Naïve Attention and Extrapolative Beliefs: Evidence from Digital Footprints of Mutual Fund Investment*

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Abstract

Using account-level digital footprints on a major Chinese fintech platform, we find that retail investors who pay more attention to their mutual fund investments have lower subsequent performance. The negative correlation can be attributed to trend-chasing behavior induced by the investors' extrapolative beliefs, which is amplified by the "naïve attention" paid to their investment. We also find that younger investors suffer more from this naïve attention effect. Overall, our results suggest that investor attention can be a double-edged sword: its effect on investment performance hinges on how the attention is triggered and allocated.

Keywords: Naïve attention, Extrapolative beliefs, Digital footprints, Retail investors, Fintech platform, Mutual fund

*The authors acknowledge and appreciate the supports from the Digital Economy Open Research Platform (www.deor.org.cn). All data was sampled and desensitized, and was remotely analyzed on the Ant Open Research Laboratory in an Ant Group Environment which is only remotely accessible for empirical analysis.

1 Introduction

The investment landscape has been transforming with the emergence of new fintech platforms. Empowered by technological innovations and massive user bases, these platforms provide convenient, simple, and engaging investment services on mobile apps with low commissions, thereby enhancing financial inclusion (Hong, Lu, and Pan, 2023b). Such fintech platforms have been attracting young investors – Generation Z and Millennials in particular – who tend to have lower financial literacy and are more susceptible to behavioral biases (Brad M. Barber, Huang, et al., 2022)[1]. While more rational attention allocation can lead to better investment performance in general (L. Peng and Xiong, 2006; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016; Gargano and Rossi, 2018), young investors who are more susceptible to behavioral biases may suffer from more attention allocation (Odean, 1999; Brad M. Barber and Odean, 2001, 2008; Bailey, Alok Kumar, and Ng, 2011). It is thus interesting and relevant to examine whether the attention allocation of young investors to their investment information on fintech platforms improves the performance or harms it instead.

To answer the question, we utilize an ideal dataset obtained from Alipay, a leading fintech platform in China. Our data comprises detailed account-level information regarding both attention and trading behavior of more than 58,000 users between August 2020 and December 2021. Within the dataset, we can observe investors' demographic characteristics, monthly login activities, and monthly transaction records on the Alipay mutual fund platform. Our login activity data allows us to track how much time each investor spends on the trading platform, serving as a direct measure of investors' attention. With this attention measure, we can conduct a comprehensive examination of attention mechanisms and their interactions with behavioral biases at the account level.

We first explore the effect of investor attention on investors' performances. We show that investors who pay more attention on fintech mutual fund platform will have significantly lower investment return in the subsequent month. This effect is also economically substantial since a standard-deviation increase in investor attention on the fintech platform is associated with a 0.89% decrease in annualized investment return. The results are consistent when we use several alternative measures of attention, such as time spent on different pages of Alipay mutual fund platform.

We examine two potential channels relating attention to investment underperformance: trading behavior and trading strategy. For trading behavior channel, we find that investors who pay more attention on fintech platform tend to have higher transaction volumes and more frequent transactions. Besides, investors still engage in more frequent trading even when we control their overall transaction volume. However, this attention-induced trading behavior, which is characterized by excessive trading activity of investors with high attention, will result in investment underperformance. This finding aligns with the well-documented phenomenon that increased attention tends to amplify investors' tendency towards excessive trading behavior (Brad M. Barber and Odean, 2008) which can be detrimental to

[1] For example, Robinhood's average customer is young and lacks investing know-how. The average age is 31 and half of its customers had never invested before. https://www.nytimes.com/2020/07/08/technology/robinhood-risky-trading.html

investment performance (Odean, 1999; Brad M. Barber and Odean, 2000, 2001; Escobar and Pedraza, 2023).

In terms of trading strategy, attention can also lead to trend-chasing strategy (Brad M Barber, Odean, and Zhu, 2009), wherein investors tend to follow prevailing trends when selecting mutual funds. We discover that investors paying higher attention systematically choose mutual funds with higher return in the previous month. Nevertheless, strong recent performance of mutual funds cannot persist into future but rather suffers from return reversal in the subsequent month. Therefore, such performance-chasing strategy of mutual fund investors on fintech platforms is related to behavioral biases rather than to rational choice based on past performance of funds (Bailey, Alok Kumar, and Ng, 2011; Ben-David, Li, et al., 2022) and leads to suboptimal outcomes for investors (Brad M. Barber, Huang, et al., 2022; Fang, Peress, and Zheng, 2014).

Next, we aim to understand attention's role in shaping investor perceptions and expectations, and how these beliefs ultimately impact investment outcomes. In particular, we examine the extrapolative beliefs of Fintech investors which are closely related to excessive trading behavior and trend-chasing trading strategy (Barberis, Greenwood, et al., 2018; Cassella and Gulen, 2018; Da, Huang, and Jin, 2021; Liao, C. Peng, and Zhu, 2022; Jin and Sui, 2022). Return extrapolation refers to the tendency of individuals to project future returns of a stock based on its recent past performance. In other words, investors rely on the assumption that a stock's recent positive returns will continue into the short future. We use mutual fund purchase volume to proxy investors' expectation for future return (Brad M Barber, Odean, and Zhu, 2009) and confirm empirically that investors do exhibit extrapolative beliefs. By regressing investors' expectation on the past returns of mutual funds selected by investors, we find that recent past return coefficients are positive and significant, while distant past return coefficients are generally lower than recent past return coefficients at the same time, indicating return extrapolation.

We then investigate the economic mechanism relating attention to extrapolative beliefs and reveal how attention amplifies investors' extrapolative beliefs. Following Da, Huang, and Jin (2021), we decompose investor expectations into two components: a predicted extrapolative component explained by past mutual fund returns and a residual component orthogonal to past returns. After introducing interaction terms between attention measures and different expectation components into difference-in-difference regressions, we find that investor attention only exacerbates the negative impact of extrapolative beliefs on future performance, while attention have no significant impact on non-extrapolative beliefs. Moreover, without the amplification effect on extrapolation, attention has a positive effect on investment performance. Besides, we construct an alternative investor-level degree of extrapolation measure (DOX) as the weighted average past return based on the transactions in the current month (Liao, C. Peng, and Zhu, 2022). Similarly, DOX negatively predicts future investment performance and attention amplifies the negative impact of DOX. Moreover, our results are robust when we only consider the initial buy which is regarded as a better proxy for beliefs (Liao, C. Peng, and Zhu, 2022)[2]. Conclusively, inexperienced investors' extrapolation beliefs are biased (Cassella and Gulen, 2018; Da, Huang, and Jin, 2021) while attention amplifies extrapolative beliefs distortion.

We define the attention allocated by young and unsophisticated fintech investors as *naïve attention*, since those investors suffer from, rather than benefit from, the extrapolation-amplification effect of attention. We further conduct various robustness tests and the negative effect of investor attention on investment performance and the amplification effect on extrapolation beliefs are robust under various subsamples and various definitions of variables. Overall, our findings not only provide novel evidence on how attention affects investors' behavior on fintech mutual funds platforms but also reveal the mechanism of how investor attention amplifies the distortion of extrapolative beliefs. Rational investors leverage attention to collect useful information to improve investment performance (Gargano and Rossi, 2018) while irrational ones pay naïve attention only to amplify their behavior biases (Brad M. Barber, Huang, et al., 2022). Hard work pays off, but dumb work wastes off.

Related Literature Our paper makes contributions to the growing literature that studies the behavior of investors on fintech platforms. Studies show that the introduction of fintech tools and platforms indeed breaks down households' participation barriers and encourages financial participation in the financial market (Hong, Lu, and Pan, 2023a; D'Acunto, Prabhala, and Rossi, 2019) and changes investors' behavior, such as increasing financial risk-taking (Hong, Lu, and Pan, 2023a; Loos et al., 2020) and amplifying performance-chasing behavior (Hong, Lu, and Pan, 2023a). Brad M. Barber, Huang, et al. (2022) show that Robinhood users are prone to attention-driven herding: investors on Robinhood platforms intensely buy a small subset of stocks that have recently grabbed attention through extreme returns or high trading volume. This herding behavior temporarily induces future underperformance of those stocks, which have large negative abnormal returns of around -20% over the subsequent month. We contribute to this literature by providing evidence on how attention influences young and unsophisticated investors' behaviors on fintech platforms.

Our paper also belongs to the literature on the mechanism of investors' attention. Prior researches have explored the effect of investor attention in various markets, including the stock market (Brad M. Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Andrei and Hasler, 2015; Yuan, 2015; Brad M. Barber, Huang, et al., 2022), mutual fund markets (Fang, Peress, and Zheng, 2014) and ETF markets (Ben-David, Franzoni, et al., 2023). These studies show various channels and consequences of the attention effect on trading volume (Brad M. Barber and Odean, 2008), price turbulence (Lou, 2014), and return patterns (Da, Engelberg, and Gao, 2011; Yuan, 2015; Brad M. Barber, Huang, et al., 2022). However, obtaining account-level attention data can be challenging in empirical research. As a result, many studies resort to using proxy measures for investor attention and conduct their analyses at the security level instead of the individual account level., such as Google search volume (Da, Engelberg, and Gao, 2011; Yuan, 2015; Da, Hua, et al., 2023), news coverage (Brad M. Barber and Odean, 2008), EDGAR log data (Iliev, Kalodimos, and Lowry, 2021), news searching and news reading activity (Ben-Rephael, Da, and Israelsen, 2017) and "Top Movers" list (Brad M. Barber, Huang, et al.,

[2]Initial buy is the purchase of an investment not currently held in the portfolio

2022). To our knowledge, only five papers use similar account-level data to measure attention as our paper. Karlsson, Loewenstein, and Seppi (2009), Gherzi et al. (2014) and Sicherman et al. (2016) focus on factors that determine investors' attention allocation. Dierick et al. (2019) find that more attentive investors trade less in line with the disposition effect with a dataset from the largest Belgian discount broker. Gargano and Rossi (2018), using a brokerage account dataset, show that attention is positively related to investment performance, at both the portfolio return level and the individual trades level. We differentiate from previous researches by focusing on young and inexperienced fintech investors rather than traditional brokerage clients examined previously. Specifically, our study identifies the attention of unsophisticated investors on fintech platform as *naïve attention* which refers to the attention magnifying investors' extrapolation level, inducing excessive trading and irrational trend-chasing strategy, leading to poor future investment performance. Additionally, we provide the first evidence of how investor attention influences investors' perceptions and expectations, particularly by amplifying extrapolative beliefs of unsophisticated investors.

We also contribute to the debate on the effect of attention on behaviors. While attention has been shown to be beneficial for investment performance in traditional platforms (Gargano and Rossi, 2018), its impact in fintech platforms with unsophisticated investors is controversial. Brad M. Barber, Huang, et al. (2022) and Welch (2022) find that Robinhood traders hold attention-grabbing securities, experiencing subsequent underperformance. Similarly, Ben-David, Franzoni, et al. (2023) show less sophisticated investors favor attention-grabbing specialized ETFs and disappoint in the future. Psychology reveals further pitfalls of misguided attention – allocating more time to easy versus difficult questions breeds overconfidence (Ehrlinger, Mitchum, and Dweck, 2016), and tailored information promotes confirmation bias (Vogrin, Wood, and Schmickl, 2023). Related researches in social media which leverages similar algorithms as fintech to provide personalized services, show that attention often amplifies behavioral biases. For instance, TikTok unconsciously spurs consumption (Erizal, 2021) and distorts time perception (Qin, Omar, and Musetti, 2022). Such attention-hijacking algorithms commonly alter human behavior, especially among youth (Hou et al., 2019; Wang et al., 2022). Our paper provides novel evidence of how naïve attention changes investment behaviors, causing suboptimal decisions. Furthermore,our results demonstrate that, without amplification effect on extrapolative beliefs, attention remains beneficial for investors. Our findings contribute to a better understanding of cognitive processes influencing investment decision-making.

Our paper is also related to an emerging literature on the extrapolative beliefs of investors. Extrapolative beliefs, in which investors overweight recent relative to distant past returns when forming expectations, have been proven to be an important pattern of investor behavior. Most recent works explore extrapolative beliefs through both theoretical (e.g. Barberis, Greenwood, et al., 2015, 2018; Nagel and Xu, 2022; Jin and Sui, 2022) and survey-based methods (e.g. Greenwood and Shleifer, 2014; Cassella and Gulen, 2018; Kuchler and Zafar, 2019; Da, Huang, and Jin, 2021). Extrapolative beliefs have also been used to explain various market anomalies. Cassella and Gulen (2018) and Da, Huang, and Jin (2021) show that return extrapolation can negatively predict future returns, indicating return reversal. Liao, C. Peng, and Zhu (2022) find that the interaction between extrapolative beliefs and disposition effects could explain the sharp rise in prices and volume observed in historical financial bubbles. We contribute to this stream of literature by showing that, attention can amplify extrapolative beliefs distortion among young and inexperienced fintech platform investors, leading to poor investment performance. Our research provides novel insights into the relationship between investor attention and extrapolative beliefs, which, to our knowledge, has not been previously explored.

The rest of the article is organized as follows. In Section 2, we develop our main hypothesis. Section 3 describes our Alipay dataset and provides summary statistics. Section 4 presents our baseline result on the impact of investor attention on investment performance and explores two channels related to excessive trading behavior and trend-chasing trading strategy. Section 5 establishes the relationship between investor attention and extrapolative beliefs. We discuss various robustness tests in Section 6. Section 7 concludes.

2 Hypothesis Development

Investors' attention, which is the foundation of learning, beliefs, and trading, serves as the fuel for investment decisions. However, investors suffer from limited attention problem since attention is a scarce cognitive resource (Kahneman, 1973). Thus, if investors are rational, attention-constrained investors will get more information by allocating more attention to acquiring information and they can also process these acquired information properly. Rational investors possess the ability to effectively analyze and interpret the information they gather. This involves critically evaluating the credibility and relevance of the information, considering various perspectives, and applying sound analytical techniques to derive meaningful insights. In this case, investors can obtain more useful information by paying more attention and, therefore, achieve better investment performance and exhibit less behavior biases. (e.g. L. Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2009; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016). Gargano and Rossi (2018) and Dierick et al. (2019) provide empirical evidence to this notion when they investigate sophisticated and experienced investors in the professional brokerage account.

However, investors are far from rational. Vast number of literatures have documented that individual investors are suffering from different kinds of behaviour biases, both in stock markets (e.g. Odean, 1998, 1999; Brad M. Barber and Odean, 2001) and in mutual fund markets (e.g. Bailey, Alok Kumar, and Ng, 2011). More attention may not always be a good sign for these irrational individual investors because they can not necessarily process their information correctly. For example, attention may induce investors to trade excessively through the channel of news overextrapolation (Brad M. Barber and Odean, 2008) and increase investors' risk-taking (Arnold, Pelster, and Subrahmanyam, 2022). Additionally, more attention may lead to information overload, where investors are exposed to an overwhelming amount of data and news. This can result in investors' decision paralysis or inability to filter out relevant information from noise, leading to suboptimal investment choices. In this case, high attention may amplify investors' behavioural mistakes, resulting in poor performance.

Additionally, fintech platforms that attract young investors with low financial literacy tend to induce further behavioural biases in investors. Compared with traditional investment platforms, fintech platforms provide investment services as a supplement to payment services. Accordingly, investors are mostly normal consumers who use fund services for convenience rather than prudent investors choosing between different platforms. Young and inexperienced investors are susceptible to behavioural biases associated with lower returns (Greenwood and Nagel, 2009; Bailey, Alok Kumar, and Ng, 2011). High attention may amplify these young and inexperienced investors' behavioural mistakes than other retail investors (Brad M. Barber, Huang, et al., 2022). Moreover, as investors have limited attention, these fintech platform, as the suppliers in the investment service market, will choose to compete for investors' attention (Bordalo, Gennaioli, and Shleifer, 2016). To attract consumers, fintech platform can use new technology to provide personalized investment suggestions, notices, and advertisements to investors, which will lead to attention-induced trading on these platforms followed with further future underperformance (Brad M. Barber, Huang, et al., 2022; Ben-David, Franzoni, et al., 2023).

Taken all together, we have the following hypothesis on the relationship between attention and return for fintech platform investors.

Hypothesis 1 *Fintech platform investors paying more attention tend to have lower future returns.*

Attention may induce underperformance through several channels. One possible channel for investors to lose from higher attention is through over transactions. Much research has explored how investors with higher trading volume, turnover, and numbers of transactions get lower returns. For instance, Odean (1999) found that investors who trade more frequently tend to earn lower returns after accounting for fees. Furthermore, Brad M. Barber and Odean (2000) demonstrated that active trading strategies generally underperform a passive buy-and-hold strategy. The catalyst of excessive trading, including overconfidence (Odean, 1999; Brad M. Barber and Odean, 2001; Statman, Thorley, and Vorkink, 2006; Grinblatt and Keloharju, 2009), sensation-seeking (Grinblatt and Keloharju, 2009), and attention (Brad M. Barber, Huang, et al., 2022; Pedersen, 2022), results in negative returns for investors in the future. Literature of attention-induced trading and returns predict that investors will high attention are more likely to engage in intense buying followed by negative abnormal returns, especially for relatively inexperienced investors. (e.g. Brad M. Barber and Odean, 2008; Brad M. Barber, Huang, et al., 2022). While some studies suggest risk-taking stemming from behavioural biases can partially offset this negative effect, the net result is still lower average returns (Statman, Thorley, and Vorkink, 2006). Therefore, attention-induced excessive trading for fintech platform investors may induce future losses for investors. So, we present Hypothesis 2 as follows.

Hypothesis 2 *Fintech Platform investors paying more attention tend to have more transactions. And the excessive trading induced by attention is negatively related to future returns.*

Another channel that may induce underperformance is through choosing the wrong fund. There is much evidence documenting that retail investors tend to chase good performance investments. Greenwood and Nagel (2009) show that young and inexperienced investors are more likely to exhibit trend-chasing behaviour. Gargano and Rossi (2018) discover that relatively sophisticated brokerage account investors with high attention to their trading accounts tend to trade stocks that have appreciated greatly in the past. However, such trend-chasing strategy often has poor future performance. Bailey, Alok Kumar, and Ng (2011) show that behaviourally biased investors typically make poor decisions about trading strategy, such as trend-chasing. Trend chasing appears related to behavioural biases, rather than to rationally inferring managerial skill from past performance. Brad M. Barber, Huang, et al. (2022) also finds that Robinhood investors engage in more intense buying of attention-induced trading stocks, such as stocks with high past performance but intense buying by Robinhood users forecasts negative returns. Therefore, as high attention may amplify investors' behavioural biases, we could reasonably argue that investors in fintech platform with high attention tend to pick investments with higher past return. But these investments will have poor future performance.

Excessive trading and performance chasing is consistent with extrapolative beliefs. Return extrapolation refer to the tendency of individuals to project future returns of a stock based on its recent past performance (Barberis, Greenwood, et al., 2015; Da, Huang, and Jin, 2021). As extrapolative investors overweight recent returns compared to more distant returns, they are more inclined to invest in assets that have demonstrated strong recent performance. Consequently, this behaviour leads to a trend-chasing strategy and high trading volume as extrapolators flip-flop between buying and selling (Barberis, Greenwood, et al., 2018; Liao, C. Peng, and Zhu, 2022). Additionally, young and inexperienced investors tend to be trapped by extrapolative beliefs. Cassella and Gulen (2018) estimate the degree of extrapolative weighting (DOX) in beliefs. They show that DOX is higher when young investors are a bigger part of the market. Da, Huang, and Jin (2021) show that degree of extrapolation is stronger among nonprofessional Forcerank users. However, extrapolative belief is biased, and investing according with extrapolative belief may lead to underperformance, driving short-term return reversals (Cassella and Gulen, 2018; Da, Huang, and Jin, 2021).

How does attention effect the extrapolation level of our Fintech platform investors? On fintech platforms, investors are often presented with an overwhelming wealth of real-time information, market data, news, and investment recommendations. This influx of information, combined with heightened attention, can intensify the tendency to focus on recent trends and project them into the future, especially for the less sophisticated investor on fintech platform. As a result, fintech platform investors may overestimate the persistence or significance of these trends, leading to an amplification of their extrapolative beliefs on fintech platform compared to retail investors in traditional brokerage account platform. Besides, humans have confirmation bias, which is a pervasive phenomenon that humans tend to prefer information that confirms their presupposed ideas, theories, or opinions, and to interpret ambiguous information in a way that is supportive of their already existing beliefs (Vogrin, Wood, and Schmickl, 2023). Therefore, after fintech platform investors formed their biased extrapolative beliefs, investors are more likely to search and read information which support their extrapolative beliefs according to confirmation bias. In the traditional platform that does not filter information to fit users' tastes, investors are exposed to a wide range of news and opinions, allowing investors to explore different perspectives and make more informed decisions. Mature investors with more attention may consciously direct some attention to diverse perspectives. In this case, individuals can counteract the natural tendency to seek out confirming information and more attention can help alleviate extrapolative bias. However, the personalized nature of fintech platforms, where algorithms and recommendation systems tailor content to individual preferences, can contribute to the strengthening of extrapolative beliefs by more attention. Naïve investors with more attention will receive more tailored information that aligns with their existing beliefs and preferences unconsciously. This information can reinforce their confidence in the accuracy and reliability of their extrapolations, potentially leading to greater amplification of extrapolation beliefs bias. Besides, Ehrlinger, Mitchum, and Dweck (2016) reveal that attention allocation matters in establishing overconfidence. They find that people who allocate more time to easy questions than difficult questions tend to be more overconfident. Directing people's attention to difficult questions will diminish overconfidence. Fintech platforms, however, breed users with personalized service and also try their best to simplify the problems investors are facing. Tailored information, though representing extreme convenience, also replaces the traditional hard-working style that cultivates inexperienced investors from scratch. Instead, young investors, though seemingly getting everything with a click, miss the training of dealing with difficulties in collecting information. Therefore, being trapped in those simple questions may induce investors' overconfidence and behavioural biases.

Accordingly, we have Hypothesis as follows:

Hypothesis 3 *Fintech platform investors paying more attention tend to pick funds with higher recent history return and their extrapolation level will be magnified by paying more attention. The extrapolation belief and trend-chasing strategy are negatively related to future returns.*

3 Data and Summary Statistics

We utilize a unique novel dataset consisting of individual mutual fund account data from the Ant Group, an affiliate company of the Chinese conglomerate Alibaba Group. Ant Group is a leading fintech giant in China with over one billion global users and over 4.1 trillion CNY under management[3]. Alipay, as one of the key products of Ant Group, can provide customers with different kinds of financial services, including payment and investment services. Investors can buy various kinds of financial products on Alipay, such as bonds, mutual funds, and insurances. The Ant Group became one of the top non-money market mutual fund seller by 2021's first quarter in China[4].

This study was remotely conducted on the Ant Open Research Laboratory[5] in an Ant Group Environment. All data was sampled and desensitized, and was analyzed on the Ant Open Research

[3] Ant Group Co., Ltd IPO Prospectus on Chinese STAR Market, August 23 2020: http://static.sse.com.cn/stock/information/c/202008/e731ee980f5247529ea824d20fcdb293.pdf

[4] http://www.xinhuanet.com/enterprise/2021-05/14/c_1211155206.htm

[5] https://www.deor.org.cn/labstore/laboratory

Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are invisible. The main regression variables include basic variables, investment variables, and consumption variables. We obtained de-identified data on monthly mutual fund transactions from randomly selected individual users of Alipay from August 2020 to December 2021. We get 58953 accounts after we remove zombie account (Accounts that do not have any transactions or any account activity data during our sample periods). Our data include information on

1. Investor demographics: one observation per account about personal account holder characteristics, including their age, gender, birthplace and their mutual fund investment amount category among all investors on Alipay platform. [6]

2. Investor monthly payment and wealth data: one observation per account per month on total amount that investors use Alipay to pay for their consumption and the end-of-month account balance on Yuebao.

3. Investor monthly transaction data for each fund: one observation per account per month per fund on total profit, end-of-month investment balance, total trading amount and trading frequencies for investor purchases and redemptions.

4. Investor monthly account activity data: one observation per account per month on the number of logins and the number of seconds that investors spent on different pages of Alipay mutual fund platform.

We also collect fund information and market performance from the China Stock Market and Accounting Research (CSMAR) database, such as fund code, fund monthly return, fund monthly market return.

In this paper, we utilize three measures of investor attention. The first measure, which we refer to as *Fund_all_stay*, represents the total number of seconds that investors spend on the Alipay mutual fund platform and serves as our primary attention metric. The second measure, *Hold_all_stay*, captures the total number of seconds that investors dedicate to pages associated with their own investment portfolios. Lastly, the third measure, *Market_all_stay*, accounts for the total number of seconds that investors spend on pages containing market information. We utilize *Hold_all_stay* and *Market_all_stay* metrics to investigate whether the impact of attention on investor behaviour and market outcomes varies differs based on the specific content or category of information that investors pay attention to: information on their own investment portfolios and market-related information.

Some literature also uses the number of logins to the same pages as robustness purposes. Using the total number of seconds that investors spend on some pages may overestimate the attention level since there is possibility of individuals staying on the website while performing other activities. However, the number of logins is not good measure here, especially in fintech platform such as Alipay. Some

[6] Alipay classify all investors into three categories (low, medium and high) based on their investment amount in 2021.

investors may just tap into some pages accidentally and they exit shortly. A brief visit may not provide sufficient time for users to fully understand the information presented, particularly in the case of complex reports or analyses. Besides, fintech platforms are more likely to display various kinds of advertisements on their platform to induce investors to use their investment services. In the case of investors who are primarily interested in just want to use payment or other services on Alipay, accidental interactions with these ads can redirect them to mutual fund platforms, resulting in a quick exit from the redirected page. Therefore, there will be large measurement error to use the number of logins as robustness purposes. Giving the importance of careful consideration in investment decision, we prioritize tracking the number of seconds spent on the website as the measure of attention since this metric emphasizes the depth of engagement and suggests that users are actively consuming and comprehending the content.

Next, we need to construct investment return measure. Since we only have the fund amount of each account at the end of each month and monthly aggregated purchase and redemption records, we cannot observe the exact timestamp, price and volume for each purchase or redemption records. Therefore, we calculate investors' monthly return as monthly profit divided by the average of fund amount at the beginning of the month and fund amount at the end of the month (*Ret1*). We use fund amount at the end of the last month of beginning-of-month fund amount if it's not missing, otherwise we calculate beginning-of-month fund amount as end-of-month fund amount plus monthly redemption amount subtracting monthly purchase amount and monthly profit. We also use monthly profit divided by end-of-month fund amount as an alternative measure of monthly return (*Ret2*).

Table 1 reports the summary statistics for our sample. Panel A shows the biographical traits of Alipay fund sample investors: age and gender. Although the maximum age of investors in our sample is 85, but the average age of is approximately 36 and the median age is 33. And more than one quarter of investors are under 30 and approximately three quarters of investors are under 40. The investors in our sample are much younger compared to brokerage account investors in Gargano and Rossi (2018) and Dierick et al. (2019), in which the average of investors in their sample are both approximately 50. Our sample demonstrates the fact that fintech platform are more likely to attract young and relatively inexperienced investors (Brad M. Barber, Huang, et al., 2022). 45% investors in our sample are female, which is largely higher compared to 27% in Gargano and Rossi (2018), 21% in Brad M. Barber and Odean (2001) and 12% in Dierick et al. (2019).

Panel B presents the summary statistics of investors' average monthly payment and Yuebao Balance. We found great variation in monthly payment and wealth among investors. The average monthly payment of investors through Alipay is 6500 yuan while the maximum is 1.48 million yuan and the minimum is 0.01 yuan. The average Yuebao Balance is 19,560 yuan while the maximum is 3.13 million and the minimum is 0. It should be noted that the balance in Yuebao accounts and payment through Alipay represent only a portion of investors' overall wealth and payment activities in China. Chinese individuals commonly deposit their wealth in commercial banks, and payment methods such as WeChat Pay are widely used for various transactions apart from Alipay. While Yuebao balances and monthly Alipay payments may not capture the complete picture of individuals' financial situations, they can still provide valuable insights as proxies for payment activities and wealth in China given the popularity of Alipay and the widespread use of mobile payments in the country.

Next, we turn to the characteristics of attention measures, trading behaviour and monthly returned for Alipay fund investor, with summary statistics reported in Panel C, D, E, respectively. These measures are computed as average first in the time-series dimension at the account-holder level and then summary statistics are computed cross-sectionally. First, great variations exist in attention behaviours. On average, investors had a monthly stay time of 55 minutes on the mutual fund platform (*Fund_all_stay*), with a minimum of 0 (indicating investors who do not pay any attention) and a maximum of 3 days (4318 minutes / 60 = 72 hours = 3 days). Additionally, investors dedicate approximately 13.5 minutes per month to their own portfolios (*Hold_All_Stay*) and 41.5 minutes to market information (*Market_All_Stay*), indicating a preference for browsing market-related information.

Second, Panel D displays substantial differences in trading behavior among investors. The average fund investment was 48,356 yuan and a median of 11,889 yuan. The minimum investment amount was 0, and the maximum was 19.24 million yuan, indicating that a few investors held vast amounts of investment. The average monthly purchase amount is 9246 yuan and average redemption count is 7821 yuan. However, the maximum purchase amount reached 3 million yuan, and the maximum redemption amount reached 2.56 million yuan. Moreover, the average monthly purchase count and redemption count were less than 10 times, but the maximum purchase count reached 2675, and the redemption count reached 953, indicating that some investors engaged in extremely frequent trading on Alipay.

Third, with various trading behaviours, investors in our sample also exhibited various return patterns, as reported in Panel E. The maximum average monthly return reached 14.3% and 19.9% for Ret1 and Ret2 while the minimum reached -14.7% and -15.4%. The mean of average monthly return is 0.45% and 0.49% for Ret1 and Ret2, respectively. Additionally, some accounts exhibited extreme return volatility, reaching 20.5% and 25.0%.

[Insert Table 1 Here]

4 Investor Attention and Investment Performance

In this section, we delve into the impact of attention on investors' mutual fund performance using Ant data. Initially, we explore the direct influence of attention on investors' future mutual fund returns. We then investigate two potential channels: excessive trading and trend-chasing trading strategy.

4.1 Attention and Investment Performance: Baseline Result

Firstly, we examine how investor attention on the investment platform in the current month affects investors' investment return in the following month. We define the monthly total time an investor spent on Alipay mutual fund platform as the monthly attention. Additionally, we calculate their monthly return based on the overall returns from their mutual fund investments during that month.

Specifically, we examine the attention effect on investors' mutual fund investment performance by estimating the following model with basic controls, as well as additional fixed effects in subsequent tests:

$$\text{Investment\_ret}_{i,t} = \alpha + \beta\text{Attention}_{i,t-1} + \text{Controls}_{i,t-1} + \text{FEs} + \epsilon_{i,t} \tag{1}$$

where the dependent variable, investment_ret$_{i,t}$, is the monthly return of investor i in month t expressed in percentage points and winsorized at 0.01 and 0.99 percentile. We employ *Ret1* as our primary return measure and *Ret2* serves as an alternative return measure to ensure robustness, where *Ret1* and *Ret2* are defined in Section 3. attention$_{i,t-1}$, is the monthly attention indicator represented by the time investor i stays on the pages in month $t-1$. Hence, β captures the effect of investor attention on investors' investment return in the following month. We control for investors characteristics including monthly consumption and wealth. Furthermore, we control investor and month fixed effects in the regressions. By including these variables and controlling for fixed effects, we aim to isolate the specific effect of attention on investors' investment performance while accounting for other investor-specific or market-specific factors that may influence trading decisions. Karlsson, Loewenstein, and Seppi (2009) and Sicherman et al. (2016) reveal the "ostrich effect" of attention: investors will pay more attention to their finances after good news than after bad news. Therefore, to alleviate the reverse causality problem, we use predictive regression in our specification with lagged monthly investment return as our control variable. Additionally, according to the yearly report of Ant Mutual Fund Platform in 2021, the average holding period of investors on Alipay mutual fund platform is longer than a half of year. [7] Considering this relatively long holding period, our research examining the influence of attention on returns in the subsequent month is reasonable and consistent with users behaviour observed on the platform.

We utilize three measures of investor attention that are defined in Section 3: *Fund_all_stay* (the total time investors spend on the Alipay mutual fund platform, the primary attention metric), *Hold_all_stay* (the total time investors spend on pages associated with their own investment portfolios) and *Market_all_stay* (the total time investors spend on pages containing market information). *Hold_all_stay* assesses the degree of attention towards their own portfolios, such as performance, asset allocation, or individual stock analysis. *Market_all_stay* reflects attention towards market-related information like trends, economic indicators, news events, and industry analysis. By comparing the effects of *Hold_all_stay* and *Market_all_stay* on actions and performance, we determine whether attention to different information types leads to divergent outcomes.

Table 2 presents the results of this baseline specification. Panel A use *Ret1* and Panel B use *Ret2* as dependent variable. In both panels, column (1) - (3) ((4) - (6), (7) - (9)) show results using

[7] https://www.cafr.cn/Contents/images/Research/20210720024558.pdf

Fund_all_stay (*Hold_all_stay*, *Market_all_stay*, respectively) as attention measure. All attention measures are represented in hours and standard errors are clustered at the investor level in all regressions to account for potential heteroscedasticity or correlation. We find a significantly negative relationship between attention and future performance, aligning with Hypothesis 1. The coefficients of investor attention are significant at 1% level in all regression settings. One hour increase of overall attention on the platform leads to a decrease in monthly mutual fund investment return of 0.052% to 0.226%, after we include all controls and fixed effects. One hour increase of attention on individual investment portfolios leads to a 0.163% to 0.861% decrease in investment performance while one hour increase of market-induced attention results in a 0.062% to 0.256% decrease. In terms of economic magnitude, when we include all controls and fixed effects, one-standard-deviation increase in overall attention on the Alipay mutual fund investment platform leads to an 0.84% ((0.052 * (141.8 / 60) /1.749) * 12 / 100) decrease in annualized portfolio performance of. As the average annual return of investors in our sample are 5.436% (0.453 * 12 / 100), one-standard-deviation increase in overall attention on the platform results in a 16.4% (0.89 / 5.436) decrease in their next month's investment performance, which is quite substantial. For *Hold_all_stay* and *Market_all_stay*, with all control variables and fixed effects, one-standard-deviation increase in attention on individual portfolios indicates an 0.60% ((0.163 * (32.4 / 60) /1.749) * 12 / 100) decrease in annualized performance and one-standard-deviation increase in market-induced attention information leads to an 0.83% ((0.062 * (117.1 / 60) /1.749) * 12 / 100) decrease in annualized performance . Therefore, attention on the market is more detrimental compared with attention on investors' own portfolio. Panel B demonstrates that the results are similar when we use *Ret2* as dependent variable. Overall, the baseline regression supports the finding that attention on Alipay mutual fund platform, though have various magnitude of effect, are likely to be harmful for investment performance in the future.

[Insert Table 2 Here]

4.2 Attention and Investment Performance: Channels

In this section, we try to explore channels that could contribute to the negative effect of investor attention described in Section 4.1. We first study whether more attentive investors are more likely to engage in excessive trading, which will lead to future underperformance. Then the second test explores whether investors with higher attention will purchase funds with higher recent history return and future underperformance.

4.2.1 Attention and Excessive Trading

There is a substantial body of research that has explored the relationship between investor trading behavior and investment returns. Studies have consistently found that investors with higher trading volumes, turnover, and numbers of transactions tend to experience lower returns. For instance, Odean (1999) found that investors who trade more frequently tend to earn lower returns after accounting for transaction fees. Furthermore, Brad M. Barber and Odean (2000) demonstrated that active trading strategies generally underperform a passive buy-and-hold strategy. Literature that focusses on attention-induced trading and its impact on returns suggest that investors with high levels of attention are more likely to engage in intense buying activity, which is followed by negative abnormal returns, particularly among relatively inexperienced investors. Notable studies include Brad M. Barber and Odean (2008) and the more recent work by Brad M. Barber, Huang, et al. (2022). In this subsection, we aim to test the Hypothesis 2 in Section 2 that the negative attention effect on investment performance can be driven by excessive attention-induced trading behaviour. We firstly test if attention affects individuals' investment behaviours by estimating the following regression:

$$\text{Trading}_{i,t} = \alpha + \beta \text{Attention}_{i,t} + \text{Controls}_{i,t} + \text{FEs} + \epsilon_{i,t} \tag{2}$$

The dependent variable, $\text{Trading}_{i,t}$, is the trading behaviours of investors i in month t. To measure investors' trading activities, we define three indicators: Monthly Fund Purchase Amount (in RMB 1e4 Yuan), which captures the total amount of funds purchased by the investor during the month; Monthly Fund Purchase Frequency (in 100 times) that measures the number of times the investor made fund purchases during the month and Monthly Excess Fund Purchase Frequency (in 100 times). Excess Purchase Frequency is defined as the regression residuals of Purchase Frequency onto Purchase Amount. This indicator captures the deviation in purchase frequency that is not explained by the amount of funds purchased. β represents the attention effect on investors trading behaviours in mutual fund investment. We control for similar variables and fixed effect as in Regression 1. The standard errors are clustered at the investor level.

In Panel A of Table 3, the results indicate that the coefficients of attention against trading variables are all positive and significant at the 1% level, regardless of the attention measures or trading behaviour measures used. This suggests that investors who allocate more attention tend to exhibit higher trading volumes and engage in more transactions, which is consistent with the attention-induced behaviour often observed among inexperienced investors (Brad M. Barber and Odean, 2008; Brad M. Barber, Huang, et al., 2022). To further demonstrate the impact of excessive trading on future returns on the Alipay platform, we run a similar regression as Regression 1, but replace the attention variable with the trading behavior variable. The results in Panel B of Table 3 confirm investors engaging in excessive trading behaviors experience lower future returns, statistically significant at the 1% level. These findings support Hypothesis 2, suggesting investors allocating more attention on the platform tend to make more transactions. However, such attention-induced trading behavior is detrimental to future returns.

[Insert Table 3 Here]

One potential reason that excessive trading by individual investors is deleterious to performance because individuals execute frequent small trades and face higher commission costs when they trade more (Brad M. Barber and Odean, 2000). To investigate whether the negative effect of attention on investment performance is driven by high commission costs associated with excessive trading, we construct a new investment performance measure that incorporates transaction fees. We adjust the original investment return measure (*Ret1*) by adding the transaction fee back into the monthly profit and the month-end fund amount. On the Alipay mutual fund platform, the commission fee rate for purchasing mutual funds is typically 0.1%, while the rate for selling mutual funds is 0.2%. Using this adjusted investment return measure, we rerun Equation 1 to examine the relationship between attention and future investment returns. The results are reported in Appendix, Table A1. Comparing these to the baseline results in Table 2, we observe the absolute values of the attention coefficients against future returns are slightly smaller, but remain negative and statistically significant at the 1% level, consistent with the baseline findings. These results suggest commission fees alone cannot fully explain the inferior performance of high attention investors. While high commission costs associated with excessive trading may contribute to lower returns, the negative effect of attention on performance persists after accounting for fees. This indicates other factors related to attention, like suboptimal decision-making or behavioral biases discussed in the following subsections, may play a key role in explaining the puzzling negative attention effect.

4.2.2 Attention and Trading Strategy

In this section, we explore the historical and future performance of mutual funds that investors with high attention are inclined to select.

There is much evidence documenting the tendency of retail investors to pursue investments displaying recent favourable performance (Greenwood and Nagel, 2009; Gargano and Rossi, 2018). However, the future performance of such trend-chasing strategy remains uncertain. Some literature finds that the good past performance of trend-chasing strategy persists into the future several months because of strong momentum effect in American stock markets (Jegadeesh and Titman, 1993; Moskowitz, Ooi, and Pedersen, 2012; Gargano and Rossi, 2018). Conversely, other literature indicates that trend-chasing strategies often exhibit poor future performance, as they are frequently associated with behavioural biases (Bailey, Alok Kumar, and Ng, 2011; Brad M. Barber, Huang, et al., 2022).

To elucidate the trading strategy channel of the attention effect, we conduct the following regression:

$$\text{Fund\_Return}_{j(i,t),s} = \alpha + \beta \text{Attention}_{i,t} + \text{FEs}(i,j,t) + \epsilon_{i,j,t} \tag{3}$$

The independent variable, $\text{attention}_{i,t}$, is the attention of investor i in month t as defined above. Again, we use three types of attention indicators here: $Fund\_all\_stay$, $Hold\_all\_stay$, $Market\_all\_stay$. $j(i,t)$ means the mutual fund j that is purchased by investor i in month t. The independent variable $\text{fund\_return}_{j(i,t),s}$ is the return in month s of mutual fund j that is purchased by investor i in month t. We only keep observations where investors' monthly fund net purchase is greater than zero (purchase amount is greater than redemption amount). $\text{FEs}(i,j,t)$ represents investor, mutual fund and month fixed effect. Table 4 showcases the regression results. In Panel A, the dependent variable is represented by $\text{fund\_return}_{j(i,t),t-1}$, which denotes the previous month's return of mutual fund j, purchased by investor i in month t. The coefficients associated with attention against $\text{fund\_return}_{j(i,t),t-1}$ are all positive and statistically significant. This indicates that investors with higher attention tend to select mutual funds that have higher returns in the previous month which aligns with the characteristics of a trend-chasing strategy. To further examine the future performance of this trend-chasing strategy, we replace the dependent variable with the mutual fund return in the subsequent month: $\text{fund\_return}_{j(i,t),t+1}$. The results are summarized in Panel B of Table 4. With investor, fund, and month fixed effects, the coefficients of attention against $\text{fund\_return}_{j(i,t),t+1}$ are negative and statistically significant which implies that funds chosen by more attentive investors experience poorer performance in the subsequent month. Therefore, our findings suggest that although investors paying high attention tend to pursue mutual funds with impressive recent performance, they will ultimately suffer losses due to the subsequent reversal in returns.

[Insert Table 4 Here]

To verify the regression-based results reported above, we also provide evidence based on portfolio sorts. Concretely, at the end of each month, we sort all investors' mutual funds purchases into quintile portfolios based on investors' attention level. Then we form portfolios with investor purchase amount on the mutual fund as their weight. The results are detailed in Table A2 of Appendix. The result uncovers a very strong relation between the attention spent by investors and proceeding month returns of the mutual funds they trade. For example, when we sort portfolios based on investors' attention on Alipay mutual fund platform, the average past performance of the high-attention buys equals 2.608%, the past performance of the low-attention buys equals 0.546%, and the difference in performance between the high- and low-attention buys is statistically significant at 1% level. Regarding future performance, although the disparity between the future performance of the high-attention buys and low-attention buys is not statistically significant, their differences are still negative. Consequently, these findings reinforce the conclusion that high-attention investors tend to engage in trend-chasing strategies but ultimately underperform in the future.

In addition, we investigate the relationship between investor's current attention and the longer-term historical return of the selected mutual funds. As demonstrated in Table A3 in Appendix, mutual fund returns within recent two months having a significantly positive relation with current attention while historical returns three months before are inversely related to current attention. Interestingly, the absolute value of coefficients on distant past returns are generally lower than those on recent past returns, suggesting investors with higher attention assign larger weight to recent past returns compared to distant past returns in their selection process. This observation aligns with the pattern of return extrapolation, which will be discussed more comprehensively in the subsequent section.

5 Attention and Extrapolative Beliefs

In the previous section, we find that investor who pay more attention on Alipay mutual fund platform will underperformance in the subsequent month and we explore two channels to explain such puzzling phenomena: excessive trading behaviour and trend-chasing trading strategy. As investors forms beliefs before executing tradings, we aim to explore the expectation behind trading behaviors and role of attention in crystallization of the belief.

Excessive trading and performance chasing is consistent with extrapolative beliefs. Return extrapolation refer to the tendency of individuals to project future returns of a stock based on its recent past performance (Barberis, Greenwood, et al., 2015; Da, Huang, and Jin, 2021). As extrapolative investors overweight recent returns compared to more distant returns, they are more inclined to invest in assets that have demonstrated strong recent performance. Consequently, this behaviour leads to a trend-chasing strategy and high trading volume as extrapolators flip-flop between buying and selling (Barberis, Greenwood, et al., 2018; Liao, C. Peng, and Zhu, 2022). Therefore, we examine the relationship between investor attention and extrapolative beliefs in this section. Our first objective is to verify the presence of extrapolative beliefs among investors on the Alipay mutual fund platform. We adopt the following linear regression using return expectation as the dependent variable and past mutual fund returns as the explanatory variables:

$$\text{Expectation}_{i,j,t} = \alpha + \sum_{s=1}^{5} \beta_{2,s} \text{Fund\_Return}_{j,t-s} + \text{FEs}(i,j,t) + \epsilon_{i,j,t} \tag{4}$$

where $\text{expectation}_{i,j,t}$ represents the expectation of investor i in month t towards the recent future performance of mutual fund j. Following Brad M Barber, Odean, and Zhu (2009)'s intuition, we use purchase amount of mutual funds to proxy investors' expectation for future mutual fund return. The logic is simple: investors will allocate more weight onto the investments which they believe will have superior performance in the future. We also use purchase frequency of mutual fund as an alternative return expectation for robustness. The results are reported in Table 5. Column 1, 2, 3 use fund purchase amount as return expectation proxy and Column 4, 5, 6 use fund purchase frequency as proxy. After controlling investor, month and mutual fund fixed effect, the results show clear evidence of extrapolative belief among Alipay mutual fund platform investors: almost all coefficients on the past five monthly mutual fund returns are positive and significant and the coefficients on recent past returns are in general higher than those on distant past returns.

[Insert Table 5 Here]

To explore how attention influenced on extrapolation, we firstly refine extrapolative beliefs from overall expectation. Following Da, Huang, and Jin (2021), we decompose return expectation into two components: a predicted component and the residual. where we use mutual fund purchase amount as return expectation proxy. The predicted component, labelled as predicted amount, is computed as the fitted value from Regression 4 using past 5 monthly mutual fund returns as the explanatory variables. In other words, it is the weighted average of past 5 monthly returns that best predicts return expectation and represents the extrapolative belief of investors. The residual of this regression, labelled as the residual amount, is orthogonal to past mutual fund return, denoting the non-extrapolative expectation. We thus regress mutual fund's future return on investors' expectation measure, attention measure and their interaction term and results are reported in Table 6. Column 1, 2, 3 report the results when we only include extrapolative belief and its interaction with investor attention measures and Column 4, 5, 6 only include non-extrapolative expectation and its interaction with investor attention measures. Predicted amount and residual amount and their interaction terms with investor attention measures are all included in Column 7, 8, 9.

Several intriguing findings have emerged from our analysis. Firstly, we observe that the coefficients associated with predicted amount and residual amount in relation to future mutual fund returns are consistently negative and statistically significant. This indicates a systematic bias in both extrapolative and non-extrapolative beliefs of investors. In other words, when investors hold an optimistic outlook regarding future mutual fund returns, actual returns tend to be lower. This aligns with the findings of Cassella and Gulen (2018) and Da, Huang, and Jin (2021). Second, only the coefficients preceding the interaction term between attention and predicted amount exhibit negative and statistically significant effects at a 1% level. Conversely, the coefficients preceding the interaction term between attention and residual amount are statistically insignificant. This interesting result suggests that attention primarily amplifies the bias stemming from extrapolative beliefs, while having no discernible impact on the bias associated with non-extrapolative beliefs. Furthermore, we uncover an interesting observation that when we introduce the interaction term between attention and predicted amount into the regression analysis, the coefficients associated with attention become positive and statistically significant. This implies that in the absence of extrapolative beliefs, attention can facilitate accurate investment decision-making by assisting investors in selecting mutual funds that are likely to outperform in the subsequent month.

[Insert Table 6 Here]

Apart from preceeding investor-month-fund level evidence, we provide another evidence verifying attention's amplification on extrapolation bias at the investor-month level. We apply the method of Liao, C. Peng, and Zhu (2022) to construct a degree of extrapolation (DOX) measure at the investor-month level. Specifically, we construct DOX as the weighted average past return based on investor purchases in current month:

$$DOX_{i,t} = \frac{\sum_j (\text{Fund\_Purchase\_Amount}_{i,j,t}\text{Fund\_ret}_{j,t-1})}{\sum_j \text{Fund\_Purchase\_Amount}_{i,j,t}} \tag{5}$$

Then we run the regression in Equation 1 again, incorporating DOX and its interaction term with investor attention measure in the independent variables. Table 7 reports the results. The results are similar with those in Table 6: The coefficients associated with DOX are negative and significant and the coefficients of interaction term between investor attention DOX are negative and significant. The coefficients of investor attention are positive, although insignificant.

[Insert Table 7 Here]

One potential concern towards our finding is the application of purchasing amount as the proxy for investor expectation. Mutual fund purchase may be associated with mechanisms other than beliefs, such as realization utility (Barberis and Xiong, 2012) and cognitive dissonance (Chang, Solomon, and Westerfield, 2016). Liao, C. Peng, and Zhu (2022) suggest that the main mechanism underlying investors' initial buying behavior is beliefs, defining an initial buy as the purchase of a stock not currently held in the portfolio. Consequently, we re-estimate our regressions presented in Table 6 using a subsample of initial buy transactions. The results are detailed in Table A4 of the Appendix. Additionally, we construct the DOX (degree of extrapolation) measure solely based on the purchase amounts associated with initial buy transactions. We then conduct similar regression analyses as those presented in Table 7, utilizing the initial buy DOX measure. The outcomes are reported in Table A5 of the Appendix. Importantly, these supplementary analyses serve as a cross-validation, and we find similar results to those reported in Table 6 and Table 7. This suggests that our findings are not driven by a unique definition of extrapolation. Taken together, our findings provide support for Hypothesis 3, indicating that attention serves as an amplifier for the bias associated with extrapolation beliefs among investors on the Alipay mutual fund platform.

6 Further Analysis

6.1 Discussion

The above analysis indicates a strong and positive cross-sectional relation between attention and performance, which seems different from the conclusion reached by Gargano and Rossi (2018). We speculate that the disparity lies in the variation of financial literacy among the fintech platform investors in our Alipay sample compared to the investors in Gargano and Rossi (2018)'s brokerage account. In our Alipay sample, the average age of investors is 35, with a median age of 33. But in Gargano and Rossi (2018)'s study, the average age of investors is 51, with a median age of 51. The investors in our sample are notably younger and less experienced.[8] As we discussed in Section 2, younger and less experienced investors, who are more likely to have lower financial literacy, are more likely to be irrational, and more attention may lead to information overload on these investors, leading to suboptimal investment choices. To show that how financial literacy will influence the negative effect of investors' attention on investment performance, we rerun regression 1 adding interaction term of attention and financial literacy in our independent variables.

[8] http://pdf.dfcfw.com/pdf/H301_AP202104021480703215_1.pdf

We propose two variables to serve as proxies for financial literacy. The first is investor age, as younger investors tend to have lower financial literacy and more behavioral biases (Greenwood and Nagel, 2009; Bailey, Alok Kumar, and Ng, 2011; Korniotis and A. Kumar, 2011; Brad M. Barber, Huang, et al., 2022). We report the result of investor age in the Panel A of Table 8. All coefficients before the interaction term of investor age and investor attention are positive and significant, which means that the negative attention effect on investment performance will be mitigated when people are older, i.e., have higher financial literacy. The second financial literacy measure we utilize is the ranking of fund investment amount [9]. Investors with higher financial literacy are more likely to be wealthier and be more sophisticated in their trading strategy (Bailey, Alok Kumar, and Ng, 2011; Lusardi and Mitchell, 2014). Therefore, they often have a deeper knowledge of investment products, risk management techniques, and market dynamics. This enhanced understanding enables them to make informed investment decisions and take calculated risks. Consequently, they may feel more confident in their ability to navigate the investment landscape, leading them to allocate larger amounts of capital to their portfolios. Therefore, we can reasonably infer that fund investment amount ranking can provide some insight into an individual's financial literacy. Panel B of Table 8 presents the regression result when we use fund investment amount ranking as an indicator of financial literacy. In the first three columns, when *Ret1* is used as the measure of investment performance, all coefficients prior to the interaction term are positive and statistically significant at a 95% confidence level, regardless of the attention measure employed. In the last three columns, when the alternative investment return measure, *Ret2*, is utilized, the coefficient of the interaction term is positive and significant at 90% confidence level when employing the primary attention measure, *Fund_all_stay*. Although the coefficients of the interaction term are not statistically significant at a 90% level when using *Hold_all_stay* and *Market_all_stay* as attention measures, they are still positive. In summary, investors with higher investment amounts on the Alipay mutual fund platform appear to be less influenced by negative attention effect.

[Insert Table 8 Here]

According to existing literature, young and inexperienced return are more prone to forming biased extrapolation beliefs because of low financial literacy (Cassella and Gulen, 2018; Da, Huang, and Jin, 2021). As Table 6 shows that investors gain from attention without extrapolation, we further examine whether the financial literacy mitigate the negative attention effect by reducing the amplification effect of attention on extrapolative beliefs. Therefore, we run a triple-difference regression using the methodology similar with Table 6 but add the triple interaction term of investor age, investor attention and investor expectation components (Age * Attention * Expectation Component). Results are reported in Table 9. The coefficients before the triple interaction term of extrapolation belief (Age * Attention * Predicted) are all positive and significant, which implies that younger investors are more susceptible to the amplification effect of attention on extrapolation bias. Therefore, young and inexperienced return are not only more prone to forming biased extrapolation beliefs because of

[9] Alipay categorizes mutual fund investors on their platform into three groups (Low, Medium and High) based on their overall investment amounts in 2021

low financial literacy (Cassella and Gulen, 2018; Da, Huang, and Jin, 2021), but also suffer from the amplification effect of attention on biased beliefs. Consequently, the combination of biased beliefs and attention-amplified mechanism contribute to lower future returns for these young and inexperienced investors.

[Insert Table 9 Here]

As the negative influence of attention can be mitigated by higher financial literacy, our result not only converges to the result in Gargano and Rossi (2018) but also is consistent with the behavior literature that higher attention can hinder investment performance of investors with low financial literacy (Brad M. Barber and Odean, 2008; Jiang et al., 2022).

Besides, it's worth noting that Gargano and Rossi (2018) also discover the fact that investors with high attention to their trading accounts tend to trade attention-grabbing stocks that have appreciated greatly in the past. What's different is that the good past performance of the high-attention buys in Gargano and Rossi (2018) persists into the future up to four to five months because of strong momentum effect in American stock markets (Jegadeesh and Titman, 1993; Moskowitz, Ooi, and Pedersen, 2012). However, in this paper, we study the fintech platform investors in Chinese mutual fund market. Studies have not found momentum or reverse-momentum effect in the cross-section of Chinese stocks across various horizons (Liu, Stambaugh, and Yuan, 2019; Jiang et al., 2022) and there is also no evidence documenting momentum effect in mutual fund market of China. Moreover, our analysis shows mutual funds with exceptionally recent high returns are more prone to future reversal. Consequently, Chinese mutual fund investors are unlikely to benefit from investing in these attention-grabbing funds despite substantial recent appreciation.

6.2 Robustness Tests

One potential concern regarding our findings pertains to the measurement of our investment performance. Currently, our investment returns (*Ret1* and *Ret2*) are calculated as raw returns. While it is generally preferable to assess investment performance in terms of excess returns relative to a benchmark. we would like to emphasize that our results remain unaffected by this issue, since our baseline findings continue to hold with month fixed effects, which accounts for benchmark performance. Nevertheless, in order to further address this concern, we have conducted an additional analysis where we re-estimate Regression 1 using excess investment returns as the dependent variables. In this analysis, we utilize the monthly returns of the SSE Fund Index [10] as the benchmark for the mutual fund market in China. Excess return is calculated as the difference between *Ret1* and the monthly return of the SSE Fund Index. The results of this regression analysis are presented in Column 1, 3, and 5 of Panel A in Table 10. We observe that the coefficients of investor attention with respect to future excess returns are all identical to the results in our baseline analysis (Panel A in Table 2).

[10]The SSE Fund Index, compiled by the Shanghai Stock Exchange, reflects the overall performance of the Shanghai Mutual Fund Market.

Another potential concern regarding our investment performance measure lies in the mismatch in timing between the measurement of investment returns (*Ret1* and *Ret2*) and investor attention. Specifically, *Ret1* and *Ret2* capture investment performance in the subsequent month, while attention measures reflect investor attention in the current month. According to our common sense, attention tends to influence trading behavior contemporaneously. Consequently, our current performance measure may not accurately capture the performance induced by attention in the previous month, as it includes profits or losses resulting from trading behaviors in the subsequent month. To address this issue, we propose an alternative performance measure as follows:

$$\text{Investment\_Return}_{i,t} = \frac{\sum_{j=1}^{J} \text{Fund\_Amount\_MonthBegin}_{i,j,t}\text{Fund\_Return}_{j,t}}{\sum_{j=1}^{J} \text{Fund\_Amount\_MonthBegin}_{i,j,t}} \tag{6}$$

Here, $\text{Fund\_Amount\_MonthBegin}_{i,j,t}$ represents the amount of mutual fund j in investor i's portfolio at the beginning of month t, and $\text{Fund\_Return}_{j,t}$ represents the monthly return of mutual fund j in month t. This alternative measure captures investment performance under the assumption that investors do not engage in any trading behavior during month t. We replace the dependent variable in Regression 1 with this new investment return measure and present the results in Column 2, 4, and 6 of Panel A in Table 10. Once again, we find that the coefficients of investor attention with respect to future excess returns remain negative and statistically significant.

It is plausible to consider that the negative attention effect observed may be attributed to market conditions. During periods of poor market performance, investors may struggle to accurately analyze market information, potentially leading to the observed negative attention effect on investment performance. To empirically test this claim, we classify our sample into two groups: the Bull Market group (consisting of months in which fund market returns are above 0) and the Bear Market group (consisting of months in which fund market returns are below 0). The results are presented in Table 10, Panel B, using the SSE Fund Index as the representative Chinese mutual fund market index. Remarkably, the negative attention effect maintains its statistical significance in both Bull and Bear markets, regardless of the attention measure employed. Besides, the negative attention effect is more pronounced during Bear markets. Specifically, an additional platform attention hour during a Bear market associates with a 0.186% subsequent monthly return decrease. In contrast, the attention effect is milder in Bull markets, with an additional platform hour relating to a 0.021% subsequent return decrease. Results are similar for the *Hold_all_stay* and *Market_all_stay* attention measures. Thus, while market conditions can influence the negative attention effect by mitigating it in favorable periods, they do not explain the origin of such effect. Regardless of whether market conditions are favorable or unfavorable, rational investors are expected to gain more valuable information by paying higher attention but unsophisiticated investors will suffer from naïve attention and biased beliefs.

Finally, in order to capture the potential heterogeneous impact of investor attention, we conduct a further analysis by dividing the entire sample based on investors' gender and present the results in Table 10, Panel C. Interestingly, female investors appear to be more susceptible to the attention effect compared to their male counterparts. Specifically, female investors experience a 0.068% decrease in investment performance for each additional hour spent on the Alipay mutual fund platform, whereas male investors incur a slightly lower loss of 0.043%. Furthermore, when examining the attention effects on investor portfolio-related information and market-related information, we observe a similar pattern between male and female investors. The attention effects for both genders exhibit consistent trends. These findings suggest that the impact of investor attention is not uniform across genders, with female investors being more significantly influenced by attention in terms of their investment performance.

[Insert Table 10 Here]

In conclusion, our findings consistently demonstrate the robustness of the negative effect of investor attention on future investment performance. This effect holds true across different attention measures, various investment performance measures, and different gender groups. While favorable market conditions may alleviate the negative attention effect, the root cause of this effect appears to be linked to the low financial literacy levels of investors using the Alipay mutual fund platform.

7 Conclusion

Our study sheds light on the impact of attention on investors' behavior and returns within the context of fintech platforms. Utilizing a unique Alipay mutual fund transaction dataset, we uncover a significant relationship between higher attention and lower future returns. We refer to this attention effect as 'Naïve Attention'. This negative relationship is primarily driven by excessive trading and trend-chasing among high attention investors. Furthermore, we reveal Alipay investors are particularly susceptible to biased extrapolative beliefs, which attention amplifies, resulting in biases that ultimately lead to underperformance.

Our findings provide a novel insight into the mechanism of investors' attention, demonstrating its influential role in shaping beliefs and guiding investment strategies. By expanding the existing literature on the relationship between attention and extrapolative beliefs, our study carries important implications for individual investors, financial advisors, and policymakers. It provide the insight to examine the role of attention in a different investment landscape. It also highlights the role of attention in amplifying behavioural biases, such as extrapolative beliefs, and underscores the subsequent impact on future underperformance. These insights contribute to a deeper understanding of the decision-making process of young and inexperienced retail investors on fintech platforms.

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Table 1: Summary Statistics

This Table presents summary statistics of the biographic characteristics (panel A), consume and wealth characteristics (panel B), the attention behavior (panel C), the trading behavior (panel D) and investment return (panel E) of investors in Alipay dataset. For each variable in each panel, we report the sample mean (Mean), standard deviation (Std), minimum (Min), maximum (Max) and Quartiles (P25, Median, P75). Monthly Pay, Yu'ebao Balance, are reported in yuan unit. Monthly Pay, Yu'ebao Balance, Fund Amount, Fund Purchase Amount, Fund Redemption Amount are reported in yuan unit. Fund_all_stay, Hold_all_stay and Market_all_stay are reported in minutes. *Ret*1 and *Ret*2 are expressed in percentage points and winsorized at 0.01 and 0.99 percentile. The statistics reported in panels A are computed across investors. The statistics in panels B,C,D,E are computed average first in the time-series dimension at the account-holder level. Then statistics are computed cross-sectionally.

Variable	N	Mean	Std	Min	P25	Median	P75	Max
Panel A: Investor Biographic Characteristics								
Age	58,953	35.569	9.712	20	28	33	41	85
Gender	58,953	0.452	0.498	0	0	0	1	1
Panel B: Investor Consume and Wealth								
Monthly Pay	58,953	6500	18,147	0.01	1504	3232	6544	1,483,213
Yu'ebao Balance	58,953	19,560	52,373	0	1168	5457	18,690	3,136,326
Panel C: Investor Attention Measure: Page Visit Time (In Minutes)								
Fund_all_stay	58,953	55.050	141.784	0.006	3.438	12.977	47.102	4317.927
Hold_all_stay	58,953	13.531	32.419	0.006	1.293	4.609	13.530	1719.032
Market_all_stay	58,953	41.519	117.144	0	1.766	7.471	31.803	3527.980
Panel D: Investor Trading Behavior								
Fund Amount	58,953	48,356	161,964	0	2304	11,889	42,883	19,235,320
Fund Purchase Count	58,953	8.639	35.246	0.063	0.400	1.467	5.875	2675.188
Fund Redemption Count	58,953	1.491	6.984	0	0.125	0.5	1.25	953
Fund Purchase Amount	58,953	9246	36,432	0.006	388	1968	7158	3,088,793
Fund Redemption Amount	58,953	7821	33,580	0	107	1228	5363	2,561,623
Panel E: Investor Investment Return (In Percentage Points)								
*Ret*1	58,950	0.453	1.749	-14.696	-0.020	0.326	0.893	14.279
*Ret*2	58,958	0.492	1.500	-15.448	-0.007	0.380	1.075	19.941
*Ret*1 Volatility	58,953	4.286	2.531	0	2.720	4.379	5.904	20.489
*Ret*2 Volatility	58,953	4.504	2.645	0	2.807	4.533	6.248	25.024

Table 2: Attention and Future Return: Baseline Regression

This Table presents return predictability of investor's attention at monthly level. Sample period is from August 2020 to December 2021. The dependent variable is *Ret*1 in Panel A and *Ret*2 in Panel B. *Ret*1 and *Ret*2 are expressed in percentage points and winsorized at 0.01 and 0.99 percentile. In each panel, lag of three different measures of investors' attention (in hours) are used as independent variable respectively: Fund_all_stay, Hold_all_stay, Market_all_stay. We include investors' monthly consumption, wealth and lagged monthly return as control variables. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable: $Ret1_{i,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fund_all_stay$_{i,t-1}$	-0.226***	-0.226***	-0.052***						
	(0.007)	(0.007)	(0.003)						
Hold_all_stay$_{i,t-1}$				-0.861***	-0.867***	-0.163***			
				(0.035)	(0.035)	(0.013)			
Market_all_stay$_{i,t-1}$							-0.256***	-0.255***	-0.062***
							(0.008)	(0.008)	(0.004)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.063	0.064	0.379	0.062	0.063	0.379	0.062	0.063	0.379
N	721,467	721,467	721,467	721,467	721,467	721,467	721,467	721,467	721,467
Panel B: Dependent Variable: $Ret2_{i,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fund_all_stay$_{i,t-1}$	-0.221***	-0.221***	-0.045***						
	(0.007)	(0.007)	(0.004)						
Hold_all_stay$_{i,t-1}$				-0.831***	-0.835***	-0.135***			
				(0.035)	(0.035)	(0.014)			
Market_all_stay$_{i,t-1}$							-0.250***	-0.250***	-0.055***
							(0.009)	(0.009)	(0.005)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.068	0.068	0.345	0.068	0.068	0.345	0.067	0.068	0.345
N	696,996	696,996	696,996	696,996	696,996	696,996	696,996	696,996	696,996

Standard errors in parentheses

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

Table 3: Attention, Trading Behaviour and Investment Performance

This Table presents the relationship between attention, Trading Behaviour and Investment Performance. Sample period is from August 2020 to December 2021. Panel A presents contemporaneous regression results of investor attention onto investor trading behaviour variables and Panel B presents predictive regression results of investor trading behaviour variables onto investment performance in the subsequent month. In each panel, three different measures of investors trading behaviour are employed: Monthly Fund Purchase Amount (in 1e4 RMB Yuan), Monthly Fund Purchase Frequency (Count) (in 10 times) and Monthly Excess Fund Purchase Frequency (in 10 times). Excess Purchase Frequency is defined as the regression residuals of Purchase Frequency onto Purchase Amount. Panel A use three investors' attention measure: Fund_all_stay, Hold_all_stay and Market_all_stay (in hours) as independent variables. Panel B use $Ret1$ as dependent variable. We include investors' monthly consumption, wealth and lagged monthly return as control variables. Investor fixed effect and month fixed effect are included in all regressions of Panel A. The Standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Attention and Trading Behaviour

	Fund Purchase Amount$_{i,t}$			Fund Purchase Frequency$_{i,t}$			Excess Purchase Frequency$_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fund_all_stay$_{i,t}$	0.489***			0.370***			0.317***		
	(0.026)			(0.016)			(0.016)		
Hold_all_stay$_{i,t}$		1.616***			1.810***			1.633***	
		(0.112)			(0.102)			(0.100)	
Market_all_stay$_{i,t}$			0.574***			0.380***			0.318***
			(0.032)			(0.017)			(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.449	0.444	0.448	0.768	0.776	0.764	0.758	0.765	0.754
N	781,959	781,959	781,959	781,959	781,959	781,959	781,959	781,959	781,959

Panel B: Trading Behaviour and Investment Performance

	$Ret1_{i,t}$			$Ret1_{i,t}$			$Ret1_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Purchase Amount$_{i,t-1}$	-0.029***	-0.028***	-0.009***						
	(0.007)	(0.007)	(0.002)						
Purchase Frequency$_{i,t-1}$				-0.045***	-0.044***	-0.009***			
				(0.005)	(0.005)	(0.002)			
Excess Frequency$_{i,t-1}$							-0.033***	-0.031***	-0.005***
							(0.004)	(0.004)	(0.002)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.058	0.059	0.379	0.058	0.059	0.379	0.058	0.058	0.379
N	721,467	721,467	721,467	721,467	721,467	721,467	721,467	721,467	721,467

Standard errors in parentheses

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

Table 4: Attention and Trading Strategy: Regression-Based Analysis

This Table presents results of following regression:

$$\text{fund\_return}_{j(i,t),s} = \alpha + \beta_1 \text{attention}_{i,t} + \text{FEs}(i,j,t) + \epsilon_{i,j,t}$$

i, j, t is denoted as investors, fund, month. $j(i,t)$ means the mutual fund j that is purchased by investor i in month t. fund_return$_{j(i,t),s}$ is the return in month s of mutual fund j that is purchased by investor i in month t. The sample period is from August 2020 to December 2021. We only keep observations where investors' monthly fund net purchase is greater than zero (purchase amount is greater than redemption amount). Panel A (B) show the results of fund_return$_{j,t-1}$(fund_return$_{j,t+1}$). fund_return are expressed in percentage points. In each panel, lag of three different measures of investors' attention (in hours) are used as independent variable respectively: Fund_all_stay, Hold_all_stay, Market_all_stay. FEs(i,j,t) represents investor, fund and month fixed effect. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable: fund_return$_{j,t-1}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fund_all_stay$_{i,t}$	0.280***	0.073***	0.058***						
	(0.019)	(0.007)	(0.006)						
Hold_all_stay$_{i,t}$				0.753***	0.147***	0.121***			
				(0.099)	(0.029)	(0.023)			
Market_all_stay$_{i,t}$							0.330***	0.093***	0.074***
							(0.025)	(0.009)	(0.007)
R^2	0.096	0.323	0.397	0.092	0.322	0.396	0.094	0.323	0.397
N	1,664,124	1,664,124	1,664,124	1,664,124	1,664,124	1,664,124	1,664,124	1,664,124	1,664,124
Panel B: Dependent Variable: fund_return$_{j,t+1}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fund_all_stay$_{i,t}$	-0.107***	-0.005	-0.009**						
	(0.013)	(0.003)	(0.004)						
Hold_all_stay$_{i,t}$				-0.230***	-0.010	-0.019**			
				(0.049)	(0.008)	(0.008)			
Market_all_stay$_{i,t}$							-0.136***	-0.006	-0.011**
							(0.016)	(0.005)	(0.005)
R^2	0.043	0.357	0.388	0.041	0.357	0.388	0.042	0.357	0.388
N	1,698,352	1,698,352	1,698,352	1,698,352	1,698,352	1,698,352	1,698,352	1,698,352	1,698,352
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes	No	No	Yes

Standard errors in parentheses

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

Table 5: Extrapolation: Expectation and Past Mutual Fund Performance

This Table presents results of following regression:

$$\text{expectation}_{i,j,t} = \alpha + \sum_{s=1}^{5} \beta_{2,s} \text{fund\_return}_{j,t-s} + \text{FEs}(i,j,t) + \epsilon_{i,j,t}$$

where i, j, t is denoted as investors, fund, month. The sample period is from August 2020 to December 2021. We only keep observations where investors' monthly fund net purchase is greater than zero (purchase amount is greater than redemption amount). We use Mutual Fund Purchase Amount and Purchase Frequency as proxies for investors' return expectation for mutual fund. Fund Purchase Amount are expressed in 1e3 yuan unit. Fund Return are expressed in percentage points. FEs(i, j, t) represents investor, month and fund fixed effect. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Fund Purchase Amount$_{i,j,t}$			Fund Purchase Frequency$_{i,j,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
fund_return$_{j,t-1}$	0.023***	0.018***	0.029***	0.006***	0.007***	0.012***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
fund_return$_{j,t-2}$	0.001	0.006*	0.017***	0.004***	0.005***	0.008***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
fund_return$_{j,t-3}$	-0.004**	-0.007***	0.009***	0.007***	0.003***	0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
fund_return$_{j,t-4}$	-0.019***	-0.006***	0.008***	-0.009***	0.003***	0.007***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
fund_return$_{j,t-5}$	-0.027***	-0.023***	-0.001	-0.003***	-0.000	0.003***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes
R^2	0.370	0.370	0.383	0.369	0.373	0.412
N	1,633,268	1,633,268	1,633,268	1,633,268	1,633,268	1,633,268

Standard errors in parentheses

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

Table 6: Extrapolation: Investor Attention and Expectation Decomposition

This table shows how attention can magnify investors' expectation bias. We regression mutual fund's future return (Fund_Return) on investors' expectation measure, attention measure and their interaction term. Following Da, Huang, and Jin (2021), the investors' expectation measure (Purchase Amount) are decomposed into two components: a predicted component (Predicted Amount) explained by past mutual fund returns and the residual component (Residual Amount) that is orthogonal to past mutual fund returns. We only keep observations where investors' monthly fund net purchase is greater than zero (purchase amount is greater than redemption amount). Predicted Amount and Residual Amount as used as different expectation measure. We use Fund_all_stay, Hold_all_stay, Market_all_stay as investor attention measures. Mutual Fund future return Fund_Ret is expressed in basis points and investor attention are represented in hours. Fund purchase amount are represented in 1000 yuan unit. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Fund_Return$_{j,t+1}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Attention × Predicted$_{i,j,t}$	-2.040***	-4.908**	-2.674***				-2.041***	-4.946**	-2.674***
	(0.457)	(2.013)	(0.508)				(0.457)	(2.005)	(0.508)
Attention × Residual$_{i,j,t}$				0.001	-0.015	0.002	0.001	-0.018	0.002
				(0.004)	(0.019)	(0.004)	(0.003)	(0.019)	(0.003)
Predicted Amount$_{i,j,t}$	-723.894***	-727.838***	-724.001***				-723.894***	-727.793***	-724.005***
	(3.411)	(3.477)	(3.260)				(3.410)	(3.471)	(3.260)
Residual Amount$_{i,j,t}$				-0.092**	-0.066*	-0.096**	-0.100***	-0.063*	-0.104***
				(0.043)	(0.038)	(0.041)	(0.038)	(0.036)	(0.036)
Fund_all_stay$_{i,t}$	0.746**			-0.907**			0.747**		
	(0.355)			(0.377)			(0.355)		
Hold_all_stay$_{i,t}$		1.478			-1.972**			1.538	
		(1.011)			(0.897)			(1.013)	
Market_all_stay$_{i,t}$			1.001**			-1.126**			0.999**
			(0.448)			(0.527)			(0.448)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.389	0.389	0.389	0.428	0.428	0.428	0.389	0.389	0.389
N	1,633,254	1,633,254	1,633,254	1,633,254	1,633,254	1,633,254	1,633,254	1,633,254	1,633,254

Standard errors in parentheses

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

Table 7: Extrapolation: Investor Attention and DOX

This Table presents the relationship between extrapolation degree and Investor Attention, Investor Future Return. Sample period is from August 2020 to December 2021. Degree of extrapolation measures DOX are constructed following Liao, C. Peng, and Zhu (2022). We regress *Ret*1 on DOX, attention and their interaction term. DOX and investment return are expressed in percentage points and investor attention are represented in hours. We include investors' monthly consumption, wealth and lagged monthly return as control variables. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Ret1_{i,t}$		
	(1)	(2)	(3)
Attention × $\text{DOX}_{i,t-1}$	-0.002***	-0.003**	-0.003***
	(0.000)	(0.001)	(0.000)
$\text{DOX}_{i,t-1}$	-0.066***	-0.070***	-0.066***
	(0.002)	(0.002)	(0.002)
$\text{Fund\_all\_stay}_{i,t-1}$	0.002		
	(0.004)		
$\text{Hold\_all\_stay}_{i,t-1}$		0.007	
		(0.013)	
$\text{Market\_all\_stay}_{i,t-1}$			0.002
			(0.005)
Controls	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
R^2	0.518	0.518	0.518
N	236,118	236,118	236,118

Standard errors in parentheses

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

Table 8: Attention and Future Return: Interaction with Financial Literacy

This Table presents results for linear regression of investors' monthly investment return (Two measures: $Ret1$ and $Ret2$) onto monthly attention measures and their interaction with different financial literacy proxies. In each panel, we use one financial literacy proxy measure to interact with attention measures. Panel A(B) use investor age (Fund Investment Amount Ranking) as financial literacy proxy. Interaction is the interaction term between attention measures and financial literacy proxy measure. $Ret1$ and $Ret2$ are expressed in percentage points and winsorized at 0.01 and 0.99 percentile. In each panel, lag of three different measures of investors' attention (in hours) are used as independent variable respectively: Fund_all_stay, Hold_all_stay and Market_all_stay.We include investors' monthly consumption, wealth and lagged monthly return as control variables. Investor fixed effect and month fixed effect are included in all regressions. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Ret1$			$Ret2$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Interaction with Investor Age						
$\text{Interaction}_{i,t-1}$	0.001^{***}	0.004^{***}	0.001^{***}	0.001^{***}	0.003^{***}	0.001^{***}
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
$\text{Fund\_all\_stay}_{i,t-1}$	-0.099^{***}			-0.081^{***}		
	(0.012)			(0.014)		
$\text{Hold\_all\_stay}_{i,t-1}$		-0.338^{***}			-0.258^{***}	
		(0.044)			(0.050)	
$\text{Market\_all\_stay}_{i,t-1}$			-0.116^{***}			-0.098^{***}
			(0.015)			(0.017)
R^2	0.379	0.379	0.379	0.345	0.345	0.345
Panel B: Interaction with Fund Investment Amount Ranking						
$\text{Interaction}_{i,t-1}$	0.031^{**}	0.131^{**}	0.035^{**}	0.025^{*}	0.096	0.028
	(0.013)	(0.061)	(0.017)	(0.014)	(0.062)	(0.017)
$\text{Fund\_all\_stay}_{i,t-1}$	-0.145^{***}			-0.118^{***}		
	(0.039)			(0.041)		
$\text{Hold\_all\_stay}_{i,t-1}$		-0.548^{***}			-0.418^{**}	
		(0.182)			(0.184)	
$\text{Market\_all\_stay}_{i,t-1}$			-0.165^{***}			-0.136^{***}
			(0.049)			(0.051)
R^2	0.379	0.379	0.379	0.345	0.345	0.345
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	721,467	721,467	721,467	696,996	696,996	696,996

Standard errors in parentheses

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

Table 9: Extrapolation: Attention, Expectation Decomposition and Investor Age

This table shows how attention can magnify investors' expectation bias. We regression mutual fund's future return (Fund_Return) on investors' expectation measure, attention measure, investor age and their interaction term. Following Da, Huang, and Jin (2021), the investors' expectation measure (Purchase Amount) are decomposed into two components: a predicted component (Predicted Amount) explained by past mutual fund returns and the residual component (Residual Amount) that is orthogonal to past mutual fund returns. We only keep observations where investors' monthly fund net purchase is greater than zero (purchase amount is greater than redemption amount). Predicted Amount and Residual Amount as used as different expectation measure. We use Fund_all_stay, Hold_all_stay, Market_all_stay as investor attention measures. Mutual Fund future return Fund_Ret is expressed in basis points and investor attention are represented in hours. Fund purchase amount are represented in 1000 yuan unit. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$\text{Fund\_Return}_{j,t+1}$		
	(1)	(2)	(3)
Age × Attention × $\text{Predicted}_{i,j,t}$	0.158***	0.565***	0.191***
	(0.028)	(0.129)	(0.033)
Age × Attention × $\text{Residual}_{i,j,t}$	0.000*	0.001	0.001*
	(0.000)	(0.002)	(0.000)
Attention × $\text{Predicted}_{i,j,t}$	-9.390***	-30.273**	-11.655***
	(1.407)	(6.256)	(1.629)
Attention × $\text{Residual}_{i,j,t}$	-0.020	-0.060	-0.023
	(0.012)	(0.076)	(0.014)
Predicted $\text{Amount}_{i,j,t}$	-719.143***	-724.751***	-719.342***
	(3.526)	(3.571)	(3.335)
Residual $\text{Amount}_{i,j,t}$	-0.075**	-0.060*	-0.079**
	(0.037)	(0.035)	(0.036)
$\text{Fund\_all\_stay}_{i,t}$	0.807**		
	(0.354)		
$\text{Hold\_all\_stay}_{i,t}$		1.583	
		(1.047)	
$\text{Market\_all\_stay}_{i,t}$			1.090**
			(0.441)
Investor FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
R^2	0.428	0.428	0.428
N	1,633,254	1,633,254	1,633,254

Standard errors in parentheses

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

Table 10: Attention and Future Return: Robustness

This Table presents robustness test for baseline regression. Sample period is from August 2020 to December 2021. Panel A employ investors Excess Return$_{i,t}$ (Alternative Return$_{i,t}$) in Columns 1, 3 and 5 (Columns 2, 4 and 6) as dependent variable. Excess Return$_{i,t}$ is defined as the difference between Ret1$_{i,t}$ and the monthly return of the SSE Fund Index in month t. Alternative Return$_{i,t}$ calculate investment performance under the assumption that investors i does not engage in any trading behavior in the month t. Panel B divides the whole sample into two groups by fund market return: Bull (Bear) Market is defined as months when the fund market returns are above (below) 0. We use SSE fund index (SHA: 000011) to represent China's mutual fund market index. Panel C divides the whole sample into two groups by gender: Male and Female. The dependent variable in Panel B and C is Ret1$_{i,t}$. $Ret1$ is expressed in percentage points and winsorized at 0.01 and 0.99 percentile. In each panel, lag of three different measures of investors' attention (in hours) are used as independent variable respectively: Fund_all_stay,Fund_all_stay, Hold_all_stay and Market_all_stay. We include investors' monthly consumption, wealth and lagged monthly return as control variables. Investor fixed effect and month fixed effect are included in all regressions. Standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Attention: Fund_all_stay		Attention: Hold_all_stay		Attention: Market_all_stay	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Different Investment Performance Measure						
	Excess Return$_{i,t}$	Alternative Return$_{i,t}$	Excess Return$_{i,t}$	Alternative Return$_{i,t}$	Excess Return$_{i,t}$	Alternative Return$_{i,t}$
Attention$_{i,t-1}$	-0.052***	-0.054***	-0.162***	-0.192***	-0.062***	-0.062***
	(0.003)	(0.003)	(0.013)	(0.012)	(0.004)	(0.004)
R^2	0.518	0.404	0.518	0.404	0.518	0.404
N	721,467	701,423	721,467	701,423	721,467	701,423
Panel B: Subsample Analysis by Mutual Fund Market Condition						
	Bear Market	Bull Market	Bear Market	Bull Market	Bear Market	Bull Market
Attention$_{i,t-1}$	-0.186***	-0.021***	-0.657***	-0.058***	-0.211***	-0.025***
	(0.008)	(0.004)	(0.037)	(0.013)	(0.010)	(0.004)
R^2	0.411	0.425	0.411	0.425	0.411	0.425
N	294,648	426,819	294,648	426,819	294,648	426,819
Panel C: Subsample Analysis by Investor Gender						
	Male	Female	Male	Female	Male	Female
Attention$_{i,t-1}$	-0.043***	-0.068***	-0.130***	-0.221***	-0.051***	-0.082***
	(0.004)	(0.005)	(0.016)	(0.019)	(0.005)	(0.007)
R^2	0.373	0.389	0.373	0.389	0.373	0.389
N	389,598	331,869	389,598	331,869	389,598	331,869
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Appendix

Table A1: Attention and Future Return: Commission Fee

This Table presents return predictability of investor's attention at monthly level. Sample period is from August 2020 to December 2021. The dependent variable is $Ret1$ with commission fee. In each panel, lag of three different measures of investors' attention (in hours) are used as independent variable respectively: Fund_all_stay, Hold_all_stay, Market_all_stay. We include investors' monthly consumption, wealth and lagged monthly return as control variables. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: $Ret1_{i,t}$ with Commission Fee								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fund_all_stay$_{i,t-1}$	-0.223***	-0.224***	-0.049***						
	(0.007)	(0.006)	(0.003)						
Hold_all_stay$_{i,t-1}$				-0.852***	-0.859***	-0.153***			
				(0.035)	(0.035)	(0.013)			
Market_all_stay$_{i,t-1}$							-0.252***	-0.253***	-0.058***
							(0.008)	(0.008)	(0.004)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.066	0.067	0.376	0.066	0.067	0.376	0.066	0.067	0.376
N	723,005	723,005	723,005	723,005	723,005	723,005	723,005	723,005	723,005

Standard errors in parentheses

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

Table A2: Attention and Trading Strategy: Protfolio-Sort Analysis

This table reports the past performance and past performance of portfolios ranked by investor attention. At the end of each month, we sort all investors' mutual funds purchases into quintile portfolios based on investors' attention level. Then we form portfolios with investor purchase amount on the mutual fund as their weight. We use Fund_all_stay, Hold_all_stay and Market_all_stay as our attention measures. Past return and future return are reported in percentage points. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Past Performance: $\text{fund\_return}_{j,t-1}$			
Quintiles	Fund_all_stay	Hold_all_stay	Market_all_stay
1 (Low)	0.546	0.768	0.594
2	1.186	1.491	1.160
3	1.763	1.844	1.843
4	2.256	2.235	2.251
5 (High)	2.608	2.592	2.606
High - Low	2.062	1.823	2.012
t-stats	2.905***	2.997***	2.961***

Panel B: Future Performance: $\text{fund\_return}_{j,t+1}$			
Quintiles	Fund_all_stay	Hold_all_stay	Market_all_stay
1 (Low)	0.667	0602	0.653
2	0.426	0.377	0.414
3	0.450	0.466	0.461
4	0.449	0.539	0.440
5 (High)	0.409	2.592	0.456
High - Low	-0.210	-0.193	-0.197
t-stats	-0.311	-0.337	-0.302

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

Table A3: Extrapolation: Attention and Past Fund Performance

This Table presents results of following regression:

$$\text{fund\_return}_{j(i,t),t-s} = \alpha + \beta_{1,s}\text{attention}_{i,t} + \text{FEs}(i,j,t) + \epsilon_{i,j,t}$$

where $s = 1, 2, 3, 4, 5$. i, j, t is denoted as investors, fund, month. $j(i,t)$ means the fund j that is purchased by investor i in month t. The sample period is from August 2020 to December 2021. We only keep observations where investors' monthly fund net purchase is greater than zero (purchase amount is greater than redemption amount). Panel A (B, C) use Fund_all_stay (Hold_all_stay, Market_all_stay) as attention_var. fund_ret are expressed in percentage points. Attention_var are expressed in hours. FEs(i, j, t) represents investor, month and fund fixed effect. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	fund_return$_{j,t-1}$	fund_return$_{j,t-2}$	fund_return$_{j,t-3}$	fund_return$_{j,t-4}$	fund_return$_{j,t-5}$
Panel A: Attention Variable: Fund_all_stay					
Attention$_{i,t}$	0.058***	0.011**	-0.018***	-0.017***	-0.023***
	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.397	0.424	0.429	0.459	0.480
N	1,664,124	1,659,725	1,653,354	1,644,333	1,633,268
Panel B: Attention Variable: Hold_all_stay					
Attention$_{i,t}$	0.121***	0.018**	-0.053***	-0.028***	-0.035***
	(0.023)	(0.009)	(0.011)	(0.010)	(0.010)
R^2	0.396	0.424	0.429	0.459	0.480
N	1,664,124	1,659,725	1,653,354	1,644,333	1,633,268
Panel C: Attention Variable: Market_all_stay					
Attention$_{i,t}$	0.074***	0.015***	-0.020***	-0.023***	-0.031***
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
R^2	0.397	0.424	0.429	0.459	0.480
N	1,664,124	1,659,725	1,653,354	1,644,333	1,633,268
Investor FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table A4: Extrapolation: Investor Attention and Expectation Decomposition Within Initial Buy

This table shows how attention can magnify investors' expectation bias. We regression mutual fund's future return (Fund_Return) on investors' expectation measure, attention measure and their interaction term. Following Da, Huang, and Jin (2021), The investors' expectation measure (Purchase Amount) are decomposed into two components: a predicted component (Predicted Amount) explained by past mutual fund returns and the residual component (Residual Amount) that is orthogonal to past mutual fund returns. We only keep observations where investors' monthly fund net purchase is greater than zero (purchase amount is greater than redemption amount) and the observation of initial buys. Predicted Amount and Residual Amount as used as different expectation measure. We use Fund_all_stay, Hold_all_stay, Market_all_stay as investor attention measures. Mutual Fund future return Fund_Ret is expressed in basis points and investor attention are represented in hours. Fund purchase amount are represented in 1000 yuan unit. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Fund_Return$_{j,t+1}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Attention × Predicted$_{i,j,t}$	-1.510**	-5.631**	-1.681**				-1.511**	-5.640**	-1.683**
	(0.611)	(2.723)	(0.702)				(0.611)	(2.718)	(0.703)
Attention × Residual$_{i,j,t}$				-0.001	-0.003	-0.001	0.001	-0.005	0.001
				(0.002)	(0.022)	(0.002)	(0.002)	(0.022)	(0.002)
Predicted Amount$_{i,j,t}$	-855.250***	-856.274***	-856.567***				-855.289***	-856.300***	-856.603***
	(6.521)	(6.459)	(6.428)				(6.522)	(6.454)	(6.430)
Residual Amount$_{i,j,t}$				-0.099**	-0.103**	-0.099**	-0.133***	-0.119***	-0.133***
				(0.043)	(0.048)	(0.041)	(0.040)	(0.045)	(0.039)
Fund_all_stay$_{i,t}$	0.893			0.318			0.896		
	(0.588)			(0.615)			(0.586)		
Hold_all_stay$_{i,t}$		1.384			0.327			1.403	
		(1.305)			(1.034)			(1.304)	
Market_all_stay$_{i,t}$			1.222			0.447			1.227
			(0.776)			(0.857)			(0.774)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.472	0.472	0.472	0.423	0.423	0.423	0.472	0.472	0.472
N	438,943	438,943	438,943	438,943	438,943	438,943	438,943	438,943	438,943

Standard errors in parentheses

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

Table A5: Extrapolation: Investor Attention and Initial Buy DOX

This Table presents the relationship between extrapolation degree and Investor Attention, Investor Future Return. Sample period is from August 2020 to December 2021. Degree of extrapolation measures Initial Buy DOX are constructed following Liao, C. Peng, and Zhu (2022). We regress $Ret1$ on Initial Buy DOX, attention and their interaction term. Initial Buy DOX and investment return are expressed in percentage points and investor attention are represented in hours. We include investors' monthly consumption, wealth and lagged monthly return as control variables. The standard errors, clustered by investor, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Ret1_{i,t}$		
	(1)	(2)	(3)
Attention × Initial Buy DOX$_{i,t-1}$	-0.001***	-0.002	-0.001***
	(0.000)	(0.001)	(0.000)
Initial Buy DOX$_{i,t-1}$	-0.012***	-0.014***	-0.012***
	(0.002)	(0.002)	(0.002)
Fund_all_stay$_{i,t-1}$	-0.011**		
	(0.005)		
Hold_all_stay$_{i,t-1}$		-0.035**	
		(0.016)	
Market_all_stay$_{i,t-1}$			-0.013**
			(0.006)
Controls	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
R^2	0.561	0.561	0.561
N	131,090	131,090	131,090

Standard errors in parentheses

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