Paying Attention*

Marc Arnold [†] Matthias Pelster [‡] Marti G. Subrahmanyam [§]

March 17, 2019

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 stocks to retail investors. This micro-level data allows us to isolate the push messages as individual stock-attention triggers. We exploit a difference-in-differences setting to investigate the impact of these attention triggers on individual trading. Our analysis highlights how attention affects investors' trading intensity, risk taking, portfolio composition, and performance. We also derive novel insights on the impact of attention on trading such as an attention satiation effect.

Keywords: Investor Attention; Trading Behavior; Risk Taking; Portfolio Composition;

JEL Classification: G10, G11, G12.

*We thank Bernd Braun, Sarah Herwald, Marco Kerkemeier, and Marcel Lengacher for outstanding research support. We are grateful for helpful comments and suggestions from Alastair Lawrence, Sönke Sievers, Sebastian Schrön, Maik Dierkes, Andreas Pfingsten, and seminar participants at Paderborn University, the HVB seminar in Siegen, and the OR AG FIFI Workshop 2019. Matthias Pelster gratefully acknowledges the warm hospitality of the NYU Stern School of Business during his visit. Marti Subrahmanyam acknowledges generous financial support from the NYU Center for Global Economy and Business, the Volkswagen Foundation, and the Anneliese Maier Research Award of the Alexander von Humboldt Foundation. Any errors, misrepresentations, and omissions are our own.

[†] University of St. Gallen, Tigerbergstrasse 9, 9000 St. Gallen, Switzerland, Phone: +41 (71) 224-7413, e-mail: *marc.arnold@unisg.ch*

[‡] Paderborn University. Warburger Str. 100, 33098 Paderborn, Germany, Phone: +49 (5251) 60-3766, e-mail: *matthias.pelster@upb.de.*

[§] Stern School of Business, New York University, 44, West Fourth Street # 9-68, New York, NY 10012, USA, Phone: +1 (212) 998-0348, e-mail: *msubrahm@stern.nyu.edu.*

Attention has an important bearing on financial markets. Previous studies find that aggregate investor attention affects 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 and performance. Filling this gap in the existing literature is important to obtain a better understanding of individual investor behavior. The main challenge behind analyzing individual attention is twofold. First, it is difficult to identify the triggers of individual attention. Second, it is challenging to isolate the marginal impact of this trigger on a particular individual's trading.

In this study, we investigate how individual investor attention affects their respective trading behavior and risk taking. We address the challenges behind analyzing individual attention through our access to a novel dataset, which contains the trading records of a brokerage service that sends standardized push messages to retail investors. By using these push messages, we observe a *trigger* of individual investor attention towards a certain stock that we can *directly* link to the same individual's trading behavior. As the dataset also contains the trading records of individuals who do not receive a push message at times when other individuals receive a message, we can empirically isolate the marginal impact of the attention trigger on trading.

Our analysis of these trading records provides three primary results. First, a stock-attention trigger stimulates long and short trading of that stock within several hours. Second, whereas attention triggers improve investors' portfolio diversification, they also induce investors to buy stocks with higher idiosyncratic risk. Third, attention leads to inferior investment performance. Besides these primary results, we also provide several novel insights into the impact of attention on investors. For example, we find evidence of an attention satiation effect.

We obtain our dataset from a discount brokerage service that offers retail investors a trading platform to trade contracts for difference (CFD) on a large set of European and

US blue chip companies.[1] The broker sends push messages to investors. Each push message reports one publicly observable feature about a particular stock such as the past stock performance. We carefully isolate push messages as attention triggers that are not associated with novel information or news from those push messages that are. The data allow us to simultaneously observe two groups of investors at the same time, namely those who obtain a push message (treated) and those who do not obtain such a message (control). Comparing the trading of these two groups of investors 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. The main concern with this empirical approach is that the broker could send more push messages to investors who are more likely to react to a message in a certain way. Whereas we match the treated and control groups on observable investor characteristics such as trading intensity, the broker could still have inside knowledge on how an investor may react to the attention stimulus. To mitigate this concern, we only incorporate the first push message that the broker sends to an investor on a certain stock in our empirical analysis. For this message, the broker has no observable data on how the investor reacts to a message on that stock.

Our 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 and trading 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. We label trades that an investor executes in a stock up to 24 hours after she receives a push message referring to that stock "attention trades." On average, a push message increases the number of

[1]Contracts for difference (CFD) are financial contracts between investors and a financial firm. At the maturity of the CFD, the two parties exchange the difference between the opening and the maturity prices of the underlying (e.g., stocks, commodities, or foreign exchange). Appendix A provides a brief introduction to CFDs. Brown et al. (2010) describe these contracts in detail.

long and short trades by 102% and 132%, respectively, compared to the average trading intensity. An investor's median reaction time after the receipt of the message is around 90 minutes. This result provides a novel insight into short selling based on our individual attention data that is not evident from analyzing aggregate investor attention.

Our second result relates attention to risk taking. We highlight two main channels of this relation, namely the impact of attention on (i) individual risk taking and (ii) portfolio diversification. First, we show that attention trades entail, on average, more leverage and more volatile stocks than non-attention trades. The economic magnitude of the volatility result is very large. Specifically, attention trade stocks feature a volatility that is 41% larger than the average volatility of our sample. We also find that this result is mainly driven by idiosyncratic risk. Second, an advantage of our individual trading data is that we also observe the portfolio of each investor at each point in time, which allows us to investigate the impact of attention on portfolio diversification. Specifically, we investigate how attention trades fit an investor's portfolio by using several proxies of the diversification benefit of the trade. We find that attention trades have a higher portfolio diversification benefit than non-attention trades. Overall, our analysis reveals two opposing channels for the impact of attention triggers on risk taking. Whereas attention triggers induce investors to trade riskier stocks (i), these triggers also stimulate portfolio diversification (ii). We show that channel (ii) usually dominates channel (i) such that attention, on average, reduces investors' portfolio risk.

Our final main result is that attention reduces investors' trading performance. We explore the reason behind this result and find two primary factors. First, attention trades have a shorter holding period than non-attention trades. Thus, attention trades bear a higher proportional trading cost, which reduces their net performance. Second, attention trades exhibit higher idiosyncratic risk, resulting in a lower performance than non-attention trades.

We provide a battery of robustness tests to confirm our conjectures and exclude alternative explanations for our results. The main caveat of our empirical strategy is that the broker may have privileged knowledge on how an individual investor reacts to push messages, and use this information to target messages at investors with a certain pattern of trading behavior. Hence, the broker's message sending behavior could affect the results. Our approach of only considering the first message to each investor on a certain stock in the main analysis mitigates this concern because for such messages, the broker has no past experience on how the investor reacts to the message. In addition, we match treated investors, based on observable heterogeneity, to counterfactual investors, and also employ investor-fixed effects to control for unobservable heterogeneity between the investors. Furthermore, we present alternative robustness settings to address the concern about the broker's message-sending behavior. For example, we only incorporate investors who receive a push message. In this setting, the treated investors are those who conduct an attention trade as in our main analysis. The counter-factual, however, is now based on investors who also receive a push message but trade a stock that is not mentioned in the message. The idea behind this approach is that whereas the broker determines who receives a push message, it 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. We show that our results are robust to this alternative setting, and similar approaches to cancel the impact or the broker's message-sending behavior.

Another concern is that we measure a dimension of news trading instead of attention. Our difference-in-differences approach mitigates this concern because we compare attention trades to non-attention trades at the same time, which should cancel out the impact of aggregate news. The broker, however, may send push messages to selected investors who have a higher exposure to news than those investors who do not receive a push message. Thus, we repeat our analysis by filtering out push messages that are associated with news. Our conjectures are robust to these alternative settings.

We present additional robustness analyses. For example, we confirm that our results are not driven by momentum and contrarian trading, or by the message content. We also repeat our analysis by incorporating whether investors click on a push message. As expected, our results also hold when we compare investors who click on a message to those that do not read the message.

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, aggregate trading patterns, and bid-ask spreads (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; Lawrence et al., 2018; Peress and Schmidt, 2018). 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 underlying attention. Micro-level attention patterns may well cancel out in the aggregate data simply because some type of investors do not receive the attention trigger, 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.

Sicherman et al. (2015) provide profound insights into the determinants of individual financial attention and the trading conditional on attention by using online account logins. As they neither observe the attention trigger nor the trades without attention, however, they do not analyze the impact of individual attention on individual trading.[2]

First, the main differences between this prior literature and our study are that we can (i) identify the stock that triggers an individual investor's attention, (ii) link the individual attention trigger to the same individual's trading, and (iii) observe the trades of investors without an attention trigger at the same time. These items allow us to contribute to the attention literature by providing novel insights on the micro-foundation of attention.

[2] An account login shows that an investor pays financial attention but not to which stock she pays attention. In addition, an investor in their sample can only trade if she has logged into the account and, hence, pays attention.

Specifically, we can and do derive novel predictions on the impact of individual attention on individual trading, risk-taking, and stock selection that are not evident in the aggregate data. In addition, these points help us to empirically isolate the impact of attention from that of potential confounding factors such as economic news.

Second, several studies analyze the relation between aggregate attention and stock return patterns. They show that greater 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). Peress and Schmidt (2018) develop a model to link retail investor attention to stock return patterns. They empirically confirm the model's prediction that higher retail attention is associated with larger trading volume, liquidity, volatility, and price reversals among stocks owned predominantly by individual investors. Our evidence on the micro-foundation of attention complements these studies by providing novel predictions on the cross-sectional difference regarding the impact of attention on different stocks.

Third, we provide micro-level insights into the home-bias literature initiated 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.

Fourth, 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 of marketing to a firm's stock risk.

Finally, we complement the studies that explore the reason behind retail investors' mistakes (Coval et al., 2009; Choi et al., 2009; Carlin, 2009; Carlin and Manso, 2011; Henderson and Pearson, 2011; Célérier and Vallée, 2017; Li et al., 2018; Egan, forthcoming). This literature shows that behavioral or cognitive biases, product complexity, ignorance of fees, obfuscation, or lack of financial sophistication can partially explain these mistakes.

We show that attention triggers are another important reason as they induce retail investors to trade more frequently and incur larger idiosyncratic risk, which reduces their investment performance.

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 additional implications of attention on trading. The final section concludes.

1 Data and methodology

1.1 Data

The novel dataset used for this study is from a discount brokerage firm offering an online trading platform to retail investors under a UK broker license. The broker allows retail investors to trade contracts for difference (CFD) on a large set of blue chip stocks. The brokerage firm charges transaction costs when investors close a position. Transaction costs are moderate and amount to 24 basis points. The broker does not provide its clients any professional investment advice, but allows them to share their capital market transactions with other traders (similar to "myForexBook" described in Heimer, 2016).

Our data sample contains all trades that the investors executed with the broker between January 1^{st}, 2016 and March 31^{st}, 2018.[3] A trade is defined as the opening or closing of a position. The trading data also includes investors' basic demographic information (age, gender, and nationality), the exact time-stamp of the trade, the specific stock underlying, an indicator for long or short positions, the executed rate, the leverage, and the investment. We omit inactive investors from the sample, i.e., investors who never trade a stock during our sample period.

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

The dataset quotes the stock prices and trades in USD irrespective of the currency in which the underlying stock trades. It provides returns after adjusting for stock splits, dividends, and transaction costs. In total, our dataset contains 3,519,118 transactions (3,393,140 round trips and 125,978 openings of a position) from 112,242 investors over 5,190,338 investor-weeks.

On February 27^{th}, 2017, roughly in the middle of our sample, the broker started to send standardized push messages to the investors for several events. There are three categories of push messages: Large price changes for a stock on a given day, streaks that highlight stock price changes in the same direction over several days, and earnings reports that depict a company's scheduled earnings announcement press call.[4] Typical messages read "*$AFSI shares down over -5.2%.*" or "*$HRI shares up over 5.0%*". An important feature of these messages is that they only contain publicly available information and, thus, do not provide news, as such. This feature helps us to isolate the impact of attention on trading from that of news. The broker determines the investors to whom it sends a certain message.

We complement the trading 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 for each company the average sentiment of all the articles (within the last 24 hours) in these news sources. This variable takes values between -5 (extremely negative coverage) and +5 (extremely positive coverage); a score of zero indicates an absence of articles for that company on that day. In addition, the variable *News Volume* captures the number of news articles about a company that are published and parsed on a given day.[5]

[4]For example, on November 13th, 2017 the broker sent a push message to some of its client investors indicating the upcoming earnings report of Home Depot before the opening bell on Tuesday, November 14th, 2017.

[5]Quandl evaluates the 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 Variables

We make use of the following variables in our empirical analysis. First, we measure investors' trading characteristics by their *trades/week*, which denotes the number of trades an investor executes over a week. In some instances, we separately report the number of trades for long and short positions using *long trades/week* and *short trades/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, i.e., the portfolio weight of the trade. The *holding period* measures the timespan between the opening and closing of a position in hours.

Second, we employ several measures to account for stock characteristics. In particular, we estimate the stochastic *volatility* of a stock using a GARCH(1,1)-model. We estimate the *beta* of a stock as the CAPM-Beta using rolling regressions over the last 262 trading days. For each stock, we use the major stock market index of the corresponding country, where it is primarily listed. Thus, we use the FTSE 100 Index for UK-stocks and the S&P500 for US-stocks, etc. We calculate idiosyncratic volatility (*IVOL*) as the standard deviation of the residuals from the rolling regressions over the last 262 trading days.

Third, to measure trade profitability, we use the *ROI* of a trade which denotes the daily return on investment net transaction costs. We also make use of the *Sharpe ratio*, which is defined as ROI/volatility of the stock, and the *Risk-adjusted ROI*, which is the daily risk-adjusted return on investment (net transaction costs) calculated with the CAPM market model.[6] Finally, to isolate the impact of transaction costs on investors' trade profitability, we also estimate these three measures using raw returns that are not corrected for transaction costs (*ROI (raw)*, *Sharpe ratio (raw)*, and *risk-adjusted ROI (raw)*).

Fourth, we account for investors' portfolio features using the *# stocks* which denotes the number of different stocks in an investor's portfolio at a given point in time and the Herfindahl-Hirschman index (*HHI*) as a simple measure of diversification based on the

[6] Note that we cannot estimate the *Risk-adjusted ROI* for intraday trades in our dataset as we only have daily market data available.

sum of squared portfolio weights (Dorn et al., 2008; Ivkovich et al., 2008; Bhattacharya et al., 2012). As an additional measure of portfolio diversification, we use the *home bias*, which 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 (see also Bhattacharya et al., 2012). Moreover, for each additional stock added to an investor's portfolio, we calculate the average correlation with all stocks contained in the portfolio at the time of the purchase (*stock correlation*). To account for the total risk of an investor's portfolio, we include *portfolio risk*. The *portfolio risk* is estimated based on the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights (investment) and denoted in % per annum. We also estimate the unsystematic portfolio risk (*portfolio variance*) separately, relying only on the diagonal entries of the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights. The *idiosyncratic risk share* denotes the portion of portfolio risk attributed to the unsystematic volatility of the portfolio estimated based on the diagonal entries of the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights divided by the total portfolio risk.

Finally, we create a dummy variable *News event* that takes a value of one on or following a day with at least one news article recorded in the Quandl FinSentS Web News Sentiment, zero otherwise.

1.3 Methodology

It is straightforward to measure the trading behavior of an investor, after her attention has been triggered. The empirical challenge to analyzing the marginal impact of an attention trigger on trading, however, is to control for the 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.

1.3.1 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 on that stock. We only use the first push message an investor receives on any given stock for two reasons. First, it mitigates the confounding effects of previous messages on the same stock. Second, it eliminates the concern that the broker could learn the reaction of the investor to the push message and, hence, send subsequent messages according to that reaction. 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 also consider all stock trades of the investor within 180 days prior to the treatment time (*prior trading intensity*) for our matching procedure.

Second, we collect a sample of comparable investors from all investors in the database who do not receive a push message in the observation and treatment periods. 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 (prior trading intensity), the date, gender, and age group. This matching addresses the concern that the broker may select the investors to whom it sends the first push message on a stock based on observable investor characteristics.

Third, we calculate the difference between the trading of the treated investors and that of the comparable investors in the observation period. This step controls for heterogeneity between the treated and comparable investors that is not captured by our 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 marginal impact of the attention trigger on trading then corresponds to the difference between these two differences. Formally, we estimate

$$
\begin{aligned}
X_{ijt} = \alpha &+ \beta_1 \text{treatment group}_{ij} \times \text{post trading}_t + \beta_2 \text{treatment group}_{ij} \\
&+ \beta_3 \text{post trading}_t + \sum_{k=4}^{K+3} \beta_k Investor_i^k + \sum_{l=K+4}^{L+K+3} \beta_l Stock_j^l + \sum_{m=L+K+4}^{M+L+K+3} \beta_m Time_t^m + \varepsilon_{ijt},
\end{aligned} \tag{1}
$$

where X_{ijt} denotes the trading intensity of investor i in stock j at time t. *treatment group* is a dummy variable that takes a value of one for investor-stock pairs of the treatment group and zero otherwise; *post trading* is a dummy variable that takes a value of one for the treatment period and zero otherwise. Our coefficient of interest is β_1 that captures the impact of the attention trigger on the trading intensity.

Our specification also includes full sets of investor, stock, and time dummies to control for unobserved heterogeneity across investors and stocks as well as aggregate time-trends. These fixed effects are important in our analysis to address the concern that the broker's message sending behavior affects our conjecture. For example, the broker may have information on investors beyond the observable characteristics to which we have access, which may explain investors' trading patterns, and send more messages to investors with specific characteristics.[7] The investor fixed-effects capture the impact of this potential behavior. Similarly, the broker may send more messages on certain stocks that usually feature different trading characteristics than other stocks. The stock fixed-effects cancel the impact of this potential behavior. Finally, the time-fixed effects mitigate the impact of the possibility that the broker mainly sends messages on dates with special trading patterns.

To obtain a comprehensive picture of the impact of attention on investors' trading intensity, we apply our difference-in-differences approach along other granular trading dimen-

[7]For example, in addition to the information provided to us, the broker may also have information on the wealth of investors, the amount they have deposited with the broker, their address, or their stock market experience.

sions. Specifically, we differentiate between stock buying and short selling. In addition, we consider the case in which investors already hold a position in the stock referred to in the push message. We use this case to investigate additional trades of already existing stock positions and the closing of positions.

1.3.2 Attention and trade characteristics

In our analysis of how attention affects trade characteristics, we incorporate the investors' leverage, holding period, and investment size. We also consider several proxies for stock and portfolio riskiness. The main steps of our analysis are similar in spirit to those of Section 1.3.1. We start by identifying the time-stamp (treatment time) of the first push message that the broker sends to an investor on a given stock. Next, we consider the last trade of this 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). If an investor trades the stock referred to in the push message within 24 hours after the treatment time, we consider this trade as an *attention trade*. We also regard trades as attention trades if an investor trades other stocks before the attention trade as long as the attention trade occurs within the 24 hours window. If an investor does not trade in the observation or the treatment period, she is excluded from this analysis.

We consider trades within 24 hours as attention trades for two reasons. First, our data shows a distinct spike in trading activity over around one day after the push messages (see Figure 3). Thus, by considering all trades in the same stock within 24 hours, it is unlikely that many trades that are, in fact, attention trades will be assigned to the group of non-attention trades.[8] Also, by considering a rather short time period after the push message, we minimize the likelihood that additional news occurred which trigger the trading of investors. Second, measuring trading patterns over one attention day is standard in the literature (Barber and Odean, 2008; Peress and Schmidt, 2018).

We then collect our sample of comparable investors from all investors in the database that do not receive a push message on the stock during the seven days around the treatment

[8]Note that assigning attention trades to the group of non-attention trades will bias our results downwards.

time. Again, we consider the last trade of this investor in any stock within seven days prior to the (counter-factual) treatment time (observation period) and the first trade of the investor after the treatment time (treatment period). We run a nearest-neighbor matching routine to match investor-stock pairs of the treatment group with those of the comparable investors based on the date, gender, age group, and the previous trading intensity (i.e., the investor's trading activity over the previous 180 days).[9] Finally, we estimate the difference-in-differences equation (1) for the trade characteristics and our portfolio diversification measures.

2 Summary statistics

Figure 1 presents the evolution of the number of push message events per month over our sample period. On average, the broker sends messages on approximately 750 different events per month. Figure 2a shows that the broker evenly spreads push messages over the different weekdays, and Figure 2b suggests that most push messages are sent during the afternoon.

Panel A of Table 1 provides summary statistics of the push messages that the broker sends to investors. We dissect price changes and streaks into "positive" messages that report a stock price increase and "negative" 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 minimum of the positive price changes and the maximum of the negative price changes suggest that the broker sends a push message once a stock's daily return exceeds 3%. The average magnitude of a reported price change is quite large, namely 6.67% and −5.87% for positive and negative price changes, respectively. For positive and negative streaks, the average magnitude is 21.38% and −20.01%, respectively. The minimum and maximum of the streaks imply that the broker sends a push message once a stock return over several days exceeds 15%. On average, more than 2,000 investors receive a message per price change event and more than 1,000

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

investors receive a message per streak event. A comparison of the number of investors receiving a message per event to the total number of investors in our sample (see Table A.2) 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 receive a push message throughout our observation period (not tabulated). The last column of Panel A shows that the broker sends around half of the push messages on or immediately around a day with at least one news article (according to the Quandl data).

Panel B of Table 1 provides summary statistics on investors' reaction to push messages. In total, the broker sends over 20 million push messages to investors during our sample period. For approximately 16% of the push messages, the investor has already traded the stock mentioned in the message before she receives the message. On average, 8.2% of investors click on the push message. We also calculate the average trades on messages, i.e., the fraction of push messages that are followed by an attention trade. On average, 1.39% of the push messages trigger an attention trade.[10] We provide additional information on the direction of attention trades. Specifically, the column "momentum trade" shows the attention trades that investors trade in the direction of the push message content and the column "contrarian trade" those that investors trade in the opposite direction of the push message content. Most attention trades are contrarian. This result is mainly driven by long attention trade positions, which investors take after negative push messages. The median reaction time to the push message of investors who conduct an attention trade is quite short, namely 1.35 hours. Finally, investors invest a significant portion of their portfolio in attention trades (12.53%, on average).

— Place Figure 1, Table 1 and Figure 2 about here —

We also provide graphical evidence that attention trades are triggered by push messages. Figure 3 plots the distribution of the time difference between push messages and attention

[10] In comparison, results from the marketing literature report that SMS advertising campaigns yield an average purchase rate of 5.2% in response to messages (Rettie et al., 2005).

trades. For both long and short trades, Panels a) and b) show a distinct attention trade spike in the first five hours after the broker sends the message.

— Place Figure 3 about here —

In Table 2, we summarize simple statistics to provide a first indication that attention trading differs from non-attention trading (see also Figures 4 and 5).[11] Panel A shows that during push-message weeks, investors are more active (1.06 trades per week) than during non-push message weeks (0.37 trades per week).[12] In addition, this panel suggests that attention trades feature a higher leverage and a shorter holding period than non-attention trades. In Panel B, we consider our proxies for the riskiness of an investment: On average, we observe higher risk measures for attention trades than for non-attention trades. Panel C suggests that attention trades feature lower investment performance than non-attention trades. In Panel D, we summarize the average portfolio features of investors with and without push messages. To be consistent with Panels A-C, we only consider investors who hold at least one stock in their portfolio at a given time. On average, portfolios contain more stocks and more foreign stocks after the investor executed an attention trade. Investors also add stocks with lower average correlation to their portfolios when executing attention trades. Moreover, their HHI measure decreases significantly following attention trades, which indicates an increase in portfolio diversification. Finally, investors' portfolio risk is smaller following push messages.

— Place Table 2 about here —

[11] We present summary statistics on the overall trading data in Table A.1 in the Appendix. In Panel A, 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 an 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 their trades on, or directly following, a day with at least one important news event for the company of the underlying stock. Panel B of Table A.1 summarizes the risk measures of the stocks in our sample.

[12] In comparison, results from the marketing literature also report a significantly larger average daily expenditure of customers exposed to mobile advertising compared to those customers who are not exposed to mobile advertising (Merisavo et al., 2006).

Most investors in our sample are male and between 25 and 34 years old (see Table A.2 in the Appendix). We now investigate the impact of attention on trading by using our difference-in-differences approach.

3 The implications of push messages on trading

In this section, we summarize the implications of push messages as an attention trigger on individual trading. We start with an analysis of the impact of the attention trigger 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 1.3.1). 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 who do not receive a push message in the same week.

— Place Table 3 about here —

Table 3 summarizes the results of our regression analysis using equation (1) for the impact of attention on stock trading. In Column (1), we investigate stock buying and see 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 investors' long trades of that stock by 0.0084 trades in the subsequent week. As a stock's mean weekly number of long trades is 0.0082 (not tabulated), the magnitude of the treatment coefficient is 102% of this mean and, thus, economically important. This result is consistent with previous findings in the literature (Seasholes and Wu, 2007; Barber and Odean, 2008; Lou, 2014; Peress and Schmidt, 2018).

Column (2) shows that push messages also induce investors to short a stock. 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 subsequent week. The quantitative impact of attention on short selling is even stronger than that on stock buying. Specifically, a stock's mean weekly number of short trades is 0.0009 (not tabulated). Thus, the magnitude of the treatment coefficient is 132% of this mean.

A potential objection to our trading analysis is that investors' trading intensity may be cyclical over time and the broker could send more first push messages to investors who currently trade more frequently. In this case, our matching based on past trading intensity could fail to cancel out an investor's non-attention trading intensity. To address this concern, we apply a simple placebo test. Specifically, we measure the impact of each push message on the trading of stocks that are not mentioned in the message. If cyclical trading drives our results, we should observe a significant treatment coefficient for non-message stocks. Columns (3) and (4) of Table 3 summarize the results. We omit the stock-fixed effects in these tests as we capture the trading of any stock besides the message stock. The number of observations is smaller than in Columns (1) and (2), as we need to omit messages that are followed by an additional message to the same investor on any other stock within one week. The treatment coefficients in Columns (3) and (4) imply that the push messages have no impact on either the short or long trading of non-message stocks.

In Columns (5) and (6) of Table 3, we again measure the impact of push messages on message stocks. The only difference with respect to Columns (1) and (2) is that we now apply the message sample and fixed-effects of Columns (3) and (4) to confirm that the attention trading of message stocks is also significant in the setting of the placebo test. As expected, attention trading is still significant, both for long and short trades of message stocks. Thus, Columns (3) to (6) imply that cyclical trading does not explain our attention trading results.

Overall, our analysis shows that attention stimulates long and short trading. To the best of our knowledge, we are the first to show that attention is important for short selling.

Barber and Odean (2008) focus on the sale of existing positions rather than on short selling. They argue that because attention is a scarce resource, the impact of attention on retail trading depends on the size of the choice set. Specifically, they find that attention affects buying—where investors search across thousands of stocks —more than the sale of existing positions—where investors choose only from the few stocks that they own. An alternative explanation to the result that attention is more important for buying than for selling existing positions is selective attention. In particular, Karlsson et al. (2009) and Sicherman et al. (2015) suggest that retail investors pay more financial attention to good news than to bad news. Hence, if retail investors are, on average, momentum traders, attention could be more important for buying than for selling simply because they pay more selective attention to good news. Our result on short selling helps to distinguish these two explanations. Specifically, the choice set for short selling is clearly much larger than that for selling an existing position.[13] Thus, our conjecture that attention is also important for stock selling when we focus on short sales supports the argument of Barber and Odean (2008).

3.2 Attention and trade characteristics

We now investigate how attention affects investors' trade characteristics in our difference-in-differences approach of Section 1.3.2. Again, we make use of equation (1) in our estimations; however, instead of using the trading intensity as our dependent variable, we now use investors' trading characteristics as dependent variables. The treatment group contains attention trades, while the counterfactual is the first trade after the treatment time of matched investors who did not receive a push message. Table 4 shows the results for the leverage, holding period, and investment amount of long trades. We first focus on long trades because these trades represent the majority of our sample. We present the results for short trades in Section 5.1.

— Place Table 4 about here —

[13] Using CFDs, investors can trade all stocks in our sample long or short, rather than being confined only to the stocks they currently hold.

Column (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 conduct attention trades with a 0.0910 higher leverage than non-attention trades. The magnitude of this coefficient corresponds to approximately 1.5% of the mean leverage of 6.108 in Table A.1. Column (2) analyses the impact of the attention trigger on investors' holding period. The treatment coefficient indicates that, on average, investors hold attention positions 25.16 hours shorter than non-attention positions. The average stock holding period of investors in our sample is only 243.215 hours (see Table A.1). Thus, the magnitude of the treatment coefficient corresponds to approximately 10% of the average holding period, which is economically important. Finally, Column (3) shows that the investment amount of attention trades is not statistically different from that of non-attention trades. Table 3 and Column (2) of Table 4 imply that, whereas attention has a strong effect on the decision whether to trade, it has no impact on the decision how much to trade. These results are consistent with the findings in Peress and Schmidt (2018). They are supportive of models assuming a fixed attention cost for stock market participation (Stapleton and Subrahmanyam, 1977, 1980; Merton, 1987; Abel et al., 2007; Chien et al., 2012), but difficult to reconcile with models in which investors gradually increase trading with attention (Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2010).

To shed additional light on the impact of attention on risk-taking, we now investigate our stock risk measures in the difference-in-differences approach. As our dependent variables in these analyses are a set of rather persistent stock-specific measures, we omit the stock-fixed effects of equation (1). Column (1) of Table 5 compares the volatility of attention trade stocks with that of non-attention trade stocks. The positive treatment coefficient indicates that, on average, attention trades are more volatile than non-attention trades. The economic magnitude of the treatment coefficient is very large. It corresponds to 41% of the average stock volatility of our sample (see Table A.1). Column (2) shows that the beta of attention trade stocks is also higher than that of non-attention trade stocks. The economic magnitude of the treatment coefficient, however, is modest, corresponding to

7.8% of the average beta of our sample (see Table A.1). Finally, Column (3) suggests that attention trade stocks exhibit larger idiosyncratic risk than do non-attention trade stocks. The economic magnitude of the treatment coefficient implies that attention trade stocks feature an idiosyncratic risk that is 32% larger than the average idiosyncratic risk of our sample (see Table A.1).

— Place Table 5 about here —

Together, Columns (1) to (3) imply that attention trades are riskier than non-attention trades. The intuition behind this result is that riskier stocks are more likely to experience extreme price movements and, hence, trigger attention. For example, the correlation between the stock volatility and the number of push messages on a stock in our sample is 0.67. This idea is consistent with the observation of Fang and Peress (2009) that media coverage is positively related to idiosyncratic stock volatility. Thus, if investors trade on attention triggers, they end up trading more volatile stocks. Our analysis in Table 4, however, shows that attention also stimulates additional dimensions of risk taking such as leverage, which cannot be explained by this simple explanation.

Next, we turn to the question how attention affects the extent to which investors select a stock that fits their existing portfolio. We start from the observation that investors in our sample only hold a limited amount of, on average, 4.41 stocks in their portfolio.[14] This under-diversification of individual investors is well-established in the literature (Barber and Odean, 2008), which underpins the importance of incorporating a portfolio view when analyzing investors' risk taking. An advantage of our individual trading data is that we can observe the portfolio of each investor over time, which allows us to investigate how attention affects portfolio risk.

Table 6 applies equation (1) of our difference-in-differences approach to several proxies that capture the diversification benefit of a traded stock (including short sales) to each

[14]This number includes investor-weeks in which the investor does not hold any stocks in her portfolio. We cannot observe stock trades in our dataset that add to investors' portfolio before January 1^{st}, 2016. Given the average stock holding period of around 10 days, however, we expect that this limitation only has a minor impact on our calculation of the average number of stocks in a portfolio.

individual investor's portfolio. The treatment group contains attention trades, whereas the counterfactual consists of the first trades after the treatment time of matched investors who did not receive a push message. Throughout our portfolio analysis, we also match investors based on the number of stocks they hold in their portfolio just before the treatment time, because one additional stock has a much larger impact on the risk of a portfolio consisting of few stocks than many stocks. Note that we also consider stocks that constitute a short position in investors' portfolios. In addition, we only consider investors who hold at least one stock in their portfolio immediately before the push messages are sent (39% of our sample), because it is not possible to interpret the diversification benefit of investors who do not hold a stock.[15]

In Column (1), we follow Bhattacharya et al. (2012) and use the home bias as a proxy of diversification. Specifically, the *home bias*-dummy (our dependent variable) is one, if an investor trades a stock of a company with the headquarter in the same country as the investor's domicile. The treatment coefficient suggests that attention induces investors to add foreign stocks to their portfolio. Next, we compare the average correlation of attention trades and non-attention trades with an investor's existing portfolio by using the variable *stock correlation* as the dependent variable. As this variable is based on the portfolio of the investor, we omit the stock-fixed effects. The treatment coefficient in Column (2) implies that attention trades feature a lower average correlation to the investor's portfolio than non-attention trades. In Column (3), we investigate how attention affects the number of different stocks in a portfolio. The treatment coefficient shows that treated investors increase the number of different stocks in their portfolio compared to investors who trade without receiving a push message. This increase occurs mainly because treated investors tend to trade novel stocks that they do not already hold in their portfolio, whereas the counter-factual investors have a higher propensity to trade stocks they already hold in their portfolio. In Column (4), we apply a commonly accepted and simple measure of portfolio diversification, namely the Herfindahl-Hirschman index HHI (Dorn et al., 2008; Ivkovich et al., 2008). The lower the HHI, the better the investor's

[15] An exception to this restriction is the analysis of the home bias in Column (1), which does not require stocks in an investor's portfolio to allow interpretation of the results.

portfolio diversification. The treatment coefficient suggests that the HHI is significantly smaller for treated than for counter-factual investors. Overall, the diversification proxies in Table 6 suggest that attention improves investors' portfolio diversification.

— Place Table 6 about here —

Tables 5 and 6 highlight a trade-off regarding the impact of attention on investors' risk-taking. On the one hand, attention induces investors to trade riskier stocks. On the other hand, attention stimulates portfolio diversification. In Table 7, we investigate which channel dominates in the portfolio perspective. To this end, we apply equation (1) (without stock-fixed effects) of our difference-in-differences approach to the investors' portfolio risk. The treatment group considers attention trades, whereas the counterfactual consists of the first trades after the treatment time of matched investors who did not receive a push message. Column (1) shows that attention reduces investors' portfolio risk. Thus, the "better diversification channel" dominates the "more risky stock channel" in the portfolio. Finally, Column (2) shows how attention affects the idiosyncratic risk share of a portfolio. The treatment coefficient is positive but not significant. Thus, whereas attention trades bear a significantly higher risk than non-attention trades (see Table 5), this effect is insufficient to cause a significant treatment coefficient on the portfolios' idiosyncratic risk share.[16]

We repeat the analysis in Table 7 by including the 61% of investors who do not hold any stock in their portfolio immediately before the treatment event, which shuts down the diversification channel for the majority of investors (not tabulated). In this case, the treatment coefficient on portfolio risk becomes significantly positive, mainly because the messages induce treated investors who do not hold a stock to buy a riskier stock compared to comparable investors (see Table 5, Column (1)).

— Place Table 7 about here —

[16] The impact of one additional stock on a portfolio's idiosyncratic risk share depends not only on the new stock's variance, but also on the stock's covariances with the portfolio stocks and the weights invested in each portfolio stock.

Finally, we turn to the performance of attention trades in Panel A of Table 8. Column (1) shows that attention has a negative impact on daily returns. Specifically, the treatment coefficient suggests that investors' yearly performance is 2.95% (-0.0117 x 252 days) lower with attention trades than with non-attention trades. Column (2) repeats the analysis with raw returns that do not incorporate trading costs. It suggests that investors' raw yearly performance is only 1.69% (-0.0067 x 252 days) lower with attention trades than with non-attention trades. Thus, the treatment coefficients in Columns (1) and (2) imply that the absolute performance of attention trades compared to non-attention trades is 1.26% (2.95%-1.69%) lower when we incorporate trading costs. This result suggests that trading costs are an important determinant of the inferior performance of attention trades, explaining 43% (1.26%/2.95%) of the average return difference between attention and non-attention trades. Finally, Columns (3) to (6) of Panel A in Table 8 show that the Sharpe ratio of attention trades is smaller than that of non-attention trades and the risk-adjusted return is not significantly different.

— Place Table 8 about here —

An alternative reason for the return difference between attention and non-attention trades could be that attention stocks have, on average, different characteristics than non-attention stocks. These characteristics could be associated with abnormal returns. Table 5, for example, shows that attention trades have a higher idiosyncratic volatility, and Ang et al. (2006) find that such stocks carry lower abnormal returns. In addition, Fang and Peress (2009) illustrate that higher idiosyncratic volatility induces higher media coverage, and stocks with higher media coverage feature lower abnormal returns. To test whether heterogeneity in stock characteristics explain the remaining return difference, we repeat our return analysis in Panel B of Table 8 by including stock fixed effects. Column (2) in Panel B shows that the raw return difference declines in magnitude and significance compared to Panel A once we control for fixed stock characteristics. The remaining raw return difference is only marginally significant. Thus, the fact that, on average, stocks with attention triggers feature different characteristics than stocks without that trigger also explains part of the return difference. The coefficient in Column (1), however, is still highly significant, supporting our argument that trading costs are a primary reason behind the inferior performance of attention trades.

As the broker charges equally on each trade, the trading cost of attention trades require an explanation. Column (2) of Table 4 shows that the holding period of attention trades is shorter than that of non-attention trades. Thus, the trading costs over the entire holding period of each trade convert into a higher transaction cost per day for attention trades than for non-attention trades. We conduct a simple plausibility test to check whether this explanation can quantitatively explain the higher trading cost of attention trades in Table 8. In particular, the average holding period of the attention trades in Table 4 is 7.23 days (not tabulated), which leads to an average trading cost per day of 3.32 bps (24 bps/7.23 days). The treatment coefficient in Column (2) of Table 4 implies that attention trades have, on average, a 1.05 day shorter holding period than non-attention trades. Thus, non-attention trades have an average trading cost per day of 2.90 bps (24 bps/(7.23+1.05)). The 0.42 bps (3.32 bps-2.90 bps) difference of the daily trading cost between attention and non-attention trades converts into a yearly performance difference of 1.06% (0.42 bps x 252 days). This magnitude reflects the 1.26% performance difference caused by the trading costs in Panel A of Table 8 very well.[17] Thus, the larger trading cost of attention trades due to their shorter holding period is a plausible explanation of these trades' inferior performance.

Overall, our analysis implies that attention decreases the trading performance of investors for two reasons, namely (i) because attention reduces the stock holding period and (ii) because stocks with more attention have different characteristics than stocks with less attention. Thus, investors, in fact, pay for attention.

[17] We work with averages in this simple example. Thus, the example merely serves as a plausibility test of the economic magnitude.

4 Robustness analyses

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

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 different risk than those investors who do not receive a push message. We address this concern in three ways, namely with an alternative difference-in-differences approach, by only considering the first message over all stocks, and with an alternative matching approach.

First, we investigate the impact of the attention trigger in an alternative difference-in-differences 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 now based on investors who do not conduct an attention trade. Specifically, these investors receive a push message at the same time as the treated investors, but trade a stock that is not mentioned in this message. The idea behind this approach is that whereas the broker determines who receives a push message, the broker cannot determine who reacts to the attention trigger. Thus, the broker's behavior cannot allocate investors to either the treated investors or the counter-factual. Panel A in Table 9 shows that our conjectures on risk taking are robust to this alternative setting. In terms of statistical and economic impact, the results mirror those of our main analyses.

— Place Table 9 about here —

We present a variant of this approach in Panel B of Table 9. Specifically, we consider the investors who actually click on the push message in the treatment group and the investors who do receive a push message but do not click on the message in the control group. This variant offers the advantage that clicking on a push message is an intuitive proxy of higher attention compared to not clicking on a push message. In addition, the broker cannot determine who clicks on the push message. Our results are robust to this setting as well.

Second, we repeat our main analysis by only considering push messages to investors who have never received a push message on any stock before they receive the first push message on a certain stock. For such messages, the broker has no prior information on how an investor's stock trading reacts to a push message. Thus, the broker cannot bias the results by selecting the investors to whom it sends a push message according to the investors' previous reaction to the attention trigger. Panel C of Table 9 shows that our main conjecture on risk taking holds in this robustness test.[18] We also conduct this analysis by only considering push messages to investors who have never received a push message on any asset class (commodities, foreign exchange, etc.) before they receive the first push message on a certain stock (not tabulated). Even though we only have around 5,000 observations in this test, the treatment coefficients on investors' risk taking (leverage, stock volatility, and IVOL) are statistically significant and have the expected sign.

Third, we use an alternative matching approach. In particular, we also match investors based on their historical risk taking besides our standard matching metrics. To this end, we consider the volatility of the last stock purchase prior to the treatment event as an additional matching variable, and repeat our main difference-in-differences analyses. The goal behind this approach is to cancel out the impact of the broker's potential tendency to send more first push messages to investors who usually trade with higher risk. Our results are robust to this alternative matching approach, as shown in Panel D of Table 9.

[18]The only difference is that the treatment coefficient of the portfolio risk is not significant. Hence, the diversification channel does not dominate the risky stock channel.

4.2 Attention and news

Another concern with our results is 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 the four alternative settings in Table 10.

— Place Table 10 about here —

First, we omit earnings report push messages in Panel A to address the concern that such messages could reveal some non-public news to investors or induce investors to trade on the actual earnings announcement rather than the push message.

Second, we omit push messages that the broker sends on or the day directly following news. We identify news-days from the Quandl Alpha One Sentiment Data. Panel B in Table 10 repeats our difference-in-differences analysis in this setting.

Next, we apply a news filter for each of our risk measure in Panel C. 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 explained by news. We then repeat our difference-in-differences approach by using these residuals as the dependent variable to measure the impact of the attention triggers on investors' leverage decision. Column (1) shows the results of this analysis. We apply the same procedure for the *holding period*, *investment*, *volatility*, *beta*, $IVOL$, and $portfolio\ risk$ in Columns (2) to (7).

In Panel D of Table 10, we filter the attention trigger with respect to news information. The idea behind this approach is to put less weight on push messages that the broker sends on or the day directly following news than on push messages that the broker sends on news-days. Specifically, we first 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-differences analysis by the residuals of this regression. Columns (1) to (7) in Panel D summarize the results of using this filter.

Overall, Table 10 shows that the treatment coefficients and the levels of statistical significance are very similar to those of our main analysis. The only meaningful differences to our main results are that the treatment coefficient of investment becomes significantly negative and the treatment coefficient on portfolio risk is insignificant in Panel B. We, therefore, conclude that the push message trigger explains risk taking beyond news-induced trading.

4.3 Attention and message content

We also investigate to what extent the message content affects our results to exclude that style trading such as momentum trades drive our conjecture. We omit earnings reports in this analysis because it is challenging to unambiguously classify their content. In Panel A of Table 11, we incorporate the sign of a push message's reported stock price change. Specifically, we interact the treatment coefficient with the "positive"-dummy that is one if the reported stock price change is positive. The treatment coefficients are very similar to our main regressions in Tables 4 and 5, only that on portfolio risk is not significant. Thus, push messages that report a stock price decline also stimulate investors to take higher risk but the diversification channel does not dominate the risky stock channel. The coefficients of the interactions of the treatment with the positive-dummy are only significant for volatility and IVOL. Hence, we observe a slightly higher impact of the attention triggers on risk taking for positive messages. For example, Column (6) suggests that attention trades after negative messages have a 0.0800 higher idiosyncratic volatility than non-attention trades, and attention trades after positive messages have a 0.1028 (0.0800 + 0.0228) larger idiosyncratic volatility than non-attention trades.

— Place Table 11 about here —

In a similar vein, we study in Panel B of Table 11 whether investors' reaction to attention depends on the magnitude of the return reported in the push message. To this end, we incorporate the interaction between the treatment coefficient and the *strong*-dummy in our analysis. This dummy equals one if a message's absolute price changes is larger than the median reported price change, and zero otherwise. The treatment and interaction coefficients in Columns (1) to (7) suggest that both weak and strong messages stimulate risk taking. The impact of attention is higher for strong messages than for weak messages. For instance, the difference in leverage between attention trades and non-attention trades is about twice as large after strong messages than after weak messages. As in Panel A, the treatment and interaction coefficients on portfolio risk are not significant. Thus, the diversification channel does not dominate the risky stock channel.

Overall, the results in Table 11 indicate that the increased willingness of investors to trade riskier stocks is primarily driven by the attention trigger, and not by the message content.

4.4 Do investors read the push messages?

A potential objection to our results is that investors may not read the push messages. Thus, we repeat our analysis by only considering those investors who actually click on the push message in the treatment group. Table 12 shows that our results are robust to this alternative setting.

— Place Table 12 about here —

5 Further analyses

5.1 Attention and risk taking in short selling

Our analysis in Section 3.1 suggests that attention stimulates both long and short trading. We now investigate whether attention also increases the risk of short trades. To this end, we apply our difference-in-differences setting of Section 3.2 to short sales. Specifically, we compare the risksiness of short attention trades to that of short non-attention trades. Table 13 summarizes the results. The treatment coefficients in Columns (1) to (6) suggest that short trades feature higher risk taking upon attention. The results, however, are less pronounced than those with long trades in Tables 4 and 5. Specifically, the impact of attention on leverage, the holding period, and beta is not significant. In addition, the coefficients of volatility and IVOL are smaller than those in our main analysis of long trades.

— Place Table 13 about here —

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 14 shows that investors are more likely to increase (Column (1)) and to close (Column (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 14 about here —

5.3 Attention Satiation

We now investigate whether the impact of an attention trigger depends on how many push messages an investor has already received before that attention trigger. To address this issue, we categorize each push message by how many messages an investor has received up to and including that message. Then, we summarize the success rate of each message category. The success rate is the portion of push messages that is followed by a trade in the underlying mentioned in the push message within 24 hours, i.e. by an attention trade. Figure 6 plots the success rate for each message category together with the 99% confidence intervals.[19] The plot shows that the success rate declines with the number of

[19]This interval is based on the standard deviation of the success rate across different message-events.

push messages an investor has already received. This pattern suggests that investors are subject to attention satiation.

— Place Figure 6 about here —

6 Conclusion

This study presents novel evidence on the micro-foundation of attention based on a unique dataset of trading records. The main advantages of our 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 standard difference-in-differences methodology, accompanied by a large set of robustness tests to the data, we find that attention stimulates investors' long and short trading, as well as their risk taking. Specifically, whereas the attention triggers induce investors to trade riskier stocks, these triggers also stimulate portfolio diversification. We show that the diversification-channel dominates the riskier stock-channel such that attention, on average, reduces investors' portfolio risk. Furthermore, we show that attention leads to an inferior investment performance. Thus, retail investors pay for attention.

We provide additional novel insights into individual attention to stimulate further research. For instance, we document a link between attention and the home bias by showing that the impact of attention is stronger for stocks of companies located outside the country of the investor. In addition, we find that attention is subject to a satiation effect.

A limitation of our study is that the customers of the brokerage service may not be representative of the individual investor. Instead, they may select the brokerage service based on their preferences.

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 financial markets.

References

Abel, Andrew B., Janice C. Eberly, and Stavros Panageas, 2007, Optimal inattention to the stock market, *American Economic Review* 97, 244–249.

Andrei, Daniel, and Michael Hasler, 2014, Investor attention and stock market volatility, *The Review of Financial Studies* 28, 33–72.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *The Journal of Finance* 61, 259–299.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *The Review of Financial Studies* 21, 785–818.

Bhattacharya, Utpal, Andreas Hackethal, Simon Kaesler, Benjamin Loos, and Steffen Meyer, 2012, Is unbiased financial advice to retail investors sufficient? answers from a large field study, *The Review of Financial Studies* 25, 975–1032.

Brown, Christine, Jonathan Dark, and Kevin Davis, 2010, Exchange traded contracts for difference: Design, pricing, and effects, *The Journal of Futures Markets* 30, 1108–1149.

Carlin, Bruce, 2009, Strategic price complexity in retail financial markets, *Journal of Financial Economics* 91, 278–287.

Carlin, Bruce, and Gustavo Manso, 2011, Obfuscation, learning, and the evolution of investor sophistication, *The Review of Financial Studies* 24, 754–785.

Célérier, Claire, and Boris Vallée, 2017, Catering to investors through security design: Headline rate and complexity, *The Quarterly Journal of Economics* 132, 1469–1508.

Chen, Honghui, Gregory Noronha, and Vijay Singal, 2005, The price response to S&P 500 index additions and deletions: Evidence of asymmtry and new explanation, *The Journal of Finance* 59, 1901–1930.

Chien, Yi Li, Harold Cole, and Hanno N. Lustig, 2012, Is the volatility of the market price of risk due to intermittent portfolio rebalancing?, *American Economic Review* 102, 2859–96.

Choi, James, David Laibson, and Brigitte Madrian, 2009, Why does the law of one price fail? an experiment on index mutual funds, *The Review of Financial Studies* 23, 1405–1432.

Coval, Joshua, Jakub Jurek, and Erik Stafford, 2009, The economics of structured finance, *Journal of Economic Perspectives* 23, 3–25.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *The Journal of Finance* 66, 1461–1499.

Dorn, Daniel, Gur Huberman, and Paul Sengmueller, 2008, Correlated trading and returns, *The Journal of Finance* 63, 885–920.

Egan, Mark, forthcoming, Brokers vs. retail investors: conflicting interests and dominated products, *The Journal of Finance* .

Fang, Lily, and Joel Peress, 2009, Media coverage and the cross-section of stock returns, *The Journal of Finance* 64, 2023–2052.

Financial Services Authority, 2007, Disclosure of contracts for difference: Consultation and draft handbook, Consultation Paper 07/20.

French, Kenneth, and James M. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review. Papers and Proceedings* 81, 222–226.

Grullon, Gustavo, George Kanatas, and James P. Weston, 2004, Advertising, breadth of ownership, and liquidity, *The Review of Financial Studies* 17, 439–461.

Heimer, Rawley Z., 2016, Peer pressure: Social interaction and the disposition effect, *The Review of Financial Studies* 29, 3177–3209.

Henderson, Brian J., and Neil D. Pearson, 2011, The dark side of financial innovation: A case study of the pricing of a retail financial product, *Journal of Financial Economics* 100, 227–247.

Ivkovich, Zoran, Clemens Sialm, and Scott Weisbenner, 2008, Portfolio concentration and the performance of individual investors, *Journal of Financial and Quantitative Analysis* 43, 613–655.

Karlsson, N., G. Loewenstein, and D. Seppi, 2009, The ostrich effect: Selective attention to information, *Journal of Risk and Uncertainty* 38, 95–115.

Lawrence, Alastair, James Ryans, Estelle Sun, and Nikolav Laptev, 2018, Earnings announcement promotions: A yahoo finance field experiment, *Journal of Accounting and Economics* 66, 399–414.

Lehavy, Reuven, and Richard G. Sloan, 2008, Investor recognition and stock returns, *The Review of Accounting Studies* 13, 327–336.

Li, Xindan, Avanidhar Subrahmanyam, and Xuewei Yang, 2018, Can financial innovation succeed by catering to behavioral preferences? evidence from a callable options market, *Journal of Financial Economics* 128, 38–65.

Lou, Dong, 2014, Attracting investor attention through advertising, *The Review of Financial Studies* 27, 1797–1829.

Luo, Xueming, and C.B. Bhattacharya, 2009, The debate over doing good: Corporate social performance, strategic marketing levers, and firm-idiosyncratic risk, *Journal of Marketing* 73, 198–213.

McAlister, Leigh, Raji Srinivasan, and MinChung Kim, 2007, Advertising, research and development, and systematic risk of the firm, *Journal of Marketing* 71, 35–48.

Merisavo, Marko, Jari Vesanen, Antti Arponen, Sami Kajalo, and Mika Raulas, 2006, The effectiveness of targeted mobile advertising in selling mobile services: an empirical study, *International Journal of Mobile Communications* 4, 119–127.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *The Journal of Finance* 42, 483–510.

Odean, Terrance, 1999, Do investors trade too much?, *American Economic Review* 89, 1279–1298.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Peress, Joel, and Daniel Schmidt, 2018, Glued to the tv: Distracted noise traders and stock market liquidity, *Working Paper* .

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *The Review of Financial Studies* 22, 435–480.

Rego, Lopo L., Matthew T. Billett, and Neil A. Morgan, 2009, Consumer-based brand equity and firm risk, *Journal of Marketing* 73, 47–60.

Rettie, Ruth, Ursula Grandcolas, and Bethan Deakins, 2005, Text message advertising: Response rates and branding effects, *Journal of Targeting, Measurement and Analysis for Marketing* 13, 304–312.

Seasholes, Mark S., and Guojun Wu, 2007, Predictable behavior, profits, and attention, *Journal of Empirical Finance* 14, 590–610.

Sicherman, Nachum, George Loewenstein, Duane J. Seppi, and Stephen P. Utkus, 2015, Financial attention, *The Review of Financial Studies* 29, 863–897.

Stapleton, Richard C., and Marti G. Subrahmanyam, 1977, Market imperfections, capital market equilibrium and corporation finance, *The Journal of Finance* 32, 307–319.

Stapleton, Richard C., and Marti G. Subrahmanyam, 1980, *Capital Market Equilibrium and Corporation Finance* (JAI Press, Greenwich, CT).

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2010, Information acquisition and underdiversification, *Review of Economic Studies* 77, 779–805.

A Contracts for difference

A contract for difference (CFD) is a financial contract designed such that its price equals that of the underlying security.[20] 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).

[20] 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.

Panel A:

Type	Number of events	min(price change)	Avg.(price change)	max(price change)	Avg. number of messages	Events with news
Positive price change	3,667	3.00	5.73	12.38	2,605.47	0.48
Negative price change	4,709	-13.09	-5.76	-3.00	2,217.83	0.48
Positive streak	446	15.01	21.38	46.69	1,588.75	0.42
Negative streak	215	-41.89	-20.01	-15.04	1,001.74	0.46
Earnings report	932	-	-	-	833.05	0.69
	9,969	-	-	-	2,176.59	0.50

Panel B:

Type	Number of messages	Traded before	Click on message	Trade on message	Momentum trade	Contrarian trade	mean (reaction time)	median(reaction time)	Investment
Positive price change	9,554,260	0.1499	0.0871	0.0140	0.0062	0.0078	5.4406	1.2322	14.25
Negative price change	10,443,759	0.1461	0.0752	0.0125	0.0040	0.0085	5.3726	1.2133	11.47
Positive streak	708,583	0.1583	0.0983	0.0127	0.0069	0.0058	1.6954	0.8321	10.68
Negative streak	215,375	0.3679	0.1182	0.0276	0.0100	0.0177	1.7182	0.8829	10.50
Earnings reports	776,403	0.3003	0.0923	0.0298	-	-	13.6585	21.6785	9.75
	21,698,380	0.1559	0.0822	0.0139	0.0050	0.0079	5.8567	1.3500	12.53

Table 1: 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 retail investors 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 reports* are the messages that report earnings announcements. *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. *Avg. number of messages* is the average number of messages per event that the broker sent to investors. *Events with news* is 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. *Number of messages* is the number of messages the broker sent to investors. *Traded before* is a dummy variable that takes a value of one if the investor has traded in the underlying referred to in the push message before receiving the push message, zero otherwise. *Click on messages* is a dummy variable that takes a value of one if the investor clicks on the push message. *Trade on messages* is a dummy variable that takes a value of one if the push message is followed by a trade in the underlying referred to in the push message within 24 hours. *Momentum trade* is a dummy variable that takes a value of one if the push message is followed by a trade in the direction of the change of the underlying referred to in the push message within 24 hours. *Contrarian trade* is a dummy variable that takes a value of one if the push message is followed by a trade in the opposite direction of the change of the underlying referred to in the push message within 24 hours. *Reaction time* is the time in hours between the push message and the trade of an investor who received the push message in the underlying referred to in the push message. *Investment* denotes the trade amount's fraction of total assets deposited with the online broker, i.e., the portfolio weight of the trade.

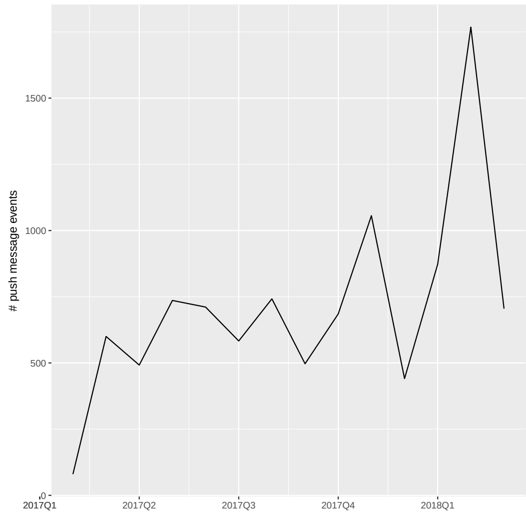
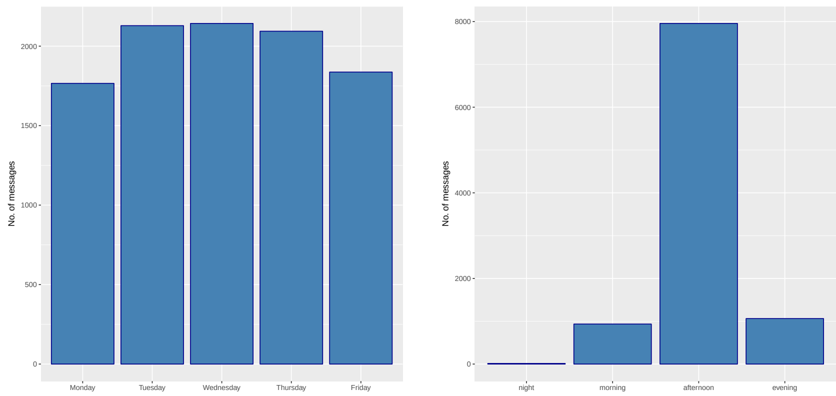


Figure 1: Number of push message events over time

This figure presents the evolution of the number of daily push-events over our sample period. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

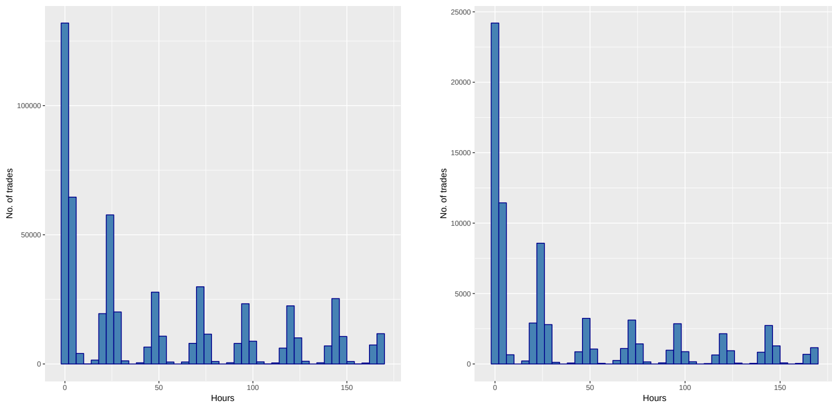


(a) Day of the week-distribution

(b) Time of the day-distribution

Figure 2: 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

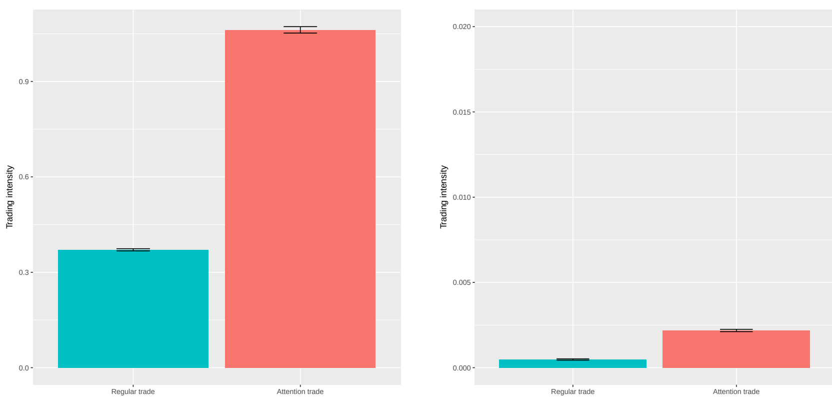


(a) Opening of a long position

(b) Opening of a short position

Figure 3: 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 are from a discount brokerage firm that offers a trading platform to retail investors 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 4: Stock-specific trading intensity after receiving push message

This figure presents investors’ average trading intensity (with 99% confidence intervals) in our trade data. Green bars show non-attention trades; red bars show attention trades. “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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: Trade characteristics						
Type	trades/week	leverage	investment	holding period		
Non attention trade	0.37	6.07	12.83	268.82		
Attention trade	1.06	6.53	12.73	178.61		
t-test	10.05	4.27	0.16	4.96		
Panel B: Stock characteristics						
Type	volatility	beta	IVOL			
Non attention trade	0.3616	1.25	0.2918			
Attention trade	0.5428	1.46	0.3972			
t-test	18.70	7.15	16.77			
Panel C: Trade profitability						
Type	ROI	Sharpe ratio	risk-adjusted ROI	ROI (raw)	Sharpe ratio (raw)	risk-adjusted ROI (raw)
Non attention trade	-0.0071	-0.0040	-0.0056	-0.0223	-0.0113	-0.0056
Attention trade	-0.0133	-0.0099	-0.0063	-0.0235	-0.0154	-0.0062
t-test	7.70	0.50	0.20	6.21	1.66	0.20
Panel D: Portfolio features						
Type	home bias	stock correlation	# stocks	HHI	portfolio risk	portfolio variance
Non attention trade	0.058	0.28	6.61	0.40	0.30	0.26
Attention trade	0.039	0.23	8.24	0.33	0.28	0.25
t-test	6.75	13.55	7.68	11.29	2.96	3.03

Table 2: 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 retail investors 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 (*non attention trade*). The second line summarizes all trades that following a push message in the same underlying within 24 hours (*attention trade*). *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; ROI denotes the return on investment net transaction costs; *Sharpe ratio* is the daily risk-adjusted return on investment (net transaction costs) defined as roi/volatility of the stock; $Risk - adjusted\ ROI$ is the daily risk-adjusted return on investment (net transaction costs) calculated with the CAPM market model (omitting day trades); ROI (raw) denotes the return on investment not corrected for transaction costs; *Sharpe ratio* (raw) is the daily risk-adjusted return on investment (not corrected for transaction costs) defined as roi/volatility of the stock; $Risk - adjusted\ ROI$ (raw) is the daily risk-adjusted return on investment (not corrected for transaction costs) calculated with the CAPM market model (omitting day trades); *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; *stock correlation* denotes the average correlation of the stock which was last added to the portfolio with the stocks previously contained in the portfolio; # *stocks* denotes the number of different stocks in an investor's portfolio; HHI denotes the Herfindahl-Hirschman index as a measure of diversification; $portfolio\ risk$ denotes the volatility of the portfolio estimated based on the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights; $portfolio\ variance$ denotes the unsystematic volatility of the portfolio estimated based on the variance entries of the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights. The t-test reports results from equality tests of non-treated versus treated trades, clustered over time.

	(1)	(2)	(3)	(4)	(5)	(6)
	Messages stocks		Non-messages stocks		Messages stocks	
	long positions	short positions	long positions	short positions	long positions	short positions
Treatment	0.0084	0.0012	−0.0001	0.0002	0.0152	0.0014
	(2.30)	(2.95)	(−0.01)	(0.17)	(3.52)	(3.08)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,287,258	2,323,914	298,348	298,348	298,348	298,348
R^2	0.26	0.21	0.67	0.61	0.50	0.50

Table 3: Stock-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. Columns (1), (3), and (5) report long positions; Columns (2), (4), and (6) show results for short-selling positions. Columns (1) and (2) consider trades in message stocks. Columns (3) and (4) consider trades in non-message stocks. Investors who receive multiple messages within the considered time period are omitted from the sample in Columns (3) to (6). 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 stock 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. 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 stock-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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) Leverage	(2) Holding period	(3) Investment
Treatment	0.0910	−25.1582	0.0201
	(3.48)	(−4.74)	(0.19)
Investor-fixed effects	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	1,040,208	1,040,208	1,040,208
Adj. R^2	0.63	0.37	0.70

Table 4: 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. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) volatility	(2) beta	(3) IVOL
Treatment	0.1212	0.0771	0.0798
	(13.31)	(4.49)	(14.61)
Investor-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	1,040,208	1,040,208	1,040,208
Adj. R^2	0.32	0.28	0.36

Table 5: 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. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) home bias	(2) stock correlation	(3) No. of stocks	(4) HHI
Treatment	−0.0035	−0.0283	0.0813	−0.0069
	(−2.34)	(−7.08)	(2.31)	(−3.18)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	1,040,208	897,008	897,305	897,305
Adj. R^2	0.68	0.43	0.72	0.61

Table 6: Attention and additional stocks: difference-in-differences analysis

This table reports results from a difference-in-differences regression analysis on the home bias of investors and average new stock correlations in our trade data. For each investor we take the last trade immediately before the treatment event and 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. *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. *stock correlation* denotes the average correlation of the stock which was last added to the portfolio with the stocks previously contained in the portfolio. $No.\ of\ stocks$ denotes the number of different stocks in an investor's portfolio. HHI denotes the Herfindahl-Hirschman index as a measure of diversification; $Treatment$ 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. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) portfolio risk	(2) idiosyncratic risk share
Treatment	−0.0037	0.0207
	(−2.81)	(1.21)
Investor-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	897,305	897,305
Adj. R^2	0.53	0.03

Table 7: Attention and portfolio risk: difference-in-differences analysis

This table reports results from a difference-in-differences regression analysis on the portfolio risk of investors in our trade data. For each investor we take the portfolio risk immediately before the treatment event and the portfolio risk after 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. $portfolio\ risk$ denotes the volatility of the portfolio estimated based on the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights; *idiosyncratic risk share* denotes the portion of portfolio risk attributed to the unsystematic volatility of the portfolio estimated based on the variance entries of the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights divided by the total portfolio risk. $Treatment$ 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. 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 previous trading activity prior to the (counter-factual) treatment time, and the size of the portofolio (number of stocks) 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: no stock-fixed effects						
	(1) ROI	(2) ROI raw	(3) Sharpe ratio	(4) Sharpe ratio raw	(5) Risk-adjusted ROI	(6) Risk-adjusted ROI raw
Treatment	−0.0117	−0.0067	−0.0151	−0.0094	0.0002	0.0002
	(−3.71)	(−2.54)	(−1.71)	(−1.39)	(0.26)	(0.27)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	No	No	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,040,208	1,040,208	1,040,208	1,040,208	846,814	846,814
Adj. R^2	0.04	0.03	0.07	0.05	0.47	0.47
Panel B: with stock-fixed effects						
	(1) ROI	(2) ROI raw	(3) Sharpe ratio	(4) Sharpe ratio raw	(5) Risk-adjusted ROI	(6) Risk-adjusted ROI raw
Treatment	−0.0084	−0.0041	−0.0092	−0.0026	−0.0005	−0.0005
	(−2.94)	(−1.70)	(−1.23)	(−0.45)	(−1.14)	(−1.13)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,040,208	1,040,208	1,040,208	1,040,208	846,814	846,814
Adj. R^2	0.04	0.03	0.08	0.06	0.48	0.48

Table 8: Attention and profitability: difference-in-differences analysis

This table reports results from a difference-in-differences regression analysis on the profitability of stock trades that investors pursue in our trade data. For each investor we take the profitability of the last trade within seven days before the treatment event and the profitability 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. *ROI* is the daily return on investment (net transaction costs); *Sharpe ratio* is the daily risk-adjusted return on investment (net transaction costs) defined as roi/volatility of the stock; $Risk - adjusted\ ROI$ is the daily risk-adjusted return on investment (net transaction costs) calculated with the CAPM market model; $ROI\ (raw)$ is the daily return on investment (not corrected for transaction costs); *Sharpe ratio* (*raw*) is the daily risk-adjusted return on investment (not corrected for transaction costs) defined as roi/volatility of the stock; $Risk - adjusted\ ROI\ (raw)$ is the daily risk-adjusted return on investment (not corrected for transaction costs) calculated with the CAPM market model; $Treatment$ 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. Columns (5) and (6) do not include day trades. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL	(7) portfolio risk
Panel A: Treated investors							
Treatment	0.0924	−21.5356	−0.1055	0.1442	0.0941	0.0958	−0.0056
	(3.58)	(−4.26)	(−0.87)	(15.31)	(5.24)	(16.95)	(−2.44)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,041,061	1,041,061	1,041,061	1,041,061	1,041,061	1,041,061	1,148,453
Adj. R^2	0.64	0.40	0.70	0.32	0.26	0.36	0.48
Panel B: Click on push message vs. no click on push message							
Treatment	0.0843	−12.4438	−0.1140	0.0982	0.0441	0.0682	−0.0093
	(2.31)	(−1.90)	(−0.72)	(9.33)	(2.72)	(10.77)	(−3.12)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	284,893	284,893	284,893	284,893	284,893	284,893	217,162
Adj. R^2	0.63	0.42	0.71	0.32	0.28	0.36	0.54
Panel C: Very first message							
Treatment	0.2911	−24.6639	1.1628	0.1232	0.0945	0.0709	−0.0023
	(4.30)	(−3.01)	(4.03)	(9.15)	(3.90)	(7.92)	(−0.64)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	353,487	353,487	353,487	353,487	353,487	353,487	15,298
Adj. R^2	0.71	0.48	0.74	0.57	0.48	0.52	0.75

Table 9: Robustness: Message-sending behavior of the broker

	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL	(7) portfolio risk
Panel D: Matching based on risk taking							
Treatment	0.0948	−26.2099	0.0353	0.1369	0.1035	0.0878	−0.0038
	(3.58)	(−4.65)	(0.34)	(14.15)	(5.77)	(14.82)	(−2.98)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,066,761	1,066,761	1,066,761	1,066,761	1,066,761	1,066,761	1,001,612
Adj. R^2	0.62	0.38	0.69	0.31	0.28	0.36	0.53

Table 9: Robustness: Message-sending behavior of the broker (continued)

This table reports results from a regression analysis on the risk taking of different subsamples of investors. Panel A compares investors who receive a push message and trade on the push message to investors who also receive a push message but do not trade on the push message. Panel B compares investors who click on the push message to investors who receive a push message but do not click on the push message. Panel C compares investors who receive the very first push message to investors who do not receive a push message. Panel D compares investors who receive a push message to investors who do not receive a push message. Differently from our main analysis, investors from the treatment and control group are also matched based the volatility of the last stock traded before the treatment event (in addition to the treatment time, gender, age group, and the previous trading activity prior to the (counter-factual) treatment time). *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; *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); *portfolio risk* denotes the volatility of the portfolio estimated based on the variance-covariance matrix of past stock returns of the stocks in the portfolio according to their portfolio weights; *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. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL	(7) portfolio risk
Panel A: No earnings reports							
Treatment	0.1422	−24.6538	0.0085	0.1380	0.0907	0.0903	−0.0029
	(5.90)	(−4.27)	(0.08)	(14.78)	(5.14)	(15.76)	(−2.07)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	952,115	952,115	952,115	952,115	952,115	952,115	811,959
Adj. R^2	0.63	0.37	0.70	0.32	0.28	0.36	0.53
Panel B: no news trading							
Treatment	0.0617	−24.0162	−0.5298	0.1191	0.0426	0.0856	0.0004
	(1.67)	(−3.92)	(−3.65)	(10.37)	(1.86)	(13.18)	(0.24)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	373,095	373,095	373,095	373,095	373,095	373,095	410,796
Adj. R^2	0.69	0.41	0.74	0.39	0.39	0.43	0.54
Panel C: filtered trading							
Treatment	0.0705	−28.1018	−0.1614	0.1196	0.0686	0.0764	−0.0038
	(2.68)	(−5.33)	(−1.56)	(12.95)	(4.02)	(13.81)	(−2.89)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,040,208	1,040,208	1,040,208	1,040,208	1,040,208	1,040,208	899,636
Adj. R^2	0.62	0.35	0.69	0.27	0.23	0.31	0.52

Table 10: Risk taking and the impact of news (Panels A - C)

	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL	(7) portfolio risk
Panel D: filtered message							
Treatment	0.0981	−27.9478	−0.0070	0.1129	0.0644	0.0745	−0.0048
	(3.59)	(−4.94)	(−0.06)	(11.85)	(3.62)	(13.44)	(−3.48)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,040,208	1,040,208	1,040,208	1,040,208	1,040,208	1,040,208	899.636
Adj. R^2	0.63	0.37	0.70	0.32	0.28	0.36	0.53

Table 10: Risk taking and the impact of news (Panel D)

This table reports results from a difference-in-differences regression analysis on trading characteristics and risk measures 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. In the *no earnings reports*-model we omit all messages that are associated with reporting earnings announcements. 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 trading characteristics and risk measures at time t using the regression

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

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 stock-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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: positive message							
	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL	(7) portfolio risk
Treatment	0.1254	−22.0627	−0.0634	0.1233	0.0771	0.0800	−0.0016
	(3.20)	(−2.51)	(−0.43)	(9.40)	(2.81)	(9.84)	(−1.03)
Positive message	−0.0096	−0.8893	0.0486	−0.0034	−0.0082	−0.0038	−0.0002
	(−1.37)	(−0.53)	(1.13)	(−3.42)	(−3.00)	(−4.77)	(−0.21)
Treatment × Positive message	0.0872	−11.0501	0.2586	0.0331	0.0266	0.0228	−0.0027
	(1.56)	(−1.18)	(1.26)	(2.08)	(0.76)	(1.95)	(−0.87)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	955,723	955,723	955,723	955,723	955,723	955,723	809,832
Adj. R^2	0.63	0.37	0.70	0.33	0.28	0.36	0.52
Panel B: strong message							
	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL	(7) portfolio risk
Treatment	0.1034	−26.2095	−0.0649	0.0993	0.0751	0.0760	−0.0016
	(3.30)	(−3.91)	(−0.39)	(9.74)	(3.66)	(10.28)	(−0.77)
Strong message	0.0247	1.5085	−0.1773	0.0005	−0.0063	0.0005	0.0042
	(3.55)	(0.92)	(−4.40)	(0.45)	(−2.08)	(0.53)	(3.49)
Treatment × Strong message	0.1102	−1.9497	0.2196	0.0676	0.0248	0.0255	−0.0022
	(2.45)	(−0.22)	(1.02)	(4.20)	(0.76)	(2.43)	(−0.76)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	955,723	955,723	955,723	955,723	955,723	955,723	809,832
Adj. R^2	0.63	0.37	0.70	0.33	0.28	0.36	0.52

Table 11: Message characteristics and risk taking: difference-in-differences analysis

This table reports results from a difference-in-differences regression analysis on investors' trading characteristics and positive messages (Panel A) [strong messages (Panel B)] in our trade data. For each investor we take the trading characteristic and risk measure of the last trade within seven days before the treatment event and the trading characteristic and risk measure 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. $Positive\ message$ is a dummy variable that takes a value of one if the message reports a positive stock price development, zero otherwise. $Strong\ message$ is a dummy variable that takes a value of one if the message reports a large stock price development, zero otherwise. Earnings reports 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL	(7) portfolio risk
Treatment	0.1090	−22.7475	−0.0375	0.1044	0.0415	0.0695	−0.0129
	(3.01)	(−3.23)	(−0.25)	(10.23)	(2.37)	(11.46)	(−4.42)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	260,278	260,278	260,278	260,278	260,278	260,278	187,789
Adj. R^2	0.63	0.39	0.72	0.32	0.27	0.35	0.58

Table 12: Risk taking of investors who click on push message

This table reports results from a regression analysis on the risk taking of investors who click on the push message in our trade data. For each investor we take the trading characteristic and risk measure of the last trade within seven days before the treatment event and the trading characteristic and risk measure 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 click on 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. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

	(1) leverage	(2) holding period	(3) investment	(4) volatility	(5) beta	(6) IVOL
Treatment	0.0298	−4.4306	0.2762	0.1033	0.0023	0.0520
	(0.46)	(−0.80)	(0.63)	(10.16)	(0.10)	(8.56)
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	No	No	No
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	98,032	98,032	98,032	98,032	98,032	98,032
Adj. R^2	0.74	0.46	0.77	0.55	0.52	0.54

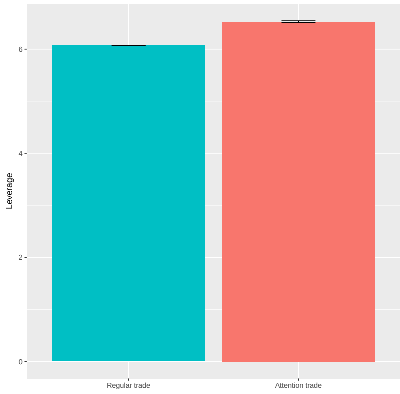
Table 13: Attention and risk taking in short selling

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 and risk measure of the last trade within seven days before the treatment event and the trading characteristic and risk measure 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. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

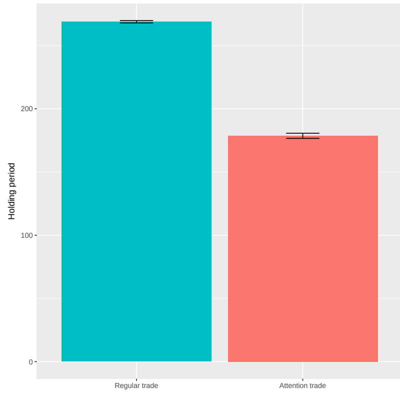
	(1) Increasing position	(2) Closing position
Treatment	0.07	0.05
	(17.20)	(13.47)
Controls	Yes	Yes
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	640,262	640,262
Adj. R^2	0.08	0.15

Table 14: Receiving push messages while holding a position

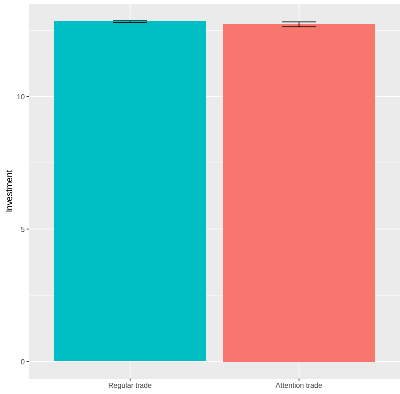
This table reports results from a regression analysis on the increasing and closing of an existing position in our trade data. In Model (1), the dependent variable is an indicator variable that equals one if the investor adds to an existing position within 24 hours, zero otherwise. In Model (2), the 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. 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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.



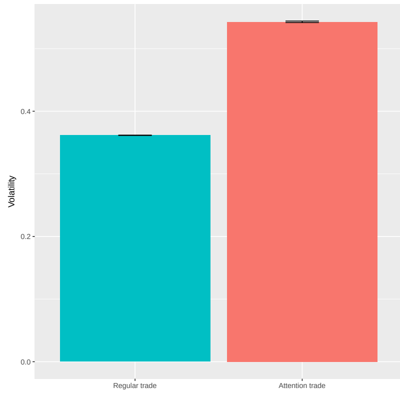
(a) Leverage



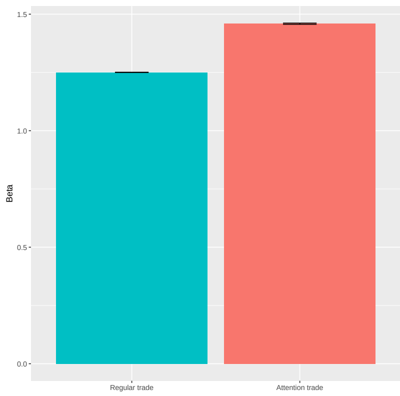
(b) Holding period



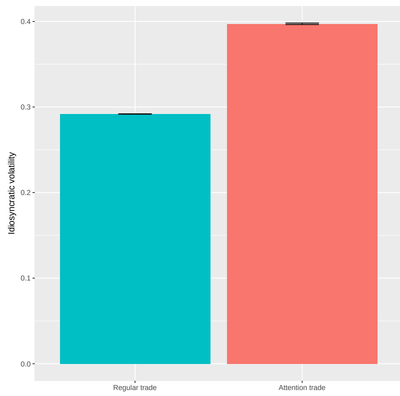
(c) Investment



(d) Volatility



(e) Beta



(f) Idiosyncratic volatility

Figure 5: The impact of attention of investors' trading behavior

This figure presents investors' average trading characteristics (with 99% confidence intervals) in our trade data. Green bars show non-attention trades; red bars show attention trades. "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 are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

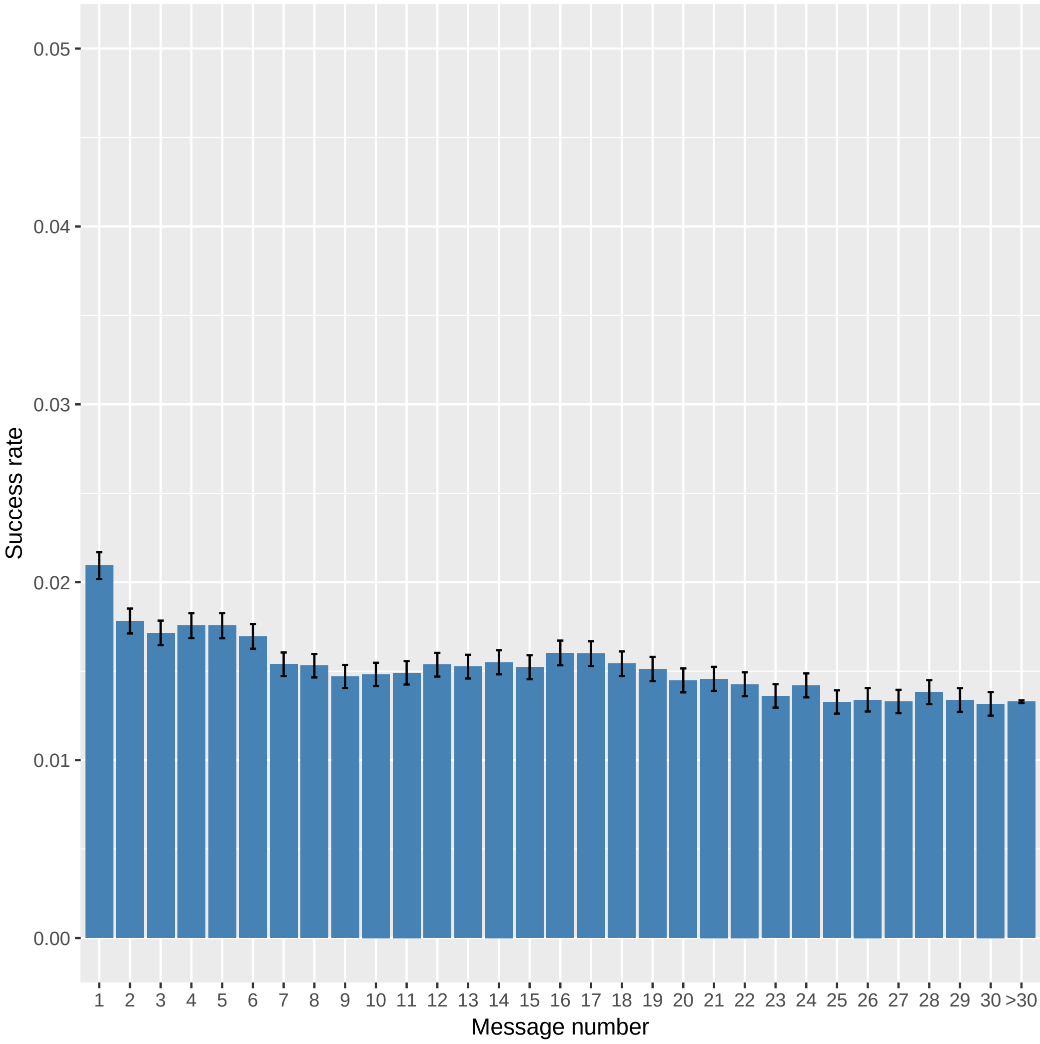


Figure 6: Saturation of attention

This figure presents the success rates of push messages with respect to the message number (with 99% confidence intervals). Message number numbers the messages sent to an investor in chronological order. A push message is denoted as successful if the push message is followed by a trade in the underlying referred to in the push message within 24 hours. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contains all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: Trade data						
	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	3,393,140	243.215	474.081	4.759	69.033	237.730
ROI	3,393,140	−0.005	0.037	−0.0003	0.00004	0.0004
ROI (raw)	3,393,140	−0.002	0.035	−0.0002	0.0001	0.001
News event	3,519,118	0.603	0.489	0	1	1
Panel B: Stock data						
	Obs.	Mean	SD	P25	P50	P75
Volatility	1,224,189	0.293	0.155	0.197	0.252	0.335
Beta	1,224,189	0.987	0.400	0.734	0.961	1.209
IVOL	1,224,189	0.246	0.133	0.163	0.208	0.288

Table A.1: Summary statistics of the trade and stock data

The table shows summary statistics of the trade data from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license (Panel A) and the stock characteristics (Panel B). 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, i.e., the portfolio weight of the trade; *Holding period* measures the timespan between the opening and closing of a position in hours; *ROI* denotes the daily return on investment net transaction costs; *ROI* (*raw*) denotes the daily raw return on investment not corrected for transaction costs; *News event* is a dummy variable that takes a value of one if the trade is executed on or following a day with at least one news article recorded in the *Quandl FinSentS Web News Sentiment*, zero otherwise; *volatility* denotes the yearly Garch-volatility of stock returns; *beta* is the CAPM-Beta of a given stock; *IVOL* denotes the yearly idiosyncratic volatility of stock returns.

	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 A.2: Summary statistics of demographic information

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