold riskier portfolios, which could potentially lead to suboptimal performance [71]. However, risk-seeking behaviors caused by a higher level of overconfidence after going online are likely to be limited for risk-averse investors due to their inherent hesitation toward uncertainty and risky behaviors [12, 26]. In this vein, the negative consequences of risky behaviors on performance, if any, would likely be minimal for risk-averse investors compared to their risk-seeking counterparts.

In sum, as the impact of online trading channel use intensity on trading performance could be either positive or negative, we rely on the underlying overconfidence mechanism to understand how risk preferences shape the relationship between online trading and trading performance. In particular, overconfidence bias, which undermines trading performance, is likely the strongest among risk-seeking investors given their preference for uncertainty [12, 26]. In this case, risk-seeking investors, relative to their risk-neutral counterparts, may attain relatively worse performance because they likely suffer more from the undesirable influence associated with overconfidence bias. Accordingly, we formally propose the following:

> *Hypothesis 3a (Risk-aversion, Online Intensity and Performance): Risk preferences moderate the relationship between online trading channel use intensity and trading performance such that this relationship is stronger for risk-averse than risk-neutral investors.*

> *Hypothesis 3b (Risk-seeking, Online Intensity and Performance): Risk preferences moderate the relationship between online trading channel use intensity and trading performance such that this relationship is weaker for risk-seeking than risk-neutral investors.*

Method

Research Setting

We obtained rare archival data from a large brokerage firm in China listed on the Shanghai Stock Exchange (SSE), and is included as part of the Shanghai Stock Exchange Constituent Index. Our data come from 7,164 individual customers (investors) of the aforementioned brokerage firm between 2010 and 2013. During the data-collection period, these investors had two dominant options to conduct transactions—an online self-service Internet channel and an offline service personnel–facilitated counter channel[4]—with investors migrating to the online channel over time. With the rapid growth of Internet coverage in China [43], many investors transitioned directly from the offline counter channel to the online channel without using a traditional phone channel as a middle step. While this approach was different from what individuals in more developed countries typically did at the time [21], it was not uncommon in Asia because many countries in Asia exhibited this “leapfrogging” phenomenon [54]. Thus, this institutional setting in China provided a unique opportunity for us to investigate how investors’ trading behaviors and performance change as their online use intensity changes over time.

[4] The brokerage firm did not provide a mobile app channel in our sample period.

Data and Variables

We collected data on the monthly financial profile of investors including their stock portfolio holdings, total assets, the market value of their stocks valued at the end of each month, and cash flow for each month. Furthermore, the dataset contains their demographics (e.g., gender, education, age, profession); monthly transactions, assets, and profits/losses; daily transactions through different channels (e.g., online or offline) and for different types of stocks; and risk profiles (risk-averse, risk-neutral, or risk-seeking). The main dependent variable *risk-adjusted returns* is calculated by subtracting risk-free returns (China's federal bank interest rate) of month *t* from the return of individual investor *i* in month *t*.[5]

Our channel use variable describes how intensively investors used a specific channel. We coded two channel use variables: $OnlineUseIntensity\%_{it}$ *and* $CounterUseIntensity\%_{it}$ based on the use of online Internet channel, and the use of physical face-to-face counter channel for the customer *i's* transactions during the month *t*. We calculated the use intensity of channel *j* in month *t* as trading frequency in channel *j* divided by the total trading frequency in month *t*.

We collected data on investors' risk profiles from the focal securities brokerage firm, which used a standard financial risk tolerance questionnaire. The China Securities Regulatory Commission (CSRC) requires all security brokerage firms in China to ask every investor to complete the risk preference survey every other year so that firms can alert investors when they choose financial products that are riskier than their preference [20]. The instrument consists of 12 questions, including explicit financial risk assessment and implicit psychological risk evaluation

[5] Our index for China stock and federal bank was obtained from the RESSET database [82], which is a leading financial data provider of model testing and investment research and reliable data sources sponsored by leading China research institutions, such as Tsinghua University and Peking University. We calculated the end-of-month return of individual *i* based on the weighted returns of the portfolio hold by her.

questions, to categorize investors into five different risk preference groups (i.e., risk-seeking, moderate risk-seeking, risk-neutral, moderate risk-averse, and risk-averse).

There are several reasons we believe our risk preference data were collected in a formal and professional fashion that reflects the actual risk preferences of individual traders. First, the risk tolerance questionnaire follows the industry standard, and guidelines of the CSRC in China. Use of such questionnaires appears to have become a standard practice after the global financial crisis in 2008. Second, the financial risk tolerance questionnaire is well-designed and generally consists of two sets of questions that include implicit psychological risk preference questions and explicit financial risk preference questions. The psychological risk preference questions are similar to choice dilemmas, which are a popular method to assess risk preferences and present scenarios asking respondents to make a risky choice for themselves regarding an everyday life event [18]. These questions evaluate individual characteristics that affect risk tolerance [33]. The financial risk preference questions deal with investors' financial-related situations, such as their investment objectives, financial knowledge, investment period, etc. [61].

Using a financial risk tolerance questionnaire is common practice in the global finance and security industry to assess investors' risk preferences. For example, in the United States, the US Securities and Exchange Commission (SEC) recommends that investors understand their risk tolerance levels before investing [91], and the risk tolerance questionnaire is frequently used by large Fortune 100 financial services organizations, such as Merrill Lynch, Société Générale, and Teachers Insurance and Annuity Association of America (TIAA) [89]. Appendix B provides questions from the original risk tolerance questionnaire, including both the original Chinese version and the English translation version.

In summary, we collected records on monthly channel use for more than 7,000 customers (investors) from January 2010 to August 2013. Table 1 shows the variable descriptions. Table 2 offers additional details and summary statistics on our key measures. To limit the potential influence of data errors and inconsistencies, we excluded all customers younger than the legal age for security transactions, and those with negative values or non-values for their total assets or market value, and we also winsorized values of key variables. The final sample consists of 77,430 monthly observations from 7,164 investors.[6]

Table 3 shows the number of *risk preference* changes an investor had during the sampling period. We found that risk preference is relatively stable for each investor, which is consistent with prior studies [37, 83]. Table 4 shows the correlations among the variables. We found that *OnlineUseIntensity%* has a positive association with *risk-adjusted returns*, *assets*, *trading frequency*, and *trading volume* but a negative association with *age* and *trading experience* with the company.

Empirical Models and Econometric Considerations

To estimate the impact of online channel trading on investor-level stock portfolio outcomes, we began with a panel-data framework:

$$Outcomes_{it} = \eta_t + \lambda_i + \beta_1 \times OnlineUseIntensity_{it} + \sum_{k=1}^{4} \gamma_k \times Risk_{k,it} + \theta \times X_{it} + \varepsilon_{it} \qquad \text{(eq. 1)}$$

where *i* indexes investors and *t* indexes time periods. We examined three outcome variables: $TradingFrequency_{it}$, measured as investor *i*'s total number of trading transactions in month *t*; $TradingVolume_{it}$, measured as investor *i*'s trading volume normalized by the number of

[6] The sample size for trading performance is reduced due to missing data when calculating *risk-adjusted returns*. We report the analysis of trading behaviors with the full sample to avoid losing further observations unnecessarily, and the results for trading behaviors with the reduced sample are broadly similar to the results from the full sample.

transactions in month *t*; and $Performance_{it}$, measured as investor *i*'s *risk-adjusted return* by $(R_{it}-R_{ft})$ in month *t*. Specifically, we calculated the monthly *risk-adjusted returns* for individual investors by subtracting China's federal bank interest rate of month *t*, R_{ft}, from the return, R_{it}, earned by individual investor *i* in month *t*. The main independent variable $OnlineUseIntensity\%_{it}$ denotes the percentage of transactions completed through the online Internet channel for investor i in month *t*. $\sum_{k=1}^{4} Risk_{k,it}$ represents the different risk preference dummies; specifically, we identified four different risk preferences, represented by *k* in our model: risk-seeking, moderate risk-seeking, moderate risk-averse, and risk-averse. As such, we included two outermost risk types and, importantly, two moderate risk types and used risk-neutral as the baseline, which is omitted in the model.

In addition, we included X_{it}, a set of control variables representing individual-level financial status and experience with stock trading, which can affect an investor's trading outcomes. Our financial performance–related controls include *total assets* valued at the end of month *t*, which we used as a control for an investor's wealth level since we did not directly observe individual investors' income [79], the *market value* of all stocks held by investor *i* using the market price of each stock on the last day of month *t*, and the accumulated amount of cash flow for individual *i* during month *t*. *Trading frequency* and *trading volume* were also included as controls if the dependent variable was *trading performance*. Further, we controlled for personal *trading experience* as investors' tenure with the company. We also included individual demographic controls in our model (time-invariant variables, such as *gender*, *education*, and *profession*, are dropped in our individual fixed-effects models).

Notwithstanding the richness of our dataset, it is possible that unobserved factors affected investment performance across individuals or over time. Thus, we employed a full set of investor fixed effects to absorb cross-sectional differences and month fixed effects for non-linear economic trends in investor performance not directly associated with online channel use. In particular, we controlled for time-invariant unobservable investor characteristics by including investor fixed effects, λ_i , to absorb cross-sectional differences [38]. We also included month fixed effects, η_t, to control for economy-wide shocks in portfolio returns not directly associated with channel use [38]. We report the main estimates for an unbalanced panel with no missing data for all variables for a total of 77,430 observations from 7,164 investors over 44 months from January 2010 to August 2013.[7]

To examine the moderating effect of *risk preferences* and test our hypotheses, we added the interaction terms of *OnlineUseIntensity%* and *risk preferences* in Equation 2:

$$Outcomes_{it} = \eta_t + \lambda_i + \beta_1 \times OnlineUseIntensity\%_{it} + \sum_{k=1}^{4} \gamma_k \times Risk_{k,it} + \sum_{k=1}^{4} \delta_k \times Risk_{k,it} \cdot OnlineUseIntensity\%_{it} + \theta \times X_{it} + \varepsilon_{it} \quad \text{(eq. 2)}$$

where δ_k is the main interest when estimating Equation 2.

Results

Online Channel Use Intensity, Risk Preferences, and Trading Frequency

Since *trading frequency* is a discrete variable and the distribution of *trading frequency* is right skewed, we used the natural logarithm of count data *trading frequency* in our analysis.[8] Columns 1 and 2 of Table 5 present the regression results of the fixed-effects panel-data model (eq.1) with *logged trading frequency* as the dependent variable. Column 1 shows a positive association between the *OnlineUseIntensity%* and *trading frequency*. The estimates also suggest that investors with larger assets appear to trade more aggressively in terms of trading frequency.

[7] The panel does not include months when an investor did not make a transaction because both *trading frequency* and *trading volume* are 0, and *OnlineUseIntensity%* is not defined when the number of transactions is 0. We obtained a smaller sample size for trading performance due to missing data when calculating *risk-adjusted returns*.
[8] Because the natural log of 0 is not defined, we added 1 to *trading frequency* before taking the natural log.

Further, in Column 2, there is a positive coefficient for each interaction term, with different risk groups representing additional incremental gains for having that particular risk preference compared to the risk-neutral group (the omitted reference group).

Specifically, the positive and significant coefficient (0.010) for the interaction term of *OnlineUseIntensity%* × *Risk-Averse* provides support for the Risk-aversion, Online Intensity and Trading Frequency Hypothesis (H1a), which posits that the relationship between online channel use intensity and trading frequency is stronger for risk-averse investors than risk-neutral investors. Further, the coefficient for *OnlineUseIntensity%* × *Moderate Risk-Averse* is also positive and significant (0.001), suggesting that the relationship holds the same for moderate risk-averse investors. Note that the difference in the coefficients for *OnlineUseIntensity%* × *Risk-Averse* (0.010) and *OnlineUseIntensity%* × *Moderate Risk-Averse* (0.001) is statistically significant (p-value < 0.001), suggesting that risk-averse investors trade online more frequently than moderate risk-averse investors.

Similarly, we observe that the coefficient for the interaction term of *OnlineUseIntensity%* × *Risk-Seeking* is positive and significant (0.003), indicating that the link between online channel use intensity is stronger for risk-seeking investors than risk-neutral investors. Thus, the Risk-seeking, Online Intensity and Trading Frequency Hypothesis (H1b) is supported. Although the coefficient for *OnlineUseIntensity%* × *Moderate Risk-Seeking* is also positive and significant (0.001), it is statistically smaller than the coefficient for *OnlineUseIntensity%* × *Risk-Seeking* (p-value < 0.001), suggesting that risk-seeing investors trade online more frequently than moderate risk-seeking investors.

Figure 1 illustrates the effect of online channel use intensity on trading frequency across the risk preference continuum based on the estimates from Column 2 of Table 5. Holding everything else equal, we plotted the increase in *trading frequency* associated with 10% higher online channel use intensity. The graph shows a U-shape with two ends corresponding to larger incremental effects of online channel use intensity for risk-seeking and risk-averse investors. For example, a 10% growth in online use intensity is associated with an 18.53% increase in *trading frequency* for risk-averse investors, which means they execute approximately 5.3 more trades each month (vis-à-vis before increasing their online use intensity) given that the average trading frequency in the sample is 28.63 times per month ($28.63 \times 0.185 = 5.3$). For risk-seeking investors, the magnitude is large as well: a 10% growth in the intensity of online use is associated with a 10.52% increase in trading frequency. In other words, with 10% higher online channel use intensity, risk-seeking investors execute about 3 more trades each month ($28.63 \times 0.105 = 3.0$).

Online Channel Use Intensity, Risk Preferences, and Trading Volume

Columns 3 and 4 of Table 5 report the results for *trading volume* normalized by the number of transactions in each month. The result show that online channel use intensity is positively associated with *trading volume*, and the effect is statistically and economically significant. Specifically, the coefficient of *OnlineUseIntensity%* on *trading volume* is 0.290 in the full model (Column 4), suggesting that a 10% increase in online channel use intensity leads to additional buy/sell activity of 2,900 CNY (approximately 470 USD[9]) per transaction for risk-neutral investors holding everything else equal. This result is consistent with previous literature showing that after going online, investors tend to trade more speculatively [7]. Interestingly, the positive effect of online use intensity on trading volume is unequally distributed across the risk preference continuum. Again, the coefficients of the interaction terms between *OnlineUseIntensity%* and the

[9] We used the exchange rate of the Chinese yuan to the US dollar on Jan 18, 2013, which is 6.21 CNY to 1 USD.

different *risk preference* dummies represent the incremental effect of a particular risk preference group relative to the risk-neutral group (the omitted reference group).

Specifically, the negative and significant coefficient (-0.219) for the interaction term of *OnlineUseIntensity%* × *Risk-Averse* suggests that the relationship between online channel use intensity and trading volume is weaker for risk-averse investors than for risk-neutral investors. The Risk-aversion, Online Intensity and Trading Volume Hypothesis (H2a) is thus supported. Next, the interaction effect for moderate risk-averse is also negative and significant (-0.083), but the effect size is significantly smaller than that for the risk-averse group as the equality hypothesis is rejected at the 5% level. The coefficient for the interaction term *OnlineUseIntensity%* × *Risk-Seeking* is positive and significant (0.279), indicating that risk-seeking investors increase their trading volume significantly more than risk-neutral investors with increased online channel use intensity. Thus, the Risk-seeking, Online Intensity and Trading Volume Hypothesis (H2b) is also supported. Finally, the coefficient for *OnlineUseIntensity%* × *Moderate Risk-Seeking* (0.112) is much smaller than that for the risk-seeking group as the equality hypothesis is rejected at the 1% level with a *p*-value of 0.004.

Figure 2 illustrates the marginal effect of online channel use intensity on trading volume based on the estimates in Column 4 of Table 5. Figure 2 shows that the marginal effect of *OnlineUseIntensity%* grows gradually from the risk-averse group to the risk-seeking group. More specifically, holding everything else equal, 10% higher online use intensity is associated with a 710 CNY (approximately 114 USD) higher trading volume for risk-averse investors, while 10% higher online use intensity is associated with a 5,690 CNY (approximately 916 USD) higher trading volume for risk-seeking investors. This effect is also considered economically significant. For example, holding the trading frequency at the sample mean (14.20 times per month), the total monthly increase in trading volume associated with 10% higher online use intensity is only 10,074.9 CNY for risk-averse investors but is 80,741.1 CNY for risk-seeking investors, which is eight times the trading volume of risk-averse investors.

Overall, our results show that online trading channel use intensity has a strong influence on investors' trading behaviors both in terms of how actively (trading frequency) and how speculatively (trading volume) they trade. These results provide strong support for the moderating effects of risk preferences. Notably, the magnitude of the increase in trading frequency and trading volume varies gradually across the risk preference continuum. In particular, higher online use intensity is associated with significant increase in trading frequency for the two extreme risk preference groups (risk-averse and risk-seeking) compared to the risk-neutral group. For trading volume, higher online use intensity is associated with a moderate increase in trading volume for risk-averse investors but a substantial increase for risk-seeking investors.

Online Channel Use Intensity, Risk Preferences, and Investor Performance

Table 6 reports the results for online channel use intensity and investors' trading performance, measured as their risk-adjusted returns. The positive and significant coefficient (0.052) for *OnlineUseIntensity%* in Column 1 indicates that online trading channel use intensity has a positive association with investors' trading performance.

Next, Column 3 of Table 6 shows that the interaction term involving online channel use intensity and risk-aversion (0.105) is significant and positive at the $p < 0.1$ level, indicating that the positive relationship between online channel use intensity and risk-adjusted returns is stronger for risk-averse investors than for risk-neutral investors. Thus, the Risk-aversion, Online Intensity and Performance Hypothesis (H3a) is supported. More specifically, based on the estimates in Column 3 of Table 6, a 10% increase in online channel use intensity for risk-averse investors, relative to their risk-neutral counterparts, is associated with a 1.05% higher risk-adjusted return each month. This performance is impressive, considering that the average risk-adjusted return during our sample period is -2.25%.

However, the coefficient of the interaction term *OnlineUseIntensity%* × *Risk-Seeking* is insignificant. Therefore, we did not find support for the Risk-seeking, Online Intensity and Performance Hypothesis (H3b), which predicts that risk-seeking investors, compared to risk-neutral investors, gain less in terms of trading performance as a result of their online channel use intensity.

Further, because trading frequency and trading volume might affect performance, we included *trading frequency* and *trading volume* in Equations 1 and 2 and report results respectively in Columns 2 and 4 of Table 6, respectively [7]. The coefficient for *trading frequency* is statistically significant, but the coefficient for *trading volume* is not. The coefficient (0.099) for *OnlineUseIntensity%* × *Risk-Averse* (Column 4, Table 6) remains both statistically and economically significant, consistent with the Risk-aversion, Online Intensity and Performance Hypothesis (H3a). This result suggests that even after accounting for trading frequency and trading volume, risk-averse investors still outperform other risk preference groups. This coefficient for *OnlineUseIntensity%* × *Risk-Averse* captures the performance gain not fully explained by trading frequency or trading volume.

Robustness Tests

Three-factor model and four-factor model. As reported in this subsection, we followed the standard procedure to further examine investors' performance using the Fama-French three-factor model and the Carhart four-factor model (Carhart 1997; Fama and French 1996). These models incorporate a size factor (SMB), book-to-market factor (HML), market factor (MKT), and momentum factor (UMD) to account for pricing anomalies. Specifically, we used the following equation:

$$RiskAdjustedReturn_{it} = \alpha + \beta_1 \times OnlineUseIntensity\%_{it} + \sum_{k=1}^{4} \gamma_k \times Risk_{k,it}$$
$$+\theta \times X_{it} + \beta_2 \times \left(R_{Mt} - R_{ft}\right) + \beta_3 \times SMB_t + \beta_4 \times HML_t + \beta_5 \times UMD_t + \varepsilon_{it} \qquad \text{(eq. 3)}$$

where *i* indexes the individual investor, and *t* indexes each observed month. Similar to Equations 1 and 2, we calculated the monthly risk-adjusted returns for individual investor *i* as her portfolio returns in month *t* minus the monthly risk-free rate, R_{ft}. Further, R_{Mt} is the monthly market returns (thus, $R_{Mt} - R_{ft}$ represents MKT). SMB_t, HML_t, and UMD_t represent the size factor, book-to-market factor, and momentum factor, respectively, in month *t* [17, 27]. The rest of the variables are similar to those used in Equation 1 and to those used in Equation 2 if the interaction terms of *OnlineUseIntensity%* and *Risk Preferences* are included.

Table 7 shows the results, with the three-factor model in Panel A and the four-factor model in Panel B. The coefficient of the interaction term (*OnlineUseIntensity% × Risk-Averse*) is positive and statistically significant (0.138). Based on the estimates of the four-factor model in Column 4 of Table 7, a 10% increase in online channel use intensity for risk-averse investors, compared to their risk-neutral counterparts, is associated with a 1.38% higher risk-adjusted return in a month. These additional results suggest that the positive relationship between online channel use intensity and risk-adjusted returns is significantly stronger for more risk-averse investors, lending further support to the Risk-aversion, Online Intensity and Performance Hypothesis (H3a). Similar to the results of our main analyses, we did not find support for the Risk-seeking, Online Intensity and Performance Hypothesis (H3b).

Finally, we also conducted additional analyses and robustness tests (see Online Appendix).[10] We provide additional empirical evidence based on a propensity score–matched sample and instrumental variable method. Furthermore, we conducted an additional analysis to identify the direct effect of investors' online channel use intensity on their trading behaviors and trading performance by exploring the abnormal increases in online channel use intensity. The findings from abnormal increases in online channel use intensity echo our evidence from panel data model (Columns 1 and 3 in Table 5 and Columns 1 and 2 in Table 6). On the whole, these analyses provide further confidence in the main results and an assessment of causality and plausibility of the effect of online channel use [66, 68].

Table 8 shows a summary of results for hypotheses.

Discussion

Main Findings and Contributions

Our primary goal in this research was to examine how investors' risk preferences moderate the relationship between their use of online self-service investment channels (relative to offline channels) and their trading behaviors and performance. We used panel data from more than 7,000 investors in the Chinese stock market over 44 months to test our hypotheses. Even though online stock trading has changed over the years, our use of a historically relevant dataset with key variables of interest provides several interesting and generalizable findings.[11] Namely, we find that investors with a higher level of online channel use intensity are more likely to experience higher

[10] We thank an anonymous AE and reviewers for some of these analyses.

[11] We thank the AE for emphasizing the need for studies involving historical archival datasets for assessing the generalizability of theories beyond the period of the data itself. Certainly, the issues of risk preferences of investors and the extent to which they should engage in online trading continue to be of importance, even though online stock trading has changed over the years. Indeed, IS researchers often use such archival data for addressing enduring and fundamental questions [45, 67, 88]. Economists also do not hesitate to use data from the 1930s in Germany [42] just because of the age of the data. Scientific understanding depends on a focus on the importance and relevance of the research question rather than the currency of data itself as the sole criterion.

trading frequency, a larger trading volume, and better investment performance. Interestingly, the gains from using online self-service channels are not equally distributed across investors with different risk preferences. Our study suggests that although both risk-seeking and risk-averse investors behave similarly in terms of high trading frequency (as reflected in the U-shaped relationship between risk preferences and trading frequency in Figure 1), we found a much lower effect on trading volume for risk-averse investors than for risk-seeking investors (Figure 2). Importantly, while the results reveal no significant difference in investment performance between risk-seeking and risk-neutral investors, we found that investment returns are higher for risk-averse investors than for risk-neutral investors.

With these findings, this study makes several contributions. First, our findings extend the stream of IS literature on technology in the financial services industry [4, 11, 97]. From the ATM networks of banks [22] and peer-to-peer lending [92] to crowdfunding [14] and social trading [1, 94], the financial services sector has experienced the emergence of new technological innovations. Against this backdrop, this study illustrates that the Internet and online trading channels change investors' trading behaviors and performance where individuals' risk preferences play an important contingent role [7, 8, 21] responding to calls for an investigation into the role of risk preferences in shaping investment-related behaviors [e.g., 3, 12]. This study is among the first to examine and illustrate how investment performance resulting from the use of online self-service channels varies across investors with different risk preference profiles. By focusing on the contingent role of risk preferences, this study challenges the assumption that the benefits of the Internet and online self-service technologies are distributed *evenly* across all investors [41, 55]. These findings are also practically important because they shed light on investors' behaviors and outcomes in countries that have witnessed or are experiencing increasing online trading.

Second, we complement and extend prior IS research examining the effects of online channel use for products (e.g., books, CDs) and services (e.g., banking services) on investors' responses and economic outcomes [15, 40, 93]. Specifically, we both theoretically and empirically enrich this line of research by exploring this phenomenon in the stock trading setting, which bears significant theoretical and economic implications given the widespread use of online trading. We also contribute to the literature on self-service technologies. While extant research on self-service technologies focuses primarily on technology *adoption* and the associated performance outcomes [15, 65, 93], our study goes beyond this and provides a theoretical account of how individual investors' personal traits infuence their investment performance through the use of online self-service channels. Doing so extends the current literature on self-sevice technologies and sheds light on the psychological and behavioral mechanisms underlying the phenomenon.

Implications for Research

This study has important implications for research. First, we found that individuals' risk preferences explain why some types of investors outperform others. This finding highlights the contingent role of individuals' risk profiles in shaping their online investment behaviors and performance. We call for further work to extend this line of research by examining the role of other individual characteristics, such as personality and espoused cultural values, in shaping individuals' online trading behavior.

Second, our finding that trading through online channels generally leads to better performance compared to trading through offline channels in China highlights the need to exercise caution in interpreting findings from prior studies suggesting lower returns for online investors in the United States in the late 1990s [72]. Such a distinction may be attributed to differences in the studies' research designs, the time periods of different studies (the late 1990s versus the early

2010s), and differences between the United States and China. To explore whether cultural or market-specific factors can explain these performance differences across offline versus online channels, we encourage future research to test the generalizability of our results by conducting similar studies across countries preferably using data from similar and comparable brokerage firms during the same time period. Such studies will complement prior IS research examining cross-country differences in other relationships [24, 84].[12]

Finally, our research provides insight into the individual differences that impact online investment performance. Future research could aim to understand how a broader spectrum of online behaviors, such as homophily in social media use [6], herding [7], and following crowds versus experts in trading [8], impact investors' stock trading outcomes. In addition, the recent advancements in AI-based chatbots, such as Chat GPT [28, 36], raise the question whether the use of AI will help investors to do "alpha–picking and beta-surfing" [29] while also raising the prospects of job losses for white-collar workers including financial advisors. Further research could explore the comparison between the assistance provided by human financial advisors, which has been shown to be beneficial to investors in online settings [57], and AI chatbots.

Managerial Implications

Our findings also hold several important implications for practice. From the individual investor's perspective, the results of this study provide useful insights into the use of online self-service channels. Compared with traditional offline channels, digital self-service investment channels enabled by the Internet provide a variety of economic and informational benefits. These benefits include flexible and convenient service (anytime, anywhere), faster access to additional investment-related information, and even some decision support systems that can facilitate

[12] We thank the anonymous AE for pointing to this discussion and the value of conducting studies across countries.

investment decisions and portfolio management [59]. Nonetheless, these benefits do not guarantee superior investment performance. Indeed, online channels may foster the illusion of control and overconfidence in one's ability to judge investment opportunities and market situations, thereby leading to undesirable performance outcomes [7]. Our results suggest that while using online self-service channels can lead to higher performance, the benefits are larger for risk-averse investors. Therefore, individual investors should carefully consider their own risk preferences and the potential performance impact of their risk preferences on their online investment activities.

For policymakers, our findings provide insights into the role of digital technologies in nudging retail investors, particularly risk-seeking investors, to commit higher dollar amounts by increasing trading volume. While financial service providers could encourage investors to embrace the benefits of technology, regulators and policymakers should understand the drawbacks of online trading to balance the interests of securities firms and investors, given that securities firms stand to gain more in terms of commissions when investors invest higher amounts per trade.

Limitations and Suggestions for Future Research

Like most empirical work, this study has some limitations, which also create opportunities for future research. First, our findings reveal a performance gain associated with risk-averse investors' use of online self-service channels. While trading frequency and trading volume may not fully explain risk-averse investors' performance gain in this study, we encourage interested scholars to explore other possible mechanisms.[13] One possible direction is to compare and contrast the decision-making processes of investors who use online channels versus those who use offline

[13] We find evidence for mediation via trading frequency but did not find evidence for the mediation via trading volume [96]. We thank Xinshu Zhao and John Lynch for helpful and clarifying comments about the role of R-squared in tests for mediation that are largely based on statistical significance of the product terms involved in mediation.

channels for investment and how differences in their decision-making processes, if any, lead to their differential investment outcomes.

Second, as our longitudinal data were gathered from a lager brokerage firm in China, caution should be exercised when generalizing the findings to other national and cultural settings. In particular, the Chinese government was relatively lenient in regulating financial technologies such as digital payments (e.g., WeChatPay and AliPay) and P2P lending, and although some other countries such as India also followed a similar approach, the extent to which such regulatory approaches affect investments in stock markets needs further research. The growth of domestic markets in countries like Brazil, India, and South Africa calls for more research into these developing economic regions and other digital economies in Asia, as also called for by other researchers [54]. Third, future research can also explore how less experienced investors can follow experts' trades via social media, online communities, and financial columns of web portals to improve their trading performance [19], which is similar to herding and "follow-the-leader" behaviors in other contexts [48]. Finally, mobile technology is poised to become the future of trading technology. Specifically, there is some evidence that the adoption of mobile trading has a substantial impact on investors' trading behaviors and outcomes [58]. Future research could delve into the differences between online trading versus mobile app trading, and explore how such usage of technology shapes investors' trading behaviors and outcomes.

To conclude, this study examined how investors' risk preferences and online channel use intensity jointly influence their trading behaviors and performance. Our analyses of rare micro-level historical dataset from more than 7,000 investor accounts over a 44-month period during 2010-2013 in China provide new insights despite continuing changes in the nature of financial markets. The findings indicate that online channel use intensity has strong positive effects on transaction frequency for both risk-seeking and risk-averse investors, it has a much lower effect on trading volume for risk-averse investors than for risk-seeking investors. In addition, risk-averse investors with higher online channel use intensity outperform investors with other risk preferences in terms of investment performance. This paper contributes to the emerging literature at the intersection of information systems and behavioral finance by shedding light on investors' behaviors and outcomes as they engage in increased online trading. Our findings suggest that individual investors should carefully consider their own risk preferences and the potential performance impact of their risk preferences on their online investment activities. The findings are also informative for regulators and policymakers to understand the drawbacks of online trading to balance the interests of securities firms and investors.

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Figure 1. Marginal effect of online channel use intensity on trading frequency

This chart shows the percentage change in trading frequency per month with 10% higher online channel use intensity holding everything else equal.

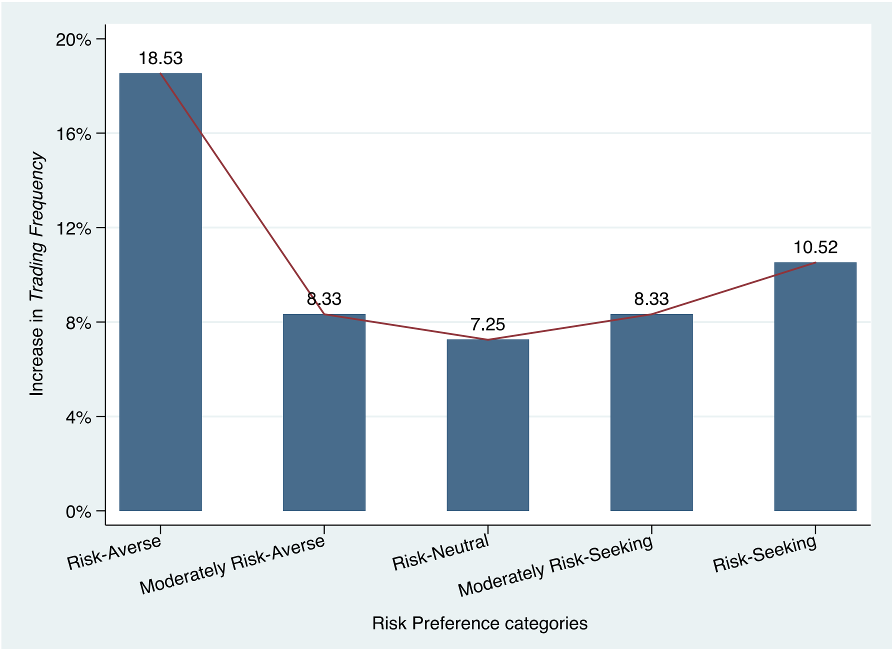


Figure 2. Marginal effect of online channel use intensity on trading volume

This chart shows the change in trading volume with 10% higher online channel use intensity holding everything else equal.

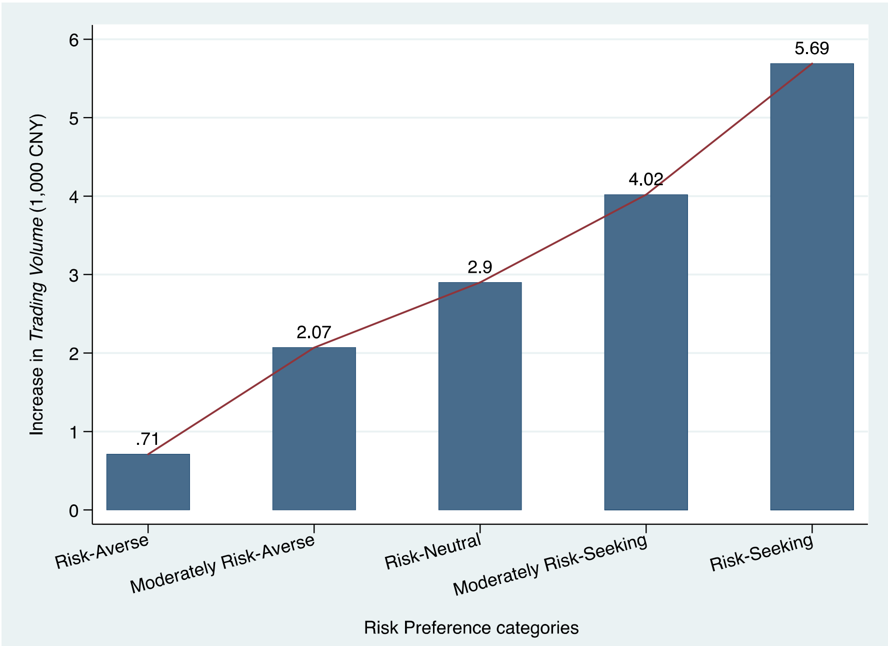


Table 1. Variable definitions

Variable Names	Variable Definitions
Risk-Adjusted Return$_{it}$ (Customers' Performance)	The monthly risk-adjusted return for individual investor is calculated by subtracting the return on China federal bank interest rate from the end-of-month return by individual investor *i* in month *t*.
OnlineUseIntensity%$_{it}$	Online channel use intensity is measured as the percentage of transactions completed using the *Internet* channel for customer *i* in month *t*.
CounterUseIntensity%$_{it}$	Counter channel use intensity is measured as the percentage of transactions completed using the *counter* channel for customer *i* in month *t.*
Risk Preference$_{it}$	Customer *i*'s risk preference in month *t.* A group of dummies specify the risk preferences: *Risk-Seeking, Risk-Averse, Moderate Risk-Seeking, Moderate Risk-Averse,* and *Risk-Neutral.*
Total Assets$_{it}$	Total assets of customer *i* at the end of month *t* (CNY).
Trading Frequency$_{it}$	Customer *i*'s total number of trading transactions in month *t.*
Trading Volume$_{it}$	Customer *i*'s trading volume standardized by the number of transactions in month *t.*
Market Value$_{it}$	Market value of customer *i*'s total assets at the end of month *t* (CNY).
Cash Flow$_{it}$	Customer *i*'s total volume of cash flow in month *t.*
Trading Experience$_{it}$	Customer *i*'s experience (years) with the security company in month *t.*

Table 2. Descriptive statistics

Variable Names	Mean	Std. Dev.	Min	Max
Risk-Adjusted Return (%)	-2.25	15.28	-98.01	260.92
OnlineUseIntensity%	81.04	35.39	0	100
CounterUseIntensity%	18.96	35.39	0	100
Risk-Seeking	0.06	0.23	0	1
Moderate Risk-Seeking	0.29	0.45	0	1
Risk-Neutral	0.58	0.49	0	1
Moderate Risk-Averse	0.06	0.23	0	1
Risk-Averse	0.01	0.12	0	1
Total Assets (1,000 CNY)	294.69	632.94	0	15,820.28
Trading Frequency	14.20	30.17	1	1,372
Trading Volume (1,000 CNY)	28.64	84.25	0	3,462.33
Market Value (1,000 CNY)	248.45	569.24	0	14,461.96
Cash Flow (CNY)	3,367.08	317,747.80	-16,800,000	12,000,000
Age	44.48	11.56	18	89
Trading Experience	5.70	4.87	0	20

Notes: [a] Obs.: *Risk-Adjusted Return* = 63,457, and all other rows = 77,430.

[b] The sample size for trading performance is reduced due to missing data when calculating *risk-adjusted returns*. We still report analysis of trading behaviors with the full sample and avoid losing observations unnecessarily. The results for trading behaviors from the reduced sample are similar to results from the full sample.

[c] Age is dropped in the panel data fixed-effects model because for each individual, age shows collinearity with the variable trading experience (years of experience with the focal firm).

Table 3. Number of risk preference changes for each customer during our sample period

No. of risk preference changes	Freq.	Percent	Cum.
0	6,095	85.08	85.08
1	1,031	14.39	99.47
2	38	0.53	100
Total	7,164	100	

Table 4. Pairwise correlations

Variables	1	2	3	4	5	6	7	8	9
1. *OnlineUseIntensity (%)*	1.000								
2. *CounterUseIntensity (%)*	-1.000	1.000							
3. *Risk-Adjusted Return*	0.146*	-0.146*	1.000						
4. *Total Assets (1,000 CNY)*	0.025*	-0.025*	0.042*	1.000					
5. *Trading Frequency*	0.188*	-0.188*	0.065*	0.189*	1.000				
6. *Trading Volume (1,000 CNY)*	0.154*	-0.154*	0.035*	0.408*	0.047*	1.000			
7. *Cash Flow*	0.004	-0.004	-0.007	0.263*	0.016*	0.016*	1.000		
8. *Age*	-0.043*	0.043*	0.004	0.147*	0.090*	0.046*	-0.002	1.000	
9. *Trading Experience*	-0.064*	0.064*	-0.008*	0.094*	-0.007	0.038*	-0.002	0.422*	1.000

N = 77,430. Correlations with * are statistically significant at $p < 0.05$.

Table 5. Online channel, risk preferences, and trading behaviors

Variables	***log(Trading Frequency)***		***Trading Volume***	
	(1)	**(2)**	**(3)**	**(4)**
OnlineUseIntensity%	0.007***	0.007***	0.327***	0.290***
	(0.000)	(0.000)	(0.010)	(0.010)
OnlineUseIntensity% × *Risk-Averse*		0.010***		-0.219***
		(0.001)		(0.044)
OnlineUseIntensity% × *Moderate Risk-Averse*		0.001***		-0.083***
		(0.000)		(0.032)
OnlineUseIntensity% × *Moderate Risk-Seeking*		0.001***		0.112***
		(0.000)		(0.020)
OnlineUseIntensity% × *Risk-Seeking*		0.003***		0.279***
		(0.000)		(0.056)
Risk-Averse	0.250***	0.153***	-23.012***	-19.970***
	(0.056)	(0.055)	(4.814)	(4.671)
Moderate Risk-Averse	0.114***	0.117***	-4.557**	-4.534**
	(0.022)	(0.022)	(1.999)	(2.011)
Moderate Risk-Seeking	-0.019	-0.020	-6.883***	-7.105***
	(0.016)	(0.016)	(1.811)	(1.802)
Risk-Seeking	0.087***	0.095***	-18.295***	-17.732***
	(0.028)	(0.028)	(3.726)	(3.726)
Log(Total Asset)	0.086***	0.085***	2.334***	2.324***
	(0.003)	(0.003)	(0.361)	(0.361)
Log(Market Value)	0.001	0.001	-0.441***	-0.453***
	(0.002)	(0.002)	(0.162)	(0.162)
Trading Experience	-0.018*	-0.017	6.142***	6.180***
	(0.010)	(0.010)	(0.927)	(0.927)
Investor & Month FE	Yes	Yes	Yes	Yes
Observations	77,430	77,430	77,430	77,430
# of Account	7,164	7,164	7,164	7,164
R-squared	0.636	0.637	0.509	0.510

Notes: [a] Since trading frequency (*Trading Frequency*) is a count variable and the distribution of the trading frequency is highly right-skewed, we used the natural logarithm of the trading frequency *Log(Trading Frequency)* in our analysis. The results from the negative binomial model with trading frequency as the dependent variable are qualitatively similar.

[b] All models include an intercept and cash flow (omitted for brevity). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *OnlineUseIntensity%* is centered at the mean value in the sample.

[c] The VIF values are less than 2.5 for all of our variables, and the mean VIF value is 1.58, much lower than the typical threshold of 10., suggesting that collinearity is not a serious concern.

[d] The risk-neutral group is the omitted group in the model, and the coefficients of each risk preference group should be interpreted in comparison to the risk-neutral group.

Table 6. Online channel, risk preferences, and trading performance

Variables	***Risk-Adjusted Return***			
	(1)	**(2)**	**(3)**	**(4)**
OnlineUseIntensity%	0.052***	0.048***	0.050***	0.047***
	(0.002)	(0.002)	(0.002)	(0.003)
OnlineUseIntensity% × *Risk-Averse*			0.105*	0.099*
			(0.058)	(0.058)
OnlineUseIntensity% × *Moderate Risk-Averse*			-0.003	-0.004
			(0.009)	(0.009)
OnlineUseIntensity% × *Moderate Risk-Seeking*			0.006	0.005
			(0.004)	(0.004)
OnlineUseIntensity% × *Risk-Seeking*			-0.008	-0.010
			(0.008)	(0.008)
log(Trading Frequency)		0.499***		0.492***
		(0.081)		(0.080)
Trading Volume		0.045		0.068
		(1.099)		(1.101)
Risk-Averse	2.583*	2.429	1.201	1.129
	(1.541)	(1.542)	(1.698)	(1.699)
Moderate Risk-Averse	-0.375	-0.428	-0.343	-0.395
	(0.376)	(0.376)	(0.376)	(0.376)
Moderate Risk-Seeking	0.799**	0.821***	0.766**	0.789**
	(0.311)	(0.310)	(0.311)	(0.311)
Risk-Seeking	0.096	0.056	0.085	0.046
	(0.538)	(0.538)	(0.538)	(0.538)
Log(Total Asset)	0.478***	0.392***	0.474***	0.390***
	(0.097)	(0.098)	(0.097)	(0.098)
Log(Market Value)	-0.238***	-0.231***	-0.236***	-0.229***
	(0.053)	(0.053)	(0.053)	(0.053)
Trading Experience	-4.530***	-4.507***	-4.536***	-4.514***
	(0.140)	(0.139)	(0.140)	(0.139)
Investor & Month FE	Yes	Yes	Yes	Yes
Observations	63,457	63,457	63,457	63,457
# of Account	6,629	6,629	6,629	6,629
R-squared	0.394	0.395	0.394	0.395

Notes: [a] All models include an intercept and cash flow (omitted for brevity). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[b] *Risk-adjusted returns* were scaled up by multiplying by 100. *OnlineUseIntensity%*, *Trading Volume*, and *log(Trading Frequency)* are centered at the mean values in the sample, and *Trading Volume* was scaled down by dividing 1,000.

[c] The VIF values are less than 2.5 for all of our variables, and the mean VIF value is 1.58, much lower than the typical threshold of 10., suggesting that collinearity is not a serious concern.

[d] The risk-neutral group is the omitted group in the model, and the coefficients of each risk preference group should be interpreted in comparison to the risk-neutral group.

Table 7. Trading performance in the three-factor model and four-factor model

	Panel A: Three-Factor Model		***Panel B: Four-Factor Model***	
Variables	***Risk-Adjusted Return***			
	(1)	**(2)**	**(3)**	**(4)**
OnlineUseIntensity%	0.099^{***}	0.097^{***}	0.093^{***}	0.091^{***}
	(0.004)	(0.005)	(0.004)	(0.005)
OnlineUseIntensity% × *Risk-Averse*		0.138^{**}		0.138^{**}
		(0.062)		(0.062)
OnlineUseIntensity% × *Moderate Risk-Averse*		-0.016		-0.011
		(0.015)		(0.015)
OnlineUseIntensity% × *Moderate Risk-Seeking*		0.010		0.011
		(0.009)		(0.009)
OnlineUseIntensity% × *Risk-Seeking*		-0.004		-0.010
		(0.015)		(0.015)
log(Trading Frequency)	0.590^{***}	0.588^{***}	0.629^{***}	0.627^{***}
	(0.055)	(0.055)	(0.055)	(0.055)
Trading Volume	1.037	1.029	1.053	1.051
	(0.754)	(0.754)	(0.752)	(0.752)
UMD_t			-47.058^{***}	-47.081^{***}
			(2.087)	(2.087)
MKT_t	1.013^{***}	1.013^{***}	1.046^{***}	1.046^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
SMB_t	3.664	3.630	11.007^{***}	10.973^{***}
	(2.397)	(2.397)	(2.384)	(2.384)
HML_t	51.771^{***}	51.711^{***}	29.388^{***}	29.316^{***}
	(2.984)	(2.984)	(3.031)	(3.029)
Risk-Averse	5.393^{***}	3.158^{***}	5.317^{***}	3.069^{***}
	(1.127)	(0.993)	(1.122)	(0.998)
Moderate Risk-Averse	-0.034	0.172	-0.083	0.068
	(0.247)	(0.298)	(0.246)	(0.299)
Moderate Risk-Seeking	0.472^{***}	0.334^{**}	0.433^{***}	0.282^{*}
	(0.123)	(0.167)	(0.123)	(0.168)
Risk-Seeking	1.075^{***}	1.130^{***}	1.091^{***}	1.233^{***}
	(0.278)	(0.331)	(0.278)	(0.331)
Investor Level Controls	Yes	Yes	Yes	Yes
Observations	55,998	55,998	55,998	55,998
R-squared	0.279	0.279	0.286	0.286

Notes: [a] *Risk-adjusted returns* and *MKT* were scaled up by multiplying by 100. All models include an intercept (omitted for brevity). Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *OnlineUseIntensity%*, *Trading Volume*, and *log(Trading Frequency)* are centered at the mean values in the sample, and *Trading Volume* was scaled down by dividing by 1,000.

[b] The risk-neutral group is the omitted group in the model, and the coefficients of each preference group should be interpreted in comparison to the risk-neutral group.

Table 8. Summary of hypotheses

Hypotheses Name (Notation)	Variable	Coefficient	Location	Supported (Y/N)
Risk-aversion, Online Intensity and Trading Frequency Hypothesis (H1a)	*OnlineUseIntensity%* × *Risk-Averse*	0.010^{***}	Table 5, Column 2	Y
Risk-seeking, Online Intensity and Trading Frequency Hypothesis (H1b)	*OnlineUseIntensity%* × *Risk-Seeking*	0.003^{***}	Table 5, Column 2	Y
Risk-aversion, Online Intensity and Trading Volume Hypothesis (H2a)	*OnlineUseIntensity%* × *Risk-Averse*	-0.219^{***}	Table 5, Column 4	Y
Risk-seeking, Online Intensity and Trading Volume Hypothesis (H2b)	*OnlineUseIntensity%* × *Risk-Seeking*	0.279^{***}	Table 5, Column 4	Y
Risk-aversion, Online Intensity and Performance Hypothesis (H3a)	*OnlineUseIntensity%* × *Risk-Averse*	0.105^{*} 0.099^{*}	Table 6, Column 3 Table 6, Column 4	Y
Risk-seeking, Online Intensity and Performance Hypothesis (H3b)	*OnlineUseIntensity%* × *Risk-Seeking*	-0.008 -0.010	Table 6 Column 3 Table 6, Column 4	N

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

28 February 2023

ONLINE APPENDICES

Appendix A. Selected Studies on Online Trading

Study	Data, Research Setting and Approach	Main IV(s)	Main DV(s)	Key Findings
Barber and Odean [1]	- 1,607 investors who switched from phone-based trading to online self-service trading with brokerage accounts at a large discount brokerage firm.	Phone to online	Monthly returns, such as raw returns, market-adjusted returns, and risk-adjusted returns	- Those who switched to the online platform traded more actively and speculatively and attained lower profits.
Bogan [3]	- The Health and Retirement Survey (HRS) with information about age, income, wealth, education, and stock market participation at the household level.	Computer / Internet (online trading)	Stock holding	- Computer/Internet-using households raised stock market participation in online trading substantially more than did non-computer-using households.
Choi et al. [4]	- Two large companies (>5,000 participants) that had recently introduced Web access to their 401(k) plans and collected at least one year of data, both before and after Web introduction.	Phone to Web-based trading	Trades (the percent of participants who trade) Turnover (total dollar amount traded) Asset-allocation performance	- Trading frequency doubled relative to a control group of firms without a Web channel. - Turnover on the Web is smaller and is not statistically significant; Web traders tend to have smaller portfolios than other traders. - No significant difference in the performance of Web traders vs. phone traders.
Looney et al. [8]	- Survey of 326 students	Online investment self-efficacy	Performance related outcome expectancy Personal outcome expectancy	- Perceptions about what one can accomplish through online investing technologies can lead investors to exaggerate their capabilities, which, in turn produces elevated expectancies of financial payoffs and nonmonetary rewards.
Teo et al. [11]	- Usable responses from a survey totaled 208 for adopters and 222 for non-adopters.	Demographic, security of Internet stock trading, and cost	Adoption of Internet stock trading	- Demographic, security of Internet trading, and cost are the determinants of adoption regarding Internet stock trading.
Dorn and Huberman [5]	- A sample of clients at one of Germany's three largest online brokers. - Secondary data analysis, and survey	Risk-aversion on a four-point scale	Portfolio volatility Portfolio diversification	- The investor's risk attitude explains cross-sectional variation in both portfolio diversification and turnover.

Study	Data, Research Setting and Approach	Main IV(s)	Main DV(s)	Key Findings
Dorn and Sengmueller [6]	- 1,000 German brokerage clients for whom both survey responses and actual trading records are available. - Secondary data analysis, and survey	Turnover	Enjoyment of investing Enjoyment of risky propositions Affinity for gambling	- Investors who report enjoying investing or gambling turn over their portfolios at twice the rate of their peers.
This study	- *A unique data set of more than 7,000 customer accounts over a 44-month period (2010–2013) at a large Chinese securities firm.* - *Panel data regressions with monthly data at the investor level*	*Online channel use intensity*	*Trading frequency* *Trading volume per transaction* *Trading performance*	- *Risk-averse investors reap higher* benefits *from online investing among all types of risk profiles.* - *Both risk-seeking and risk-averse investors behave similarly in terms of high transaction frequency in online channels. However, they appear to be driven by different psychological mechanisms, as reflected in much lower trading volume per transaction for risk-averse investors than for risk-seeking investors.*

Note: The purpose of this table is to highlight the unique contributions of this study vis-à-vis related prior work.

Appendix B: Selected Questions from the Securities Client Risk Tolerance Questionnaire in Chinese with English Translation

1. 某大企业想邀请您任职公司部门主管，薪金比现在高 20%，但您对此行业一无所知，您是否考虑接受这个职位？ (a) 不用想便立即接； (b) 接受职位，但却担心自己未必能应对挑战； (c) 不会接受；(d) 不肯定。
   Translation: A large company S would like to offer you the position of Department Head. The salary is 20% higher than your current salary, but you have little knowledge about this industry. Will you consider accepting the offer? I will accept without hesitation; (b) I will accept, but would be concerned about whether I am capable of taking on the challenge; (c) I will NOT accept; (d) Uncertain

2. 您认为买期指会比买股票更容易获取利润？(a) 绝对是； (b) 可能是；(c) 可能不是； (d) 一定不是； (e) 不肯定。
   Translation: You believe it is easier to make profits by investing in index funds than stocks. (a) Absolutely; (b) Maybe; (c) Maybe not; (d) Absolutely not; (e) Uncertain.

3. 如果您需要把大量现金整天携带在身的话，您是否会感到非常焦虑？(a) 非常焦虑； (b) 会有点焦虑； (c) 完全不会焦虑。
   Translation: Will you feel anxious if you need to carry a large amount of cash with you in person every day? (a) Very much; (b) A bit; (c) Not at all.

4. 您于上星期用 25 元购入一只股票，该股票现在升到 30 元，而根据预测，该只股票下周有一半的机会升到 35 元，另一半机会跌到 25 元，您现在会： (a) 立即卖出； (b) 继续持有； (c) 不知道。
   Translation: You bought a stock at $25 per share last week. The price has now risen to $30. According to the forecast, there is a 50-50 chance that it will go up to $35 or drop to $25 next week. What will you do right now? (a) Sell the stock immediately; (b) Hold; (c) No idea.

5. 当您作出投资决定时，以下哪一个因素最为重要？(a) 保本； (b) 稳定增长； (c) 抗通胀； (d) 短期获利； (d) 获取高回报。
   Translation: When making an investment, which of the following is the most important for you? (a) Breakeven; (b) Stable growth; (c) Anti-inflation; (d) Short-term profit; (e)High return.

Appendix C: Additional Analyses and Robustness Checks

This appendix reports further robustness checks and additional analyses.[1]

Propensity Score Matching

To alleviate the concern regarding the differences between high versus low online use intensity users and to gauge if the changes in trading outcomes are due to heterogeneity of individual characteristics, we performed the propensity score matching (PSM) analysis. Specifically, we match individuals with high Internet use intensity and low Internet use intensity to assess their trading outcomes. In this analysis, we split the sample into high and low Internet use intensity user groups by the median of the average use intensity of the Internet channel for each individual over the sample period.[2] Next, we match the high and the low Internet use intensity users by calculating the propensity score based on each individual's gender, education, profession, age, and tenure, which are shown to be the significant determinants for trading online [1, 11]. Then, a one-to-one nearest neighbor matching without replacement allows us to identify a subsample with matched high Internet use intensity users and low Internet use intensity users with similar demographics. The caliper was set to 0.0001.

Figure C.1 shows the distribution of the propensity score before and after matching. The propensity score has similar distribution between high versus low Internet use intensity user groups after matching, suggesting that the matching is properly conducted. So are the sample means of all matched variables.

Table C.1 provides the balance tests for all variables. We observed that the differences between the two groups are not significant anymore after matching. Then, we apply the baseline model (eq.1) and full model (eq.2) to the matched sample, and the estimates (see Table C.2) are broadly similar to what we present in the main results (Table 5 and Columns (1) and (3) in Table 6).

Heteroskedasticity-based Instruments

We conducted an instrumental variable (IV) estimation using heteroskedasticity-based instruments. Following Baum and Schaffer [2], we generated instruments using Lewbel [7] method, which allows the identification of structural parameters in regression models with endogenous or mismeasured regressors in the absence of external instruments or repeated measurements. Table C.3 reports results of this IV estimation using heteroskedasticity-based instruments, in which *OnlineUseIntensity%* and its related interaction terms have been instrumented. Again, the estimates derived from this method are qualitatively similar to our main results (Table 5 and Columns (1) and (3) in Table 6)

Direct Effect of Increase in Online Channel Use Intensity

Even though we do not have any specific hypotheses related to the direct effect of online use intensity, we assessed the causal interpretation of the direct effect by leveraging the abnormal increase of one's online channel use intensity. Specifically, we identify a "treatment" as *abnormal increase of online channel use intensity*. In other words, an $ab\_OnlineUseIntensity_i$ variable was constructed as 1 if *abnormal increase of online channel use intensity* was observed during sample period for investor i and otherwise 0. $After_t$, on

[1] Although we do not have any specific hypotheses related to the direct effect of online use intensity on trading behaviors and trading performance, we provide a set of analyses in this regard in response to some review comments.
[2] The results are similar when we use mean, 6th decentile, or 4th quantile to split the sample.

the other hand, is a binary variable indicating the time periods after the *abnormal increase of online channel use intensity* was first observed.[3] We estimate the following equation:

$$TradingOutcomes_{i,t} = \beta \times ab\_OnlineUseIntensity_i \times After_t + \gamma \times Controls_{i,t} + \lambda_i + \eta_t + \varepsilon_{i,t} \quad \text{(eq. 4)}$$

where $TradingOutcomes_{it}$ is *trading frequency*, *trading volume*, or *risk-adjusted return* for investor *i* in month *t*. Similar to our main specification eq. 1, we include investor fixed effect, month fixed effect, and a full set of control variables. $ab\_OnlineUseIntensity_i$ and $After_t$ would be dropped because we control both investors fixed effect and month fixed effect.

For this analysis, we defined *abnormal increase of online channel use intensity* when the monthly online use intensity increases by 50% (approximately 1.5 standard deviations of online use intensity). These estimates are reported in Panel A of Table C.4. There are multiple ways to define the *abnormal increase of online channel use intensity*. The coefficients of $ab\_OnlineUseIntensity_i$ are consistently positive for trading outcomes regardless the ways to define the *abnormal increase of online channel use intensity*.[4]

We also assessed the effect of the abnormal increase in online channel use intensity over time. We replaced the $ab\_OnlineUseIntensity_i \times After_t$ variable with the following time dummies – first six months after the abnormal increase (1 if in the six months after the first-time abnormal increase in online use intensity, 0 otherwise), second six months after the abnormal increase, third six months after the abnormal increase, and fourth six months and after, so as to examine the effect of abnormal increase in online channel use intensity over time (see Panel B of Table C.4). We find that trading frequency linearly increases over time, while trading volume reaches the maximum in about one year after the first abnormal increase of online channel use intensity. In addition, trading performance is not strong at the beginning, but the benefits of online trading emerge in the beginning of second year and later. Taken together, investors may quickly adjust trading behaviors after they suddenly increase online use intensity and realize the benefits of online trading on easy management and low search cost; however, the gains on online trading performance are realized over time rather than immediately.

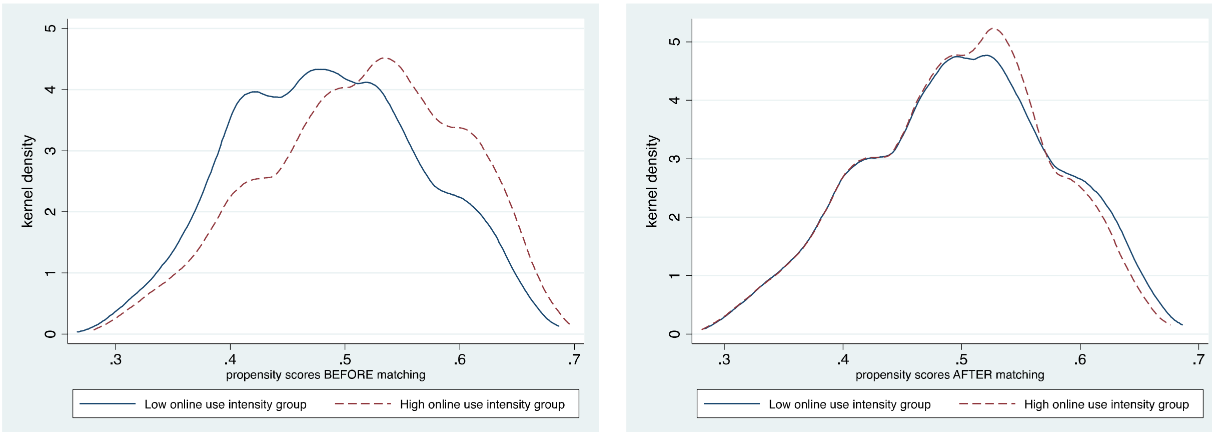
On the whole, the additional analyses and robustness checks reported here complement the findings reported in the main paper and provide further confidence in our main results with additional details on the direct effect of online channel use intensity and plausibility of estimates [9, 10]. Our findings suggest that individual investors should carefully consider their own risk preferences and the potential performance impact of their risk preferences on their online investment activities. The findings are also informative for regulators and policymakers to balance the interests of securities firms and investors.

[3] If *abnormal increase of online channel use intensity* was never observed for investor *i* during the sample period, $ab\_OnlineUseIntensity_i$ variable is coded as 0 for investor *i* and $After_t$ variable is coded as 0 across all time periods as well.

[4] We obtain qualitatively similar results using multiple ways to define the abnormal increase of online channel use intensity, such as (1) monthly online use intensity is increased by 50% (approximately 1.5 standard deviations of online use intensity), (2) monthly online use intensity greater than personal median online use intensity during the sample period, and (3) 100% of the monthly trading was conducted online. For brevity, we only report results for (1) in Panel A of Table C.4.

Figure C.1: Distribution of propensity score between high and low online use intensity users before and after matching

Before Matching | After Matching



Note: These two figures show that high and low online use intensity users are similar in the distribution of their propensity scores after matching.

Table C.1: Balance for covariates before and after propensity score matching

Panel A: Continuous variables - *Gender*, *Age*, and *Trading Experience*

	Before matching			After matching		
Variables	Low Internet (N= 3,582)	High Internet (N= 3,582)	Difference (t-stat.)	Low Internet (N= 3,016)	High Internet (N= 3,016)	Difference (t-stat.)
Age	44.638	43.002	1.636***	43.993	43.994	-0.001
Gender (Female)	0.52	0.4	0.120***	0.459	0.472	-0.013
Trading Experience	5.996	5.201	0.795***	5.623	5.729	-0.107

*** $p < 0.01$

Panel B: Categorical variable - Education

	Before matching		After matching	
Education	Low Internet (N= 3,582)	High Internet (N= 3,582)	Low Internet (N= 3,016)	High Internet (N= 3,016)
No Education Info	1,337	1,100	1,049	1,067
Bachelor	676	690	592	592
College	525	599	457	463
High school diploma	403	467	355	343
Junior school and below	323	409	293	279
Master	31	32	27	29
Ph.D.	2	1	0	1
Technical secondary school	285	284	243	242
Chi^2 test (*p*-value)	0.000		0.969	

Panel C: Categorical variable - Profession

Profession	Before matching		After matching	
	Low Internet (N= 3,582)	High Internet (N= 3,582)	Low Internet (N= 3,016)	High Internet (N= 3,016)
Education	257	196	187	194
Farmer	23	27	23	19
Finial sector	0	1	0	0
Junior in public section	950	968	790	812
Military	0	1	0	0
Other	1,321	1,206	1,081	1,086
Private firm	547	669	507	482
Retired senior in public section	115	115	101	100
Senior in public section	132	152	119	114
Student	38	44	34	32
Unemployed	199	203	174	177
Chi^2 test (*p*-value)	0.001		0.990	

Table C.2: Propensity score matching sample

Variables	***log(Trading Frequency)***		***Trading Volume***		***Risk-Adjusted Return***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
OnlineUseIntensity%	0.007^{***}	0.006^{***}	0.322^{***}	0.292^{***}	0.052^{***}	0.051^{***}
	(0.000)	(0.000)	(0.010)	(0.011)	(0.002)	(0.003)
OnlineUseIntensity% ×		0.009^{***}		-0.217^{***}		0.121^{*}
Risk-Averse		(0.001)		(0.046)		(0.068)
OnlineUseIntensity% ×		0.002^{***}		-0.089^{**}		-0.006
Moderate Risk-Averse		(0.000)		(0.037)		(0.010)
OnlineUseIntensity% ×		0.001^{***}		0.095^{***}		0.003
Moderate Risk-Seeking		(0.000)		(0.021)		(0.004)
OnlineUseIntensity% ×		0.004^{***}		0.236^{***}		-0.009
Risk-Seeking		(0.000)		(0.056)		(0.009)
Observations	64,956	64,956	64,956	64,956	53,325	53,325
R-squared	0.639	0.640	0.527	0.528	0.392	0.393
# of Account	6,032	6,032	6,032	6,032	5,587	5,587

Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *OnlineUseIntensity%* is centered at the mean value in the sample. *Risk-Adjusted Return* has been scaled up by multiplying 100. All models include an intercept, risk dummies, investor level controls, investor FE, and month FE.

Table C.3: Instrumental variables estimation using heteroskedasticity-based instruments

Variables	*log(Trading Frequency)*		*Trading Volume*		*Risk-Adjusted Return*	
	(1)	(2)	(3)	(4)	(5)	(6)
OnlineUseIntensity%	0.007*** (0.001)	0.005*** (0.000)	0.475*** (0.105)	0.405*** (0.049)	0.039*** (0.015)	0.046*** (0.008)
OnlineUseIntensity% × *Risk-Averse*		0.012*** (0.001)		-0.374*** (0.065)		0.103** (0.051)
OnlineUseIntensity% × *Moderate Risk-Averse*		0.003*** (0.000)		-0.171*** (0.048)		-0.003 (0.010)
OnlineUseIntensity% × *Moderate Risk-Seeking*		0.002*** (0.000)		0.012 (0.045)		0.009 (0.007)
OnlineUseIntensity% × *Risk-Seeking*		0.005*** (0.001)		0.196*** (0.065)		-0.005 (0.010)
Observations	77,430	77,430	77,430	77,430	63,457	63,457
# of Account	7,164	7,164	7,164	7,164	6,629	6,629
Cragg-Donald Wald F stats	276.622	500.046	276.622	500.046	201.115	464.301
Stock-Yogo critical value, 10% max IV size	33.84	52.77	33.84	52.77	33.84	52.77

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *OnlineUseIntensity%* is centered at the mean value in the sample. *Risk-Adjusted Return* has been scaled up by multiplying 100. All variables are centered to remove individual fixed effects and month fixed effects[5]. All models include an intercept, risk dummies, investor level controls, investor FE, and month FE.

Table C.4: The effect of abnormal increase of online channel use intensity

	Panel A: ab_OnlineUseIntensity is based on the monthly online use intensity increased by 50%			*Panel B: The effect of abnormal increase of online channel use intensity over time*		
	log(Trading Frequency)	***Trading Volume***	***Risk-Adjusted Return***	***log(Trading Frequency)***	***Trading Volume***	***Risk-Adjusted Return***
	(1)	(2)	(3)	(4)	(5)	(6)
ab_OnlineUseIntensity × After	0.127*** (0.011)	10.189*** (1.025)	1.473*** (0.191)			
Post (First Six Month)				0.153*** (0.011)	6.300*** (1.060)	0.396* (0.202)
Post (Second Six Month)				0.193*** (0.016)	8.799*** (1.969)	0.316 (0.294)
Post (Third Six Month)				0.237*** (0.022)	8.029*** (1.948)	1.142*** (0.366)
Post (Fourth Six Month and after)				0.304*** (0.022)	4.640** (2.252)	1.007*** (0.360)
Observations	77,430	77,430	63,457	77,430	77,430	63,475
R-squared	0.612	0.501	0.389	0.613	0.501	0.388
# of Account	7,164	7,164	6,629	7164	7164	6629

Note: *Risk-Adjusted Return* has been scaled up by multiplying 100. Robust standard errors are in parentheses, *** $p <0.01$, ** $p < 0.05$, * $p < 0.1$. All models include an intercept, risk dummies, investor level controls, investor FE, and month FE.

[5] We used stata commend *ivreg2h* to perform instrumental variables estimation using heteroskedasticity-based instruments. It does not provide any explicit support for panel data. So, centering to remove fixed effect is necessary and recommended for panel data. http://fmwww.bc.edu/RePEc/bocode/i/ivreg2h.html

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