Does it Pay to Pay Attention?

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We employ a novel brokerage account dataset to investigate the relation between individual investor attention and performance. Attention is positively related to investment performance, both at the portfolio return level and the individual trades level. We establish causality using an identification strategy that instruments investors' attention using local weather conditions and provide evidence that the superior performance of high-attention investors arises because they behave as momentum traders that purchase stocks early in their momentum cycle. Finally, we show that paying attention is particularly profitable when trading stocks with high uncertainty, but for which a lot of public information is available.

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1 Introduction

Traditional asset pricing models assume that investors continuously incorporate all the available information into their investment decisions. In reality, however, attention is a scarce resource and individuals display limited attention. Rational models argue that attention-constrained investors should benefit from paying attention and should pay attention up to the point where the improvement in investment performance equals the costs of information acquisition (see, among others, Peress (2004), Peng and Xiong (2006), Van Nieuwerburgh and Veldkamp (2009, 2010), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016)). The behavioral literature, on the other hand, shows that investors tend to be overconfident and are subject to numerous biases, such as the disposition effect, suggesting that paying more attention may harm rather than improve investor performance (see, among others, Odean (1998a,b, 1999), Barber and Odean (2001), Guiso and Jappelli (2006)).

While the number of normative models on the behavior of attention-constrained investors has exploded in recent years, lack of data on individual attention has made it virtually impossible to test directly many of the theories and the literature is still lacking satisfactory answers to seemingly simple questions, such as, how often do investors pay attention to their investment portfolio? What individual characteristics lead certain investors to pay more attention to their investment portfolios compared to others? And, more importantly, does paying more attention lead to better or worse investment decisions?

We answer these questions using a unique novel brokerage account dataset. The dataset is unique in that it contains – at the individual investor level – detailed information regarding both investor attention and trading behavior. For approximately 11,000 accounts, we observe the time-stamp of investors' login to the brokerage account website, what webpages they browse within the brokerage account domain, and how much time they spend on each webpage. We use this information to construct various measures of attention, such as the number of minutes spent on the brokerage account website, the number of webpages browsed, and the number of log-ins. The extreme granularity of our data allows us to even identify what type of information and what stocks investors focus their attention on. For the same accounts, we also have detailed trading activity information. For every trade placed

by each investor, we observe whether it is a buy or a sell, an identifier of the security traded, the time-stamp of when the trade is ordered and executed, the quantity traded, and the price. Finally, the dataset contains quarterly holdings information and clients' biographical characteristics.

We provide a number of novel findings. First, we find a strong and positive cross-sectional relation between attention and performance, in that more attentive investors achieve higher risk-adjusted returns and portfolio Sharpe ratios – even after controlling for covariates related to investment style. Our baseline results show that a standard deviation increase in overall attention is associated with a 1.5% (0.00 p-value) increase in annualized risk-adjusted returns and a 0.09 (0.00 p-value) increase in investors' annualized Sharpe ratios. The results are consistent when we use other measures of attention – such as the amount of time spent on the research pages of the brokerage account website. Finally, the results that use the number of pages browsed or the number of logins as measures of attention are qualitatively similar, but economically smaller, suggesting that – compared to seconds – pages and logins may be poorer proxies for the process of information acquisition.

Our cross-sectional analysis cannot distinguish whether investors perform well because they pay more attention from the alternative hypothesis that investors pay more attention because their portfolio has been performing well. To disentangle the two effects, we present results for panel regressions that relate each investor attention to future performance. The additional advantage is that panel regressions allow us to control for (average) investor skills using fixed effects and overall market conditions using time-effects. At the one-month horizon, we find that a one standard deviation increase in attention is associated with an annualized increase in portfolio risk-adjusted performance of 0.38% (0.02 p-value). The effect increases to 0.62% (0.00 p-value) at the two-month horizon and decreases slightly to 0.55% (0.00 p-value) at the three-month horizon, indicating that paying attention allows individual investors to improve their portfolio performance in the short-term, and suggesting that the improvement in performance hinges on attentive investors being able to purchase (sell) stocks that realize relatively large positive (negative) returns in the short-run. Controlling for trading fees does not have a significant impact on our results.

While our panel regressions do not suffer from reverse-causality concerns, they cannot establish a causal relation between attention and investment performance, because paying attention is inherently

endogenous and unobservable factors may increase both investors' attention as well as the future performance of their investment portfolio. Hence we propose an identification strategy that uses poor local weather conditions as an instrument for attention, the rationale being that investors face a lower opportunity cost of paying attention to their investment portfolio in days where weather conditions are poor for outdoor activities. We find a positive and significant causal relation between attention and investment performance.

Finally, we find that the effect of attention is stronger for those investors that are – on average – less attentive. In particular, we divide our investors in five quintiles based on their unconditional attention and show that the effect of attention on future performance is monotonically decreasing across the five groups. Furthermore, while the coefficients on attention for the first four groups are positive and significant, the coefficient on attention for the last group is small, negative, and not statistically different from zero – indicating that there are diminishing marginal returns to attention.

Because portfolio performance does not necessarily capture investors' active management, we provide results on the relation between attention and the performance of individual trades. Attention is positively related to the future performance of the stocks purchased up to four months after the trade is placed. The economic magnitudes are large. At the three-month horizon, for example, a unit-standard deviation increase in attention increases the average annualized adjusted returns of the stocks purchased by 2.13% (0.00 p-value). We find – on the other hand – no discernible effect of attention on the performance of the stocks sold.

To understand the economic mechanism relating attention to the performance of the stocks traded, we conduct a number of auxiliary exercises. First, by analyzing the performance of the stocks before they are traded, we show that high-attention trades are profitable, because they resemble momentum trades in stocks early in their momentum cycle – approximately a quarter before reversal sets in.

Second, we show that attention is particularly profitable when investors trade stocks with high market capitalization, trading volume, volatility, number of analysts, dispersion of analyst forecasts, and news – indicating that it is for the stocks with high uncertainty, but for which a lot of public information is available, that it pays to pay attention.

Third, we show that Odean (1999)'s result that the stocks sold by individuals outperform the ones purchased disappears for high-attention trades, but is very strong for low-attention trades. For high-attention trades the average annualized three-month abnormal return of the stocks purchased equals 3.16%, the one for the stocks sold equals 4.20%, and their difference is statistically insignificant, with a p-value of 0.29. For low-attention trades, on the other hand, the average annualized three-month abnormal return of the stocks purchased equals -0.28%, the one for the stocks sold equals 3.08%, and their difference is statistically significant, with a p-value of 0.00.

The final set of results pertains to the determinants of investor attention, that is, the relation between investor characteristics and investor attention. We find that there is a very large heterogeneity in attention across investors and show that this heterogeneity can be explained by the size and risk of investor portfolios, as well as by investor trading habits and demographic characteristics. Account holders with higher invested wealth and higher exposure to small capitalization stocks, growth stocks, momentum stocks, and the overall market, are more attentive. The same is true for investors that trade more frequently. On the other hand, those investors that hold a higher fraction of their invested wealth in cash or ETFs are less attentive. Finally, we find that males pay more attention than females and attention is an increasing function of investors' age.

Taken together, the determinants of attention results and the ones relating attention and portfolio performance show that attention has an indirect as well as a direct effect on investor performance. The indirect effect is the one related to the type of investment decisions attentive investors make compared to inattentive investors. The direct effect, on the other hand, is the effect of attention on performance, after controlling for style and other characteristics. Taking the relation between momentum exposure, attention and risk-adjusted performance as an example, our results relating investor characteristics and attention show that more attentive investors tend to be momentum investors, buying (selling) stocks that have increased (decreased) in price over the previous 12 months. The results relating attention and performance uncover instead the direct effect of attention, in that attention remains positively related to performance even after controlling for momentum exposure.

2 Related Literature

Our paper is related to the literature that studies the performance of individual investors. Odean (1999) and Barber and Odean (2000) show that – on average – individual investors trade too frequently and that trading is detrimental to their wealth. More recently, a number of studies have uncovered substantial cross-sectional variation among investors' trading performance. In particular, superior trading performance has been linked to investors' IQ (Grinblatt, Keloharju, and Linnainmaa (2012) and Korniotis and Kumar (2013)), education (Von Gaudecker (2015)), wealth (Calvet, Campbell, and Sodini (2007)), experience (Korniotis and Kumar (2011) and Nicolosi, Peng, and Zhu (2009)), and portfolio concentration (Ivkovic, Sialm, and Weisbenner (2008)). Our results provide novel empirical evidence on the relation between attention and trading performance. If investors acquire valuable information while spending time on the trading platform, we expect their trades to be more profitable as they pay more attention. If investors are incapable of processing the information they acquire, on the other hand, we expect to find no relation between performance and attention. Finally, if investors systematically misinterpret the information they acquire, we expect to find a negative relation between performance and attention. The fact that we find a positive relation between attention and performance is an indication that – at least certain – investors are systematically able to understand and exploit the information they acquire.

We also contribute to the empirical literature that investigates investor attention, its determinants, and its impact on asset prices. Since its inception, this literature has faced significant challenges in measuring attention itself, leading researchers to resort to attention proxies such as trading volume (Gervais, Kaniel, and Mingelgrin (2001)), price limits (Li and Yu (2012) and Seasholes and Wu (2007)), and news (Yuan (2015) and Barber and Odean (2007)), and making the implicit assumption that investors are likely to pay attention to stocks that are mentioned in the news or that have been heavily traded on a given day. More recently, Da, Engelberg, and Gao (2011) propose the use of Google searches as a direct measure of aggregate attention and – using Google searches – Vlastakis and Markellos (2012) and Andrei and Hasler (2015) show that aggregate attention varies as a function of stock market volatility. The advantage of using aggregate Google web-searches over news is that they identify the information investors actively seek, rather than the information they

are potentially exposed to. A key shortcoming, on the other hand, is that they are not specific to the individual investor and therefore cannot shed new light on how attention and the process of information acquisition relates to trading at the individual investor level.

The only studies that obtain direct measures of investor attention at the individual level – and are therefore closest to ours – are Karlsson, Loewenstein, and Seppi (2009), and Sicherman et al. (2016). Using a large panel of investors' logins to 401K accounts as a measure of attention, they show that investors pay less attention to their investment portfolio after stock market declines. They also show that investors' attention vary as a function of portfolio holdings, wealth, and demographic characteristics – such as age and gender. While it confirms many of the findings in Sicherman et al. (2016), our work is different along several dimensions. First, we have information on brokerage rather than 401K accounts. This is important, because 401K investors can only choose among a limited number of fixed income and equity funds, and are completely unable to purchase or sell individual stocks. Furthermore, as shown by Agnew, Balduzzi, and Sunden (2003), Madrian and Shea (2001) and Sialm, Starks, and Zhang (2015), 401K investors display very limited trading, a high degree of inertia, and extreme asset allocations.[1] Second, our measures of attention are not limited to investors' login, because – for each investor – we observe what information he/she browses and how much time he/she spends doing it. This means that we are able to provide results regarding what information investors pay attention to and how much time they spend thinking about their portfolio decisions. Finally, we have detailed information regarding investors' portfolio allocation and trades, meaning that we can relate investors attention to the type of stocks they own and to the performance of the stocks they purchase and sell.

Our paper is also related to the theoretical literature that studies the optimal inattention behavior of informationally constrained investors. One strand of this literature focuses on the time-series dimension of inattention and shows that, if information acquisition is costly, it is optimal to alternate long periods of inaction to brief spurs of attention, where information is acquired and investment decisions are made (see Gabaix and Laibson (2002), Abel, Eberly, and Panageas (2007, 2013), Huang and Liu (2007), and Alvarez, Guiso, and Lippi (2012)). We contribute to this literature by providing

[1] As reported in Agnew, Balduzzi, and Sunden (2003), the distribution of allocations to stocks across 401K investors is strongly bimodal: 48 percent of the average annual equity allocations are zero, while 22 percent are 100 percent.

empirical evidence on the actual patterns of investor attention and trading. That is, how often investors pay attention to their investment portfolio, whether they evaluate their portfolio allocations at equally spaced intervals – as many of the theoretical models predict – or they alternate periods of high attention to periods of low attention. Finally, we study what demographic and portfolio characteristics are associated with higher or lower degrees of attention.

The rest of the paper is organized as follows. Section 3 describes the web-activity data and explains how we extract our measures of attention. Section 4 provides summary statistics on investor portfolio allocation as well as their trading and attention habits. Section 5 analyzes the relation between investor attention and portfolio performance. Section 6 studies the relation between investor attention and the performance of their trades. Section 7 provides additional tests, including an in-depth analysis of who are the most attentive investors. Section 8 concludes.

3 Measuring Attention Using Investor Web-Activity

In this section, we discuss the measures of attention used in the paper. We start by presenting the data we have access to in terms of investors' web-activity and we show that – once aggregated across all the investors in our dataset – the information measures we construct have an information content similar to that of Google's Search Volume Index. The advantage of our measures, however, is that they are available for each investor and therefore allow us to study the relation between attention and investment decisions at the individual level.

3.1 The web activity we observe

Before describing the measures of attention we construct, we provide an example of the web-activity we observe for each investor in our sample. Table 1 shows the web behavior of a sample account holder on January 28, 2014.[2] To preserve the anonymity of the brokerage account house, we mask the URLs we have access to and, rather than reporting the full string characterizing each URL, we only report

[2]In compliance with the US privacy law, no Personally Identifiable Information (PII) was provided by the brokerage house. For example, each account holder has been anonymized using a numeric account identifier.

the content of the webpage each URL is associated with.

The table shows that the account holder had a total of four sessions over the day. The first connection occurred at 7:58:05 am (Central Time) and, after logging to the homepage, the investor checked his/her balances and positions as well as his/her stocks' watchlist. The balances and positions page does not report only the amount of wealth invested in each stock, but also important stock information such as past returns; historical and forecasted earnings and dividends; key accounting information such as price-to-book and price-to-earnings ratios; basic facts such as revenues and institutional ownership; and a summary of analysts' opinions as well as recent news. The watchlist is instead a webpage containing information on all the stocks and other assets the investor decides to pay attention to.

The second session starts only thirty minutes later, two minutes after the markets open in New York. This second session is much longer, approximately forty minutes, and entails more actions. The investor first checks the research page of the website detailing the latest news on the SPX, the S&P 500 index. Right after, he/she connects to the page displaying his stocks' watchlist to quickly switch to the research page relative to the VIX. The rest of the session is dedicated to assessing balances and positions of his/her trading account and the watchlist.

The third session occurs right around lunch time, it lasts a little more than eighteen minutes, and it involves a look at the watchlist as well as the balances and positions pages. Finally, the last session of the day occurs at 14:28:54 pm, 30 minutes before the markets close. It lasts only forty seconds and involves just a quick look at his/her balances and positions and the watchlist.

3.2 From links to attention

The web activity information presented in Table 1 is a small example of the web-activity data we were granted access to. In particular, as part of a large SQL relational database described in more details in Appendix A, the brokerage house gave us access to a web-activity table containing the web pages visited – within its website domain – for approximately 11,000 randomly chosen accounts over the period January 2013 – June 2014. The dataset is very granular and contains in excess of 17 million observations. Each observation contains a unique numeric account identifier, the URL of the webpage

visited within the brokerage account domain, the date and time of the first click on the page, the number of seconds spent on the page, and the number of the web-sessions within the trading day. Next, we explain how we use this data to construct a variety of attention measures.

3.2.1 Overall attention measures

The first set contains three measures of attention related to the overall attention paid by investors to their brokerage account. The first measure is the number of seconds spent on the brokerage account website over a given time interval. The second measure computes the total number of pages visited by the investor. Finally, the third measure is the number of investor logins to the brokerage account website.

Using three measures is important for robustness purposes. One may prefer the number of pages visited rather than the number of seconds spent on the website, because it is possible for some individuals to stay logged into the brokerage account website and leave it in the background, while performing other activities. On the other hand, one may prefer the number of seconds rather than the number of pages visited, because it is unlikely for someone to understand the content of a stock report if he/she only spends one or two seconds reading it. Considering the number of logins is also important, because it potentially allows us to distinguish between the extensive and intensive margin of investors' attention. For example, an investor that connects multiple times a day, but stays connected for a few seconds, is probably looking for very different information compared to an investor that connects once or twice, but spends an hour or longer on the trading platform.

To show that the attention measures we extract from our data are related to the ones that have been proposed in the literature, we present in Figure 1 the time-series – at the weekly frequency – of the total number of seconds aggregated across all investors, and four attention proxies:[3] the Google Search Volume Index for the word "S&P 500" (Panel A), the total number of news pertaining to stocks in the S&P 500 (Panel B), the trading volume on the S&P 500 (Panel C), and the State Street Investor Confidence Index (Panel D).[4] Each panel reports our measure of attention as a red dashed

[3] The results for the total number of pages visited and the total number of logins are very similar.

[4] The total number of news pertaining to the stocks in the S&P 500 Index are obtained from Capital IQ, while we downloaded the S&P 500 trading volume from Yahoo! Finance.

line and one of the alternative measures as a solid blue line. The plots clearly show that there is a very tight relation between our attention measure and both the Google's Search Volume Index for the S&P 500 (78.2% correlation, statistically significant at the 1% level) – as well as the trading volume on the S&P 500 (66.1% correlation, statistically significant at the 1% level). The news variable is also quite related to our attention measure (43.1% correlation, statistically significant at the 1% level), while the correlation with the confidence index is relatively low – at only 27.7% – and is statistically insignificant.

3.2.2 Categorical attention measures

The second set of attention measures also uses seconds, pages and number of logins, but focuses on the various sections of the website visited by the investors. The brokerage account website has a hierarchical structure, whereby – for example – all the web-pages related to specific tickers like SPX and VIX fall under the "Research" category. By parsing all the URLs and categorizing them, we can obtain many other categories such as "Home Page", "Balances and Positions" and "Watchlist." To maintain parsimony, we classify all the available URLs into 14 categories: Balances and Positions, Research, Trading, Homepage, Account, Watchlist, History Statement, Bank, Mail, Tax, Help, Search, Retirement, and Client.[5]

Panel A of Table 2 reports the daily total number of hours spent across investors for the top six categories. The most viewed section of the website is – on average – "Balances and Positions." This page does not only contain information regarding investors' performance and portfolio weights, but also important stock information such as past returns; historical and forecasted earnings and dividends; key accounting information such as price-to-book and price-to-earnings ratios; basic facts such as revenues and institutional ownership; and a summary of analysts' opinions as well as recent news. The average time spent across all investors is 787 hours per day, but this aggregate measure has a large standard deviation equal to 412, so the total number of hours spent ranges from 516 to 930 hours for the 25th and 75th percentiles, respectively. Research is the second most popular category,

[5]These categories are the ones that the brokerage account website is divided into and allow us to categorize 99% of the URLs.

with 483 hours per day, followed by Trading and Homepage. The remaining categories are much less visited by the investors. For example, the average number of hours spent on Watchlist is only 46 per day.

Focusing on the various sub-categories is important because it allows us to discern whether looking at different types of information leads to different trading behavior and performance.

3.2.3 Stock attention measures

The third and final set of attention measures uses only information associated with the "Research" URLs and focuses on the tickers researched by investors. Panel B of Table 2 reports the Top 20 companies and ETFs researched by the investors in our dataset over the time-period October 1, 2013 – June 10, 2014.[6]

To compute the table, we first sum the number of minutes spent on each ticker across all the account holders in our dataset and over the full sample. We then report the rank of each company (or ETF) according to the number of minutes (first column), pages (second column) and visits (third column).

Starting from the first column, the table shows that individual investors focus on companies that belong to the consumer-tech space. Interestingly, while we find tech giants such as Facebook and Apple ranked first and second, respectively, we also find companies that have much smaller market capitalization, such as Twitter (7), AT&T (6), Verizon (10), Tesla (11), Sirius XM (15) and Netflix (19), ranked higher or similarly to much larger firms such as Microsoft (14). All in all, it is remarkable that 11 out of the top 20 stocks researched by investors are in the technology space. As expected, also large conglomerates and banks populate the list. For example, among the companies listed we find Bank of America (3), Ford (4) and General Electric (9). Finally, we find four ETFs in the list, i.e. SPDR S&P 500 ETF (5), SPDR Gold Trust (17), SPDR Dow Jones ETF (18) and Market Vectors ETF (20).

The results in the second and third columns are similar, indicating that number of minutes, pages

[6]The sample is dictated by data-availability, i.e. the complete URLs that include ticker information are available from October 1, 2013 until the end of our sample.

and visits capture similar patterns of behavior.

4 Summary Statistics

The source of the proprietary data used in this study is a large US discount broker. Unlike the discount brokers described in Odean (1999), today's discount brokers operate online and – while providing access to analysts' research, market news, and a large number of tools to help investors with their trading – they charge very small trading fees (less than $10 per trade). We relegate to Appendix A the detailed description of the various databases employed in our study, and proceed to present the key summary statistics of our final dataset below.

Table 3 reports the summary statistics for the subset of accounts (approximately 11,000) for which we have web-activity information.[7,8] Starting from the biographical traits, the first row of Panel A shows that the average age of account holders in our dataset is approximately 51, the second row shows that 73% of the account holders are males. While the average and median age are very much aligned with the ones of previous studies, our dataset has a slightly higher percentage of women – 27% in our study compared to 21% in Barber and Odean (2001), for example. The average number of accounts per client is 1.34. This occurs because – while 80% of the clients have only one account – 20% of the clients have more than two accounts. Finally, as of June 2014, the average account age is 8.55, which suggests that the average account holder in our sample is quite experienced.

Next, we turn to the portfolio characteristics of account holders as of March 31, 2014. As reported in Panel B, the average (median) household has a portfolio value that equals $94,000 ($18,000) dollars, indicating that the distribution is heavily skewed to the right. Cash holdings average $16,000 and their distribution is also heavily skewed to the right. Conditional on having at least one stock in the portfolio, the average account holds 6.51 stocks worth $82,000 and the median counterpart is four

[7] Even though these accounts were randomly selected from the full set of accounts of the brokerage account house, we allay concerns regarding their representativeness by recomputing the statistics in Table 3 using the entire universe of accounts of the brokerage account house (approximately 3.5 millions). The results, reported in Table Online I, show that the biographic and portfolio characteristics statistics are very similar across the two samples.

[8] Because our brokerage house has millions of clients, our sample is likely to be representative of the population of US stock investors.

stocks for a total of \$15,000.[9] The median values for stock holdings are in line with those in Barber and Odean (2000), who report that the median household holds 2.61 stocks worth \$16,210.

Panel C of Table 3 reports summary statistics for the trading behavior of account holders. The results are computed as follows. In the first step, we compute the results for each account holder using his/her full time-series, eliminating the days when the stock markets are closed – mainly week-ends and holidays – as individuals tend to connect much less at those times. In the second step, we compute cross-sectional results across account holders. The first row shows that, on average, investors trade on 3% of the days, with 50% of the investors not trading at all, and 1% of the investors trading more than 44% of the days. For those investors placing at least two trades, the number of days between trades averages 47, resulting in approximately one trade every two months. The median counterpart is 25 days. Conditioning on placing a trade, the average investor places 1.72 trades per day, the median being 1.31. This indicates that investors tend to cluster their trades, consistent with the idea that – once they decide to re-optimize their investment positions – investors like to make multiple transactions on the same day. Finally, the average trade size is \$16,000, in line with Barber and Odean (2000) who report an average trade size of \$13,707 (\$11,205) for stock purchases (sales).

Panel D reports summary statistics for the attention behavior of account holders. The average percentage of days with logins (across investors) equals 17% – which is almost six times larger than the trades' frequency. The most active 1% of the investors logs-in 96% of the days, while the median investor logs-in 6% of the days. The number of days between logins also shows that login and trading behaviors are quite different in terms of magnitudes. The average number of days between logins averages 27.51 across account holders, while the median value is 11.20. Note that these numbers are not only much smaller than their trades counterparts, but they are also computed using information for twice as many account holders, i.e. those accounts that do not trade at all over our sample.

Conditional on logging-in, investors re-visit their trading account several times within a given day – the average is 10.61 and the median is 7.33. This indicates that there is a large degree of clustering in the visits we observe and that investors do not log-in at regular intervals. Once they decide to pay attention, investors seem to spend a substantial amount of time on the trading platform. In particular,

[9] All dollar figures have been rounded to the nearest thousand upon request of the data provider.

the average number of minutes spent on the website – conditional on logging-in – equals 29, while the median value is 8. As expected, the shortest 1% of the sessions lasts only 18 seconds, while the longest 1% of the sessions can be as long as 366 minutes (more than 6 hours).

To help the visualization of the cross-sectional variation in investor attention and to display how the within-investor attention varies over time, we use a heat-map graph in Figure 2. The figure is constructed as follows. For each account holder, we generate a time-series from January 2013 through June 2014, eliminating the days when the stock markets are closed – mainly week-ends and holidays – as individuals tend to connect much less at those times. We then compute, for each investor, the daily number of minutes spent on their investment account.[10] Finally, to ease the visualization, we sort the accounts by the total number of minutes over the full sample, so that the more active accounts are at the top of the figure. Figure 2 uncovers considerable heterogeneity in behavior across accounts. At the top, we find the more attentive investors that consistently log-in and spend about one to two hours per day on their account. At the very bottom, on the other hand, we find those individuals that rarely log-in. The figure also highlights some heterogeneity in individual accounts' behavior over time. For example, the horizontal lines of "colder" colors – that appear in multiple parts of the figure – identify periods where a given investor pays more attention than usual to its investment portfolio. The opposite holds true for the horizontal lines of "warmer" colors, even though these are harder to discern. The first eight days of the sample are characterized by lighter colors for all clients. This is because the company was introducing and testing the tracking system over that week and the system was not fully functional. We do not include these observations in the computation of the results reported in the rest of the paper.

Taken together, these findings represent a new benchmark for the models of optimal inattention, that often imply inattention intervals much longer than the ones we observe. For example, the model of Gabaix and Laibson (2002) imply an inattention interval of approximately 12 months, the one by Abel, Eberly, and Panageas (2007) an inattention interval of 8 months. With values slightly greater than one month, the only model that predicts inattention intervals in line with the ones we find in

[10] For ease of visualization, we winsorize the number of minutes at the 95-th percentile, which results in the number of winsorized minutes to range from zero to 150. The summary statistics reported in Tables 3 are computed using non-winsorized data.

the data is the one by Abel, Eberly, and Panageas (2013). Our findings also show that it is crucial for inattention models to capture the asynchronicity between attention and trading, as featured in Abel, Eberly, and Panageas (2013) and Alvarez, Guiso, and Lippi (2012). Finally, the clustering of attention, whereby investors pay attention to their portfolios for several days or weeks and then decide to be inattentive for months (or even years) is difficult to reconcile with standard models of optimal inattention – that predict instead regular inattention intervals.

5 Attention and Performance: Evidence from Portfolio Returns

We now turn to the main set of results relating investor attention and portfolio performance. Investors that spend more time acquiring information are likely to receive more trading signals. If these investors are able to correctly process these signals, we would expect them to achieve superior portfolio performance. On the other hand, if they systematically misinterpret these signals, we would expect them to perform poorly. To estimate what relation holds in the data, we propose two baseline strategies and one identification strategy. The first baseline strategy uses cross-sectional regressions and addresses the question of whether investors that pay more attention perform better. The second baseline strategy implements panel regressions and uses within-individual variation over time to assess whether changes in investor attention are associated with performance differentials. In both cases, we find a positive relation between attention and investment performance.

The two baseline strategies cannot establish a causal relation between attention and investment performance, because the choice of paying attention is inherently endogenous. Hence, we propose an identification strategy that uses poor weather conditions as an instrument, the rationale being that investors face a lower opportunity cost of paying attention to their investment portfolio in days where weather conditions are poor for outdoor activities. We find a positive causal relation between attention and investment performance.

5.1 Cross-sectional regressions

In Table 4 we evaluate the relation between investor attention and risk-adjusted performance, where the former is measured as overall, research, or balances and positions attention and the latter is measured as the DGTW abnormal return of the investor portfolio.[11] We estimate the following cross-sectional regression:

$$AVG\_DGTW\_Ret_i = \alpha + \beta \ Attention_i + \boldsymbol{x}_i' \ \boldsymbol{\gamma} + \epsilon_i \qquad for \ i = 1, \ldots, N,$$

where $AVG\_DGTW\_Ret_i$ is the annualized average percentage DGTW abnormal return of investor i over the sample, $Attention_i$ is the total attention spent on the brokerage web-site by account holder i over the sample and $\boldsymbol{x}_i$ is a subset of the covariates that explain the cross-section of investor attention – as shown in Section 7.3.[12] All regressors are standardized so that they have zero mean and unit standard deviation.

The results highlight a statistically and economically significant relation between attention and performance. For overall attention (Panel A), the coefficient in the first specification equals 1.531% and is significant at the one percent level. The corresponding coefficient estimates for research (Panel B) and balances and positions (Panel C) are 0.988% and 1.267%, respectively. The results imply – taking overall attention as an example – that a one standard deviation increase in attention is associated with an increase in the investor's DGTW abnormal return of 1.53%, which is economically rather large. A common feature of the results reported in this section – as well as the subsequent ones – is that balances and positions attention has sometimes a stronger impact on performance, compared to research attention. While surprising at first sight, the results may be driven by the fact that investors obtain important research information also on the balances and positions portion of the website. The information includes stocks' past returns; historical and forecasted earnings and dividends; key accounting information such as price-to-book and price-to-earnings ratios; basic

[11] The DGTW-adjusted portfolio return is computed as in (Wermers, 2003, Equation (1) on page 7) and (Daniel et al., 1997, Equation (1) on page 1,041).

[12] Compared to the covariates in Table 11 of Section 7.3, we do not include the regressors related to risk-factor exposures, that is, the loadings on the market, Small-Minus-Big, High-Minus-Low and Momentum factors, because these exposures are directly controlled for by the DGTW procedure.

facts such as revenues and institutional ownership; and a summary of analysts' opinions as well as recent news. Research pages, on the other hand, contain in-depth analyst reports and balance sheet information for each company. Also, because investors spend almost double the time on balances and positions pages compared to research pages – as shown in Table 2 – it may be that the amount of time spent on the balances and positions pages is a more precise estimate of the process of information acquisition, particularly for those investors that acquire information also through other sources such as Yahoo Finance or Bloomberg, for example.

In order to control for possible differences in information acquisition capabilities, Specification 2 in each panel includes demographic characteristics as control variables. Adding these regressors leaves the effect of attention on investment performance largely unchanged for all attention measures, indicating that the relation between these additional regressors and performance is largely orthogonal to that of attention. Among the newly added covariates, the ones significant at the 5% level are age and the brokerage dummy. The first has a negative coefficient – indicating that younger investors achieve a better risk-adjusted performance on their investment portfolio. The second shows instead that brokerage accounts seem to outperform IRA and other accounts, on average, possibly because investors in these accounts are actively seeking underpriced stocks rather than holding broad and diversified passive portfolios.

Finally, Specification 3 adds – as further controls – regressors related to portfolio size, portfolio allocation, and trading activity. The inclusion of these additional covariates increases the effect of attention on performance by 35-50%, depending on the specification: the overall attention coefficient increases to 2.326%, the research attention coefficient increases to 1.776% and the balances and positions coefficient increases to 2.007%. All coefficients remain statistically significant at the 1% level, indicating that, even after controlling for portfolio composition and trading frequency, the effect of attention is significantly related to the performance of the investors in our sample.

As for the effect of the additional controls, we find a negative relation between portfolio size and number of trades and performance. Interestingly, we find that including the number of trades as a control variable increases the effect of attention on performance, suggesting that paying attention attenuates the negative effects of excessive trading documented in the literature, see Barber and Odean

(2000).

As a first robustness exercise, Table Online II shows the results that use number of pages (Panel B of Table Online II) or logins (Panel C of Table Online II) as measures of attention. While the results are qualitatively similar, they are economically smaller, suggesting that – compared to seconds – pages and logins may be poorer proxies for the process of information acquisition. As a second robustness exercise, we use the full sample Sharpe ratio as a measure of risk-adjusted performance. The results, reported in Table Online III, highlight a statistically and economically significant relation between attention and performance. For overall attention, the coefficient in the first specification equals 0.090 and is significant at the one percent level. The corresponding coefficient estimates for research and balances and positions are 0.108 and 0.137, respectively. The results imply – taking balances and position attention as an example – that a one standard deviation increase in attention is associated with an increase in the investor's Sharpe ratio of 0.137. Economically, this quantity is quite large, because the average Sharpe ratio across the investors in our sample is 1.316.[13] As a third robustness exercise, we implement the calendar-time approach of Barber and Odean (2000). We first sort the investors into five groups according to attention. We then compute daily weighted returns for each group and estimate Carhart 4-factor regressions on these portfolios. Going from low- to high-attention, we find that the five groups have the following daily alpha estimates (0.016%, 0.011%, 0.013%, 0.017%, 0.028%) with p-values equal to (0.14, 0.22, 0.07, 0.02, 0.00). The alphas increase in significance as we move from the first to the fifth portfolio and only the top two portfolios are significant at the 5% level, confirming that risk-adjusted performance is positively related to attention.

The results reported so far show that investor attention is positively related to risk-adjusted performance, even after controlling for investor characteristics and investment style. As we detail in Section 7.3 and the associated Table 11, account holders with higher exposure to small capitalization stocks, growth stocks, momentum stocks, and the overall market, are more attentive. Jointly, therefore, the results reported in Table 11 and Table 4 show that attention has an *indirect* and a *direct* effect on investor performance. The indirect effect is the one related to the type of investment decisions attentive investors make compared to inattentive investors. The direct effect, on the other hand, is the effect of

[13] While this average Sharpe ratio may seem rather large, note that – for the same period – the market Sharpe ratio (computed using returns and volatility on a NYSE/AMEX/NASDAQ value-weighted index) has been 2.62.

attention on performance, controlling for style and other characteristics. Taking the relation between momentum exposure, attention and risk-adjusted performance as an example, our results in Table 11 uncover the indirect effect of attention on performance, in that more attentive investors tend to follow momentum strategies – buying (selling) stocks that have increased (decreased) in price over the previous 12 months. The results in Table 4, on the other hand, uncover the direct effect of attention on performance, in that attention retains a positive effect on performance even after controlling for momentum using the DGTW procedure.

5.2 Panel data regressions

The results reported so far potentially suffer from a reverse-causality problem: it may not be that investors perform better because they pay more attention, but that investors pay more attention because they have been performing better.

The cross-sectional regressions cannot distinguish between these two alternative hypotheses, because they compute performance and attention over the full sample. To separate the two effects, we next estimate panel regressions that identify the effect of attention on performance from time-series variations in attention – measured at the individual level. Our baseline specification is:

$$DGTW\_Ret_{i,t:t+k} = \alpha_i + \beta_M + \gamma \; Abn\_Attention_{i,t} + \epsilon_{i,t:t+k}, \tag{1}$$

where $DGTW\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return of account-holder i over the time interval $t : t+k$ and k equals 21, 42 and 63 days – depending on the specification;[14,15] $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; finally, α_i and β_M represent account-holder fixed effects and monthly time-effects, respectively.

Following Da, Engelberg, and Gao (2011), we use abnormal attention – rather than attention – to capture time trends and other low frequency seasonalities in investors' attention. This is important,

[14] The DGTW-adjusted portfolio return is computed as in (Wermers, 2003, Equation (1) on page 7) and (Daniel et al., 1997, Equation (1) on page 1,041).

[15] The results are economically similar if we use simple returns or market-adjusted returns.

because investors tend to pay more attention to their investment portfolios right after opening their accounts and they tend to lose interest subsequently. Furthermore, even though time-effects are included in the regressions, they are unlikely to capture a large part of the time-variation in investors' attention, because individual investors hold relatively few stocks. It may therefore be that certain investors pay a lot of attention in certain periods – because the stocks they own (or they want to purchase) are in the news – and other investors in other periods. Finally, to ease the comparison across the specifications, we standardize *Abn_Attention* so that it has zero mean and unit standard deviation.

To guarantee that our results are not specific to the type of clustering used in the computation of the standard errors, we report two sets of p-values. The first – in round brackets – are computed using standard errors that are double-clustered by account-holder and time, see Petersen (2009). The second – in square brackets – are computed using Driscoll and Kraay (1998) standard errors. We base our discussion on the double-clustered standard errors, because they result in more conservative estimates on our data.

Reported in Panel A of Table 5 are the results based on the overall attention measure. Across all horizons, the estimates highlight a positive and significant effect of abnormal attention on performance. Statistically, the results are significant at the 5% level for the one month horizon and the 1% level at the two- and three-month horizons. Economically, the effect of overall abnormal attention is quite large. At the one-month horizon, we find that a one standard deviation increase in attention is associated with an annualized increase in portfolio DGTW-adjusted performance of $0.032 \cdot 12 = 0.38\%$ per year. The effect increases to $0.103 \cdot 6 = 0.62\%$ at the two-month horizon and decreases slightly to $0.138 \cdot 4 = 0.55\%$ at the three-month horizon. This indicates that paying attention allows individual investors to improve their portfolio performance in the short-term, suggesting that the improvement in performance hinges on attentive investors being able to purchase (sell) stocks that – in the short run – realize relatively large positive (negative) returns.

Panels B and C report the results for research attention and balances and positions attention, respectively. The results show that, while the effect of balances and positions attention is economically stronger than overall attention, the effect of research attention is somewhat weaker. For example, the

annualized effect for the two-month horizon specification equals $0.135 \cdot 6 = 0.81\%$ for balances and positions attention and $0.078 \cdot 6 = 0.47\%$ for research attention. In both cases the coefficients are statistically significant at the 5% level. Across all panels, the coefficients are always more significant if we use Driscoll and Kraay (1998) standard errors.

Finally, Table Online IV shows that the results reported above are generally less significant when we measure attention using number of pages or logins instead of seconds, suggesting – again – that the latter two measures may be poorer proxies for the process of information acquisition.

The results in Table 5 do not account for trading fees. Barber and Odean (2000) show that transaction costs can substantially reduce the post-fee returns of individual investors, as the average total cost of a round-trip trade was approximately 4% in 1999. Thanks to technological progress and increased competition among brokers, trading fees are much lower nowadays: it is possible to trade many ETFs without incurring any fee and the majority of the brokers charge less than \$10 for on-line trades – a very small amount compared to the average trade size of \$16,000 reported in Table 3. Furthermore, brokers often offer their customers promotions whereby trading fees are waived for a certain number of trades and/or a certain period of time. Because we do not observe these promotions in our dataset, we assume that every trade is charged the maximum fee advertised by our broker and re-estimate Equation (1) using abnormal DGTW returns adjusted for trading fees. Compared to Table 5, the coefficients in Table Online V are only slightly smaller, but still strongly significant, indicating that controlling for trading fees does not affect our results.

Finally, while the results in Table 5 use monthly time-effects, we find that the results are virtually unchanged when we use daily time-effects – as we show in Table Online VI.

5.3 Identification Strategy

The findings reported so far suggest that – at the portfolio level – it pays to pay attention. But the results cannot be interpreted causally, because the decision to pay attention is endogenous. In particular, it may be that certain unobservable factors increase both investors' attention and the future performance of their investment portfolio. For example, it may be that an increase in market volatility

increases both investors' attention as well as the future performance of their portfolios. While our results use returns that are risk-adjusted using the DGTW benchmarks, it could be that – among the stocks in the various DGTW portfolios – the individual investors in our sample hold the ones that are particularly sensitive to changes in aggregate volatility and – as a result – the DGTW procedure incorrectly benchmarks the returns of these stocks.

Concerns about endogeneity are potentially relevant, because our baseline panel regressions exploit within-investor variation in attention over time. If investors' attention varied because of underlying unobservables that also affected the future performance of investors' portfolios, our baseline results would document a spurious relation between attention and investment performance.

The ideal source of exogenous variation should not be related to financial market developments, but should affect investors' attention to their investment portfolio. Such a source of exogenous variation would allow us to test the causal relation between attention and investment performance. To get close to such an ideal source of variation, we propose an instrumental variable identification strategy. We instrument investors' daily attention using local weather conditions. The rationale is that investors face a lower opportunity cost of paying attention to their investment portfolio in days where weather conditions are poor for outdoor activities. The instrument is likely to be relevant as weather conditions and air pollution have been shown to have an impact on individual investors' trading activity, see Schmittmann et al. (2014) and Meyer and Pagel (2016). We document the relevance of the instrument below.

We implement our instrumental-variable strategy by estimating a two-stage least-squares specification that parallels the baseline specification reported in Equation (1). To this end, we collect daily weather data at the zip-code level from Wunderground and we categorize as poor weather days those with rain, snow, especially cold or especially hot temperatures, where the latter are classified as the 20% coldest and hottest zip-code days over our sample period, respectively.[16] We then instrument investors' abnormal attention on any given day using the weather conditions of the zip-code where the

[16]Our results are similar when we use alternative definitions of poor weather conditions for outdoor activities.

investor resides. Specifically, we estimate:

$$Abn\_Attention_{i,t} = \alpha_i + \beta_M + \gamma \; Bad\_Weather_{i,t} + \epsilon_{i,t}, \tag{2}$$

where $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; $Bad\_Weather_{i,t}$ is a dummy that takes the value 1 if account holder i experiences poor weather conditions on day t and is equal to 0 otherwise; α_i and β_M represent account-holder fixed effects and monthly time-effects, respectively.

In the second stage, we use the instrumented attention on the LHS of Equation (2) as the main covariate in the following specification – which is otherwise identical to our baseline regression in Equation (1):

$$DGTW\_Ret_{i,t:t+k} = \alpha_i + \beta_M + \gamma \; \widehat{Abn\_Attention}_{i,t} + \epsilon_{i,t:t+k},$$

where $DGTW\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return of account-holder i over the time interval $t : t + k$ and k equals 21, 42 and 63 days.

To assess the validity of our instrument, we verify its relevance and discuss whether the exclusion restriction needed for causal interpretation holds. In terms of relevance, the instrument needs to be sufficiently correlated with the endogenous regressor, because a weak instrument could lead to inconsistent estimates and invalidate inference in the second stage. Relevance does not seem to be a concern in our analysis, as the first-stage Cragg-Donald Wald F-statistics are larger than 15.8 across all the specifications reported in Table 6.

To interpret the coefficient $\hat{\gamma}$ causally, we need to assume an exclusion restriction. Local weather should affect future investment performance only through its effect on attention. This exclusion restriction cannot be tested directly, but we argue that it is plausible for two reasons. First, while aggregate weather conditions could conceivably have an impact on current (or potentially future) aggregate stock returns, we use local weather conditions – measured at the zip-code level. Second, while weather has been shown to affect investors' risk-preferences, see Bassi, Colacito, and Fulghieri

(2013), our estimates are based on risk-adjusted returns, so weather-induced changes in investors' risk-aversion cannot be driving our results.

The results for overall attention, reported in Table 6, confirm the ones of the baseline specifications. The coefficient on instrumented attention is positive at all horizons and it is significant at the 10% level at the 42 and 63 days horizons – suggesting that there is a positive causal relation between attention and performance. The coefficient estimates in Table 6 are larger than the ones reported in Table 5, because the instrumented regressor in Table 6 has not been standardized, so it does not have a unit standard deviation. If we compute the first stage, standardize the predicted values of the endogenous regressor and estimate the second stage, we obtain the coefficients 0.45, 1.42, and 1.98 at the one-, two- and three-month horizons respectively. In line with the results reported so far in the paper, the (unreported) results for research pages are weaker and the ones for balances and positions stronger.

6 Attention and Performance: Evidence from Investor Trades

In an effort to understand the mechanism through which higher investor attention leads to superior portfolio performance, in this section we analyze how attention affects the profitability of investors' active management decisions, that is, their trades. We first relate the performance of the stocks bought and sold by individual investors to the attention they pay to their investment portfolio in the month preceding each trade. We take each individual's trade as the unit of observation and we measure performance as the risk-adjusted returns of the stock over the one-, two- all the way to twelve-month period after the trade has been placed. The adjustment for risk is performed using the DGTW model, see Daniel et al. (1997), but the results are similar if we use simple or market-adjusted returns.

We then provide results showing that the positive effect of attention is – at least in part – due to the fact that high-attention individuals tend to behave as momentum traders that purchase stocks early in the momentum cycle, several months before reversal sets in.

6.1 Baseline parametric results

We start by presenting in Table 7 pooled regression estimates, testing whether there is a positive relation between investor attention and stock performance. We separate the buys and the sells, and estimate the regressions:

$$DGTW\_Ret\_Buys_{i,j,t:t+k} = \alpha + \beta\ Attention_{i,j,t} + \epsilon_{i,j,t:t+k}, \tag{3}$$

$$DGTW\_Ret\_Sells_{i,j,t:t+k} = \alpha + \beta\ Attention_{i,j,t} + \epsilon_{i,j,t:t+k}, \tag{4}$$

where $DGTW\_Ret\_Buys_{i,j,t:t+k}$ ($DGTW\_Ret\_Sells_{i,j,t:t+k}$) are the cumulative abnormal returns of security j bought (sold) by investor i over the time interval $t : t+k$, computed using the DGTW model; $Attention_{i,j,t}$ is the (log) number of seconds spent on the brokerage account website by investor i over the month preceding the trade in stock j that occurs at time t. Note that – to make the results more interpretable – we scale $Attention_{i,j,t}$ so that it has zero mean and unit variance. Finally, cumulative abnormal returns are computed at the one-, two-, three-, four-, five-, six- and twelve-month horizons.

Panel A focuses on the returns of the buys as a function of overall attention, research attention and balances and positions attention. We find a positive relation (statistically significant at the 5% level) between the total attention investors spend on the trading platform and the performance of their trades at the two-, three-, four-, and five-month horizons. The relation is also positive, but only statistically significant at the 10% level, at the one month horizon. The results are also economically significant. At the three-month horizon, for example, a unit-standard deviation increase in attention increases the average annualized adjusted returns of the stocks purchased by $0.533\% \cdot 4 = 2.13\%$. The results for the two specialized measures of attention are very much in line with the overall attention results. For example, at the three-month horizon the effect equals $0.489\% \cdot 4 = 1.96\%$ and $0.408\% \cdot 4 = 1.63\%$ for research and balances and positions attention, respectively. Compared to overall attention, research attention seems to have a stronger effect at the one-month horizon and a slightly smaller effect at the five-month horizon. Finally, the results for balances and positions are somewhat weaker, as the results are significant at the two- and three-month horizons, but they just miss significance – with a p-value of 0.13 – at the four- and five-month horizons.

Panel B reports the performance of the sells as a function of attention. For overall attention, we find that none of the coefficients is significant at the 5% level, and only one coefficient is significant at the 10% level – indicating that there is virtually no relation between overall attention and the performance of the stocks sold by investors. Once again, the results for research attention and balances and positions attention are very much aligned. The only exception is the relation between research attention and returns at the one- and two-months horizons, which is positive and significant at the 5% level.

Overall, the results in Table 7 show that there is a positive effect of attention on the stocks purchased, but not on the stocks sold. This suggests both that the time spent on the brokerage account website is dedicated to searching for new stocks and that the investors are able to translate the information they acquire into profitable trades.[17]

6.2 Non-parametric results

To corroborate the parametric results reported above, we now report evidence based on portfolio sorts. Before analyzing the effect of attention on trading performance, we first confirm the findings in Odean (1999) that – unconditionally – the stocks purchased by individual investors systematically underperform the ones sold. Panel A.I. of Table 8 reports the average cumulative abnormal returns at the one-, two-, three-, four-, five-, six- and twelve-month horizons after stock purchases and sales. For every horizon, we also report the difference in performance between the two groups and a bootstrap p-value testing whether the difference is equal to zero.[18] We find that, at every horizon, the stocks sold outperform the ones purchased and the difference is statistically significant for three out of seven horizons. For example, the average annualized three-month abnormal return of the stocks purchased equals $0.37\% \cdot 4 = 1.48\%$, the one for the stocks sold equals $0.91\% \cdot 4 = 3.64\%$, and their difference is statistically significant with a p-value of 0.01. While in line with Odean (1999), our results are somewhat weaker, possibly due to our sample covering the 2013-2014 bull market.

[17] Table Online VII shows that the results are similar, but less significant, when we measure attention using number of pages or logins instead of seconds.

[18] All p-values in this section are computed using the bootstrap procedure suggested by Barber, Lyon, and Tsai (1999) with 10,000 bootstrap iterations.

Panel A.II. conditions the trades on the overall attention paid by investors to their investment portfolio in the month preceding each trade. We divide the buys in two groups – low and high – and report their performance. We do the same for the sells. The results indicate that overall attention has a strong effect on investor performance. First, we find that – on the one hand – the high-attention buys do not underperform the high-attention sells in a statistically significant fashion: the average annualized three-month abnormal return of the stocks purchased equals $0.79\% \cdot 4 = 3.16\%$, the one for the stocks sold equals $1.05\% \cdot 4 = 4.2\%$ and their difference is statistically insignificant, with a p-value of 0.29. On the other hand, we find that the low-attention buys strongly underperform the low-attention sells in a statistically significant fashion: the average annualized three-month abnormal return of the stocks purchased equals $-0.07\% \cdot 4 = -0.28\%$, the one for the stocks sold equals $0.77\% \cdot 4 = 3.08\%$, and their difference is statistically significant, with a p-value of 0.00.

Second – and more importantly – we find that the high-attention buys strongly outperform the low-attention buys up to four months and the difference becomes insignificant thereafter. Economically, the difference in performance is large: the average annualized three-month difference between high- and low-attention purchases equals $3.16\% - (-0.28\%) = 3.44\%$ and is statistically significant, with a p-value of 0.00. Finally, we find no significant impact of overall attention on the performance of the stocks sold as low- and high-attention sells have similar performance.

The results reported above show that, the more time investors spend on their trading account, the higher the performance of the stocks they buy. In an effort to uncover the main drivers of the results, we show below that the more investors pay attention to their brokerage account the more they behave as momentum traders, and this seems to be the source of their outperformance.

6.3 Understanding the results

While on the brokerage account website, investors may be looking at a wide range of information, such as firms' accounting data, news, and analysts' reports – for example. One obvious piece of information investors are likely to look at is the past performance of the securities they are considering buying or selling. To see whether this is the case, we conduct two complementary exercises. First, we estimate the relation between investors' attention and the past performance of the stocks they trade using a

non-parametric symmetric nearest neighbor approach. Second, we repeat the analysis contained in Panel A of Table 8, but focus on the performance of the stocks *before* the trades occur, rather than *after*. The results of this analysis are reported in Panel B of Table 8.

Starting from the unconditional results, Panel B.I. shows that investors tend to both buy and sell stocks that have appreciated in the past, as shown in Odean (1999). Panel B.II. sharpens the results, as it uncovers that there is a very strong relation between the attention spent by investors and the risk-adjusted returns of the stocks they trade. For example, at the one-month horizon, Panel B.II of Table 8 shows that the average past performance of the high attention buys (sells) equals 3.13% (3.55%), the past performance of the low attention buys (sells) equals 0.70% (1.19%), and the difference in performance between the high and low attention buys (sells) is statistically significant, with a p-value equal to 0.00 (0.00). For the same one-month horizon, Panel A of Figure 3 displays a very strong positive and virtually monotonic relation between log attention and past performance.[19] The remaining panels of Figure 3 and the remaining columns of Panel B.II. of Table 8 show that the pattern is very robust across horizons.

These results – in conjunction with the ones contained in Table 7 and Panel A of Table 8 – paint the following picture. Investors that pay a lot of attention to their trading accounts tend to trade stocks that have appreciated greatly in the past. The good past performance persists into the future for the purchases, as we find that the high-attention buys significantly outperform the low-attention buys up to four months. The outperformance is relatively short-lived, however, as we find that it disappears for horizons greater than five months. Our interpretation of the results is that high-attention trades resemble momentum trades in stocks early in their momentum cycle, approximately a quarter before reversal sets in.

7 Extensions and Additional Analyses

In the previous sections we showed that higher attention leads to superior performance. To understand the potential mechanisms driving our results, we now provide a set of additional analyses.

[19] These plots exclude the top 5 percentiles of log-attention, because the data is more sparse in that region of the support, and the nearest neighbor estimates more erratic.

We start by providing extensions of the baseline panel results and show that the positive relation between attention and performance is mainly driven by the positive effect of attention for those investors that, in general, are rather inattentive.

We then provide extensions of the baseline trading results and show that paying attention is particularly profitable when trading stocks that have high market capitalization, trading volume, volatility, number of analysts, dispersion of analyst forecasts, and news.

Finally, we provide novel evidence on who are the most attentive investors and what demographic and portfolio characteristics explain the cross-section of investor attention.

7.1 Panel portfolio results by investor type

To assess whether the effects estimated in Table 5 are driven by those investors that – on average – pay a lot of attention or by those that rarely pay attention, we divide our account-holders in five quintiles based on their overall total attention over the sample and – for each group – we re-estimate Equation (1). Table 9 presents the results for the 21, 42 and 63 days horizons in panels A, B, and C, respectively.

Moving from left to right, the results for columns Q1 through Q5 report estimates for account-holders with greater degrees of overall attention. For the shortest horizon of 21 days (Panel A), only the investors with low to medium attention (Q1 through Q3) seem to benefit from paying more attention. The effect is instead not statistically significant for high attention investors (Q4 and Q5). Furthermore, the coefficients are monotonically decreasing as we move from low attention to high attention individuals. The results in panels B and C display similar patterns. The coefficients on abnormal attention decrease as average attention increases and become negative for the investors that pay the most attention. Also, the coefficients for the first four groups are all consistently significant at the 5% level. For the last group, on the other hand, we never find a significant effect of attention on performance.

Taken together, the results in Table 9 uncover diminishing returns to abnormal attention. Abnormal attention for those investors that rarely pay attention to their account seems to improve their

portfolio allocation. On the other hand, those that tend to spend a lot of time on their brokerage account do not seem to benefit from additional time researching stocks and worrying about their portfolio positions.

7.2 Investor trades results controlling for stock characteristics

To sharpen the results in Table 7 and understand under what circumstances it pays the most to pay attention, we condition the performance of the trades on the characteristics of the stocks traded. We use the volume of the stock on the day of the trade, its volatility, and the disagreement between analysts' earnings-per-share forecasts as alternative measures of valuation uncertainty. We use instead the market capitalization of the company, the number of analysts, and the number of news as proxies for the amount of public information available when placing a trade. For each conditioning variable we divide the trades in two groups: the low group contains the trades associated with firms whose characteristic is below the median; the high group contains the trades associated with firms whose characteristic is above the median. We then re-estimate Equations (3) and (4) separately for each group.

The results, displayed in Table 10, are based on the 3-month horizon and are reported separately for stock purchases (Panel A) and sales (Panel B).[20] A clear pattern emerges from Panel A. Attention is associated with higher future returns when account holders trade companies with high valuation uncertainty, that is, stocks with high volume, volatility, and analysts' disagreement. The same is true for companies with larger amount of public information, that is, stocks with greater market capitalization, number of analysts, and number of news.

Statistically, all coefficients in the high group are significant at the 1% level, while only one coefficient is significant in the low group – the one associated with volatility. The two groups also differ in terms of economic significance. For example, a one standard-deviation increase in attention leads to a $0.764\% \cdot 4 = 3.06\%$ increase in future adjusted returns for stocks with high market capitalization, while for stocks with low market capitalization the increase is $0.261\% \cdot 4 = 1.04\%$.

While weaker than the results for the buys, attention seems to be related to the performance of

[20] The results are qualitatively the same when we use 1-month to 5-month return horizons.

the sells for stocks with high uncertainty and high levels of public information. For two conditioning variables out of five – market capitalization and number of analysts – the coefficients are significant at the 1% level for the high group. Furthermore, for high analysts' disagreement and news, the coefficients on attention are significant at the 5% and 10% level, respectively. The fact that higher attention is related to greater future performance after stock sales, combined with the known fact that investors rarely realize losses, possibly suggests that – in situations of high uncertainty – paying high attention leads investors to sell their stocks too early, while they are still appreciating. None of the coefficients for the low group are significant at the 1% level and only one coefficient – the one for volatility – is significant at the 10% level.

7.3 Who are the most attentive investors?

In this closing section, we relate the number of minutes investors spend on the brokerage account website – and its various sections – to their portfolio holdings, as well as trading and demographic characteristics. We estimate the following cross-sectional regression at the account level:

$$Attention_i = \alpha + \boldsymbol{x}_i' \, \boldsymbol{\beta} + \epsilon_i, \qquad for \; i = 1, \ldots, N, \tag{5}$$

where $Attention_i$ is the (log) total number of minutes spent over our 18 months period on the brokerage account website by account holder i and N is the total number of accounts in our dataset. We divide the conditioning variables into three groups. The first group comprises demographic variables: *Male*, a male dummy variable; *Brokerage*, a brokerage account dummy; *Age*, the age of the investor; and *Account Age*, the age of the account.

The second category comprises portfolio holdings variables as of December 31, 2013: *Portfolio Value*, the total value of the invested portfolio; *Fr. in Cash*, *Fr. in ETF*, and *Fr. in Mutual Fund*, the fraction of wealth held in cash, traded funds and mutual funds, respectively.

The third category comprises regressors related to portfolio risk and trading activity: *Beta Mkt*, *Beta SMB*, *Beta HML*, and *Beta MOM*, the loadings on the Market, Small-Minus-Big, High-Minus-Low, and Momentum factors – computed using daily returns over the full sample; and *N. of Stocks*

Traded, the number of stocks traded over the period.

To ease the economic interpretation of our estimates, we de-mean and standardize all regressors so that they have unit variance.[21] The results for this cross-sectional regression are reported in Panel A of Table 11. The first column reports the coefficient of each regressor, the second its p-value, and the third its economic magnitude. This last column is computed as follows. We first compute the number of minutes spent on the brokerage account website by the base-case investor, which equals 820.91 minutes, or 13.6 hours. We then multiply $e^{\beta_k} - 1$ to this base number for each coefficient β_k where $k = 1, \dots, K$.[22] For example, the economic magnitude of the *Brokerage* dummy is computed as $820.91 \cdot (e^{0.590} - 1) = 660.11$, meaning that brokerage account holders spend 660.11 additional minutes – or 11.1 hours – compared to non-brokerage account holders, for a total of 820.91+660.11=1,481.02 minutes. This result is quite remarkable, as it shows that brokerage account investors spend twice as much time on their account compared to IRA, and other account-type holders.

The remaining regressors associated with demographic characteristics show that, first, males pay more attention than women to their investment portfolios – by an average of 299.14 minutes. Second, investors pay more attention to their investment portfolios as they get older. The effect is also quite strong, as a standard deviation increase in age is associated with an increase in attention of 277.52 minutes. Third, investors' attention does not increase with the amount of time investors have had their account open.

Turning to the regressors associated with portfolio characteristics, we find that investors with higher wealth pay more attention, while attention is negatively related to the fraction of the portfolio invested in cash or in exchange traded funds. Finally, the fraction of wealth invested in mutual funds does not seem to be related to attention in any significant manner.

In terms of portfolio performance and risk, we find that investors that have greater exposure to the

[21] We do not standardize the dummy variable regressors *Male* and *Brokerage*.

[22] Because we are estimating a log-linear regression, the economic interpretation of each coefficient β_k is computed as $e^{\beta_k} - 1$, and is interpreted as the percentage change in the number of minutes spent on the brokerage account website when the k-th regressor increases by one standard deviation. Finally – because all regressors have been de-meaned – the number of minutes spent on the brokerage account website by non-male and non-brokerage account holders, that are average in terms of all the other conditioning variables, represent our "base-case investor." The number of minutes the base-case investor spends on the brokerage account website can be computed as $e^{\hat{\alpha}} \cdot N^{-1} \sum_{i=1}^{N} e^{\hat{\epsilon}_i}$, where $\hat{\alpha}$ and $\hat{\epsilon}_i$ are obtained from Equation (5), see Duan (1983).

aggregate stock market, as measured by the beta of their portfolio with respect to the market factor, pay more attention. The same is true for those investors that are more exposed to the SMB and MOM factors, indicating that those investors that invest in small caps and momentum stocks are, overall, more attentive to their portfolios. The opposite holds for HML exposure, where we find that investors that focus on growth stocks, as opposed to value stocks, are more attentive. The final regressor in this category is the number of trades undertaken by the account holders over our sample. As expected, the more trades they place, the greater the degree of attention they pay to their investment portfolio. The coefficient for this regressor is both statistically and economically very significant: a standard deviation in the number of trades is associated with an increase in attention of 1,030.81 minutes (17.2 hours) over the sample.

Panels B and C of Table 11 show that the results are similar when using Research and Balances and Positions as measures of attention, and Table Online VIII shows that our results are robust to using number of pages and logins.

8 Conclusions

We use a novel brokerage account dataset to study the relation between investor attention and performance – both at the portfolio returns level and at the individual trades level. For the relation between attention and overall portfolio returns, we find a strong and positive cross-sectional relation between attention and performance, in that more attentive investors achieve higher portfolio risk-adjusted returns and Sharpe ratios, even after controlling for covariates related to investment style. Using panel regressions that control for investor skills using fixed effects, we also show that periods of higher attention are related to superior future portfolio performance. Finally, we propose an identification strategy that uses poor local weather conditions as an instrument for attention, and find a positive and significant causal relation between attention and investment performance.

We find similar results when we focus on the performance of individual trades. Attention is positively related to the future performance of the stocks purchased up to four months after the trade is placed. We find – on the other hand – no discernible effect of attention on the performance of the

stocks sold.

To understand the economic mechanism relating attention and trading profitability, we conduct a number of auxiliary exercises. First, we show that attention is particularly profitable when investors trade stocks with high market capitalization, trading volume, volatility, number of analysts, dispersion of analyst forecasts, and news – indicating that it is for the stocks with high uncertainty, but for which a lot of public information is available, that it pays to pay attention. Second, we show that Odean (1999)'s result that the stocks sold by individuals outperform the ones purchased is very strong among low-attention trades, but disappears for high-attention trades. Finally, by analyzing the performance of the stocks before they are traded, we show that high-attention trades are profitable, because they resemble momentum trades in stocks early in their momentum cycle – approximately a quarter before reversal sets in.

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Appendix A Data Construction

In this appendix, we describe the auxiliary datasets we use in our study. As mentioned in Section 3.2, our data source gave us access to data structured as a SQL relational database. Besides the *Web-activity* table described at length in Section 3, this study uses four additional tables named *Trades*, *Clients*, *Accounts*, and *Account Holdings*, respectively. Finally, the study also uses information from a variety of standard data sources. Further details are provided below.

Trades

The *Trades* table includes the record of all the trades made by account holders over the period January 2010 through June 2014. This table contains information regarding 3,528,001 accounts. The *Trades* table has a total of 197,870,535 observations and each observation contains the following information: *Acct_id*, a unique numeric account identifier; *Client_id*, a unique numeric client identifier; *Ord_ts*, the time-stamp of the trade order; *Exec_ts*, the time-stamp of the trade execution; *Scrty_type_descr*, denoting whether the security traded is a stock, a bond, an option or a mutual fund; *Cusip_id*, the CUSIP code of the security traded; *Action*, denoting whether the action is a buy or a sell; *Trd_prncpl_amt*, the amount traded; *Trd_qty*, the number of stocks traded; *Chnl*, denoting whether the trade is web-based or phone based. In our sample, 99% of the trades are web-based, showing how much the broking business has changed compared to the Barber and Odean (2002) data.

The *Trades* table also contains information on the type of account associated with a trade. This variable is named *Acct_type* and takes on 61 values such as 401K, 403B, IRA, and many others. In much of the analysis performed in the paper, we group individual brokerage accounts and Joint Tenants with Right of Survivorship (JTWROS) accounts as one broad category that comprises 57.6% of all accounts in our data.

Clients

The *Clients* table contains information on the characteristics of the clients. This file has 2,812,877 observations. Comparing the total number of accounts reported above to the total number of clients

shows that many clients have more than one account. In fact, 83.9% of the clients have only one account, 2.5% of them have two accounts, and 3.5% of them have three or more accounts. Clients that have multiple accounts usually have an individual account and an IRA account. Out of the *Clients* table, we use the following variables: *client_id*, a unique numeric client identifier; and *Client_age*, the age of the account holder.

Accounts

The *Accounts* table includes data on the characteristics of the accounts. This file has 3,528,001 observations and, for each observation, we make use of the following variables: *Acct_id*, a unique numeric account identifier; *Client_id* a unique numeric client identifier; *Gender*, the gender of the account holder; *Stnd_pstl_cd*, the zip-code of the account-holder; *Acct_open_dt*, the account opening date; and *Acct_close_dt*, the account closing date.

Account Holdings

The *Account Holdings* table includes quarterly holdings for every account in the dataset. This file has 194,438,993 observations and the following variables: *Acct_id*, a unique numeric account identifier; *mkt_close_dt*, the date of the holdings snapshot; *Cusip_id*, the CUSIP code of the security held by the account holder; *Scrty_type_descr*, denoting whether the security held is a stock, a bond, an option, or a mutual fund; *Qty*, the quantity held; and *Amt*, the dollar value of the quantity held. The *Account Holdings* table also contains cash-holdings information. We construct account holdings at the daily frequency by merging the *Account Holdings* table with the *Trades* table.

Additional Data Sources

Stock market information such as prices, returns and trading volumes – among others – is obtained from CRSP, CRSP OTC and CRSP Mutual Funds. Stocks' accounting information is obtained from COMPUSTAT. Benchmark returns are obtained from the Fama-French website and by constructing DGTW returns at the daily frequency. News concerning stocks are obtained from Capital IQ. Analysts'

information is obtained from I/B/E/S. Finally, information regarding zip-codes' latitude and longitude is obtained from Census.

Construction of the Final Dataset

The final dataset is obtained in two steps. In the first, we merge the contents of the *Web-activity*, *Trades*, *Clients*, *Accounts* and *Account Holdings* tables using the *acct_id* identifier. In the second, we merge the resulting dataset with the additional data sources using either the stocks' *Cusip_id* or *ticker* as identifiers.

Table 1. Example of Web Activity Within the Brokerage Account Website

Timestamp	Masked URL	Duration	Session
28jan2014 07:58:05	Homepage	00:00:13	1
28jan2014 07:58:18	Balances and Positions	00:00:08	1
28jan2014 07:58:26	Watchlist	00:00:06	1
28jan2014 08:32:16	Research / Stocks Overview	00:00:02	2
28jan2014 08:32:18	Research / Ticker Symbol=SPX	00:05:33	2
28jan2014 08:37:51	Watchlist	00:00:06	2
28jan2014 08:37:57	Watchlist / Refresh	00:00:27	2
28jan2014 08:38:24	Research / Stocks Overview	00:00:01	2
28jan2014 08:38:25	Research / Ticker Symbol=VIX	00:00:47	2
28jan2014 08:39:12	Watchlist	00:00:04	2
28jan2014 08:39:16	Watchlist / Refresh	00:06:16	2
28jan2014 08:45:32	Balances and Positions	00:00:05	2
28jan2014 08:45:37	Watchlist	00:00:29	2
28jan2014 08:46:06	Watchlist / Refresh	00:26:00	2
28jan2014 09:12:06	Balances and Positions	00:00:04	2
28jan2014 09:12:10	Watchlist	00:02:38	2
28jan2014 12:59:46	Balances and Positions	00:00:18	3
28jan2014 13:00:04	Watchlist	00:17:53	3
28jan2014 14:28:54	Homepage	00:00:12	4
28jan2014 14:29:06	Balances and Positions	00:00:05	4
28jan2014 14:29:11	Watchlist	00:00:23	4

This table displays the web activity – within the brokerage account website – of an account holder, on January 28, 2014. *Timestamp* includes the date, hour, minute and second of the first click on the webpage; *Masked URL* is the masked URL of the webpage browsed by the investor. *Duration* is the number of seconds spent on the page, and *Session* is the web-session number within the trading day. The URLs presented in the table have been masked to preserve the anonymity of the brokerage account house.

Table 2. Summary Statistics of Investor Attention

Panel A. Total daily number of hours spent across all accounts on the top six sections of the brokerage account website

	Mean	**St. Dev**	**p.25**	**p.50**	**p.75**
Balance and Positions	787	412	516	669	930
Research	438	281	260	381	523
Trading	415	263	213	353	561
Homepage	370	143	271	346	438
Account	61	47	35	53	76
Watchlist	46	21	35	42	52

Panel B. Rank of the Top 20 Companies and ETFs Researched by Brokerage Account Investors

	Rank by Minutes	**Rank by Pages**	**Rank by Visits**
Facebook	1	2	2
Apple	2	1	1
Bank of America	3	6	6
Ford	4	5	5
SPDR S&P 500 ETF Trust	5	12	21
AT&T	6	4	4
Twitter	7	11	16
General Electric	8	3	3
3D System	9	10	10
Verizon	10	9	8
Tesla Motors	11	8	9
Gilead Sciences	12	19	27
JC Penney	13	15	19
Microsoft	14	7	7
Sirius XM	15	18	17
Amazon	16	14	15
SPDR Gold Trust	17	26	32
SPDR Dow Jones Industrial Average ETF	18	23	41
Netflix	19	13	11
Market Vectors ETF Trust	20	33	43

This table reports summary statistics of investor attention. Panel A reports summary statistics of the total daily number of hours spent across all account holders on various sections of the brokerage account website. For each section, we report the mean ($Mean$), the standard deviation ($St.Dev$), and the 25th, 50th, and 75th percentiles of the daily number of hours – all computed in the time-series dimension. Panel B reports the top 20 companies and ETFs researched by brokerage account investors. The three columns show the rank based on the number of minutes, pages and visits, respectively.

Table 3. Summary Statistics

Panel A. Characteristics of Clients

	Mean	Median	St.Dev
Age	50.93	51	15.91
Gender	0.73	1	0.44
Number of Accounts	1.34	1	0.68
Account age	8.55	7.52	5.54

Panel B. Portfolio Characteristics

	Mean	Median	St.Dev
Portfolio Value	\$94,000	\$18,000	\$368,000
Cash Holdings	\$16,000	\$1,000	\$72,000
Stock Holdings	\$82,000	\$15,000	\$341,000
Number of Stocks	6.51	4	8.77

Panel C. Trading Behavior

			Percentiles				
	Mean	St.Dev	1st	25th	50th	75th	99th
Fraction of Days with Trades	0.03	0.08	0	0	0	0.01	0.44
Days Between Trades	46.63	60.76	1.41	10	25.39	58.46	322
Number of Trades Per Day	1.72	1.80	1	1	1.31	1.89	7.80
Dollar Value of Trades	\$16,000	\$64,000	–	–	–	–	–

Panel D. Attention Behavior

			Percentiles				
	Mean	St.Dev	1st	25th	50th	75th	99th
Fraction of Days with Logins	0.17	0.24	0	0.02	0.06	0.21	0.96
Days Between Logins	27.51	47.59	1.14	3.95	11.20	30.00	247
Number of Logins Per Day	10.61	17.69	1.50	4.72	7.33	11.59	61.44
Number of Minutes	28.74	288.69	0.30	3.77	8.00	17.45	366.35

This table reports summary statistics of the biographic characteristics (Panel A), the portfolio characteristics (Panel B), and the trading (Panel C) and attention behavior (Panel D) of the brokerage account holders in our web-activity dataset. For each variable in each panel, we report the sample mean ($Mean$), median ($Median$), and standard deviation ($St.Dev$). The statistics reported in Panels A and B are computed across accounts. The statistics in Panels C and D are computed first in the time-series dimension at the account-holder level, considering only days when the stock markets are open. They are then computed cross-sectionally across account holders. All dollar values were rounded to the nearest thousand and the percentiles of "dollar value of trades" have been masked upon request of the data provider for confidentiality reasons.

Table 4. Attention and Portfolio Performance: Cross-Sectional Results

	Panel A. Overall			Panel B. Research			Panel C. Balances & Positions		
	Spec 1	Spec 2	Spec 3	Spec 1	Spec 2	Spec 3	Spec 1	Spec 2	Spec 3
Attention	1.531***	1.600***	2.326***	0.988**	1.309***	1.776***	1.267***	1.321***	2.007***
	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Brokerage		1.991**	1.905**		2.203**	2.238***		2.222**	2.231**
		(0.02)	(0.03)		(0.01)	(0.01)		(0.01)	(0.01)
Male		0.631	0.605		0.669	0.659		0.734	0.734
		(0.48)	(0.49)		(0.45)	(0.46)		(0.41)	(0.41)
Age		-1.038***	-0.964**		-0.934**	-0.832**		-0.971**	-0.892**
		(0.01)	(0.02)		(0.02)	(0.04)		(0.01)	(0.03)
Account Age		0.043	0.056		0.016	0.021		0.021	0.025
		(0.92)	(0.89)		(0.97)	(0.96)		(0.96)	(0.95)
Portfolio Value			-0.553**			-0.481**			-0.539**
			(0.02)			(0.02)			(0.02)
Fr. in Cash			0.136			0.080			0.193
			(0.85)			(0.91)			(0.79)
Fr. in ETF			0.438			0.385			0.444
			(0.31)			(0.37)			(0.30)
Fr. in Mutual Fund			0.580			0.566			0.557
			(0.10)			(0.11)			(0.11)
N. of Stocks Traded			-1.320***			-1.045***			-1.225***
			(0.00)			(0.00)			(0.00)
Constant	1.920***	0.710	0.935	2.004***	0.633	0.778	1.897***	0.451	0.562
	(0.00)	(0.36)	(0.24)	(0.00)	(0.41)	(0.32)	(0.00)	(0.56)	(0.48)
R-Square	0.1%	0.3%	0.4%	0.1%	0.2%	0.3%	0.1%	0.2%	0.3%
N	8,340	7,476	7,468	8,340	7,476	7,468	8,340	7,476	7,468

This table reports regression results on the relation between portfolio performance and investor attention. We estimate the following baseline cross-sectional regression:

$$AVG\_DGTW\_Ret_i = \alpha + \beta \ Attention_i + \boldsymbol{x}_i' \ \boldsymbol{\gamma} + \epsilon_i \qquad for \ i = 1, \ldots, N$$

where $AVG\_DGTW\_Ret_i$ is the annualized percentage average DGTW abnormal return of investor i over the sample, $Attention_i$ is the total attention spent on the brokerage web-site by account holder i over the sample period, $\boldsymbol{x}_i$ is a vector of covariates associated with account holder i and N is the total number of account holders included in the analysis. Attention is measured as the log of the total number of minutes spent on the brokerage account website in Panel A, the log of the total number of minutes spent on the Research pages of the brokerage account website in Panel B, and the log of the total number of minutes spent on the Balances and Positions pages of the brokerage account website in Panel C. Each panel contains three specifications. The first specification uses attention as the sole covariate. The second specification includes a group of covariates that control for investor demographic characteristics: *Brokerage*, a brokerage account dummy; *Male*, a male dummy variable; *Age*, the age of the investor; *Account Age*, the age of the account. The third specification includes portfolio holdings and trading activity variables: *Portfolio Value*, the total value of the invested portfolio; *Fr. in Cash*, *Fr. in ETF*, and *Fr. in Mutual Fund*, the fraction of the total wealth in the brokerage account held in cash, traded funds and mutual funds, respectively; and *N. of Stocks Traded*, the number of stocks traded over the period. Displayed are the ordinary least squares coefficient estimates and associated p-values. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 5. Attention and Performance: Panel Regression Results

Panel A. Overall

	21 Days	42 Days	63 Days
Abn. Attention	0.032**	0.103***	0.138***
	(0.02)	(0.00)	(0.00)
	[0.02]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.14%	0.27%	0.38%
N. Obs	2,573,951	2,377,766	2,187,222

Panel B. Research

	21 Days	42 Days	63 Days
Abn. Attention	0.023	0.078**	0.105**
	(0.17)	(0.01)	(0.02)
	[0.09]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.14%	0.27%	0.38%
N. Obs	2,573,951	2,377,766	2,187,211

Panel C. Balances and Positions

	21 Days	42 Days	63 Days
Abn. Attention	0.046***	0.135***	0.175***
	(0.00)	(0.00)	(0.00)
	[0.00]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.14%	0.27%	0.38%
N. Obs	2,573,951	2,377,766	2,187,211

This table reports panel regression results on the relation between portfolio performance and investor attention. We estimate the following baseline panel regression:

$$DGTW\_Ret_{i,t:t+k} = \alpha_i + \beta_M + \gamma \ Abn\_Attention_{i,t} + \epsilon_{i,t:t+k} \qquad for \ i = 1, \ldots, N \ \ \& \ \ t = 1, \ldots, T,$$

where $DGTW\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return of account-holder i over the time interval $t : t + k$; $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; finally, α_i and β_M represent account-holder fixed effects and monthly time-effects, respectively. Attention is measured as the number of seconds spent on the brokerage account website in Panel A, the number of seconds spent on the Research pages of the brokerage account website in Panel B, and the number of seconds spent on the Balances and Positions pages of the brokerage account website in Panel C. Each panel reports results for different horizons, i.e. k = 21, 42, and 63 days. Displayed are the ordinary least squares coefficient estimates and two sets of p-values. The first – in round brackets – are computed using standard errors that are double-clustered by account-holder and time, see Petersen (2009). The second – in square brackets – are computed using the Driscoll and Kraay (1998) standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively, according to the double-clustered standard errors.

Table 6. Instrumental Variable Results: Attention and Performance

	21 Days	42 Days	63 Days
Abn. Attention	3.377	11.066*	14.590*
	(0.17)	(0.08)	(0.09)
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
Cragg-Donald Wald F-Statistic	18.59	15.84	16.19
N. Obs	2,566,885	2,370,761	2,180,249

This table reports second-stage regression coefficient estimates, and associated p-values, for a two-stage least squares panel regression relating portfolio performance and investor attention. We estimate the following first stage:

$$Abn\_Attention_{i,t} = \alpha_i + \beta_M + \gamma\ Bad\_Weather_{i,t} + \epsilon_{i,t};$$

and the following second stage:

$$DGTW\_Ret_{i,t:t+k} = \alpha_i + \beta_M + \gamma\ \widehat{Abn\_Attention}_{i,t} + \epsilon_{i,t:t+k},$$

where $DGTW\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return of account-holder i over the time interval $t : t+k$; $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; $Bad\_Weather_{i,t}$ is a dummy that takes the value 1 if account holder i experiences poor weather conditions on day t and is equal to 0 otherwise. Poor weather days are those with rain, snow or especially cold and hot temperatures – where the latter are classified as the 20% coldest and hottest zip-code days over our sample period. Weather conditions are computed at the zip-code level using data from Wunderground. The coefficients α_i and β_M represent account-holder fixed effects and monthly time-effects, respectively. Attention is measured as the number of seconds spent on the brokerage account website. Results are reported for three different horizons, i.e. $k = 21$, 42, and 63 days. At each horizon, we report the first-stage Cragg-Donald Wald F-Statistic, the second-stage coefficient estimates and their p-values computed using clustered standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 7. Trading Performance and Investor Attention: Baseline Regression Results

Panel A. Performance of Buys

	1-Month	2-Months	3-Months	4-Months	5-Months	6-Months	12-Months
Overall Attention	0.147*	0.342***	0.533***	0.383**	0.441**	0.197	0.009
	(0.07)	(0.00)	(0.00)	(0.03)	(0.02)	(0.35)	(0.98)
Constant	-0.139*	0.152	0.349**	0.479***	0.622***	0.691***	0.502
	(0.09)	(0.20)	(0.02)	(0.01)	(0.00)	(0.00)	(0.10)
R^2	0.01%	0.03%	0.05%	0.02%	0.02%	0.00%	0.00%
N	24,139	24,103	24,064	24,001	23,947	23,887	23,436

	1-Month	2-Months	3-Months	4-Months	5-Months	6-Months	12-Months
Research Attention	0.393***	0.536***	0.489***	0.339*	0.352	0.051	-1.773***
	(0.00)	(0.00)	(0.00)	(0.09)	(0.10)	(0.81)	(0.00)
Constant	-0.140*	0.156	0.363**	0.489***	0.635***	0.699***	0.536*
	(0.09)	(0.19)	(0.02)	(0.01)	(0.00)	(0.00)	(0.08)
R^2	0.10%	0.08%	0.04%	0.02%	0.01%	0.00%	0.15%
N	24,139	24,103	24,064	24,001	23,947	23,887	23,436

	1-Month	2-Months	3-Months	4-Months	5-Months	6-Months	12-Months
Bal. & Pos. Attention	0.079	0.230*	0.408***	0.276	0.314	-0.001	0.135
	(0.33)	(0.06)	(0.01)	(0.13)	(0.13)	(1.00)	(0.68)
Constant	-0.133	0.165	0.369**	0.494***	0.639***	0.700***	0.502
	(0.10)	(0.17)	(0.02)	(0.01)	(0.00)	(0.00)	(0.10)
R^2	0.00%	0.02%	0.03%	0.01%	0.01%	0.00%	0.00%
N	24,139	24,103	24,064	24,001	23,947	23,887	23,436

Panel B. Performance of Sells

	1-Month	2-Months	3-Months	4-Months	5-Months	6-Months	12-Months
Overall Attention	0.103	0.130	0.287*	0.119	0.118	-0.027	-0.425
	(0.22)	(0.30)	(0.07)	(0.51)	(0.56)	(0.90)	(0.26)
Constant	-0.023	0.376***	0.914***	1.008***	1.090***	1.182***	1.366***
	(0.79)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-Square	0.01%	0.01%	0.02%	0.00%	0.00%	0.00%	0.01%
N	19,435	19,373	19,320	19,257	19,200	19,142	18,777

	1-Month	2-Months	3-Months	4-Months	5-Months	6-Months	12-Months
Research Attention	0.196**	0.344**	0.312*	0.073	0.019	-0.367	-2.618***
	(0.04)	(0.01)	(0.09)	(0.71)	(0.93)	(0.10)	(0.00)
Constant	-0.014	0.392***	0.928***	1.012***	1.090***	1.166***	1.246***
	(0.87)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-Square	0.03%	0.04%	0.02%	0.00%	0.00%	0.01%	0.29%
N	19,435	19,373	19,320	19,257	19,200	19,142	18,777

	1-Month	2-Months	3-Months	4-Months	5-Months	6-Months	12-Months
Bal. & Pos. Attention	0.060	0.041	0.149	-0.038	0.006	-0.050	-0.158
	(0.52)	(0.76)	(0.41)	(0.85)	(0.98)	(0.84)	(0.71)
Constant	-0.025	0.375***	0.909***	1.010***	1.089***	1.184***	1.372***
	(0.77)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
N	19,435	19,373	19,320	19,257	19,200	19,142	18,777

This table reports regression results on the relation between investor attention and trading performance. We separate the buys (i.e. stock purchases) and the sells (i.e. stock sales) and estimate the following pooled regressions:

$$DGTW\_Ret\_Buys_{i,j,t:t+k} = \alpha + \beta\ Attention_{i,j,t} + \epsilon_{i,j,t:t+k},$$
$$DGTW\_Ret\_Sells_{i,j,t:t+k} = \alpha + \beta\ Attention_{i,j,t} + \epsilon_{i,j,t:t+k},$$

where $DGTW\_Ret\_Buys_{i,j,t:t+k}$ ($DGTW\_Ret\_Sells_{i,j,t:t+k}$) are the cumulative abnormal returns of security j bought (sold) by investor i over the time interval $t:t+k$, computed using the DGTW model; $Attention_{i,j,t}$ is the (log) number of seconds spent on the brokerage account website by investor i over the month preceding the trade in stock j that occurs at time t. Cumulative abnormal returns are computed at the one-, two-, three-, four-, five-, six- and twelve-month horizons. Panel A reports results for stock purchases, and measures attention as, alternatively, the total number of seconds spent on the brokerage account website, the total number of seconds spent on the research section of the brokerage account website, and the total number of seconds spent on the balances and positions section of the brokerage account website. Panel B repeats the exercise for stock sales. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 8. Trading Performance and Investor Attention: Portfolio Results

Panel A: Future Returns

Panel A.I. Unconditional Results

Return Horizon	**1-Month**	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Buy	-0.13%	0.17%	0.37%	0.50%	0.64%	0.70%	0.50%
Sell	-0.02%	0.38%	0.91%	1.01%	1.09%	1.18%	1.37%
Buy-Minus-Sell	-0.11%	-0.21%	-0.54%***	-0.51%*	-0.45%	-0.48%	-0.86%**
p-val	(0.33)	(0.19)	(0.01)	(0.05)	(0.17)	(0.20)	(0.04)

Panel A.II. Results Conditional on Overall Attention

Return Horizon	**1-Month**	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Buy-High	0.00%	0.42%	0.79%	0.85%	0.98%	0.88%	0.35%
Buy-Low	-0.28%	-0.10%	-0.07%	0.12%	0.28%	0.51%	0.67%
Sell-High	0.06%	0.38%	1.05%	0.92%	1.00%	0.92%	0.69%
Sell-Low	-0.11%	0.37%	0.77%	1.10%	1.18%	1.45%	2.05%
Buy-High Minus Sell-High	-0.06%	0.04%	-0.26%	-0.07%	-0.02%	-0.04%	-0.34%
p-val	(0.68)	(0.84)	(0.29)	(0.83)	(0.96)	(0.94)	(0.54)
Buy-Low Minus Sell-Low	-0.17%	-0.48%**	-0.84%***	-0.98%***	-0.89%**	-0.94%**	-1.39%***
p-val	(0.31)	(0.05)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)
Buy-High Minus Buy-Low	0.28%**	0.53%***	0.86%***	0.73%**	0.70%	0.36%	-0.32%
p-val	(0.03)	(0.00)	(0.00)	(0.03)	(0.24)	(0.73)	(0.56)
Sell-High Minus Sell-Low	0.17%	0.01%	0.28%	-0.18%	-0.17%	-0.53%	-1.36%**
p-val	(0.30)	(0.97)	(0.46)	(0.73)	(0.83)	(0.45)	(0.03)

Panel B: Past Returns

Panel B.I. Unconditional Results

Return Horizon	**1-Month**	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Buy	1.95%	3.42%	5.03%	7.14%	8.33%	10.30%	26.75%
Sell	2.38%	3.93%	5.21%	6.97%	8.12%	9.76%	22.08%
Buy-Minus-Sell	-0.43%***	-0.51%***	-0.18%	0.17%	0.21%	0.53%*	4.67%***
p-val	(0.00)	(0.00)	(0.48)	(0.47)	(0.44)	(0.08)	(0.00)

Panel B.II. Results Conditional on Overall Attention

Return Horizon	**1-Month**	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Buy-High	3.13%	4.83%	6.98%	9.99%	11.56%	14.09%	34.50%
Buy-Low	0.70%	1.92%	2.96%	4.11%	4.91%	6.27%	18.51%
Sell-High	3.55%	5.40%	6.92%	9.37%	10.88%	13.17%	30.57%
Sell-Low	1.19%	2.43%	3.46%	4.51%	5.30%	6.29%	13.43%
Buy-High Minus Sell-High	-0.42%***	-0.57%**	0.06%	0.62%*	0.67%*	0.93%**	3.94%***
p-val	(0.01)	(0.01)	(0.85)	(0.05)	(0.07)	(0.03)	(0.00)
Buy-Low Minus Sell-Low	-0.49%***	-0.51%***	-0.50%**	-0.40%	-0.39%	-0.02%	5.08%***
p-val	(0.00)	(0.00)	(0.05)	(0.17)	(0.26)	(0.96)	(0.00)
Buy-High Minus Buy-Low	2.43%***	2.91%***	4.02%***	5.88%***	6.65%***	7.82%***	15.99%***
p-val	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sell-High Minus Sell-Low	2.36%***	2.97%***	3.46%***	4.85%***	5.58%***	6.88%***	17.14%***
p-val	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

This table reports portfolio results on the relation between investor attention and the performance of the stocks before (Panel B) and after (Panel A) they are traded. Each panel reports the average cumulative DGTW-adjusted returns at the one-, two-, three-, four-, five-, six- and twelve-month horizons. Panel A.I. and Panel B.I. present the unconditional results and – for every horizon – report the difference in performance between the stocks purchased and sold as well as the *p*-value testing whether the difference in performance is equal to zero. Panel A.II. and Panel B.II. condition on the overall attention paid by the account holders in the month preceding each trade. We divide the buys in two groups – low and high – based on overall attention and report the performance of the the low- and high-attention buys, respectively. We repeat the same procedure to compute low- and high-attention sells. For every horizon, we report the difference in performance between: 1) high-attention buys and high-attention sells; 2) low-attention buys and low-attention sells; 3) high-attention buys and low-attention buys; and 4) high-attention sells and low-attention sells. In each case, we also report the *p*-value testing whether the difference in performance is equal to zero. All *p*-values are based on the bootstrap procedure suggested by Barber, Lyon, and Tsai (1999). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 9. Attention and Performance: Panel Regression Results By Groups

Panel A. 21 Days

	Q1	Q2	Q3	Q4	Q5
Abn. Attention	0.241**	0.086*	0.070*	0.039	-0.023
	(0.03)	(0.08)	(0.05)	(0.28)	(0.28)
Time FE	✓	✓	✓	✓	✓
Acct Holder FE	✓	✓	✓	✓	✓
R^2	0.13%	0.13%	0.14%	0.13%	0.18%
N	421,489	510,043	531,510	537,771	573,138

Panel B. 42 Days

	Q1	Q2	Q3	Q4	Q5
Abn. Attention	0.412**	0.206**	0.222***	0.113***	-0.012
	(0.02)	(0.01)	(0.00)	(0.01)	(0.73)
Time FE	✓	✓	✓	✓	✓
Acct Holder FE	✓	✓	✓	✓	✓
R^2	0.25%	0.25%	0.27%	0.23%	0.32%
N	390,144	471,115	490,610	496,060	529,837

Panel C. 63 Days

	Q1	Q2	Q3	Q4	Q5
Abn. Attention	0.588**	0.271**	0.415***	0.161**	-0.066
	(0.02)	(0.01)	(0.00)	(0.01)	(0.19)
Time FE	✓	✓	✓	✓	✓
Acct Holder FE	✓	✓	✓	✓	✓
R^2	0.36%	0.36%	0.36%	0.33%	0.44%
N	359,282	433,371	451,065	455,663	487,830

This table reports panel regression results on the relation between portfolio performance and investor attention for five groups of account holders (columns $Q1$ to $Q5$) based on the total number of seconds spent on the brokerage account website. $Q1$ denotes the bottom quintile, i.e. the least attentive group of account holders, while $Q5$ denotes the top quintile, i.e. the most attentive group of account holders. We estimate the following baseline panel regression:

$$DGTW\_Ret_{i,t:t+k} = \alpha_i + \beta_M + \gamma \; Abn\_Attention_{i,t} + \epsilon_{i,t:t+k} \qquad for \; i = 1, \ldots, N \;\;\&\;\; t = 1, \ldots, T,$$

where $DGTW\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return of account-holder i over the time interval $t : t + k$; $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; finally, α_i and β_M represent account-holder fixed effects and monthly time-effects, respectively. Attention is measured as the seconds spent on the brokerage account website. Panels A, B, and C report results for $k = 21$, 42, and 63 days, respectively. Displayed are the ordinary least squares coefficient estimates and associated p-values, computed using standard errors that are double-clustered by account-holder and time, see Petersen (2009). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 10. Trading Performance and Investor Attention: Regression Results Conditioning on Stock Characteristics

Panel A. Performance of Buys

	Volume		Size		Volatility		Disagreement		Num. Analysts		News	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Attention	0.346	0.706***	0.261	0.764***	0.330***	0.773***	0.233	0.824***	0.318	0.711***	0.091	0.859***
	(0.17)	(0.00)	(0.40)	(0.00)	(0.00)	(0.00)	(0.22)	(0.00)	(0.23)	(0.00)	(0.75)	(0.00)
Constant	0.140	0.535***	0.261	0.416***	0.178*	0.610**	0.793***	0.435*	0.527*	0.387***	0.288	0.423***
	(0.58)	(0.00)	(0.41)	(0.00)	(0.07)	(0.03)	(0.00)	(0.09)	(0.05)	(0.00)	(0.32)	(0.01)
R^2	0.02%	0.11%	0.01%	0.45%	0.10%	0.06%	0.01%	0.09%	0.01%	0.24%	0.00%	0.22%
N	11,450	12,614	10,886	13,178	10,892	12,309	12,266	11,178	12,223	11,648	10,431	13,633

Panel B. Performance of Sells

	Volume		Size		Volatility		Disagreement		Num. Analysts		News	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Attention	0.390	0.253	0.074	0.427***	0.205*	0.219	0.049	0.515**	0.182	0.392***	0.261	0.306*
	(0.12)	(0.21)	(0.82)	(0.00)	(0.06)	(0.45)	(0.79)	(0.05)	(0.51)	(0.01)	(0.39)	(0.07)
Constant	0.291	1.499***	1.098***	0.767***	0.023	1.892***	0.852***	1.382***	1.305***	0.712***	0.915***	0.915***
	(0.25)	(0.00)	(0.00)	(0.00)	(0.84)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.03%	0.02%	0.00%	0.15%	0.04%	0.01%	0.00%	0.04%	0.00%	0.08%	0.01%	0.03%
N	9,401	9,919	8,711	10,609	9,057	9,685	9,928	8,896	9,744	9,427	8,290	11,030

This table reports regression results on the relation between investor attention and trading performance, conditioning on the characteristics of the stocks traded. We separate the buys (i.e. stock purchases) and the sells (i.e. stock sales) and estimate the following pooled regressions:

$$DGTW\_Ret\_Buys_{i,j,t:t+k} = \alpha + \beta \; Attention_{i,j,t} + \epsilon_{i,j,t:t+k},$$
$$DGTW\_Ret\_Sells_{i,j,t:t+k} = \alpha + \beta \; Attention_{i,j,t} + \epsilon_{i,j,t:t+k},$$

where $DGTW\_Ret\_Buys_{i,j,t:t+k}$ ($DGTW\_Ret\_Sells_{i,j,t:t+k}$) are the cumulative abnormal returns of security j bought (sold) by investor i over the time interval $t : t+k$, computed using the DGTW model; $Attention_{i,j,t}$ is the (log) number of seconds spent on the brokerage account website by investor i over the month preceding the trade in stock j that occurs at time t. Cumulative abnormal returns are computed at the three–month horizon. Panel A reports results for stock purchases, and measures attention as overall attention. The results are computed separately for stocks with low and high values of the conditioning variables. The conditioning variables used are – from left to right: *Volume*, the volume of the stock on the day of the trade; *Size*, computed as the log of the market price multiplied by the number of shares outstanding; *Volatility*, computed as the realized volatility of the stock over the previous month; *Disagreement*, the standard deviation of the analysts' earnings-per-share forecasts; *Num. Analysts*, the log of the number of analysts covering the stock during the quarter the trade takes place; and *News*, the number of news from Capital IQ over the previous month. Panel B repeats the exercise for stock sales. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 11. Characteristics of Attentive Investors

	Panel A. Overall			Panel B. Research			Panel C. Balances & Positions		
	Coeff	***p*-val**	**Magnitude**	**Coeff**	***p*-val**	**Magnitude**	**Coeff**	***p*-val**	**Magnitude**
Brokerage	0.590***	(0.00)	660.109	0.407***	(0.00)	31.899	0.371***	(0.00)	128.979
Male	0.311***	(0.00)	299.143	0.350***	(0.00)	26.633	0.261***	(0.00)	85.684
Age	0.291***	(0.00)	277.522	0.218***	(0.00)	15.446	0.286***	(0.00)	94.878
Account Age	0.033	(0.12)	27.720	0.085***	(0.00)	5.625	0.061**	(0.01)	17.922
Portfolio Value	0.164***	(0.01)	145.975	0.117***	(0.01)	7.889	0.195***	(0.01)	61.645
Fr. in Cash	-0.101***	(0.00)	-78.669	-0.077***	(0.00)	-4.724	-0.197***	(0.00)	-51.274
Fr. in ETF	-0.097***	(0.00)	-76.177	-0.058**	(0.02)	-3.603	-0.104***	(0.00)	-28.270
Fr. in Mutual Fund	-0.005	(0.80)	-4.006	-0.012	(0.58)	-0.754	0.019	(0.37)	5.360
Beta Mkt	0.106***	(0.00)	92.019	0.095***	(0.00)	6.323	0.160***	(0.00)	49.906
Beta SMB	0.091***	(0.00)	78.478	0.003	(0.88)	0.222	0.091***	(0.00)	27.324
Beta HML	-0.062***	(0.01)	-48.974	-0.041*	(0.07)	-2.535	-0.061**	(0.01)	-16.877
Beta MOM	0.113***	(0.00)	98.496	0.097***	(0.00)	6.458	0.113***	(0.00)	34.214
Number of Stocks Traded	0.813***	(0.00)	1,030.815	0.746***	(0.00)	70.350	0.939***	(0.00)	447.053
Constant	4.749***	(0.00)	820.91	1.595***	(0.00)	63.50	3.212***	(0.00)	286.98
R-Square		22.9%			16.0%			22.9%	
N		8,574			8,574			8,574	

This table reports regression results on the relation between the time spent on the brokerage account website and the characteristics of the account holders. We estimate the following baseline cross-sectional regression:

$$Attention_i = \alpha + \boldsymbol{x}_i' \,\boldsymbol{\beta} + \epsilon_i \qquad for\ i = 1, \ldots, N$$

where $Attention_i$ is the total attention spent on the brokerage web-site by account holder i over the sample period, $\boldsymbol{x}_i$ is a vector of covariates associated with account holder i and N is the total number of account holders included in the analysis. Attention is measured as the log of the total number of minutes spent on the brokerage account website in Panel A, the log of the total number of minutes spent on the Research pages of the brokerage account website in Panel B, and the log of the total number of minutes spent on the Balances and Positions pages of the brokerage account website in Panel C. What follows is a description of the covariates included. The first group comprises demographic variables: *Brokerage*, a brokerage account dummy; *Male*, a male dummy variable; *Age*, the age of the investor; *Account Age*, the age of the account. The second category comprises portfolio holdings variables: *Portfolio Value*, the total value of the invested portfolio; *N. of Assets*, the total number of stocks, mutual funds and exchange traded funds held; *Fr. in Cash*, *Fr. in ETF*, and *Fr. in Mutual Fund*, the fraction of the total wealth in the brokerage account held in cash, traded funds and mutual funds, respectively. The third category comprises regressors related to portfolio risk and trading activity: *Beta Mkt*, *Beta SMB*, *Beta HML*, and *Beta MOM*, the loadings on the market, Small-Minus-Big, High-Minus-Low and Momentum factors computed using the full sample available using daily returns; and *N. of Stocks Traded*, the number of stocks traded over the period. Within each panel we display the ordinary least squares coefficient estimates ($Coeff$), the associated p-values (p-val), and the economic magnitudes ($Magnitude$) – computed as described in Section 7.3. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

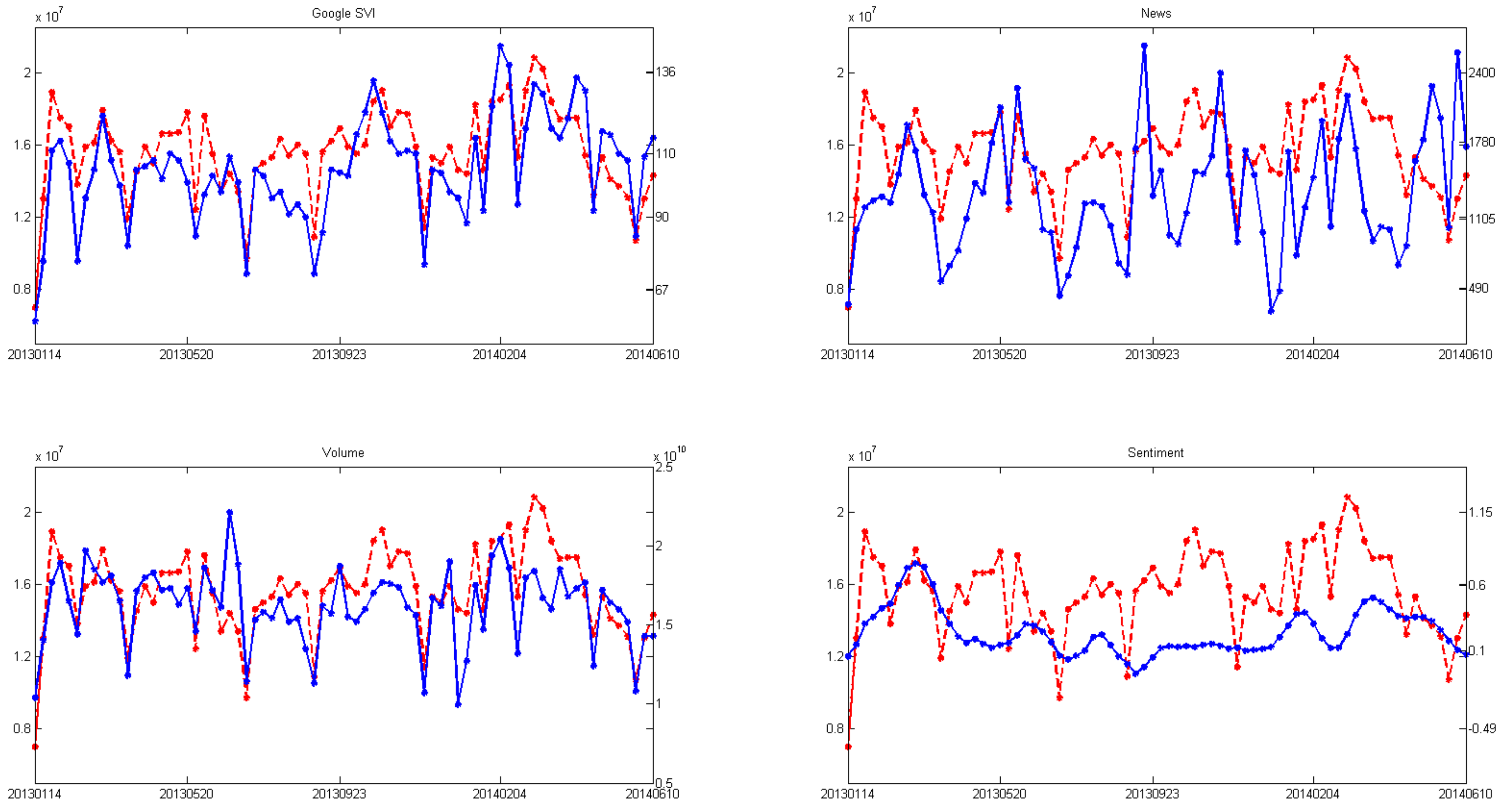

Figure 1: This figure compares the weekly total number of seconds spent on the brokerage account website – computed across all account holders – to four proxies of investor attention that have been proposed in the literature: the Google Search Volume Index for the word "S&P 500," reported in the top-left panel; the total number of news pertaining to stocks in the S&P 500, reported in the top-right panel; the trading volume on the S&P 500, reported in the bottom-left panel; and the State Street Investor Confidence Index, reported in the bottom-right panel. In each panel, our measure of attention is reported as a red dashed line, while the alternative measure of attention is reported as a blue solid line.

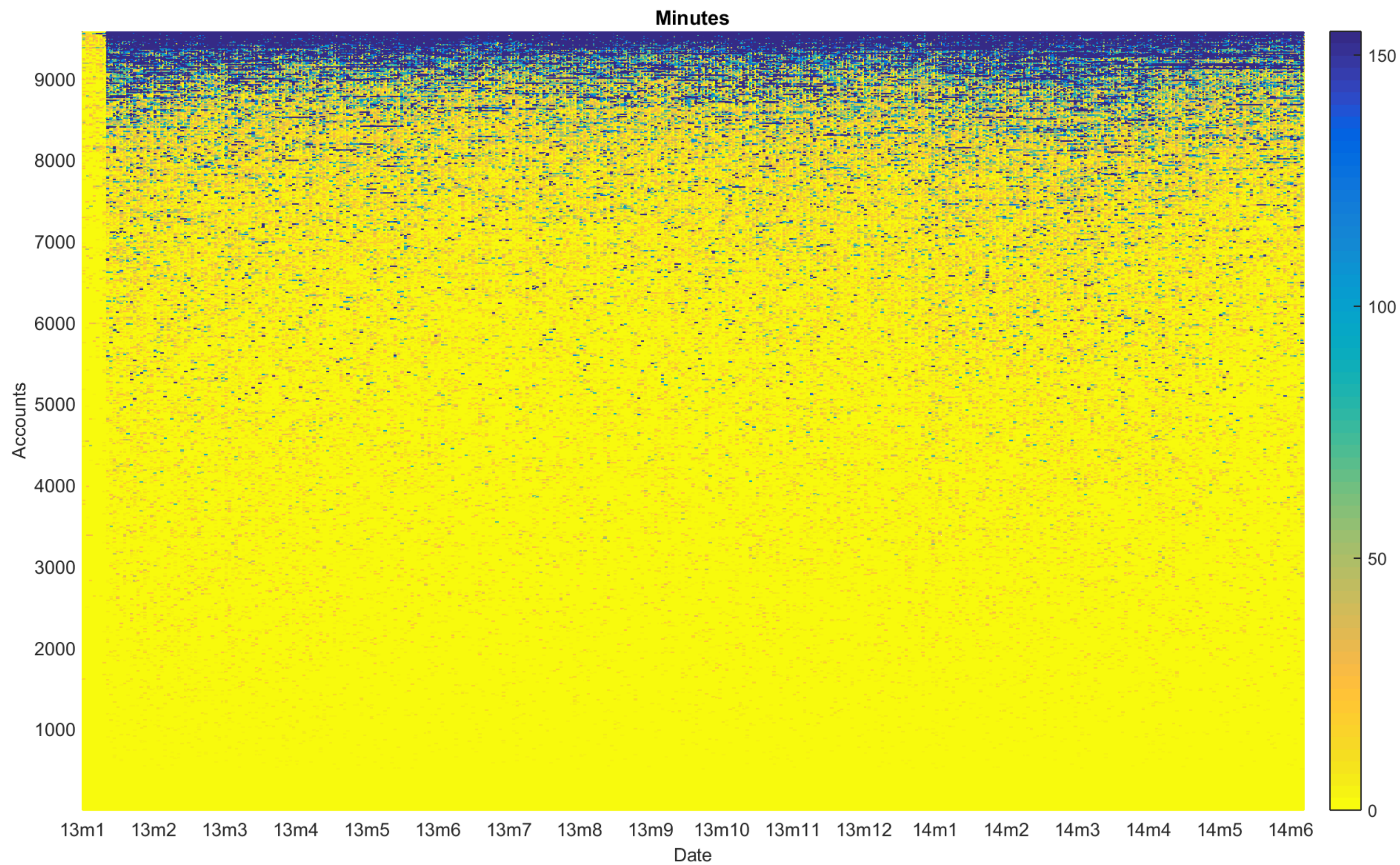

Figure 2: This figure reports the heat-map of the daily number of minutes spent on the brokerage account website by each account holder. Each point on the x-axis represents a business day, and each point on the y-axis represents an account holder. By focusing on one value on the y-axis and moving from left to right, the reader can assess how the attention of an individual investor varies over time. Likewise, by focusing on one value on the x-axis and moving from top to bottom, the reader can observe how – for a given day – attention varies across account holders. The accounts are sorted by the total number of minutes spent on the brokerage account website over the full sample, so that the more active investors are at the top of the figure. The number of minutes is winsorized at the 95-th percentiles, so that the number of minutes spent on the brokerage account website ranges from zero to 150.

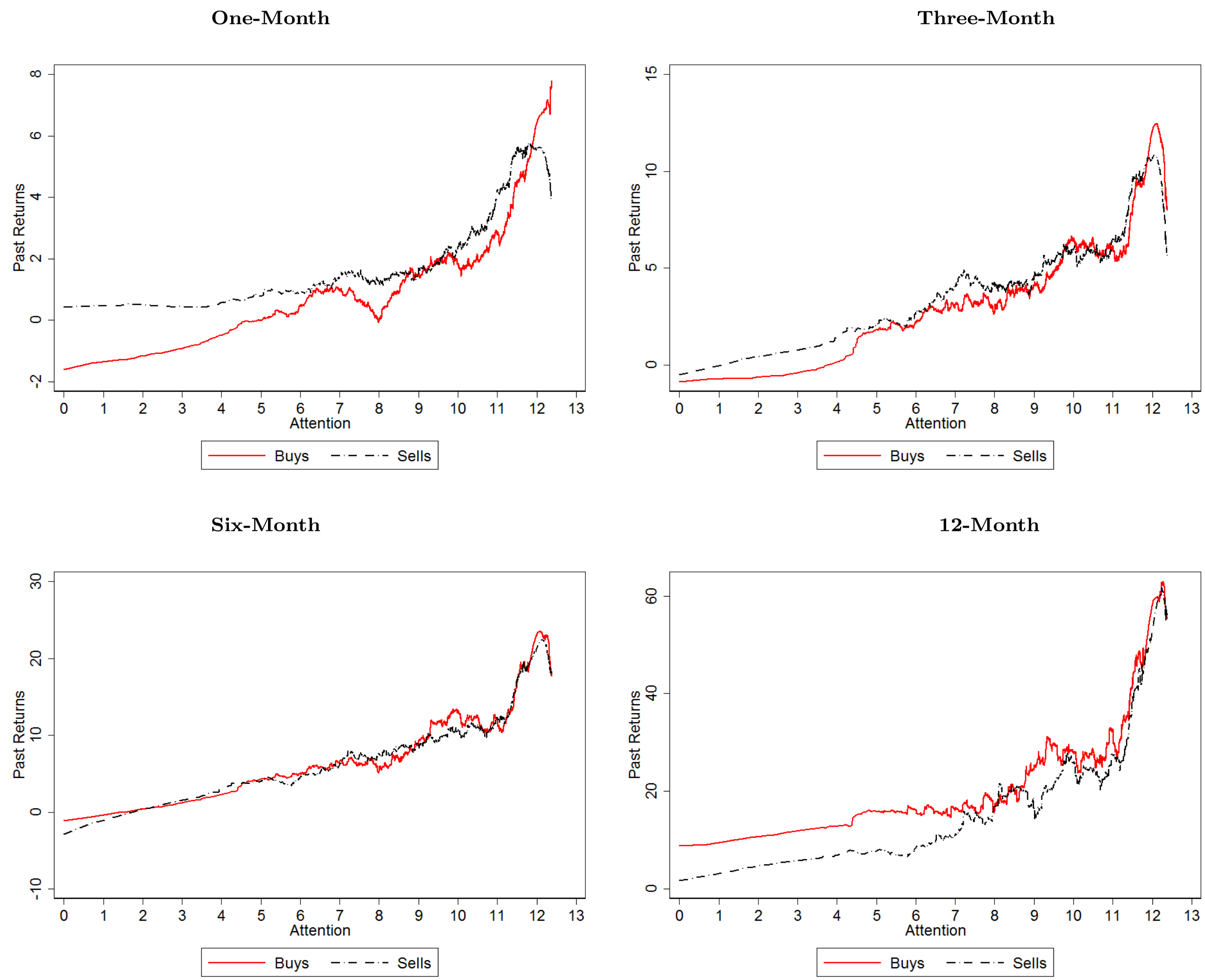

Figure 3: This figure reports the relation between investors' attention and the past performance of the stocks they trade using a non-parametric symmetric nearest neighbor approach. Attention is computed as the log total number of seconds spent by each investor over the month preceding each trade. Stocks' past performance is computed over the previous month in the top-left panel, the previous three months in the top-right panel, the previous six months in the bottom-left panel and the previous twelve months in the bottom-right panel. In each panel, the trades are divided into stock purchases and stock sales. The past performance of the stocks purchased is represented by a solid red line, while the past performance of the stocks sold is represented by a dashed black line.

Table Online I. Summary Statistics

	Panel A. Characteristics of Clients				Panel B. Portfolio Characteristics		
	Mean	Median	St.Dev		Mean	Median	St.Dev
Age	50.80	51	16.56	Portfolio Value	\$90,000	\$14,000	\$422,000
Gender	0.72	1	0.45	Cash Holdings	\$15,000	\$1,000	\$75,000
Number of Accounts	1.25	1	0.60	Stock Holdings	\$77,000	\$11,000	\$352,000
Account age	8.55	7.63	5.51	Number of Stocks	6.18	3	10.09

	Panel C. Trading Behavior						
			Percentiles				
	Mean	St.Dev	1st	25th	50th	75th	99th
Fraction of Days with Trades	0.04	0.08	0	0	0.01	0.03	0.43
Days Between Trades	55.24	65.48	1	12.50	31.20	70.33	367
Number of Trades Per Day	1.65	1.77	1	1	1.22	1.73	8
Dollar Value of Trades	\$17,000	\$69,000	–	–	–	–	–

This table reports summary statistics of the biographic characteristics (Panel A), the portfolio characteristics (Panel B), and the trading (Panel C) behavior of the entire universe of accounts in our data, excluding the ones in the web-activity dataset. For each variable in each panel, we report the sample mean (*Mean*), median (*Median*), and standard deviation (*St.Dev*). The statistics reported in Panels A and B are computed across accounts. The statistics in Panels C are computed first in the time-series dimension at the account-holder level. They are then computed cross-sectionally across account holders. All dollar values were rounded to the nearest thousand and the percentiles of "dollar value of trades" have been masked upon request of the data provider for confidentiality reasons.

Table Online II. Robustness for Attention and Portfolio Performance: Cross-Sectional Results

	Panel A. Minutes			Panel B. Pages			Panel C. Logins		
Attention	1.531***	1.600***	2.326***	0.635***	0.665***	1.065***	0.597**	0.640**	1.011***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.03)	(0.02)	(0.00)
Brokerage		1.991**	1.905**		2.158**	2.103**		2.269***	2.292***
		(0.02)	(0.03)		(0.01)	(0.02)		(0.01)	(0.01)
Male		0.631	0.605		0.709	0.676		0.740	0.723
		(0.48)	(0.49)		(0.42)	(0.44)		(0.40)	(0.42)
Age		-1.038***	-0.964**		-0.946**	-0.869**		-0.946**	-0.876**
		(0.01)	(0.02)		(0.02)	(0.03)		(0.02)	(0.03)
Account Age		0.043	0.056		0.051	0.070		0.059	0.085
		(0.92)	(0.89)		(0.90)	(0.87)		(0.89)	(0.84)
Portfolio Value			-0.553**			-0.543**			-0.532**
			(0.02)			(0.02)			(0.02)
Fr. in Cash			0.136			0.130			0.142
			(0.85)			(0.86)			(0.85)
Fr. in ETF			0.438			0.417			0.416
			(0.31)			(0.33)			(0.33)
Fr. in Mutual Fund			0.580			0.562			0.572
			(0.10)			(0.11)			(0.10)
Number of Stocks Traded			-1.320***			-1.214***			-1.104***
			(0.00)			(0.00)			(0.00)
Constant	1.920***	0.710	0.935	-1.310	-2.827*	-4.696***	-0.108	-1.722	-2.879**
	(0.00)	(0.36)	(0.24)	(0.36)	(0.05)	(0.00)	(0.93)	(0.16)	(0.02)
R-Square	0.1%	0.3%	0.4%	0.1%	0.2%	0.3%	0.1%	0.2%	0.3%
N	8,340	7,476	7,468	8,340	7,476	7,468	8,340	7,476	7,468

This table reports regression results on the relation between portfolio performance and investor attention. We estimate the following baseline cross-sectional regression:

$$AVG\_DGTW\_Ret_i = \alpha + \beta\ Attention_i + \boldsymbol{x}_i'\ \boldsymbol{\gamma} + \epsilon_i \qquad for\ i = 1, \ldots, N$$

where $AVG\_DGTW\_Ret_i$ is the annualized percentage average DGTW abnormal return of investor i over the sample, $Attention_i$ is the total attention spent on the brokerage web-site by account holder i over the sample period, $\boldsymbol{x}_i$ is a vector of covariates associated with account holder i and N is the total number of account holders included in the analysis. Attention is measured as the log of the total number of minutes spent on the brokerage account website in Panel A, the log of the total number of pages browsed in Panel B, and the log of the total number Logins in Panel C. Each panel contains three specifications. The first specification uses attention as the sole covariate. The second specification includes a group of covariates that control for investor demographic characteristics: *Brokerage*, a brokerage account dummy; *Male*, a male dummy variable; *Age*, the age of the investor; *Account Age*, the age of the account. The third specification includes portfolio holdings and trading activity variables: *Portfolio Value*, the total value of the invested portfolio; *Fr. in Cash*, *Fr. in ETF*, and *Fr. in Mutual Fund*, the fraction of the total wealth in the brokerage account held in cash, traded funds and mutual funds, respectively; and *N. of Stocks Traded*, the number of stocks traded over the period. Displayed are the ordinary least squares coefficient estimates and associated p-values. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table Online III. Attention and Investor Sharpe Ratio: Cross-Sectional Results

	Panel A. Overall			Panel B. Research			Panel C. Balances & Positions		
	Spec 1	Spec 2	Spec 3	Spec 1	Spec 2	Spec 3	Spec 1	Spec 2	Spec 3
Attention	0.090***	0.086***	0.049***	0.108***	0.103***	0.065***	0.137***	0.132***	0.089***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Brokerage		-0.059**	-0.049**		-0.054**	-0.048**		-0.055**	-0.049**
		(0.02)	(0.03)		(0.03)	(0.03)		(0.02)	(0.03)
Male		-0.046*	-0.010		-0.049*	-0.013		-0.049*	-0.012
		(0.07)	(0.66)		(0.05)	(0.56)		(0.05)	(0.58)
Age		0.016	0.025**		0.018	0.026**		0.010	0.022**
		(0.20)	(0.02)		(0.15)	(0.02)		(0.43)	(0.05)
Account Age		0.094***	0.063***		0.092***	0.061***		0.092***	0.061***
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
Portfolio Value			0.073***			0.073***			0.070***
			(0.00)			(0.00)			(0.00)
Fr. in Cash			-0.150***			-0.151***			-0.145***
			(0.00)			(0.00)			(0.00)
Fr. in ETF			-0.027			-0.027			-0.025
			(0.25)			(0.24)			(0.28)
Fr. in Mutual Fund			0.017			0.018			0.017
			(0.16)			(0.15)			(0.17)
Beta Mkt			0.465***			0.464***			0.462***
			(0.00)			(0.00)			(0.00)
Beta SMB			-0.186***			-0.184***			-0.187***
			(0.00)			(0.00)			(0.00)
Beta HML			-0.007			-0.007			-0.007
			(0.57)			(0.58)			(0.62)
Beta MOM			0.305***			0.305***			0.304***
			(0.00)			(0.00)			(0.00)
N. of Stocks Traded			0.021*			0.018			0.005
			(0.10)			(0.16)			(0.71)
Constant	1.308***	1.368***	1.313***	1.309***	1.369***	1.315***	1.298***	1.358***	1.309***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-Square	0.6%	1.4%	24.3%	0.9%	1.6%	24.4%	1.4%	2.1%	24.6%
N	8,641	8,512	8,500	8,641	8,512	8,500	8,641	8,512	8,500

This table reports regression results on the relation between portfolio performance and investor attention. We estimate the following baseline cross-sectional regression:

$$Sharpe_i = \alpha + \beta \; Attention_i + \boldsymbol{x}_i' \, \boldsymbol{\gamma} + \epsilon_i \qquad for \; i = 1, \ldots, N$$

where $Sharpe_i$ is the Sharpe ratio of investor i over the sample, $Attention_i$ is the total attention spent on the brokerage web-site by account holder i over the sample period, $\boldsymbol{x}_i$ is a vector of covariates associated with account holder i and N is the total number of account holders included in the analysis. Attention is measured as the log of the total number of minutes spent on the brokerage account website in Panel A, the log of the total number of minutes spent on the Research pages of the brokerage account website in Panel B, and the log of the total number of minutes spent on the Balances and Positions pages of the brokerage account website in Panel C. Each panel contains three specifications. The first specification uses attention as the sole covariate. The second specification includes a group of covariates that control for investor demographic characteristics: *Brokerage*, a brokerage account dummy; *Male*, a male dummy variable; *Age*, the age of the investor; *Account Age*, the age of the account. The third specification includes portfolio holdings, portfolio risk and trading activity variables: *Portfolio Value*, the total value of the invested portfolio; *Fr. in Cash*, *Fr. in ETF*, and *Fr. in Mutual Fund*, the fraction of the total wealth in the brokerage account held in cash, traded funds and mutual funds, respectively; *Beta Mkt*, *Beta SMB*, *Beta HML*, and *Beta MOM*, the loadings on the market, Small-Minus-Big, High-Minus-Low and Momentum factors computed using daily returns over the full sample; and *N. of Stocks Traded*, the number of stocks traded over the period. Displayed are the ordinary least squares coefficient estimates and associated p-values. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table Online IV. Robustness for Attention and Performance: Panel Regression Results

Panel A. Seconds

	21 Days	42 Days	63 Days
Abn. Attention	0.032**	0.103***	0.138***
	(0.02)	(0.00)	(0.00)
	[0.02]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.14%	0.27%	0.38%
N. Obs	2,573,951	2,377,766	2,187,222

Panel B. Pages

	21 Days	42 Days	63 Days
Abn. Attention	0.018*	0.057***	0.061***
	(0.09)	(0.00)	(0.00)
	[0.03]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.14%	0.27%	0.38%
N. Obs	2,573,951	2,377,766	2,187,211

Panel C. Logins

	21 Days	42 Days	63 Days
Abn. Attention	0.007	0.032***	0.024
	(0.43)	(0.01)	(0.12)
	[0.41]	[0.02]	[0.08]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.14%	0.27%	0.38%
N. Obs	2,573,951	2,377,766	2,187,211

This table reports panel regression results on the relation between portfolio performance and investor attention. We estimate the following baseline panel regression:

$$DGTW\_Ret_{i,t:t+k} = \alpha_i + \beta_M + \gamma \; Abn\_Attention_{i,t} + \epsilon_{i,t:t+k} \qquad for \; i = 1, \ldots, N \;\; \& \quad t = 1, \ldots, T,$$

where $DGTW\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return of account-holder i over the time interval $t : t + k$; $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; finally, α_i and β_M represent account-holder fixed effects and monthly time-effects, respectively. Attention is measured as the seconds spent on the brokerage account website in Panel A, the number of pages browsed on the brokerage account website in Panel B, and the number of logins to the brokerage account website in Panel C. Each panel reports results for different horizons, i.e. $k = 21$, 42, and 63 days. Displayed are the ordinary least squares coefficient estimates and two sets of p-values. The first – in round brackets – are computed using standard errors that are double-clustered by account-holder and time, see Petersen (2009). The second – in square brackets – are computed using the Driscoll and Kraay (1998) standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively, according to the double-clustered standard errors.

Table Online V. Attention and Performance Net of Trading Fees: Panel Regression Results

Panel A. Overall

	21 Days	42 Days	63 Days
Abn. Attention	0.027*	0.090***	0.110***
	(0.06)	(0.00)	(0.00)
	[0.00]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.15%	0.27%	0.39%
N. Obs	2,492,150	2,299,617	2,113,051

Panel B. Research

	21 Days	42 Days	63 Days
Abn. Attention	0.021	0.074**	0.096**
	(0.19)	(0.01)	(0.03)
	[0.09]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.15%	0.27%	0.39%
N. Obs	2,492,150	2,299,617	2,113,051

Panel C. Balances and Positions

	21 Days	42 Days	63 Days
Abn. Attention	0.042***	0.125***	0.158***
	(0.00)	(0.00)	(0.00)
	[0.00]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	0.15%	0.27%	0.39%
N. Obs	2,492,150	2,299,617	2,113,051

This table reports panel regression results on the relation between portfolio performance and investor attention. We estimate the following baseline panel regression:

$$DGTW\_NET\_Ret_{i,t:t+k} = \alpha_i + \beta_M + \gamma\ Abn\_Attention_{i,t} + \epsilon_{i,t:t+k} \qquad for\ i = 1, \ldots, N \quad \& \quad t = 1, \ldots, T,$$

where $DGTW\_NET\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return – net of trading fees – of account-holder i over the time interval $t : t+k$; $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; finally, α_i and β_M represent account-holder fixed effects and monthly time-effects, respectively. Attention is measured as the number of seconds spent on the brokerage account website in Panel A, the number of seconds spent on the Research pages of the brokerage account website in Panel B, and the number of seconds spent on the Balances and Positions pages of the brokerage account website in Panel C. Each panel reports results for different horizons, i.e. k = 21, 42, and 63 days. Displayed are the ordinary least squares coefficient estimates and two sets of p-values. The first – in round brackets – are computed using standard errors that are double-clustered by account-holder and time, see Petersen (2009). The second – in square brackets – are computed using the Driscoll and Kraay (1998) standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively, according to the double-clustered standard errors.

Table Online VI. Attention and Performance: Panel Regression Results with Daily Time-Effects

Panel A. Overall

	21 Days	42 Days	63 Days
Abn. Attention	0.025*	0.097***	0.134***
	(0.08)	(0.00)	(0.00)
	[0.01]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	1.54%	1.45%	0.98%
N. Obs	2,573,951	2,377,766	2,187,211

Panel B. Research

	21 Days	42 Days	63 Days
Abn. Attention	0.022	0.081***	0.108**
	(0.19)	(0.01)	(0.02)
	[0.09]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	1.54%	1.45%	0.97%
N. Obs	2,573,951	2,377,766	2,187,211

Panel C. Balances and Positions

	21 Days	42 Days	63 Days
Abn. Attention	0.038***	0.129***	0.170***
	(0.01)	(0.00)	(0.00)
	[0.00]	[0.00]	[0.00]
Time FE	✓	✓	✓
Account Holder FE	✓	✓	✓
R^2	1.54%	1.45%	0.98%
N. Obs	2,573,951	2,377,766	2,187,211

This table reports panel regression results on the relation between portfolio performance and investor attention. We estimate the following baseline panel regression:

$$DGTW\_Ret_{i,t:t+k} = \alpha_i + \beta_t + \gamma \; Abn\_Attention_{i,t} + \epsilon_{i,t:t+k} \qquad for \; i = 1, \ldots, N \;\; \& \;\; t = 1, \ldots, T,$$

where $DGTW\_Ret_{i,t:t+k}$ is the DGTW-adjusted portfolio return of account-holder i over the time interval $t : t+k$; $Abn\_Attention_{i,t}$ is account-holder i abnormal attention at time t, computed as the difference between the (log) attention on day t and the (log) average attention over the previous 21 business days; finally, α_i and β_t represent account-holder fixed effects and daily time-effects, respectively. Attention is measured as the number of seconds spent on the brokerage account website in Panel A, the number of seconds spent on the Research pages of the brokerage account website in Panel B, and the number of seconds spent on the Balances and Positions pages of the brokerage account website in Panel C. Each panel reports results for different horizons, i.e. $k = 21$, 42, and 63 days. Displayed are the ordinary least squares coefficient estimates and two sets of p-values. The first – in round brackets – are computed using standard errors that are double-clustered by account-holder and time, see Petersen (2009). The second – in square brackets – are computed using the Driscoll and Kraay (1998) standard errors. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively, according to the double-clustered standard errors.

Table Online VII. Robustness for Trading Performance and Investor Attention

Panel A. Performance of Buys

	1-Month	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Seconds	0.147*	0.342***	0.533***	0.383**	0.441**	0.197	0.009
	(0.07)	(0.00)	(0.00)	(0.03)	(0.02)	(0.35)	(0.98)
Constant	-0.139*	0.152	0.349**	0.479***	0.622***	0.691***	0.502
	(0.09)	(0.20)	(0.02)	(0.01)	(0.00)	(0.00)	(0.10)
R^2	0.01%	0.03%	0.05%	0.02%	0.02%	0.00%	0.00%
N	24,139	24,103	24,064	24,001	23,947	23,887	23,436

	1-Month	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Pages	0.068	0.246**	0.429***	0.249	0.293	0.117	-0.175
	(0.42)	(0.05)	(0.01)	(0.20)	(0.18)	(0.60)	(0.59)
Constant	-0.135*	0.156	0.354**	0.485***	0.629***	0.695***	0.510*
	(0.10)	(0.19)	(0.02)	(0.01)	(0.00)	(0.00)	(0.10)
R^2	0.00%	0.02%	0.03%	0.01%	0.01%	0.00%	0.00%
N	24,139	24,103	24,064	24,001	23,947	23,887	23,436

	1-Month	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Logins	0.173**	0.358***	0.551***	0.338*	0.406**	0.203	-0.408
	(0.03)	(0.00)	(0.00)	(0.06)	(0.05)	(0.36)	(0.19)
Constant	-0.140*	0.152	0.350**	0.482***	0.625***	0.692***	0.518*
	(0.09)	(0.20)	(0.02)	(0.01)	(0.00)	(0.00)	(0.09)
R-Square	0.02%	0.04%	0.05%	0.01%	0.02%	0.00%	0.01%
N	24,139	24,103	24,064	24,001	23,947	23,887	23,436

Panel B. Performance of Sells

	1-Month	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Seconds	0.103	0.130	0.287*	0.119	0.118	-0.027	-0.425
	(0.22)	(0.30)	(0.07)	(0.51)	(0.56)	(0.90)	(0.26)
Constant	-0.023	0.376***	0.914***	1.008***	1.090***	1.182***	1.366***
	(0.79)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-Square	0.01%	0.01%	0.02%	0.00%	0.00%	0.00%	0.01%
N	19,435	19,373	19,320	19,257	19,200	19,142	18,777

	1-Month	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Pages	0.032	-0.007	0.249	0.003	-0.013	-0.075	-0.591
	(0.71)	(0.96)	(0.14)	(0.99)	(0.95)	(0.74)	(0.16)
Constant	-0.023	0.376***	0.914***	1.008***	1.090***	1.182***	1.363***
	(0.79)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-Square	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.02%
N	19,435	19,373	19,320	19,257	19,200	19,142	18,777

	1-Month	**2-Months**	**3-Months**	**4-Months**	**5-Months**	**6-Months**	**12-Months**
Logins	0.104	0.073	0.276*	-0.026	-0.008	-0.230	-1.110***
	(0.21)	(0.55)	(0.09)	(0.89)	(0.97)	(0.30)	(0.00)
Constant	-0.024	0.375***	0.911***	1.009***	1.090***	1.185***	1.376***
	(0.78)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-Square	0.01%	0.00%	0.01%	0.00%	0.00%	0.01%	0.05%
N	19,435	19,373	19,320	19,257	19,200	19,142	18,777

This table reports regression results on the relation between investor attention and trading performance. We separate the buys (i.e. stock purchases) and the sells (i.e. stock sales) and estimate the following pooled regressions:

$$DGTW\_Ret\_Buys_{i,j,t:t+k} = \alpha + \beta \; Attention_{i,j,t} + \epsilon_{i,j,t:t+k},$$
$$DGTW\_Ret\_Sells_{i,j,t:t+k} = \alpha + \beta \; Attention_{i,j,t} + \epsilon_{i,j,t:t+k},$$

where $DGTW\_Ret\_Buys_{i,j,t:t+k}$ ($DGTW\_Ret\_Sells_{i,j,t:t+k}$) are the cumulative abnormal returns of security j bought (sold) by investor i over the time interval $t : t+k$, computed using the DGTW model; $Attention_{i,j,t}$ is the (log) number of seconds spent on the brokerage account website by investor i over the month preceding the trade in stock j that occurs at time t. Cumulative abnormal returns are computed at the one-, two-, three-, four-, five-, six- and twelve-month horizons. Panel A reports results for stock purchases, and measures attention as, alternatively, the total number of seconds spent on the brokerage account website, the total number of pages browsed, and the total number of logins into the brokerage account website. Panel B repeats the exercise for stock sales. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table Online VIII. Robustness for Characteristics of Attentive Investors

	Panel A. Minutes			Panel B. Pages			Panel C. Logins		
	Coeff	***p*-val**	**Magnitude**	**Coeff**	***p*-val**	**Magnitude**	**Coeff**	***p*-val**	**Magnitude**
Brokerage	0.590***	(0.00)	660.109	0.412***	(0.00)	203.028	0.250***	(0.00)	21.565
Male	0.311***	(0.00)	299.143	0.243***	(0.00)	109.610	0.211***	(0.00)	17.792
Age	0.291***	(0.00)	277.522	0.197***	(0.00)	86.925	0.212***	(0.00)	17.917
Account Age	0.033	(0.12)	27.720	0.014	(0.41)	5.702	0.002	(0.88)	0.186
Portfolio Value	0.164***	(0.01)	145.975	0.151***	(0.01)	64.985	0.146***	(0.00)	11.946
Fr. in Cash	-0.101***	(0.00)	-78.669	-0.095***	(0.00)	-36.008	-0.113***	(0.00)	-8.105
Fr. in ETF	-0.097***	(0.00)	-76.177	-0.068***	(0.00)	-26.319	-0.064***	(0.00)	-4.738
Fr. in Mutual Fund	-0.005	(0.80)	-4.006	0.012	(0.45)	4.685	0.007	(0.66)	0.496
Beta Mkt	0.106***	(0.00)	92.019	0.103***	(0.00)	43.085	0.087***	(0.00)	6.888
Beta SMB	0.091***	(0.00)	78.478	0.046***	(0.01)	18.712	0.042**	(0.01)	3.218
Beta HML	-0.062***	(0.01)	-48.974	-0.044**	(0.01)	-16.988	-0.039**	(0.02)	-2.905
Beta MOM	0.113***	(0.00)	98.496	0.087***	(0.00)	36.370	0.071***	(0.00)	5.597
Number of Stocks Traded	0.813***	(0.00)	1,030.815	0.715***	(0.00)	415.940	0.637***	(0.00)	67.604
Constant	4.749***	(0.00)	820.914	4.771***	(0.00)	398.253	3.244***	(0.00)	75.888
R-Square		22.9%			24.3%			22.2%	
N		8,574			8,574			8,574	

This table reports regression results on the relation between the time spent on the brokerage account website and the characteristics of the account holders. We estimate the following baseline cross-sectional regression:

$$Attention_i = \alpha + \boldsymbol{x}_i' \, \boldsymbol{\beta} + \epsilon_i \qquad for \; i = 1, \ldots, N$$

where $Attention_i$ is the total attention spent on the brokerage website by account holder i over the sample period, $\boldsymbol{x}_i$ is a vector of covariates associated with account holder i and N is the total number of account holders included in the analysis. Attention is measured as the log of the total number of minutes in Panel A, the log of the total number of pages browsed in Panel B, and the log of the total number of logins in Panel C. What follows is a description of the covariates included. The first group comprises demographic variables: *Brokerage*, a brokerage account dummy; *Male*, a male dummy variable; *Age*, the age of the investor; *Account Age*, the age of the account. The second category comprises portfolio holdings variables: *Portfolio Value*, the total value of the invested portfolio; *N. of Assets*, the total number of stocks, mutual funds and exchange traded funds held; *Fr. in Cash*, *Fr. in ETF*, and *Fr. in Mutual Fund*, the fraction of the total wealth in the brokerage account held in cash, traded funds and mutual funds, respectively. The third category comprises regressors related to portfolio risk and trading activity: *Beta Mkt*, *Beta SMB*, *Beta HML*, and *Beta MOM*, the loadings on the market, Small-Minus-Big, High-Minus-Low and Momentum factors computed using the full sample available using daily returns; and *N. of Stocks Traded*, the number of stocks traded over the period. Within each panel we display the ordinary least squares coefficient estimates ($Coeff$), the associated p-values (p-val), and the economic magnitudes ($Magnitude$) – computed as described in Section 7.3. Standard errors are adjusted for heteroskedasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.