Paying Attention*

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Abstract This paper investigates the impact of attention on individual investors' trading behavior. We analyze a large sample of trading records from a brokerage service that sends push messages on stock performance to some of its client investors. This micro-level data allows us to exploit a clean difference-in-difference setting to isolate the push messages as individual attention triggers. By linking these triggers to the same individuals' trading behavior, we derive novel insights on how attention affects investors' trading behavior as measured by trading intensity and risk taking.

Keywords: investor attention; trading behavior; risk taking;

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Recent research has found that aggregate investor attention has an important bearing on the ownership, liquidity, return, correlation, and volatility of stocks (Grullon et al., 2004; Barber and Odean, 2008; Da et al., 2011; Andrei and Hasler, 2014; Lou, 2014). Surprisingly, relatively little is known about the fundamental driver behind *aggregate* attention, namely *individual* investor attention. For example, it is unclear how individual attention relates to the same individual's trading behavior, or how different investors react to attention triggers. Filling this gap in the literature is important to understand the mechanism behind the impact of aggregate attention on trading, and to gauge cross-sectional differences of this impact. The main challenge behind analyzing individual attention, however, is the difficulty in identifying the triggers of individual attention.

In this paper, we investigate how individual investor attention affects trading behavior and risk taking. To this end, we analyze a novel dataset containing the trading records of a brokerage service that sends standardized push messages to some of its client investors. These records present a unique opportunity to investigate the impact of individual investor attention on trading for two reasons. First, by using the push messages, we observe a *trigger* of individual investor attention that we can *directly* link to their trading behavior. Thus, we use a *direct* measure of individual attention to examine the impact of attention on investors' trading activity. Second, as we also observe the trading behavior of individuals who do not observe a push message at the same time, we can empirically isolate the pure effect of the attention trigger on trading.

Our analysis provides three novel results. First, attention triggers stock buying and selling within several hours after the attention trigger. Second, attention enhances individuals' risk taking. Third, attention is more important for the individuals' decisions regarding foreign stocks.

We obtain our dataset from a discount brokerage service that allows its international customer-base to trade a large set of European and US blue chip companies under a UK broker license. The data allow us to simultaneously observe both investors who obtain push messages and those who do not obtain such messages at the same time. Importantly, the dataset comprises of only push messages that contain public information such as past stock returns. We carefully isolate push messages as attention triggers that are not associated with novel information from those that are. Comparing the trading behavior of investors who receive a push message, to that of investors who do not, sets up a natural experiment for a standard difference-in-differences approach, which measures the marginal impact of an attention trigger on individual stock trading. Our difference-in-difference setting provides a clear-cut identification that addresses several concerns associated with the literature's standard approach of using aggregate attention proxies when measuring the impact of attention on trading. For example, omitted variables or events may affect both investor attention and trading at the same time. In addition, unusual trading patterns can trigger aggregate investor attention, raising the legitimate question about causality. Finally, aggregate measures of attention may absorb many conflicting effects, particularly when certain groups of investors, e.g., more sophisticated investors, counter the trades of attention-driven traders.

Our first main result is that attention stimulates stock trading. On average, a push message increases the number of buy and sell trades within a 24 hour window after a push message by 102% and 132%, respectively. The trading investors' median reaction time after the receipt of the push message is around three hours. This result provides a novel insight on short selling from our individual attention data that is not evident from analyzing aggregate investor attention.

Our second result relates attention to risk taking. We show that attention induces investors to trade with higher leverage and a shorter holding period. Also, investors trading after the attention trigger buy stocks with larger total volatility and higher idiosyncratic risk than those without such a trigger. This insight is important to shed light on the potential channels through which attention affects aggregate risk.

Third, we show that attention is more important for foreign than for home stocks. This result suggests that investors react more to attention when triggered towards less familiar stocks, which they may otherwise not follow as closely.

We provide a battery of robustness tests to confirm our conjectures and address possible alternative explanations for our findings. One concern is that the broker may send more messages on days with (public) news or with higher aggregate attention. Our difference-in-differences approach mitigates this concern because we compare the trading of investors with push messages to that of investors without push messages at the same time. Thus, we cancel out the impact of aggregate attention or news on trading and isolate the pure impact of the attention trigger. Aggregate attention or news could, however, still affect our conjecture if the broker sends more push messages to investors who are more likely to receive the news or who have a higher exposure to aggregate attention. Thus, we repeat our main analysis by filtering out messages that are associated with news or aggregate attention. Our results are robust to this filtering.

As an alternative to the difference-in-difference approach, we also compare investors' trading activity after receiving a push message to their trading activity before they received the push message. This alternative comparison confirms our conjectures. In another robustness check, we also make sure that our results are not driven by investors who trade on large positive (or negative) returns, but instead are explained by the push message that draws the investors' attention.

We contribute to various strands of the existing literature. First, Odean (1999) suggests that investors manage the problem of selecting a few among a large universe of stocks by limiting their choice to those stocks that have caught their attention. Several studies build on this insight and conclude that aggregate attention has an important bearing on stock returns and aggregate trading patterns (Chen et al., 2005; Seasholes and Wu, 2007; Barber and Odean, 2008; Lehavy and Sloan, 2008; Fang and Peress, 2009; Da et al., 2011; Lou, 2014). The common approach of these studies is to investigate how proxies of aggregate investor attention such as internet search volume, extreme stock return events, news coverage, additions/deletions from prominent stock indices, among other metrics, are correlated with stock characteristics. Whereas this literature provides important insights into the macroeconomic implications of attention, it provides limited results on the microeconomic foundation behind attention. Specifically, micro-level attention patterns may well cancel out in the aggregate data simply because some type of investors do not receive the attention triggers, do not react to them, or even counter the trading patterns of other traders who react to them. Indeed, in this vein, Barber and Odean (2008) and Seasholes and Wu (2007) find that the trading strategies of rational institutional traders often counter the attention-driven trades of retail investors. We contribute to this literature by linking individual investor attention to individual trading. This link provides important insights into attention-driven trading patterns that are not evident in the aggregate data. For instance, we show how attention triggers affect individual stock selling and risk taking.

Second, a recent literature investigates individual attention by using online account logins as a proxy of attention (Sicherman et al., 2015). The main differences between this literature and our study are that we (i) directly observe the attention triggers, (ii) identify the stock that triggers attention, and (iii) observe the trades of investors without attention. These differences are crucial to our trading and risk-taking conjectures and enrich the empirical results we obtain.

Third, several studies analyze the relation between aggregate attention and stock return patterns. They show that higher attention leads to higher stock prices, larger return volatility, and a delayed return reversal (e.g., Lehavy and Sloan, 2008; Fang and Peress, 2009; Da et al., 2011; Andrei and Hasler, 2014). We complement these studies by linking individual investor attention to the investors' trading behavior. Through this link, we are able to provide a rationale for the attention-return patterns discussed in the literature. In addition, our results are crucial to understanding the cross-sectional differences regarding the impact of attention on different stocks.

Fourth, we also provide some micro-level insights into the home-bias literature documented by French and Poterba (1991). In contrast to the portfolio-level results that are the mainstay of that literature, we are able to provide some color to the drivers of this bias through the information filtering process of investors.

Finally, our study speaks to the relation between marketing and finance. This strand of the literature concludes that marketing activities tend to increase a firm's idiosyncratic risk and to reduce its systematic risk (e.g., McAlister et al., 2007; Luo and Bhattacharya, 2009; Rego et al., 2009). As marketing aims at drawing attention, our study provides important insights into a potential micro-level channel behind the link between marketing and a firm's stock risk.

The remainder of our paper proceeds as follows. In Section 1 we present our dataset and discuss our identification strategy. Section 2 presents summary statistics before Section 3 discusses the impact of the attention trigger on investors' trading and risk taking. In Section 4, we discuss several alternative explanations to our findings. Section 5 studies the impact of attention of short selling and existing positions as well as the effect in the home bias. The final section concludes.

1 Data and methodology

1.1 Data

The novel dataset for this research is from a discount brokerage firm offering a trading platform to its customers under a UK broker license. The broker does not offer its clients any professional investment advice. The broker allows its clients to trade contracts for difference (CFD) on a large set of blue chip stocks.[1] This dataset contains all trades that customers executed with the online broker between January 1^{st}, 2016 and March 31^{st}, 2018.[2] It also includes the investors' basic demographic information (age, gender, and nationality). A trade is defined as the opening or closing of a position. The trading data contain the exact time-stamp of the trade, the specific underlying stock, an indicator for long or short positions, the executed rate, the leverage, and the investment as a fraction of the investor's total assets deposited with the broker.

The stock prices and trades in the dataset are quoted in USD irrespective of the currency in which the underlying stock trades. Returns are computed after adjusting for stock

[1] Contracts for difference (CFD) are financial contracts between investors and a spread-betting firm. At the maturity of the CFD, the two parties exchange the difference between the opening and the closing prices of the underlying (e.g., stocks, commodities, or foreign exchange). Appendix A provides a brief introduction to CFDs. For additional information, the interested reader is referred to Brown et al. (2010).

[2] We do not have information as to whether the investors in our dataset make use of other brokerage accounts. As a result, our results may exhibit a downward bias in terms of investors' trading activities.

splits, dividends, and transaction costs. In total, our dataset contains 3,519,118 transactions (3,393,391 round trips and 125,727 openings of a position) from 112,242 investors over 5,190,338 investor-weeks.

On February 27^{th}, 2017, roughly in the middle of the sample, the broker started to send standardized push messages to the investors for several events. In particular, push messages were sent for large price changes, streaks (i.e., stock price movements in the same direction) with a duration of three to seven days, and earnings announcements. An important feature of these messages in the context of isolating the impact of attention on trading is that they only contain public information. Thus, the messages do not reveal any novel information but merely relay publicly available information. The broker determines which customers receive the messages through a self-learning algorithm. Details of this algorithm, which affects both the timing and content of the message, are not available.

We complement our data with *Quandl Alpha One Sentiment Data* to control for firm-specific news. The news scores of Quandl are based on articles aggregated from over 20 million news sources. The variable *Article Sentiment* captures the average sentiment of all the articles (from the last 24 hours) in these news sources that refer to a specific company. This variable contains values between -5 (extremely negative coverage) and 5 (extremely positive coverage); a score of zero indicates an absence of articles for that day. In addition, the variable *News Volume* captures the number of news articles about this stock, published and parsed on a given day. The variable *News Buzz* measures the rate of change in news coverage of a given stock on a certain day, normalized on a scale from 1 to 10. This variable measures the change in the standard deviation of periodic news volume. It can be thought of as the "rate of change of news" and, thus, serves as a risk alert indicator. In our analysis, we rely on the *Article Sentiment* and *News Volume* variables.[3]

[3]Quandl evaluates news based on a machine-learning algorithm for events of the following sixteen event groups: accounting actions, legal actions, criminal actions, employment actions, financing actions, stock activities, company earnings, general business actions, business concerns, corporate governance, government, mergers and acquisitions, contracts, product development, disaster, and rumors.

1.2 Methodology

It is straightforward to measure the trading behavior of an investor, after her attention has been triggered. The empirical challenge to analyzing the impact of an attention trigger on trading, however, is to control for an investor's "normal" trading behavior, which is the trading behavior in case the investor's attention had not been triggered. Our data offers a unique opportunity to overcome this challenge in a standard difference-in-differences setting. Specifically, it allows us to compare the trading behavior of treated investors in the treatment period to that of similar investors who do not obtain a push message during the treatment period.

1.2.1 Attention and trading intensity

To analyze the impact of attention on an investor's trading intensity, we conduct the following three main steps:

First, for each investor-stock pair, we identify the time-stamp (treatment time) of the first push message that the broker sends to an investor in that stock. Using this time-stamp, we consider the investor's trades in that stock, seven days prior to the treatment time (observation period), and seven days after the treatment time (treatment period). The advantage of using a relatively short observation period before the treatment time is that this choice mitigates the impact of potential time-variation in the determinants of investors' trading activity (Petersen, 2009). We only use the first push message an investor receives on any given stock in order to mitigate the confounding effects of previous messages in the same stock, and obtain a clean identification strategy. At the same time, using the first push message eliminates the influence of the self-learning algorithm that determines which investors receive a push message as the algorithm would have less information on the reaction of customers to messages.

Second, we collect our sample of comparable investors from all investors in the database who do not receive a push message in the seven days around the treatment time. Specifically, we run a nearest-neighbor matching routine to match investor-stock pairs from the treatment group with those of the comparable investors based on the previous trading in the stock, the date, gender, age group, and the previous trading intensity.

Third, we calculate the difference between the trading of treated investors and that of the comparable investors in the observation period before the treatment date. This step controls for heterogeneity between treated and comparable investors that are not captured by the matching procedure. We also measure the difference between the trading of the treated investors and that of the comparable investors in the treatment period. The impact of the attention trigger on trading then corresponds to the difference between these two differences. Formally, we estimate

$$X_{it} = \alpha + \beta_1 \text{treatment group}_i \times \text{post trading}_t + \beta_2 \text{treatment group}_i + \beta_3 \text{post trading}_t + \varepsilon_{it}, \quad (1)$$

where X_{it} denotes the trading intensity of investor i at time t. *treatment group* is a dummy variable that takes a value of one for investors of the treatment group, zero otherwise; *post trading* is a dummy variable that takes a value of one for the treatment period, zero otherwise. Our coefficient of interest is β_1 that captures the impact of the attention trigger on the trading intensity. When estimating equation (1), we specify that the error term, ε, contains a fixed effect for the investor-instrument pair, which is perfectly collinear with the dummy variable *treatment group*. We also include time fixed effects to control for aggregate time-trends. The time effects are collinear with *post trading*.

To obtain a comprehensive picture of the impact of attention on investors' trading intensity, we apply this approach along several trading dimensions. Specifically, we differentiate between stock buying and (short) selling. In addition, we consider the case that investors already hold a position in the stock when receiving the push message to analyze both the closing of existing positions and additional trades in an already existing position.

1.2.2 Attention and risk taking

To investigate how attention affects risk taking, we consider proxies from both investors' trade characteristics and traded stock characteristics. Regarding trade characteristics, we incorporate the investors' leverage, holding period, and investment size. Regarding stock characteristics, we estimate the volatility of the traded stock with a standard Garch model, the beta with rolling regressions over the previous 262 trading days, and the idiosyncratic volatility of the stock with rolling regressions over the previous 262 trading days.

The main steps of our analysis are similar to those in Section 1.2.1. We start by identifying the time-stamp of the first push message that the broker sends to an investor in a given stock. Next, we consider the last trade of the investor in any stock within seven days prior to the treatment time (observation period) and the first trade of the investor after the treatment time (treatment period) within 24 hours. If the investor trades in stocks other than that referred to in the push message before he trades in the push message stock, we still count the later trade as an attention trade as long it occurs within 24 hours after the push message. If an investor does not trade in the observation or the treatment period, she is excluded from our sample.

We then collect our sample of comparable investors from all investors in the database that do not receive a push message in the stock in the seven days around the treatment time. We run a nearest-neighbor matching routine to match investors from the treatment group with those of the comparable investors based on the date, gender, age group, and the previous trading intensity.[4] Finally, we estimate the difference-in-differences equation (1) for our risk-taking proxies.

[4] We consider different matching routines in the robustness section of our paper.

2 Summary statistics

Table 1 provides the demographic statistics of the active investors in our sample. It shows that most investors are male and between 25 and 34 years old.

— Place Table 1 about here —

In Table 2, we summarize the characteristics of the trades in our sample. On average, investors conduct 0.61 long trades and 0.065 short trades per week. The average leverage of a trade is 6.11% and the average trade size is 12.82% of the investor's assets with the broker. On average, an investor holds a position for 243.20 hours and realizes a net return around zero. Investors execute 60.3% of trades on, or directly following, a day with at least one important news event for the particular stock.

— Place Table 2 about here —

Table 3 provides summary statistics of the push messages that the broker sends to investors. We distinguish *price changes* that report a change in a stock price on a certain day, *streaks* that report stock price changes over several days, and earnings announcements. We also dissect price changes and streaks into "positive" push messages that report a stock price increase and "negative" push messages that report a stock price decline. In total, there are 9,969 events about which the broker sends a message to investors. Price changes are the most frequent events. The magnitude of the reported price changes is quite large. Specifically, it is 6.67% and −5.87% for positive and negative price changes, respectively, and 21.38% and −20.01% for positive and negative streaks, respectively. On average, more than 2,000 investors receive a message per price change event and more than 1,000 investors receive a message per streak event. A comparison of the number of investors receiving a message per event to Table 1 shows that the broker only sends messages to a relatively small subset of investors per event. Yet almost all investors receive a message at some point; only 2,302 investors never received a push message (not tabulated) throughout our observation period. We also calculate the success rate of messages, i.e., the fraction of push messages that are followed by an attention trade. We use the term "attention trade" for trades in the same stock (for which the investor receives a push message) within 24 hours after the message. On average, 1.6-3.6% of the push messages trigger an attention trade. The median reaction time of investors that conduct an attention trade is quite short, namely 3.39 hours after receiving the message.

Push messages are sent Monday to Friday in a similar fashion. Most messages are sent during the afternoon (see Figure 1).

— Place Table 3 and Figure 1 about here —

In Table 4, we summarize the average features of attention trades and non-attention trades. During push-message weeks investors are more active and execute 1.06 trades/week compared to only .37 trades/week in non-push message weeks. Attention trades feature a higher leverage, a lower investment amount, and a shorter holding period than non-attention trades. Additionally, we consider the following three risk measures to proxy for the riskiness of an investment. In particular, *volatility* denotes the Garch-volatility of stock returns, *beta* denotes the CAPM-Beta of a given stock, and *IVOL* denotes the idiosyncratic volatility of stock returns. On average, we observe higher risk measures for attention trades than for non-attention trades.

Of course, there are many potential explanations behind the simple result that attention trades are, on average, riskier than non-attention trades, such as message timing or message underlying concerns. We address this issue, in detail, in the next section, when we turn to our difference-in-differences analysis.

— Place Table 4 about here —

We now provide first evidence that our attention trades are indeed triggered by investors' attention. Figure 2 summarizes the distribution of the time difference between push messages and attention trades. For both long and short trades, Panels a) and b) show a distinct trade spike in the first five hours after the broker sends the message.

— Place Figure 2 about here —

3 The implications of push messages on trading

In this section, we summarize the implications of push messages on individual trading. We start with an analysis of the impact of attention on the frequency with which investors trade, before we turn to the impact of the attention trigger on trade characteristics and risk-taking.

3.1 Attention and trading intensity

To study the impact of attention on investors' trading intensity, we apply our difference-in-differences approach (see Section 1.2.1). Specifically, we measure whether investors trade a certain stock more frequently in the week after receiving a push message on that stock compared to investors that do not receive a push message at the same time.

— Place Table 5 about here —

Table 5 summarizes the results for the impact of attention on stock trading. Model 1 investigates stock buying, and shows that push messages induce investors to buy a stock. Specifically, the treatment coefficient suggests that, on average, a push message on a stock increases the number of the investor's buy trades of that stock by 0.0084 trades in the week after receiving the message. The magnitude of the coefficient is economically important, suggesting that push messages increase the stock-specific mean buying intensity of 0.0082 (standard deviation of 0.16) by 102%.

Model 2 shows that push messages also induce investors to short a stock more frequently. Specifically, the treatment coefficient suggests that, on average, a push message on a stock increases the number of investors' short trades of that stock by 0.0012 trades in the week after receiving the message. The quantitative impact of attention on short selling is even stronger than on stock buying. Specifically, the magnitude of the coefficient suggests that a push message increases the stock-specific mean selling intensity of 0.0009 (standard deviation of 0.04) by 132%.

Overall, the analysis shows that attention has a profound impact on investors' buying and selling intensity. Attention induces more trading, both short and long. We consider the impact of the attention-trigger on existing positions in Section 5.2. Our conjecture on stock buying is consistent with Seasholes and Wu (2007); Barber and Odean (2008) and Lou (2014). To the best of our knowledge, we are the first to show that attention is also relevant for short selling.

3.2 Attention and trade characteristics

We now investigate how attention affects investors' trade characteristics and risk taking in our difference-in-differences approach outlined in Section 1.2.2. Table 6 shows the results of the regressions for the leverage, holding period, and investment of stock buying trades. We first focus on long positions because these trades represent the majority of our sample. We present the results on the risk taking of investors for short sales in Section 5.1.

— Place Table 6 about here —

Model 1 shows that push messages induce investors to trade at a higher leverage compared to non-attention trades. The treatment coefficient suggests that, on average, investors trade with a 1.5% higher leverage for attention trades. Model 2 analyses the impact from the attention trigger on investors' holding period. The treatment coefficient indicates that investors hold positions resulting from attention trades, on average, 1.5 days shorter than those from non-attention trades. Compared to the average holding period of investors in our sample of approximately 10 days, this effect is economically important. Lastly, Model 3 studies the investment weight of attention trades compared to non-attention trades, and suggests that investors, on average, reduce their investment significantly in the former case.

To shed additional light on the impact of attention on risk-taking, we also consider a set of stock risk measures. We use the volatility of a stock, its beta, and its idiosyncratic volatility ($IVOL$) to proxy for stock riskiness. The results of our difference-in-differences estimation procedure are presented in Table 7.

Model 1 compares the volatility of attention purchases with that of non-attention purchases. The positive treatment coefficient indicates that, on average, investors buy riskier stocks after an attention trigger. Compared to the average volatility of stocks in our sample (mean = .018; sd = 0.0098), the magnitude of the coefficient of .0056 is also economically important. Model 2 investigates the beta of attention purchases and shows that these trades are not different from regular stock purchases. Thus, the larger volatility of attention trades cannot be explained by their average beta. Instead, Model 3 shows that the larger idiosyncratic volatility of attention trades explains the larger volatility in Model 1.

— Place Table 7 about here —

Overall, Table 6 and Table 7 suggest that attention stimulates investors to implement a larger leverage, hold positions for a shorter time period, and buy riskier stocks. These results highlight the potential micro-level channels behind the observation in the recent aggregate attention literature. Specifically, the larger leverage and riskier exposure due to individual attention triggers in our sample provide a potential rationale for the observation that aggregate attention increases stock volatility (e.g., Andrei and Hasler, 2014). Similarly, the shorter holding periods of attention trades could explain the pronounced return reversals shortly after aggregate attention events (e.g., Lehavy and Sloan, 2008; Fang and Peress, 2009; Da et al., 2011).

4 Robustness analyses

In this section, we consider various alternative empirical tests to confirm the robustness of our conjectures.

4.1 The broker's message sending behavior

A concern with our empirical strategy is that the broker's message sending behavior could affect our conjecture. Specifically, the broker may send the first push message to investors who usually trade with higher risk. We address this concern in two ways, namely with an alternative difference-in-difference approach and with an alternative matching approach.

First, we investigate the impact of the attention trigger in a difference-in-difference approach, in which we only incorporate investors who receive a push message. The treated investors are those that conduct an attention trade as in our main analysis. The counter factual, however, is based on investors who do not react to the attention trigger. Specifically, they receive a push message at the same time as the treated investors, but trade a stock that is not referred to in this message. The idea behind this approach is that whereas the broker determines who receives a push message, he cannot determine who reacts to the push message. Thus, the broker's behavior cannot allocate investors to either the treated investors or the counter factual. Table 8 shows that our finding that attention trades are riskier than non-attention trades is robust to this alternative setting. In terms of statistical and economic impact, the results reflect those of our main analyses.

— Place Table 8 about here —

Second, we adjust our matching algorithm to account for this potential endogeneity. In particular, we also match investors based on their willingness to trade risky stocks, and not only based on their age, gender, and previous trading intensity. To this end, we add the volatility of the last stock purchase prior to the treatment event as an additional matching variable, and repeat our main difference-in-difference analyses. The results of our adjusted matching analysis are summarized in Table 9.

— Place Table 9 about here —

The table shows that our results are robust to this alternative matching procedure. All but one coefficient are very similar to our baseline specification. The only exception is the coefficient on systematic risk, which is now much larger than in the baseline analysis (.039 compared to .020) and also statistically significant.

4.2 Mechanical relation between attention and stock risk

Another objection to our story could be that risky stocks draw more attention and, hence, the observation that investors trade riskier positions after an attention trigger is just a natural consequence of the fact that they react to attention. Note, however, that by exploiting the details of the individual trade data, we are able to study the impact of attention on risk taking beyond this potential mechanical relation. Specifically, when a message triggers an investor's attention towards a particular stock, the investor faces two decisions: First, she decides whether to trade that stock and second, she establishes the leverage at which she trades this underlying asset. The second (leverage) decision is independent of the potential relation that riskier stocks draw more attention.

4.3 Attention and news

Another concern with our results may be that they could be driven by news that is correlated with both trading and the broker's tendency to send push messages to investors. Our difference-in-differences approach mitigates this concern because we compare the trading of investors with push messages to the trading of investors without push messages at the same time, which should cancel out the aggregate impact of news on trading. Nevertheless, the broker may send push messages to investors who are more likely to receive the news than investors who do not receive the news. To address this concern, we repeat our main analysis with three alternative news-filters.

First, we only consider stock-observation days without any news on or the day directly preceding the treatment day. We identify news-days from the Quandl Alpha One Sentiment Data. Model 1 of Table 10 repeats our difference-in-differences analysis in this setting. The coefficient on the treatment remains virtually unchanged (0.0912 compared to 0.0934 in our unfiltered analysis), suggesting that the results are not driven by news.

— Place Table 10 about here —

Next, we apply a less restrictive filter by using our news data to estimate how investors' leverage choice depends on news. Specifically, we first regress *Leverage* on *News volume*, *News sentiment* and standard controls. The residuals of this regression capture the dimension of the investors' leverage decision that is not associated with news. Model 2 of Table 10 repeats our main risk taking analysis by using these residuals as the dependent variable. The results mirror those in Table 6. The treatment coefficient amounts to .0846 compared to .0934 in our main analysis.

Finally, we filter the attention trigger with respect to news information. The idea behind this approach is to put less weight on push messages that are sent on or the day directly following news. This procedure helps us to isolate the impact of push messages as the trigger of attention trades from news as the trigger of those trades. First, we regress the push message dummies on *News volume*:

$$\text{Push message dummy} = \alpha + \beta \cdot \text{News volume} + \varepsilon.$$

Next, we replace the dummy variable *post trading* in our difference-in-difference analysis by the residuals of this regression. The results in Model 3 of Table 10 show that our results of Table 6 are also robust to this alternative news filtering approach. Both the treatment coefficient and the level of statistical significance are very similar to our main analysis.

Overall, this section suggests that our results on risk taking are not driven by news events. Thus, we conjecture that the push message trigger explains risk taking beyond news-induced trading.

4.4 Positive vs. negative attention triggers

It may be possible that investors do not react to push messages but instead are momentum traders who trade on positive returns. To distinguish between the attention and momentum channels, we use the push message content. Specifically, we add a dummy variable for positive messages to our main regression models and summarize the results in Table 11.

— Place Table 11 about here —

If investors were trading on positive past returns, we should observe a positive loading on this dummy variable. The results, however, show a coefficient on *Positive* that is not significantly different from zero (the largest t-statistic we observe across our dependent variables is 1.43 for investment). We, however, observe a positive coefficient on the interaction between the treatment variable and the dummy, which suggests that investors are even taking higher risk when receiving a positive attention trigger. Specifically, whereas the increase in leverage is 1.4% (coefficient of .0851) for negative messages, we observe an increase in leverage of 3.3% for positive messages. Similar patterns hold for the volatility and idiosyncratic volatility of the traded stock. In addition, we find that the decline in the average holding period is significantly larger for positive messages (52 hours) compared to negative messages (19.7 hours). For investment, the results are not as clear-cut. The coefficient on the interaction term of the treatment variable and *Positive message* is positive but not significant. Overall, the analysis shows that, independent of the push message content, the attention trigger induces investors to take higher risk.

In Panel B of Table 11 we shed additional light on how investors' reaction to attention depends on the message content. Model 1 is restricted to positive push messages and Model 2 studies the impact of negative push messages. These analyses confirm our conjecture that the impact of positive push messages is about twice as large as that of negative push messages (3.5% increase in leverage for positive messages, compared to 1.6% increase for negative messages).

In a similar vein, we study whether investors' reaction to attention differs depending on the magnitude of the return reported in the push message, as the prior literature on investor attention suggests that investors are particularly sensitive towards daily winners and losers, rather than stocks with extreme returns (e.g., Kumar et al., 2018). If investors were trading on daily winners or losers, our findings should be driven by messages reporting large price changes. Thus, we split our sample with respect to the magnitude of the price change reported in the message, and consider large and smaller price changes separately. *Strong* messages are defined as message with price changes larger than the median change, whereas *weak* messages are defined as price changes lower than the median value.

Model 3 in Panel B of Table 11 considers *strong* messages, and Model 4 considers *weak* messages. Whereas the impact for strong messages (3% increase in leverage) is larger than that for weak messages (1.9% increase in leverage), both effects are statistically significant and economically meaningful.

Overall, these results indicate that the increased willingness of investors to take risk is primarily driven by the attention trigger, and not by the size of past returns.

4.5 Time-variant trading

An objection to our analyses on investors' trading intensity could be that this intensity is time-variant. Hence, if the broker tends to send investors more push messages during times in which they trade more frequently, our matching approach may fail to cancel out an investor's non-attention trading intensity. To address this concern, we measure the impact of each push message on the trading of stocks that are not referred to in the push message. If time-variant trading drives our results, we should also observe a significant difference-in-differences coefficient for non-message stocks. Table 12, however, shows that the push messages have no impact on either the short or long trading of the stocks that are not referred to in the push message, which confirms our attention hypothesis.

— Place Tables 12 and 13 about here —

Note that the number of observations is smaller in the sample of Table 12 than in that of Table 5, because we omit messages that are followed by an additional message to the same investor on another stock within one week. Table 13 shows that our main results from Table 5 also hold in this smaller sample. In fact, we observe that the effect on investors' buying intensity is larger (0.015 additional trades, compared to .0084 additional trades in our main analysis, see Table 5). This result suggests that investors' attention is more important if an investor only receives one push message over a given period of time. In contrast, attention is less stimulating for one specific stock if an investor receives multiple messages. This is intuitively appealing as investors' attention may be focused on one specific stock, if they only receive one push message over a given period of time, while the attention has to be divided if investors receive multiple messages. The coefficients on investors' short selling intensity are of similar magnitude (.0014 compared to .0012).

5 Further analyses

5.1 Attention and risk taking in short selling

Our analysis in Section 3.1 indicates that investors increase both their buying and their selling intensity in response to the attention trigger. For investors' buying behavior, our results in Section 3.2 suggest that they also execute their attention trades in a more risky manner compared to their regular trades. In this section, we turn to the short-selling trades of investors triggered by attention, and study the risk taking implied by these trades.

We again apply our difference-in-differences setting and compare how investors execute their attention trades compared to investors who do not receive a push message at the same time. Table 14 summarizes the results. Overall, our results look very similar compared to the buying behavior of investors. Attention trades are executed with larger amounts of leverage (Model 1) and shorter holding periods (Model 2). Compared to the buying case, the reduction in the average holding period is significantly smaller, though, as investors "only" reduce their average holding period by 12 hours. Model 3 indicates that investors also reduce *investment* when trading in response to the attention trigger.

— Place Table 14 about here —

Models 4-6 of Table 14 consider the risk of stocks that investors sell short. The results show that investors tend to trade in riskier stocks when trading on attention compared to their normal trading behavior. Our results do not provide any indication on where the additional volatility originates, as both the coefficients on the beta and the idiosyncratic volatility are individually statistically not different from zero.

5.2 The impact of attention on existing positions

To shed additional light on the impact of attention on stock buying and selling, we investigate the impact of the attention trigger on existing positions.

Our treatment group consists of all open stock positions for which the investor receives a push message in the same stock while holding the position. We then derive our control group from all trades, which were established in the same stock, and at a similar entry price ("comparable trades"), and are still open at the time the push message was send to the treated investor. For all trades in our control group, we require that the investor did not receive a push message concerning that stock while holding the position. From the group of comparable trades, we obtain our control group with a "nearest-neighbor" matching routine. We match trades from the treatment group with trades from the group of comparable trades based on the stock, the entry price, gender and age group of the investor, and the leverage and investment volume of the trade. We assign the time of the message of the matching trade from the treatment to the trade from the control group.

We create two dummy variables to study the impact of the attention trigger on the existing position. First, we create a dummy variable *Increasing position* that equals one, if the investor adds to an existing position within 24 hours after receiving a push message, zero otherwise. Second, we create a dummy variable *Closing position* that takes a value of one if the investor closes (or reduces) a position within 24 hours. Finally, we run a difference-in-differences estimation with the indicator variables as dependent variables.

Table 15 shows that investors are more likely to increase (Model 1) and to close (Model 2) the existing position within 24 hours, when receiving a stock-specific push message.

In particular, investors are 7% more likely to increase their existing position within 24 hours, and 5% more likely to close their position within 24 hours. Hence, our results suggest that attention induces more trading, both short and long, also when investors already have an existing position in the underlying referred to in the push message.

— Place Table 15 about here —

5.3 Attention and the home bias

We also investigate whether the home bias (French and Poterba, 1991) mitigates the impact of attention in Table 16.[5]. The investor demographic details in our dataset contain information about the investors' nationality. We use this information details to study the impact of the home bias on investors' trading intensity in a specific stock. In particular, we create a dummy variable *Home bias* that is equal to one, if the nationality of the investor is the same as the home country of the firm of the underlying stock. Our conjecture is—in line with the literature on the home bias—that investors display a higher trading intensity for stocks of companies based in their own country. Moreover, we also argue that the home bias mitigates the influence of attention on investors' trading intensity. As emphasized in his presidential address, Merton (1987) argues that "an investor uses security k in constructing his optimal portfolio only if the investor knows about security k."[6] Thus, when investors receive a push message concerning a given stock, the investor may learn about the existence of that particular stock and, as a result, buy the stock. However, we argue that it is more likely that the investors indeed learns about the stock when the particular stock is a foreign stock as it is more likely that she already knows about the home bias stock. Thus, we expect the home bias to mitigate the impact of attention on investors' trading intensity in a particular stock.

[5] The literature offers various explanations for the strong preference for domestic equities by investors in international markets such as the barriers to international investment, foreign taxes, transaction costs, asymmetric information, and geographical distance (e.g., Black, 1974; Stulz, 1981; Brennan and Cao, 1997; Coval and Moskowitz, 1999)

[6] Stapleton and Subrahmanyam (1977) make a similar assumption in their analysis of the effect of transaction costs on capital market equilibrium and corporate financial decisions.

Model 1 of Table 16 shows that the attention trigger indeed has a stronger impact for stocks of companies that are located outside the individual's home country. In fact, we find that the attention trigger has almost no effect on stocks that are located in the investor's home country. The size of the positive coefficient on $Treatment$ (.0061) is only slightly larger compared to the size of the negative coefficient on the interaction with the *Home bias* variable (-.0053). Additionally, the model provides support for the home bias as we observe a significantly positive coefficient on our *Home bias*-variable (additional .0028 trades for stocks with a home country of the firm equal to the nationality of the investor).

— Place Table 16 about here —

To provide additional support for our analysis, we split our sample with respect to *known* and *unknown* stocks. A *known stock* is a stock which the investor traded prior to receiving the first stock-specific push message. An *unknown stock* is a stock which the investor did not trade prior to receiving the first stock-specific push message. In line with our hypothesis, we find that the attention-effect is mainly driven by unknown stocks (Model 3). While our treatment coefficient on known stocks is not significantly different from zero, the treatment coefficient for unknown stocks amounts to .0188 additional trades which is significantly larger than for our full sample (.0061 additional trades, see Model 1). This observation also provides additional support to the argument of Merton (1987) and Odean (1999) who suggest that investors manage the problem of selecting among a large universe of stocks by limiting their choice to those stocks that have caught their attention.

6 Conclusion

This study presents novel evidence on the micro-foundation of attention based on a unique dataset of trading records. The main advantage of this dataset is that it allows us to directly observe the trigger of individual investor attention and to link this trigger to the individuals' trading behavior. In addition, the dataset also contains comparable trading records of investors who do not receive an attention trigger, which allows us to empirically isolate the pure effect of the attention trigger on individual trading. Applying a difference-in-differences methodology to the data, we find that attention stimulates individuals' stock trading and risk taking.

We provide additional evidence in support of our main conjecture that trading is driven by attention. For example, we incorporate the push message content and find that our results are independent of whether the push message reports a stock price increase or a decline. In addition, our results are robust to filtering out news, i.e., the effect of attention survives even after the impact of news is filtered out. We also document a stronger impact of attention for stocks of companies located outside the country of the investor.

Our micro-level evidence on the impact of individual attention triggers on individual trading complements the existing literature on the effect of aggregate attention on stock markets (Grullon et al., 2004; Barber and Odean, 2008; Da et al., 2011; Andrei and Hasler, 2014; Lou, 2014). We look forward to future research on the channels through which individual attention triggers aggregate to the macro-level impact of attention on stock markets.

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A Contracts for difference

A contract for difference (CFD) is a financial contract designed such that its price equals that of the underlying security.[7] In a CFD, the two counterparties agree to replicate the underlying security and settle the change in its price when the position closes. A CFD has no explicit maturity date. It can be closed out at any time at a price equal to the underlying price prevailing at the closing time. Common underlying securities for CFDs are stocks, indexes, currency pairs, and commodities. CFDs allow market participants to implement strategies involving short positions, and to achieve leverage. CFDs may be used to hedge existing positions and also offer tax benefits to investors (see, e.g., Brown et al., 2010).

Originally introduced in the London market in the early 1990s aimed at institutional investors, CFDs have since become popular with retail investors and have been introduced in many countries (Brown et al., 2010). In 2007, the value of transactions of CFDs amounted to around 35% of the value of London Stock Exchange equity transactions (Financial Services Authority, 2007).

[7] Brown et al. (2010) provide an empirical analysis on the pricing of CFDs and show that these instruments trade at a price close to that of the underlying security.

	Gender		Age					
	Female	Male	18-24	25-34	35-44	45-54	55-64	≥65
Total	8,281	103,961	17,703	46,857	28,519	13,136	4,781	1,246

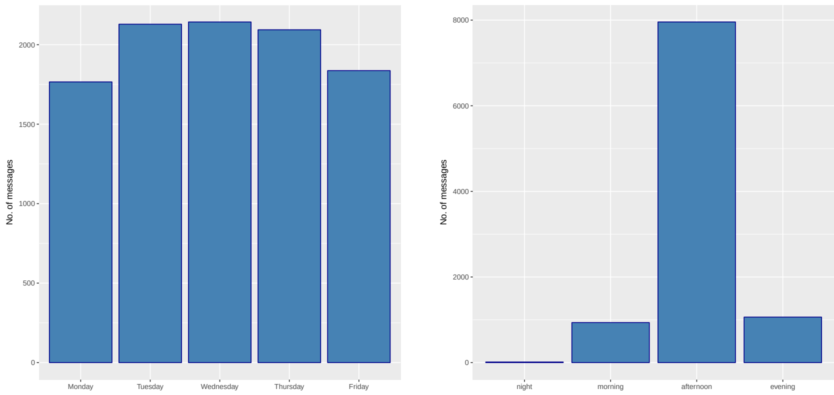
Table 1: Summary statistics of demographic information

This table reports the gender and age distributions of the investors in our dataset. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license. Our dataset contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Investor-weeks / Obs.	Mean	SD	P25	P50	P75
Long trades/week	5,190,338	0.613	3.536	0	0	0
Short trades/week	5,190,338	0.065	2.027	0	0	0
Leverage	3,519,118	6.108	3.219	5	5	10
Investment	3,519,118	12.818	18.883	1.890	5.900	14.650
Holding time	3,393,391	243.196	474.064	4.755	69.026	237.714
ROI	3,393,391	0.0001	0.003	−0.0004	0.0001	0.001
News event	3,519,118	0.603	0.489	0	1	1

Table 2: Summary statistics of the trade data

The table shows summary statistics of the trade data from a discount brokerage firm that offers a trading platform to its customers under a UK broker license. Our dataset contains all trades on the platform between January 1, 2016 and March 31, 2018. *Long trades/week* denotes the average number of long position openings per investor-week; *Short trades/week* denotes the average number of short position openings per investor-week; *Leverage* denotes the leverage employed for a trade; *Investment* is measured as the trade amount's fraction of total assets deposited with the online broker; *Holding period* measures the timespan between the opening and closing of a position in hours; *ROI* denotes the return on investment net transaction costs;

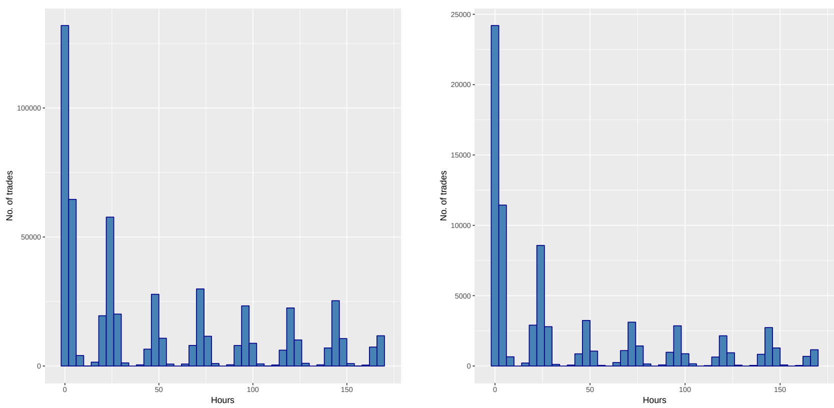


(a) Day of the week-distribution

(b) Time of the day-distribution

Figure 1: Distribution of push message over day of the week and time of the day

This figure presents the distribution of the push messages over the days of the week and over the time of day in our trade data. We split the day into four periods of 6 hours, from midnight to 6am (night), from 6am to noon (morning), from noon to 6pm (afternoon), and from 6pm to midnight (evening). The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.



(a) Opening of a long position

(b) Opening of a short position

Figure 2: Time difference between push message and attention trades

This figure presents the distribution of the time difference between push messages and attention trades in our trade data. The time difference is measured in hours. Push messages are sent at time 0. "Attention trades" are all trades by investors in the underlying referred to in the push message within 24 hours after receiving the message. We distinguish between long and short positions. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

Type	Number of events	Price change	Success rate	Avg. Number of messages	Success rate of messages	Avg. reaction time	Median reaction time	Events with news
Positive price change	3,667	6.67	0.76	2,605.47	0.02	5.65	3.62	0.48
Negative price change	4,709	5.87	0.69	2,217.83	0.02	5.41	3.16	0.48
Positive streak	446	21.38	0.86	1,588.75	0.02	1.77	1.61	0.42
Negative streak	215	20.01	0.79	1,001.74	0.02	1.84	1.68	0.46
Earnings	932	-	0.74	833.05	0.04	13.66	14.64	0.69
Total	9,969	-	0.73	2176.59	0.02	6.01	3.39	0.50

Table 3: Summary statistics of push message data

This table shows summary statistics of the push messages of the trade data from a discount brokerage firm that offers a trading platform to its customers under a UK broker license. Our dataset contains all trades on the platform between January 1, 2016 and March 31, 2018. *Positive price change* are all messages that report a stock price increase on a certain day. *Negative price change* are all messages that report a stock price decline on a certain day. *Positive streak* are all messages that report a stock price increase over several days. *Negative streak* are all messages that report a stock price decline over several days. *Earnings* are the messages that entail earnings announcement. *Number of Events* is the number of stock events about which the Broker sent a message. *Price change* lists the average stock price change that is announced in the messages. *Success rate* is the fraction of push message events that are followed by a trade of the message underlying within 24 hours by at least one investor. *Avg. Number of messages* is the average number of messages per event that the broker sent to investors. *success rate of messages* is the fraction of push message that are followed by a trade of the message underlying within 24 hours by the same investor that receives the message. *Avg. reaction time* is the average time in hours between the push message and the trade of an investor who received the push message in the underlying of the push message. *Events with news* are the fraction of events for which the *Quandl FinSentS Web News Sentiment* data records at least one news article over the three day period surrounding the push message.

Type	trades/week	leverage	investment	holding period	volatility	beta	IVOL
No push message	0.37	6.07	12.83	268.82	0.0228	1.25	0.0184
Push message	1.06	6.53	12.73	178.61	0.0342	1.46	0.0250
t-test	167.01	75.146	2.858	102.81	369.18	192.48	305.34

Table 4: Trading activity after push messages

This table reports summary statistics of investors' trading activity in the trade data from a discount brokerage firm that offers a trading platform to its customers under a UK broker license. Our dataset contains all trades on the platform between January 1, 2016 and March 31, 2018. The first line summarizes all trades that are not following a push message in the underlying within 24 hours. The second line summarizes all trades that following a push message in the same underlying within 24 hours. *trades/week* denotes the average number of trades of an investor in weeks where the investor receives (does not receive) a push message; *leverage* denotes the investor's leverage for the trade; *investment* is the investment amount in a given stock trade expressed as a fraction of the total assets deposited by the investor at the broker; *holding period* denotes the time between opening and closing of the same position in hours; *volatility* denotes the Garch-volatility of stock returns; *beta* is the CAPM-Beta of a given stock; *IVOL* denotes the idiosyncratic volatility of stock returns. The t-test reports results from equality tests of non-treated versus treated trades.

	Model 1 long positions	Model 2 short positions
Treatment	0.0084	0.0012
	(2.30)	(2.95)
Trader-fixed effects	Yes	Yes
Instrument-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	2,287,258	2,323,914
R^2	0.26	0.21

Table 5: Instrument-specific trading intensity after receiving message

This table reports results from a difference-in-differences regression analysis on our trade data at the stock level of investors around the treatment date. Model 1 reports long positions; Model 2 shows results on short-selling positions. Trading intensity (the dependent variable) is the average number of trades in a given stock seven days before (observation period) and after investors receive a push message for the specific instrument for the first time (treatment period). *Treatment* is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. We obtain our control group from all investors who trade in the same stock and have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a nearest-neighbor matching routine. We match investor-stock pairs from the treatment group with investor-stock pairs from the group of comparable investors based on the stock, the treatment week, gender, age group, and the instrument-specific trading intensity 6 months days prior to the (counter factual) treatment date. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 Leverage	Model 2 Holding period	Model 3 Investment
Treatment	0.0934	−36.5376	−0.6909
	(3.57)	(−8.22)	(−8.05)
Trader-fixed effects	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	1,040,135	1,040,135	1,040,135
Adj. R^2	0.63	0.37	0.70

Table 6: Attention and trading characteristics: difference-in-differences analysis

This table reports results from a difference-in-differences regression analysis on the characteristics of trades that investors initiate in our trade data. For each investor we take the trading characteristic of the last trade within seven days before the treatment event and the trading characteristic of the *attention trade* (for the treatment group) [first trade after the treatment event within seven days (for the control group)]. The treatment event is the first message an investor receives for a given stock. An attention trade is a trade in the same stock as referred to in the push message that happens within 24 hours after the push message. *Leverage* denotes the leverage employed for a trade; *Holding period* measures the timespan between the opening and closing of a position in hours; *Investment* is measured as the trade amount's fraction of total assets deposited with the online broker; *Treatment* is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. We obtain our control group from all investors who have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a nearest-neighbor matching routine. We match investors from the treatment group with investors from the group of comparable investors based on the treatment time, gender, age group, and the previous trading activity prior to the (counter factual) treatment time. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; *t*-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 volatility	Model 2 beta	Model 3 IVOL
Treatment	0.0056	0.0204	0.0026
	(10.89)	(1.29)	(8.41)
Trader-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	1,040,135	1,040,135	1,040,135
Adj. R^2	0.26	0.26	0.27

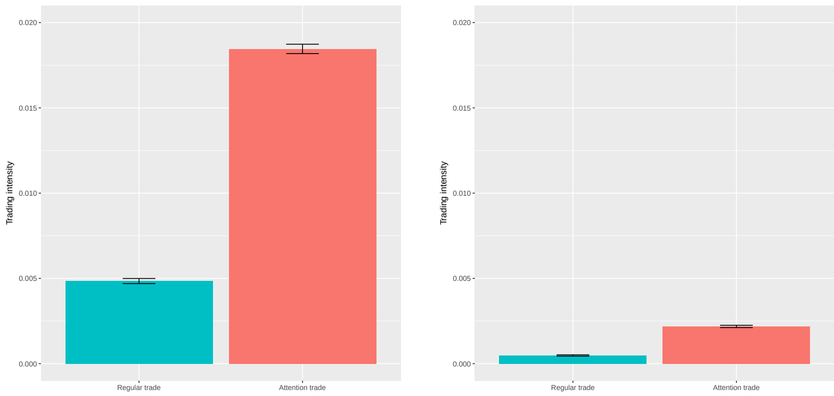
Table 7: Attention and stock riskiness: difference-in-differences analysis

This table reports results from a difference-in-differences regression analysis on the riskiness of stocks that investors buy in our trade data. For each investor we take the risk measure of the stock of the last trade within seven days before the treatment event and the risk measure of the stock of the *attention trade* (for the treatment group) [first trade after the treatment event within seven days (for the control group)]. The treatment event is the first message an investor receives for a given stock. An attention trade is a trade in the same stock as referred to in the push message that happens within 24 hours after the push message. *Volatility* is measured with a standard GARCH(1,1) model; *Beta* is measured with rolling window regressions over the last 262 days (one year); *IVOL* (idiosyncratic volatility) is measured with rolling window regressions over the last 262 days (one year); *Treatment* is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. We obtain our control group from all investors who have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a nearest-neighbor matching routine. We match investors from the treatment group with investors from the group of comparable investors based on the treatment time, gender, age group, and the previous trading activity prior to the (counter factual) treatment time. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 leverage	Model 2 holding period	Model 3 investment	Model 4 volatility	Model 5 beta	Model 6 IVOL
Attention trade	0.1301	−29.7712	−0.6064	0.0055	0.0208	0.0026
	(5.27)	(7.70)	(7.17)	(10.92)	(1.37)	(9.20)
Trader-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,206,469	1,155,067	1,206,469	1,190,210	1,190,210	1,190,210
Adj. R^2	0.64	0.39	0.70	0.24	0.24	0.25

Table 8: Risk taking of treated investors

This table reports results from a regression analysis on the risk taking of investors who receive a push message in our trade data. For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the *attention trade* (for the reacting group) [first trade after the treatment event within seven days that is not an attention trade (for the not-reacting group)]. The treatment event is the first message an investor receives for a given stock. An attention trade is a trade in the same stock as referred to in the push message that happens within 24 hours after the push message. *Attention trade* is a dummy variable that takes a value of one for attention trades, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.



(a) Long positions (b) Short positions

Figure 3: Instrument-specific trading intensity after receiving push message

This figure presents the means of the fitted values of the difference-in-differences analysis on investors' trading intensity (with 99% confidence intervals) in our trade data. Regression results are presented in Table 5. Green bars show non-attention trades ($treatment = 0$); red bars show attention trades ($treatment = 1$). "Attention trades" are all trades by investors in the underlying referred to in the push message within 24 hours after receiving the message. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 leverage	Model 2 holding period	Model 3 investment	Model 4 volatility	Model 5 beta	Model 6 IVOL
Treatment	0.0917 (3.1263)	−38.6978 (−7.1093)	−0.6375 (−6.9221)	0.0064 (12.6183)	0.0390 (2.2491)	0.0034 (10.6387)
Trader-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,065,910	1,065,910	1,065,910	1,065,910	1,065,910	1,065,910
Adj. R^2	0.62	0.37	0.70	0.26	0.26	0.29

Table 9: Matching based on previous risk taking

This table reports results from a difference-in-differences regression analysis on trading characteristics of trades that investors initiate in our trade data. For each investor we take the trading characteristic of the last trade within seven days before the treatment event and the trading characteristic of the *attention trade* (for the treatment group) [first trade after the treatment event within seven days (for the control group)]. The treatment event is the first message an investor receives for a given stock. An attention trade is a trade in the same stock as referred to in the push message that happens within 24 hours after the push message. *Leverage* denotes the leverage employed for a trade; *Holdingperiod* measures the timespan between the opening and closing of a position in hours; $Investment$ is measured as the trade amount's fraction of total assets deposited with the online broker; $Volatility$ is measured with a standard GARCH(1,1) model; *Beta* is measured with rolling window regressions over the last 262 days (one year); $IVOL$ (idiosyncratic volatility) is measured with rolling window regressions over the last 262 days (one year); $Treatment$ is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. We obtain our control group from all investors who have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a nearest-neighbor matching routine. We match investors from the treatment group with investors from the group of comparable investors based on the treatment time, gender, age group, the volatility of the last stock before the treatment event, and the previous trading activity prior to the (counter factual) treatment time. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 no news trading	Model 2 filtered trading	Model 3 filtered message
Treatment	0.0912	0.0846	0.1120
	(3.0898)	(3.3441)	(4.4542)
Trader-fixed effects	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	453,132	1,227,694	1,227,694
Adj. R^2	0.69	0.63	0.64

Table 10: Leverage and the impact of news

This table reports results from a difference-in-differences regression analysis on leverage usage of investors around the treatment date in our trade data. *Treatment* is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. In the *no news trading*-model we omit all trades that are executed on or following news days. In the *filtered trading*-model we replace the trading intensity measure with the residual from the following regression. In a first stage regression, we filter investor i's leverage usage at time t using the regression

$$\text{Leverage}_{it} = \alpha + \beta \text{News volume}_t + \gamma \text{Sentiment}_t^2 + \delta' \text{Controls}_{it} + \varepsilon_{it},$$

where controls include investors' age and gender and a set of time dummies to control for unobserved aggregate covariates. *News Volume* captures the number of news articles, published and parsed on a given day from over 20 million news sources (from last 24 h) that are related to a specific company provided by *Quandl FinSentS Web News Sentiment*. *Sentiment* captures the average sentiment of articles aggregated from these news sources that are related to a specific company. In the *filtered message*-model we replace the dummy variable *post trading* with the residual ε from the probit regression model

$$\text{Push message dummy} = \alpha + \beta \text{News volume} + \varepsilon.$$

Then, *Treatment* denotes the interaction term of ε with *treatment group*.
We obtain our control group from all investors who trade in the same stock and have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a nearest-neighbor matching routine. We match investors-stock pairs from the treatment group with investor-stock pairs from the group of comparable investors based on the stock, the treatment week, gender, age group, and the instrument-specific trading intensity 6 months days prior to the (counter factual) treatment date. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 leverage	Model 2 holding period	Model 3 investment	Model 4 volatility	Model 5 beta	Model 6 IVOL
Treatment	0.0851	−19.7155	−0.8700	0.0052	0.0052	0.0021
	(2.82)	(−2.45)	(−7.72)	(6.90)	(0.20)	(4.12)
Positive message	−0.0029	−1.4218	0.0458	−0.0000	−0.0008	−0.0001
	(−0.48)	(−1.03)	(1.43)	(−0.16)	(−0.31)	(−0.75)
Treatment × Positive message	0.1161	−32.5370	0.2808	0.0033	0.0652	0.0024
	(2.75)	(−3.68)	(1.63)	(3.32)	(1.85)	(3.23)
Trader-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	951,847	951,847	951,847	951,847	951,847	951,847
Adj. R^2	0.63	0.38	0.70	0.26	0.27	0.27

Table 11: Message characteristics and risk taking: difference-in-differences analysis (Panel A)

This table reports results from a difference-in-differences regression analysis on investors' trading characteristics (Panel A) and the leverage of trades that investors initiate (Panel B) in our trade data. For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the *attention trade* (for the treatment group) [first trade after the treatment event within seven days (for the control group)]. The treatment event is the first message an investor receives for a given stock. An attention trade is a trade in the same stock as referred to in the push message that happens within 24 hours after the push message. *Treatment* is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. *Positive message* is a dummy variable that takes a value of one if the message reports a positive stock price development, zero otherwise. Earnings announcement messages are omitted from the analysis. We obtain our control group from all investors who have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a nearest-neighbor matching routine. We match investors from the treatment group with investors from the group of comparable investors based on the treatment time, gender, age group, and the previous trading activity prior to the (counter factual) treatment time. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 positive messages	Model 2 negative messages	Model 3 strong messages	Model 4 weak messages
Treatment	0.2165	0.0950	0.1847	0.1183
	(7.54)	(3.17)	(6.39)	(4.44)
Trader-fixed effects	Yes	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	479,995	476,903	569,058	387,840
Adj. R^2	0.63	0.64	0.64	0.63

Table 11: Message characteristics and risk taking: difference-in-differences analysis (Panel B)

	Model 1 Buying intensity	Model 2 Selling intensity
Post trading	−0.0001 (−0.0114)	0.0002 (0.1729)
Trader-fixed effects	Yes	Yes
Message dummies	Yes	Yes
Obs.	298,348	298,348
Adj. R^2	0.3487	0.2127

Table 12: Trading in other stocks after receiving push message

This table reports results from a fixed effects regression analysis on treated investors' trading intensity in other instruments around the treatment date in our trade data. Trading intensity (the dependent variable) is the average number of trades in all stocks but the stock referred to in the push message three days before (observation period) and after investors receive a push message for the specific stock for the first time (treatment period). Model 1 studies buying intensity while Model 2 studies selling intensity. *Post trading* is a dummy variable that takes a value of one in the treatment period, zero otherwise. We include a dummy variable for each push message to control for unobserved heterogeneity. Investors who receive multiple messages within the considered time period are omitted from the sample. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 long positions	Model 2 short positions
Post trading	0.0152 (3.5191)	0.0014 (3.0804)
Trader-fixed effects	Yes	Yes
Message dummies	Yes	Yes
Obs.	298,348	298,348
R^2	0.5017	0.5002
Adj. R^2	0.0034	0.0004

Table 13: Trading in stock after receiving stock-specific push message

This table reports results from a fixed effects regression analysis on treated investors' trading intensity in a specific instrument around the treatment date in our trade data. Trading intensity (the dependent variable) is the average number of trades in the stock referred to in the push message three days before (observation period) and after investors receive a push message for the specific stock for the first time (treatment period). Model 1 studies buying intensity while Model 2 studies selling intensity. *Post trading* is a dummy variable that takes a value of one in the treatment period, zero otherwise. We include a dummy variable for each push message to control for unobserved heterogeneity. Investors who receive multiple messages within the considered time period are omitted from the sample. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 leverage	Model 2 holding period	Model 3 investment	Model 4 volatility	Model 5 beta	Model 6 IVOL
Treatment	0.0922	−11.9906	−0.7828	0.0030	−0.0059	0.0005
	(2.1926)	(−3.7517)	(−2.5602)	(4.6813)	(−0.3713)	(1.5303)
Trader-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	98,335	98,335	98,335	98,335	98,335	98,335
Adj. R^2	0.74	0.46	0.77	0.52	0.53	0.49

Table 14: Attention and risk taking in short selling

This table reports results from a difference-in-differences regression analysis on trading characteristics of short trades that investors initiate in our trade data. For each investor we take the trading characteristic of the last trade within seven days before the treatment event and the trading characteristic of the *attention trade* (for the treatment group) [first trade after the treatment event within seven days (for the control group)]. The treatment event is the first message an investor receives for a given stock. An attention trade is a trade in the same stock as referred to in the push message that happens within 24 hours after the push message. *Leverage* denotes the leverage employed for a trade; *Holdingperiod* measures the timespan between the opening and closing of a position in hours; *Investment* is measured as the trade amount's fraction of total assets deposited with the online broker; *Volatility* is measured with a standard GARCH(1,1) model; *Beta* is measured with rolling window regressions over the last 262 days (one year); *IVOL* (idiosyncratic volatility) is measured with rolling window regressions over the last 262 days (one year); *Treatment* is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. We obtain our control group from all investors who have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a nearest-neighbor matching routine. We match investors from the treatment group with investors from the group of comparable investors based on the treatment time, gender, age group, and the previous trading activity prior to the (counter factual) treatment time. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	Model 1 Increasing position	Model 2 Closing position
Treatment	0.07	0.05
	(17.20)	(13.47)
Controls	Yes	Yes
Trader-fixed effects	Yes	Yes
Instrument-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	640,262	640,262
Adj. R^2	0.08	0.15

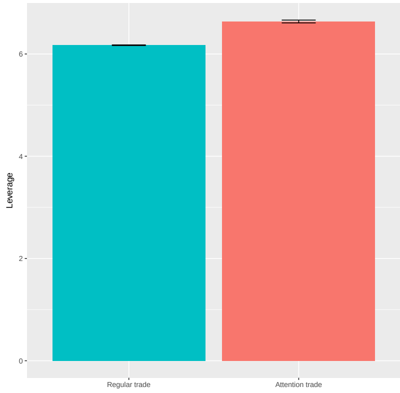
Table 15: Receiving push messages while holding a position

This table reports results from a regression analysis on the increasing and closing of an existing position in our trade data. In Model (1), the dependent variable is an indicator variable that equals one if the investor adds to an existing position within 24 hours, zero otherwise. In Model (2), the dependent variable is a dummy variable that takes a value of one if the investor closes (or reduces) a position within 24 hours. *Treatment* is a dummy variable that takes a value of one for investors of the treatment group ($treatment\ group = 1$) in the treatment period ($post\ trading = 1$), zero otherwise; *treatment group* and *post trading* are perfectly collinear with fixed effects. Control variables included are the leverage and investment volume of the original position. For our analysis, we create a matched sample using a nearest-neighbor matching routine: We obtain our control group from all trades that were established in the same stock and at a similar entry price ("comparable trades") and are still open at time of the push message. For all trades in our control group, we require that the investor did not receive a push message concerning that stock while holding the position. From the group of comparable trades, we obtain our control group with a nearest-neighbor matching routine. We match trades from the treatment group with trades from the group of comparable trades based on the stock, the entry price, gender and age group of the investor, and the leverage and investment volume of the trade. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

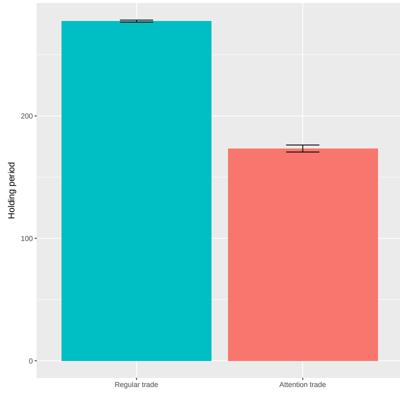
	Model 1 all stocks	Model 2 known stocks	Model 3 unknown stocks
Treatment	0.0061	0.0007	0.0188
	(2.60)	(0.46)	(5.69)
Home bias	0.0028	0.0012	0.0107
	(1.91)	(1.41)	(3.14)
Treatment× Home bias	−0.0053	−0.0003	−0.0173
	(−2.96)	(−0.25)	(−5.48)
Investor-fixed effects	Yes	Yes	Yes
Instrument-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	3,306,766	2,326,356	980,410
R^2	0.21	0.25	0.24

Table 16: Does the home bias moderate impact of attention on trading?

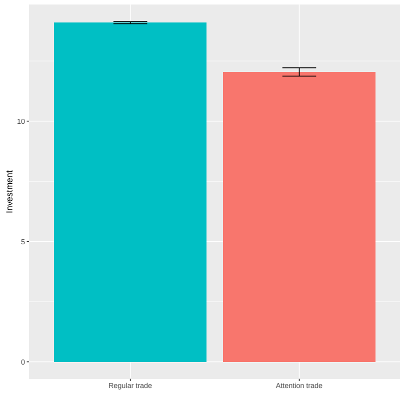
This table reports results from a difference-in-differences regression analysis on aggregated trade data at the stock level of investors around the treatment date in our trade data. The dependent variable *Trading intensity* is the average number of trades in a given stock seven days before (observation period) and after investors receive a push message for the first time (treatment period). A *known stock* is a stock which the investor traded prior to receiving the first stock-specific push message. An *unknown stock* is a stock which the investor did not trade prior to receiving the first stock-specific push message. *Treatment* is a dummy variable that takes a value of one for investors of the treatment group (*treatment group* = 1) in the treatment period (*post trading* = 1), zero otherwise; *treatment group* is perfectly collinear with trader-instrument fixed effects; *post trading* is collinear with time-fixed effects. *Home bias* is a dummy variable that takes a value of one for investors who have the same nationality as the stock (Stock country = investor country), zero otherwise. We obtain our control group from all investors who trade in the same stock and have not been treated previous to the treatment date of the treated investor ("comparable investors"). From the group of comparable investors, we obtain our control group with a matching routine. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.



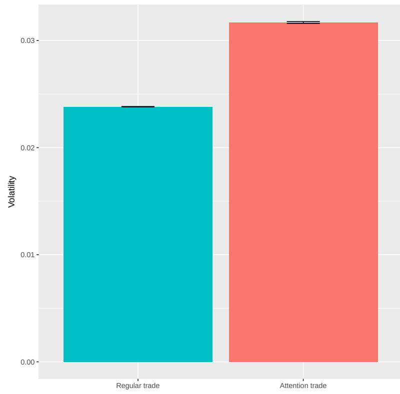
(a) Leverage



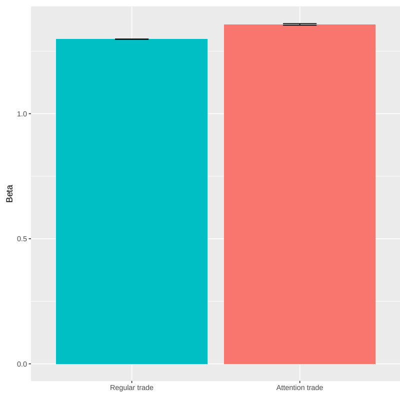
(b) Holding period



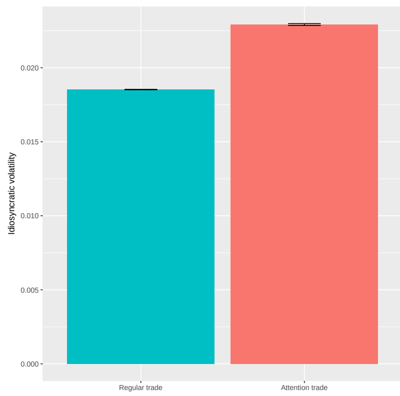
(c) Investment



(d) Volatility



(e) Beta



(f) Idiosyncratic volatility

Figure 4: The impact of attention of investors' trading behavior

This figure presents the means of the fitted values of the difference-in-differences analysis on investors' trading characteristics (with 99% confidence intervals) in our trade data. Regression results are presented in Tables 6 and 7. Green bars show non-attention trades ($treatment = 0$); red bars show attention trades ($treatment = 1$). "Attention trades" are all trades by investors in the underlying referred to in the push message within 24 hours after receiving the message. The data is from a discount brokerage firm that offers a trading platform to its customers under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.