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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. By exploiting the data in a difference-in-differences (DID) setting, we find that attention triggers increase investors' risk-taking. Our DID coefficient implies that attention trades carry, on average, a 19-percentage point higher leverage than non-attention trades. 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: G11, G40, G41.

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1 Introduction

The contemporary digital environment overwhelms investors with attention stimuli from manifold sources such as emails, advertising, social media messages, and push notifications. Such stimuli are intended to attract investors' attention. While 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, risk-taking, remains 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 (e.g., Liu et al., 2010; Charness and Gneezy, 2012; Lian et al., 2018). Second, there is growing theoretical recognition that investor attention 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). The main challenge for researchers in analyzing the link between individual attention stimuli and financial risk-taking is to isolate an exogenous trigger that stimulates a particular individual's attention towards a specific stock.

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 who sends standardized push messages to retail investors' cell phones. Each message reports publicly observable information on one specific stock. The messages allow us to observe exogenous triggers of individual investor attention towards the particular stock. We show that these 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 platform to trade contracts for difference (CFDs) on a large set of blue chip companies. CFDs are derivative contracts designed such that their prices mirror those of the underlying securities. CFD trading represents a substantial fraction of the overall trading volume in Europe and Asia. In the UK, for example, the notional value of the annual transactions was estimated to be approximately 35% of the value of London Stock Exchange equity transactions in 2007 (Financial Services Authority, 2007; Brown et al., 2010). The Financial Conduct Authority (2016) estimates that the 97 FCA-authorized UK retail CFD providers held approximately GBP 3.5 billion in client money in 2016. In Germany, the CFD trading volume in 2018 was approximately 1,600 billion euros with almost 70 million transactions (CFD Verband e.V.). In light of the intense discussion on the causes and consequences of speculative trading in different segments of the financial market (Han and Kumar, 2013; Heimer and Simsek, 2019), understanding the drivers of risk-taking in such a large market is important, both for regulators and investors.

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, we can interpret the push messages as individual attention triggers. Attention triggers are conceptually different from the individual attention proxies in the prior literature that capture the extent to which an investor pays attention (see, e.g., Gargano and Rossi, 2018). The psychology literature distinguishes between "endogenous" attention, which refers to the willingness to deliberately deal with a matter, and "exogenous" attention, which refers to the process by which external stimuli involuntarily redirect an individual's attention, independent of the individual's goals, intentions, and awareness (Theeuwes, 1994a,b; Mulckhuyse and Theeuwes, 2010; Theeuwes, 2010). Proxies for paying attention typically capture endogenous attention, as investors determine the extent to which they deal with a matter. In contrast, the broker initiates the push notifications, which thus represent exogenous attention stimuli. Identifying exogenous attention is crucial to address our research question because the extent to which an investor decides to pay (endogenous) attention is likely to be influenced by the riskiness of her planned trade.

Second, investors have considerable flexibility in selecting the leverage of each individual CFD trade. Leverage is a key dimension of risk-taking because it allows investors to increase the scope for extreme returns (Heimer and Simsek, 2019). Thus, CFDs allow investors to separate the choice of an important risk-taking dimension from the stock selection itself. This separation is critical to address the concern that our conjectures are simply driven by the risk characteristics of the stocks about 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.

Third, our data contain the trading records both of investors who obtain a push message (treated investors) and those who do not obtain this attention trigger (counterfactual investors). We label the trades that a treated investor executes in a stock within 24 hours of receiving 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 reveals the marginal impact of the attention trigger on individual risk-taking in a standard difference-in-differences (DID) approach. The established attention measures in 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 the influence of attention triggers 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 coefficient corresponds to 12.5% of the average within variation of investors' leverage choice. The economic magnitude of the effect is remarkable, given that we only consider simple push messages 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-taking. This literature concludes that "affective" processes play a key role in individual risk-taking (Figner and Weber, 2011; Weber, 2010). Various stimuli can influence affective processes that rapidly, spontaneously, and automatically influence human behavior (Galvan et al., 2006; Weber et al., 2004). Researchers argue that affective responses provide individuals with a fast, but crude, assessment of the behavioral options that they face, which enables individuals to take rapid actions by interrupting and redirecting slower cognitive processing towards 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 message and an attention trade is only 1.35 hours. Thus, the investors' median reaction time is very short, particularly because some time may pass between the moment that the push message is received and when it is read by the investor.

As the finance and psychology literature highlight that the impact of attention depends on the decision domain, individuals' demographics, and the decision context, we provide additional cross-sectional refinements of our main result. Specifically, we show that male, younger, and less experienced investors in particular increase their risk-taking after the attention trigger. 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 risk-taking for stocks that tend to attract more endogenous attention.

We carefully address the main concerns with our identification strategy. First, the broker may not send the messages to investors at random, and thus, her message-sending behavior could bias our conjecture from the DID analysis. 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 offer the opportunity to address this concern in a difference-in-difference-in-differences (DDD) setting. Specifically, we can explore the lack of congruence between investors' status of being message recipients or non-recipients and investors' stock trades. Each push message refers to only one stock (the message stock), whereas message recipients may trade many other stocks that are not referred to in the message. Similarly, non-recipients may also trade the stock referred to in the message sent to the recipients. The first difference in the DDD setting, i.e., the difference in risk-taking between recipients and non-recipients for all trades to which the message does not refer, controls for the possibility that recipients generally change their risk-taking compared to non-recipients around the treatment. The second difference, i.e., the difference in risk-taking between message and non-message stocks for all trades of non-recipients, controls for the possibility that message stocks are generally traded with a higher leverage than non-message stocks around the treatment. Therefore, the coefficient of interest in the DDD setting measures the impact of attention triggers on risk-taking net of (i) how the general risk-taking of recipients differs from that of non-recipients and (ii) how the general risk-taking for message stocks differs from that of non-message stocks. Thus, the DDD approach alleviates concerns that the broker may send messages to investors or on stocks for which she correctly anticipates an increase in risk-taking without the need to define the channels behind this anticipation. The DDD analysis supports our result that attention stimulates risk-taking.

The DDD approach, however, cannot control for the possibility that the broker may anticipate a change in risk-taking for specific investor-stock pairs and send the messages according to this anticipation. To address this remaining concern, we incorporate 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 changes, which allows her to anticipate future risk-taking after comparable changes. We use the trading data of the treated investors in our sample from the subperiod before the broker started sending push messages to study 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 subperiod. This comparison supports our conjecture that attention triggers stimulate risk-taking.

Second, the broker may observe the research activity of specific investors on specific stocks on her homepage. Such research can indicate future trading (Gargano and Rossi, 2018; Sicherman et al., 2015) and thus may also signal future risk-taking. Consequently, 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 also robust to this setting.

Third, the literature on risk-taking concludes that personal experiences are a key driver of 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; Malmendier et al., 2020). Whereas our DDD approach controls for a potential impact of general differences in personal experiences, it cannot address the concern that the broker may use specific investors' past experience with a specific stock to anticipate changes in their risk-taking. Thus, we repeat our main test with investors who have never traded the message stock before receiving a message because the broker has no information about these investors' past experiences. Our results are robust to this test.

Finally, we discuss several additional insights from our data. We find that attention triggers stimulate stock trading and induces investors to increase their position size, which we interpret as alternative evidence of an increase in risk-taking after attention triggers. In addition, we link our attention triggers to an individual attention measure in the spirit of Gargano and Rossi (2018).

We provide a battery of robustness tests to confirm our conjecture and exclude alternative explanations for our results. For example, we control for news, message content (positive, negative, strong, weak), and potential self-selection of investors. We also repeat our analysis by only considering the first message to an investor on any stock or 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. Finally, we also test our conjecture for FX trades. 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 derives 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 triggers on risk-taking. Section 7 provides cross-sectional refinements of our main result. In Section 8, we discuss additional insights and link our attention triggers to an established individual attention measure. In Section 9, we exclude alternative explanations for our results. The final section concludes the paper.

2 Related literature

We contribute to various strands of the extant literature. First, several studies investigate the determinants of investors' risk-taking at the microlevel.[1] This literature concludes that emotions, expectations, and personal experiences affect risk-taking. We add to this literature by showing that individual attention stimuli are an important dimension of investors' risk-taking decisions.

Second, our study is closely related to the literature on the impact of attention on financial markets and trading. Studies on aggregate attention highlight that attention has an important bearing on stock returns, stock ownership, trading patterns, return volatility, liquidity, correlation, bid-ask spreads, and financial contagion.[2] Several studies in this vein also investigate the origins or triggers of aggregate attention (Focke et al., 2020; Ungeheuer, 2018). Recent work examines individual investor attention by deriving proxies for how investors pay attention at the individual level based on their online account logins or web browsing behavior on the brokerage account. This literature provides profound insights into how individuals allocate their attention and how paying attention influences trading, performance, the transmission from beliefs to portfolio allocation, 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). While the attention literature discusses important macroeconomic and microeconomic implications of attention, it does

[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).

[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); Hasler and Ornthanalai (2018); Lawrence et al. (2018); Peress and Schmidt (2020); Huang et al. (2019); Fedyk (2019); Kumar et al. (2019).

not link attention directly to risk-taking. We contribute by establishing this link at the microlevel.

Third, our paper also speaks to the literature that analyzes retail trading in financial markets. A longstanding view is that retail trading is driven by behavioral biases. Indeed, several empirical papers highlight that retail investors trade for speculative reasons, such as overconfidence (Barber and Odean, 2001), sensation seeking (Grinblatt and Keloharju, 2009), or skewed preferences (Kumar, 2009). Established theories provide evidence that such behavioral biases can induce investors to undertake speculative trades that lower their own welfare (Odean, 1998; Gervais et al., 2001). Heimer and Simsek (2019) show that by providing leverage to traders, financial intermediation exacerbates speculation, which reduces social welfare. Our analysis adds to this discussion by identifying attention triggers as a key stimulus of speculative trading.

3 Hypotheses

Economics has increased its interdisciplinary character in recent years using developments from sociology, psychology, and even neurology to better understand the economic behavior of individual agents and markets. In financial economics, researchers have identified various psychological judgment biases, which are highly relevant for individual financial decisions (Barberis and Thaler, 2003). A prominent theme in this so-called "behavioral finance" literature relates to dual-process theories of cognition. These theories distinguish between "affective" and "cognitive" systems. The automatic, innate, affective system quickly generates perceptions and judgments, and the slower, more effortful, cognitive system monitors and revises such judgments as time, data, and circumstances permit (Kahneman et al., 1982; Stanovich, 1999; Haidt and Kesebir, 2010). Whereas the affective system can facilitate the rapid use of urgent information for immediate and spontaneous reactions, it also interrupts detailed analysis and creates problems of self-discipline in financial decisions (Slovic et al., 2002; Hirshleifer, 2013). The behavioral finance literature stresses the importance of the affective system that explains many prominent psychological biases (Kahneman, 2011; Hirshleifer, 2013).

Our hypotheses are motivated by this interdisciplinary link of the behavioral finance literature to the evolutionary and psychological roots of human behavior. Specifically, experimental psychology, neurobiology, and neuroscience studies distinguish between endogenous and exogenous attention. Endogenous attention refers to the willingness or the process to deliberately deal with a matter. Exogenous attention refers to the process by which external stimuli involuntarily redirect an individual's attention, independent of the individual's goals, intentions, and awareness (Theeuwes, 1994a,b; Mulckhuyse and Theeuwes, 2010; Theeuwes, 2010). Thus, exogenous attention can be conceptualized as an interruption of endogenous attention (Carretié, 2014). This concept is strongly related to the dual-process theories of cognition in behavioral finance because exogenous attention stimuli can trigger affective processes (Loewenstein et al., 2001; Weber et al., 2004; Galvan et al., 2006). Importantly, this literature highlights a link between attention stimuli and risk-taking in everyday situations that has thus far been overlooked in the broader finance literature by showing that affective processing stimuli increase risk-taking in traffic, sports, and the use of illicit substances (e.g., Figner et al., 2009; Casey et al., 2008). Inspired by this notion, we argue that external attention stimuli may 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 analyze the cross-sectional differences in the influence of attention stimuli on risk-taking along several dimensions. First, the neuroscience literature shows 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 how investor demographics influence the impact of attention triggers on risk-taking. 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 more closely attend to the relevant aspects of stimuli than do novices (Jarodzka et al., 2010).

Moreover, the finance literature finds that novice investors' financial attention is more exogenously oriented than that of professionals (Li et al., 2016). In addition, trading experience reduces investors' susceptibility to "unintentional" trading behavior (Feng and Seasholes, 2005; Kaustia and Knüpfer, 2008; Kaustia et al., 2008). Therefore, we expect that trading experience mitigates the impact of attention triggers on risk-taking.

Third, the psychology literature compares the influence of novel and well-known stimuli in everyday situations. Johnston et al. (1990, 1993), for example, suggest that novel stimuli attract more exogenous attention than familiar stimuli. Regarding risk-taking, Mitchell et al. (2016) conclude that exposure to novel stimuli leads to more risk-taking than exposure to familiar stimuli. We expect that these notions transfer to the finance domain.

Fourth, Gargano and Rossi (2018) show that certain stock characteristics, such as higher analyst coverage or trading volume, induce investors to conduct more research on a stock, i.e., attract more endogenous investor attention. Intuitively, we expect that stimuli relating to stocks with such characteristics have a stronger impact on risk-taking than stimuli relating to stocks without such characteristics.

Overall, these arguments lead to our second hypothesis:

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

a) investors who are more susceptible to attention triggers,

b) investors with less trading experience,

c) stocks with which the investor is less familiar, and

d) stocks that attract more endogenous attention.

4 Data, variables, and methodology

In this section, we describe our dataset, variables, and empirical identification strategy.

4.1 Data

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 CFDs on a large set of international blue chip stocks, foreign exchange rates, and cryptocurrencies. We focus on stocks in this paper and provide some supplementary evidence on foreign exchange. CFDs are financial contracts between investors and a financial firm that replicate the performance of the underlying asset. Section 4.2 provides a brief introduction to CFDs. The broker allows investors to flexibly select the leverage for each individual trade. Regulations restrict the maximum leverage for CFD trades on stocks to ten. A leverage of two, for example, induces a loss of 2% if the underlying asset of a long trade declines by 1%. 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. These costs are moderate and amount to 24 basis points per stock trade. The choice of leverage does not affect this cost.

Our data sample comprises all trades that the investors executed with the broker between January 1, 2016, and March 31, 2018. A trade is defined as the opening, increasing, decreasing, or closing of a position. Our data contain the exact timestamp of each trade, the specific underlying stock, an indicator for long or short positions, the execution price, 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 active investors, of whom 112,242 trade and 131,375 only receive a push message but do not 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 includes 3,519,118 transactions (3,393,140 round trips and 125,978 openings of a position).

On February 27, 2017, the broker started to send standardized push messages to investors. Our data contain detailed information on the push messages sent during the sample period. Specifically, for each push message, we observe the category, the entire content, the timestamp when the message was sent, and an indicator for whether an investor clicked on the message. There are three categories of push messages sent by the broker: large price changes for a stock on a single day; streaks that highlight stock price changes in the same direction over several days; and earnings report dates. Earnings report dates simply note a company's predetermined, upcoming date of an earnings announcement. This date is already publicly accessible from a company's web page before a push message is sent. A typical message reads "*$AFSI shares down over -5.2%.*" or "*$HRI shares up over 5.0%*". Thus, we observe the underlying and reported price changes of the price change and streak messages. The messages only contain publicly available information and, thus, do not reveal any new information. This feature assists us in isolating the impact of attention on risk-taking from that of new information. The broker selects the investors to whom she sends a certain message and the stock to which the message refers.

The broker summarizes stock information for her clients. Specifically, investors can access information pages on the broker's website that provide information on stock prices, key financial variables, and latest news on a company. We also have the time stamp when investors accessed these information pages.

Finally, the trading data include basic demographic information (age and gender) and details about investors' self-reported previous trading experience measured in predefined categories (e.g., "none", "less than one year") and supplied in response to a questionnaire issued by the broker.

We complement the brokerage data with Quandl Alpha One Sentiment Data to control for firm-specific news. Quandl aggregates and analyzes news from over 20 million news sources based on a machine-learning algorithm. We further collect data on firm and stock characteristics from Thomson Reuters, Datastream, and Worldscope.

4.2 Contracts for difference

A CFD is a financial contract designed such that its price equals that of the underlying security.[3] 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 assets for CFDs are stocks, stock indexes, currency pairs, and commodities. CFDs also allow investors to implement short positions and to achieve leverage with greater ease. They may be used to hedge existing positions and can offer tax benefits to investors (see, e.g., Brown et al., 2010).

Originally introduced in the London market in the early 1990s and targeting institutional investors, CFDs have since become popular with retail investors and have been introduced in many countries (Brown et al., 2010).

CFD investors are exposed to the counterparty risk of the broker (Brown et al., 2010). Specifically, investors usually become unsecured creditors if the broker fails, particularly if the funds with the broker are not properly segregated (European Securities and Markets Authority, 2013). Thus, investors bear the risk of losing their money in the funded CFD account or their profits in open positions. Several regulatory authorities impose protection schemes, which compensate clients in the event of a shortfall of the clients' funds due to broker insolvency (European Securities and Markets Authority, 2013). In the UK, the Financial Services Compensation Scheme (FSCS) offers coverage for up to 85,000 GBP of each client's total eligible deposits.

4.3 Variables

We employ the following variables in our empirical analysis. The main variable of interest, *Leverage*, denotes the leverage of a trade. We use this measure throughout our analysis as a metric of risk-taking. *Trades* is the number of trades that an investor executes in a

[3] Brown et al. (2010) describe these contracts in greater detail. They show that these instruments trade in fact at a price close to that of the underlying security.

given time period. Several dummy variables 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 trade position expressed as a fraction of the investor's total nominal amount of assets that she deposited with the broker. Unfortunately, we do not have access to investors' absolute nominal amounts. *Risk exposure* denotes the change in an investor's position size due to a given trade, expressed as a fraction of the total assets that the investor deposits with the broker. Trades that establish a new long or short position increase risk exposure; trades that close an existing long or short position decrease risk exposure. *Short sale* is a dummy variable that takes a value of one if trade takes a short position and zero otherwise. *Holding period* measures the time span between the opening and closing of a position in hours. Finally, we measure a trade's profitability by the *ROI* of the trade, which is the return on investment net of the transaction cost charged by the broker.

We also employ several stock characteristic measures. 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. The *Beta* of a stock is the CAPM beta from 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 country in which the stock is primarily listed. Thus, we use the FTSE 100 Index for UK stocks, the S&P500 for U.S. stocks, and so forth. We calculate the idiosyncratic volatility (*IVOL*) as the standard deviation of the residuals from our market model.

Several variables refer to the push messages. The dummy *Click on message* equals one if the investor clicks on the push message to open the broker's app and zero otherwise. *Attention trade* takes a value of one, if the investor trades the stock mentioned in the push message within 24 hours after receiving this message, and zero otherwise. Finally, we define *Duration* as the difference in hours between the timestamp at which an investor receives a push message and that at which she executes an attention trade.

In addition, we use the timestamp data to create a dummy variable *Research* that takes a value of one, if the investor visits the broker's information page on a given day, and zero otherwise. We also create a dummy variable *Research7* that takes a value of one, if the investor visits the broker's information page within seven days prior to trading the particular stock, and zero otherwise.

Finally, we extract several variables from Quandl. The variable *Article sentiment* captures, for each company, the average sentiment of all of the news articles on the company (within the last 24 hours) from all news sources. This variable takes values between -5 (extremely negative coverage) and +5 (extremely positive coverage); a score of zero indicates the absence of articles, or a neutral sentiment for that company on that day. Furthermore, the variable *News volume* captures the number of news articles on a company that are published and parsed on a given day from over 20 million news sources (from the last 24 hours). We also create a dummy variable *News event.* If Quandl FinSentS Web News Sentiment records at least one news article on a stock, *News event* takes a value of one for this stock on that day and the day thereafter, and zero otherwise.

4.4 Methodology

The empirical challenge in analyzing the marginal impact of an attention trigger on investors' risk-taking is to net out "normal" risk-taking, i.e., risk-taking in the alternative case in which an investor's attention had not been triggered. Our data offer the opportunity to overcome this challenge in a standard DID setting. Specifically, they allow us to compare the risk-taking of treated investors after receiving a push message to that of comparable investors who do not obtain a push message during the same period, conditional on trading. To this end, we apply three main steps.

First, for each investor-stock pair, we identify the timestamp of the first message that the broker sends to the investor on that stock (treatment time). We only use this first message to mitigate the potential confounding effects of previous messages on an investor's risk-taking in that particular stock. In addition, this approach eliminates the concern that the broker could observe the reaction of the investor to a message on a specific stock and send subsequent messages according to that reaction. Using the timestamp, we consider the last trade of treated investors in any stock within seven days (one day in an alternative specification) prior to the treatment time (observation period) if such a trade exists in the data.[4] Using data both before and after treatment allows us to reduce the risk of bias due to imperfect randomization in our DID design (Atanasov and Black, 2016). The advantage of using a relatively short observation period is that it mitigates the impact of potential time variation in investors' risk-taking (Petersen, 2009). We incorporate the first trade in the message stock within 24 hours after the message (treatment period). It is difficult to assess 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 suggest that the messages influence investors' trading decision for approximately 24 hours, as shown by the distinct spike in the treated investors' trading activity in the message stock after an attention stimulus (see Figure 2). Second, measuring trading patterns over one attention day is standard in the attention literature (Barber and Odean, 2008; Peress and Schmidt, 2020). Third, Frijda et al. (1991) suggest that affective phenomena typically last from several seconds to several hours.

Second, we collect our counterfactual sample from the trades of all investors in the database who do not receive a message on the message stock during the observation period, treatment period, and before these periods. We record 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 counterfactual investors during the observation period. This step controls for potential heterogeneity between the treated and counterfactual investors. We also measure the difference between the risk-taking of the treated investors and that of the counterfactual 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

[4] As our analysis on investors' risk-taking is conditional on trading, we do not include investors who do not trade in our analysis. We study investors' trading intensity in Section 8.1.

these two differences. Formally, we estimate the following:

$$\begin{aligned}\text{Leverage}_{ijt} = \alpha + \beta_1 \text{treat}_{ij} \times \text{post}_t + \beta_2 \text{treat}_{ij} + \beta_3 \text{post}_t \\ + \text{investor}_i + \text{stock}_j + \text{time}_t + \varepsilon_{ijt}, \quad (1)\end{aligned}$$

where Leverage_{ijt} denotes the leverage of investor i in stock j at time t; *treat* is a dummy variable that takes a value of one for investors in the treatment group, and zero otherwise; *post* is a dummy variable that takes a value of one for the treatment period, and zero otherwise; and β_1, our coefficient of interest, captures the impact of the attention trigger on risk-taking. The specification includes investor fixed effects to control for observed and unobserved heterogeneity across investors, such as their gender, age, individual wealth, invested amount, domicile, or stock market experience. We also incorporate stock dummies to control for stock-specific risk-taking. Finally, we include time dummies to account for aggregate time trends. As Dinc (2005) and Atanasov and Black (2016) note, fixed effects (in our case, investor fixed effects) can help to address covariate imbalance between the treatment and control groups. We double-cluster standard errors at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation (Petersen, 2009) and report t-statistics in parentheses.

5 Summary statistics

We first discuss the demographic characteristics of the investors in our sample. Most investors are male and are between 25 and 44 years of age (see Panel A of Table A.1 of the Appendix), which is consistent with previous studies on active investors (e.g., Linnainmaa, 2003). Panel B of Table A.1 in the Appendix shows that our dataset contains both novices and experienced traders. Around half of the investors had previous stock trading experience when they opened their account with the broker (not tabulated).

We present the distribution of investors' trading frequency with CFDs on stocks in Figure 1. Most investors trade, on average, less than one stock per week, and only a few trade more than five stocks per week. In addition, Table A.2 in the Appendix shows that the mean number of long and short trades per week is 0.613 and 0.065, respectively. Thus, whereas the trading frequency in our CFD sample is larger than that in studies on retail trading, the trading frequency distribution is comparable (e.g., Nicolosi et al., 2009).

— Place Figure 1 about here —

Next, we describe the push messages in our data. Of the investors in our sample, 99.1% receive at least one push message on any instrument, and 98.5% of the investors receive at least one push message on any stock (not tabulated). Table 1 provides summary statistics on the push messages in our sample. Panel A summarizes the different events on 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 indicate that the broker sends a push message once a stock's absolute daily return exceeds 3%. The average magnitude of positive and negative price change events is 6.67% and −5.87%, 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's absolute 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. Given the 243,617 individuals in our sample (see Table A.1 of the Appendix), these numbers suggest that the broker only sends messages to a relatively small subset of investors per event.

Panel B of Table 1 provides summary statistics on the message recipients' behavior. 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 visits the research page of the message stock within seven days prior to receiving the message. For 16% of the messages, the investor has already traded the message stock before receiving the message. For 2.8% of the messages, the investor holds the message stock in her portfolio when receiving the message. On average, 8.2% of investors click on the message that they receive. We observe that investors have lower average click rates on Fridays than on the remaining workdays (not tabulated). This observation is in accordance with Dellavigna and Pollet (2009), who argue that investors are less attentive on Fridays because they are distracted by the upcoming weekend. Approximately 3.1% of investors visit the message stock's research page within 24 hours after receiving the message. We also calculate the proportion of messages that are followed by an "attention trade" within 24 hours after the message. On average, 1.39% of the messages trigger an attention trade. The median duration between the time that 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 their median reaction time is relatively short.[5]

— Place Table 1 about here —

Figure 2 plots the distribution of the average trading activity in the message stock around push messages for treated and counterfactual investors. It shows a distinct spike for treated investors in the first eight hours after a message, which suggests that the messages stimulate attention trades. We also observe a small increase in the trading activity of treated and counterfactual investors just before a push message. This increase, however, is negligible compared to that of the treated investors at treatment.

— Place Figure 2 about here —

Table 2 shows that attention trades feature, on average, an 8% higher leverage than non-attention trades. Thus, it provides a first indication that investors' risk-taking after a push message differs from their regular risk-taking.

— Place Table 2 about here —

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

6 Implications of attention triggers for risk-taking

We now investigate the impact of attention triggers on individual risk-taking by applying our DID approach.

6.1 Difference-in-differences analysis

We first apply Equation (1) of our DID approach in Section 4.4 to investors' leverage. We consider both long and short trades. Table 3 summarizes the results.

— Place Table 3 about here —

Our main specification in Column (1) shows that push messages induce investors to trade the message stock at a higher leverage than investors who did not receive the message but who trade the same stock. The treatment coefficient indicates that, on average, attention trades entail a 0.1865 higher leverage than non-attention trades. Quantitatively, this coefficient corresponds to 12.5% of the average within variation of investors' leverage of 1.49 (not tabulated). Given that we only consider simple message stimuli that contain no fundamental news, this economic magnitude is remarkable. In comparison, Andersen et al. (2019) report that an incisive experience, namely, a personal loss from the default on bank stocks in the aftermath of the Global Financial Crisis, leads to an average reduction in an investor's risky asset share of 37.5% of the average within variation of this share.

We provide a more granular view of the impact of attention triggers on risk-taking in Figure 3. This figure plots the evolution of the average leverage in the message stock for treated and counterfactual investors from before the treatment event (pre-message) up to 24 hours after the treatment. It only considers the first trade in the message stock after the treatment. The pattern shows that the leverage of the treated investors spikes immediately after the push message and slowly declines thereafter.[6] This pattern is consistent with the notion from psychology studies that attention triggers stimulate

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

quick affective reactions that involve higher risk (e.g., Figner et al., 2009; Casey et al., 2008).

— Place Figure 3 about here —

A potential concern affecting our analysis is that the broker could observe investors' reactions to previous messages and then bias our results by selecting subsequent message recipients according to such observations. As our empirical setting excludes subsequent messages on the same stock, this behavior is unlikely to drive our results. We nonetheless provide additional evidence to rule out this conjecture. Specifically, we repeat our main analysis by only considering the first message to an investor on any stock (Column (2)) and on any asset class (Column (3)). The idea behind this approach is that the broker has no information about how an investor reacts to messages on stocks (Column (2)) and to messages in general (Column (3)). The results show that the treatment coefficients on risk-taking become even larger when we exclude observations with previous messages on assets other than the message stock.

We also address the concern that our results are driven by a trend in the treated investors' risk-taking prior to the treatment in three different ways. First, we repeat our analysis in Column (4) of Table 3 by considering only the trades within 24 hours before the treatment in our observation period. In this case, the treatment coefficient is even larger than in our main analysis. Second, we investigate the parallel trends assumption in Figure 4 by plotting the average leverage of all trades in the message stock within 40 days around the treatment. The figure reveals no pre-trend before the treatment.[7] In addition, the figure indicates that treated investors have a higher pretreatment leverage than counterfactual investors. Whereas such a pretreatment difference is not critical in a DID design, we nonetheless address this difference in complementary tests in Sections 6.2 and 6.4.

Third, Atanasov and Black (2016) suggest that applying placebo shocks during the pre-treatment period is a useful test to study pretreatment trends in a DID setting. Thus, we

[7]Some investors execute multiple trades in the message stock over the several days following a push message. We include subsequent trades besides the last trade before and the first trade after the treatment in this figure. The figure also shows that these investors, on average, continue to trade the message stock at a higher leverage than investors who do not receive a push message.

generate three placebo events to estimate Equation (1) by advancing the timestamp of the messages 24 (48/72) hours before the actual treatment event. Significant coefficients on the corresponding interactions *treat* $\times$ *post* would reveal a pretreatment trend. As an additional placebo test, we randomly generate 10,000 treatment events defined by a timestamp and a message stock, and then randomly assign these placebo events to the investors in our treatment group. A significant coefficient on *treat* $\times$ *post* in this test would reveal a systematic difference between treated and control investors. The results in Table A.3 of the Appendix show that the placebo messages do not yield statistically significant results.

— Place Figure 4 about here —

Next, Column (5) of Table 3 shows the results when we only include the trades in the message stock during the observation period before the treatment time instead of the trades in any stock. This test mitigates the concern that the broker biases our conjecture by sending messages on those stocks for which investors tend to use higher leverage. The disadvantage of this setting 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 from that in Column 1.[8]

In Columns (6) and (7), we separately study the streak and price change messages, respectively. Both coefficients are similar to that in Column (1). The coefficient on streaks, however, barely reaches the 5% significance level (t-statistic: 1.93).

Finally, we also discuss potential indirect treatment effects (spillovers). The total effect of a treatment may consist of direct and indirect effects (Boehmer et al., 2020). Indirect effects relate to the *stable unit treatment value assumption* (SUTVA) of the Rubin causal model, which includes the condition that treating one subject does not affect other treated or control subjects (Atanasov and Black, 2016). Indirect effects in a DID may arise due

[8]The stock fixed effects in our main test already capture the possibility that some stocks may be traded with a higher leverage than others. The difference between the fixed effects and the specification in Column (5) is that the former control for a stock's average leverage, whereas the latter controls for the last trade's leverage of the treated investor.

to externalities through which the treatment influences the control group. For example, Ouimet and Tate (2020) show that the trading of peers influences other investors' trading. Thus, indirect effects in our setting could occur if the risk-taking of treated peers influences the risk-taking of other investors. The coefficient β_3 in Equation (1) measures this indirect treatment effect (see Boehmer et al., 2020). Our main specification in Column (1) suggests that such indirect effects are unimportant in our case, as the coefficient β_3 is insignificant (-0.0000 with a t-statistic of 0.0006). In some of our other specifications, the coefficient is positive but small compared to the direct effect.

Overall, Table 3 implies that attention triggers stimulate risk-taking, which supports our main Hypothesis 1: Financial attention stimuli increase financial risk-taking.

6.2 Difference-in-difference-in-differences analysis

An important consideration is that the broker might not send messages to investors at random.[9] Thus, the concern with our DID analysis is that the broker's message-sending behavior could bias our conjecture. Specifically, the broker may anticipate a change in the risk-taking of certain investors or for certain stocks, and send messages according to this anticipation. One example of such a message-sending behavior concern stems from the broker's counterparty risk. In principle, our DID setting cancels the impact of this risk because it simultaneously compares the risk-taking between treated and counterfactual investors with the same broker. The broker, however, may tend to send more messages to investors who recently increased or decreased their exposure to the broker's counterparty risk. Thus, if investors' individual counterparty exposure influences their willingness to take leverage, such message-sending behavior could bias our conjecture.

It is impossible to identify all of the potential channels through which the broker's message-sending behavior could affect our conjecture. Importantly, however, our data offer the opportunity to address this concern without the need to identify the channels behind a potential message-sending behavior bias. Specifically, we exploit the lack of

[9]We analyze the message-sending behavior in detail in Section A of the Appendix.

congruence between investors' status of being a message recipient or non-recipient and the stocks that they trade. For example, a message only refers to the message stock, and recipients often trade non-message stocks. Similarly, non-recipient also trade the message stock. This lack of congruence allows us to explore the following DDD analysis in the spirit of Gruber (1994) and Puri et al. (2011):

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

The coefficient β_5 captures the general change in the message recipients' risk-taking around the treatment compared to that of non-recipients as measured from all non-message stock trades. Thus, it controls for the possibility that the broker sends messages to investors who generally change their risk-taking around the treatment due to reasons other than the attention trigger. Similarly, the coefficient β_6 captures the general change in risk-taking for message stocks around the treatment compared to non-message stocks as measured from all of the message stock trades of non-recipients. Consequently, it controls for the possibility that the broker sends messages on stocks that may feature a change in leverage around the treatment due to reasons other than the attention trigger.[10] Our coefficient of interest, β_7, then captures the impact of the attention trigger on leverage, net of how the risk-taking of recipients differs from that of non-recipients and the risk-taking for message stocks differs from that for non-message stocks around the treatment. 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. Therefore, by exploring the structure of our data, we do not need to characterize the potential channels through which the broker's message-sending behavior could bias our results along the dimensions of "recipient selection" or "message stock selection." Instead, the DDD directly controls for any differences along these dimensions around the treatment event.

Column (8) of Table 3 shows the coefficient of interest, β_7, in the line *treat* $\times$ *post* $\times$

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

stock. It implies that our conjecture on leverage is robust to the DDD setting.

6.3 Additional tests to rule out a message-sending bias

β_5 and β_6 of the DDD in Equation 2 control for the message-sending behavior along the recipient selection or message stock selection dimensions. The broker, however, may also anticipate changes in the risk-taking of specific investors in specific stocks around the treatment time and send messages according to this investor-stock pair anticipation. As the DDD analysis cannot directly address a potential bias of our conjecture from this caveat, we conduct three additional tests that incorporate the investor-stock pair information to which the broker has access.

First, the broker may observe a risk-taking pattern for specific investors in specific stocks after large stock price movements. To mitigate the concern that the broker biases our results by sending messages according to this observation, we divide our data sample into two subperiods. The "no-message sub-period" before February 27, 2017, comprises the period before the broker started sending push messages, and the "message sub-period" comprises the period after this date during which the broker sent messages. We then compare the risk-taking of each treated investor after receiving a message in the message subperiod to that of the same investor in the same stock after a comparable stock price change during the no-message subperiod. We regard stock price changes of at least three percent as comparable to push messages (see Table 1). This test also provides a natural complement to our DID approach because the DID, by definition, cannot compare the risk-taking of a treated investor to that of the same, but untreated, investor. The results of this test in Table 4 support our conjecture that attention triggers stimulate risk-taking.

— Place Table 4 about here —

Second, the broker collects information on investors' research activity on her 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. For example, Panel B of Table A.4 in the Appendix indicates that the broker is more likely to send push messages to investors on stocks for which the investor has recently visited the message stock's research page. Therefore, we repeat our main analysis by conditioning our observations on investors' past research activity. Specifically, Column (1) of Table 5 excludes all investors who visited the message stock's information page within seven days prior to the treatment, and Column (2) excludes all investors who ever visited an information page of any stock prior to the treatment. The treatment coefficients in these tests are significant, and very similar to, the coefficient in our main specification, which suggests that the broker's observation of investors' past research activity does not bias our conjecture. For completeness, Column (3) also reports the results for the case when we condition our observations on the investors who had visited the message stock's information page at any point prior to the treatment.

To provide a more comprehensive picture of how investors' past research may affect our results, we provide two additional tests. In Column (4), we apply a three-way interaction of $research7$ with our *treat* and *post* dummies. The coefficient on the three-way interaction term is insignificant, and the interaction coefficient on $treat \times post$ remains positive. This result confirms that our conjecture is not driven by investors' past research.

In Column (5), we include the additional interactions with $research7$ in our DDD setting of Section 6.2, and estimate a four-way interaction of $research7$ with the *treat*, *post*, and *stock* dummies. This DDDD approach controls for the impact of past research on investors' risk-taking along multiple dimensions. Specifically, it nets out the general impact of past research on the risk-taking of treated investors as measured from all their non-message stock trades that are executed following research activity on these stocks. In addition, it nets out the impact of past research on the risk-taking in the message stock as measured from all message stock trades of the counterfactual investors that are executed following research activity on message stocks. The coefficient on the four-way interaction term is positive at the 10% level, which suggests that message recipients who have researched the message stock increase their risk-taking to a larger extent than recipients without previous research. Importantly, the coefficient on $treat \times post \times stock$

is significantly positive and larger than the four-way interaction coefficient. Thus, the increase in the risk-taking of the treated investors is primarily driven by push messages.

— Place Table 5 about here —

Finally, the literature on risk-taking concludes that personal experiences constitute 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. Table A.4 in the Appendix motivates this concern by showing that more recipients than non-recipients traded the message stock before the treatment. We, therefore, repeat our main test by separating the observations into investors with and without prior trading experience in the message stock before the treatment. Columns (6) and (7) in Table 5 show that our conjecture is robust to these variations, which suggests that the broker does not bias our results by sending messages according to investors' past trading experience.

6.4 Additional tests addressing identification concerns

We now summarize additional tests to address potential identification issues affecting our DID analysis. The first concern is that treated and counterfactual investors may differ with respect to both observable and unobservable characteristics. Whereas a non-exogenous treatment shock, i.e., a message-sending behavior that is related to these characteristics, does not generally invalidate the DID design, it raises the concern that treated investors may react differently to the messages simply because they differ in some characteristics from counterfactual investors. Thus, a non-exogenous treatment would allow us to estimate an average treatment effect for the treated sample (ATT), but it would not allow us to estimate an average treatment effect for the entire sample (see, e.g., Atanasov and Black, 2016). In principle, the coefficient β_5 of our DDD approach already addresses this concern. We additionally discuss the covariate balance in our sample to provide complementary evidence that potential differences in risk-taking due to diverging characteristics of treated and counterfactual investors do not affect our conjecture.

To this end, we first investigate the common support of covariates between the treated and counterfactual investors. We find common support on all covariates, as summarized in Section A of the Appendix (Table A.4). Next, we exploit the common support of the treated and counterfactual investors by balancing the treatment and control groups on covariates to ensure that the two groups are as similar as possible. We follow this approach because a combined DID/balancing design enhances the credibility of the inference (Atanasov and Black, 2016). We match the treated with the counterfactual investors by using a nearest-neighbor matching routine based on the Euclidean distance with respect to standard controls for risk-taking, such as gender, age, overall trading intensity over the previous 180 days, and the investor's average leverage over the previous 180 days. Next, we run our DID with the matched investors. Table A.5 of the Appendix shows that our results are robust to this approach.

Further potential concerns with the DID approach refer to the treatment shock, i.e., the push message. Specifically, the shock should be isolated, strong enough, and ideally only have one level of treatment (Atanasov and Black, 2016). We discuss all three dimensions of this concern. First, we restrict our analysis to a short time period around the push messages, which mitigates the concern that other shocks could influence investors' trading behavior. Second, while, ex ante, we have no information regarding the extent to which the messages affect investors' risk-taking, evidence from the "nudging" literature shows that simple text messages can have important implications for peoples' behavior (Hardy et al., 2011; Kamal et al., 2015; Leon et al., 2015; Marteau et al., 2011; Castleman and Page, 2014).[11] Therefore, we expect the shock strength to be sufficiently large. Third, the push messages report different levels of returns, which violates the SUTVA of only

[11] For example, simple text messages can remind patients to take their medications on time, thereby improving medication adherence (Hardy et al., 2011; Kamal et al., 2015; Leon et al., 2015; Marteau et al., 2011), or remind students of important deadlines, which increases the persistence of college enrollment and graduation rates (Castleman and Page, 2014).

one level of treatment. Atanasov and Black (2016), however, argue that this assumption can be relaxed. Therefore, we further address treatment levels in Section 9, in which we separately investigate the impact of weak and strong messages on investors' risk-taking.

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

To provide a deeper understanding of our main result, we now test Hypotheses 2a to 2d, i.e., whether investor and stock characteristics influence the impact of attention stimuli on risk-taking. To this end, we split our sample along several investor and stock characteristics. In the case of continuous characteristics, we split the sample at the median.

7.1 The influence of investor demographics

We start by investigating Hypothesis 2a. Panels A and B of Table 6 suggest that the increase in risk-taking due to the attention stimuli is stronger for younger, male investors than for older, female investors. The average increases in risk-taking according to the point estimates of our regressions amount to 19.9 percentage points for male investors and 7.3 percentage points (not significantly different from zero) for female investors, and their difference is statistically significant with a p-value of <0.01 (Welch-Satterthwaite t-test). Similarly, the coefficients in Panel B decrease with investors' age, from 20.7 percentage points for investors between 18 and 34 years of age to 13.9 percentage points for investors who are at least 55 years of age, yielding an economically important difference of 6.8 percentage points (p-value of <0.01). As the psychology literature suggests that young or male individuals are more susceptible to exogenous attention stimuli (Syrjänen and Wiens, 2013; Hahn et al., 2006), our results support Hypothesis 2a. Therefore, we extend the notion 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 attention triggers on individual risk-taking.

— Place Table 6 about here —

We now turn to Hypothesis 2b. Panel C of Table 6 shows that trading experience reduces the impact of the attention stimuli on risk-taking. The difference in the coefficients is 3.45 percentage points (p-value of <0.01), which supports Hypothesis 2b. This result complements the literature suggesting that investment experience reduces behavioral errors, increases the use of sophisticated trading tactics, and improves investment performance (Feng and Seasholes, 2005; Kaustia and Knüpfer, 2008; Kaustia et al., 2008; Nicolosi et al., 2009; Da Costa et al., 2013).

7.2 The influence of investors' familiarity

Next, we analyze Hypothesis 2c. To proxy for an investor's familiarity with a stock, we use her previous trading or research experience with that stock. Intuitively, an investor should be more familiar with a stock if she has previously traded or researched that stock than an investor who has not done so. In Panel A of Table 7, we condition our analysis on different levels of this proxy. Specifically, Column (1) considers investors who have traded and researched the message stock, Column (2) contains investors who have traded but not researched the message stock, Column (3) considers investors who have not traded but researched the message stock, and Column (4) concerns investors who have neither traded nor researched the message stock. The treatment coefficients are significant across all specifications. The size and significance of the coefficients, however, suggest that the impact of attention triggers on risk-taking is stronger if the investor is less familiar with a stock than if she is more familiar. They also imply that this effect is primarily driven by previous trading.

— Place Table 7 about here —

Motivated by the observation that previous trading affects our results, we now focus on the past return, which has received particular attention in the literature on the impact of past experience on risk-taking (Thaler and Johnson, 1990; Brockner, 1992; Weber and Camerer, 1998; Imas, 2016; Meyer and Pagel, 2020). This literature concludes that past personal realized or paper losses and gains influence risk-taking. Thus, we additionally investigate how past realized or paper performance influences our results. Columns (1) and (2) of Panel B in Table 7 show that the increase in risk-taking following attention triggers is 6.3 (= 14.14-7.81) percentage points higher following realized losses than following realized gains. The difference is statistically significant with a p-value of <0.01. Similarly, the difference between our point estimates following paper gains in Column (3) (0.0229, not significantly different from zero) and paper losses in Column (4) (0.1498) is economically and statistically significant (12.7 percentage points, p-value of <0.01). These results highlight an important interaction between the impact of personal experiences and attention stimuli on risk-taking. Specifically, losses amplify the impact of attention triggers on risk-taking, which suggests that attention triggers serve as a catalyst through which personal experiences are transmitted or even amplified into risk-taking.

7.3 The influence of stock characteristics

We now turn to Hypothesis 2d. The literature identifies several stock characteristics that tend to attract (endogenous) investor attention. For our analysis, we use the stock attention proxies suggested by Gargano and Rossi (2018), i.e., the number of analysts covering a stock, the number of news events associated with a stock, a stock's trading volume, and a stock's turnover. In addition, we consider a stock's volatility because Barber et al. (2009) argue that extreme returns are a useful attention proxy. Finally, we also use a company's total market capitalization as, intuitively, large firms may attract more attention. We report the sample split results along these dimensions in Table 8.[12]

Whereas we do not observe a meaningful difference between the treatment coefficients for

[12] We split the sample based on the median at the stock level and not the observed trade level. Thus, the split samples in our analyses do not have the same number of observations.

the "small firm" and "large firm" samples (0.1936 vs. 0.1959), the other sample splits reveal economically and statistically significant differences in the coefficients. The differences range from 3.3 percentage points (trading volume) to 10.2 percentage points (turnover). Overall, the results suggest that attention triggers have a stronger impact on risk-taking for stocks that tend to attract more endogenous attention.

— Place Table 8 about here —

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

8 Additional results

In this section, we consider alternative trading dimensions, link our study to the recent literature on individual investor attention, and present trading performance implications.

8.1 Attention triggers and trading

We first study the impact of attention triggers on individual trading intensity. To this end, we define the dependent variable *Trading intensity*, which denotes the number of an investor's trades in a certain stock on a given day. We then apply a variant of our DID approach in Equation (1) by comparing the trading intensity in the message stock of the treated investors to that of the counterfactual investors who do not receive the message around the treatment. We use a one-day (24-hour) window for the treatment period and a seven-day observation period before the treatment.[13] We also apply this DID approach

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

along several granular trading dimensions. Specifically, we differentiate between long and short trades, as well as message stock and non-message stock trades.

Panel A of Table 9 summarizes the results on the impact of attention triggers on investors' stock-specific trading intensity. In Column (1), we investigate long trades, which include the opening or increase of a long position and the closing of a short position. The treatment coefficient indicates that, on average, a push message increases investors' long trading intensity in the message stock by 0.0047 trades on the subsequent day. The magnitude of this coefficient is economically important, given that the mean daily number of investors' long trades in a specific stock is only 0.000153 (not tabulated).

— Place Table 9 about here —

Column (2) shows that the messages also stimulate short trades (i.e., the closing of a long position or the initiation of a short position). The treatment coefficient suggests that, on average, a message increases investors' short trading intensity in the message stock by 0.0094 trades on the subsequent day. The magnitude of this coefficient is economically important, given that the mean daily number of investors' short trades in a stock is only 0.000146 (not tabulated). Moreover, the quantitative impact of attention triggers on short trades in Column (2) is even stronger than that on long trades in Column (1).

Barber and Odean (2008) find that the influence of attention on retail stock buying is stronger than that on stock selling (i.e., the closing of a long position). Their argument is that because attention is a scarce resource, the influence depends on the size of the choice set. This size is larger for stock buying—where investors search across thousands of stocks—compared to stock selling—where investors only select from the few stocks that they own. Our result that attention triggers are also important for short trades is consistent with this notion because we incorporate short sales in addition to the closing of long positions when we define short trades. Following the argument of Barber and Odean (2008), the choice set is large for short sales, as investors can sell short any stock rather than being confined to the stocks that they already hold in their portfolio.

Next, we investigate the impact of push messages on the trading intensity of non-message stocks. We now omit the stock fixed effects because we measure the trading intensity in *any* stock besides the message stock. The treatment coefficients in Columns (3) and (4) of Table 9 imply that the messages have no impact on either the long or short trading intensity of non-message stocks.

As push messages stimulate long and short trades, it is unclear whether they increase or decrease an investor's stock market exposure. Thus, we complement our analysis by investigating the influence of attention triggers on *Risk exposure*, which measures an investor's message stock position size. Trades that establish a new long or short position increase the investor's position size, and trades that reduce an existing long or short position decrease the position size. We estimate the DID Equation (1) for *Risk exposure* and present the results in Panel B of Table 9. The positive treatment coefficient (β = 3.74; t-statistic: 5.76) suggests that investors, on average, increase their message stock risk exposure after an attention trigger.

Overall, the results in this section have three primary implications. First, they complement the existing literature on the influence of aggregate attention on aggregate trading (Barber and Odean, 2001; Seasholes and Wu, 2007; Barber and Odean, 2008; Lou, 2014; Peress and Schmidt, 2020) by providing evidence of this link at the microlevel. Second, we contribute to this literature by providing the novel insight that attention triggers are also relevant for short trading. Third, as trading intensity and risk exposure can be interpreted as alternative risk-taking measures, the results support our conjecture that attention triggers increased investors' risk-taking.

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 that of exogenous attention triggers. Specifically, to investigate risk-taking, it is crucial to apply an exogenous attention trigger instead of an endogenous attention proxy because an investor's decision to pay more (endogenous) attention is likely to be related to the riskiness of her planned trade. The concepts of exogenous and endogenous attention, however, are closely related. The psychology literature 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 an endogenous individual attention measure.

We first estimate the DID Equation (1) of Section 4.4 by using *research* as the dependent variable, which is the number of investors' daily page views of the message stock. This endogenous attention proxy is in the spirit of Gargano and Rossi (2018), who also use the web activity within the brokerage account website to proxy for investors' attention by counting the number of page views. As investors decide which pages on the website they visit, the measure can be classified as an endogenous attention measure. We investigate how a message influences investors' research in the 24 hours after this attention trigger and report the results in Table 10. Column (1) shows that the treated investors' research increases significantly compared to that of non-recipients.

— Place Table 10 about here —

In Columns (2) and (3), we separately investigate investors' research after positive and negative messages. The research increases after both message types but to a slightly greater extent after positive 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 the individuals' research for investors who already hold the message stock when receiving the message (Column (4)) and investors who do not hold this stock (Column (5)). We observe that investors particularly increase their research after an attention trigger if they already hold the stock. Importantly, however, the messages also increase research for 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 previously researched the message stock. Columns (5) and (6) highlight the role of the push messages as exogenous attention triggers. Specifically, the increase in research cannot simply be explained by endogenous attention, i.e., by the broker sending messages after an investor studies the message stock. We complement this argument with the simple statistic that 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 broker's data on investors' page views to measure the duration between an investor's last visit to a certain stock's web page and her trade of that stock. We interpret this measure as a proxy for cognitive processing because an investor has more research time available if the duration is longer. Investors, on average, conduct an attention trade 1.31 hours after the last page visit, whereas they conduct a non-attention trade, on average, 2 hours after this visit (not tabulated). This result supports our notion that push messages stimulate affective processing because they reduce endogenous attention before a trade.

Overall, the results in this section indicate that our individual attention triggers share some basic properties with the individual endogenous attention measures from the extant literature. Importantly, they also imply that, in contrast to the individual endogenous attention measures, the push messages that we consider are a useful proxy for individual exogenous attention triggers.

8.3 Performance analysis

We now investigate the effect of messages as attention triggers on investors' trading performance. A primary channel that could affect investors' performance is that the broker may send messages on stocks that subsequently perform differently from non-message stocks. Figure 5 plots the cumulative average returns of message stocks (green) and non-message stocks (red) with the corresponding standard errors over the first 100 days after the treatment. The figure shows that the returns are not significantly different.

Place Figure 5 about here

Although message and non-message stocks tend to have the same performance, the leverage increase due to the attention triggers may nonetheless influence investors' trading performance. Thus, we analyze the relation between the attention triggers and trading performance with the following panel regression in the spirit of Gargano and Rossi (2018):

$$\begin{aligned}\mathrm{ROI}_{ijkt} &= \alpha + \beta \cdot m + \gamma \text{Attention trade}_{ijkt} + \delta \text{Holding period}_{ijkt} \\ &+ \zeta \text{Short sale}_{ijkt} + \text{investor}_i + \text{stock}_j + \text{time}_t + \varepsilon_{ijkt}, \qquad (3)\end{aligned}$$

ROI_{ijkt} is the holding period return of investor i in stock j with trade k at time t. *Attention trade* is a dummy that equals one if a trade is an attention trade and zero otherwise. We control for *Holding period* because the trades have different holding periods and *Short sale* because our sample contains both long and short trades. We repeat regression 3 by using the Sharpe ratio and the risk-adjusted return as the dependent variable.[14] We use the market return of the main index of the country of the corresponding company's headquarters to calculate the risk-adjusted returns. The panel specification includes investor, stock, and time fixed effects to control for heterogeneity across investors, heterogeneity across stocks, and aggregate time trends.

Panel A of Table 11 shows that the push messages as attention triggers have no impact on returns (Column (1)), Sharpe ratios (Column (2)), or risk-adjusted returns (Column (3)). In Panel B, we repeat the regressions without the stock fixed effects because they partially capture the message stock selection dimension, which is the main determinant of investors' trading performance. This omission leads to the same conjecture.

— Place Table 11 about here —

[14] In the later two panel regressions, we omit the intraday trades because we lack the data on the majority of stocks that are necessary to calculate the intraday volatility and beta.

Overall, we find no statistically significant impact of messages on investors' individual trade performance. A limitation of our analysis, however, is that it does not speak to the long-run performance impact of messages. Section 8.1, for example, shows that the messages stimulate investors' trading of the message stock. As a high trading intensity causes higher transaction costs and, hence, inferior net returns (Barber and Odean, 2000), frequent messages could lead to inferior long-term net trading performance.

9 Robustness analyses

We now provide alternative empirical tests to study the robustness of our main results.

9.1 Do investor decisions bias the results?

The investors can decide whether they read a push message, allocate endogenous attention to the message stock after reading a message, or entirely block the messages on their cell phones. These decisions raise three potential concerns with our results. First, investors may not even read the messages. Second, reading a message could stimulate the treated investors' endogenous attention, i.e., induce them to deliberately deal with the message stock. Thus, the increase in risk-taking could be driven by investors who collect more information on the message stock. Third, the counterfactual may contain investors who block the messages, which could introduce self-selection bias if the tendency to block messages is correlated with risk-taking.

We address the first caveat by exploiting the information in our data on whether an investor clicks on a push message. A click suggests that a message recipient most likely reads the message. Thus, we repeat our main DID analysis but only consider the treated investors who click instead of all message recipients. The counterfactual comprises the non-recipients as in our main analysis. Column (1) of Table 12 suggests that our conjecture on risk-taking is robust to the critique that investors may not read the messages.

— Place Table 12 about here —

Next, we analyze the endogenous attention concern by dividing the treated investors who click on the message into those who research and those who do not research the message stock between receiving the message and trading. Intuitively, clicking on the message and then researching the message stock could indicate that the attention trigger stimulates endogenous attention on the part of the investor. However, the treatment coefficients in Columns (2) and (3) of Table 12 that result from this division are virtually identical, which suggests that our results are not driven by investors who devote higher endogenous attention to the message stock after receiving the exogenous attention trigger.

Finally, we address the self-selection concern. We would ideally condition our main test on all of the investors who have not blocked the messages. Unfortunately, we cannot directly observe whether or when an investor blocks or disables the messages on her cell phone. As an alternative approach in Column (4) of Table 12, we only incorporate the investors in the counterfactual group who click on any message within seven days before and after the treatment time. This approach only includes investors in the counterfactual group who are unlikely to have the messages blocked around the treatment time.[15] The treatment coefficient shows that our DID result on risk-taking is robust to this alternative test. Therefore, the self-selection of investors does not drive our conjecture.

9.2 Attention and message content

We now investigate how the message content affects our results. We omit the earnings report date messages in this analysis, as their content is not positive or negative and does not report a return. In Panel A of Table 13, we separately study the impact of negative and positive push messages on risk-taking. We distinguish between long and short positions to capture style trading, such as momentum and contrarian trading. We interpret investors who take a long position after positive messages and a short position after negative messages as momentum traders and investors who take a long position after negative messages and a short position after positive messages as contrarian traders. The

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

treatment coefficients in Columns (1) and (3) are similar to those in our main specification of Table 3. Thus, risk-taking for long positions increases after attention triggers for both momentum and contrarian traders. The treatment coefficients for short positions in Columns (2) and (4) are also positive. However, as the coefficient in Column (4) is not significant, contrarian traders do not seem to increase risk-taking after positive messages.

— Place Table 13 about here —

We also study how the impact of attention triggers depends on the magnitude of the return reported in a message. To this end, we create a tercile split based on the messages' reported absolute return and separately study the impact of the messages in each tercile. Panel B of Table 13 shows that investors increase their risk-taking after an attention trigger in each tercile. However, we observe a larger effect in the upper tercile of the reported return magnitude, which we attribute to the higher salience of those messages.

The results in Table 13 have three key implications. First, they suggest that the increase in risk-taking is primarily driven by the attention trigger and not by the message content. Second, they mitigate the concern that momentum or contrarian trading drives our inference and that leverage is merely a proxy for the conviction of trade. Finally, they also address the caveat that investors perceive the messages (or the salience of the associated stock price jumps) as a resolution of uncertainty, which could induce them to increase their risk-taking. Specifically, a well-established stock market regularity is that negative equity jumps lead to greater uncertainty than positive jumps (Bollerslev and Todorov, 2011). Panel A of Table 13, however, shows that the increase in risk-taking is similar after messages that report a negative jump and those that report a positive jump, which contradicts the notion that the resolution of uncertainty drives our results.

9.3 Attention and news

Another caveat with our main result is that it could be driven by news that is correlated with both risk-taking and the broker's tendency to send push messages to investors. Our

DID approach mitigates this concern because we compare the increase in the 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. In addition, our DDD approach controls for the possibility that the broker tends to send messages to specific investors with recent news that stimulate risk-taking. The broker, however, may also tend to send messages according to investor stock-specific news. For example, she may send messages to specific investors who are more likely to receive stock-specific news on the message stock that stimulates risk-taking. As this remaining concern is not addressed by our DDD approach, we repeat our main analysis with four alternative settings in Table 14.

— Place Table 14 about here —

First, we omit the earnings report date messages in Column (1) of Table 14 to address the concern that such messages could stimulate risk-taking. Second, we omit the messages that the broker sends on or the day directly following message stock news in Column (2). Third, we apply a news filter for leverage usage in Column (3). Specifically, we filter investor i's leverage for stocks on firm j at time t using the first-stage regression:

$$\text{Leverage}_{ijt} = \alpha + \beta \text{News volume}_{jt} + \gamma \text{Sentiment}^2_{jt} + \delta' \text{Controls}_{it} + \varepsilon_{ijt}, \tag{4}$$

where the controls include investors' age and gender and a set of time dummies to control for unobserved aggregate covariates. 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.

Fourth, we define *Abn. turnover* on day t, AV_t as

$$AV_{it} = \frac{V_{it}}{\bar{V}_{it}},$$

where V_{it} denotes the volume turnover in the underlying stock i on day t and $\bar{V}_t$ denotes the average volume turnover in that stock over the past six months. We use this measure because Barber and Odean (2008) argue that, similar to news, the abnormal trading volume may direct investors' attention towards a particular stock. We then apply a three-way interaction of *Abn.turnover* with our *treat* and *post* dummies in Column (4) of Table 14. The coefficient on this three-way interaction term is insignificant, while the interaction coefficient on *treat* $\times$ *post* remains positive, suggesting that attention-grabbing events do not influence our results.

Overall, Table 14 shows that our conjecture on the influence of attention triggers on risk-taking is robust to the alternative specifications and, thus, not biased by news.

9.4 Attention triggers and risk-taking in the FX market

In this section, we apply our analysis to the FX trades in our CFD dataset. For FX trades, the available leverage ranges from 1 to 400. Panel A of Table 15 suggests that attention trades have higher leverage than non-attention trades. Panel B confirms that attention triggers risk-taking for FX trades in our main DID setting. Importantly, the magnitude of this effect is comparable to that of our main specification in Table 3 of Section 6. Specifically, the treatment coefficient corresponds to 10% of the average within variation of investors' leverage choice on FX trades, which is close to the 12.5% on the stock market (see Section 6.1). Therefore, the results from FX trading are broadly consistent with those from stock trading. This insight mitigates the potential concern that the effect of exogenous attention triggers on risk-taking is driven by a stock-trading-specific setting and may not apply to other asset classes. In addition, the general validity of our results for trades in different markets highlights their regulatory relevance.

— Place Table 15 about here —

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 these data is that we directly observe a trigger of individual investor attention and can link this trigger to individuals' risk-taking. The data also contain the message stock trading of investors who do not receive an attention trigger. As a consequence, 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 triggers stimulate individual 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 risk-taking following an attention trigger is also stronger for stocks that tend to attract more endogenous attention.

A profound comprehension of individual risk-taking is critical 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). Illustrating the causal mechanisms that underlie financial risk-taking also provides us with entry points for the design of interventions that can successfully modify speculative trading in situations in which decision-makers and society desire such changes.

A potential limitation of our study is that CFD investors could represent a special clientele, such as risk-seeking investors. Understanding the behavior of this clientele, however, is important because CFD trading represents a crucial portion of the overall trading volume in Europe and Asia. In addition, our CFD data contain a manifold diversity of CFD investors, such as experienced traders, novices, and investors who are also active in the common stock market. This diversity allows us to draw a comprehensive picture of the influence of attention triggers on different types of investors. As attention stimuli in general and individual attention stimuli in particular are omnipresent in the contemporary digital environment, we believe that studying the impact of such stimuli on additional investment dimensions such as portfolio composition could provide a fruitful avenue for future research.

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A Message-sending behavior

In this appendix, we analyze the broker's message-sending behavior. We first discuss the message stocks and compare the volatility of stocks in message months to that of stocks in non-message months in Panel A of Table A.4. On average, push message stocks are more volatile than non-message stocks. The beta and idiosyncratic risks of push message stocks are also higher than those of non-message stocks. Overall, the panel implies that push message stocks are riskier than non-message stocks. The intuition is that riskier stocks are more likely to experience extreme price movements and, hence, trigger push messages. As Table 1 makes clear, most messages are sent following large stock price movements.

— Place Table A.4 about here —

Next, we study the investor dimension of message sending. We compare investors who receive a push message at a given point in time to investors who do not receive such a push message as follows: 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. We provide summary statistics of the sample resulting from this procedure in Panel B of Table A.4. We focus on various proxies for investors' trading and research activities, prior reactions to pushing messages, and demographics that may influence the broker's message-sending decision.

While the summary statistics show that the broker, on average, sends push messages to investors who trade more actively and take more risk (with an average leverage of 5.6 for non-message recipients and 6.27 for message recipients), 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. We observe a reasonable "common support," i.e., reasonable overlap between treated and control investors on all covariates (see, e.g., Atanasov and Black, 2016). Note that for each event, the broker sends push messages to approximately 1-2% of its customers. Thus, for every investor who receives a 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 exploit this overlap in our robustness analysis, where, among other tests, we employ a matching procedure between message recipients and non-recipients.

Figure 1: Trade frequency of investors

This figure presents the distribution of the average weekly trade frequency in CFDs on stocks of investors in our sample. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contain all trades on the platform between January 1, 2016, and March 31, 2018.

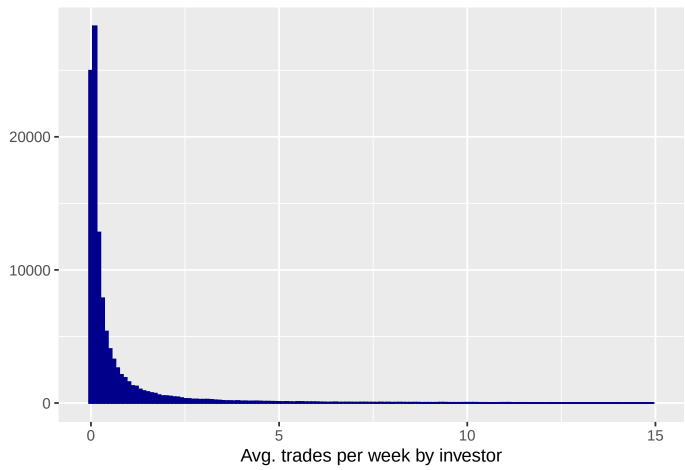

Figure 2: Trading activity around push messages

This figure presents the distribution of the average trading activity of investors in the message stock around the time that the broker sends push messages. The time difference is measured in hours. Push messages are sent at time zero. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contain all trades on the platform between January 1, 2016, and March 31, 2018.

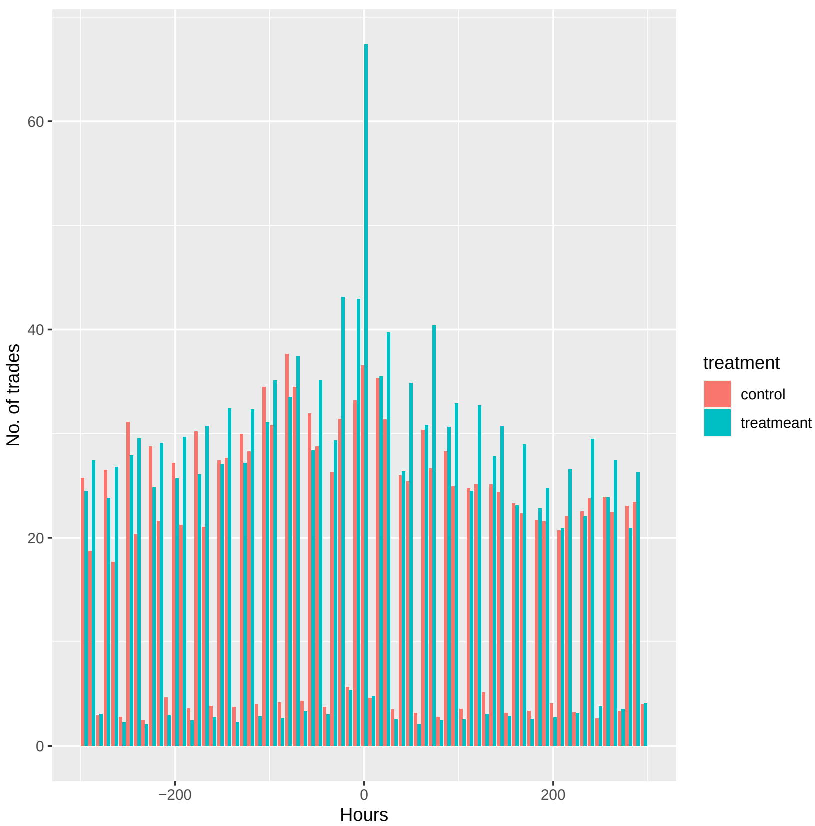

Figure 3: Risk-taking within 24 hours after a push message

This figure presents the average usage of leverage by 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 message stock within 24 hours after receiving the message. The pre-message shows the average usage of leverage of investors in the message stock between January 1, 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 occurs 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

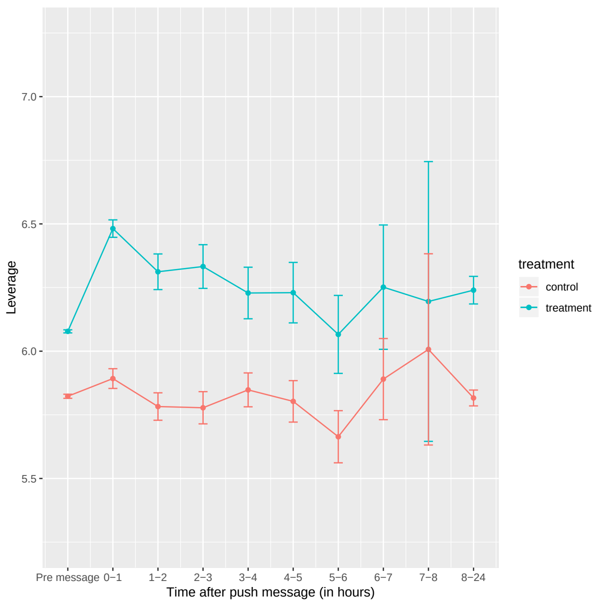

Figure 4: Risk-taking around the treatment events

This figure presents the average usage of leverage by 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 message stock 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

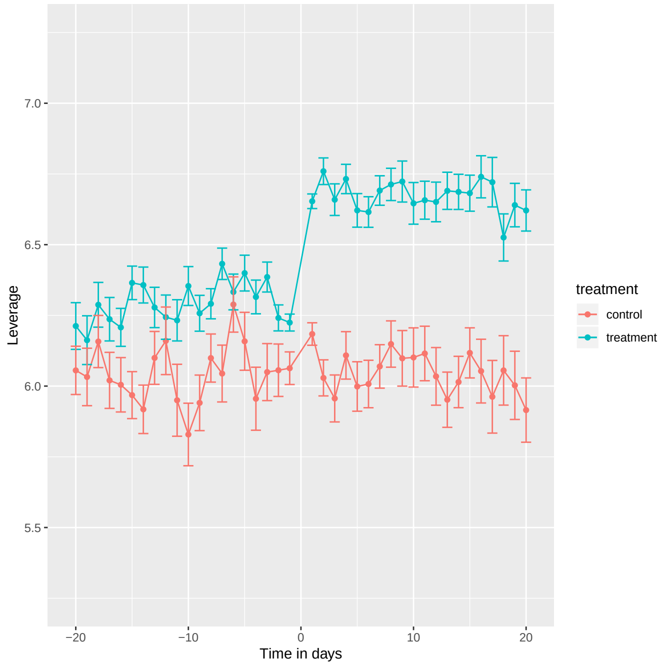

Figure 5: Attention triggers and performance of stocks traded

This figure presents the relation between the average performance of message stocks and the average performance of the stocks that non-recipients trade. Stock performance is computed using log returns for an investment on the message day based on stocks' closing prices. Message stocks are in green. The control group (red) comprises stocks traded by non-message recipients on the day the push message was sent. 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.

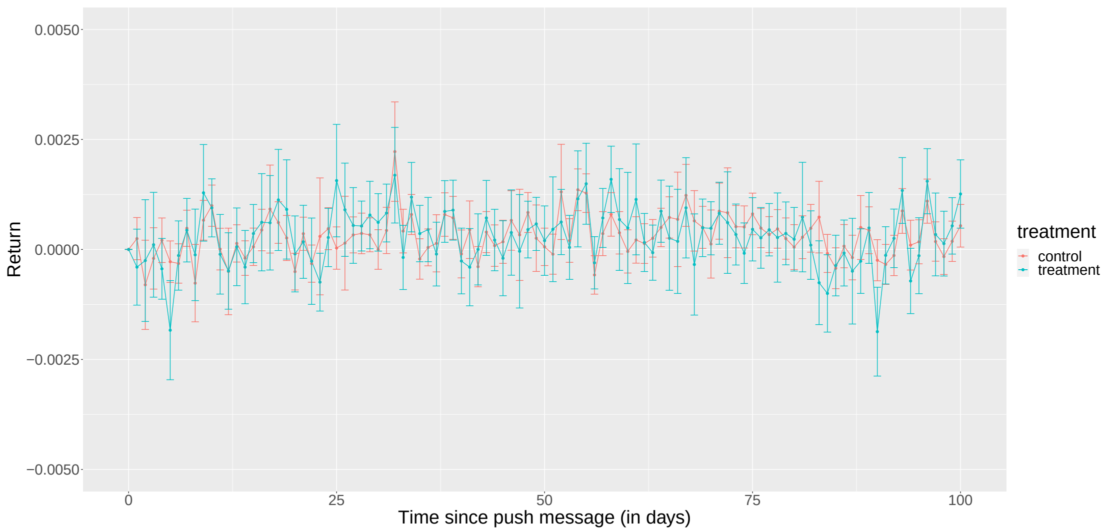

Table 1: Summary statistics of push message data

This table shows summary statistics of the push messages from the data of a discount brokerage firm that offers a trading platform to retail investors under a UK broker license. *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 report dates* are the messages that report the dates of 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 that the broker sent to investors. *Research before* is a dummy variable that takes a value of one if the investor researched the message stock within the seven days before receiving the push message and zero otherwise. *Traded before* is a dummy variable that takes a value of one if the investor traded in the message stock before receiving the push message and zero otherwise. *Hold stock* is a dummy variable that takes a value of one if the investor holds the message stock in her portfolio when receiving the push message and zero otherwise. *Click on messages* is a dummy variable that takes a value of one if the investor clicks on the push message and zero otherwise. *Research on messages* is a dummy variable that takes a value of one if the push message is followed by a visit to the message stock research page within 24 hours and zero otherwise. *Attention trade* is a dummy variable that takes a value of one if the push message is followed by a trade in the message stock within 24 hours and zero otherwise. *Duration* is the duration between a push message and the attention trade of an investor who received the push message in hours.

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 dates	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	Attention trade	Mean (duration)	Median (duration)
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 report dates	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 recipients in the message stock within 24 hours after receiving the message. "Non-attention trades" are all other trades. *Leverage* denotes the investor's average leverage. The t-test reports results from an equality test 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: Attention and leverage: Difference-in-differences analysis

This table reports results from a difference-in-differences (Columns 1-7) [difference-in-difference-in-differences analysis (Column 8)] regression analysis on the leverage of trades that investors initiate in our trade data. Columns 1-7 estimate Equation (1), and Column 8 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 within 24 hours after the treatment event. In Columns 1-7, we only consider the leverage of the first trade in the message stock after the treatment event. In Columns 1 and 4 to 7, the treatment event is the first message that an investor receives for a given stock. In Column 2, the treatment event is the first message that an investor receives for any stock. In Column 3, the treatment event is the first message that an investor receives for any instrument. In Column 4, we restrict the observation period to the last 24 hours before the treatment event. In Column 5, we restrict the trades in the observation period to the message stock. In Column 6, we restrict the sample to push messages on streaks. In Column 7, we restrict the sample to push messages on price changes. *Leverage* denotes the leverage employed for a trade; *treat* is a dummy variable that takes a value of one for investors in 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 heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Dependent var.	(1) Leverage Main specification	(2) Leverage First message any stock	(3) Leverage First message any instrument	(4) Leverage 24-hour observation	(5) Leverage Message stock observation	(6) Leverage Streaks	(7) Leverage Price changes	(8) Leverage DDD
treat	−0.0120	0.0212	−0.0291	−0.0290	−0.0340	0.0552	−0.0118	−0.0252
	(−1.70)	(1.90)	(−1.40)	(−2.10)	(−2.57)	(2.14)	(−1.52)	(−5.16)
post	−0.0000	0.0426	0.0475	0.0324	−0.0296	−0.0158	0.0379	0.0345
	(−0.00)	(2.42)	(1.98)	(2.39)	(−1.88)	(−0.37)	(3.53)	(9.35)
treat × post	0.1865	0.1954	0.2019	0.2151	0.1834	0.1671	0.1887	0.1094
	(7.20)	(3.22)	(1.97)	(7.36)	(6.86)	(1.93)	(7.46)	(8.82)
stock								0.0643
								(6.38)
treat × stock								−0.0171
								(−1.02)
post × stock								−0.0687
								(−4.14)
treat × post × stock								0.0972
								(3.30)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,294,093	271,735	211,586	866,794	657,108	384,707	1,212,561	2,424,742
Adj. R^2	0.62	0.69	0.68	0.61	0.64	0.60	0.62	0.62

Table 4: Investors' risk-taking over time

This table reports results from an ordinary least squares regression analysis on investors' leverage usage for the time period before push messages were sent (January 1, 2016, to February 26, 2017) and the push-message regime (February 27, 2017, to March 31, 2018). The push-message regime considers all "attention trades". "Attention trades" are all of the trades by investors in the message stock within 24 hours after receiving the message. The time period before push messages were sent considers the trades in investor-stock pairs during which 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 heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

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

Table 5: Prior experience with 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 researched (Columns (1)-(5)) [invested in (Columns (6) and (7))] the message stock. Column (1) is restricted to investors who did not view the message-stock-specific information page of the broker within seven days prior to the treatment event. Column (2) is restricted to investors who never visited any information page of the broker prior to the treatment event. Column (3) is restricted to investors who visited the message-stock-specific information page of the broker at any point in time prior to the treatment event. Columns (4) and (5) contain the full sample. Column (6) is restricted to investors who have no prior trading experience in the message stock; Column (7) is restricted to investors who 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 in the message stock after the treatment event within 24 hours. The treatment event is the first message that 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 in 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; *research7* is a dummy variable that takes a value of one if the investor has visited the stock-specific information page of the traded stock within seven days prior to the trade, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent var.	Leverage	Leverage	Leverage	Leverage	Leverage	Leverage	Leverage
Sample	No prior research stock	No prior research all	Prior research	Full sample	Full sample	No prior trading	Prior trading
treat	−0.0104	−0.0077	−0.0229	−0.0123	−0.0220	0.0042	−0.0335
	(−1.68)	(−1.00)	(−2.43)	(−1.76)	(−3.62)	(0.82)	(−3.32)
post	0.0024	0.0034	0.0044	0.0181	0.0321	0.0416	−0.0128
	(0.17)	(0.21)	(0.21)	(3.91)	(7.43)	(3.15)	(−0.70)
treat × post	0.1889	0.1928	0.1689	0.1255	0.1194	0.1442	0.1032
	(7.24)	(6.62)	(5.03)	(8.17)	(8.89)	(4.95)	(3.36)
research7				0.0811	0.0692		
				(4.26)	(3.68)		
treat × research7				−0.0211	−0.0091		
				(−2.28)	(−1.05)		
post × research7				−0.0050	0.0066		
				(−0.87)	(1.12)		
treat × post × research7				−0.0085	−0.0266		
				(−0.62)	(−1.95)		
stock					0.0504		
					(4.55)		
treat × stock					−0.0023		
					(−0.13)		
post × stock					−0.0558		
					(−3.27)		
stock × research7					0.0370		
					(2.53)		
treat × post × stock					0.0751		
					(2.45)		
treat × stock × research7					−0.0389		
					(−2.07)		
post × stock × research7					−0.0347		
					(−2.13)		
treat × post × stock × research7					0.0569		
					(1.82)		
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,108,056	718,676	438,027	2,424,742	2,424,742	655,622	638,471
Adj. R^2	0.61	0.60	0.64	0.62	0.62	0.61	0.65

Table 6: 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. The results are computed separately for investors with respect to the conditioning variables. The conditioning variables used are (from Panels A to C): investors' gender, investors' age, and investors' trading experience (self-assessment). 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 message stock after the treatment event within 24 hours. The treatment event is the first message that an investor receives on a given stock. *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain 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	−0.0240	−0.0142	
	(−1.82)	(−1.96)	
post	0.0482	0.0014	
	(1.84)	(0.09)	
treat × post	0.0733	0.1987	
	(1.39)	(7.52)	
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	$\geq$ 55
treat	−0.0131	−0.0196	0.0078
	(−1.53)	(−2.40)	(0.65)
post	0.0058	0.0037	−0.0027
	(0.35)	(0.21)	(−0.09)
treat × post	0.2068	0.1841	0.1386
	(6.28)	(6.71)	(3.03)
Obs.	650,812	661,188	107,717
Adj. R^2	0.62	0.63	0.65
Panel C: Investors' trading experience (self-assessment)			
	(1)	(2)	
Dependent var.	Leverage	Leverage	
Sample	Low experience	High experience	
treat	−0.0081	−0.0199	
	(−1.03)	(−2.51)	
post	−0.0070	0.0092	
	(−0.41)	(0.57)	
treat × post	0.2130	0.1785	
	(6.31)	(6.78)	
Obs.	600,123	823,089	
Adj. R^2	0.60	0.64	
All panels:			
Investor fixed effects	Yes	Yes	
Stock fixed effects	Yes	Yes	
Time fixed effects	Yes	Yes	

Table 7: 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. In Panel A, Column (1) is restricted to investors who researched and traded the message stock prior to the treatment date. Column (2) is restricted to investors who traded but did not research the message stock prior to the treatment date. Column (3) is restricted to investors who researched but did not trade the message stock prior to the treatment date. Column (4) is restricted to investors who have not researched or traded the message stock prior to the treatment date. Panel B is restricted to investors who traded the message 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 message stock after the treatment event within 24 hours. The treatment event is the first message that an investor receives on a given stock. *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Panel A: Prior contact with message stock

	(1)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	Trade & research	Trade & no research	Research & no trade	No trade & no research
treat	−0.0412	−0.0294	−0.0004	−0.0005
	(−3.23)	(−3.06)	(−0.05)	(−0.10)
post	−0.0396	0.0013	0.0376	0.0489
	(−1.83)	(0.07)	(1.67)	(3.92)
treat × post	0.1158	0.1116	0.1432	0.1410
	(3.37)	(3.31)	(3.47)	(4.87)
Investor fixed effects	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Obs.	238,689	493,415	199,338	562,847
Adj. R^2	0.67	0.65	0.63	0.61

Panel B: Prior gains or losses in message stock

	(1)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	Realized gains	Realized losses	Paper gains	Paper losses
treat	−0.0231	−0.0162	−0.0379	−0.0237
	(−2.11)	(−1.37)	(−2.53)	(−1.43)
post	−0.0225	0.0036	−0.0040	−0.0298
	(−1.17)	(0.14)	(−0.16)	(−1.03)
treat × post	0.0781	0.1414	0.0229	0.1498
	(2.07)	(3.09)	(0.49)	(2.82)
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 8: Attention triggers and leverage usage: Regression results conditioning on stock characteristics

This table reports the results from a difference-in-differences regression analysis on investors' leverage usage conditioned on the characteristics of the stocks. The results are computed separately for stocks with low and high values of the conditioning variables (median split). The conditioning variables used are firm size, computed as the log of the market price multiplied by the number of shares outstanding; analyst coverage, the log of the number of analysts covering the stock; news coverage, the number of news items from Quandl; stock volume, the average trading volume of the stock; turnover, computed as the stock's volume divided by the shares outstanding; and volatility, computed as the GARCH(1,1) volatility of 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 message stock after the treatment event within 24 hours. The treatment event is the first message that an investor receives on a given stock. *treat* is a dummy variable that takes a value of one for investors in the treatment group and zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Sample split	Firm size		Analyst coverage		News coverage		Trading volume		Turnover		Volatility	
	Small	Large	Low	High	Low	High	Low	High	Low	High	Low	High
treat	−0.0142	−0.0075	−0.0157	−0.0054	0.0014	−0.0115	0.0043	−0.0153	−0.0064	−0.0190	−0.0002	−0.0184
	(−2.16)	(−0.73)	(−1.57)	(−0.77)	(0.15)	(−1.17)	(0.69)	(−1.69)	(−0.61)	(−1.93)	(−0.02)	(−2.40)
post	0.0176	−0.0194	0.0042	0.0145	0.0548	−0.0106	0.0395	−0.0073	0.0157	0.0010	−0.0021	−0.0047
	(1.42)	(−0.89)	(0.24)	(1.12)	(2.86)	(−0.63)	(2.85)	(−0.41)	(0.66)	(0.07)	(−0.08)	(−0.31)
treat × post	0.1936	0.1959	0.1780	0.2146	0.1178	0.2007	0.1658	0.1979	0.1262	0.2286	0.1521	0.1964
	(6.18)	(5.03)	(5.15)	(6.94)	(2.79)	(6.03)	(4.95)	(5.91)	(3.75)	(6.17)	(3.42)	(7.60)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	560,511	690,191	770,137	505,022	171,602	929,610	343,546	1,017,510	392,273	667,750	369,322	987,785
Adj. R^2	0.69	0.61	0.62	0.70	0.71	0.60	0.68	0.61	0.65	0.63	0.65	0.64

Table 9: 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. Panel B considers all executed trades that open or close a position. In Panel A, trading intensity is the average number of daily trades in the message stock over the last seven days before (observation period) and in the first 24 hours after investors receive a push message on the specific stock for the first time (treatment period). We obtain our control group by randomly drawing investors from all active investors who do not receive a given push message ("comparable investors"). In Panel B, 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. We obtain our control group from the trades of all investors in the database who do not receive a message on the message stock during the observation and treatment periods and did not receive a push message on the message stock earlier and conduct a trade in both the observation and the treatment period. *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Panel A: Trading intensity				
	(1)	(2)	(3)	(4)
Dependent var.	trading intensity	trading intensity	trading intensity	trading intensity
Sample	Messages stocks		Non-message stocks	
Position	long positions	short positions	long positions	short positions
treat	0.0136	0.0109	0.0435	0.0359
	(7.98)	(8.95)	(7.05)	(6.48)
post	0.0038	0.0053	−0.0096	−0.0097
	(2.71)	(3.67)	(−2.24)	(−1.81)
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)
Dependent var.	risk exposure
treat	−0.4813
	(−4.31)
post	3.9256
	(7.95)
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 10: Stock-specific research after receiving message

This table reports results from a difference-in-differences regression analysis on research at the stock level of investors around the treatment date. Column (1) reports research for all push messages; Column (2) [(3)] reports research only after positive (negative) push messages; Column (4) is restricted to investors who hold the message stock in their portfolio at the time of the message; Column (5) is restricted to investors who do not hold the message stock in their portfolio at the time of the message; and Column (6) is restricted to investors who never research the message stock prior to the time of the message. For each investor, we take the average of daily research over the last seven days before the treatment event and the research within the first 24 hours after the treatment event. The treatment event is the first message that an investor receives for a given stock. *Research* is the number of daily visits of a website that contains stock-specific information for a given stock. *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var.	Research	Research	Research	Research	Research	Research
Sample	All push messages	Positive messages	Negative messages	Holding stock	Not holding stock	No prior research
treat	0.0219	0.0186	0.0287	−0.0757	0.0127	−0.0001
	(4.77)	(3.68)	(4.55)	(−1.56)	(4.57)	(−0.20)
post	0.0147	0.0175	0.0101	0.4152	0.0108	0.0031
	(4.09)	(3.83)	(2.56)	(5.32)	(4.46)	(4.10)
treat × post	0.0598	0.0631	0.0518	0.3421	0.0462	0.0226
	(5.60)	(5.03)	(4.70)	(4.70)	(6.02)	(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	466,746	29,297,604	27,710,234
Adj. R^2	0.10	0.11	0.12	0.42	0.05	0.02

Table 11: Attention triggers and performance

This table reports results on the performance implications of the attention triggers in our sample. The table reports panel regression results on the relation between attention triggers and trading performance using Equation (3). *Holding period return* denotes the holding period return on a given trade; *Sharpe ratio* denotes the Sharpe ratio on a given trade; $Risk - adjusted\ return$ denotes the risk-adjusted return on a given trade, adjusted for the respective market return; *attention trade* is a dummy variable that takes a value of one for all trades by push message recipients in the message stock within 24 hours after receiving the message, zero otherwise; *Holding period* denotes the holding period in hours; and *Short sale* is a dummy variable that takes a value of one for short positions, zero otherwise. We report Sharpe ratios and risk-adjusted returns omitting intraday trades. Standard errors are clustered at the user and at the instrument level and over time to address the fact that returns to individual stocks during overlapping periods are not independent and to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016,s and March 31, 2018.

Panel A: Panel regression results with stock fixed effects			
Dependent var.	(1) Holding period return	(2) Sharpe ratio	(3) Risk-adjusted return
Attention trade	−0.0277	−0.0069	−0.7566
	(−0.05)	(−0.45)	(−0.69)
log(Holding period)	0.7366	−0.0246	1.5341
	(3.27)	(−3.24)	(2.67)
Short sale	−2.5631	−0.0887	−5.8750
	(4.62)	(4.19)	(5.65)
Investor fixed effects	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Obs.	3,495,629	2,202,901	2,202,901
Adj. R^2	0.09	0.12	0.11

Panel B: Panel regression results without stock fixed effects			
Dependent var.	(1) Holding period return	(2) Sharpe ratio	(3) Risk-adjusted return
Attention trade	−0.8451	−0.0221	−1.7511
	(−1.44)	(−1.42)	(−1.58)
log(Holding period)	0.7488	−0.0235	1.5048
	(3.39)	(−3.08)	(2.63)
Short sale	−2.8456	−0.0921	−6.3974
	(5.11)	(4.38)	(6.53)
Investor fixed effects	Yes	Yes	Yes
Stock fixed effects	No	No	No
Time fixed effects	Yes	Yes	Yes
Obs.	3,495,629	2,202,901	2,202,901
Adj. R^2	0.08	0.11	0.09

Table 12: Push message clicks

This table reports additional results from difference-in-differences regression analyses on the leverage of trades that exploit information about whether investors click on a push message. Column (1) 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 it are omitted from the analysis. Column (2) is additionally restricted to investors who do not research the message stock between receiving the push message and trading. Column (3) is additionally restricted to investors who research the message stock between receiving the push message and trading. In Column (4), different 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. 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 message stock after the treatment event within 24 hours. The treatment event is the first message that an investor receives on a given stock. *Leverage* denotes the leverage employed for a trade; *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise; *click* is a dummy variable that takes a value of one for investors who click on the push message, zero otherwise; and *immediate research* is a dummy variable that takes a value of one if investors visit the research page of the message stock after receiving the message and before conducting the attention trade, zero otherwise. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license and contain all trades on the platform between January 1, 2016, and March 31, 2018.

	(1)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	Click	Click & no research	Click & research	Control click
treat	−0.0096	−0.0158	−0.0314	−0.0115
	(−1.37)	(−2.29)	(−0.63)	(−1.51)
post	0.0001	−0.0025	−0.1787	−0.0110
	(0.00)	(−0.17)	(−5.58)	(−0.56)
treat × post	0.1555	0.1617	0.1629	0.1996
	(5.31)	(4.85)	(3.05)	(7.18)
Investor fixed effects	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Obs.	1,241,433	1,156,210	96,704	888,008
Adj. R^2	0.62	0.62	0.66	0.61

Table 13: 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. Panel A distinguishes positive and negative messages for long- and short-sale positions; Panel B distinguishes strong and weak messages (tercile split). Earnings report date 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 message stock after the treatment event within 24 hours. The treatment event is the first message that an investor receives on a given stock. *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Panel A: Positive and negative messages				
	(1)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	Negative message	Negative message	Positive message	Positive message
Position	Long	Short	Long	Short
treat	−0.0379	−0.0180	−0.0417	0.0859
	(−2.17)	(−0.44)	(−2.06)	(1.96)
post	−0.0260	0.0177	0.0285	0.1438
	(−1.37)	(0.42)	(1.30)	(2.98)
treat × post	0.1553	0.2293	0.1801	0.0630
	(4.99)	(3.11)	(4.73)	(0.89)
Obs.	276,273	30,113	281,476	35,422
Adj. R^2	0.65	0.75	0.62	0.71
Panel B: Strong and weak messages				
	(1)	(2)	(3)	
Dependent var.	Leverage	Leverage	Leverage	
Message strength	Lower tercile	Medium tercile	Upper tercile	
treat	−0.0124	0.0236	−0.0635	
	(−0.46)	(1.72)	(−2.14)	
post	−0.0004	0.0101	0.0623	
	(−0.01)	(0.45)	(2.17)	
treat × post	0.1333	0.1362	0.1972	
	(3.30)	(3.82)	(4.34)	
Obs.	208, 249	502, 723	197, 007	
Adj. R^2	0.62	0.62	0.64	
All panels:				
Investor fixed effects	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes

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. In the *no earnings report dates* model, we omit all messages that report the dates of the 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 leverage with the residual from the first-stage regression (4). The *abnormal turnover* model includes the full sample. 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 message stock after the treatment event within 24 hours. The treatment event is the first message that an investor receives on a given stock. *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, and zero otherwise; and *Abn. turnover* denotes the volume turnover in the underlying stock on day t divided by the average volume turnover in that stock over the last six months. 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

	(1)	(2)	(3)	(4)
Dependent var.	Leverage	Leverage	Leverage	Leverage
Sample	No earnings report dates	No news trading	Filtered trading	Abnormal turnover
treat	−0.0147	−0.0208	−0.0135	−0.0167
	(−1.76)	(−2.52)	(−1.68)	(−1.95)
post	0.0315	0.0015	−0.0351	−0.0335
	(2.99)	(0.09)	(−2.24)	(−1.29)
treat × post	0.1917	0.1662	0.1458	0.1699
	(7.62)	(5.56)	(5.20)	(4.46)
Abn. turnover				0.0187
				(3.45)
treat × Abn. turnover				0.0034
				(1.38)
post × Abn. turnover				0.0046
				(0.76)
treat × post × Abn. turnover				−0.0010
				(−0.11)
Investor fixed effects	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Obs.	1,025,676	436,258	1,086,213	1,214,652
Adj. R^2	0.62	0.68	0.59	0.60

Table 15: Attention triggers and risk-taking for foreign exchange trades

This table reports results on our analysis on CFDs on foreign exchange (FX). Panel A reports summary statistics of investors' leverage usage. "Attention trades" are all trades by push message recipients in the message FX within 24 hours after receiving the message. "Non-attention trades" are all other trades. The t-test reports results from an equality test of non-treated versus treated trades, clustered over time. Panel B reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate in our trade data. We estimate Equation (1). Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity and serial correlation. 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 within 24 hours after the treatment event. We only consider the leverage of the first trade in the message FX after the treatment event. The treatment event is the first message that an investor receives on a given foreign exchange rate. *Leverage* denotes the leverage employed for a trade. *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise. 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Panel A: Summary statistics by attention trade	
Non-attention trade	138.45
Attention trade	165.38
t-test	2.98
Panel B: Difference-in-differences analysis	
Dependent var.	Leverage
treat	−0.0256
	(−0.07)
post	−1.2506
	(−0.69)
treat × post	6.3747
	(2.12)
Investor fixed effects	Yes
FX fixed effects	Yes
Time fixed effects	Yes
Obs.	3,092,440
Adj. R^2	0.68

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 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 trades per investor-week; *Short trades/week* denotes the average number of short trades 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; *Profit* denotes the percentage return on investment on a closed position; *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* is measured with a standard GARCH(1,1) model; *Beta* is measured with rolling window regressions over the last 262 days (one year); and *IVOL* (idiosyncratic volatility) is measured with rolling window regressions over the last 262 days (one year).

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	3,519,110	6.108	3.219	5	5	10
Position size	3,519,110	12.818	18.883	1.890	5.900	14.650
Holding period	3,495,629	309.891	677.780	5.435	71.530	265.178
Profit	3,495,629	0.866	26.754	−4.316	1.500	9.740
News event	3,519,110	0.721	0.448	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: Difference-in-differences analysis: Placebo events

This table reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate in our trade data. We estimate Equation (1). For each investor, we take the leverage of the last trade within seven days before the placebo treatment event and the leverage of the first trade in the message stock within 24 hours after the placebo treatment event. For Panels A to C, placebo treatment events are 24 (48 / 72) hours before the actual treatment event. For Panel D, we randomly generate 10,000 treatment events and assign these placebo events to investors in our treatment group. *Leverage* denotes the leverage employed for a trade; *treat* is a dummy variable that takes a value of one for investors in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Dependent var. Sample	Leverage 24 hours	Leverage 48 hours	Leverage 72 hours	Leverage random
treat	−0.0142	−0.0202	−0.0157	−0.0000
	(−1.86)	(−2.79)	(−2.25)	(−0.01)
post	−0.0688	−0.0302	0.0191	0.0277
	(−1.87)	(−0.57)	(0.58)	(0.71)
treat × post	−0.0215	−0.0083	0.0057	−0.0538
	(−0.51)	(−0.14)	(0.12)	(−1.13)
Investor fixed effects	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Obs.	343,138	278,493	263,774	386,653
Adj. R^2	0.65	0.66	0.67	0.61

Table A.4: Message-sending behavior for push messages (Panel A)

This table reports details on the broker's message-sending behavior. Panel A reports average measures of stock risk aggregated by stock-month. Panel B reports average investor (trading) characteristics. Non-message months denote months without a push message for a given stock; message months denote months 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; *research pages* denotes the number of times that the investor visits a stock research pages during the week before the given push message; *research stock* denotes the number of times that the investor visits the message stock research page during the week before the given push message; *prior push* denotes the number of push messages sent to the investor before the given push message; *prior click* denotes the number of prior push messages on which the investor clicked; *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; *age*25 is a dummy variable that takes a value of one if the investor is between 25 and 34 years of age, zero otherwise; *age*35 is a dummy variable that takes a value of one if the investor is between 35 and 44 years of age, zero otherwise; *age*45 is a dummy variable that takes a value of one if the investor is between 45 and 54 years of age, zero otherwise; *age*55 is a dummy variable that takes a value of one if the investor is between 55 and 64 years of age, zero otherwise; and *age*65 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 contain 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

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
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 push	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 A.5: 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 message stock after the treatment event. The treatment event is the first message that 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 in the treatment group, zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, zero otherwise; and *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 prior to the treatment date of the treated investor ("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 (counterfactual) treatment time and their average usage of leverage within 180 days prior to the (counterfactual) treatment time. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroskedasticity 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 contain all trades on the platform between January 1, 2016, and March 31, 2018.

Panel A: Difference-in-differences analysis	
Dependent var.	Leverage
treat	0.0037
	(0.17)
post	−0.0393
	(−1.93)
treat × post	0.1227
	(4.63)
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	
Dependent var.	Leverage
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