Attention Triggers and Investors' Risk-Taking*

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Abstract This paper investigates how individual attention triggers influence financial risk-taking based on a large sample of trading records from a brokerage service that sends standardized push messages on stocks to retail investors. Our micro-level data allow us to isolate these push messages as individual stock-attention triggers. By exploiting the data in a difference-in-differences setting, we find that attention triggers increase investors' risk-taking. We provide a battery of cross-sectional analyses to identify the groups of investors and stocks for which this effect is stronger.

Keywords: Investor Attention; Trading Behavior; Risk-Taking;

JEL Classification: G10, G11, G12.

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1 Introduction

Today's digital environment overwhelms investors with attention stimuli from many sources such as advertising, emails, social media messages, push notifications and many more. Such stimuli are intended to attract the investors' attention. Whereas the finance literature recognizes the importance of attention for individual investor behavior and financial markets (Barber and Odean, 2008; Gargano and Rossi, 2018), the influence of attention triggers on a key investment dimension, namely risk-taking, is still unexplored. This void is surprising for at least three reasons. First, explaining the risk-taking behavior of individuals is fundamental to the study of choice under uncertainty, a better understanding of financial markets, and financial stability more generally (e.g. Liu et al., 2010; Charness and Gneezy, 2012; Lian et al., 2018). Second, there is a growing theoretical recognition that investor attention behavior has key implications for asset prices (Chien et al., 2012; Andrei and Hasler, 2014). Third, psychology research offers an intuitive link between attention and risk-taking by concluding that affective attention triggers play an important role in individuals' risk-taking (Figner et al., 2009; Weber, 2010). However, the main challenge for researchers to analyze the link between attention stimuli and financial risk-taking is to observe the exogenous triggers of individual attention. Specifically, it is hard to identify and isolate those particular triggers of the many potential triggers that, in fact, stimulate an individual's attention.

In this study, we investigate the influence of individual attention triggers on individual risk-taking. We address the challenge of analyzing this influence through our access to a novel dataset. This dataset contains the trading records of a large broker that sends standardized push messages to retail investors. Each message reports publicly observable information on the past return of one specific stock. The messages allow us to observe exogenous triggers of individual investor attention towards the particular stock. Thus, we can empirically isolate the impact of the attention triggers on the recipients' risk-taking. Our analysis shows that attention triggers induce investors to take higher risk. The impact of attention on risk-taking is stronger for male, younger, and less experienced investors. In addition, we highlight the relation between certain stock characteristics and the influence of exogenous attention on risk-taking.

The broker offers retail investors a trading platform to trade contracts for difference (CFDs) on a large set of European and US blue chip companies. CFDs are derivative contracts designed such that their prices mirror those of the underlying securities. CFDs are widely popular in Europe and Asia. 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 in 2018 was approximately equal to the total transaction volume of the Deutsche Börse AG (CFD Verband e.V.). Given the large trading volume, studying the risk-taking of investors in this market is an important undertaking.

The broker's dataset 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 particular trades. Leverage is a major catalyst of speculative trading because it allows investors to increase the scope for extreme returns (Heimer and Simsek, 2019). Importantly, leverage is a key dimension of risk-taking that is not determined by the selection of the stock itself. Indeed, CFDs allow investors to separate the choice of the stock to trade, long or short, from the leverage they wish to employ in that particular transaction. Observing such a risk-taking 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 endogeneity concern would arise, for example, for the volatility or beta of a stock, which are inevitably determined by the stock selection itself.

Second, the push messages are external attention stimuli that are initiated by the broker. In contrast, the individual attention proxies primarily applied in the prior literature are typically determined by the investor who conducts a trade. For example, Gargano and Rossi (2018) explore individuals' online research behavior as a proxy of paying (endogenous) attention. However, for our research question, we cannot simply apply such endogenous attention proxies because an individual's decision to research a certain stock is typically endogenous to the riskiness of the planned trade.

Third, our data contain both the trading records of investors who obtain a push message (treated investors) and the trading records of investors who do not obtain such a message (counterfactual 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 as "attention trades." Importantly, the broker only sends messages to a small subset of investors on each event, which allows us to compare the risk-taking for attention trades to that of the counterfactual investors in the same stock at the same time. This comparison provides a natural experiment for a standard difference-in-differences (DID) approach, which measures the marginal impact of the attention trigger on individual risk-taking. Common attention measures of the literature such as the aggregate attention proxies in Barber et al. (2009) or the individual account logins in Sicherman et al. (2015) do not allow us to observe the risk-taking of counterfactual trades that we need to isolate to measure the impact of attention on individual risk-taking.

Our main result is that attention triggers stimulate financial risk taking. Specifically, the DID coefficient implies that attention trades bear, on average, a 19 percentage point higher leverage than non-attention trades. Quantitatively, this average coefficient corresponds to 12.5% of the average within variation of investors' leverage. The economic magnitude of this effect is remarkable, given that we only consider simple push message stimuli that contain no fundamental news.

Our notion of a relation between attention triggers and financial risk-taking is based on the psychology literature on individual risk behavior. This literature concludes that "affective" processes play a key role for individual risk-taking (Figner and Weber, 2011; Weber, 2010). Affective processing is triggered by various stimuli and influences human behavior rapidly, spontaneously, and automatically (Galvan et al., 2006; Weber et al., 2004). Researchers argue that such rapid affective responses provide individuals with a fast, but crude, assessment of the behavioral options they face, which makes it possible to take rapid actions by interrupting and redirecting the slower cognitive processing toward potentially high-priority concerns (Loewenstein et al., 2001). In line with this concept, we find that the median time span between the sending of a push message and an attention trade is only 1.35 hours. Thus, the investors' median reaction time is very short, particularly because many investors are likely to read the message some time after the receipt.

As both the finance and psychology literature highlight that the impact of attention depends on the decision domain, the individuals' demographics, and the decision context, we provide additional cross-sectional results. Specifically, we show that male, younger, and less experienced investors particularly increase their risk-taking after an attention stimulus. We also find that the impact of the attention triggers on risk-taking is weaker for stocks that are more familiar to the investor. We complete the picture by analyzing the relation between our main result and stock characteristics. This analysis suggests that attention triggers have a stronger impact on the risk-taking for stocks that tend to attract more endogenous attention.

We next address a number of potential concerns with our approach. First, the broker may not send the messages randomly to 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 between the investors' status of being a message receiver or non-receiver and the investors' stock trades. For example, each push message refers to only one stock, whereas message receivers can trade many stocks that are not referred to in the message. Similarly, non-receivers may also 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 is differentiated from that of non-receivers and (ii) how the general risk-taking for message-stocks is differentiated 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 she correctly anticipates a change in risk-taking. The DDD-setting confirms our conjecture that attention indeed 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 her 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 its home page. Such research can indicate potential 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 did not research a given stock on the broker's website 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 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. 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 link our attention triggers to the endogenous attention measures suggested in the literature.

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, in any asset class. In addition, we match treated and control 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.

The remainder of our paper proceeds as follows. The next section discusses the related literature. Section 3 presents our hypotheses. In Section 4, we present our dataset and discuss our identification strategy. Section 5 presents summary statistics before Section 6 discusses the impact of the attention trigger on investors' risk-taking. Section 7 provides cross-sectional analyses to further study the implications of push messages on different types of investors and stocks. In Section 8, we provide additional results on trading and discuss the relationship between attention triggers and retail investors' information acquisition on a particular stock. In Section 9, we discuss several alternative explanations to our findings. The final section concludes.

2 Related literature

We contribute to various strands of the existing literature. First, several studies investigate the determinants of investors' risk-taking at the microlevel.[1] This literature concludes that emotions, expectations, and personal past experiences affect individual risk-taking. We add an additional dimension to this literature by showing that individual attention triggers are important stimuli that affect investors' risk-taking. In addition, we provide evidence that attention triggers are a key catalyst through which personal experiences are transmitted into risk-taking.

Second, 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 endogenous 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, do not link attention to risk taking. Thus, we contribute to the individual attention literature by providing novel insights on how exogenous attention triggers influence investors' risk-taking at the micro level.

Third, the literature on aggregate attention highlights that attention has an important bearing on stock returns, stock ownership, trading patterns, return volatility, liquidity,

[1] See, e.g., Gneezy and Potters (1997); Barberis et al. (2001); Caplin and Leahy (2001); Holt and Laury (2002); Coval and Shumway (2005); Köszegi (2006); Kaustia and Knüpfer (2008); Choi et al. (2009); Karlsson et al. (2009); Liu et al. (2010); Chiang et al. (2011); Malmendier and Nagel (2011); Kaustia and Knüpfer (2012); Cohn et al. (2015); Kuhnen (2015); Imas (2016); Knüpfer et al. (2017); Beshears et al. (2016); Ben-David et al. (2018); Andersen et al. (2019).

correlation, and bid-ask spreads.[2] Several studies in this vein also identify the origin or triggers of aggregate attention (Focke et al., 2019; Ungeheuer, 2018). Whereas this literature provides important results on the macroeconomic implications of aggregate 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 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 enrich this literature by providing novel insights on the micro foundation of attention with respect to individual risk-taking.

3 Hypotheses

We derive the hypotheses we test from the experimental psychology, neurobiology, and neuroscience literatures on decision-making and risk-taking in everyday situations. The experimental psychology literature distinguishes between endogenous and exogenous attention. Exogenous attention refers to the process of involuntary directing of individual attention due to an external stimulus (Theeuwes, 2010), independent of the individual's goals, intentions, and awareness (Theeuwes, 1994a,b; Mulckhuyse and Theeuwes, 2010). Thus, exogenous attention can be conceptualized as an interruption of endogenous attention (Carretié, 2014). Exogenous attention stimuli can trigger affective processes, which interrupt and redirect the slower cognitive processes, thereby inducing rapid and spontaneous reactions (Loewenstein et al., 2001; Weber et al., 2004; Galvan et al., 2006). This literature highlights an important link between attention stimuli and risk-taking (Figner et al., 2009). Specifically, affective processing stimuli increase risk-taking in traffic, sports,

[2] See, e.g., Odean (1999); 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).

or the use of illicit substances (e.g. Figner et al., 2009; Casey et al., 2008).[3]

Inspired by this literature, we argue that external stimuli could also lead to increased risk-taking in the financial domain. Thus, our first hypothesis is as follows:

Hypothesis 1: Financial attention stimuli increase financial risk-taking.

Next, we discuss the background of our main hypothesis in more detail, and analyze the cross-sectional differences in the influence of attention stimuli on risk-taking along several dimensions. First, the neuroscience literature provides evidence that demographic factors, such as gender or age, influence the impact of exogenous attention triggers (Merritt et al., 2007; Carretié, 2014; Hahn et al., 2006; Syrjänen and Wiens, 2013). Against the backdrop of this literature, we investigate the influence of investor demographics on the individuals' risk-taking reaction to attention triggers. Intuitively, financial attention triggers should exhibit a stronger influence on investors who are more susceptible to exogenous attention triggers.

Second, experimental evidence from the psychology literature shows that experts attend more closely to the relevant aspects of stimuli compared to novices (Jarodzka et al., 2010). In addition, the finance literature on investor attention provides evidence that the novices' attention tends to be more exogenously oriented than the intermediates' or professionals' attention (Li et al., 2016). Finance studies also show that trading experience reduces the investors' susceptibility towards unintentional trading behavior (Feng and Seasholes, 2005; Kaustia and Knüpfer, 2008; Kaustia et al., 2008). Thus, we expect that trading experience mitigates the impact of attention triggers on risk-taking.

Third, the psychology literature investigates the difference between the influence of novel and well-known stimuli in everyday situations. Johnston et al. (1990, 1993), for example, suggest that novel stimuli particularly attract exogenous attention compared to familiar stimuli. In the context of risk-taking, Mitchell et al. (2016) conclude that exposure to novel stimuli leads to more risk-taking as compared to exposure to familiar stimuli. We expect that these reflections also transfer to the finance domain.

[3] The neurobiology literature analyzes the drivers of this mechanism in the central nervous system and in the human brain. It proposes the somatic marker hypothesis that links the processes of the response to external stimuli with risk-related behaviors (Damasio et al., 1996).

Fourth, Gargano and Rossi (2018) show that specific stock characteristics such as greater analyst coverage or trading volume attract more endogenous investor attention. Thus, investors seem to consider certain stock characteristics as more "interesting," which induces them to conduct more research on the stocks with these characteristics. Intuitively, we expect that stimuli that attract the investors' attention towards a stock with more interesting features have a stronger impact on risk-taking than stimuli on stocks with less interesting features.

Overall, these arguments lead to our second hypothesis:

Hypothesis 2: The influence of financial attention stimuli on financial risk-taking is stronger for investors

a) who are more susceptible to attention triggers,

b) with less trading experience,

and stocks

c) for which the investor has no experience compared to stimuli on stocks that are well-known to the investor, and

d) that capture more endogenous attention.

4 Data and methodology

4.1 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. This 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. In this sense, CFDs are a type of leveraged contract on the underlying asset with the choice of leverage left to the buyer of the contract. Appendix A provides a brief introduction to CFDs. The minimum amount per CFD trade with the broker is $50 and the minimum opening account balance 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.

Our data sample contains all trades that the investors executed with the broker between January 1^{st}, 2016 and March 31^{st}, 2018.[4] A trade is defined as the opening or closing of a position. Our data contain the exact time-stamp of the trade, the specific underlying stock, an indicator for long or short positions, the executed rate, the leverage, and the investment. We only consider "active" investors in our sample, i.e., investors who 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. 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 sent by the broker: 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. Earnings reports highlight a company's predetermined, upcoming date of the earnings announcement that is already known to the public. 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 any new information, as such. Thus, this feature helps us to isolate the impact of attention on risk-taking from that of new information. The broker determines

[4]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 characteristics of this brokerage service, such as attention.

the investors to whom it sends a certain message, the content of the message, 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 regarding 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 on the broker's website that provide information on stock prices, key financial variables, and latest news on the company. We also have the data on exactly when the investors access these information pages. Finally, the trading data also include the investors' basic demographic information (age, gender, and nationality), and some other information supplied in response to a questionnaire issued by the broker. Specifically, the data contain details about the investors' 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.

4.2 Variables

We apply the following variables in our empirical analysis. The main variable of interest, *Leverage*, denotes the leverage employed for a trade. We use this measure throughout our analysis as a metric of risk-taking. Besides *Leverage*, we define several additional trading variables. *Trades* denotes the number of trades, which an investor executes in 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 nominal amount of a position expressed as a fraction of the investor's total nominal amount of assets that she deposited with the broker. Closely related, *Risk exposure* denotes the change in the total position size of an investor due to a given trade, expressed as a fraction of the total assets deposited by the investor with the broker. 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. *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 by 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 additional 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 using a simple market model: $R_i = \alpha + \beta_i R_M + \varepsilon_i$. 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 market model regressions over the last 262 trading days.

Third, we create several dummy variables with respect to the push messages. We create a dummy variable, *Click on message*, that takes a value of one, if the investor clicks on the push message to open the brokerage app, and 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, and 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, and 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 news articles on the company (within the last 24 hours) from all 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, or neutral sentiment, on that day. In addition, the variable *News Volume* captures the number of news articles about a company that are published and parsed on a given day.[5] 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, and zero otherwise.

4.3 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 triggers on an investor's risk-taking, we apply 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, this approach mitigates the potential confounding effects of

[5]Quandl evaluates news based on a machine-learning algorithm for events for 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.

previous messages on an investor's trading behavior in that stock. Second, it eliminates the concern that the broker could observe the reaction of the investor to a push message and, hence, send subsequent messages according to that reaction. Using the time-stamp, we consider the last trade of treated investors in any stock within seven days (1 day in an alternative specification) prior to the treatment time (observation period). The advantage of using a relatively short observation period before the treatment time is that this choice mitigates the impact of potential time-variation in the determinants of investors' risk-taking (Petersen, 2009). We also consider the "attention trades" after the push message. We label the trade of a treated investor an *attention trade*, if this investor trades the message-stock within 24 hours after the treatment time.[6] It is difficult to asses the exact duration during which an attention trigger can influence an investor's cognitive processes. We consider a 24-hour window for the treatment period for three reasons. First, our data suggests that the messages influence the investors' trading decision for around 24 hours, as shown by the distinct spike in a message-stock's trading activity after an attention stimulus (see Figure 1). Second, measuring trading patterns over one attention day is standard in the attention literature (Barber and Odean, 2008; Peress and Schmidt, 2018). Third, Frijda et al. (1991) suggest that affective phenomena typically last from several seconds to several hours.

We then collect our counter-factual sample 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. 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.

Third, we calculate the difference between the risk-taking of the treated investors and that of the counter-factual investors during the observation period. This step controls for potential heterogeneity between the treated and counter-factual investors. We also measure the difference between the risk-taking of the treated investors and that of the counter-factual 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

[6] 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.

these two differences. Formally, we estimate

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

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, β_1, captures the impact of the attention trigger on risk-taking. Our specification includes investor fixed effects to control for observed and unobserved heterogeneity across investors such as their gender, age, individual wealth, their investment amount 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 account for aggregate time-trends.

5 Summary statistics and message sending

5.1 Summary statistics

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

Next, we describe the push messages in our data. First, we observe that 99.1% of investors in our sample receive at least one push message on any instrument, and 98.5% of investors in our sample receive at least one push message on stocks. Thus, the data contain only a small minority of investors that never receive a push message, indicating that only a few investors may be ignored by the broker or may have disabled the push messages in their brokerage account. It is unlikely that these investors would bias our conjecture.[7]

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. 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. The last column of Panel A shows that the broker sends around half of the push messages on, or immediately around a day with at least one news article (according to the Quandl data).

Panel B of Table 1 provides summary statistics on investors' reaction to push messages. In total, the broker sends over 20 million push messages to investors during our sample period. For approximately 3.6% of the push messages, the investor 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.

[7]We present a robustness analysis in Section 9.1 to address the remaining concern that investors who disable push messages may bias our conjecture.

On average, 8.2% of investors click on the push message they receive. 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 on the particular stock within 24 hours after the push message. On average, 1.39% of the push messages trigger an attention trade. The median duration between the time the broker sends a push message and an attention trade is 1.35 hours. As investors are unlikely to notice each message immediately, this number suggests that the median reaction time is relatively fast.[8]

— 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. The figure shows a distinct attention trade spike in the first five hours after the broker sends a 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. The table suggests that attention trades feature a higher leverage compared to non-attention trades. Specifically, attention trades indicate an 8% higher leverage, on average.

[8]Unfortunately, we do not have data on when an investor reads a push-message.

— Place Table 2 about here —

5.2 Message sending behavior

We shed light on the message sending behavior of the broker. We begin by discussing the stocks for which the 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. 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 such 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 (with average leverage of 5.6 for non-message investors and 6.27 for message investors), the table also underlines the common support of the distributions of investors, who receive a push message at a given point in time, and those, who do not. In other words, we observe a reasonable overlap between treated and control investors on all covariates. 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, amongst other tests, we 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 in our investigation, and in our robustness analyses in Section 9. We now investigate the impact of attention on risk-taking by using our difference-in-differences approach.

6 The implications of push messages on risk-taking

In this section, we analyze the implications of attention triggers on individual risk-taking to address Hypothesis 1.

6.1 Difference-in-differences analysis

We first apply equation (1) of our difference-in-differences approach of Section 4.3 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 0.1865 higher leverage than non-attention trades. Quantitatively, this average coefficient corresponds to 12.5% of the average within variation of investors' leverage of 1.49 (untabulated). Given that we only consider simple push message stimuli that contain no fundamental news, the economic magnitude of this coefficient is remarkable. In comparison, Andersen et al. (2019) investigate the impact of an incisive, personal experience on individual risk-taking, namely the personal loss from the default of bank stocks in the aftermath of the Global Financial Crisis. They show that this experience leads to an average reduction of an investor's risky asset share of 37.5% of the average within variation of this share.

We also provide a more granular view on the impact of attention triggers on risk taking in Figure 2. This figure plots the evolution of the average leverage in the message-stocks for treated and counterfactual investors up to 24 hours after the treatment compared to the average usage of leverage in the message-stock of trades before the treatment event (pre message). We only consider the first trades in the message-stock after the treatment event. The pattern suggests that the leverage of the treated investors spikes immediately after the push message and slowly declines thereafter.[9] This pattern is consistent with the notion from the psychology literature that attention triggers stimulate a quick affective reaction that involves higher risk.

— Place Figure 2 about here —

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 a push message. The treatment coefficient remains virtually unchanged. To more generally address the concern that our results are driven by a trend in the risk-taking of the treated investors before the treatment event, we investigate the parallel trend assumption in Figure 3. We plot the average usage of leverage of all trades in the message-stock within 40 days around the treatment time. We do not restrict ourselves to the last trade before, and the first trade after, the push message to be able to plot the average usage of leverage over a longer time period. A number of investors execute more than one trade following

[9]The confidence intervals tend to become larger after a few hours because the number of trades in the message-stock declines with the duration after a push message.

the push message, and continue to trade in the message-stock in the following days. The figure shows that these investors, on average, continue to do so with a higher leverage compared to investors who do not receive the push message.

— Place Figure 3 about here —

Panel C also shows the result when we only incorporate the trades in the message-stock during the observation period before the treatment time instead of the trades in any stock. The advantage of this test is that it mitigates the concern that the broker biases our conjecture by tending to send messages on those stocks for which investors commonly use more leverage. The disadvantage is that we lose many observations, because numerous investors have never traded the message-stock before the treatment. The test shows that the treatment coefficient is virtually unchanged compared to Panel A.[10]

Overall, Panels A to C of Table 4 imply that attention stimulates risk-taking and provide support for our main Hypothesis 1.

6.2 Difference-in-difference-in-differences analysis

The broker may not send the messages randomly to the investors in its database (see Section 5.2). Thus, the main caveat with our DID-analysis is that the broker's message sending behavior could bias our conjecture due to endogeneity. 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 offer 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

[10] At this point, it is worthwhile to note that the stock fixed effects in our specification already capture the possibility that some stocks may be traded with higher leverage than others. The difference between the fixed effect and the alternative specification in Panel C is that the fixed effects control for a stocks' average leverage, whereas the specification in Panel C captures the leverage of the last trade.

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):

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

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 who 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.[11] Our coefficient of interest, β_7, then captures the impact of the attention trigger on leverage, net of how the risk-taking of receivers is differentiated from that of non-receivers around the treatment event, and of how the risk-taking for message-stocks is differentiated 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 she 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 along these

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

dimensions around the treatment event for whatever reasons these differences occur.

Panel D 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.

6.3 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 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 the fact 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 consider stock price moves of at least three percent (positive or negative) as a comparable stock price move for push messages that indicate a stock price move above plus and minus three percent, respectively (see Table 1). 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 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 Column (1) of Panel A of Table 6.

— Place Table 6 about here —

Third, the literature on risk-taking concludes that personal experiences 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 this dimension, 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. Highlighting this concern, 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. Column (1) of Panel A of 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 she 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, β_5 and β_6, in our DDD-approach would, however, 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 (see Panel A of Table A.3), and the first message to an investor on any asset class (see Panel B of Table A.3). In both cases, our results on risk-taking are even stronger than in our main specification.

Finally, we run a nearest-neighbor matching routine in our DID- and DDD-approach (see Table A.4 in the Appendix). Specifically, we match the investors from the treatment group with comparable investors from the counterfactual based on the Euclidean Distance with respect to standard controls for risk-taking such as gender and age, overall trading intensity over the previous 180 days, and the average leverage taken by investors over the previous 180 days. 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, β_5 and β_6, in our DDD-approach should cancel out this effect. Thus, the matching provides complementary evidence beyond the DDD that differences in risk-taking between message receivers and non-receivers do not affect our conjecture. The results are robust to matching investors.

To summarize, the evidence in this section provides robust evidence in support for our main Hypothesis 1: Financial attention stimuli increase financial risk-taking.

7 How does the influence of attention stimuli on risk-taking depend on investor and stock characteristics?

To provide a better understanding of our main result, we now test our hypotheses 2a to 2d (see Section 3), i.e., whether investor and stock characteristics influence the impact of attention stimuli on risk-taking. We condition the risk-taking of the trades on several investor, situational, and stock characteristics. Specifically, we divide the sample into two groups according to the characteristic. For investor and situational characteristics, we obtain clear-cut 0/1 splits of our sample. For continuous stock characteristics, we divide the sample into two groups based on the median: the low group contains the trades associated with stocks whose characteristic is below the median; the high group contains the trades associated with stocks whose characteristic is above the median.[12]

7.1 The influence of investor demographics

We start by investigating Hypothesis 2a. Panels A and B of Table 8 suggest that the increase in risk-taking due to the attention stimuli is stronger for young, male investors compared to older, female investors. As the psychology literature suggests that young

[12]Note that we implement the sample splits based on the median at the stock level, not the observed trade level. As a result, the samples in our analyses are not necessarily the same size.

or male individuals are more susceptible to exogenous attention stimuli (Syrjänen and Wiens, 2013; Hahn et al., 2006), our results support Hypothesis 2a.

This result extends the general idea that investor demographics are a significant determinant of individual trading behavior (Barber and Odean, 2001; Sicherman et al., 2015) and risk-taking (He et al., 2008; Morin and Suarez, 1983; Powell and Ansic, 1997) to the impact of exogenous attention triggers on individual risk-taking.

We now turn to Hypothesis 2b. We proxy trading experience with the investors' self-assessment in the broker's questionnaire. Panel C of Table 8 shows that trading experience reduces the impact of the attention stimuli on risk-taking, which supports our Hypothesis 2b. This observation complements the literature suggesting that more experienced investors conduct fewer behavioral errors and use more sophisticated trading tactics (Feng and Seasholes, 2005; Kaustia and Knüpfer, 2008; Kaustia et al., 2008). Specifically, we show that experience also mitigates the impact of exogenous stimuli on the investors' trading behavior.

— Place Table 8 about here —

7.2 The influence of investors' familiarity

Next, we analyze Hypothesis 2c. To this end, we use a dummy that is one for a stock, if an investor has previously traded or researched that stock, and zero otherwise, to capture investors' familiarity with a particular stock. Intuitively, investors should be more familiar with stocks on which they have previous experience.

The results in Table 9 suggest that exogenous stimuli on novel stocks have a stronger impact on risk-taking compared to stimuli on familiar stocks. Thus, the evidence is in line with our Hypothesis 2c.

— Place Table 9 about here —

One dimension of personal experience which has received particular attention in the risk-taking literature is the past return with a certain stock (Thaler and Johnson, 1990; Brockner, 1992; Weber and Camerer, 1998; Imas, 2016). This literature concludes that risk-taking is influenced by losses and gains as well as by whether a return is realized or just on paper. Thus, we additionally investigate how the past realized or paper performance with the message-stock influences the impact of attention triggers on risk-taking. Columns (1) to (4) of Table 10 show that attention triggers have a stronger impact on risk taking when they follow after a loss in the message-stock, compared to a gain. In addition, Column (3) implies that they do not affect the risk-taking of investors with paper gains.

— Place Table 10 about here —

Our results provide evidence that attention triggers are a key catalyst through which personal experiences are transmitted into risk-taking.

7.3 The influence of stock characteristics

Finally, we turn to Hypothesis 2d. The literature suggests several stock characteristics that tend to attract investor attention. For our analysis, we use all the stock attention proxies suggested by Gargano and Rossi (2018), namely the number of analysts covering a stock, the total number of news events associated with a stock, a stock's trading volume, and a stock's turnover. In addition, we use a stock's volatility based on the argument of Barber et al. (2009) that extreme returns are a useful attention proxy. Lastly, we also utilize the total market capitalization of a company because, intuitively, large firms tend to attract more attention.

The results of our analyses in Panels A-F of Table 11 suggest that attention triggers have a stronger impact on risk-taking for stocks that tend to attract more endogenous attention.

— Place Table 11 about here —

Overall, our results imply that the impact of attention triggers on risk-taking is more pronounced for people who are more susceptible to exogenous attention stimuli, for less experienced investors, and for novel stocks with characteristics that tend to attract more endogenous attention. Thus, our analysis is consistent with Hypothesis 2.

8 Additional results

In this section, we provide additional results on attention trading and relate our study to the recent literature on individual investor attention. In doing so, we also throw light on the impact of attention on other dimensions of risk-taking, trading intensity, and overall risk exposure.

8.1 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.[13]

Our dependent variable *Trading intensity* denotes the number of trades an investor executes in a certain 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 triggers on investors' trading intensity, we apply our DID-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).

[13] A caveat of this analysis is that the broker sends many first push messages to the 131,375 inactive investors, who never conducted a trade during our sample period. Thus, these investors appear in our treatment group. In the set of comparable investors, however, we only consider active investors to ensure that our results are not driven by comparable investors who are inactive. This allocation introduces a bias against finding a positive impact of push messages on the trading intensity.

Panel A of Table 12 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 includes increasing a 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 12 about here —

Column (2) shows that push messages also stimulate investors to sell a stock (i.e. closing a long position or initiating 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 stock selling in Column (2) is even stronger than that on stock buying in Column (1).

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. Our results do not contradict this notion because we also consider short sales besides the selling of existing positions. Following the argument of Barber and Odean (2008), attention triggers should also 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 any and all stocks, rather than being confined to the stocks they already hold in their portfolio.

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 12 summarize the results. We omit the stock-fixed effects in these tests as we capture the trading in *any* stock besides the message-stock after the push message. 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.

As push messages influence both stock buying and selling, it is not obvious whether they increase or decrease the investors' overall (stock) market exposure. To investigate the impact of attention triggers on investors' risk exposure, we, therefore, analyze the change in a message-stock's position size upon a push message. Trades that establish a new long or short position increase the investor's total position size, and trades that close an existing long or short position reduce an investor's total position size. We estimate the DID-equation (1) for *Risk exposure* and present the results in Panel B of Table 12. The positive treatment coefficient ($\beta = 3.74$; t-statistic: 5.76) suggests that investors, on average, increase their exposure in the message-stock after an attention trigger. Thus, when using stock exposure as an alternative risk-taking measure, the test confirms our conjecture the attention triggers increase investors' risk-taking.

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 at the micro level that individual attention triggers stimulate the individual trading intensity. In addition, we contribute by showing that individual attention triggers are also relevant for stock selling.

8.2 Relation to alternative individual attention measures

Several recent studies investigate endogenous investor attention at an individual level. They typically measure an individual's involvement, engagement, or focus on a certain asset by, for example, using data on investors' account logins or page-views (e.g. Karlsson et al., 2009; Gargano and Rossi, 2018). This concept of paying endogenous attention is different from our exogenous attention trigger approach. Specifically, to investigate risk-taking, it is crucial to apply an exogenous attention trigger instead of an endogenous attention proxy because an investors' decision to pay more (endogenous) attention is likely to be related to the riskiness of his planned trade. The concepts of exogenous and endogenous attention, however, are closely related. The psychology literature, for example, conceptualizes exogenous attention as an involuntary interruption of endogenous attention due to an external stimulus (Carretié, 2014). Therefore, we now discuss the relation of our exogenous individual attention triggers to the existing endogenous individual attention measures.

We first estimate Equation (1) of Section 4.3 by using *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 the 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 the investors' page-views following positive and negative push messages. The page-views increase after both message types, but to a slightly greater extent after positive push messages. This observation is in line with the "ostrich effect", a term coined by Galai and Sade (2006), suggesting that investors pay more attention following market increases than market declines (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 after 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 conducting 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 exogenous attention triggers. They suggest that the messages are not simply a consequence of investors' endogenous attention towards a stock but also exogenously trigger attention. We complement this argument with a simple statistic. Specifically, the broker sends 87.45% of the first push messages on a stock to investors who have never traded or researched that stock before receiving the message (not tabulated).

We also use the data on investor research to investigate how much (endogenous) attention investors allocate to a certain stock before trading that stock. We find that for attention trades, investors already trade the stock, on average, 1.31 hours after visiting the research page of the stock, whereas they trade the stock, on average, 2 hours after visiting the research pages for non-attention trades (not tabulated). This result confirms the affective processing intuition behind our main result because attention triggers reduce the amount of (cognitive) research in which the investors engage before a trade.

Overall, the results suggest that our individual attention trigger measure shares some basic properties with the individual (endogenous) attention measures that are suggested in the literature. Importantly, however, our analysis also implies that, in contrast to the existing individual attention measures, the push messages that we consider are a useful proxy for exogenous individual attention triggers.

9 Robustness analyses

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

9.1 The investors' decision to neglect or block messages

The investors can decide whether they read a push message or even block these messages entirely. These decisions raise two potential objections to our results. First, investors may not even read the push messages. Second, investors' tendency to block the messages could be correlated with risk-taking and, thus, induce a self-selection bias. We address these potential caveats by exploiting the information in our data on whether an investor actually clicked on a push message.

In Panel A of Table 13, we repeat our main analysis, but only consider those investors who actually clicked on the push message in the treatment group instead of all investors who received the message. A click indicates that the treated investor has most likely read the message. The counterfactual group consists of the investors who do not receive a push message as in our main analysis. The positive treatment coefficient suggests that our conjecture on risk-taking is robust to the potential concern that treated investors may not even read a message.

— Place Table 13 about here —

Next, we address the self-selection concern that arises because specific counterfactual investors have blocked the messages. Ideally, we want to condition our test on all the investors who have not blocked the messages. Unfortunately, we cannot directly observe whether and when an investor blocks or disables the push messages on her cell phone. Also, by definition, the counterfactual investors do not receive the specific push message of interest. Therefore, we only incorporate the investors in the counterfactual who click on any push message within seven days before and after the treatment time. This approach assures that we only include investors who are unlikely to have the messages blocked around the treatment time in the counterfactual.[14] Panel B of Table 13 shows that our did-result on risk-taking is robust to this alternative test. Thus, self-selection of the investors does not drive our conjecture.

9.2 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

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

DID-approach mitigates this concern because we compare the increase in risk-taking of investors with push messages to that 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 such 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 the 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' 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. Table 14 shows that our conjecture on the impact of attention triggers on risk-taking is robust to the alternative specifications and, hence, not driven by news.

9.3 Attention and message content

We now investigate whether the message content affects our results to address the concern 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. The results suggest that the treatment coefficients on leverage are very similar to that in our main specification of Table 4 for both the positive and negative push messages. Thus, attention triggers 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 the investors' reaction to attention triggers depends on the magnitude of the reported return in the push message. To this end, we separately study weak and strong push messages in Columns (3) and (4) of Table 15. A push message is denoted to be strong if the message's reported absolute price change is larger than the median, and weak otherwise. The treatment coefficients indicate that investors increase their risk-taking, both after receiving weak and strong push messages. Yet, we observe a larger effect following strong messages, which may be attributed to the more salient return of those messages.

Overall, the results in Table 15 suggest that the increase in risk-taking is primarily driven by the attention trigger, and not by the message content.

10 Conclusion

This study presents novel evidence on the impact of exogenous attention triggers on risk-taking based on a unique dataset of trading records. The main advantage of this data is that we directly observe a trigger of individual investor attention and can link this trigger to the individuals' risk-taking. The data also contain the message-stock trading of investors who do not receive an attention trigger. Thus, we can empirically isolate the pure influence of the attention trigger on individual risk-taking. Applying a standard DID-methodology, accompanied by a large set of robustness tests, we find that attention stimulates risk-taking.

We complete the picture with several refinements of our main result. Specifically, we show that attention triggers are more relevant to the financial risk-taking of male, younger, and less experienced investors. The increase in individuals' risk-taking following an attention trigger is also stronger for stocks that are novel to investors and tend to attract more endogenous attention.

Our micro-level evidence on the impact of individual attention triggers on individual risk-taking contributes to the existing attention literature that abstracts away from the risk-taking perspective (e.g., Barber and Odean, 2008; Da et al., 2011; Sicherman et al., 2015; Gargano and Rossi, 2018). A better understanding of individual financial risk-taking is crucial to the study of choice under uncertainty, a better understanding of financial markets, and financial stability (e.g. Liu et al., 2010; Charness and Gneezy, 2012; Lian et al., 2018). Highlighting the causal mechanisms that underlie financial risk-taking provides us with entry points for the design of interventions that can successfully modify this behavior in situations, in which decision makers and society desire such changes.

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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.[15] 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). In Germany, the transaction volume in 2018 was 1.58 trillion Euro (CFD Verband e.V.), which is approximately equal to the total transaction volume of the Deutsche Börse AG.

[15] Brown et al. (2010) describe these contracts in more detail and 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.

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.

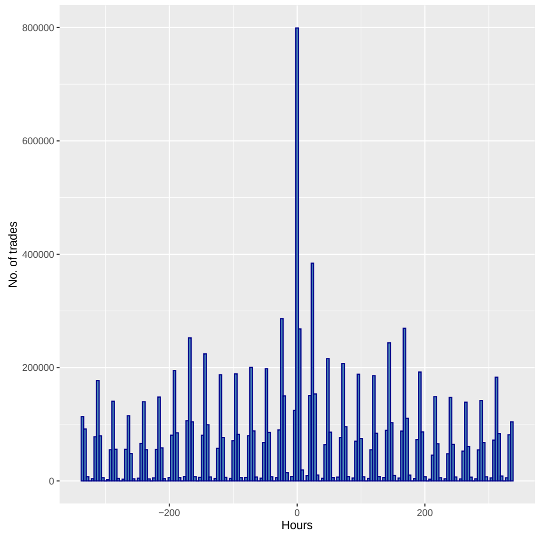

Figure 2: Risk-taking within 24 hours after a push message

This figure presents the average usage of leverage for investors in the message-stock immediately following the push message. 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 and executes an attention trade in the underlying referred to in the push message within 24 hours after receiving the message. Pre message shows the average usage of leverage of investors in the message-stock between January 1st, 2017 and the treatment time. The hourly time intervals show the average usage of leverage of first trades in the message-stock after the treatment time that occur in this interval. 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.

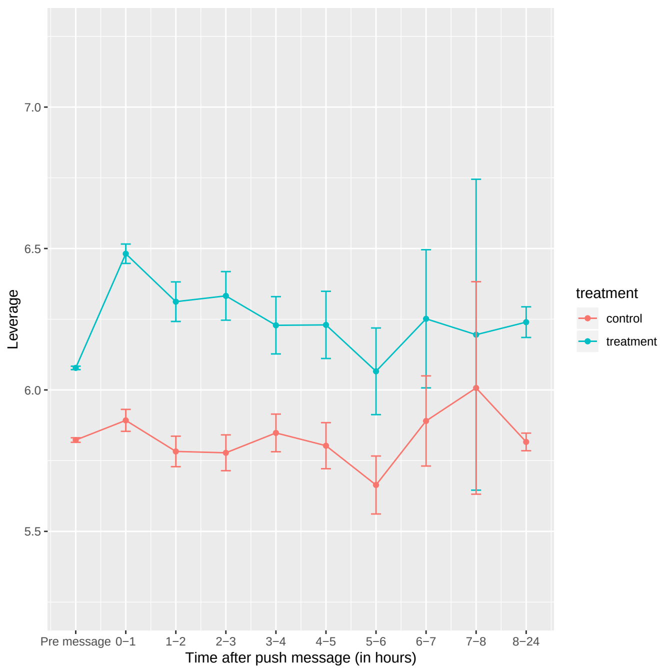

Figure 3: Risk-taking around the treatment events

This figure presents the average usage of leverage for investors in the message-stock 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 and executes an attention trade in the underlying referred to in the push message within 24 hours after receiving the message. The graph shows the average usage of leverage of all trades in the message-stock on a given day. 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.

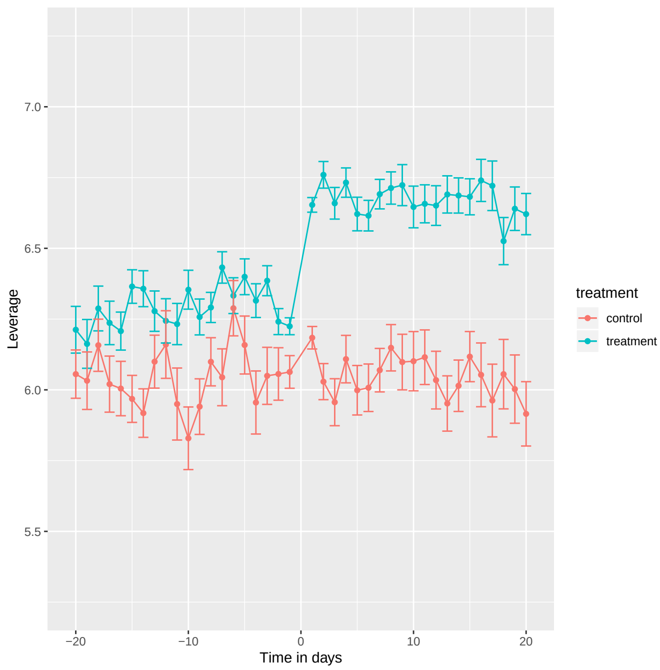

Table 1: Summary statistics of push message data

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. *Reaction time* is the duration in hours between a push message and the attention trade of an investor who received the push message.

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	mean (reaction time)	median(reaction time)
Positive price change	9,554,260	0.0353	0.1499	0.0277	0.0871	0.0343	0.0140	5.4406	1.2322
Negative price change	10,443,759	0.0329	0.1461	0.0249	0.0752	0.0269	0.0125	5.3726	1.2133
Positive streak	708,583	0.1583	0.0550	0.0267	0.0983	0.0354	0.0127	1.6954	0.8321
Negative streak	215,375	0.3679	0.1006	0.0626	0.1182	0.0591	0.0276	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	5.8567	1.3500

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. "Attention trades" are all trades by push message receivers in the underlying referred to in the push message within 24 hours after receiving the message. "Non-attention trades" are all trades that are not attention trades. *leverage* denotes the investor's average leverage. The t-test reports results from equality tests of non-treated versus treated trades, clustered over time.

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

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 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 B)

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

This table reports results from a difference-in-differences (Panels A to C) [difference-in-difference-in-differences analysis (Panel D)] regression analysis on the leverage of trades that investors initiate in our trade data. Panels A to C estimate equation (1), Panel D 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.

Panel A: difference-in-differences analysis	
treat × post	0.1865
	(7.20)
Obs.	1,294,093
Adj. R^2	0.62
Panel B: 24-hour observation period	
treat × post	0.2151
	(7.36)
Obs.	866,794
Adj. R^2	0.61
Panel C: only message-stock in observation period	
treat × post	0.1834
	(6.86)
Obs.	657,108
Adj. R^2	0.64
Panel D: difference-in-difference-in-differences analysis	
treat	−0.0252
	(−5.16)
post	0.0345
	(9.35)
stock	0.0643
	(6.38)
treat × post	0.1094
	(8.82)
treat × stock	−0.0171
	(−1.02)
post × stock	−0.0687
	(−4.14)
treat × post × stock	0.0972
	(3.30)
Obs.	2,424,742
Adj. R^2	0.62
All panels	
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes

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.

Dependent var.	Leverage
Push message regime	1.0126
	(4.68)
Obs.	318,486
Adj. R^2	0.11

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 leverage of trades that investors initiate in our trade data. Column (1) is restricted to investors who do not view the stock-specific (≡ message-stock) information page of the broker within seven days prior to the treatment event. Column (2) is restricted to investors have visisted the stock-specific (≡ message-stock) information page of the broker at any point in time 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 leverage of the last trade within seven days [average of daily information acquisition over the last seven days] before the treatment event and the leverage 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* × *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: Message-sending behavior of the broker: No stock-specific research prior to push message

	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	no prior research	prior research
treat × post	0.1889	0.1689
	(7.24)	(5.03)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	1,108,056	438,027
Adj. R^2	0.61	0.64

Panel B: Stock-specific information acquisition after receiving message

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var.	Research	Research	Research	Research	Research	Research
Sample	all push messages	positive messages	negative messages	not holding stock	holding stock	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	0.1964
	(7.03)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,191,316
Adj. R^2	0.62

Table 7: 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 table reports regression results conditioning on whether the investor has previously invested into the message-stock. Column (1) is restricted to investors who have no prior trading experience in the message-stock; column (2) is restricted to investors who do have 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* $\times$ *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.

	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	No prior experience	Prior experience
treat × post	0.1442	0.1032
	(4.95)	(3.36)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	655,622	638,471
Adj. R^2	0.61	0.65

Table 8: Attention triggers and leverage usage: regression results conditioning on investor characteristics

This table reports results from a difference-in-differences regression analysis on investors' leverage usage conditioning on the characteristics of the investors. 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 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 C): Investors' gender, investors' age, and investors' trading experience (self-assessment). *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	0.0733	0.1987	
	(1.39)	(7.52)	
Investor-fixed effects	Yes	Yes	
Stock-fixed effects	Yes	Yes	
Time-fixed effects	Yes	Yes	
Obs.	98,313	1,325,104	
Adj. R^2	0.65	0.62	
Panel B: Investors' age			
	(1)	(2)	(3)
Dependent var.	Leverage	Leverage	Leverage
Sample	18-34	35 - 54	≥ 55
treat × post	0.2068	0.1841	0.1386
	(6.28)	(6.71)	(3.03)
Investor-fixed effects	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	650,812	661,188	107,717
Adj. R^2	0.62	0.63	0.65

Table 8: Attention triggers and leverage usage: regression results conditioning on investor characteristics (cont.)

Panel C: Investors' trading experience (self-assessment)		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low experience	High experience
treat × post	0.2130	0.1785
	(6.31)	(6.78)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	600,123	823,089
Adj. R^2	0.60	0.64

Table 9: Attention triggers and leverage usage: regression results conditioning on stock familiarity

This table reports results from a difference-in-differences regression analysis on investors' leverage usage conditioning on investors' familiarity with the 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 in the stock referred to in the push message after the treatment event within 24 hours. *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.

	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Prior contact	No prior contact
treat × post	0.1347	0.1410
	(4.49)	(4.45)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	837,809	562,847
Adj. R^2	0.64	0.61

Table 10: Attention, leverage, and prior experiences: difference-in-differences analysis

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 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 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.

	(1)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	Realized gains	Realized losses	Paper gains	Paper losses
treat × post	0.0781	0.1414	0.0229	0.1498
	(2.0687)	(3.0904)	(0.4886)	(2.8182)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	242,290	128,681	124,959	96,033
Adj. R^2	0.67	0.67	0.71	0.71

Table 11: Attention triggers and leverage usage: regression results conditioning on stock characteristics

This table reports results from a difference-in-differences regression analysis on investors' leverage usage conditioning on the characteristics of the stocks. 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 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 F): 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; Turnover, computed as the stock's volume divided by the shares outstanding; Volatility, computed as Garch(1,1) volatility of the stock. *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	0.1936	0.1959
	(6.18)	(5.03)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	560,511	690,191
Adj. R^2	0.69	0.61
Panel B: Analyst coverage		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low analyst coverage	High analyst coverage
treat × post	0.1780	0.2146
	(5.15)	(6.94)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	770,137	505,022
Adj. R^2	0.62	0.70
Panel C: News stories		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low news production	High news production
treat × post	0.1178	0.2007
	(2.79)	(6.03)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	171,602	929,610
Adj. R^2	0.71	0.60

Table 11: Attention triggers and leverage usage: regression results conditioning on stock characteristics (cont.)

Panel D: Stock volume		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low volume	High volume
treat × post	0.1658	0.1979
	(4.9507)	(5.9062)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	343,546	1,017,510
Adj. R^2	0.68	0.61
Panel E: Turnover		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low turnover	High turnover
treat × post	0.1262	0.2286
	(3.75)	(6.17)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	392,273	667,750
Adj. R^2	0.65	0.63
Panel F: Stock volatility		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low stock vola	High stock vola
treat × post	0.1521	0.1964
	(3.42)	(7.60)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	369,322	987,785
Adj. R^2	0.65	0.64

Table 12: 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 change in an investors' total position size due to a given stock trade expressed as a fraction of the total assets deposited by the investor with the broker. 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.

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)	(−0.58)	(1.14)
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	3.7358
	(5.76)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,389,639
Adj. R^2	0.05

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.

Panel A: risk-taking of investors who click on push message	
Dependent var.	Leverage
Sample	click
treat × post	0.1555
	(5.31)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,241,433
Adj. R^2	0.62
Panel B: Self-selection of investors	
	Leverage
treat × post	0.1996
	(7.18)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	888,008
Adj. R^2	0.61

Table 14: risk-taking and the impact of news

This table reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate 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 leverage at time t using the regression

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

where controls include investors' age and gender and a set of time dummies to control for unobserved aggregate covariates. *News Volume* captures the number of news articles, published and parsed on a given day from over 20 million news sources (from last 24 h) that are related to a specific company provided by *Quandl FinSentS Web News Sentiment*. *Sentiment* captures the average sentiment of articles aggregated from these news sources that are related to a specific company. 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	Leverage	Leverage
Sample	No earnings reports	no news trading	filtered trading
treat $\times$ post	0.1917	0.1662	0.1458
	(7.62)	(5.56)	(5.20)
Investor-fixed effects	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	1,025,676	436,258	1,086,213
Adj. R^2	0.62	0.68	0.59

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

This table reports results from a difference-in-differences regression analysis on investors' leverage usage 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 leverage of the last trade within seven days before the treatment event and the leverage 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.

	(1)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	Negative message	Positive message	Weak message	Strong message
treat × post	0.1747	0.1843	0.1515	0.2157
	(5.28)	(4.49)	(4.32)	(6.52)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	306,386	316,898	313,270	305,368
Adj. R^2	0.65	0.62	0.62	0.65

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 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: 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' 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.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: 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.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* (Column (1)) [first push message in any instrument (Column (2))] to investors who do not receive a 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 in the stock referred to in the push message after the treatment event within seven days. *Leverage* denotes the leverage employed for a trade. $treat \times post$ 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.

	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	first stock push message	first message any instrument
treat × post	0.1954	0.2019
	(3.22)	(1.97)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	271,735	211,586
Adj. R^2	0.69	0.68

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 the leverage of trades that investors initiate 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. *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. 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 within 180 days prior to the (counter-factual) treatment time, and their average usage of leverage within 180 days 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: difference-in-differences analysis	
treat × post	0.1227
	(4.6293)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	293,436
Adj. R^2	0.62
Panel B: difference-in-difference-in-differences analysis	
treat	−0.0506
	(−4.14)
post	0.0076
	(0.58)
stock	0.2379
	(4.89)
treat × post	0.1292
	(6.15)
treat × stock	−0.1789
	(−3.65)
post × stock	−0.1926
	(−3.57)
treat × post × stock	0.1581
	(2.86)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,114,023
Adj. R^2	0.63