Attention Triggers and Investors' Risk Taking*

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Abstract This paper investigates how individual attention triggers affect financial risk taking. We analyze a large sample of trading records from a brokerage service that sends standardized push messages on stocks to retail investors. This micro-level data allows us to isolate the push messages as individual stock-attention triggers. By exploiting this data in a difference-in-differences setting, we find that attention triggers increase investors' willingness to take risk. We also provide cross-sectional analyses to identify for which investors and stocks this effect is more pronounced.

Keywords: Investor Attention; Trading Behavior; Risk Taking;

JEL Classification: G10, G11, G12.

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Explaining the risk-taking behavior of individuals is critical for the study of choice under uncertainty and fundamental to a better understanding of financial markets (e.g. Liu et al., 2010; Charness and Gneezy, 2012). Economists conclude that personal experiences or beliefs are a key driver of the heterogeneity in individuals' willingness to take risk (e.g. Kaustia and Knüpfer, 2008; Choi et al., 2009; Malmendier and Nagel, 2011; Kaustia and Knüpfer, 2012; Knüpfer et al., 2017). Whereas recent behavioral studies highlight that individual attention is an important cognitive pathway both to evaluate experiences and form beliefs (e.g. Sicherman et al., 2015; Gargano and Rossi, 2018), the influence of individual attention on individual risk-taking is yet unexplored.

Investigating the impact of attention on individuals' risk taking is likely to provide unique insights into our understanding of financial risk behavior. The main challenge behind analysing this influence is that common proxies of how individuals pay attention are likely to be endogenously related to risk taking. For example, an investor planning to incur a particularly risky financial position probably pays more attention. To overcome this challenge, one needs to observe exogenous events that trigger individuals' attention. Such triggers are typically hard to observe on an individual level.

In this study, we investigate the influence of individual attention triggers on risk taking. We overcome the challenge behind analysing this influence through our access to a novel data set. The data contain the trading records of a large broker that sends standardized push messages to retail investors. Each message reports publicly observable information on past stock returns. We use these messages as triggers of individual investor attention towards certain stocks that we can directly link to the recipients' willingness to take risk. Our analysis shows that attention stimulates risk taking. The effect is more pronounced for younger, male, and less experienced investors. In addition, our results are stronger for familiar stocks with more public information and higher valuation uncertainty.

The broker offers retail investors a trading platform to trade contracts for difference (CFD) on a large set of European and US blue chip companies. CFDs are derivative contracts designed such that their price mirrors that of the underlying security. CFDs are very popular in Europe. In the UK, for example, the value of transactions was estimated to be around 35% of the value of the London Stock Exchange equity transactions in 2007 (Financial Services Authority, 2007). In Germany, the CFD trading volume was 1.58 trillion Euro in 2018 (CFD Verband e.V.), which is approximately equal to the total transaction volume of the Deutsche Börse AG.

The broker's data provides a unique opportunity to tackle the empirical identification challenge of analyzing the link between attention triggers and individual risk taking for three reasons. First, CFDs allow investors to select the leverage of their trades, which is difficult to obtain for stocks. As noted by Heimer and Simsek (2019), leverage is a major catalyst of speculative trading, as it increases the scope of extreme returns, and enables investors to take larger positions than what they can afford with their own money. Importantly, leverage is a key dimension of risk taking that is not determined by the selection of the stock itself. Observing such a dimension is crucial to address the concern that our conjectures are simply driven by the characteristics of the stocks on which the broker sends a push message. This concern would arise, for example, for the volatility or beta of a stock, which are inevitable determined by the stock selection itself.

Second, the push messages represent attention triggers that are initiated by the broker and not by the investors who conduct the trades. This distinction is important because the decision of investors to pay attention is likely to be endogenously related to the riskiness of their planned trade.

Third, the data allow us to simultaneously observe investors who obtain a push message (treated investors) and those who do not obtain such a message (control investors). We label the trades that a treated investor executes in a stock within 24 hours after she receives a push message referring to that stock "attention trades.“ Comparing the risk taking for attention trades to the risk taking of the control investors in the same stock at the same time provides a natural experiment for a standard difference-in-differences (did) approach, which measures the marginal impact of an attention trigger on individual risk taking.

Our first main result links attention to risk taking. We find that attention trades bear a higher leverage compared to non-attention trades. Thus, attention stimulates risk taking. Individuals who trade on attention may take on more risk than they had originally planned, which may result in greater risk-taking than the investor would have initially deemed optimal. The increase in risk-taking is important for the allocation of resources. Specifically, as noted by Lian et al. (2018), increased risk-taking may help to stimulate the economy, but may also pose challenges for financial stability. The fact that investors are more willing to take risks when trading on attention may also help to explain the increase in stock volatility following attention-triggering events.

Next, we link our main result to investor characteristics. We find that male, younger, and less experienced investors particularly increase risk taking after an attention stimulus. In addition, the results are more pronounced for investors that suffered (paper and realized) losses in the message stock before receiving a push message on that stock. These results indicate that attention may serve as a catalyst for investors' tendency to increase their risk taking following losses (Kahneman and Tversky, 1979; Weber and Zuchel, 2005).

We complete the picture by analyzing the relation between our main result and stock characteristics. We find that attention triggers have a stronger impact on the risk taking for stocks of larger firms, with more analyst coverage, and more news coverage. Thus, the impact seems to be stronger for more familiar stocks.

The broker may not send the messages randomly to the investors. Thus, the main caveat with our did-analysis is that the broker's message sending behavior could bias our conjecture. For example, the broker may anticipate which investors change their risk taking around the treatment and select the message recipients according to this anticipation. Our data offers the opportunity to address this message sending behavior concern in a difference-in-difference-in-differences (DDD) setting. Specifically, we can explore the lack of congruence of the investors' status of being a message receiver or non-receiver and the investors' stock trades. For example, each push message only refers to one stock, whereas message receivers can trade many stocks that are not referred to in the message. Similarly, non-receivers may trade the stock referred to in the message to the receivers. The first difference in the DDD controls for the possibility that receivers generally change their risk taking compared to non-receivers around the treatment. This effect is measured from the difference in risk taking between receivers and non-receivers for all trades to which the message does not refer. The second difference controls for the possibility that message stocks are generally traded with a higher leverage compared to non-message stocks around the treatment. This effect is measured from the difference in risk taking between message and non-message stocks for all trades of non-receivers. Thus, the third difference in the DDD-setting measures the impact of attention on risk taking net of (i) how the general risk taking of receivers differentiates from that of non-receivers and (ii) how the general risk taking for message stocks differentiates from that of non-message stocks. Among other things, this approach alleviates concerns that the broker sends messages to investors or on stocks for which he correctly anticipates a change in risk taking. The DDD-setting confirms our conjecture that attention stimulates risk taking.

The advantage of our DDD setting is that we can address the caveat that the broker anticipates a change in the general risk taking of specific investors or for specific stocks without the need to define the potential channels behind this anticipation. The DDD approach, however, does not allow us to rule out the possibility that the broker could anticipate a change in the risk taking for specific investor-stock pairs and send the messages according to this anticipation. To address this remaining concern, we incorporate the investor-stock specific information to which the broker has access in three additional tests.

First, the broker may observe a certain risk taking pattern for specific investors in specific stocks after large stock price moves, which allows him to anticipate future risk taking behavior. We use the trading data of the treated investors in our sample from the sub-period before the broker started sending push messages to incorporate this possibility. Specifically, we compare the risk taking of a treated investor after receiving a push message to the risk taking of the same investor in the same stock after a similar stock price move during this sub-period. This comparison confirms our conjecture that attention triggers stimulate risk taking.

Second, the broker may observe the research activity of specific investors on specific stocks on his home page. Such research can indicate future trading (Gargano and Rossi, 2018;

Sicherman et al., 2015) and, thus, may also signal future risk taking. Therefore, we repeat our main analysis by only incorporating investors who do not research a given stock prior to receiving a push message on that stock. Our results are robust to this setting.

Third, the literature on risk taking concludes that personal experiences or beliefs are a key driver of the heterogeneity in individuals' willingness to take risk (e.g. Kaustia and Knüpfer, 2008; Choi et al., 2009; Malmendier and Nagel, 2011; Kaustia and Knüpfer, 2012; Knüpfer et al., 2017). Whereas our DDD approach cancels out the potential impact of general differences between investors along these dimensions, it does not address the concern that the broker may use the investors' past experience with the message stock to anticipate changes in risk-taking. We, therefore, repeat our main test with investors who have never traded the message stock before receiving a push message. For these investors, the broker has no information about the past experience of the investor with that specific stock and is unlikely to know anything about the investor's stock-specific beliefs. Our results are robust to this test.

Finally, we summarize several additional results that emerge from our data. We find that attention triggers stimulate stock trading and induce investors to increase their position size. Both results can be interpreted as alternative evidence that investors increase their risk exposure after an attention trigger. In addition, we find that attention triggers stimulate short trading.

We provide a battery of robustness tests to confirm our conjecture and exclude alternative explanations for our results. For example, we control for news, the message content, and potential self-selection of investors. We also repeat the analysis by only considering the first message to an investor on any stock and the first message to an investor on any asset class. In addition, we match treated and counterfactual investors in our did-setting based on their gender, age, average trading intensity, and risk taking. The results of these additional analyses support our conjecture.

We contribute to various strands of the existing literature. First, we contribute to the literature that studies elements that affect risk taking at the microlevel (Beshears et al., 2016; Cohn et al., 2015; Holt and Laury, 2002; Kuhnen, 2015). Amongst other things, this literature studies the dynamics of investors' willingness to take risk and non-standard factors that affect risk taking (Barberis et al., 2001; Gneezy and Potters, 1997; Caplin and Leahy, 2001; Kőszegi, 2006; Karlsson et al., 2009). This literature concludes that personal experiences such as economic fluctuations or past performance affect risk taking (Coval and Shumway, 2005; Liu et al., 2010; Malmendier and Nagel, 2011; Chiang et al., 2011; Imas, 2016; Ben-David et al., 2018). We contribute to this literature by showing that individual attention triggers are an important stimulus that affects investors' risk taking. In addition, we find that attention triggers are a key catalyst through which personal experience transmits into risk taking.

Second, the literature on aggregate attention builds on the notion of Odean (1999) suggesting 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. This literature concludes that aggregate attention has an important bearing on stock returns, stock ownership, trading patterns, return volatility, liquidity, correlation, and bid-ask spreads (Grullon et al., 2004; Chen et al., 2005; Peng and Xiong, 2006; Seasholes and Wu, 2007; Barber and Odean, 2008; Lehavy and Sloan, 2008; Corwin and Coughenour, 2008; Fang and Peress, 2009; Da et al., 2011; Andrei and Hasler, 2014; Lou, 2014; Ben-Rephael et al., 2017; Lawrence et al., 2018; Peress and Schmidt, 2018; Fedyk, 2019; Kumar et al., 2019). Studying the origins of aggregate investor attention, Ungeheuer (2018) illustrates that rankings of daily winners and losers increase aggregate investor attention. 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 and stock return patterns. Whereas this literature provides important results on the macroeconomic implications of attention, it provides limited insights on the microeconomic foundation underlying the impact of 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) show that the trading strategies of rational institutional traders often counter the attention-driven trades of retail investors. We contribute to this literature by providing novel insights on the micro foundation behind aggregate attention.

Third, our study is closely related to the recent literature on individual investor attention. This literature derives proxies of how investors pay attention at the individual level from online account logins or the web browsing behavior on the brokerage account. These studies provide profound insights on how individuals allocate their attention and how paying attention influences trading, performance, the transmission from beliefs to portfolio allocations, and the disposition effect (e.g. Karlsson et al., 2009; Sicherman et al., 2015; Gargano and Rossi, 2018; Giglio et al., 2019; Dierick et al., 2019). They, however, cannot shed light on how individual attention impacts risk taking because the investors' decision to pay attention is likely to be endogenously related to risk taking. For example, an investor planning a risky trade may spend more time browsing the stock than an investor intending a less risky trade. In contrast, we observe a trigger of individual attention that is not triggered by the investors themselves. Thus, we can contribute to the individual attention literature by providing novel insights on how attention triggers influence the individual investors' willingness to take risk.

The remainder of our paper proceeds as follows. In Section 1, we present our dataset and discuss our identification strategy. Section 2 presents summary statistics before Section 3 discusses the impact of the attention trigger on investors' risk taking. Section 4 provides cross-sectional analyses to further study the implications of push messages on different types of investors and stocks. In Section 5, we provide additional results on trading and discuss the relationship between attention triggers and retail investors' information acquisition on a particular stock. In Section 6, we discuss several alternative explanations to our findings. The final section concludes.

1 Data and methodology

1.1 Data

In this study, we use a novel dataset 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, foreign exchange rates, and cryptocurrencies. We focus on stocks in this paper. CFDs are financial contracts between investors and a financial firm that replicate the performance of the underlying asset. Appendix A provides a brief introduction to CFDs. Brown et al. (2010) describe these contracts in detail. The minimum amount per CFD trade with the broker is \$50 and the minimum total amount to open an account is \$200.

The brokerage firm charges transaction costs when investors close a position. Transaction costs are moderate and amount to 24 basis points per stock trade. 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; Heimer and Simsek, 2019).

Our data sample contains all trades that the investors executed with the broker between January 1^{st}, 2016 and March 31^{st}, 2018.[1] A trade is defined as the opening or closing of a position. The data contain 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 only consider "active" investors in our sample, i.e., investors that either trade a stock or receive a push message on a stock during our sample period. The data contain a total of 243,617 investors who either actively trade or receive a push message. 112,242 of these investors engage in active trading while the remaining 131,375 investors only receive a push message but do not execute a trade during our sample period.

[1]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).

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.[2] A typical message reads "*$AFSI shares down over -5.2%.*" or "*$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 risk taking from that of news. The broker determines the investors to whom it sends a certain message, the content, and the stock to which the message refers.

Our data contain the information on all push messages sent by the broker during our sample period. The data contain information on the category of the push message, the stock referred to, the price change, and the exact timestamp when the push messages where sent. In addition, the data contain the information whether investors clicked on the push messages to open the app of the broker.

As a service to its customers, the broker summarizes stock information for its clients. Specifically, for each stock, investors can access information pages which provide information on stock prices, key financial variables, and latest news on the company. We also have the data on when the investors access these information pages.

Finally, the trading data also includes investors' basic demographic information (age, gender, and nationality), and some information supplied in response to a questionnaire issued by the broker. Specifically, the data contain investors' self-reported willingness to

[2]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.

take risk based on their preferred return-drawdown profile and their self-reported previous trading experience.

We complement the brokerage 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.

1.2 Variables

We make use of the following variables in our empirical analysis. The main variable of interest, *Leverage*, denotes the leverage employed for a trade. Besides *Leverage*, we make use of several additional trading variables. First, *trades* denotes the number of trades an investor executes over a given week. We also create several dummy variables that capture whether an investor holds a specific stock in her portfolio at a given point in time (*hold stock*) or traded a specific stock before a given point in time (*traded before*). *Position size* is the trade nominal expressed as a fraction of the investor's total assets deposited with the broker. *Short sale* is a dummy variable that takes a value of one if the trade takes a short position, and zero otherwise. The *Holding period* measures the timespan between the opening and closing of a position in hours. Finally, we measure trade profitability. Specifically, we use the *ROI* of a trade, which denotes the daily return on investment net of the transaction cost charged by the broker.

Second, we employ several measures to account for stock characteristics. In particular, we estimate the conditional time-varying *volatility* of a stock using a GARCH(1,1)-model based on daily log returns of end-of-day stock prices from January 2012 to March 2018. 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, with respect to the push messages, we create several dummy variables. We create a dummy variable *click on message* that take a value of one if the investor clicks on the push message to open the brokerage app, zero otherwise. We also create a dummy variable that denotes whether the investor traded the stock referred to in the push message. *Trade on message* takes a value of one if the investor traded on a given push message within 24 hours after receiving the message, zero otherwise. *Momentum trade* is a dummy variable that takes a value of one if the investor trades in the direction of the stock price change referred to in the push message, zero otherwise. Similarly, *contrarian trade* is a dummy variable that takes a value of one if the investor trades in the opposite direction of the stock price change referred to in the push message, zero otherwise. Finally, we measure the difference between the time an investor receives a push message and executes a trade on the stock referred to in the push message in hours (*reaction time*, if executed within 24 hours).

Fourth, we proxy for investors' information acquisition on a given stock. Using the timestamped data on when investors access a specific stock information page, we create a dummy variable *Research* that takes a value of one if the investor visited the stock-specific information page within a 24 hour time-period, zero otherwise.

Finally, we extract several variables from Quandl. We use the variable *Article Sentiment*, which captures for each company the average sentiment of all the articles on the company (within the last 24 hours) in the 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.[3] We also 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.

[3]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.

1.3 Methodology

It is straightforward to measure the risk taking of an investor, after her attention has been triggered. The empirical challenge to analyzing the marginal impact of an attention trigger on risk taking, however, is to net out the “normal” risk taking, that is the risk taking in case an 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 risk taking of treated investors in the treatment period to that of comparable investors who do not obtain a push message during the same period.

To analyze the impact of attention on an investor’s risk taking, we conduct the following three main steps: First, for each investor-stock pair, we identify the time-stamp of the first push message that the broker sends to the investor on that stock (treatment time). We only use the first push message an investor receives on any given stock for two reasons. First, it mitigates potential confounding effects of previous messages on the same stock. Second, it eliminates the concern that the broker could observe 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 last trade of treated investors in any stock within seven days [24 hours] prior to the treatment time (observation period) and the attention trade. We label the trade of a treated investor *attention trade*, if this investor trades the message stock within 24 hours after the treatment time.[4] 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’ risk taking (Petersen, 2009). We consider a 24 hours window for the treatment period for two reasons. First, our data shows a distinct spike in a message stock’s trading activity for around 24 hours after the message (see Figure 1), which suggests that many of those trades are triggered by attention. Second, measuring trading patterns over one attention day is standard in the attention literature (Barber and Odean, 2008; Peress and Schmidt,

[4]We also consider trades as attention trades if the investor trades other stocks before the message stock as long as the message stock trade occurs within the 24 hours window.

2018).

We then collect our counter-factual from the trades of all investors in the database that do not receive a message on the message stock during the observation and treatment periods. Specifically, we consider the last trade of these investors in any stock during the observation period and the first trade in the message stock during the treatment period (24 hours after the push message was sent).

Third, we calculate the difference between the risk taking of the treated investors and that of the comparable investors during the observation period. This step controls for heterogeneity between the treated and comparable investors. We also measure the difference between the risk taking of the treated investors and that of the comparable investors in the message stock during the treatment period. The marginal impact of the attention trigger on risk taking then corresponds to the difference between these two differences. Formally, we estimate

$$\begin{aligned} &\text{Leverage}_{ijt} = \alpha + \beta_1 \text{treatment group}_{ij} \times \text{post treatment}_t + \beta_2 \text{treatment group}_{ij} \\ &+ \beta_3 \text{post treatment}_t + \sum_{k=4}^{K+3} \beta_k \text{Investor}_i^k + \sum_{l=K+4}^{L+K+3} \beta_l \text{Stock}_j^l + \sum_{m=L+K+4}^{M+L+K+3} \beta_m \text{Time}_t^m + \varepsilon_{ijt}, \end{aligned} \tag{1}$$

where Leverage_{ijt} denotes the leverage of investor i in stock j at time t. *treatment group* is a dummy variable that takes a value of one for investors of the treatment group and zero otherwise; *post treatment* 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 risk taking. Our specification includes investor fixed effects to control for unobserved heterogeneity across investors such as their individual wealth, their amount deposited with the broker, their domicile, or their stock market experience. We also consider stock dummies to control for stock-specific trading characteristics. Finally, we include time dummies to consider aggregate time-trends.

2 Summary statistics and message sending

2.1 Summary statistics

We begin by briefly discussing the demographic characteristics of investors in our sample. Most investors in our sample are young males, between 25 and 44 years of age (see Table A.1 in the Appendix). This observation is consistent with previous studies who report that the active investor is, on average, a male in his late 30s (e.g., Linnainmaa, 2003).

Next, we turn to describing the push messages in our data. Table 1 provides summary statistics of the push messages that the broker sends to investors. Panel A summarizes the different events about which the broker sends push messages. 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.[5] 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 suggest 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 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 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

[5] On average, the broker sends messages on approximately 750 different events per month. Figure A.1 in the Appendix additionally presents the evolution of the number of push message events per month over our sample period.

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 3.6% of the push messages, the investor has visited the research page of the stock referred to in the push message within seven days prior to the push message and for 16% of the push messages, the investor has already traded the stock referred to in the message before she receives the message. For 2.8% of the messages, the investor holds the message stock in her portfolio at the time she receives the push message.

On average, 8.2% of investors click on the push message. Studying average click rates over the different weekdays (untabulated), we observe that investors are slightly less attentive to push messages on Fridays, which is in line with Dellavigna and Pollet (2009) who argue that investors are distracted by the upcoming weekend and therefore more inattentive. Approximately 3.1% of investors visit the stock research page within 24 hours after receiving 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 within 24 hours after the push message. On average, 1.39% of the push messages trigger an attention trade. 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. We observe more contrarian attention trades, which is mainly driven by long attention trade positions, which investors take after receiving negative push messages.[6] This observation is consistent with the previous literature that suggests that retail investors have a tendency to be contrarians (see, e.g., Boehmer et al., 2019; Kelley and Tetlock, 2013). The median reaction time to the push message of investors who conduct an attention trade is quite short, namely 1.35 hours.

[6]The missing difference between investors trading on the message (0.0139) and the sum of momentum and contrarian trades (0.005 + 0.0079 = 0.0129) is due to trades on earnings reports, which can neither be characterized as positive or negative, as these messages simply indicate an upcoming earnings announcement.

— Place Table 1 about here —

We provide graphical evidence that push messages trigger attention trades. Figure 1 plots the distribution of the time difference between push messages and investors' trading activity. We observe a distinct attention trade spike in the first five hours after the broker sends the message. We also observe a small increase in the trading activity of investors immediately before the broker sends the push messages, which is likely explained by the stock price movements that lead to the push messages. Still, the trading activity immediately following the push messages is about 2.5 times as large as the trading activity immediately before the push messages and about four times as large as the regular trading activity.

— Place Figure 1 about here —

In Table 2, we provide a first indication that investors' risk taking following push messages differs from their non-attention risk taking.[7] The table suggests that attention trades feature a higher leverage compared to non-attention trades.

— Place Table 2 about here —

2.2 Message sending behavior

Next, we shed light on the message sending behavior of the broker. We begin by discussing for which stocks push messages are sent. Panel A of Table 3 compares the volatility of stocks in months with a push message to that of stocks in months without push messages.

[7] We present summary statistics on the overall trading data in Table A.2 in the Appendix. In Panel A of Table A.2, we summarize the characteristics of the trades in our sample. On average, investors conduct 0.61 long trades and 0.065 short trades per week. The average leverage of a trade is 6.11% and the average trade size is 12.82% of an investor's assets with the broker. On average, an investor holds a position for 243.20 hours. Thus, the CFD traders in our sample have a relatively short holding period, and are more similar to day traders than buy-and-hold investors. The average return is around zero. Investors execute 60.3% of their trades on, or directly following, a day with at least one news event for the company of the underlying stock. Panel B of Table A.2 summarizes the risk measures of the stocks in our sample.

The table indicates that, on average, push message stocks are more volatile than non-message stocks. The beta of push message stocks is also higher than that of non-message stocks. Finally, push message stocks exhibit larger idiosyncratic risk than non-message stocks. Together, the table implies that push message stocks are riskier than non-message stocks. The intuition behind this result is that riskier stocks are more likely to experience extreme price movements and, hence, trigger push messages. As can be seen from Table 1, most messages are sent following large stock price movements.

— Place Table 3 about here —

Next, we study the investor-dimension of the message sending. To compare investors who receive a push message at a given point in time to investors who do not receive a push message, we follow the following steps. First, we randomly draw one message event from the pool of 9,969 events. Second, for this message event, we randomly draw one investor who receives the push message and one investor who does not receive the push message. Third, we repeat this exercise one million times. Panel B of Table 3 provides summary statistics of the sample resulting from this procedure.

While the summary statistics indicate that the broker, on average, sends push messages to investors who trade more actively and take slightly more risk (average leverage of 5.6 for non-message investors and 6.27 for message investors), the table also underlines that the distributions of investors, who receive a push message at a given point in time, and those, who do not, overlap to a large extent. Note that for each event the broker sends push messages to approximately 1-2% of its customers. Thus, for every investor who receives a push message at a given point in time another investor with very similar features can be found from the large number of investors who do not receive a push message at this given point in time. We will make use of this overlap in our robustness analysis, where we, amongst other tests, employ a matching procedure between message and non-message investors.

We will discuss different aspects of the brokers' message sending behavior at relevant points in the further course of the manuscript and in our robustness analyses in Section

6. We now investigate the impact of attention on risk taking by using our difference-in-differences approach.

3 The implications of push messages on risk taking

In this section, we analyze the implications of attention triggers on individual risk taking.

3.1 Difference-in-differences analysis

We first apply equation (1) of our difference-in-differences approach of Section 1.3 to the investors' leverage. We consider both long and short trades. Panel A of Table 4 summarizes the results.

— Place Table 4 about here —

Panel A shows that push messages induce investors to trade the message stock at a higher leverage compared to investors who trade the same stock but do not receive a push message. The treatment coefficient suggests that, on average, attention trades entail a 0.1277 higher leverage than non-attention trades. The economic magnitude of this coefficient is important. Specifically, investors increase their leverage by 4% of the standard deviation of leverage of Table A.2 when they receive an attention trigger and by 6.8% of the standard deviation at the investor level.

In Panel B, we repeat our analysis, but only consider trades within 24 hours before the treatment time in our observation period. This mitigates the concern that treated investors may already increase their leverage over the week prior to receiving the push message. The treatment coefficient remains virtually unchanged. Overall, Panels A and B of Table 4 imply that attention stimulates risk taking.

— Place Figure 2 about here —

We complement our did results by investigating the parallel trend assumption in Figure 2. Based on this figure, we can rule out the possibility that our results are driven by a trend in the risk taking of the treated investors before the treatment event.

3.2 Difference-in-difference-in-differences analysis

The broker may not send the messages randomly to the investors (see Section 2.2). Thus, the main caveat with our did-analysis is that the broker's message sending behavior could bias our conjecture. For example, the broker may anticipate a change in risk taking of certain investors or in the risk taking for certain stocks and send the push messages according to this anticipation. It is difficult to identify all the potential channels through which the broker's message sending behavior could affect our conjecture. Importantly, however, our data offers the opportunity to generally address this concern without the need to define the potential channels behind the broker's message sending behavior. Specifically, the benefit of our data is that it lacks a congruence of the investors' status of being a message receiver or non-receiver and the stocks they trade. For example, a push message only refers to one stock and, thus, receivers often trade stocks that are not referred to in the message. Similarly, non-receivers also trade the stock that the broker refers to in the messages to the receivers. This lack of congruence allows us to explore the following difference-in-difference-in-differences (DDD) in the sprit of Gruber (1994) and Puri et al. (2011):

$$\begin{aligned} Y_{i,j,t} = {} & \beta_1 post_t + \beta_2 treat_i + \beta_3 stock_j + \beta_4 treat_i \times stock_j \\ & + \beta_5 treat_i \times post_t + \beta_6 stock_j \times post_t + \beta_7 treat_i \times stock_j \times post_t + \epsilon_{i,j,t}. \end{aligned} \tag{2}$$

The coefficient β_5 captures the general change in the message receivers' risk taking compared to that of non-receivers as measured from all non-attention trades. Thus, it separates out the impact of the possibility that the broker sends messages to investors that generally change their risk taking around the treatment event due to reasons other than attention. Similarly, the coefficient β_6 captures the general change in risk taking for message stocks compared to non-message stocks as measured from all message stock trades of investors that do not receive a message. Hence, it separates out the impact of the possibility that the broker sends messages on stocks that feature a change in leverage around the treatment due to reasons other than attention.[8] Our coefficient of interest β_7 then captures the impact of the attention trigger on leverage net of how the risk taking of receivers differentiates from that of non-receivers around the treatment event and of how the risk taking for message stocks differentiates from those of non-message stocks around the treatment event. Among other things, this approach alleviates the concern that the broker sends messages to certain investors or stocks for which he correctly anticipates a change in risk taking. Thus, by exploring the structure of our data, we do not need to characterize the potential channels through which the broker's message sending behavior along the dimensions "message receiver" selection or "stock reference" selection could bias our results. Instead, we can directly separate out any differences in these dimensions around the treatment event for whatever reasons these differences occur.

Panel C of Table 4 shows the coefficient of interest β_7 in the line treat $\times$ post $\times$ stock. This coefficient shows that our conjecture on leverage is robust to the DDD setting. In terms of economic importance, the coefficient of interest is even larger than that in Panel A of Table 4.

3.3 Additional tests to rule out a message sending bias

The DDD approach allows us to address the concern that a potential tendency of the broker to send push messages either to certain investors or on certain stocks could bias our conjecture. The broker, however, could anticipate changes in the risk taking of specific investors in specific stocks around the treatment time. If the broker sends messages according to this investor-stock pair anticipation, the message sending behavior could still

[8]Note that in our main did-setting, we net out this stock-specific effect by only comparing trades in the same stock.

bias our results because neither β_5 nor β_6 would cancel out the impact of this behavior.

To address this residual caveat, we conduct three additional tests that incorporate the investor-stock pair information to which the investor has access.

First, the broker may observe a certain risk taking pattern for specific investors in specific stocks after large stock price moves. We mitigate the concern that this observation biases our results by exploiting that our data also covers a period before the broker started sending push messages to investors. Specifically, we divide our sample into the sub-period before the broker started sending messages (no-message sub-period) and the sub-period, in which the broker sent messages (message sub-period). We then compare the risk taking of each treated investor after receiving a message in the message sub-period to that of the same investor in the same stock after a comparable stock price move during the no-message sub-period. We use a threshold of plus and minus three percent as a comparable stock price move for push messages that indicate a stock price move above plus and minus three percent, respectively. This test also provides a natural complement to our did approach that cannot, by definition, compare the risk taking of a treated investor to the risk taking of the same individual had she not been treated. The results in Table 5 confirm our conjecture that attention triggers stimulates risk taking.

— Place Table 5 about here —

Second, the broker has information on the research activity of specific investors on specific stocks on his home page. Such research activity can indicate future trading (Gargano and Rossi, 2018; Sicherman et al., 2015) and, thus, may also allow the broker to anticipate future investor-stock specific risk taking. In fact, Table 3 indicates that the broker is more likely to send push messages to investors who research a given stock. On average, message and non-message receivers have visited the research page of the message stock in the week prior to the push message 0.023 and 0.002 times, respectively. Therefore, we repeat our main analysis by only incorporating investors who do not research a given stock prior to receiving a push message on that stock. Our results are robust to this setting, as shown in Panel A of Table 6.

— Place Table 6 about here —

Third, the literature on risk taking concludes that personal experiences or beliefs are a key driver of the heterogeneity in individuals' willingness to take risk (e.g. Kaustia and Knüpfer, 2008; Choi et al., 2009; Malmendier and Nagel, 2011; Kaustia and Knüpfer, 2012; Knüpfer et al., 2017). Whereas our DDD approach cancels out the potential impact of general differences between investors along these dimensions, it does not address the concern that the broker may observe the past experience of an investor with the message stock to anticipate investor-stock specific changes in risk-taking. In support of this argument, Table 3 indicates that, on average, 15% of message receivers have traded the message stock prior to receiving the push message, whereas only 1% of non-message receivers have traded this stock before the treatment. We, therefore, repeat our main test by only incorporating investors who have never traded the message stock before receiving a push message. For these investors, the broker has no information about the past experience of an investor with the message stock. Table 7 shows that our results are robust to this setting.

— Place Table 7 about here —

We provide additional tests on the message sending behavior concern in the Appendix. For example, the broker could observe how previous push messages on other stocks affect an investor's risk taking and send messages according to this observation. Table 3 shows that message investors have, on average, received more push messages on other stocks than non-message investors before receiving the first push message on a stock. Similarly, message investors have clicked on more previous push messages on other stocks before receiving a push message (13.22 push message clicks, on average) compared to non-message investors (8.29 push message clicks, on average). Note that we only incorporate the first message that the broker sends to an investor on a certain stock throughout our main analysis. Thus, the broker does not have investor-stock specific information on how an investor reacts to a push message when he sends this first message on a certain stock.

Of course, the broker may still observe how a previous push message on a different stock or a different asset class has affected an investor's risk taking. The coefficients on β_5 and β_6 in our DDD approach, however, would isolate this dimension of a message sending behavior. To provide evidence beyond the DDD approach that this concern does not bias our conjecture, we repeat our analysis by only considering the first message to an investor on any stock in Panel A of Table A.3 and the first message to an investor on any asset class in Panel B of Table A.3. In both cases, our results on risk taking are even stronger than in our main specification.

In the appendix, we also run a nearest-neighbor matching routine in our did-approach. Specifically, we match the investors from the treatment group with comparable investors from the counterfactual based on the Euclidean Distance with respect to overall trading intensity over the previous 180 days, past average leverage-usage in any stock, gender, and age. This matching addresses the concern that the broker may anticipate that investors with certain observable characteristics change their risk taking and send the messages according to this anticipation. As in the previous example, the coefficients on β_5 and β_6 in our DDD approach should cancel out this effect. Thus, the matching provides evidence beyond the ddd for our conjecture. The results in Table A.4 in the Appendix are robust to matching investors.

Lastly, we also investigate how attention affects investors' leverage for investors who do not hold the stock when receiving the push message and for those who do hold the stock when receiving the push message, separately. The results are summarized in Table A.5 in the appendix. Panel A studies the case when investors do not hold the stock when receiving the push message. In line with our main analysis, the results indicate that investors trade stocks with higher leverage. Panel B studies the leverage of trades that increase an existing position. Again, the results support our notion that attention stimulates risk taking, even though to a lesser degree than for new positions.

4 Attention triggers, investor types, and stock characteristics

In the previous sections we show that attention triggers induce investors to increase their risk taking. To further understand our main findings we now perform a set of additional analyses.

4.1 Attention triggers and prior trading experiences

The effect of prior experiences and outcomes on investors' risk taking is well documented in the financial literature. Increased risk-taking after a loss was first documented by Thaler and Johnson (1990), who label their observation the *break-even effect* based on the argument that people are willing to take on more risk to break even. In the psychological literature, this type of behavior is well documented under the term *escalation of commitment* (Staw, 1997). Increased risk taking following losses can be explained with the value function from Prospect Theory (Brockner, 1992). Following a paper loss, investors are in the convex region of the value function and, accordingly, increase their risk-taking, as subsequent losses hurt relatively less, but any subsequent gain feels particularly good.[9] The financial literature also documents an increase in risk taking following a gain. Evidence of this behavior, labeled the *house-money effect*, is provided by Thaler and Johnson (1990). Imas (2016) reconciles the apparent contradiction between "escalation of commitment" and the "house-money effect" by stating that individuals avoid risk following a realized loss but take on greater risk if the loss is not realized and only a loss on paper. Imas (2016) documents that realized losses and paper losses influence investment behavior in different ways and labels his finding the "realization effect".

[9] Other explanations for the increase in risk taking include the *self-justification hypothesis* proposed by Staw (1976). The hypothesis argues that individuals maintain a course of action because they feel the need to justify their initial decisions. Consistent with self-justification, investors could perceive a price decrease as a good buying opportunity (Weber and Camerer, 1998). Moreover, prior gains and losses can affect risky choices under expected utility maximization, as the outcomes change current wealth. Then, increasing relative risk aversion yields escalation of commitment. Also, an investor optimizing her portfolio weights would have to rebalance her portfolio to keep the weights constant after a loss.

Consequently, we investigate how the past performance with the message stock affects the impact of attention triggers on risk taking. Columns (1) and (2) of Table 8 show that both investors with past realized gains and investors with past realized losses in the message stock increase risk taking after an attention trigger. In contrast, Columns (3) and (4) suggest that whereas attention triggers stimulate the risk taking of investors with paper losses in the message stock, they do not affect the risk taking of investors with paper gains.

— Place Table 8 about here —

4.2 Attention triggers and investor types

Gender has been documented to be a significant determinant of individual investor trading behavior (Barber and Odean, 2001) and risk taking (He et al., 2008; Powell and Ansic, 1997). With respect to our research, Sicherman et al. (2015) document lower financial attention in women, while Eckel and Grossman (2008) and Charness and Gneezy (2012) show that men are more risk-taking than women. Based on these observations studying gender differences in investors' reaction towards attention triggers is a natural step to follow. The results of our analyses are summarized in Panel A of Table 9. Columns (1) and (2) indicate that the increase in risk taking is primarily driven by male investors.

— Place Table 9 about here —

In Panel B of Table 9, we shed additional light on the importance of investors' age when it comes to the reaction to attention triggers. Similar to gender, age has been documented to have important implications for investors' risk taking. As Foerster et al. (2017) note, differences in risk aversion account for variation in risky shares in neoclassical portfolio theory. Older investors and individuals facing greater labor income risk should invest less in risky assets. This argument is in line with Morin and Suarez (1983) who suggest that investors' risk aversion increases uniformly with age. Similarly, attention varies with age

(Sicherman et al., 2015). Consistent with these studies, we observe that the impact of the attention trigger on risk taking decreases with investors' age.

Next, we turn to investors' self-reported willingness to take risk. We use investors' Mifid II replies to split our sample in investors who are less and more willing to take risk based on their preferred return-drawdown profile. Results of the analysis are reported in Panel C of Table 9. While we observe that the risk taking of investors who are more willing to take risks is more affected by push messages, more conservative investors still increase their risk taking by 3.4% of the standard deviation of leverage.

Lastly, we study the role of experience for our findings. The results are summarized in Panel D of Table 9. According to the table, investors with lower trading experience are more affected by the attention trigger. This observation is consistent with previous literature that suggests that more experienced investors make fewer behavioral errors and use more sophisticated trading tactics (Kaustia and Knüpfer, 2008; Feng and Seasholes, 2005).

To summarize, this section provides evidence that men, younger investors, and less experienced investors are more prone to the attention trigger. Perhaps most interestingly, we also show that even investors who are less risk seeking according to their self-assessment increase their risk taking in response to push messages.

4.3 Attention triggers and stock characteristics

Now we condition investors' reaction to the attention trigger on the characteristics of the message stock. We focus on the amount of public information available for a given stock and on the degree of value uncertainty. Following Gargano and Rossi (2018), we use the market capitalization of the company, the number of analysts, and the number of news as proxies for the amount of public information available when receiving a push message. The results of our analyses are presented in Panels A-C of Table 10. Our results indicate that investors increase their risk taking to a larger degree when more public information is available.

— Place Table 10 about here —

In Panels D and E of Table 10 we study the role of a stocks' valuation uncertainty for our findings. Following Gargano and Rossi (2018), we make use of the stock volume and the stock volatility as proxies for valuation uncertainty. Our analyses indicate that attention triggers have a larger impact on investors' risk taking for stocks with larger valuation uncertainty.

Taken together, our findings indicate that the impact of attention triggers on risk taking is more pronounced for stocks with more public information available and for those with higher valuation uncertainty. Interestingly, Gargano and Rossi (2018) report that paying attention increases investor performance specifically for these types of stocks. A different interpretation of our cross-sectional findings is that attention triggers have a stronger impact for more familiar stocks.

5 Additional results

In this section, we provide additional results on attention trading and relate our study to the recent literature on investor attention.

5.1 Attention and trading intensity

We first study the impact of individual attention triggers on investors' trading intensity. To this end, we apply a variation of our did approach. Specifically, we compare the trading frequency in the message stock of treated investors during the 24 hours after receiving a push message to that of investors who do not receive a push message on the same day.[10] Our dependent variable *Trading intensity* denotes the number of trades an

[10]Note that we only consider active investors, who execute at least one trade over our sample period, in the set of comparable investors to ensure that our results are not driven by inactive comparable investors. As the broker, however, sends many push messages to the 131,375 inactive investors, who receive push messages but do not trade during our sample period, and we also consider these inactive investors in our treatment group, this introduces a bias against finding an increase in investors' trading intensity.

investor executes in a given stock on a given day. It takes a value of zero if the investor does not trade the stock on this day. To obtain a comprehensive picture of the impact of attention on investors' trading intensity, we apply our difference-in-differences approach along several granular trading dimensions. Specifically, we differentiate between stock buying and selling, as well as between the trading in stocks that are mentioned in a push message (message stocks) and the trading in stocks that are not mentioned in a push message (non-message stocks).

Panel A of Table 11 summarizes the results of our regression analysis using equation (1) on the impact of attention on stock trading. In Column (1), we investigate stock buying. Stock buying entails increasing the long position or closing a short position on a stock. 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 0.0047 trades over the subsequent 24 hours. The magnitude of the treatment coefficient is economically important, given that the mean daily number of an investor's long trades in a stock is only 0.000153 (not tabulated).

— Place Table 11 about here —

Column (2) shows that push messages also stimulate investors to sell a stock (i.e. closing a long position or establishing a short position). The treatment coefficient suggests that, on average, a push message on a stock increases the number of investors' sell trades of that stock by 0.0094 trades on the subsequent day. Given that the mean daily number of an investor's sell trades in a stock is only 0.000146 (not tabulated), the magnitude of the treatment coefficient is economically important. In addition, the quantitative impact of attention on selling in Column (2) is even stronger than that on stock buying in Column (1).

Next, we measure the impact of push messages on the trading of stocks that are not mentioned in the messages. Columns (3) and (4) of Table 11 summarize the results. We omit the stock-fixed effects in these tests as we capture the trading in any stock besides the message stock. The treatment coefficients in Columns (3) and (4) imply that the push messages have no impact on either the buying or selling of non-message stocks.

We also separately analyze the impact of the attention trigger on investors' propensity to open a new short positions. To this end, we run a regression using equation (1) on *short sale*. The results in Table 12 show that the attention trigger stimulates short trading, which is consistent with the evidence presented in Table 11. In particular, the treatment coefficient suggests that a push message on a stock increases the propensity for a short sale by 2.09% trades compared to investors who do not receive the trigger.

— Place Tables 12 about here —

As push messages stimulate long *and* short selling, it is not obvious whether they increase or decrease the investors' (stock) market exposure. To investigate the impact of attention triggers on investors' risk exposure, we, therefore, investigate the change in a message stock's position size after a push message, conditional on trading. Trades that establish a new long or short position increase the investor's position size, and trades that close an existing long or short position reduce an investor's position size in the message stock. We estimate the difference-in-differences equation (1) for *Risk exposure* and present the results in Panel B of Table 11. The positive treatment coefficient ($\beta = 1.50$; t-statistic: 3.33) suggests that investors, on average, increase their exposure in the message stock after the attention triggers. Thus, this test with an alternative measure of risk taking confirms our conjecture the attention triggers increase the investors' willingness to take risk.

Overall, our analysis of the individual trading intensity complements the existing literature on the impact of aggregate attention on aggregate trading (Barber and Odean, 2001; Seasholes and Wu, 2007; Barber and Odean, 2008; Lou, 2014; Peress and Schmidt, 2018). We confirm on the micro level that individual attention triggers stimulate the individual trading intensity. To the best of our knowledge, we are the first to show that attention is important for short selling. Barber and Odean (2008), for example, focus on the sale of existing positions but do not consider short selling.

Our results help to distinguish between the scarce resource and the selective attention explanation for the observation that attention is more important for stock buying than stock selling. The scarce resource hypothesis of Barber and Odean (2008) suggests that because attention is a scarce resource, the impact of attention on retail trading depends on the size of the choice set. Thus, the impact of attention on stock buying—where investors search across thousands of stocks —should be larger than that on the selling of existing stock positions—where investors choose only from the few stocks that they own. On the other hand, selective attention suggests that retail investors pay more financial attention to good news than to bad news (Karlsson et al., 2009; Sicherman et al., 2015).[11] Hence, if attention traders are, on average, momentum traders, attention could be more important for buying than for selling due to selective attention.

Our results on the importance of attention for short selling support the scarce resource explanation. This hypothesis implies that attention should be important for short selling because the choice set for short selling is much larger than that for the selling of existing positions. Specifically, investors can sell short all stocks, rather than being confined to the stocks they already hold in their portfolio. The selective attention story, however, would imply that, as with the selling of existing positions, attention should not be important for short selling.

5.2 Relation to alternative individual attention measures

Several recent studies derive proxies of how individuals pay attention by using investors' account login or page-view data (e.g. Karlsson et al., 2009; Gargano and Rossi, 2018). For our study on risk taking, it is important to use an attention trigger that is not determined by the investor because an investors' decision to pay more attention is likely to be related to the riskiness of his planned trade.

We now highlight the relation between our push messages as attention triggers and the

[11]Such a behavior can be explained by the "ostrich effect"—a term coined by Galai and Sade (2006). The authors define the ostrich effect as "avoiding apparently risky financial situations by pretending they do not exist." Given preliminary bad news people may "put their heads in the sand" to shield themselves from further news.

individual attention proxies of the literature. To this end, we estimate Equation (1) of Section 1.3, in which we use *research* as the dependent variable. Specifically, we measure whether investors research a certain stock more frequently during the 24 hours after receiving a push message on that stock compared to investors who do not receive this push message on the same day. The results of our analysis are reported in Panel B of Table 6. Column (1) shows that the number of investors' page-views significantly increases after receiving a push message compared to non-treated investors.

In Columns (2) and (3) of Panel B, we separately investigate investors' page-views following positive and negative push messages. The page-views increase after both message types, but to a greater extent after positive push messages. This observation is in line with the "ostrich effect", suggesting that investors pay more attention following market increases than market declines (Galai and Sade, 2006; Karlsson et al., 2009; Sicherman et al., 2015; Olafsson and Pagel, 2017).

Next, we separately investigate investors' information acquisition for individuals who already hold the message stock when receiving the push message (Column (5)) and individuals who do not hold this stock (Column (4)). We observe that investors particularly increase their information acquisition for an attention trigger if they already hold the stock in their portfolio. Importantly, however, the messages also increase research for those investors who do not hold the stock. In addition, Column (6) shows that investors start doing research after an attention trigger even if they have never researched the message stock before. Thus, Columns (4) and (6) highlight the role of the messages as attention triggers. They suggest that messages are not simply an endogenous consequence of investors' attention towards a stock but rather exogenously trigger that attention.

Overall, the results suggest that our individual attention measure shares some basic properties with the individual attention measures suggested in the literature. Importantly, however, our analysis also shows that in contrast to the existing measures, the messages are an appropriate proxy of individual attention triggers.

6 Robustness analyses

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

6.1 Investor behavior

We first investigate the possibility that the investors' behavior could bias our conjecture. Specifically, a potential objection to our results is that investors may not receive or read the push messages. For example, some individuals may have disabled or blocked these push messages on their cell phone such that they not even receive the messages. We address this concern by exploiting the information in our data about whether an investor actually clicked on a message. A click indicates that the investor certainly received and most likely also noticed or read the message. Using this click-information, we perform additional analyses. In Panel A of Table 13, we repeat our main analysis, but only consider those investors who actually click on the push message in the treatment group instead of all the investors to whom the broker sends a push message. The counterfactual group consists of the investors to whom the broker does not send a push message, as in our main analysis. The positive treatment coefficient indicates that our conjecture on risk taking is robust to this alternative setting.

— Place Table 13 about here —

Next, we address the self-selection concern that arises from the possibility that some investors disable or block the broker's push messages. For instance, our counterfactual may include many investors who blocked the push messages, which could bias our conjecture if the tendency to block the messages is correlated with investors' risk taking. Unfortunately, we cannot directly observe whether and when an investor blocks the push messages as they can flexibly block the messages on their cell phones at any time. We, however, provide arguments along two lines that this self-selection concern does not affect our conjecture. First, we only consider the first push message on a stock in our main analysis and 98.5% of investors receive a first push message on a stock. Thus, the minority of investors without such a message is unlikely to bias our conjecture. Second, we repeat our main regression by only considering investors in the counterfactual that clicked on any push message within seven days before and after the treatment time, but did not receive the push message send to the treated investors. This approach mitigates the concern that we observe investors in the counterfactual that actually blocked the messages around the treatment time.[12] Panel B of Table 13 shows that our results on risk taking are robust to this test.

6.2 Attention and news

Another caveat with our results is that they could be driven by news that is correlated with both risk taking and the broker's tendency to send push messages to investors. Our did approach mitigates this concern because we compare the risk taking of investors with push messages to the risk taking of investors without push messages in the same stock at the same time, which should cancel out the aggregate impact of news on risk taking. Nevertheless, the broker may send push messages to investors who are more likely to receive certain news than investors who do not receive these news. To address this concern, we repeat our main analysis with the three alternative settings in Table 14.

— Place Table 14 about here —

First, we omit earnings report push messages in Column (1) of Table 14 to address the concern that such messages could reveal some news to investors that stimulate risk taking. Second, we omit push messages that the broker sends on or the day directly following news in Column (2). We identify news-days from the Quandl Alpha One Sentiment Data. Next, we apply a news filter for leverage usage in Column (3). Specifically, we first regress *Leverage* on *News volume*, *News sentiment*, a time dummy, and investors'

[12] Of course, it is still possible that an investor blocked the messages just before the treatment time and then unblocked it just after the treatment time. Such exceptional observations in the counterfactual, however, are unlikely to drive our conjecture.

age and gender. The residuals of this regression capture the dimension of the investors' leverage decision that is not explained by news. We then repeat our did approach by using these residuals as the dependent variable. Intuitively, this approach measures the impact of the attention trigger on the portion of the investors' risk taking decision that is not explained by news. Overall, Table 14 implies that our conjecture on risk taking is robust to the alternative specifications. We, therefore, conclude that news do not drive our conjecture that attention triggers stimulate risk taking.

6.3 Attention and message content

We now investigate to what extent the message content affects our results to exclude that style trading such as momentum trading drives our conjecture. We omit earnings announcement messages in this analysis as it is challenging to unambiguously classify their content. In Columns (1) and (2) of Table 15, we separately study the impact of negative and positive push messages on risk taking. These columns show that the treatment coefficients on leverage are very similar to that in our main specification of Table 4 for both, positive and negative push messages. Thus, push messages stimulate investors to take higher leverage, regardless of whether the messages report a positive or negative stock price change.

— Place Table 15 about here —

In a similar vein, we study whether investors' reaction to attention depends on the magnitude of the return reported in the push message in Columns (3) and (4) of Table 15. To this end, we study weak and strong push messages, separately. A push message is denoted to be strong if the message's absolute price change is larger than the median reported price change. The treatment coefficients indicate that our results on leverage is not driven by the magnitude of the reported return.

Overall, the results in Table 15 suggest that the investors' increased willingness to take risk is primarily driven by the attention trigger, and not by the message content.

7 Conclusion

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

We provide additional novel insights into the impact of attention triggers on retail investors' trading. For instance, we find that attention triggers are more relevant to the risk taking of younger, male investors with less trading experience. We also provide evidence that push messages enhance risk taking for those investors who consider themselves to be less prone to risk taking.

Our micro-level evidence on the impact of individual attention triggers on individual risk taking 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) and recent studies on attention at the individual investor level (Sicherman et al., 2015; Gargano and Rossi, 2018; Dierick et al., 2019). 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.

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A Contracts for difference

A contract for difference (CFD) is a financial contract designed such that its price equals that of the underlying security.[13] 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).

[13]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	Research before	Traded before	Hold stock	Click on message	Research on message	Trade on message	Momentum trade	Contrarian trade	mean (reaction time)	median(reaction time)
Positive price change	9,554,260	0.0353	0.1499	0.0277	0.0871	0.0343	0.0140	0.0062	0.0078	5.4406	1.2322
Negative price change	10,443,759	0.0329	0.1461	0.0249	0.0752	0.0269	0.0125	0.0040	0.0085	5.3726	1.2133
Positive streak	708,583	0.1583	0.0550	0.0267	0.0983	0.0354	0.0127	0.0069	0.0058	1.6954	0.8321
Negative streak	215,375	0.3679	0.1006	0.0626	0.1182	0.0591	0.0276	0.0100	0.0177	1.7182	0.8829
Earnings reports	776,403	0.0423	0.3003	0.0641	0.0923	0.0376	0.0298	-	-	13.6585	21.6785
	21,698,380	0.0357	0.1559	0.0280	0.0822	0.0311	0.0139	0.0050	0.0079	5.8567	1.3500

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. *Research before* is a dummy variable that takes a value of one if the investor has researched the underlying referred to in the push message within the week before receiving the push message, zero otherwise. *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. *Hold stock* is a dummy variable that takes a value of one if the investor holds the underlying referred to in the push message in her portfolio when 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. *Research on messages* is a dummy variable that takes a value of one if the push message is followed by a visit on the message stock research page within 24 hours, zero otherwise. *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, zero otherwise. *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, zero otherwise. *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, zero otherwise. *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.

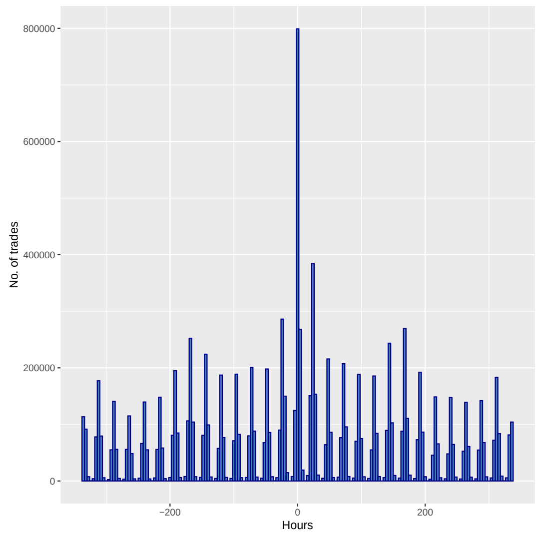

Figure 1: Trading activity around push messages

This figure presents the distribution of the trading activity of investors around the time push messages are sent. The time difference is measured in hours. Push messages are sent at time 0. 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.

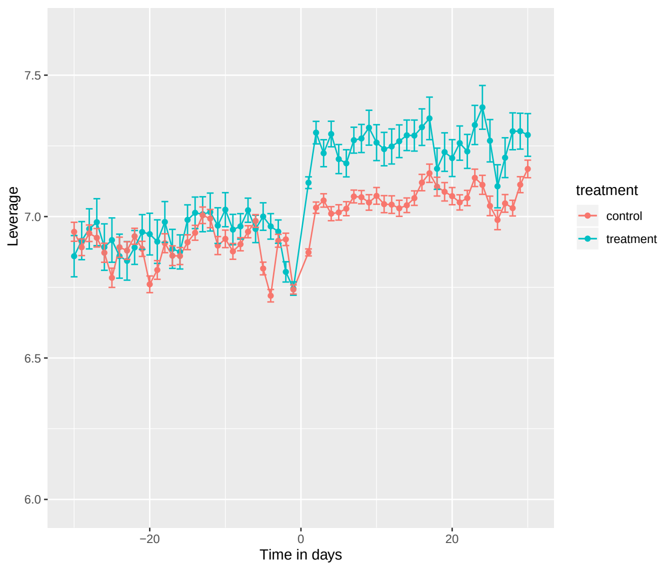

Figure 2: Risk taking around the treatment events

This figure presents the average usage of leverage for investors around the treatment times. The control group (red) comprises all investor-stock pairs where the investor did not receive a push message referring to the stock. For the treatment group, the investor receives a push message referring to a given stock at time zero. 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.

Type	leverage
Non-attention trade	6.07
Attention trade	6.53
t-test	4.27

Table 2: Risk taking after push messages

This table reports summary statistics of investors' leverage usage 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. *leverage* denotes the investor's average leverage. The t-test reports results from equality tests of non-treated versus treated trades, clustered over time.

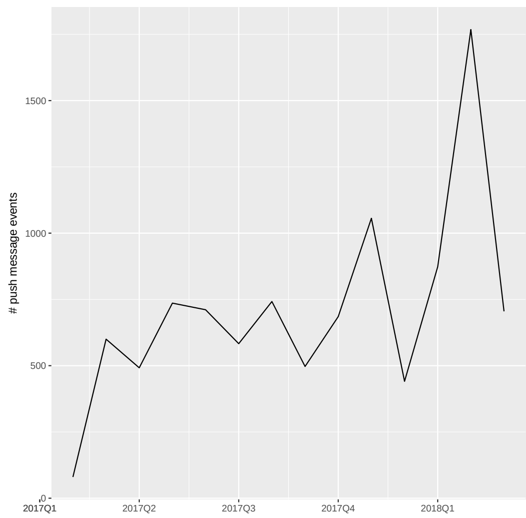

Figure A.1: Number of push message events over time

This figure presents the evolution of the number of 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.

Panel A: Stock characteristics			
	Non-message month	Message month	t-test
Volatility	0.29	0.39	9.77
Beta	0.97	1.16	7.89
IVOL	0.24	0.33	10.15

Table 3: Message sending behavior of push messages (Panel A)

This table reports details on the broker's message sending behavior. Panel A reports average measures of stock risk by aggregated by stock-month. Panel B reports aggregate average investor characteristics. Non-message month denote month without a push message for a given stock; message month denote month during which at least one push message was sent referring to the given stock. For Panel B, we first randomly draw one message event. For the message event, we randomly draw one investor who receives the message and one investor who does not receive the message. This exercise is repeated 1,000,000 times. $Volatility$ 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); *inactive* is a dummy variable that takes a value of one if the investor has not traded in the week prior to the push message, zero otherwise; *traded message stock* is a dummy variable that takes a value of one if the investor traded in the message stock within the last seven days before the message, zero otherwise; *trades* denotes the number of trades of an investor in the week prior to the push message; *leverage* denotes the investor's average leverage for trades over the previous week; *position size* is the average investment amount in a given stock trade expressed as a fraction of the total assets deposited by the investor at the broker over the previous week; *short sale* denotes the fraction of short sales of an investor over the week prior to the push message; *holding period* denotes the average time between opening and closing of the same position in hours over the previous week; *ROI* denotes the average return on investment net transaction costs over the previous week; *research pages* denotes the number of times the investor visits a stock research pages during the week before the given push message; *research stock* denotes the number of times the investor visits the message stock research page during the week before the given push message; *prior pushs* denotes the number of push messages sent to the investor before the given push message; *prior click* denotes the number of prior push messages which the investor clicked on; *prior attention trade* denotes the number of attention trades that followed previous push messages; *male* is a dummy variable that takes a value of one if the investor is male, zero otherwise; $age25$ is a dummy variable that takes a value of one if the investor is between 25 and 34 years of age, zero otherwise; $age35$ is a dummy variable that takes a value of one if the investor is between 35 and 44 years of age, zero otherwise; $age45$ is a dummy variable that takes a value of one if the investor is between 45 and 54 years of age, zero otherwise; $age55$ is a dummy variable that takes a value of one if the investor is between 55 and 64 years of age, zero otherwise; $age65$ is a dummy variable that takes a value of one if the investor is at least 65 years of age, zero otherwise. The t-test reports results from equality tests of non-message versus message months; p-values are from a Mann-Whitney U test. 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 B: Investor characteristics									
	Non-message investor				Message investor				p-value
	p25	p50	p75	mean	p25	p50	p75	mean	
Inactive	1	1	1	0.89	1	1	1	0.85	0.000
Traded message stock	0	0	0	0.01	0	0	0	0.15	0.000
Trades	1	3	8	8.54	1	4	12	12.28	0.000
Leverage	4.6	5	7.8	5.6	5	5	9.4	6.27	0.000
Position size	3	8.2	18.4	15.8	3.7	9.8	22	17.9	0.000
Short-sale	0	0	0	0.073	0	0	0	0.076	0.000
Holding period	78.8	198.9	458.3	428.04	58.3	161.4	373.1	340.5	0.000
ROI	-0.000	0.000	0.000	-0.005	-0.000	0.000	0.000	-0.007	0.038
Research pages	0	0	0	2.40	0	0	0	4.79	0.000
Research stock	0	0	0	0.002	0	0	0	0.023	0.000
Prior pushs	4	28	61	53.34	11	45	98	106.15	0.000
Prior click	0	1	6	8.29	0	1	5	13.22	0.000
Prior attention trades	0	0	1	4.18	0	0	0	3.17	0.000
Male	1	1	1	0.92	1	1	1	0.93	0.000
Age 25	0	0	1	0.42	0	0	1	0.42	0.781
Age 35	0	0	1	0.25	0	0	1	0.26	0.001
Age 45	0	0	0	0.12	0	0	0	0.12	0.000
Age 55	0	0	0	0.04	0	0	0	0.04	0.002
Age 65	0	0	0	0.01	0	0	0	0.01	0.000

Table 3: Message sending behavior of push messages (Panel B)

Panel A: difference-in-differences analysis	
treat × post	0.1277
	(5.6310)
Obs.	1,463,270
Adj. R^2	0.61
Panel B: 24-hour observation period	
treat × post	0.1276
	(5.1040)
Obs.	934,914
Adj. R^2	0.61
Panel C: difference-in-difference-in-differences analysis	
treat	0.0483
	(7.1693)
post	0.0319
	(8.4588)
stock	0.0608
	(6.0127)
treat × post	0.0197
	(2.0216)
treat × stock	−0.0950
	(−5.1160)
post × stock	−0.0672
	(−4.0041)
treat × post × stock	0.1801
	(5.8745)
Obs.	2,596,080
Adj. R^2	0.62
All panels	
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes

Table 4: Attention and leverage: difference-in-differences analysis

This table reports results from a difference-in-differences (Panels A and B) [difference-in-difference-in-differences analysis (Panel C)] regression analysis on the leverage of trades that investors initiate in our trade data. Panels A and B estimate equation (1), Panel C uses equation (2). For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the first trade after the treatment event within 24 hours. In Panels A and B, we only consider the leverage of the first trade in the stock referred to in the push message after the treatment event. The treatment event is the first message an investor receives for a given stock. In Panel B, we restrict the observation period to the last 24 hours before the treatment event. *Leverage* denotes the leverage employed for a trade; *treat* is a dummy variable that takes a value of one for investors of the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise; *stock* is a dummy variable that takes a value of one for the stock referred to in the push message, 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.

Dependent var.	Leverage
Push message regime	1.0126
	(4.6781)
Obs.	318,486
Adj. R^2	0.11

Table 5: Investors' risk taking over time

This table reports results from an ordinary least squares regression analysis on investors' leverage for the time period before push messages were sent (01-01-2016 to 02-26-2017) and the push-message regime (02-27-2017 to 03-31-2018). The push-message regime considers all "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 time period before push messages were sent considers trades in investor-stock pairs where the investor receives a push message referring to the stock in the push message regime. The table is restricted to trades executed after an absolute stock price change of at least 3% (i.e. the threshold for the broker to send push messages in the push message regime). *Leverage* denotes the leverage employed for a trade; $Push - message\ regime$ is a dummy variable that takes a value of one for trades in the push-message regime, 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.

Panel A: Message-sending behavior of the broker: No stock-specific research prior to push message

Dependent var.	Leverage
treat × post	0.1201
	(5.2817)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,262,530
Adj. R^2	0.61

Panel B: Stock-specific information acquisition after receiving message

Dependent var. / Sample	Research all push messages	Research positive messages	Research negative messages	Research not holding stock	Research holding stock	Research no prior research
treat × post	0.0598	0.0631	0.0518	0.0462	0.3421	0.0226
	(5.60)	(5.03)	(4.70)	(6.02)	(4.70)	(8.78)
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.	29,764,350	14,804,562	13,644,954	29,297,604	466,746	27,710,308
Adj. R^2	0.10	0.11	0.12	0.05	0.42	0.02

Panel C: No stock-specific research between push message and trading activity

Dependent var.	Leverage
treat × post	0.1326
	(5.4473)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,360,493
Adj. R^2	0.61

Table 6: Stock-specific information acquisition

This table reports analyses exploiting data on stock-specific information acquisition of investors. Research (Information acquisition) is the number of daily visits of a website that contains stock-specific information for a given stock. Panel A reports results from a difference-in-differences regression analysis on the characteristics of trades that investors initiate in our trade data. The panel is restricted to investors who do not view the stock-specific (≡ message stock) information page of the broker prior to the treatment event. Panel B reports results from a difference-in-differences regression analysis on information acquisition at the stock level of investors around the treatment date (first push message on stock). Column (1) reports information acquisition for all push messages; Column (2) [(3)] reports information acquisition only after positive (negative) push messages; Column (4) is restricted to investors who do not hold the message stock in their portfolio at the time of the message; Column (5) is restricted to investors who do hold the message stock in their portfolio at the time of the message; Column (6) is restricted to investors who never research the message stock prior to the time of the message. Panel C reports results from a difference-in-differences regression analysis on the characteristics of trades that investors initiate in our trade data. The panel is restricted to investors who do not view the stock-specific (≡ message stock) information page of the broker after receiving the push message prior to trading. For each investor we take the trading characteristic of the last trade within seven days [average of daily information acquisition over the last seven days] before the treatment event and the trading characteristic of the first trade in the stock referred to in the push message [information acquisition within the first 24 hours] after the treatment event within 24 hours. The treatment event is the first message an investor receives for a given stock. *Leverage* denotes the leverage employed for a trade. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), 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.

Dependent var.	Leverage
treat × post	0.1183
	(4.70)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	693,206
Adj. R^2	0.61

Table 7: No prior trading experience in message stock

This table reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate in our trade data. The analysis is restricted to investors who have no prior trading experience in the message stock. For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the first trade after the treatment event within 24 hours. The treatment event is the first message an investor receives for a given stock. *Leverage* denotes the leverage employed for a trade. *treat* × *post* is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), 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.

Dependent var. Sample	(1) Leverage Realized gains	(2) Leverage Realized losses	(3) Leverage Paper gains	(4) Leverage Paper losses
treat × post	0.0679	0.0904	−0.0028	0.1071
	(2.13)	(2.34)	(−0.07)	(2.28)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	301,078	160,530	146,878	109,457
Adj. R^2	0.65	0.64	0.69	0.69

Table 8: Attention triggers and leverage usage: regression results conditioning on prior trading experiences

This table reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate in our trade data. The analysis is restricted to investors who have traded the stock prior to the treatment date. Column (1) [(2)] is restricted to investors who have realized gains [losses] in the message stock prior to the treatment time. Column (3) [(4)] is restricted to investors who have an open position in the message stock with paper gains [losses] in the message stock at the time of the push message. For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the first trade after the treatment event within 24 hours. The treatment event is the first message an investor receives for a given stock. *Leverage* denotes the leverage employed for a trade. *treat* × *post* is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), 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.

Panel A: Investors' gender		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Female	Male
treat × post	0.0297	0.1347
	(0.6229)	(5.7390)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	103,941	1,359,329
Adj. R^2	0.64	0.61

Panel B: Investors' age			
	(1)	(2)	(3)
Dependent var.	Leverage	Leverage	Leverage
Sample	18-34	35 - 54	$\geq$ 55
treat × post	0.1395	0.1172	0.0985
	(4.9862)	(4.6029)	(1.9462)
Investor-fixed effects	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	785,635	589,646	87,989
Adj. R^2	0.60	0.62	0.64

Panel C: Investors' risk preferences (self-assessment)		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low risk	High risk
treat × post	0.1087	0.1379
	(3.7902)	(5.5822)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	520,181	942,620
Adj. R^2	0.63	0.59

Table 9: Attention triggers and leverage usage: regression results conditioning on investor characteristics

Panel D: Investors' trading experience (self-assessment)		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low experience	High experience
treat × post	0.1549	0.1169
	(5.2163)	(4.9113)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	614,567	848,491
Adj. R^2	0.58	0.63

Table 9: Attention triggers and leverage usage: regression results conditioning on investor characteristics (cont.)

This table reports results from a difference-in-differences regression analysis on investors' trading characteristics conditioning on the characteristics of the investors. 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 first trade in the stock referred to in the push message after the treatment event within 24 hours. The results are computed separately for investors with low and high values of the conditioning variables. The conditioning variables used are (from Panel A to Panel D): Investors' gender, investors' age, investors' risk preferences according to their own assessment, and investors' trading experience (self-assessment). $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), 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.

Panel A: Firm size		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	small firm	large firm
treat × post	0.1123	0.1400
	(4.0934)	(4.0132)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	570,138	714,560
Adj. R^2	0.66	0.60
Panel B: Analyst coverage		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low analyst coverage	High analyst coverage
treat × post	0.1099	0.1452
	(3.6340)	(5.1774)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	802,385	510,819
Adj. R^2	0.60	0.67
Panel C: News stories		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low news production	High news production
treat × post	0.0512	0.1355
	(1.4022)	(4.7441)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	174,820	968,529
Adj. R^2	0.69	0.59

Table 10: Attention triggers and leverage usage: regression results conditioning on stock characteristics

Panel D: Stock volume		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low volume	High volume
treat × post	0.1007	0.1304
	(3.4879)	(4.5467)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	370,912	1,038,364
Adj. R^2	0.67	0.59

Panel E: Stock volatility		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low stock vola	High stock vola
treat × post	0.1040	0.1306
	(2.6854)	(5.6083)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	378,448	1,017,777
Adj. R^2	0.64	0.62

Table 10: Attention triggers and leverage usage: regression results conditioning on stock characteristics (cont.)

This table reports results from a difference-in-differences regression analysis on investors' trading characteristics conditioning on the characteristics of the stocks. 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 first trade in the stock referred to in the push message after the treatment event within 24 hours. The results are computed separately for stocks with low and high values of the conditioning variables (median split). The conditioning variables used are (from Panel A to Panel E): Size, computed as the log of the market price multiplied by the number of shares outstanding; Num. Analysts, the log of the number of analysts covering the stock; and News, the number of news from Quandl; Volume, the average trading volume of the stock; Volatility, computed as Garch(1,1) volatility of the stock. *treat* × *post* is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), 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.

Panel A: Trading intensity				
	(1)	(2)	(3)	(4)
	Messages stocks		Non-messages stocks	
	long positions	short positions	long positions	short positions
treat × post	0.0047	0.0094	−0.0033	0.0054
	(2.00)	(4.25)	(−0.5819)	(1.1448)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	No	No
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	29,174,552	29,174,552	29,764,350	29,764,350
Adj. R^2	0.13	0.07	0.41	0.39
Panel B: Risk exposure				
	(1)			
treat × post	1.5036			
	(3.33)			
Investor-fixed effects	Yes			
Stock-fixed effects	Yes			
Time-fixed effects	Yes			
Obs.	1,846,209			
R^2	0.05			

Table 11: Stock-specific trading intensity after receiving message

This table reports results from a difference-in-differences regression analysis on the trading intensity at the stock level (Panel A) and the change in risk exposure (Panel B) of investors around the treatment date. In Panel A, columns (1) and (3) report long positions; Columns (2) and (4) show results for short positions. Columns (1) and (2) consider trades in message stocks. Columns (3) and (4) consider trades in non-message stocks. In Panel B, considers all executed trades that open or close a position. Trading intensity is the average number of daily trades in a given stock over the last seven days before (observation period) and the first 24 hours after investors receive a push message for the specific stock for the first time (treatment period). Risk exposure denotes the average investment amount in a given stock trade expressed as a fraction of the total assets deposited by the investor with the broker (i.e., the portfolio weight). Trades that establish a new position, long or short, yield an increase in risk exposure; trades that close an existing position, long or short, yield a decrease risk exposure. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treatment\ group = 1$) in the treatment period ($post\ treatment = 1$), zero otherwise. We obtain our control group by randomly drawing investors from all active investors who do not receive a given push message ("comparable investors"). 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.

	Short sale
treat × post	0.0209
	(4.8816)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,463,270
Adj. R^2	0.25

Table 12: Attention and short-selling

This table reports results from a difference-in-differences regression analysis on short sale in our trade data. For each investor we take the trading characteristic (short sale) of the last trade within seven days before the treatment event and the trading characteristic (short sale) of the first trade after the treatment event within 24 hours. We only consider the trading characteristic (short sale) of the first trade in the stock referred to in the push message after the treatment event. The treatment event is the first message an investor receives for a given stock. *short sale* is a dummy variable that takes a value of one if the position is a short position, zero otherwise; *treat* is a dummy variable that takes a value of one for investors of the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, 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.

Panel A: Risk taking of investors who click on push message	
Dependent var.	Leverage
Sample	click
treat × post	0.0931
	(3.67)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,410,610
Adj. R^2	0.61
Panel B: Self-selection of investors	
	Leverage
treat × post	0.1343
	(5.42)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,023,834
Adj. R^2	0.61

Table 13: Push message clicks

This table reports additional results from difference-in-differences regression analyses on the leverage of trades that exploit the information whether investors click on a push message. Panel A is restricted to investors who click on the push messages in the treatment group. Investors who receive a push message, but do not click on the push message are omitted from the analysis. In Panel B, differently from our main analysis, investors from the control group are required to click on a push message referring to a different underlying within seven days before the treatment event and within seven days after the treatment event. *Leverage* denotes the leverage employed for a trade; *treat* × *post* is a dummy variable that takes a value of one for investors of the treatment group (*treat* = 1) in the treatment period (*post* = 1), zero otherwise. The *t*-test reports results from equality tests of non-click versus click trades, clustered over time. 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.

Dependent var.	Leverage	Leverage	Leverage
Sample	No earnings reports	no news trading	filtered trading
treat × post	0.1347	0.1128	0.0987
	(6.3120)	(3.9647)	(3.9602)
Investor-fixed effects	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	1,168,052	498,407	1,243,152
Adj. R^2	0.61	0.67	0.59

Table 14: Risk taking and the impact of news

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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), zero otherwise. In the *no earnings reports*-model we omit all messages that report upcoming 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. 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)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	Negative message	Positive message	Weak message	Strong message
treat × post	0.1338	0.1409	0.1247	0.1481
	(4.3540)	(3.7306)	(3.9042)	(4.7229)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	359,353	375,491	361,028	379,776
Adj. R^2	0.64	0.61	0.62	0.64

Table 15: Message characteristics and risk taking: difference-in-differences analysis

This table reports results from a difference-in-differences regression analysis on investors' trading characteristics conditioning on the message content. Models (1) and (2) distinguish positive and negative messages; Models (3) and (4) distinguishes strong and weak messages (median split). Earnings reports messages are omitted from the analysis. 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 first trade in the stock referred to in the push message after the treatment event within 24 hours. The treatment event is the first message an investor receives for a given stock. *treat* × *post* is a dummy variable that takes a value of one for investors of the treatment group (*treat* = 1) in the treatment period (*post* = 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.

Panel A: Demographic characteristics								
	Gender		Age					
	Female	Male	18-24	25-34	35-44	45-54	55-64	≥65
Total	19,205	224,412	36,177	98,657	62,178	30,837	12,217	3,551
Panel B: Investors' return-drawdown profile								
	5% / -3%	10% / -6%	20% / -12%	40% / -24%	80% / -48%			
Percent	5%	8%	23%	33%	32%			
Panel C: Investors' trading experience								
	none	less than one year	one year one year	one to three years	more than three years			
Percent	26.3%	20.6%	12.2%	24.7%	16.1%			

Table A.1: Summary statistics of demographic information

Panel A reports the gender and age distributions of the investors in our dataset. Panel B reports investors' self-reported willingness to take risk. Panel C reports investors' self-reported trading experience. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license.

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
Position size	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
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.2: 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; *Position size* is measured as the trade amount's fraction of total assets deposited with the online broker; *Holding period* measures the timespan between the opening and closing of a position in hours; *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.

Panel A: first stock push message	
	Leverage
treat × post	0.1954
	(3.2221)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	271,735
Adj. R^2	0.69
Panel B: first push message any instrument	
	Leverage
treat × post	0.2019
	(1.9650)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	211,586
Adj. R^2	0.68

Table A.3: Message-sending behavior of the broker: Very first message

This table reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate in our trade data. The table compares investors who receive the *first push message in any stock* (Panel A) [first push message in any instrument (Panel B)] to investors who do not receive a push message. 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 first trade in the stock referred to in the push message after the treatment event within seven days. *Leverage* denotes the leverage employed for a trade. *treat* × *post* is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), 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.

Panel A: difference-in-differences analysis	
treat × post	0.1152
	(4.4078)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	519,092
Adj. R^2	0.63
Panel B: difference-in-difference-in-differences analysis	
treat	0.0104
	(1.0830)
post	0.0152
	(1.4525)
stock	0.1415
	(3.2026)
treat × post	0.0281
	(2.3792)
treat × stock	−0.1622
	(−3.6781)
post × stock	−0.1405
	(−2.5124)
treat × post × stock	0.1979
	(3.8269)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	764,626
Adj. R^2	0.61

Table A.4: Attention and leverage: difference-in-differences analysis (matched data)

This table reports results from a difference-in-differences (Panel A) [difference-in-difference-in-differences (Panel B)] regression analysis on short sale in our trade data. For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the first trade after the treatment event within 24 hours. In Panel A, we only consider the leverage of the first trade in the stock referred to in the push message after the treatment event. The treatment event is the first message an investor receives for a given stock. *short sale* is a dummy variable that takes a value of one if the position is a short position, zero otherwise; *treat* is a dummy variable that takes a value of one for investors of the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise; *stock* is a dummy variable that takes a value of one for the stock referred to in the push message, 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"). We obtain our control group from the group of comparable investors with a nearest-neighbor matching routine. We match investors from the treatment group with investors from the group of comparable investors based on their gender, age, the previous trading activity prior to the (counter-factual) treatment time, and their average usage of leverage 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: investors receive message on new stock	
	Leverage
treat × post	0.1201
	(5.2817)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,262,530
Adj. R^2	0.61

Panel B: investors hold stock when receiving message	
	Leverage
treat × post	0.0874
	(2.5485)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	309,206
Adj. R^2	0.67

Table A.5: Attention and leverage on additional positions: 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. Panel A is restricted to investors who do not hold the message stock in their portfolio at the time of the message; Panel B is restricted to investors who do hold the message stock in their portfolio at the time of the message. 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 first trade in the stock referred to in the push message after the treatment event within 24 hours. The treatment event is the first message an investor receives for a given stock. *Leverage* denotes the leverage employed for a trade. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), 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.