Inside the Mind of Retail Short Sellers *

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Abstract This paper exploits individual trading records from a large brokerage service to investigate the trading patterns of retail investors who take short positions in stocks. Short sellers' research activity does not suggest that they increase the amount of attention paid to stocks before taking short positions. Although short sellers report lower risk tolerance in their MiFID II questionnaires, their order behavior in short positions indicates greater risk-seeking behavior. Short positions, compared to long positions, constitute larger portions of overall portfolios and are more highly leveraged. Compared with other retail investors, short sellers perform worse, and their profit variability is greater.

Keywords short positions; trading behavior; retail investors;

JEL classification G11; G40; G41

*Data were obtained under a nondisclosure agreement with a financial institution. We thank the data provider for the use and explanation of their data. We are grateful for the excellent comments and suggestions from Nick Hirschey and participants of the Brown Bag seminar at Nova School of Business and Economics, the ecfs doctoral seminar, and the HVB doctoral seminar. Any errors, misrepresentations, and omissions are our own.

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1 Introduction

Retail investors have become increasingly important players in financial markets (Eaton et al., 2022). Today, retail investors are responsible for a large share of the trading volume in financial markets. In July and August 2020, the share volume of retail investors in U.S. equity markets amounted to more than 25% (McCrank, 2021). Even more extreme, in Asia, individual investors often account for more than 80% of trading volume (Osipovich, 2020). In Europe, the share of total trading carried out by retail investors has more than doubled since 2019, albeit at a significantly lower level (from 2% to approximately 5%, Chatterjee (2021)). Episodes such as the GameStop frenzy in 2021 further illustrate the importance of retail investors for financial markets. This frenzy showed that the new generation of retail investors is capable of moving entire markets (Pedersen, 2022).

Both retail trading and short selling trading are on the rise. While Barber and Odean (2008) report that short sales reflect only 0.3% of trades in their sample from the 1980s and 1990s, Kelley and Tetlock (2017) find that approximately 6% of the dollar volume of all executed orders are short sales. Short selling further increased following the 2018 volatility shock, the so-called "Volmageddon." Moreover, retail investors who take short positions participate in important market events such as the GameStop frenzy (Hasso et al., 2021). While the literature argues that retail short sales are informed (Kelley and Tetlock, 2017), on average, it also suggests that the new generation of retailers using fintech brokerages engages in more attention-induced trading than do other retail investors (Barber et al., 2022). In general, retail investors may behave more impulsively than do other investors or be driven by social media trends (Hu et al., 2021). Thus, whether earlier findings on retail short sellers also apply to the new generation of investors remains unclear.

As an increasing number of brokerage services allow retail investors to take short positions in stocks, either directly or via derivatives such as options (Bryzgalova et al., 2023) or contracts for differences (CFDs), an in-depth analysis of the behavior of the new generation of retail short sellers is highly relevant. In the aftermath of the GameStop saga, the

United States House Committee on Financial Services called for the Securities and Exchange Commission and the Financial Industry Regulatory Authority to draft new rules to address market risks highlighted by the frenzy. While the GameStop frenzy drove stock prices up, similar events involving short sellers may push prices down. Retail short sellers driving down the prices of financial institutions could create an even greater concern than that created when retailers drive up the prices of firms such as GameStop.

In this paper, we exploit individual trade data from a large retail brokerage service that allows its customers to take short positions using CFDs to shed light on the short trading behaviors of the new generation of retailers. Our main findings suggest that—although the literature typically portrays short sellers as sophisticated investors (Kelley and Tetlock, 2017)—the new generation of those taking short positions does not seem to align with this characterization. The investors in our sample conduct less (not more) due diligence prior to creating short positions. Short sellers also trade on the basis of attention, sentiment, and other behavioral biases, such as the alphabetical selection of stocks. Our analysis indicates that short sellers, compared to other retail investors, perform worse and that their profit variability is greater. We also find that investors who take short positions are, on average, more willing to take risks than are other investors.

We start by profiling investors who are most likely to take short positions. In our sample, the typical short seller is a young male investor with above-average trading experience and a shorter trading horizon. According to their stated preferences in the Markets in Financial Instruments Directive II (MiFID II) questionnaire, investors who take short positions are less willing to take risks than are those who do not take such positions.

We then study which stocks investors typically short. We find that investors use the same stocks to take long and short positions. Investors who take short positions are influenced by attention and sentiment, similar to other retail investors; they are also influenced by behavioral biases such as the alphabetical selection of stocks and the last month's minimum return.

On the basis of the arguments that short sellers are informed (Kelley and Tetlock, 2017) and that paying attention to particular stocks yields larger returns (Gargano and Rossi, 2018), we investigate the research activities of the investors in our sample and ask whether investors who engage in short selling are truly "paying attention." We find that short sellers are less likely to add stocks to their watchlist before trading them than are nonshort sellers. Additionally, investors who take short positions seem to pay less attention to the stocks that they short than they do to the stocks in which they take long positions.

We then turn to the *"how"* and analyze the order and trading characteristics of investors who take short positions. Their order behavior reveals that investors who take short positions make more use of limit orders and cancel their orders more frequently than do other investors. Investors who take short positions also use higher stop-loss limits than do other investors. Investors who take short positions also set higher stop-loss limits for their short positions than they do for their long positions. Higher stop-loss limits indicate a greater willingness to take losses or, in other words, a greater willingness to take risks. This finding stands in contrast to their self-stated risk preferences from MiFID II questionnaires.

Next, we turn to trading characteristics. Investors who take short positions trade more frequently, take higher leverage, and hold their positions for a shorter holding period. These investors also invest smaller portions of their portfolios in individual positions. However, when taking short positions, these are larger than their long positions, on average.

We find that retail investors who take short positions, compared to those who do not, perform worse and that their profit variability is greater. Overall, these results indicate that the new generation of investors who take short positions is not particularly sophisticated.

In our last step, we exploit the cross-country nature of our data and analyze whether the propensity to take short positions varies across Europe. We find that it does vary. In an attempt to explain why investors are more willing to take short positions in some countries than in other countries, we find that cross-country variations in market sentiment are correlated with these differences. In contrast, differences in financial literacy or cultural backgrounds do not provide convincing explanations for such cross-country variations.

This paper contributes to three strands of research. First, we contribute to the literature on retail investor behaviors that goes back to a long list of contributions by Brad Barber and Terrance Odean (Barber and Odean, 2000; Barber et al., 2009; Barber and Odean, 2013). More recently, such research has studied the behaviors of a novel group of retail investors—Robinhood investors—in great detail (Barber et al., 2022; Welch, 2022). Bryzgalova et al. (2023) and Kogan et al. (2024) extend this literature to the behaviors of retail investors in terms of options (Bryzgalova et al., 2023) and the crypto market (Kogan et al., 2024). We further extend this literature by adding a nuanced picture of the short selling activities of retail investors using CFDs.

Second, we contribute to research on the information processing of short sellers. Boehmer et al. (2008) find that as a group, short sellers are well informed. Heavily shorted stocks underperform lightly shorted stocks by a risk-adjusted average of 1.16% over the following 20 trading days. This finding suggests that short sellers are important contributors to efficient market prices. Boehmer et al. (2020) argue that short sellers know more than do analysts, given the predictive ability of short sales after controlling for information in analyst actions. Engelberg et al. (2012) conclude that institutional short sellers are skilled information processors; the authors attribute the trading advantage of short sellers to their ability to analyze publicly available information. The study by Gamble and Xu (2017) uses a dataset similar to ours at the account level and shows that some retail investors seem to be informed about particular stocks. By selling these stocks short, retailers are able to earn an alpha of 15%; when buying the stocks, they earn an alpha of 27%. We contribute to this strand of literature by analyzing whether the new generation of investors who take short positions are informed and sophisticated.

Finally, this study also sheds additional light on investors' risk-taking at the micro level. This work studies, among other things, the impact of gains and losses on future risk-taking (Kuhnen, 2015; Imas, 2016), the impact of push notifications on risk-taking (Arnold et al., 2022), and how retail investors react to new regulations that aim to curb their risk-taking (Pelster, 2024). By studying the risk-taking of investors who take short positions, we also contribute to this strand of literature. Our results indicate that short sellers are more willing to take risks, even though their self-stated risk preferences suggest the opposite, than are nonshort sellers.

This study is also related to the literature highlighting the predictive ability of (retail) short traders. Institutional short sellers help make market prices more efficient (Boehmer and Wu, 2012; Chang et al., 2014), whereas retail short sellers are able to predict negative stock returns (Boehmer and Song, 2020; Diether et al., 2008; Kelley and Tetlock, 2017). Boehmer et al. (2021) provide suggestive evidence that retail orders may contain information at the firm level before they are incorporated into prices.

The remainder of this paper proceeds as follows. In Section 2, we describe the institutional background of retail short selling. Section 3 describes our data and methodology. Section 4 presents our main results, while Section 5 tests some assertions on how geographical differences in short selling may be explained. The final section concludes the paper.

2 Institutional background

Taking short positions is a trading strategy that allows investors to bet on price declines. Short selling constitutes a significant portion of trading activity, particularly during periods of market volatility. Studies suggest that short selling accounts for approximately 24% of New York Stock Exchange (NYSE) and 31% of Nasdaq reported share volume (Diether et al., 2008). With respect to retail investors, Kelley and Tetlock (2017) find that in their data spanning from 2003 to 2007 from two related over-the-counter market centers, approximately 6% of the dollar volume of all executed trades are short sales.

In recent years, neobrokerages in particular have given retail investors access to short positions. Some brokerages allow their customers access to derivative contracts such as options or CFDs to take short positions. Retail option trading has significantly increased (Bryzgalova et al., 2023), and CFD trading has become particularly popular in Europe and Asia (Arnold et al., 2022). Other brokerages allow their customers to take outright short positions by first borrowing an asset from the broker, selling it at the current market price, and later repurchasing it at the then-prevailing market price to return the asset to the lender.

A CFD is a financial agreement where the price mirrors that of the underlying security (see, e.g., Arnold et al., 2022; Brown et al., 2010, for more details). The two parties involved agree to replicate the underlying security's price and settle the resulting price changes when the position is closed. Unlike futures contracts, CFDs do not have a fixed maturity date and can be closed at any time on the basis of the prevailing market price, which aligns with the underlying security price.

Regardless of whether investors trade options or CFDs or borrow shares directly, margin accounts play a pivotal role in enabling short selling. A margin account allows investors to borrow funds from a broker to purchase securities, using the securities and cash in the account as collateral. This approach enables trading with leverage, amplifying both potential gains and losses. Investors who initiate a short position are required to deposit a percentage of the trade's value as collateral with the broker. This margin serves as a safeguard against potential losses. Theoretically, short positions can result in unlimited losses if the asset's price increases instead of decreases.

Traditionally, trading on margin involves margin calls (Hull, 2021). A margin call occurs when the account's equity falls below the broker's required maintenance margin. The investor is then required to deposit additional funds or sell assets to restore the margin balance. The failure to meet a margin call can lead to the broker liquidating the account's holdings to cover the shortfall. However, the broker does not have to (or may not be able to) close the position, which means that investors can lose more money than was originally deposited in the margin account (unlimited liability).

However, not all margin trading comes with unlimited liability. In fact, several CFD brokers provide access to limited liability trading and limit the losses of investors to the initial margin. Limited liability means that the broker automatically closes the position if the margin is depleted. Moreover, investors are not required to make an additional payment if the margin becomes negative upon closure. Such scenarios can arise from significant price movements, particularly during periods when markets are closed.

Our data provider allows its customers to take short positions using limited liability CFD trading.

3 Data and methodology

3.1 Data

We use individual trade data from a large retail brokerage service that serves clients from various countries. The broker allows its customers to trade stocks, foreign exchange (FX), cryptocurrencies, and CFDs on various underlyings.

Our data include the trades executed with the broker between January and July 2019. Our data include more than 230,000 retail investors who executed approximately 12 million trades (round trips) during this time span. The trade records include information about the timestamp, underlyings, transaction price, whether the position is opened or closed, whether it is long or short, the portfolio weight, the leverage, and the net return for closed positions.

The data also comprise order data, which contain information on whether the orders placed are executed or canceled. When opening a position, investors are required to submit an exit strategy after gains (take-profit limit) and after losses (stop-loss limit). The data also contain both take-profit and stop-loss limits.

We also have access to daily portfolio returns on investment (ROIs) for investors with at least one open position and to investors' demographics. In addition, we can observe whether investors add specific assets to their "watchlist" or visit the research pages that comprise information on a particular asset. We use those page visits as a proxy for investors' research activities (see also Gargano and Rossi, 2018).

We collect market data such as daily stock prices, book-to-market ratios, firm sizes for individual stocks, and environmental, social, and governance (ESG) data from Eikon and U.S. (excess) market returns from Kenneth French's website. Information on short interest in a share is from Compustat.

3.2 Variables

We estimate several variables for our analyses. First, we estimate $Fraction_{it}$ as the proportion of trades in stock i in month t relative to all trades on stocks with the broker during month t.

We use several variables to analyze the factors that influence retail investors' stock selection, many of which are inspired by Koval and Steshkova (2022).

- Frequency of losses (FL_{it})/Weighted frequency of losses (WFL; WFL_{it}) denotes the ratio of days with negative returns to the total number of trading days in the previous month (Koval and Steshkova, 2022). For WFL_{it}, more recent days carry greater weight, as suggested by Da et al. (2021).

- Lottery type (LT_{it}) assigns a value of 1 for "lottery-type" stocks, as defined by Kumar (2009), and 0 otherwise.

- Max return (MAX_{it}) is the highest return in the previous month (Bali et al., 2011).

- Min return (MIN_{it}) is the lowest return in the previous month (Caglayan et al., 2023).

- Idiosyncratic volatility ($IVOL_{it}$) is calculated as the standard deviation of residuals from a time-series regression of daily excess stock returns on daily excess market returns, as well as the Fama–French factors (small minus big (SMB), high minus low

(HML), robust minus weak (RMW), conservative minus aggressive (CMA), and momentum) over month t (Ang et al., 2006).

- Alphabet ($Alphabet_{it}$) is a binary variable that takes a value of 1 for stocks with names that are alphabetically in the top 5% of all stocks in our sample and 0 otherwise.

- Size ($Size_{it}$) is defined as the logarithm of the stock price multiplied by the number of common shares (Bali et al., 2011).

- Book to market (BM_{it}) is the average ratio of book value to market value in month t.

- Market beta ($Beta_{it}$) is the slope coefficient obtained from a time-series regression of daily excess stock returns on daily excess market returns over the past 12 months (Sharpe, 1964; Lintner, 1975).

- Skewness ($SKEW_{it}$) is the skewness of daily realized stock returns over the last five years (Arditti, 1967). For stocks without a five-year history, we adjust the period accordingly.

- Momentum (MOM_{it}) denotes the cumulative return over the past 12 months (Jegadeesh and Titman, 1993).

- Short-term reversal (STR_{it}) is the return in month t (Jegadeesh, 1990).

- Illiquidity ($ILLIQ_{it}$) is measured according to the illiquidity metric proposed by Amihud (2002).

- Idiosyncratic skewness ($ISKEW_{it}$) is the skewness of the residuals from a time-series regression of daily excess stock returns on daily excess market returns and Fama–French factors (SMB, HML, RMW, CMA, and momentum) over the past five years (Mitton and Vorkink, 2007). For stocks without a five-year history, we adjust the period accordingly.

- Coskewness ($COSK_{it}$) denotes the slope coefficient from a time-series regression of daily excess stock returns on excess market returns and squared excess market returns over the past five years (Harvey and Siddique, 2000).
- ESG (ESG_{it}) denotes ESG rating data from Refinitiv at the end of 2018.

All the variables are winsorized at the 1% level to mitigate the influence of extreme values.

3.3 Summary statistics

To analyze the stock characteristics that influence retail investors in their stock selection, we first identify the 250 most frequently traded stocks in 2019, following the methodology outlined by Kogan et al. (2024). Table A.1 in the Appendix provides a complete list of these stocks. We present summary statistics for the trading data in Table A.2 in the Appendix.

First, we study how the short interest by retailers in our sample relates to aggregate market positions. To this end, we regress short interest in a share (from Compustat) on the number of short sales in our data. We summarize the regression results in Table 1. The significant coefficient of 0.020 (t-statistic of 5.00) indicates a positive correlation between increased short interest in the trading data and aggregate short market interest.

Table 1

4 Results

4.1 Short-seller characteristics

We start our main analysis by profiling investors who take short positions. Figure 1a shows that our sample comprises a high proportion of male investors, which matches the overall picture in the literature. The proportion of investors who take short positions and are male is greater than the that of investors who do not take short positions and are male (t-statistic of 11.509). Investors are considered as taking short positions if they have taken at least one short position with the broker. Investors who engage in short positions tend to be younger than investors who do not take short positions (Figure 1b). Our results further indicate that investors who take short positions tend to be more likely to be experienced investors than are those who do not take short positions (Figure 1c). Perhaps, surprisingly, Figure 1d indicates that investors who take short positions are, on average, less willing to take risks than are investors who do not take short positions. Finally, and not surprisingly, Figure 1e suggests that investors who take short positions have, on average, a short trading horizon. Table 2 summarizes supporting evidence on these observations in a regression table. Overall, the type of investor who takes short positions is a young male investor with above-average trading experience, a short trading horizon and a low willingness to take risks.

Figure 1 and Table 2

4.2 Which stocks do short sellers trade?

In our next step, we aim to identify the (type of) stocks that investors who take short positions typically short. Are those the same stocks that (other) investors trade long? Do these stocks stand out in terms of their characteristics? Do short sellers conduct momentum or contrarian trades?

We begin by identifying the 30 most traded stocks separately for long and short positions. We visualize these stocks in Figure 2. Tesla Motors takes first place in both groups. The heavy short positions in Tesla are not unique to our sample. In 2018, Tesla was one of the most heavily shorted stocks in the world. At that time, many investors were concerned with production delays and negative cash flow, believing that the company was overvalued. Elon Musk criticized short sellers publicly and, in August 2018, made comments about taking Tesla private and posted the following on Twitter (now X): "funding secured." The post triggered a short squeeze, forcing short sellers to buy back shares to cover their positions. In the following, Tesla's stock continued to attract both long and short investors, highlighting the considerable disagreement among investors.

Apart from Tesla, we also do not observe any significant differences between stocks that are used for long trades and those used for short trades. Many prominent stocks, such as those of Amazon, Apple, Facebook, Netflix, Boeing, and Microsoft, appear in list of the 30 most traded stocks.

Figure 2

Do short sellers trade these stocks following a momentum or a contrarian strategy? Inspired by Kogan et al. (2024), we investigate the relationship between past returns and the (log) active share change separately for long and short positions. We summarize the results in Table 3. In line with Barrot et al. (2016), Kogan et al. (2024), and others, we find that investors trade contrarian in stocks, both for long and for short positions. However, the degree of sensitivity is different for short and long positions. For long positions, we find a significant coefficient of -14.70 (t-statistic of 4.53), whereas the coefficient for short positions is 4.78 (t-statistic of 4.60).

Table 3

4.3 Short sellers and behavioral biases

Retail investors are known to be influenced by attention and sentiment in their trading decisions (Barber and Odean, 2008; Cookson et al., 2024). Considering that short sellers have a reputation for being informed (Kelley and Tetlock, 2017), we expect investors who take short positions to be less affected by behavioral biases such as attention and sentiment. Consequently, we investigate the extent to which attention and sentiment influence short-selling behavior.

As suggested by Cookson et al. (2024), we use the first principal component across Twitter, StockTwits, and Seeking Alpha. Cookson et al. (2024) find that the attention paid on Twitter, StockTwits, and Seeking Alpha is highly correlated, whereas sentiment is distinct across platforms. We regress the fraction of short trades for a specific stock, that is, the number of all short trades in the stock in month t, divided by the number of all trades in the stock in our data in month t, and the logarithm of the number of short (long) trades in stock i in month t, respectively, on attention (sentiment) in month t or on attention (sentiment) in the previous month $(t-1)$.

We summarize our results in Table 4. In Panel A, we focus on attention. Columns (1) and (2) indicate that the fraction of short positions increases in both contemporaneous and lagged attention. The contemporaneous correlation between attention and short trading amounts to .019 (t-statistic of 3.89). Thus, on high-attention days for a given stock, investors take more short positions than they do long positions. As this observation can be explained not only by an increasing number of short positions but also by a decreasing number of long positions, we next disentangle these effects. The results in Columns (3)–(6) suggest that both long and short trading increase in attention, but short trading increases in attention to a greater degree, thereby yielding an increase in the fraction of short positions. Thus, our results indicate that retail investors are guided by attention in their short trades, just as they are in their long trades.

Next, we turn to sentiment in Panel B. Here, we find a coefficient of -0.004, with a t-statistic of -2.157, in Column (2) on the correlation between the fraction of short positions and lagged sentiment. The coefficient on the contemporaneous correlation in Column (1) is not significantly different from 0 (t-statistic of 1.62). Again, we disentangle the effect and find negative coefficients, both contemporaneous and lagged on the number of short positions, but no effect for the number of long positions. This finding indicates that the number of short positions decreases with positive sentiment, thereby decreasing the fraction of short positions.

Overall, these findings suggest that retailers of the new generation of retail investors who take short positions are just as much affected by attention and sentiment as are investors who take long positions.

Table 4

Attention and sentiment are not the only phenomena from behavioral finance that have been documented to affect trading behaviors. In fact, the literature has shown that many stock characteristics can influence the trading behavior of retail investors. In our next step, we aim to investigate which characteristics influence retail short sellers in terms of their stock selection. Important factors from the literature are firm characteristics such as size (Hou and Van Dijk, 2019), book-to-market value (Pontiff and Schall, 1998), the alphabetical order of the firm name (Itzkowitz et al., 2016), and the ESG score (Pedersen et al., 2021). Investors are also known to be influenced by stock return characteristics such as beta (Sharpe, 1964), illiquidity (Amihud, 2002), max return (Bali et al., 2011), min return (Caglayan et al., 2023), lottery-type stocks (Kumar, 2009), and the WFL (Koval and Steshkova, 2022). Other factors are statistical indicators such as idiosyncratic volatility (Ang et al., 2009), (idiosyncratic) skewness (Mitton and Vorkink, 2007), and coskewness (Harvey and Siddique, 2000).

We estimate these factors for the 250 most traded stocks and run an ordinary least squares (OLS) regression on the fraction of trades in a particular stock relative to all trades. We separately study (1) all trades, (2) only long positions, and (3) only short positions. We summarize the results in Table 5.

The following two factors, in particular, are especially noteworthy: investors who take short positions are influenced by 1) the alphabetical order of the firm name and 2) the last month's minimum return. These observations, and the results in the table in general, underline the observation that investors who take short positions are also affected by prominent stock characteristics, similar to investors who take long positions.

Table 5

4.4 Do short sellers pay attention?

Inspired by the observation that investors who take short positions seem to be affected by similar behavioral biases as are their counterparts who take only long positions (i.e., attention and sentiment), we now turn to the question of whether investors taking short positions pay greater attention to their trading activities. The literature on (retail) short selling generally supports the idea that short sellers are informed investors (Kelley and Tetlock, 2017). Therefore, it is reasonable to expect that investors using short positions are particularly attentive to their trades. Gargano and Rossi (2018) demonstrate that researching stocks leads to higher trading returns. Given that short positions are often perceived as riskier than are long positions, it follows that investors who take short positions may dedicate significant attention to their trading strategies. To explore this situation, we leverage our data to analyze the research behaviors of investors engaging in short selling and examine whether they truly "pay attention."

First, we study whether or not investors who take short positions pay particular attention to the stocks that they trade. To proxy for "paying attention," we use two variables. We capture whether investors add a stock to their watchlist and whether they research a stock, in the spirit of Gargano and Rossi (2018). We control for demographics and make use of stock and date fixed effects. We summarize the results in Panel A of Table 6. Note that the comparison is at the investor level and that the analysis includes long positions.

The results indicate that investors who take short positions are less likely to add the stocks they trade to their watchlist than are investors who do not take short positions. This situation is true for stocks that they trade for the first time as well as for stocks that they trade at any time. We find a negative and significant coefficient of -0.057 (t-statistic of -17.27) for stocks that are traded for the first time and a negative and significant coefficient of -0.046 (t-statistic of -7.32) for stocks traded at any time.

Turning to investors' research activities, we find no differences between investors who take short positions and other investors. Columns (3) to (6) indicate coefficients that are not significantly different from 0 for both first-time positions in a stock (Columns (3) to (5)) and any-time positions in a stock (Column (6)) and for research activities immediately before the trade (Column (3)) or a longer period before the trade (Columns (4) to (6)).

Table 6

Next, we move to investors who take short positions and study whether these investors act differently when taking long versus short positions. We summarize the results in Panel B of Table 6. Perhaps surprisingly, the results suggest that investors seem to "pay less attention" to stocks when they take short positions than when they take long positions. The coefficients in Columns (1) and (2) are negative (-0.006, t-statistics greater than 3). Similarly, we find differences in investors' research activities—when they trade a stock for the first time. Columns (3) to (5) indicate negative coefficients of -0.003 to -0.004, with t-statistics close to or greater than 3. When investors trade a stock repeatedly, we do not find differences in their research activities for short positions compared with long positions (Column (6)).

Thus, investors who take short positions seem to pay less attention to the stocks they short. Of course, we cannot rule out that investors obtain their information from different sources, such as newspaper outlets or social media platforms.

Finally, we conduct an analysis in the spirit of Gargano and Rossi (2018) to study whether paying attention actually yields larger returns. We summarize the results in Table 7. The results support the findings of Gargano and Rossi (2018). The dependent variable is the investor's holding-period return (HPR). *Research* 24 is a dummy variable that takes a value of 1 if the investor has visited the research page for a stock within 24 hours prior to trading that stock and 0 otherwise. The positive coefficient of 0.34, with a t-statistic of 2.34, indicates that trades with prior research generate higher returns, as suggested by Gargano and Rossi (2018). By extending the above analysis, we study the impact of research activities on the profitability of short sales. To this end, we interact *Research* 24 with a dummy variable that takes a value of 1 for short positions and 0 otherwise (*Short sale*). We control for *holding period*. We find a negative effect on *Short sale* (-2.32, t-statistic of 3.29) and a nonsignificant coefficient on the interaction. This finding indicates that short sales, on average, yield lower HPRs than do long sales, independent of whether or not the investor researched the stock prior to the trade.

Table 7

4.5 Order behavior of short sellers

Thus far, we have studied who takes short positions and which stocks investors short. In our next step, we focus on *how* investors take short positions. To this end, we examine their order behavior and the characteristics of their trades. We begin with their order behavior.

Figures 3a and 3b show that investors who take short positions make more use of limit orders and cancel orders more frequently than do those who take long positions. This finding may be interpreted as more sophisticated order behavior. Investors plan ahead for orders to be executed for certain limits rather than using market orders. When the stock does not move in line with the limits investors have set, investors cancel the limit orders again.

Investors must set limits for closing positions when opening new positions (Heimer et al., 2024, see also). These limits reflect revealed risk preferences on the basis of incentivized behavior. Figures 3c and 3d indicate higher stop-loss and take-profit limits for short positions than for long positions. Higher stop-loss limits indicate a greater willingness to take losses, i.e., a greater willingness to take risks.

We provide a formal analysis of investors' stop-loss and take-profit limits in Table 8. Again, we compare investors who take short positions to those who do not in Panel A and focus on the differences between long and short positions for investors who take short positions in Panel B. The dependent variables are the stop-loss limit in Column (1) and the take-profit limit in Column (2). We control for leverage, as positions that are highly leveraged should be accompanied by larger limits.

We find a positive and significant coefficient of 1.23 (t-statistic of 7.02) on *short seller* in Column (1). This finding indicates that investors who take short positions show a greater willingness to take losses, or, in other words, a greater willingness to take risks than do those who do not take short positions. This observation is surprising, as it contradicts investors' self-reported risk preferences (see Figure 1d and Table 2). In Panel B, we make a similar observation at the position level. Investors who take short positions set larger stop–loss limits for their short positions than for their long positions. Therefore, short sellers are more willing to take risks with their short positions than with their long positions.

Turning to take-profit limits in Column (2), we do not observe significant differences between a) investors who take short positions and those who do not (Panel A) and b) the long and short positions of investors who take short positions (Panel B).

Figure 3 and Table 8

4.6 Trading characteristics of short sellers

Next, we analyze the trading characteristics of investors who take short positions. In particular, we study the trading intensity of investors, their average portfolio weights, the leverage of their positions, and their holding periods. Again, we compare investors who take short positions with those who do not and short and long positions for investors who take short positions. We summarize the results in Table 9.

We begin with Panel A. Beginning with investors' trading intensity, we observe that investors who take short positions are, on average, more active traders than are those who do not take short positions. Column (1) shows a coefficient of .26, with a t-statistic of 25.70. Investors who take short positions use smaller portfolio weights (Column (2), -1.02, t-statistic of 3.41); greater leverage (Column (3), 1.25, t-statistic of 19.24), which is in line with our previous willingness-to-take-risks observation from order behavior (see Table 8); and a shorter holding period for their trades (Column (2), -8.92, t-statistic of 30.68).

Focusing on investors who take short positions and a comparison between their long and short trading activities, our results show that short positions constitute slightly larger portions of their overall portfolios (.13, t-statistic of 1.80) and that the holding period is significantly shorter for short sales than for long sales (-1.93, t-statistic of 16.75). Investors who take short positions do not show significantly different leverage usage for their short sales than for their long sales (t-statistic of .80).

Table 9

4.7 Trading performance of short sellers

Finally, we turn to the trading outcomes of investors who take short positions. To this end, we estimate regressions on investors' HPRs and on the standard deviation of HPRs as a proxy for return variation, following Arnold et al. (2022) and Pelster (2024).

We summarize the results in Table 10, following the same procedure as before. Overall, investors who take short positions perform worse than do investors who do not engage in short selling. The HPR is 1.18 percentage points lower for short sellers (t-statistic of -3.95), and the standard deviation is significantly greater. This observation is in line with previous findings in the literature (Barber et al., 2023).

Investors who take short positions also perform significantly worse with their short positions than with their long positions. The performance is 2.13 percentage points lower, with a t-statistic of -3.04. At the position level, the standard deviation is lower for short positions than for long positions (-0.065, t-statistic of 3.96).

Table 10

5 Geographical differences in short selling

Having studied the "who, what, and how" of short selling, we now ask whether short selling is the same worldwide. We exploit the fact that the brokerage service is active in multiple countries. First, we examine investors' propensity to take short positions in various countries. To this end, we calculate the fraction of short positions at the country level. We summarize the results in Figure 4. Interestingly, we observe significant differences in investors' tendency to take short positions across countries in Europe. For example, short selling seems to be far less prevalent in Poland than in the UK or even in Iceland.

What factor(s) might explain these differences in short selling at the country level? We propose and test three alternative explanations. In particular, we propose that market sentiment, financial literacy, and cultural attitudes toward risk may explain cross-country differences in the propensity to take short positions.

First, we consider investor sentiment. As we have already documented in Table 4, investors take fewer short positions when sentiment is at a high level. However, sentiment may vary at the country level. Sentiment may, on average, be higher in one country than in another country. We exploit the "Twitter Sentiment Geographical Index" by Chai (2022) to study cross-country differences in market sentiment. We regress *short sale* on daily sentiment at the country level and summarize the results in Panel A of Table 11. We find a negative coefficient of -0.085, with a t-statistic of 1.99. This finding indicates that an increase in sentiment is associated with a decrease in short sales. Consistent with our analysis of the impact of sentiment at the firm level in Table 4, sentiment can explain differences in the propensity to take short positions.

Table 11

Second, we consider financial literacy. The level of financial literacy also influences retail investors' ability to engage in short selling. Taking short positions can be interpreted as a more sophisticated trading strategy than is taking only long positions. In countries where retail investors are better educated on complex financial strategies, they may be more comfortable with the risks associated with taking short positions. Conversely, in countries with lower levels of financial literacy, retail investors may shy away from short positions due to a lack of understanding. Thus, a greater financial literacy may provide investors with the self-confidence necessary to make use of such sophisticated trading strategies. In line with this argument, Lusardi and Mitchell (2014) emphasize that higher financial literacy is associated with more sophisticated investment behavior.

We exploit the Financial Literacy Around the World: Standard & Poor's Ratings Services Global Financial Literacy Survey by Klapper, Lusardi, and van Oudheusden. The survey provides financial literacy scores for various countries as of 2016. Given that financial literacy at the country level is likely relatively constant, we believe that financial literacy at the country level in 2016 is a valid proxy for financial literacy in 2019. We regress *short sale* on the financial literacy score and summarize the results in Panel B of Table 11. We find a coefficient that is not significantly different from 0 (t-statistic of 0.93). This finding indicates that financial literacy does not help explain investors' propensity to take short positions at the country level. One reason for this may be that perceived financial literacy may be more important than actual financial literacy for investors to be willing to take short positions.

Finally, we argue that the cultural background of investors may explain their propensity for various trading strategies, in line with Hofstede's (1980) cultural dimensions theory. Cultural differences also play a role in how willing retail investors are to engage in high-risk strategies like taking short positions. In countries where the culture favors risk-taking and speculative investments, retail investors may be more inclined to short positions. On the other hand, in more conservative or risk-averse cultures, taking short positions might be seen as too risky or speculative, deterring retail investors from participating. Thus, individuals from countries with lower levels of uncertainty avoidance may be more likely to engage in "riskier" investment behaviors than may those from other countries. Similarly, Chui et al. (2010) show that investors in individualistic cultures are more likely to engage in speculative trading strategies than are those in other cultures. Considering that taking short positions is a more speculative trading strategy, we expect investors from individualistic cultures to be more inclined to take short positions.

We exploit the cultural dimensions from Hofstede (1980) and summarize the results in

Panel C of Table 11. The results indicate that investors in individualistic cultures are less inclined to take short positions (coefficient of -0.02 with a t-statistic of -1.94), whereas we do not find a significant relationship between uncertainty avoidance and short selling.

Overall, this section indicates significant cross-country differences in investors' propensity to take short positions. These differences can best be explained by differences in market sentiment across countries.

6 Conclusions

Retail investors have become a transformative force in financial markets, playing a significant role in shaping market dynamics with their trading activities. This paper focuses on the behaviors and characteristics of the new generation of retail investors who take short positions. Despite its growing influence, little is known about this subset of retail investors. The findings of this paper elucidate the strategic and behavioral tendencies of retail short sellers, offering important insights.

Our analyses show that the new generation of retail short sellers differs significantly from the traditional portrayal of sophisticated and highly informed investors. In contrast to the previous literature, which focuses on a different type of retail investor and suggests that short sellers typically exhibit informed trading behaviors (Kelley and Tetlock, 2017), we find that the new generation of retail short sellers is characterized by lower levels of due diligence. Their trading decisions appear to be driven by attention and sentiment rather than by careful research. This new generation pays less attention to stocks prior to taking short positions, as evidenced by its reduced likelihood of adding these stocks to its watchlists or researching them. We also find evidence that behavioral biases such as the alphabetical selection of stocks or minimal past returns influence stock selection for short positions. Overall, these findings challenge the notion that short positions are driven primarily by sophisticated analyses and point to the growing role of heuristics and emotions in retail short selling. In line with investors paying less attention to their short positions, we also find that investors who take short positions underperform investors who do not take short positions. Similarly, short sellers realize lower returns with their short positions than with their long positions. Overall, these results indicate that the new generation of investors who take short positions is not particularly sophisticated.

We also find that retail short sellers exhibit distinctive risk preferences and trading patterns. While their stated risk preferences suggest a lower tolerance for risk, their actual behavior indicates a greater willingness to incur losses. Both the use of larger stop-loss limits and larger leveraged positions for investors who engage in short selling than for those who do not engage in short selling indicate greater risk tolerance. The profit variability of short sellers is also greater, reflecting the greater risk associated with their trades. Additionally, retail short sellers demonstrate a higher frequency of trades and shorter holding periods than do other retail investors. These characteristics highlight a more speculative approach to short selling, where the goal appears to be exploiting short-term market movements rather than engaging in long-term strategic investments. This behavior underscores the importance of understanding the psychology and motivations behind retail short sellers, as their decisions often deviate from traditional risk-return frameworks.

Overall, our findings raise important questions about the broader implications of retail short selling. While short selling can improve market efficiency by correcting overvalued stocks, the less-informed and emotion-driven nature of the new generation of retail short sellers' decisions may contribute to market distortions. Impulsive short trades, amplified or driven by social media trends or market sentiment, could exacerbate volatility and create mispricings, as already documented during the GameStop saga (Pedersen, 2022).

The rise of new brokerages such as Robinhood and the influence of online communities such as Reddit's WallStreetBets further have amplified these trends. The democratized access to financial markets allows retail investors to engage in (sophisticated) trading strategies such as short selling. However, the democratization of financial markets also presents challenges. Retail short selling, potentially lacking institutional-level expertise and resources, may inadvertently disrupt market stability. Thus, regulators must carefully consider the implications of these developments. While retail participation enriches market diversity and liquidity, it also necessitates safeguards to prevent excessive volatility and protect less experienced investors from substantial losses.

In conclusion, our study provides valuable insights into the evolving role of retail short sellers in financial markets. Future research should further investigate the drivers of retail short-selling behavior, including the role of social media, gamification, and financial education. Moreover, policymakers and market participants should collaborate to strike a balance between encouraging retail participation and ensuring market stability. Furthermore, as retail short selling continues to grow, understanding and addressing its complexities are essential for fostering a fair, efficient, and inclusive financial market ecosystem.

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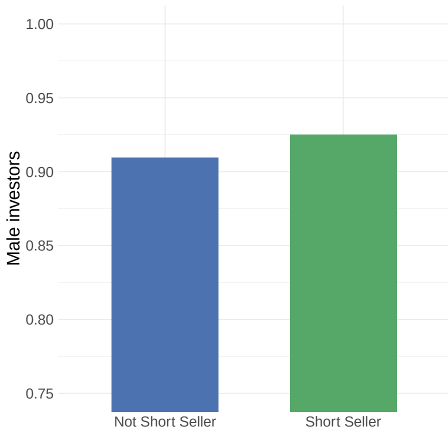
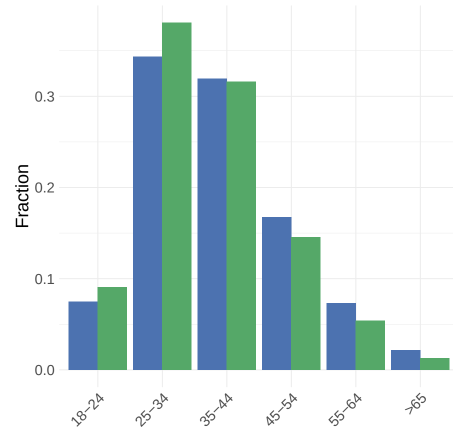
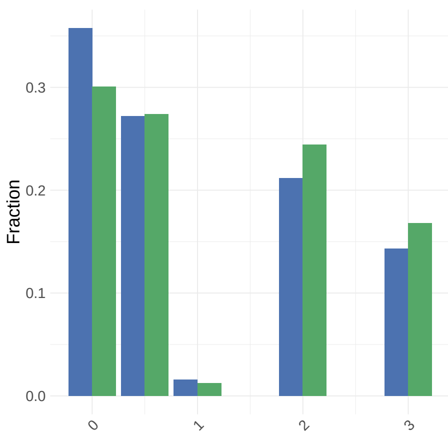


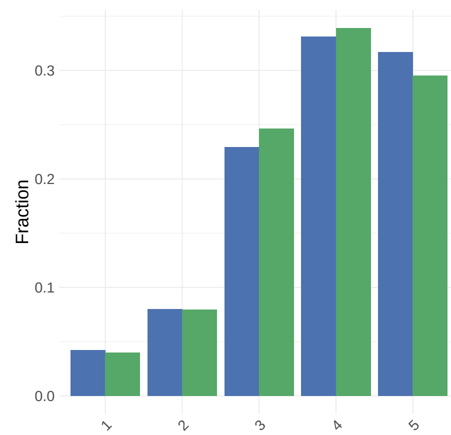
(a) Gender



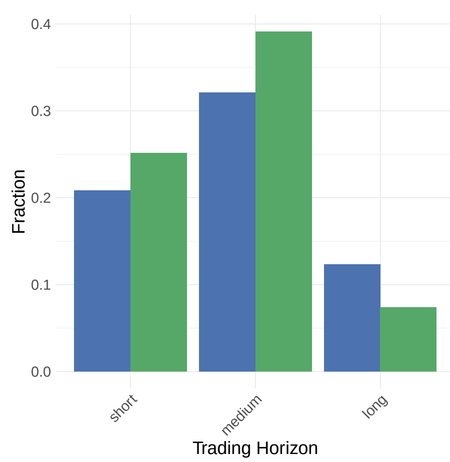
(b) Age



(c) Trading experience



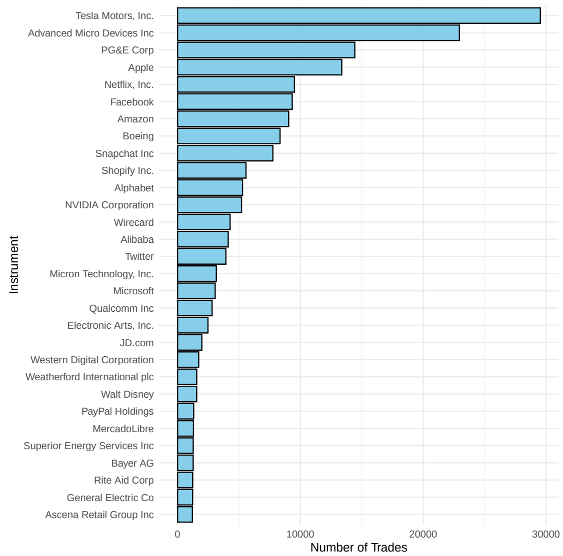
(d) Stated risk preferences



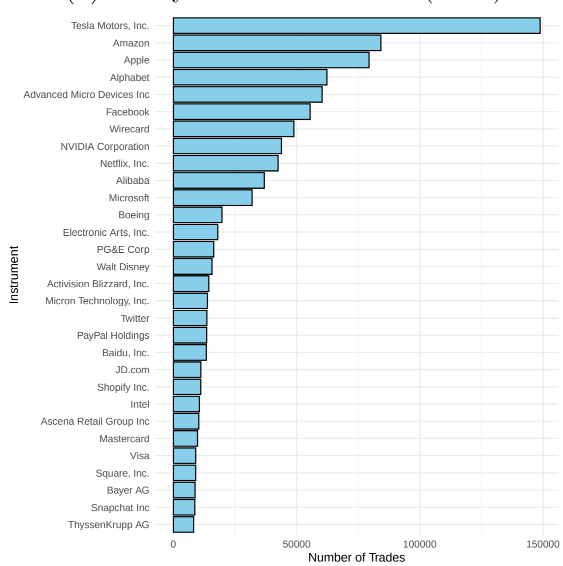
(e) Intended trading horizon

Figure 1: Investor characteristics

This figure compares investors who take short positions and those who do not take short positions with respect to various characteristics. Investors are considered "short sellers" if they take at least one short position with the broker. Panel A considers gender, Panel B considers investors' age, Panel C investors self-reported trading experience in years, Panel D investors' self-reported risk preferences on a 5-point Likert-scale, and Panel E investors' self-reported trading horizon. Data are from a questionnaire issued by the broker upon account opening. Green denotes investors who take short positions, and blue denotes investors who do not take short positions.



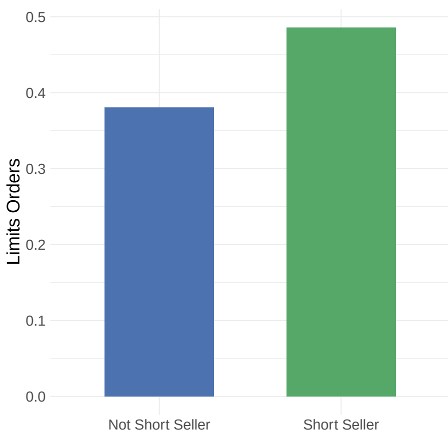
(a) Thirty most traded stocks (short)



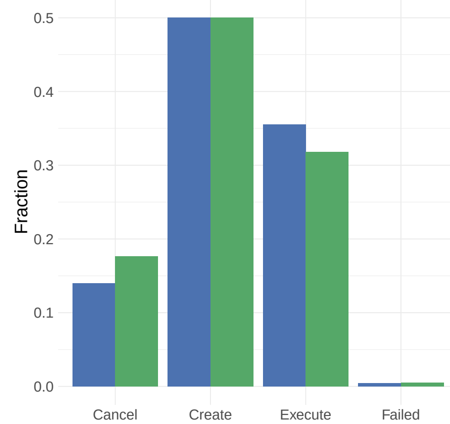
(b) Thirty most traded stocks (long)

Figure 2: Thirty most traded stocks

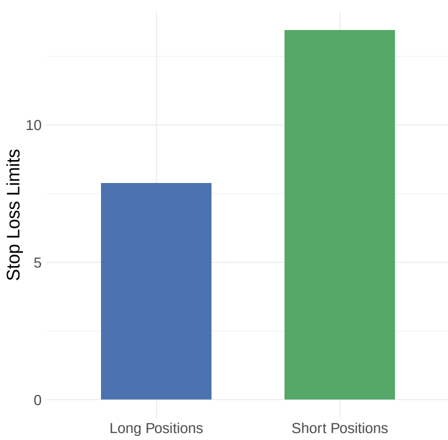
This figure shows the total number of trades for the 30 most traded stocks in our sample between January and July 2019 separately for long and short positions.



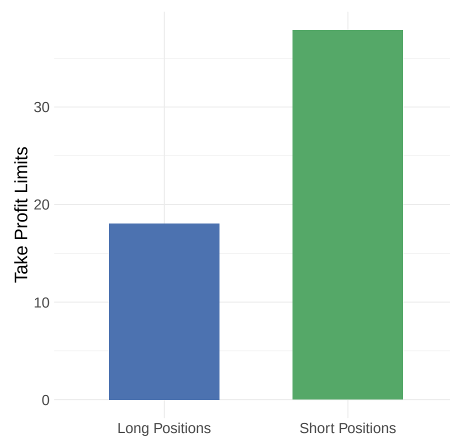
(a) Short sellers and limit orders



(b) Short sellers and order execution



(c) Short positions and stop-loss limits



(d) Short positions and take-profit limits

Figure 3: Order behavior

This figure shows the order behavior of investors. Panel A shows the use of limit orders separately for investors who take short positions and for investors who do not take short positions, Panel B shows order execution separately for investors who take short positions and for investors who do not take short positions, Panel C shows stop-loss limits separately for short positions and for long positions, and Panel D shows take-profit limits separately for short positions and for long positions. Panels C and D are restricted to orders from investors who take short positions and compare their order behavior for long and short positions. In Panel A and B, green shows investors who take short positions, and blue shows investors who do not take short positions. In Panel C and D, green shows short positions, and blue shows long positions.

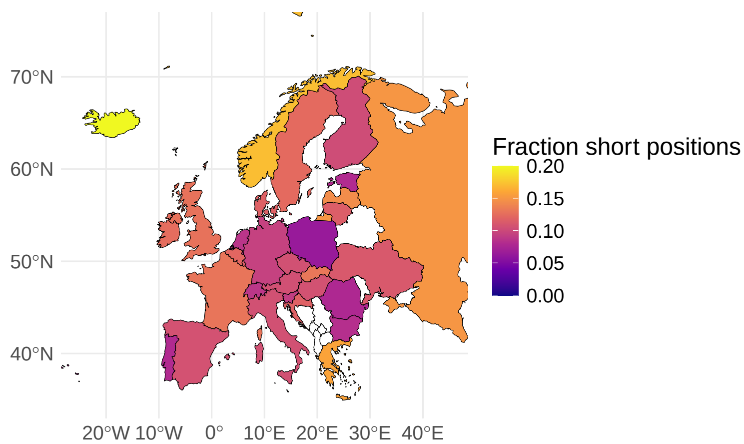


Figure 4: Fraction of short positions across Europe

This figure shows the fraction of short positions across European countries. Fraction is the number of short positions in a country divided by the number of total trades in that country from January to July 2019.

Table 1: Short interest

This table shows the results of OLS regression on the short interest in a stock. The dependent variable is the logarithm of short interest in a stock from Compustat. The independent variable is the logarithm of the number of short positions in a stock in the brokerage data. The sample runs from January to July 2019. Robust standard errors; *t*-statistics are in parentheses.

	log(short interest)
log(# short positions)	0.020
	(5.008)
Stock fixed effects	Yes
Obs.	$7,084$
Adj. R^2	0.949

Table 2: Demographics

This table shows the results of a logit regression analysis on a dummy variable that takes a value of 1 for investors who have taken at least one short position with the broker and 0 otherwise (*Short seller*). Dependent variables include investor demographics and self-reported trading preferences. Data are from a questionnaire issued by the broker upon account opening. The sample runs from January to July 2019; z-values are in parentheses.

	(1) Short seller	(2) Short seller
Female	(Baseline)	(Baseline)
Male	1.202	1.139
	(9.004)	(5.078)
Age 18-24	(Baseline)	(Baseline)
Age 25-34	0.921	0.895
	(−4.046)	(−4.074)
Age 35-44	0.822	0.791
	(−9.426)	(−8.501)
Age 45-54	0.726	0.704
	(−13.818)	(−11.690)
Age 55-64	0.618	0.607
	(−16.363)	(−13.663)
Age >65	0.504	0.475
	(−13.770)	(−12.533)
Risk preference		0.971
		(−4.796)
Experience		1.106
		(15.476)
Horizon short		(Baseline)
Horizon medium		1.006
		(0.452)
Horizon long		0.503
		(−30.822)
Obs.	233,161	154,835
Log Likelihood	−107,945.459	−74,108.586
Deviance	215,890.918	148,217.172
AIC	215,904.918	148,239.172
BIC	215,977.435	148,348.623

Table 3: Momentum or contrarian?

This table reports the results of OLS regression that investigates the relationship between past returns and the active share change. *ret* is the weekly return of a stock. *CR past* 1 *week* is the last week's cumulative return. Δ*Short positions* and Δ*Long positions* are the weekly change in the number of short and long positions in a stock, respectively. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

	(1) ΔShort positions	(2) ΔLong positions
$\log(\text{ret})_{t-1}$	4.778	-14.703
	(4.600)	(-4.532)
log(CR past 1 week)	-0.035	-1.304
	(-0.151)	(-2.706)
Stock fixed effects	Yes	Yes
Obs.	$44,545$	$44,545$
Adj. R^2	0.018	0.067
# stocks	295	295

Table 4: Attention and sentiment

This table reports the results of OLS regression on the influence of attention and sentiment on investors' trading decisions. Daily attention and sentiment measures are from Cookson et al. (2024). *Frac. short* denotes the number of short trades per stock and date divided by the number of all trades in this stock on that day. *log*(*short*) and *log*(*long*) are the logarithms of the number of short and long trades, respectively. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

Panel A: Attention						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	Frac. short	Frac. short	log(short)	log(short)	log(long)	log(long)
Attn pc$_t$	0.019		0.558		0.497	
	(3.888)		(4.792)		(4.713)	
Attn pc$_{t-1}$		0.010		0.364		0.339
		(2.949)		(4.522)		(4.623)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,860	15,860	15,860	15,860	15,860	15,860
Adj. R^2	0.254	0.251	0.698	0.668	0.776	0.756
# stocks	288	288	288	288	288	288
# dates	146	146	146	146	146	146
Panel B: Sentiment						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	Frac. short	Frac. short	log(short)	log(short)	log(long)	log(long)
Sent pc$_t$	−0.003		−0.024		−0.011	
	(−1.621)		(−2.415)		(−1.220)	
Sent pc$_{t-1}$		−0.004		−0.023		−0.014
		(−2.157)		(−2.536)		(−1.611)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,860	15,860	15,860	15,860	15,860	15,860
Adj. R^2	0.250	0.251	0.646	0.645	0.739	0.739
# stocks	288	288	288	288	288	288
# dates	146	146	146	146	146	146

Table 5: Stock characteristics

This table reports the results of OLS regression on the influence of stock characteristics on investors' trading decisions. A detailed description of the independent variables can be found in Section 3.2. The dependent variable is the fraction of trades, i.e., the number of trades in stock i in month t divided by the number of all trades in month t. Column (1) includes all trades, Column (2) includes only long trades, and Column (3) includes only short trades. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses. t-test reports equality tests on the coefficients in Columns (2) and (3).

	(1) ALL	(2) LONG	(3) SHORT	t-test
Size	0.0003	0.0004	0.0002	5.7322
	(11.9687)	(11.8185)	(11.0930)	
BM	−0.0001	−0.0001	−0.0001	−1.1440
	(−2.0191)	(−2.0410)	(−1.5655)	
Alphabet	0.0002	0.0002	0.0003	−0.3405
	(1.5181)	(1.1434)	(3.1075)	
ESG	−0.0006	−0.0008	−0.0002	−1.7781
	(−2.6141)	(−2.8435)	(−1.7622)	
Beta	0.0010	0.0013	0.0005	4.0626
	(7.4136)	(7.4439)	(5.9594)	
MOM	−0.0000	−0.0001	0.0001	−1.1408
	(−0.1352)	(−0.5687)	(1.4321)	
STR	−0.0002	−0.0004	0.0000	−0.8332
	(−0.7034)	(−0.8723)	(0.1132)	
ILLIQ	−0.0000	0.0000	−0.0000	1.0083
	(−0.2033)	(0.2144)	(−1.8541)	
MAX	0.0009	0.0014	−0.0001	0.7960
	(0.6744)	(0.8361)	(−0.1026)	
MIN	0.0021	0.0017	0.0020	−0.2059
	(1.7961)	(1.2222)	(2.9624)	
WFL	0.0002	0.0003	0.0001	0.4148
	(0.7788)	(0.8267)	(0.7446)	
LT	0.0001	0.0001	0.0001	−0.5220
	(0.7049)	(0.4100)	(2.0231)	
IVOL	0.0528	0.0569	0.0379	2.3817
	(8.8440)	(7.9284)	(10.7682)	
SKEW	−0.0003	−0.0004	−0.0001	−2.7544
	(−3.4532)	(−3.6736)	(−1.2374)	
ISKEW	0.0002	0.0003	0.0001	2.7578
	(3.3975)	(3.6862)	(1.2557)	
COSK	−0.0005	−0.0006	−0.0002	−2.1487
	(−2.9470)	(−3.1521)	(−1.5497)	
Obs.	1,275	1,275	1,275	
Adj. R^2	0.2042	0.1973	0.1984	
# month	7	7	7	

Table 6: Are short sellers paying attention?

This table reports the results of OLS regression on the research activities of investors. *Watchlist* is a dummy variable that takes a value of 1 if the stock was on the investor's watchlist before the trade and 0 otherwise. *Research* 24 is a dummy variables that takes a value of 1 if the investors visited the stock's research page within 24 hours before the trade and 0 otherwise. *Research* 168 is a dummy variable that takes a value of 1 if the investors visited the stock's research page within 168 hours (1 week) before the trade and 0 otherwise. *Research* is a dummy variable that takes a value of 1 if the investors visited the stock's research page at any point before the trade and 0 otherwise. The sample *First time* contains only the first trade of an investor in a given stock. The sample *Any time* contains the full sample. In Panel A, we compare investors who take short positions with those who do not take short positions. Investors are considered as taking short positions if they have opened at least one short position with the broker. In Panel B, we restrict the sample to investors who take short positions and compare their short and their long positions. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

Panel A: Short sellers						
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	First time	Any time	First time	First time	First time	Any time
Dep. var	Watchlist	Watchlist	Research 24	Research 168	Research	Research
Short seller	−0.057	−0.046	0.000	−0.005	−0.002	−0.003
	(−17.271)	(−7.317)	(0.001)	(−0.919)	(−0.294)	(−0.329)
Controls	Demographics	Demographics	Demographics	Demographics	Demographics	Demographics
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661,841	2,673,468	661,841	661,841	661,841	2,673,468
Adj. R^2	0.091	0.069	0.015	0.012	0.010	0.016
# stocks	1,851	1,851	1,851	1,851	1,851	1,851
# dates	164	164	164	164	164	164

Panel B: Short position						
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	First time	Any time	First time	First time	First time	Any time
Dep. var	Watchlist	Watchlist	Research	Research	Research	Research
Short position	−0.006	−0.006	−0.003	−0.004	−0.004	0.000
	(−3.155)	(−3.168)	(−2.921)	(−3.707)	(−3.791)	(0.111)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	415,022	1,934,392	415,022	415,022	415,022	1,934,392
Adj. R^2	0.404	0.539	0.815	0.851	0.880	0.945
# investors	38,233	41,064	38,233	38,233	38,233	41,064
# stocks	1,851	1,851	1,851	1,851	1,851	1,851
# dates	164	164	164	164	164	164

Table 7: Does paying attention pay off?

This table reports the results of OLS regression on the leveraged holding-period return (HPR) of a position ($Profit$). *Research* 24 is a dummy variable that takes a value of 1 if the investor visited the research page of the stock within 24 hours before the trade and 0 otherwise. *Short sale* is a dummy variable that takes a value of 1 for short sales and 0 otherwise. *Holding period* denotes the holding period of a trade in days. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

	Profit
Research 24	0.339
	(2.336)
Short sale	−2.323
	(−3.291)
log(holding period)	−0.711
	(−3.440)
Short sale × Research 24	−0.127
	(−0.604)
Obs.	2,621,105
Adj. R^2	0.077
# investors	107,242
# stocks	1,851
# dates	164

Table 8: Order behavior for short positions

This table reports the results of OLS regression on the order behavior of investors. When opening a position, investors are required to submit an exit strategy after gains (*take-profit limit*) and after losses (*stop-loss limit*). *Short seller* is a dummy variable that takes a value of 1 for investors who take short positions and 0 otherwise. *Short sale* is a dummy variable that takes a value of 1 for short positions and 0 otherwise. *Leverage* denotes the leverage employed for a trade. In Panel A, we compare investors who take short positions with those who do not take short positions. Investors are considered as taking short positions if they have opened at least one short position with the broker. In Panel B, we restrict the sample to investors who take short positions and compare their short and their long positions. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

Panel A: Short sellers		
	(1) Stop-loss limit	(2) Take-profit limit
Short seller	1.226	0.835
	(7.017)	(1.697)
Leverage	4.869	16.243
	(59.082)	(41.886)
Stock fixed effects	Yes	Yes
Date fixed effects	Yes	Yes
Obs.	2,592,937	2,592,937
Adj. R^2	0.405	0.157
# stocks	1,848	1,848
# dates	212	212

Panel B: Short position		
	(1) Stop-loss limit	(2) Take-profit limit
Short sale	0.689	1.523
	(2.845)	(0.935)
Leverage	3.080	11.698
	(41.285)	(18.585)
Investor fixed effects	Yes	Yes
Stock fixed effects	Yes	Yes
Date fixed effects	Yes	Yes
Obs.	936,008	936,008
Adj. R^2	0.751	0.552
# investors	29,890	29,890
# stocks	1,835	1,835
# dates	212	212

Table 9: Trading characteristics for short positions

This table reports the results of OLS regression on the trading characteristics of investors. *Trades* is the daily number of trades per investor. *PF weight* is the percentage share of the position in the investor's overall portfolio. *Leverage* denotes the leverage employed for a trade. *Holding period* denotes the holding period in days. *Short seller* is a dummy variable that takes a value of 1 for investors who take short positions and 0 otherwise. *Short sale* is a dummy variable that takes a value of 1 for short positions and 0 otherwise. In Panel A, we compare investors who take short positions with those who do not take short positions. Investors are considered as taking short positions if they have opened at least one short position with the broker. In Panel B, we restrict the sample to investors who take short positions and compare their short and their long positions. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

Panel A: Short sellers

	(1) Trades	(2) PF weight	(3) Leverage	(4) Holding period
Short seller	0.256	−1.020	1.249	−8.921
	(25.698)	(−3.411)	(19.235)	(−30.684)
Leverage				−1.384
				(−33.435)
Stock fixed effects	No	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Obs.	14,488,121	2,685,621	2,685,621	2,621,105
Adj. R^2	0.014	0.035	0.075	0.103
# stocks		1,851	1,851	1,851
# dates	164	164	164	164

Panel B: Short position

	(1) PF weight	(2) Leverage	(3) Holding period
Short sale	0.130	0.012	−1.932
	(1.808)	(0.803)	(−16.748)
Leverage			−0.405
			(−24.626)
Investor fixed effects	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Obs.	1,663,598	1,663,598	1,659,007
Adj. R^2	0.692	0.658	0.266
# investors	41,064	41,064	40,990
# stocks	1,846	1,846	1,846
# dates	164	164	164

Table 10: Profitability and short positions

This table reports the results of OLS regression on the performance of investors. HPR denotes the leveraged holding-period return (HPR). $SD(HPR)$ denotes the standard deviation of the leveraged HPR. *Short seller* is a dummy variable that takes a value of 1 for investors who take short positions and 0 otherwise. *Short sale* is a dummy variable that takes a value of 1 for short positions and 0 otherwise. *Holding period* denotes the average holding period in days. In Panel A, we compare investors who take short positions with those who do not take short positions. Investors are considered as taking short positions if they have opened at least one short position with the broker. In Panel B, we restrict the sample to investors who take short positions and compare their short and their long positions. The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

Panel A: Short sellers		
	HPR	SD(HPR)
Short seller	−1.175	1.970
	(−3.950)	(3.140)
log(holding period)	0.331	
	(1.666)	
Avg. log(holding period)		2.364
		(6.768)
Investor fixed effects	No	No
Date/month fixed effects	Yes	Yes
Obs.	2,621,105	198,234
Adj. R^2	0.019	0.017
# date	164	
# month		7

Panel B: Short position		
	HPR	SD(HPR)
Short sale	−2.127	−0.065
	(−3.039)	(−3.958)
log(holding period)	−1.616	
	(−7.374)	
Avg. log(holding period)		4.912
		(14.936)
Investor fixed effects	Yes	Yes
Date/month fixed effects	Yes	Yes
Obs.	1,449,124	136,945
Adj. R^2	0.037	0.615
# investors	40,995	36,501
# date	164	
# month		7

Table 11: Cross-country differences in short selling

This table reports the results of OLS regression on the cross-country differences in investors' propensity to take short positions. *Short sale* is a dummy variable that takes the value of 1 for short positions and 0 otherwise. *Sentiment* is the daily sentiment per country according to the "Twitter Sentiment Geographical Index" by Chai (2022). *Financial Literacy* is the financial literacy score per country for 2016. *Individualism* and *Uncertainty avoidance* denote the cultural dimensions of Hofstede (2001). The sample runs from January to July 2019. Robust standard errors; t-statistics are in parentheses.

Panel A: Sentiment	
	(1) Short sale
Sentiment	−0.085 (−1.991)
Stock fixed effects	Yes
Date fixed effects	Yes
Obs.	2,368,809
Adj. R^2	0.072
# stocks	1,851
# dates	164

Panel B: Financial literacy	
	(1) Short sale
Financial literacy	−0.017 (−0.929)
Stock fixed effects	Yes
Date fixed effects	Yes
Obs.	2,497,425
Adj. R^2	0.072
# stocks	1,851
# dates	164

Panel C: Cultural attitudes		
	(1) Short sale	(2) Short sale
Individualism	−0.019 (−1.941)	
Uncertainty avoidance		−0.010 (−1.051)
Stock fixed effects	Yes	Yes
Date fixed effects	Yes	Yes
Obs.	2,437,299	2,437,299
Adj. R^2	0.072	0.072
# stocks	1,851	1,851
# dates	164	164

Table A.1: 250 most traded stocks

This table reports the 250 most traded stocks with the broker during our sample period, which runs from January to July 2019.

Stock name	Stock name
3M	Commerzbank AG
AbbVie Inc	Community Health Systems Inc
Abercrombie & Fitch Company	Continental AG
Activision Blizzard	Corbus Pharmaceuticals Holding
Adidas AG	Costco Wholesale Corp
Adobe Systems Inc	Covestro
Advanced Micro Devices Inc	Cronos Group Inc
Agilent Technologies Inc	Crowdstrike Holdings
AIRBUS GROUP	CVS Health Corp
AIXTRON	CyberArk
Albemarle Corporation	Daimler AG
Alcoa	Dean Foods Co
Alibaba	Dell Technologies Inc C
Alibaba Group Holding Ltd (Hong Kong)	Delta Air Lines Inc (DE)
Allianz SE	Deutsche Lufthansa Aktiengesellschaft
Alphabet	Deutsche-Bank
Altria Group Inc	DIA S.A.
Amazon	DocuSign Inc
American Airlines Group Inc	Dominos Pizza Inc
American Express CO	Drillisch
Aphria Inc.	Dropbox Inc
Apple	DXC Technology Co
Applied Materials Inc	eBay
Aramco Saudi Arabian Oil Corp	Editas Medicine Inc
ArcelorMittal	Electronic Arts
Ascena Retail Group Inc	Eni Energy Company
ASOS PLC	Etsy Inc
AT&T Inc	EVOTEC
Aurora Cannabis Inc	Exxon-Mobil
Autodesk	Facebook
Avon Products Inc	Farfetch
Baidu	Fastly Inc
Banco Sabadell	FedEx Corporation
Banco Santander SA (US)	Ferrari NV
Bank of America Corp	First Solar
Barclays	Foot Locker Inc
Barrick Gold	Ford Motor Co
BASF SE	Fred. Olsen Energy
Bayer AG	GameStop Corp New
Bayerische Motoren Werke Aktiengesellschaft	Gap
BBVA	Gazprom OAO
Berkshire Hathaway Inc	General Electric Co
Beyond Meat Inc.	General Motors Co
Big Lots Inc	Globalstar
Biogen Inc	GoDaddy Inc.
Bitauto Holdings Limited	Goldman Sachs Group Inc
BlackBerry Limited	GoPro Inc
BNP Paribas SA	Halliburton Co
Boeing	Hertz Global Holdings Inc
BP	Hewlett Packard
Bristol-Myers Squibb Co	Home Depot Inc
Canopy Growth Corp	HUGO BOSS
Capri Holdings Ltd	IBM
Cara Therapeutics	Illumina
Caterpillar	Infineon Technologies AG
Centene Corp	Insys Therapeutics Inc
Chipotle Mexican Grill Inc	Intel
Cigna Corp	Intellia Therapeutics Inc
Cisco	Intesa Sanpaolo Group
Citigroup	iRobot Corp.
Coca-Cola	JC Penney Co Inc

Table A.1: 250 most traded stocks (Continued)

Stock name	Stock name
JD.com	Signet Jewelers Limited (us)
Johnson & Johnson	Siltronic
JPMorgan Chase & Co	Skyworks Solutions
Just Group PLC	Snapchat Inc
Juventus Football Club	Societe Generale Group
LA FRANCAISE DES JEUX	SolarEdge Technologies
Lam Research Corp	Sony
Lockheed Martin Corporation	Southwestern Energy Co
Luckin Coffee Inc.	Spotify
Lululemon Athletica Inc	Square
Macys Inc	Starbucks Corporation
Mastercard	Superior Energy Services Inc
Match Group	Swedbank AB ser A
Mattel Inc	Take Two Interactive Software Inc
McDonalds	Tapestry
Meituan Dianping	Target Corp
MercadoLibre	Telecom Argentina SA
Merck	Tencent
Metro Bank PLC	Tesla Motors
Micron Technology	Teva Pharmaceutical Industries ADR
Microsoft	The Chemours
MongoDB Inc	The Kraft Heinz Company
NetEase	Thomas Cook Group PLC
Netflix	ThyssenKrupp AG
NextEra Energy Inc	Tiffany & Co
NIKE	Tilray
Nintendo CO Ltd	TOTAL S.A.
Nio Inc.	Trade Desk Inc A
Nokia Oyj	TransEnterix Inc.
Nordex	Transocean LTD
NortonLifeLock	Trip.com Group Ltd
Norwegian Air Shuttle	TripAdvisor Inc
Nutanix Inc A	Twilio Inc A
NVIDIA Corporation	Twitter
OHL	Uber
Okta Inc	Ubisoft Entertainment SA
Oracle Corporation	UBS Group AG
Overstock.com	Ulta Beauty Inc
Owens & Minor Inc	Under Armour
Palo Alto Networks	UniCredit Commercial Bank
Pampa Energia S.A.	United Natural Foods Inc
Pandora A/S	United States Steel Corp
PayPal Holdings	UnitedHealth
PepsiCo	Uniti Group Inc
Petroleo Brasileiro SA Petrobras	Vale SA
Pfizer	Verizon
PG&E Corp	Vipshop
Philip Morris International Inc	Visa
Pinterest Inc	VMware
Procter & Gamble Co	Volkswagen AG
Puma Biotechnology Inc	Walgreens Boots Alliance Inc
Qualcomm Inc	Wal-Mart
Qudian Inc.	Walt Disney
Realogy Holdings Corp	Waste Management Inc
Rite Aid Corp	Wells Fargo & Co
Roku Inc	Western Digital Corporation
Salesforce.com Inc	Whiting Petroleum Corp
Samsung Electronics Co Ltd	Wirecard
Sangamo Biosciences Inc	Wix.com Ltd
SAP AG	Xiaomi Corp
Sarepta Therapeutics Inc	Yandex NV
Shake Shack Inc	Zalando
Shopify Inc.	Zscaler Inc
Siemens Aktiengesellschaft	Zynerba Pharmaceuticals Inc

Table A.2: Summary statistics of the trade data

This table shows the summary statistics of the trade data. *Leverage* denotes the leverage employed for a trade, *Investment* is measured as the trade amount's fraction of total assets deposited with the broker, *Short sale* is a dummy variable that takes a value of 1 for short positions and 0 otherwise, *Holding time* measures the timespan between the opening and closing of a position in days, *Profit* denotes the percentage leveraged holding-period return (HPR) on investment on a closed position, *No. trades* denotes the average number of CFD trades on stocks per investor-date. Investors who do not trade on a specific day have a trading intensity of 0 on that day, *No. assets* denotes the number of different assets in an investor's portfolio at the end of a trading day.

	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Panel A: All stock trades						
Investment	2,685,621	19.130	25.245	2.880	9.640	23.200
Leverage	2,685,621	5.034	3.892	2	5	5
Short sale	2,685,621	0.149	0.356	0	0	0
Holding time	2,621,105	10.914	28.028	0.070	1.141	7.144
Profit	2,621,105	−1.094	28.671	−5.610	0.928	7.139
Panel B: 250 stocks						
Investment	2,104,685	19.768	25.704	3.040	9.910	24.150
Leverage	2,104,685	5.189	4.020	2	5	5
Short sale	2,104,685	0.148	0.355	0	0	0
Holding time	2,057,090	10.625	27.696	0.062	1.097	7.023
Profit	2,057,090	−0.853	29.441	−5.707	1.048	7.678
Panel C: 250 stocks LONG						
Investment	1,793,496	19.014	24.946	2.960	9.710	23.130
Leverage	1,793,496	4.994	3.952	2	5	5
Holding time	1,746,603	11.897	29.434	0.088	1.915	8.123
Profit	1,746,603	−0.396	30.018	−5.274	1.230	8.180
Panel D: 250 stocks SHORT						
Investment	311,189	24.112	29.324	3.670	11.080	31.220
Leverage	311,189	6.314	4.219	5	5	5
Holding time	310,487	3.469	12.182	0.017	0.161	2.134
Profit	310,487	−3.424	25.807	−7.685	0.197	5.044
Panel E: Number of trades per day (all stock trades)						
No. trades	14,488,121	0.185	1.212	0	0	0
Panel F: Avg. number of assets in a portfolio at the end of a trading day						
	Mean	SD	Pctl(25)	Median	Pctl(75)	Pctl(99)
No. assets	1.573	2.812	0.0000	1.0000	2.0000	11.0000

Table A.3: Summary statistics

Panel A reports summary statistics for the variables introduced in Section 3.2. Panels B and C report the gender and age distributions of the investors in our dataset.

	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Panel A: Variables						
Fraction	1,584	0.001	0.002	0.0001	0.0002	0.001
Fraction short	1,584	0.0003	0.001	0.00003	0.0001	0.0002
Fraction long	1,584	0.001	0.002	0.0001	0.0003	0.001
WFL	1,581	0.459	0.149	0.346	0.451	0.565
LT	1,557	0.249	0.432	0	0	0
MAX	1,581	0.051	0.038	0.027	0.040	0.061
MIN	1,581	−0.054	0.046	−0.064	−0.042	−0.027
Alphabet	1,584	0.059	0.236	0	0	0
Beta	1,575	1.164	0.431	0.894	1.123	1.405
STR	1,581	0.005	0.139	−0.057	0.021	0.085
MOM	1,546	−0.169	0.385	−0.416	−0.182	0.063
Size	1,544	23.804	2.147	22.531	24.024	25.278
BM	1,436	0.642	0.794	0.145	0.344	0.830
COSK	1,575	1.098	0.349	0.871	1.053	1.293
ESG	1,509	0.617	0.218	0.455	0.674	0.798
ILLIQ	1,572	0.250	1.883	0.00002	0.0001	0.0004
IVOL	1,574	0.017	0.012	0.009	0.014	0.021
SKEW	1,533	−0.598	1.331	−0.984	−0.267	0.054
ISKEW	1,524	−0.560	1.637	−1.164	−0.186	0.260
Panel B: Investors' gender distribution						
	Male	Female				
Fraction	0.912	0.088				
Panel C: Investors' age distribution						
	18-24	25-34	35-44	45-54	55-64	>65
Fraction	0.078	0.350	0.319	0.164	0.070	0.020