TAXATION, ACCOUNTING, AND FINANCE
TAF WORKING PAPER

No. 55 / May 2020

Arnold, Marc / Pelster, Matthias /
Subrahmanyam, Marti G.

Attention Triggers and Investors' Risk-Taking

Paderborn University
www.taf-wps.cetar.org

Attention Triggers and Investors' Risk-Taking*

Marc Arnold † Matthias Pelster ‡ Marti G. Subrahmanyam §

May 28, 2020

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 compared to 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: G10, G11, G12.

*Data were obtained under a non-disclosure agreement with a financial institution. We thank our data provider for use and explanations of their data. We thank Bernd Braun, Sarah Herwald, Marco Kerkemeier, Marcel Lengacher, and Jake Carpenter for outstanding research support. We are grateful for helpful comments and suggestions from Yakov Amihud, Emanuele Bajo, Fabian Brunner, Maria Céu Cortez, Maik Dierkes, Anastassia Fedyk, Sascha Füllbrunn, Antonio Gargano, Thomas Gehrig, Michael Haliassos, Ryan Israelsen, Kose John, Petri Jylhä, Alastair Lawrence, Albert Menkveld, Roxana Mihet, Urvi Neelakantan, Samuel Ouzan, Andreas Pfingsten, Tarun Ramadorai, Hendrik Schmitz, Mark Seasholes, Daniel Schmidt, Wendelin Schnedler, Sebastian Schrön, Duane Seppi, Sönke Sievers, Antonios Siganos, Oscar A. Stolper, Utz Weitzel, Stefan Zeisberger, participants of the European Retail Investment Conference (ERIC) 2019, the Fourth CEPR European Workshop on Household Finance, the Conference on the Future of Financial Information (FFI), the 9th International Conference of the Financial Engineering and Banking Society (FEBS), the 2019 Behavioural Finance Working Group Conference, the 81. Jahrestagung des Verbands der Hochschullehrer für Betriebswirtschaft (VHB), the European Financial Management Association 2019 Annual Meetings, the 2019 Annual Meeting of Academy of Behavioral Finance & Economics, the American Economic Association 2020 Annual Meeting, and seminar participants at New York University, Nijmegen University, Paderborn University, St. Gallen University, Tinbergen Institute, Potsdam University, the HVB seminar in Siegen, and the OR AG FIFI Workshop 2019. Matthias Pelster gratefully acknowledges the warm hospitality of the NYU Stern School of Business during his visits. Matthias Pelster gratefully acknowledges generous financial support from the Fritz Thyssen Stiftung (grant number 50.19.0.020WW). Marti Subrahmanyam acknowledges generous financial support from the NYU Center for Global Economy and Business, the Volkswagen Foundation, and the Anneliese Maier Research Award of the Alexander von Humboldt Foundation. Any errors, misrepresentations, and omissions are our own.

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

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

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

1 Introduction

Today's digital environment overwhelms investors with attention stimuli from manifold sources such as advertising, emails, social media messages, and push notifications. Such stimuli are intended to attract investors' attention. Whereas the finance literature recognizes the importance of attention for individual investor behavior and financial markets (Barber and Odean, 2008; Gargano and Rossi, 2018), the influence of attention triggers on a key investment dimension, 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 a growing theoretical recognition that investor attention behavior has key implications for asset prices (Chien et al., 2012; Andrei and Hasler, 2014). Third, psychology research offers an intuitive link between attention and risk-taking by concluding that affective attention triggers play an important role in individuals' risk-taking (Figner et al., 2009; Weber, 2010). The main challenge for researchers to analyze 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 that 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 trading 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. The majority of CFD trading activity is caused by retail investors (Stafford and Murphy, 2018). CFD trading represents a substantial fraction of the overall trading activity in Europe and Asia. In the UK, for example, the value of transactions was estimated to be approximately 35% of the value of the London Stock Exchange equity transactions in 2007 (Financial Services Authority, 2007). In Germany, the CFD trading volume in 2018 was approximately equal to the total transaction volume of the Deutsche Börse AG (CFD Verband e.V.). In light of the intense discussion on the cause 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 on such a large market is important.

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 of 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 in 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 of paying attention typically capture endogenous attention as the investors determine the extent to which they deal with a matter. In contrast, the push messages are initiated by the broker and, thus, capture 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 to select 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 on which the broker sends a push message. This endogeneity concern would arise, for example, for the volatility or beta of a stock, which are inevitably determined by the stock selection itself.

Third, our data contain both the trading records of investors who obtain a push message (treated investors) and those of investors who do not obtain this attention trigger (counterfactual investors). We label the trades that a treated investor executes in a stock within 24 hours after she receives a push message referring to that stock as "attention trades." Importantly, the broker only sends messages to a small subset of investors on each event, which allows us to compare the risk-taking for attention trades to that of the counterfactual investors in the same stock at the same time. This comparison reveals the marginal impact of the attention trigger on individual risk-taking in a standard difference-in-differences (DID) approach. The established attention measures of the literature such as the aggregate attention proxies in Barber et al. (2009) or the individual account logins in Sicherman et al. (2015) do not allow us to observe the risk-taking of counterfactual trades that we need in order 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 points 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 for individual risk-taking (Figner and Weber, 2011; Weber, 2010).

Various stimuli can influence affective processes that influence human behavior rapidly, spontaneously, and automatically (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 toward potentially high-priority concerns (Loewenstein et al., 2001). In line with this concept, we find that the median time span between the sending of a push message and an attention trade is only 1.35 hours. Thus, the investors' median reaction time is very short, particularly because 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 particularly male, younger, and less experienced investors increase their risk-taking after receiving an attention stimulus. 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 randomly to investors 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 offers the opportunity to address this concern in a difference-in-difference-in-differences (DDD) setting. Specifically, we can explore the lack of congruence between the investors' status of being a message-receiver or non-receiver and the investors' stock trades. Each push message refers to only one stock (message-stock), whereas message-receivers can trade many stocks that are not referred to in the message. Similarly, non-receivers also trade the stock referred to in the message to the receivers. The first difference in the DDD setting, i.e., the difference in risk-taking between receivers and non-receivers for all trades to which the message does not refer, controls for the possibility that receivers generally change their risk-taking compared to non-receivers around the treatment. The second difference, i.e., the difference in risk-taking between message and non-message-stocks for all trades of non-receivers, controls for the possibility that message-stocks are generally traded with a higher leverage compared to 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 receivers differs from that of non-receivers and (ii) how the general risk-taking for message-stocks differs from that of non-message-stocks. This approach alleviates concerns that the broker may send messages to investors or on stocks, for which she correctly anticipates an increase in risk-taking. Importantly, our DDD addresses this caveat without the need to define the channels behind this anticipation. The DDD-setting supports our conjecture 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 the investor-stock specific information to which the broker has access in three additional tests. First, the broker may observe a certain risk-taking pattern for specific investors in specific stocks after large stock price 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 sub-period 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 sub-period. 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 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 induce 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. 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 to our results. The final section concludes.

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 decision.

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., 2019; Ungeheuer, 2018). Recent work examines individual investor attention by deriving proxies of how investors pay attention at the individual level from their online account logins or web browsing behavior on the brokerage account. This literature provides profound insights on 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). Whereas the attention literature discusses important macroeconomic and microeconomic implications of attention, it does not link attention to risk-taking. We contribute by establishing this link at the micro-level.

[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 (2018); Huang et al. (2019); Fedyk (2019); Kumar et al. (2019).

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

We derive our hypotheses from the experimental psychology, neurobiology, and neuroscience literatures on decision-making and risk-taking in everyday situations. The experimental psychology literature distinguishes between endogenous and exogenous attention.

Endogenous attention refers to the willingness or the process to deliberately deal with a matter. Exogenous attention refers to the process in 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). Specifically, these stimuli can trigger affective processes, which interrupt and redirect the slower cognitive processes, thereby inducing rapid and spontaneous reactions (Loewenstein et al., 2001; Weber et al., 2004; Galvan et al., 2006). Thus, exogenous attention can be conceptualized as an interruption of endogenous attention (Carretié, 2014). The literature highlights an important link between attention stimuli and risk-taking 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 stimuli may also lead to increased risk-taking in the financial domain. Thus, our first hypothesis is:

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 compared to 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 towards 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 compared to familiar stimuli. In the context of risk-taking, Mitchell et al. (2016) conclude that exposure to novel stimuli leads to more risk-taking compared to 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 larger trading volume, induce investors to conduct more research on a stock, i.e., attract more endogenous investor attention. Intuitively, we expect that stimuli on stocks with such characteristics have a stronger impact on risk-taking compared to stimuli on 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 main 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 contracts for difference (CFD) on a large set of blue chip stocks, foreign exchange rates, and cryptocurrencies. We focus on stocks in this paper. CFDs are financial contracts between investors and a financial firm that replicate the performance of the underlying asset. Appendix A provides a brief introduction to CFDs. The broker allows investors to flexibly select a leverage from one to ten for each individual trade. 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. Transaction 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 time-stamp 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 which 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^{th} 2017, the broker started to send standardized push messages to the investors. Our data contains detailed information on the push messages that are sent during the sample period. Specifically, for each push message we observe the category, the entire content, the time-stamp when the message was sent, and an indicator for whether an investor clicked on the message. There are three categories of push messages: 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 the earnings announcement. This date is already publicly accessible from a company's web page before a push message. A typical message reads "*$AFSI shares down over -5.2%.*" or "*$HRI shares up over 5.0%*". Thus, we observe the underlying and the reported price change of the price change and streak messages. The messages only contain publicly available information and, thus, do not reveal new information. This feature assists us to isolate 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 the 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 the investors' self-reported previous trading experience measured in predefined categories (i.e. "none", "less than one year", etc.) 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 analyses 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 Variables

We apply 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, which an investor executes in a 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. *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 the 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 characteristics 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, etc. 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* is 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 time-stamp at which an investor receives a push message and executes an attention trade.

In addition, we use the time-stamp 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 a day, 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.

4.3 Methodology

The empirical challenge to 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 case that an investor's attention had not been triggered. Our data offer the opportunity to overcome this challenge in a standard difference-in-differences setting. Specifically, it allows 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. To this end, we apply three main steps.

First, for each investor-stock pair, we identify the time-stamp of the first push message that the broker sends to the investor on that stock (treatment time). We only use this first push message to mitigate the potential confounding effects of previous messages on an investor's risk-taking in that stock. In addition, this approach eliminates the concern that the broker could observe the reaction of the investor to a push message on a specific stock and send subsequent messages according to that reaction. Using the time-stamp, we consider the last trade of treated investors in any stock within seven days (one day in an alternative specification) prior to the treatment time (observation period). 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 push 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 the investors' trading decision for approximately 24 hours, as shown by the distinct spike in a message-stock's trading activity after an attention stimulus (see Figure 1). Second, measuring trading patterns over one attention day is standard in the attention literature (Barber and Odean, 2008; Peress and Schmidt, 2018). Third, Frijda et al. (1991) suggest that affective phenomena typically last from several seconds to several hours.

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 these two differences. Formally, we estimate the following

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

where Leverage_{ijt} denotes the leverage of investor i, in stock j, at time t; K is the number of investors; L is the number of stocks; M is the number of time periods in our data; *treat* is a dummy variable that takes a value of one for investors of 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, their investment amount with the broker, their domicile, or their 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.

5 Summary statistics

We first discuss the demographic characteristics of the investors in our sample. Most investors are males and 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 novice investors and experienced traders. Approximately half of the investors in our dataset had previous stock trading experience when they opened their account with the broker (not tabulated).

Next, we describe the push messages in our data. 99.1% of the investors in our sample 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 of the push messages in our sample. Panel A summarizes the different events about which the broker sends push messages. We dissect price changes and streaks into "positive" messages that report a stock price increase and "negative" messages that report a stock price decline. In total, there are 9,969 events about which the broker sends a message to investors. Price changes are the most frequent events. The minimum of the positive price changes and the maximum of the negative price changes 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 portion 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.[3]

— Place Table 1 about here —

Figure 1 plots the distribution of the trading activity around push messages. It shows a distinct spike in the first five hours after the broker sends a message, which suggests that the messages stimulate attention trades. Specifically, this trading activity in the message-stock is approximately four times larger compared to the regular activity. We also observe a small increase in attention trades immediately prior to a push message. This increase, however, is negligible compared to that in the first five hours after a message.

— Place Figure 1 about here —

Table 2 shows that attention trades feature, on average, an 8% higher leverage compared to 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 —

6 Implications of attention triggers on risk-taking

We now investigate the impact of attention triggers on individual risk-taking by applying our difference-in-differences (DID) approach.

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

6.1 Difference-in-differences analysis

We first apply Equation (1) of our DID-approach in Section 4.3 to the investors' leverage. We consider both long and short trades. Panel A of Table 3 summarizes the results.

— Place Table 3 about here —

Our main specification in Panel A shows that push messages induce investors to trade the message-stock at a higher leverage compared to investors who trade the same stock but do not receive a push message. The treatment coefficient 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 push message stimuli that contain no fundamental news, this economic magnitude is remarkable. In comparison, Andersen et al. (2019) report that an incisive experience, namely the personal loss from the default of bank stocks in the aftermath of the Global Financial Crisis, leads to an average reduction of an investor's risky asset share of 37.5% of the average within variation of this share.

We provide a more granular view on the impact of attention triggers on risk-taking in Figure 2. This figure plots the evolution of the average leverage in the message-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.[4] This pattern is consistent with the notion of psychology studies that attention triggers stimulate quick affective reactions that involves higher risk (e.g., Figner et al., 2009; Casey et al., 2008).

— Place Figure 2 about here —

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

We address the concern that our results are driven by a trend in the treated investors' risk-taking before the treatment in two ways. First, we repeat our analysis in Panel B of Table 3 by only considering the trades within 24 hours before the treatment in our observation period. The treatment coefficient is even larger compared to our main analysis. Second, we investigate the parallel trend assumption in Figure 3 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.[5]

— Place Figure 3 about here —

Panel C of Table 3 shows the result when we only incorporate the trades in the message-stock during the observation period before the treatment time instead of the trades in any stock. 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 compared to Panel A.[6]

Overall, Table 3 implies that attention triggers stimulate risk-taking, which supports our main Hypothesis 1.

6.2 Difference-in-difference-in-differences analysis

The broker may not send the messages randomly to investors. Thus, the main concern with our DID-analysis is that the broker's message-sending behavior could bias our conjecture. For example, the broker may anticipate a change in the risk-taking of certain investors or in the risk-taking for certain stocks, and send the messages according to this

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

[6] The stock fixed effects in our main test already capture that some stocks may be traded with a higher leverage than others. The difference between the fixed effects and the specification in Panel C is that the former control for a stock's average leverage, whereas the latter controls for the last trade's leverage.

anticipation. It is difficult to identify all of the potential channels through which the broker's message-sending behavior could affect our conjecture. We analyze the message-sending behavior in detail in Section B of the Appendix. Importantly, 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 congruence of the investors' status of being a message-receiver or non-receiver and the stocks that they trade. For example, a message only refers to the message-stock and receivers often trade non-message-stocks. Similarly, non-receivers also trade the message-stock. This lack of congruence allows us to explore the following difference-in-difference-in-differences (DDD) analysis in the spirit of Gruber (1994) and Puri et al. (2011):

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

The coefficient β_5 captures the general change in the message-receivers' risk-taking around the treatment compared to that of non-receivers 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-receivers. Consequently, it controls for the possibility that the broker sends messages on stocks that feature a change in leverage around the treatment due to reasons other than the attention trigger.[7] Our coefficient of interest, β_7, then captures the impact of the attention trigger on leverage, net of how the risk-taking of receivers differs from that of non-receivers and the risk-taking for message-stocks differs from that of 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

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

the structure of our data, we do not need to characterize the potential channels through which the broker's message-sending behavior along the dimensions "receiver selection" or "message-stock selection" could bias our results. Instead, the DDD directly controls for any difference along these dimensions around the treatment event.

Panel D of Table 3 shows the coefficient of interest β_7 in the line treat $\times$ post $\times$ stock. This coefficient suggests 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 dimensions receiver selection or message-stock selection. 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 cannot 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 moves. To mitigate the concern that the broker biases our results by sending messages according to this observation, we divide our data sample into two sub-periods. The "no-message sub-period" before February 27, 2017 comprises the period before the broker starts sending push messages, and the "message sub-period" comprises the period after this date during which the broker sends messages. We then compare the risk-taking of each treated investor after receiving a message in the message sub-period to that of the same investor in the same stock after a comparable stock price change during the no-message sub-period. We consider stock price changes of at least three percent as comparable for 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 result of this test in Table 4 supports our conjecture that attention triggers stimulate risk-taking.

— Place Table 4 about here —

Second, the broker collects information on investors' stock specific 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.3 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 only incorporating the investors who have not researched the message-stock prior to receiving a message. Our results are robust to this setting, as shown in Column (1) of Panel A of Table 5.

— Place Table 5 about here —

Third, 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.3 in the Appendix motivates this concern by showing that more receivers have traded the message-stock compared to non-receivers before the treatment. We, therefore, repeat our main test by only incorporating the investors who have never traded the message-stock before the treatment. In this test, the broker lacks information about the investors' past experience with the message-stock. Column (1) of Panel B in Table 5 shows that our result is robust to this setting.

We provide additional tests on the message-sending behavior concern in the Appendix. For example, the broker could observe how previous push messages on other stocks affect an investor's risk-taking and send the first message on a new stock according to this observation. Table A.3 in the Appendix motivates this concern by showing that, on average, receivers have both obtained and clicked on more messages than non-receivers prior to receiving a push message.[8] In principle, our main setting and the DDD already address this concern. Specifically, the broker lacks investor-stock specific information on how an investor reacts to a message at the treatment because we only incorporate the first message that the broker sends to an investor on a specific stock throughout our main analysis. Of course, the broker may still observe how a previous message on a different stock or a different asset class has affected an investor's risk-taking prior to the treatment. The coefficients β_5 and β_6 in our DDD-approach would, however, isolate this dimension of a message-sending behavior. To provide evidence beyond the DDD that the broker's observation of the investors' previous reaction to other messages does not bias our conjecture, we repeat our main analysis by only considering the first message to an investor on any stock, and the first message to an investor on any asset class (see Table A.4 in the Appendix). In both cases, our result on risk-taking is even (slightly) stronger than in our main specification.

Finally, we run a nearest-neighbor matching routine in our DID- and DDD-approaches. Specifically, we exploit the common support of treated and counterfactual investors on covariates (see Appendix B) and match the treated investors with counterfactual investors based on the Euclidean Distance with respect to standard controls for risk-taking, such as gender and age, overall trading intensity over the previous 180 days, and the investor's average leverage over the previous 180 days. The coefficients β_5 and β_6 in our DDD-approach already control for the concern that the broker may anticipate changes in risk-taking based on investor characteristics. Thus, the results of our matching approach in Table A.5 of the Appendix provide complementary evidence that differences in risk-taking due to diverging investor characteristics between receivers and non-receivers do not affect our conjecture.

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

[8]This table, however, also shows that non-receivers have traded on more messages compared to receivers prior to receiving a push message.

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 our 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 young, male investors compared to older, female investors. The average increases in risk-taking according to the point estimates of our regressions amount 19.9 percentage points for male investors and 7.3 percentage points (statistically not 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 amounts to 3.45 percentage points (p-value of <0.01), which supports Hypothesis 2b. This result complements the literature suggesting that more experienced investors conduct fewer behavioral errors and use more sophisticated trading tactics (Feng and Seasholes, 2005; Kaustia and Knüpfer, 2008; Kaustia et al., 2008).

7.2 The influence of investors' familiarity

Next, we analyze Hypothesis 2c. Intuitively, investors should be more familiar with stocks on which they have previous experience. We define investors to be familiar with a stock if they have previously traded or researched the stock. The results in Panel A of Table 7 indicate that attention stimuli on novel stocks have a similar impact on risk-taking compared to stimuli on familiar stocks (0.1347 vs. 0.1410, respectively).

— Place Table 7 about here —

One dimension of personal experience, which has received particular attention in the risk-taking literature, is the past return (Thaler and Johnson, 1990; Brockner, 1992; Weber and Camerer, 1998; Imas, 2016). This literature concludes that past realized or paper losses and gains influence risk-taking. Thus, we additionally investigate how the 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 compared to 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, statistically not 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).

Our results highlight an important interaction between the impact of personal experiences and attention stimuli on risk-taking. Specifically, risk-taking after a loss is more pronounced following attention triggers. Therefore, our results suggest that attention triggers serve as a catalyst through which personal experiences are transmitted 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), namely the number of analysts covering a stock, the total number of news events associated with a stock, a stock's trading volume, and a stock's turnover. In addition, we 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 tend to attract more attention. We report the results in Panels A-F of Table 8.[9]

While we do not observe a meaningful difference between the coefficients for the "small firm" and the "large firm"-sample (Panel A, 0.1936 vs. 0.1959), the differences between the coefficients in our other panels range from 3.3 percentage points (Panel D, stock volume) to 10.2 percentage points (Panel E, turnover), and are economically and statistically significant. Overall, the results indicate that attention triggers have a stronger impact on the 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.

[9] 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.

8 Additional results

In this section, we investigate the impact of attention triggers on other trading dimensions that can be interpreted as alternative measures of risk-taking. In addition, we link our study to the recent literature on individual investor attention.

8.1 Attention triggers and trading

We first study the impact of attention triggers on investors' individual trading intensity. To this end, we define the dependent variable *Trading intensity*, which denotes the number of trades that an investor executes in a certain stock on a given day. We then apply a variation 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 hours) window for the treatment period and a seven-day observation period before the treatment.[10] We also apply this DID-approach along several granular trading dimensions. Specifically, we differentiate between long and short trades, as well as message-stock and non-message-stocks trades.

Panel A of Table 9 summarizes the results on the impact of attention triggers on 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 the 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 stock is only 0.000153 (not tabulated).

— Place Table 9 about here —

[10] 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.

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 the 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 besides 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 ($\beta =$

3.74; t-statistic: 5.76) suggests that investors, on average, increase their message-stock risk exposure after an attention trigger.

Overall, the results of 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, 2018) by providing evidence of this link at the micro-level. 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 increase 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 4.3 by using *research* as the dependent variable, which is the number of an investor's 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 for themselves which pages they visit, the measure can be classified as an endogenous attention measure. We investigate how a message influences the 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 significantly increases compared to that of non-receivers.

— Place Table 10 about here —

In Columns (2) and (3), we separately investigate the 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 those investors who do not hold the stock. In addition, Column (6) shows that investors start conducting research after an attention trigger even if they have never 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 researches 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 on a certain stock's web page and her trade of that stock. We interpret this measure as a proxy of cognitive processing because an investor has more available research time 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 the push messages stimulate affective processing as they reduce the 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 of 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.

9 Robustness analyses

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

9.1 The investors' decision to neglect or block messages

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

In Panel A of Table 11, we repeat our main DID-analysis, but only consider those investors in the treatment group who actually click on the push message instead of all message-receivers. A click suggests that the message-receiver has most likely read the message. The counterfactual comprises the non-receivers as in our main analysis. The positive treatment coefficient suggests that our conjecture on risk-taking is robust to the critique that treated investors may not read the messages.

— Place Table 11 about here —

Next, 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. Thus, 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.[11] Panel B of Table 11 shows that our DID-result on risk-taking is robust to this alternative test. Therefore, self-selection of the 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 dates messages in this analysis, as their content is not positive or negative, and does not report a return. In Panel A of Table 12, 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 treatment coefficients in Columns (1) and (3) are similar to that 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. As the coefficient in Column (4), however, is not significant, contrarian traders do not seem to significantly increase risk-taking after positive messages.

[11] 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.

— Place Table 12 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 consider a message to be strong if the message's reported absolute price change is larger than the median, and weak otherwise. We separately study the impact of weak and strong messages in Panel B of Table 12. The treatment coefficients indicate that investors increase their risk-taking both after weak and strong messages. We observe a larger effect following strong messages, which we attribute to the higher salience of those messages.

The results in Table 12 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. Finally, they also address the caveat that the 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 higher uncertainty compared to positive jumps (Bollerslev and Todorov, 2011). Panel A of Table 12, however, shows that the increase in risk-taking is similar after messages that report a negative jump and those that report a positive jump. This pattern contradicts the notion that the resolution of uncertainty drives our inference.

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 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 stimulate risk-taking. As this remaining concern is not addressed by our DDD-approach, we repeat our main analysis with three alternative settings in Table 13.

— Place Table 13 about here —

First, we omit the earnings report dates messages in Column (1) of Table 13 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:

$$\text{Leverage}_{ijt} = \alpha + \beta \text{News volume}_{jt} + \gamma \text{Sentiment}^2_{jt} + \delta' \text{Controls}_{it} + \varepsilon_{ijt}, \quad (3)$$

where 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. Overall, Table 13 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.

10 Conclusion

This study presents novel evidence on the impact of exogenous attention triggers on risk-taking based on a unique dataset of trading records. The main advantage of this data is that we directly observe a trigger of individual investor attention and can link this trigger to the individuals' risk-taking. The data also contain the message-stock trading of the 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 activity 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 on the influence of attention triggers on different types of investors. As attention stimuli in general and individual attention stimuli in particular are omnipresent in today's digital environment, we believe that studying the impact of such stimuli on additional investment dimensions, such as financial performance or portfolio composition, could provide a fruitful avenue for future research.

References

Andersen, Steffen, Tobin Hanspal, and Kasper Meisner Nielsen, 2019, Once bitten, twice shy: The power of personal experiences in risk taking, *Journal of Financial Economics* 132, 97 – 117.

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

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2009, Just how much do individual investors lose by trading?, *The Review of Financial Studies* 22, 609–632.

Barber, Brad M., and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *The Quarterly Journal of Economics,* 116, 261–292.

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

Barberis, Nicholas, Ming Huang, and Tano Santos, 2001, Prospect theory and asset prices, *The Quarterly Journal of Economics* 116, 1–53.

Ben-David, Itzhak, Justin Birru, and Viktor Prokopenya, 2018, Uninformative feedback and risk taking: Evidence from retail forex trading, *Review of Finance* 22, 2009–2036.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen, 2017, It depends on where you search: Institutional investor attention and underreaction to news, *The Review of Financial Studies* 30, 3009–3047.

Beshears, John, James J. Choi, David Laibson, and Brigitte C. Madrian, 2016, Does aggregated returns disclosure increase portfolio risk taking?, *The Review of Financial Studies* 30, 1971–2005.

Bollerslev, Tim, and Viktor Todorov, 2011, Tails, fears and risk premia, *The Journal of Finance* 66, 2165–2211.

Brockner, Joel, 1992, The escalation of commitment to a failing course of action: Toward theoretical progress, *The Academy of Management Review* 17, 39–61.

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

Caplin, Andrew, and John Leahy, 2001, Psychological expected utility theory and anticipatory feelings, *The Quarterly Journal of Economics* 116, 55–79.

Carretié, Luis, 2014, Exogenous (automatic) attention to emotional stimuli: a review, *Cognitive, Affective, & Behavioral Neuroscience* 14, 1228–1258.

Casey, B. J., Sarah Getz, and Adriana Galvan, 2008, The adolescent brain, *Developmental Review* 28, 62–77.

Charness, Gary, and Uri Gneezy, 2012, Strong evidence for gender differences in risk taking, *Journal of Economic Behavior & Organization* 83, 50 – 58.

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

Chiang, Yao-Min, David Hirshleifer, Yiming Qian, and Ann E. Sherman, 2011, Do investors learn from experience? Evidence from frequent IPO investors, *Review of Financial Studies* 24, 1560–1589.

Chien, Yi Li, Harold Cole, and Hanno N. Lustig, 2012, Is the volatility of the market price of risk due to intermittent portfolio rebalancing?, *American Economic Review* 102, 2859–2896.

Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick, 2009, Reinforcement learning and savings behavior, *The Journal of Finance* 64, 2515–2534.

Cohn, Alain, Jan Engelmann, Ernst Fehr, and Michel André Maréchal, 2015, Evidence for countercyclical risk aversion: An experiment with financial professionals, *American Economic Review* 105, 860–85.

Corwin, Shane A., and Jay F. Coughenour, 2008, Limited attention and the allocation of effort in securities trading, *The Journal of Finance* 63, 3031–3067.

Coval, Joshua D., and Tyler Shumway, 2005, Do behavioral biases affect prices?, *The Journal of Finance* 60, 1–34.

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

Dellavigna, Stefano, and Joshua M. Pollet, 2009, Investor inattention and friday earnings announcements, *The Journal of Finance* 64, 709–749.

Dierick, Nicolas, Dries Heyman, Koen Inghelbrecht, and Hannes Stieperaere, 2019, Financial attention and the disposition effect, *Journal of Economic Behavior & Organization* 163, 190 – 217.

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

Fedyk, Anastassia, 2019, Front page news: The effect of news positioning on financial markets, *Working Paper* .

Feng, L., and M.S. Seasholes, 2005, Do investor sophistication and trading experience eliminate behavioral biases in financial markets?, *Review of Finance* 9, 305–351.

Figner, Bernd, Rachael J. Mackinlay, Friedrich Wilkening, and Elke U. Weber, 2009, Affective and deliberative processes in risky choice: Age differences in risk taking in the columbia card task, *Journal of Experimental Psychology: Learning, Memory, and Cognition* 35, 709–730.

Figner, Bernd, and Elke U. Weber, 2011, Who takes risks when and why?: Determinants of risk taking, *Current Directions in Psychological Science* 20, 211–216.

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

Focke, Florens, Stefan Ruenzi, and Michael Ungeheuer, 2019, Advertising, attention, and financial markets, *The Review of Fiancial Studies* in press.

Frijda, Nico H., Batja Mesquita, Joep Sonnemans, and Stephanie van Goozen, 1991, The duration of affective phenomena or emotions, sentiments and passions, in K.T. Strongman, ed., *International Review of Studies on Emotion*, volume 1 of *International Review of Studies on Emotion*, 187–225 (John Wiley & Sons, Chichester).

Galai, Dan, and Orly Sade, 2006, The "ostrich effect" and the relationship between the liquidity and the yields of financial assets, *The Journal of Business* 79, 2741–2759.

Galvan, Adrian, Todd A. Hare, Cindy E. Parra, Jackie Penn, Henning Voss, Gary Glover, and Casey B. J., 2006, Earlier development of the accumbens relative to orbitofrontal cortex might underlie risk-taking behavior in adolescents, *Journal of Neuroscience* 26, 430–445.

Gargano, Antonio, and Alberto G. Rossi, 2018, Does it pay to pay attention, *Review of Financial Studies* 31, 4595–4649.

Gervais, Simon, Ron Kaniel, and Dan Mingelgrin, 2001, The high-volume return premium, *The Journal of Finance* 56, 877–919.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2019, Five facts about beliefs and portfolios, *Working Paper* .

Gneezy, Uri, and Jan Potters, 1997, An experiment on risk taking and evaluation periods, *The Quarterly Journal of Economics* 112, 631–645.

Grinblatt, Mark, and Matti Keloharju, 2009, Sensation seeking, overconfidence, and trading activity, *The Journal of Finance* 64, 549–578.

Gruber, Jonathan, 1994, The incidence of mandated maternity benefits, *The American Economic Review* 84, 622–641.

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

Hahn, Sowon, Curt Carlson, Shawn Singer, and Scott D. Gronlund, 2006, Aging and visual search: Automatic and controlled attentional bias to threat faces, *Acta Psychologica* 123, 312 – 336.

Han, Bing, and Alok Kumar, 2013, Speculative retail trading and asset prices, *Journal of Financial and Quantitative Analysis* 48, 388–404.

Hasler, Michael, and Chayawat Ornthanalai, 2018, Fluctuating attention and financial contagion, *Journal of Monetary Economics* 99, 106 – 123.

He, Xin, J. Jeffrey Inman, and Vikas Mittal, 2008, Gender jeopardy in financial risk taking, *Journal of Marketing Research* 45, 414–424.

Heimer, Rawley Z., and Alp Simsek, 2019, Should retail investors' leverage be limited?, *Journal of Financial Economics* 132, 1–21.

Holt, Charles A., and Susan K. Laury, 2002, Risk aversion and incentive effects, *The American Economic Review* 92, 1644–1655.

Huang, Shiyang, Yulin Huang, and Tse-Chun Lin, 2019, Attention allocation and return co-movement: Evidence from repeated natural experiments, *Journal of Financial Economics* 132, 369 – 383.

Imas, Alex, 2016, The realization effect: Risk-taking after realized versus paper losses, *The American Economic Review* 106, 2086–2109.

Jarodzka, Halszka, Katharina Scheiter, Peter Gerjets, and Tamara van Gog, 2010, In the eyes of the beholder: How experts and novices interpret dynamic stimuli, *Learning and Instruction* 20, 146 – 154.

Johnston, William A., Kevin J. Hawley, and James M. Farnham, 1993, Novel popout: Empirical boundaries and tentative theory, *Journal of Experimental Psychology: Human Perception and Performance* 19, 140–153.

Johnston, William A., Kevin J. Hawley, Steven H. Plewe, John M. G. Elliott, and M. Jann DeWitt, 1990, Attention capture by novel stimuli, *Journal of Experimental Psychology: General* 119, 397–411.

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

Kaustia, Markku, Eeva Alho, and Vesa Puttonen, 2008, How much does expertise reduce behavioral biases? the case of anchoring effects in stock return estimates, *Financial Management* 37, 391–412.

Kaustia, Markku, and Samuli Knüpfer, 2008, Do investors overweight personal experience? evidence from IPO subscriptions, *The Journal of Finance* 63, 2679–2702.

Kaustia, Markku, and Samuli Knüpfer, 2012, Peer performance and stock market entry, *Journal of Financial Economics* 104, 321–338.

Knüpfer, Samuli, Elias Rantapuska, and Matti Sarvimäki, 2017, Formative experiences and portfolio choice: Evidence from the finnish great depression, *The Journal of Finance* 72, 133–166.

Köszegi, Botond, 2006, Emotional agency, *The Quarterly Journal of Economics* 121, 121–155.

Kuhnen, Camelia M., 2015, Asymmetric learning from financial information, *The Journal of Finance* 70, 2029–2062.

Kumar, A., 2009, Who gambles in the stock market, *The Journal of Finance* 64, 1889–1933.

Kumar, Alok, Stefan Ruenzi, and Michael Ungeheuer, 2019, Daily winners and losers, *Working Paper* .

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

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

Li, Xian, James A. Hendler, and John L. Teall, 2016, Investor attention on the social web, *Journal of Behavioral Finance* 17, 45–59.

Lian, Chen, Yueran Ma, and Carmen Wang, 2018, Low interest rates and risk-taking: Evidence from individual investment decisions, *The Review of Financial Studies* 32, 2107–2148.

Linnainmaa, Juhani T., 2003, The anatomy of day traders, *AFA 2004 Annual Meeting* .

Liu, Yu-Jane, Chih-Ling Tsai, Ming-Chun Wang, and Ning Zhu, 2010, Prior consequences and subsequent risk taking: New field evidence from the taiwan futures exchange, *Management Science* 56, 606–620.

Loewenstein, George, Elke Weber, Christopher Hsee, and Ned Welch, 2001, Risk as feelings, *Psychological Bulletin* 127, 267–286.

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

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *The Quarterly Journal of Economics* 126, 373–416.

Malmendier, Ulrike, Demian Pouzo, and Victoria Vanasco, 2020, Investor experiences and financial market dynamics, *Journal of Financial Economics* 136, 597 – 622.

Merritt, Paul, Elliot Hirshman, Whitney Wharton, Bethany Stangl, James Devlin, and Alan Lenz, 2007, Evidence for gender differences in visual selective attention, *Personality and Individual Differences* 43, 597 – 609.

Mitchell, Simon, Jennifer Gao, Mark Hallett, and Valerie Voon, 2016, The role of social novelty in risk seeking and exploratory behavior: Implications for addictions, *PLOS ONE* 11, 1–10.

Morin, Roger-A., and A. Fernandez Suarez, 1983, Risk aversion revisited, *The Journal of Finance* 38, 1201–1216.

Mulckhuyse, Manon, and Jan Theeuwes, 2010, Unconscious attentional orienting to exogenous cues: A review of the literature, *Acta Psychologica* 134, 299 – 309.

Odean, Terrance, 1998, Are investors reluctant to realize their losses?, *The Journal of Finance* 53, 1775–1798.

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

Olafsson, Arna, and Michaela Pagel, 2017, The ostrich in us: Selective attention to financial accounts, income, spending, and liquidity, *NBER Working Paper* 23945.

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

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

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

Powell, Melanie, and David Ansic, 1997, Gender differences in risk behaviour in financial decision-making: An experimental analysis, *Journal of Economic Psychology* 18, 605 – 628.

Puri, Manju, Joerg Rocholl, and Sascha Steffen, 2011, Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects, *Journal of Financial Economics* 100, 556 – 578.

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

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

Stafford, Philip, and Hannah Murphy, 2018, Booming cfd market faces reckoning as new eu rules come into force, *Financial Times* 08/01/2018.

Syrjänen, Elmeri, and Stefan Wiens, 2013, Gender moderates valence effects on the late positive potential to emotional distracters, *Neuroscience Letters* 551, 89 – 93.

Thaler, Richard H., and Eric J. Johnson, 1990, Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice, *Management Science* 36, 643–660.

Theeuwes, Jan, 1994a, Endogenous and exogenous control of visual selection, *Perception* 23, 429–440.

Theeuwes, Jan, 1994b, Stimulus-driven capture and attentional set: Selective search for color and visual abrupt onsets, *Journal of Experimental Psychology: Human Perception and Performance* 20, 799–806.

Theeuwes, Jan, 2010, Top-down and bottom-up control of visual selection, *Acta Psychologica* 135, 77 – 99.

Ungeheuer, Michael, 2018, Stock returns and the cross-section of investor attention, *Working Paper* .

Weber, Elke U., 2010, Risk attitude and preference, *Wiley Interdisciplinary Reviews: Cognitive Science* 1, 97–88.

Weber, Elke U., Sharoni Shafir, and Ann-Renee Blais, 2004, Predicting risk sensitivity in humans and lower animals: Risk as variance or coefficient of variation, *Psychological Review* 111, 430–445.

Weber, Martin, and Colin F. Camerer, 1998, The disposition effect in securities trading: An experimental analysis, *Journal of Economic Behavior & Organization* 33, 167–184.

Appendix

A Contracts for difference

A contract for difference (CFD) is a financial contract designed such that its price equals that of the underlying security.[12] In a CFD, the two counterparties agree to replicate the underlying security and settle the change in its price when the position closes. A CFD has no explicit maturity date. It can be closed out at any time at a price equal to the underlying price prevailing at the closing time. Common underlying securities for CFDs are stocks, indexes, currency pairs, and commodities. CFDs allow market participants to implement strategies involving short positions, and to achieve leverage. CFDs may be used to hedge existing positions and also offer tax benefits to investors (see, e.g., Brown et al., 2010).

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

B 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.3. On average, push message-stocks are more volatile than non-message-stocks. The beta and idiosyncratic risk of push message-stocks are also higher than those of non-message-stocks. Together, 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

[12] Brown et al. (2010) describe these contracts in more detail, and provide an empirical analysis on the pricing of CFDs and show that these instruments trade at a price close to that of the underlying security.

messages. As can be seen from Table 1, most messages are sent following large stock price movements.

— Place Table A.3 about here —

Next, we study the investor-dimension of the 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.3. We focus on various proxies for investors' trading and research activities, prior reaction to push 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 average leverage of 5.6 for non-message investors and 6.27 for message investors), the table also underlines the common support of the distributions of investors, who receive a push message at a given point in time, and those who do not. We observe a reasonable overlap between treated and control investors on all covariates. Note that, for each event, the broker sends push messages to approximately 1-2% of its customers. Thus, for every investor who receives a push message at a given point in time, another investor with very similar features can be found from the large number of investors who do not receive a push message at this given point in time. We exploit this overlap in our robustness analysis, where, amongst other tests, we employ a matching procedure between message receivers and non-receivers.

Figure 1: Trading activity around push messages

This figure presents the distribution of the trading activity of investors 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.

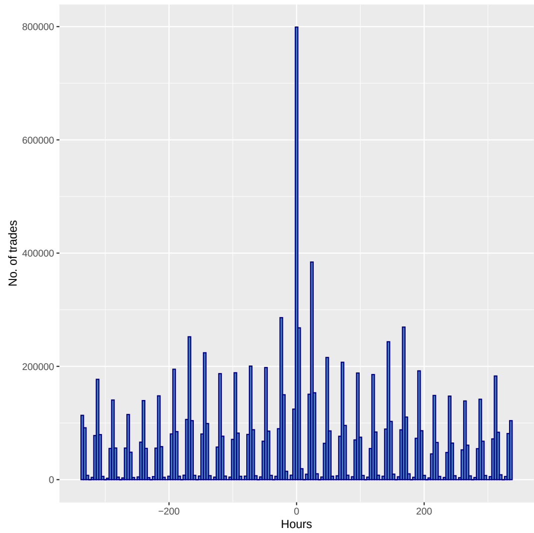

Figure 2: Risk-taking within 24 hours after a push message

This figure presents the average usage of leverage for investors in the message-stock immediately following the push message. The control group (red) comprises all investor-stock pairs where the investor did not receive a push message referring to the stock. For the treatment group, the investor receives a push message referring to a given stock at time zero, and executes an attention trade in message-stock within 24 hours after receiving the message. 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 occur in this interval. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

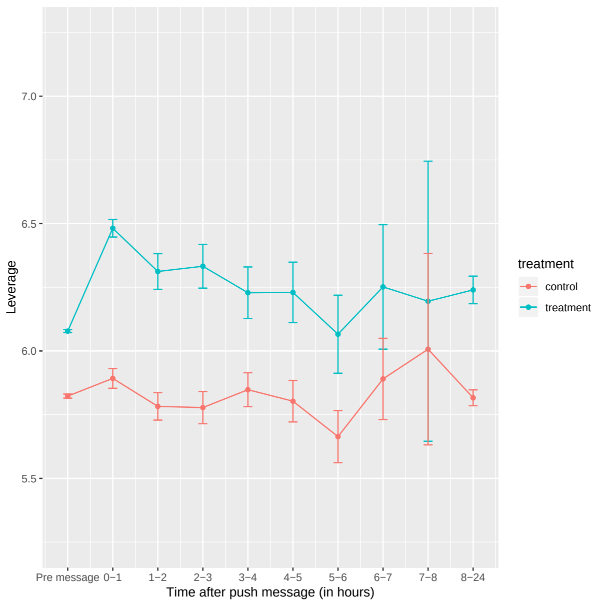

Figure 3: Risk-taking around the treatment events

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

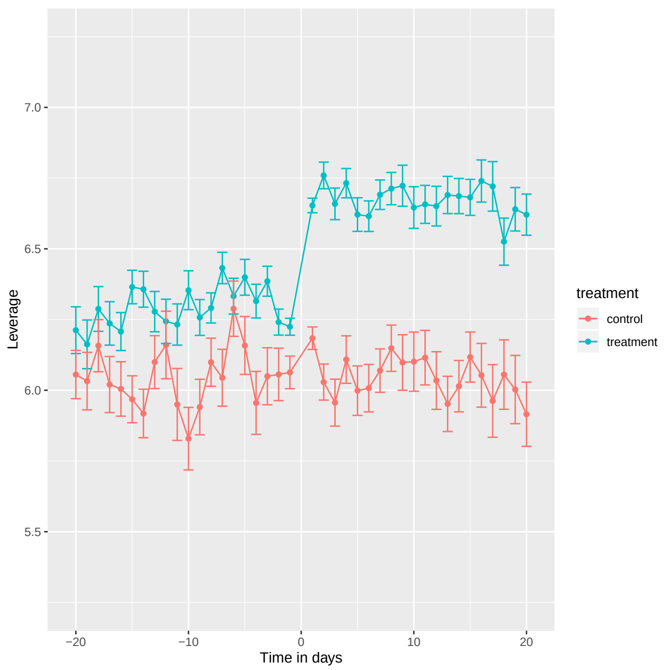

Table 1: Summary statistics of push message data

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 has 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 has 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 on 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-receivers 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 (Panels A to C) [difference-in-difference-in-differences analysis (Panel D)] regression analysis on the leverage of trades that investors initiate in our trade data. Panels A to C estimate equation (1), and Panel D uses equation (2). For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the first trade within 24 hours after the treatment event. In Panels A to C, 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. In Panel B, we restrict the observation period to the last 24 hours before the treatment event. In Panel C, we restrict the trades in the observation period to the message-stock. *Leverage* denotes the leverage employed for a trade; *treat* is a dummy variable that takes a value of one for investors of the treatment group, and zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, and zero otherwise; *stock* is a dummy variable that takes a value of one for the stock referred to in the push message, and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

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

Table 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, and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

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

Table 5: Prior experience in message-stock

This table reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate in our trade data. The table reports regression results conditioning on whether the investor has previously researched (Panel A) [invested into (Panel B)] the message-stock. In Panel A, 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 have visited the message-stock-specific information page of the broker at any point in time prior to the treatment event. In Panel B, Column (1) is restricted to investors who have no prior trading experience in the message-stock; Column (2) is restricted to investors who do have prior trading experience in the message-stock. For each investor we take the leverage of the last trade within seven days before the treatment event and the leverage of the first trade 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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: No stock-specific research prior to push message		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	No prior research	Prior research
treat × post	0.1889	0.1689
	(7.24)	(5.03)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	1,108,056	438,027
Adj. R^2	0.61	0.64
Panel B: No trading experience prior to push message		
	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	No prior trading	Prior trading
treat × post	0.1442	0.1032
	(4.95)	(3.36)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	655,622	638,471
Adj. R^2	0.61	0.65

Table 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 Panel A to Panel 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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and 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 × post	0.0733	0.1987
	(1.39)	(7.52)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	98,313	1,325,104
Adj. R^2	0.65	0.62

Panel B: Investors' age

	(1)	(2)	(3)
Dependent var.	Leverage	Leverage	Leverage
Sample	18-34	35 - 54	≥ 55
treat × post	0.2068	0.1841	0.1386
	(6.28)	(6.71)	(3.03)
Investor-fixed effects	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	650,812	661,188	107,717
Adj. R^2	0.62	0.63	0.65

Panel C: Investors' trading experience (self-assessment)

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

Table 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 have researched or traded the message-stock prior to the treatment date. Column (2) 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 have 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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: Prior contact with message-stock

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

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 × post	0.0781	0.1414	0.0229	0.1498
	(2.0687)	(3.0904)	(0.4886)	(2.8182)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	242,290	128,681	124,959	96,033
Adj. R^2	0.67	0.67	0.71	0.71

Table 8: Attention triggers and leverage usage: Regression results conditioning on stock characteristics

This table reports results from a difference-in-differences regression analysis on investors' leverage usage conditioning on the characteristics of the stocks. The results are computed separately for stocks with low and high values of the conditioning variables (median split). The conditioning variables used are (from Panel A to Panel F): 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 stories, the number of news 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 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* $\times$ *post* is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: Firm size

	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Small firm	Large firm
treat × post	0.1936	0.1959
	(6.18)	(5.03)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	560,511	690,191
Adj. R^2	0.69	0.61

Panel B: Analyst coverage

	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low analyst coverage	High analyst coverage
treat × post	0.1780	0.2146
	(5.15)	(6.94)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	770,137	505,022
Adj. R^2	0.62	0.70

Panel C: News stories

	(1)	(2)
Dependent var.	Leverage	Leverage
Sample	Low news production	High news production
treat × post	0.1178	0.2007
	(2.79)	(6.03)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	171,602	929,610
Adj. R^2	0.71	0.60

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

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

Table 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 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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

Panel A: Trading intensity				
	(1)	(2)	(3)	(4)
	Messages stocks		Non-messages stocks	
	long positions	short positions	long positions	short positions
treat × post	0.0047	0.0094	−0.0033	0.0054
	(2.00)	(4.25)	(−0.58)	(1.14)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	No	No
Time-fixed effects	Yes	Yes	Yes	Yes
Obs.	29,174,552	29,174,552	29,764,350	29,764,350
Adj. R^2	0.13	0.07	0.41	0.39
Panel B: Risk exposure				
	(1)			
treat × post	3.7358			
	(5.76)			
Investor-fixed effects	Yes			
Stock-fixed effects	Yes			
Time-fixed effects	Yes			
Obs.	1,389,639			
Adj. R^2	0.05			

Table 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 do 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; 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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and 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 × 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	27,710,308
Adj. R^2	0.10	0.11	0.12	0.42	0.05	0.02

Table 11: Push message clicks

This table reports additional results from difference-in-differences regression analyses on the leverage of trades that exploit the information about whether investors click on a push message. Panel A is restricted to investors who click on the push messages in the treatment group. Investors who receive a push message, but do not click on the push message, are omitted from the analysis. In Panel B, differently from our main analysis, investors from the control group are required to click on a push message referring to a different underlying within seven days before the treatment event and within seven days after the treatment event. 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; $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and 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.

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

Table 12: 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 (median split) for long and short-sale positions. Earnings report dates 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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and 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 × post	0.1553	0.2293	0.1801	0.0630
	(4.99)	(3.11)	(4.73)	(0.89)
Investor-fixed effects	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
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)
Dependent var.	Leverage	Leverage
Sample	Weak message	Strong message
treat × post	0.1515	0.2157
	(4.32)	(6.52)
Investor-fixed effects	Yes	Yes
Stock-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
Obs.	313,270	305,368
Adj. R^2	0.62	0.65

Table 13: 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 (3). 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. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; t-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

Dependent var.	Leverage	Leverage	Leverage
Sample	No earnings report dates	No news trading	Filtered trading
treat × post	0.1917	0.1662	0.1458
	(7.62)	(5.56)	(5.20)
Investor-fixed effects	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Obs.	1,025,676	436,258	1,086,213
Adj. R^2	0.62	0.68	0.59

Table 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; *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*, and 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); *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	3,519,118	6.108	3.219	5	5	10
Position size	3,519,118	12.818	18.883	1.890	5.900	14.650
Holding time	3,393,140	243.215	474.081	4.759	69.033	237.730
News event	3,519,118	0.603	0.489	0	1	1
Panel B: Stock data						
	Obs.	Mean	SD	P25	P50	P75
Volatility	1,224,189	0.293	0.155	0.197	0.252	0.335
Beta	1,224,189	0.987	0.400	0.734	0.961	1.209
IVOL	1,224,189	0.246	0.133	0.163	0.208	0.288

Table A.3: Message-sending behavior of 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, and 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, and zero otherwise; *trades* denotes the number of trades of an investor in the week prior to the push message; *leverage* denotes the investor's average leverage for trades over the previous week; *position size* is the average investment amount in a given stock trade expressed as a fraction of the total assets deposited by the investor at the broker over the previous week; *short sale* denotes the fraction of short sales of an investor over the week prior to the push message; *holding period* denotes the average time between opening and closing of the same position in hours over the previous week; ROI denotes the average return on investment net transaction costs over the previous week; *research pages* denotes the number of times 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, and zero otherwise; $age25$ is a dummy variable that takes a value of one if the investor is between 25 and 34 years of age, and zero otherwise; $age35$ is a dummy variable that takes a value of one if the investor is between 35 and 44 years of age, and zero otherwise; $age45$ is a dummy variable that takes a value of one if the investor is between 45 and 54 years of age, and zero otherwise; $age55$ is a dummy variable that takes a value of one if the investor is between 55 and 64 years of age, and zero otherwise; $age65$ is a dummy variable that takes a value of one if the investor is at least 65 years of age, and 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

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

Panel B: Investor characteristics									
	Non-message investor				Message investor				*p*-value
	p25	p50	p75	mean	p25	p50	p75	mean	
Inactive	1	1	1	0.89	1	1	1	0.85	0.000
Traded message-stock	0	0	0	0.01	0	0	0	0.15	0.000
Trades	1	3	8	8.54	1	4	12	12.28	0.000
Leverage	4.6	5	7.8	5.6	5	5	9.4	6.27	0.000
Position size	3	8.2	18.4	15.8	3.7	9.8	22	17.9	0.000
Short-sale	0	0	0	0.073	0	0	0	0.076	0.000
Holding period	78.8	198.9	458.3	428.04	58.3	161.4	373.1	340.5	0.000
ROI	-0.144	0.004	0.098	-0.024	-0.095	0.007	0.092	-0.012	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.4: Message-sending behavior of the broker: Very first message

This table reports results from a difference-in-differences regression analysis on the leverage of trades that investors initiate in our trade data. The table compares investors who receive the *first push message in any stock* (Column (1)) [first push message in any instrument (Column (2))] to investors who do not receive a push message. For each investor, we take the leverage of the last trade within seven days before the treatment event and the leverage of the first trade in message-stock after the treatment event within 24 hours. *Leverage* denotes the leverage employed for a trade. $treat \times post$ is a dummy variable that takes a value of one for investors of the treatment group ($treat = 1$) in the treatment period ($post = 1$), and zero otherwise. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation; *t*-statistics are in parentheses. The data are from a discount brokerage firm that offers a trading platform to retail investors under a UK broker license, and contain all trades on the platform between January 1, 2016 and March 31, 2018.

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

Table A.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 of the treatment group, and zero otherwise; *post* is a dummy variable that takes a value of one after the treatment event, and zero otherwise; *stock* is a dummy variable that takes a value of one for the stock referred to in the push message, and zero otherwise. We obtain our control group from all investors who have not been treated previous to the treatment date of the treated investor ("comparable investors") 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 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.

Panel A: Difference-in-differences analysis	
treat × post	0.1227
	(4.6293)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	293,436
Adj. R^2	0.62
Panel B: Difference-in-difference-in-differences analysis	
treat	−0.0506
	(−4.14)
post	0.0076
	(0.58)
stock	0.2379
	(4.89)
treat × post	0.1292
	(6.15)
treat × stock	−0.1789
	(−3.65)
post × stock	−0.1926
	(−3.57)
treat × post × stock	0.1581
	(2.86)
Investor-fixed effects	Yes
Stock-fixed effects	Yes
Time-fixed effects	Yes
Obs.	1,114,023
Adj. R^2	0.63