Glued to the TV:
The Trading Activity of Distracted Investors

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ABSTRACT

We investigate how inattention affects the trading behavior of retail investors. Exploiting episodes of sensational news exogenous to the stock market, we document that investors don't scale down their trades but stop trading altogether when they are distracted, consistent with the cost of attention being fixed. This phenomenon is related to, but distinct from, their documented tendency to buy attention-grabbing stocks (Barber and Odean (2008)). In contrast to this tendency, distraction affects buys and sells symmetrically. It makes trades less likely, but only for stocks in investors' consideration set. Its effect is more pronounced for more overconfident – i.e., male and active – investors. As these investors tend to trade too much, they actually benefit from inattention.

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At 1 p.m. (EST) on October 3, 1995, in what came to be known as the "Trial of the Century", a Californian jury declared football and movie star O.J. Simpson not guilty. Millions of people worldwide interrupted what they were doing to listen to the verdict announcement. Long-distance telephone call volume declined, electricity consumption surged as viewers turned on television sets, water usage decreased as they avoided using bathrooms, and trading on the stock market dropped (Dershowitz (2004)). The latter is what interests us here. Trading volume on the New York Stock Exchange plummeted by 41% in the first 5 minutes after 1 p.m., and by another 76% in the next 5 minutes, before recovering abruptly. Figure 1 depicts this dramatic swing. In this paper, we investigate how such sensational events influence the trading behavior of retail investors. Our analysis sheds light on how they make their trading decisions, and more broadly, on how attention, or the lack thereof, affects financial markets.

We track variations in investors' attention to the stock market, generated by sensational media reporting of news largely exogenous to economic fundamentals. This material draws investors' attention, and crowds out other news, including news about the stock market. Examples of such distracting news include the O. J. Simpson trial discussed above, the Cessna plane crash on the White House lawn, and the Summer Olympics in Atlanta. We identify these news episodes thanks to a variable constructed by Eisensee and Strömberg (2007), labelled "news pressure". News pressure measures the median number of minutes that U.S. news broadcasts devote to the first three news segments. For example, the O. J. Simpson trial on October 3, 1995, received sixteen minutes and thirty seconds of air time, the highest value for that year. Eisensee and Strömberg (2007) exploit news pressure to study the causal impact of media coverage on of U.S. disaster relief. We use it here as an instrument for investors' attention to the stock market.

Using detailed trading records from a large broker, we document first that distraction has a strong effect on trades at the extensive margin, but no effect at the intensive margin. That is, retail investors do not scale down their trades but stop trading altogether when they are distracted. We estimate that their propensity to trade drops by about 6%. These findings are consistent with a model of attention in which investors incur a fixed cost for deciding whether or not to trade and/or for accessing their brokerage account. They are less consistent with standard models of information acquisition in which inattentive investors adjust at the intensive margin how much information to gather (e.g., Verrecchia, 1982; Van Nieuwerburgh and Veldkamp, 2010).

Moreover, we find that the distraction effect applies equally to buys and sells. As such, it is related to, but distinct from, investors' documented tendency to buy attention-grabbing stocks (Barber and Odean (2008)). We then sort stocks into those that grab investors' attention (stocks currently in investors' portfolio, stocks with extreme returns or extreme trading volume), and those that do not. We find that distraction affects buys of attention-grabbing stocks, and these stocks only, whereas its impact on sells is equally strong for both types of stocks. These findings suggest that the trading decision process consists of two successive stages, a search stage followed by an execution stage: in the search stage, investors consider a subset of stocks for potential trading; in the execution stage, investors pull the trigger on stocks from the consideration set.[1] For buy decisions, the search stage is extremely complex and mediated by heuristics or simple rules intended to limit the choice set – such as being attracted to attention-grabbing stocks. For sell decisions, the search stage is simplified by the fact that (most) retail investors only sell stocks they already own, thus

[1] A large literature in marketing studies why and how consumers employ consider-then-choose decision processes (see, for instance, Hauser (2013)).

limiting the choice set to the few stocks already in the portfolio. Inattention can prevent a stock from entering investors' choice set (search stage), and it can distract them from trading a stock that belongs to that set (execution stage). In either case, however, a distraction effect will only be discernable for stocks that are in investors' consideration set. This is how we are able to trace the stocks that are on investors' mind.

Finally, we find that more overconfident– i.e., male and more active – investors are more likely to be distracted from trading. As these investors tend to trade too much, they actually benefit from inattention. For example, a rough calculation suggests that their annual portfolio return net of transaction costs improves by approximately 4.5% thanks to the distraction events in our sample. Given that we only observe a small fraction of all the events that distract households (not to mention private events), this number is a lower bound for the actual benefit of distraction to these investors.

Our paper makes four main contributions. First, it can be seen as a first attempt to open the black box of retail traders' decision making process. Linking our results to the existing literature, we provide a coherent account of how retail investors arrive at their trading decisions. It starts with a stock search phase, which is followed by a related but distinct trade execution phase. A stock can only be bought or sold if it goes through both phases successfully – and inattention may disrupt them both. The current theoretical literature focuses on the search phase (e.g., Peng and Xiong 2006, Van Nieuwerburgh and Veldkamp, 2010). Consistent with the notion of a two-stage process, we find that, for buys, the distraction effect is much more pronounced for attention-grabbing stocks compared to other stocks. We also show that there is a distinct distraction effect at the execution stage, as we find that retail investors are less likely to buy and sell, with comparable magnitudes. As a whole, our results suggest that, at any time, investors' choice sets primarily consist of the stocks already held and stocks that recently grabbed their attention.

Second, we contribute to the behavioral economics literature. Researchers so far have mostly examined attention separately from behavioral biases. In contrast, we consider them jointly, and investigate how they interact. Thus, we can ask whether drawing investors' attention to the stock market mitigates or exacerbates the biases which influence their trading decisions. Focusing on one pervasive behavioral bias, overconfidence, we report evidence in favor of the latter: inattention reduces the loss that overconfidence inflicts on investors. Thus, our perspective on attention is more neutral than in the literature, which typically views attention as good and inattention as bad. We show that when investors are "misbehaving" (trading too much), their behavior may actually improve when they are distracted. This insight relates to Hou, Peng and Xiong (2006). Using trading volume as a proxy for investor attention, they report that the return momentum phenomenon of Jegadeesh and Titman (1993) strengthens when trading volume is larger, whereas earnings momentum weakens. They suggest that attention has a dual role in that it can both mitigate underreaction and exacerbate bias-driven overreaction.

Third, our paper adds to the literature on retail trading. Analyzing the behavior of retail investors is not only interesting in itself; it also improves our understanding of equity markets. Indeed, a growing body of evidence shows that retail trading has an impact on stock returns. Retail trades have a common directional, i.e. systematic, component (see, for example, Kumar and Lee (2006), Dorn, Huberman, and Sengmueller (2008), and Barber, Odean, and Zhu (2009)), which has the power to move stock prices (see, for example, Kumar and Lee (2006), Dorn, Huberman, and Sengmueller (2008), Kaniel, Saar, and Titman (2008), Hvidkjaer

(2008)) and contributes to the comovement and volatility of stock returns (Kumar and Lee (2006), Foucault, Sraer and Thesmar (2010), Brandt et al. (2010)). For this reason, retail trading is generally viewed as a source of "noise" in financial markets, where noise captures shocks to asset values unrelated to fundamentals. Noise trading is an essential ingredient of most trading models (e.g., Grossman and Stiglitz (1980) and Kyle (1985)). Yet, there is little guidance from the data as to how noise trading should be formalized. Understanding its source and its characteristics is an important step toward building more realistic models.

Finally, our paper adds to the growing empirical literature that attempts to assess the implications of inattention in financial markets (see, for instance, Cohen and Frazzini (2008), DellaVigna and Pollet (2009), and Hirshleifer, Lim and Teoh (2009)). We make a methodological contribution by showing how news pressure can be used as an instrument for retail investors' attention to the stock market. This is an important contribution as empirical research on attention is challenged by difficult identification issues stemming from the endogeneity of attention: unobserved shocks common to attention and stock market activity (trading, returns, volatility…) can drive both variables, leading to a correlation without a causal relation. News pressure triggers variations in investors' attention that are largely exogenous to the stock market.

The balance of the paper is organized as follows. Section 1 reviews our methodology and data. Section 2 and 3 consider the effect of distraction on, respectively, the market at large, and on retail investors in particular. Section 4 examines the search and trade execution stages. Section 5 assesses how distraction affects trading profits, and Section 6 how it interacts with overconfidence. Section 7 presents robustness checks. Section 8 concludes.

I. Methodology and Data

A. Distracting Events

To identify distracting events, we use a measure developed by Eisensee and Strömberg (2007), and labeled *news pressure.* They measure the median number of minutes that U.S. news broadcasts devote to the first three news segments. They argue that this variable is a good indicator of how much newsworthy material is available on a given day. "For instance, on October 3, 1995, a jury found O.J. Simpson not guilty of two counts of murder. That night, ABC, CBS, and NBC devoted all of their first three news segments to that story. The top three news segments comprised an average of sixteen minutes and thirty seconds—the highest value of that year." (Eisensee and Stroemberg, 2007, p. 207). We download the news pressure variable from David Stroemberg's website (http://people.su.se/~dstro).

Daily news pressure and retail trading are relatively persistent, calling for an analysis at lower frequency. At the same time, we wish to separate extensive margin effects – the decision whether or not to trade – from intensive margin effects – how much to trade. A low frequency blurs this distinction. For example, if we found that the value of households' monthly trades is lower, we would not know whether they trade smaller amounts or whether they trade less often. To be conservative while learning as much as possible from the data, we conduct our analyses at the *weekly* frequency. We construct a weekly news pressure series by averaging daily news pressure over the trading days in a week. Weeks are thus defined from Monday to Friday. Figure 2 display weekly news pressure over 1991-1996, our main period of analysis. Weekly news pressure oscillates around a mean of 8 minutes with occasional spikes of 10 minutes and more.

It is these spikes in weekly news pressure that we are interested in. Specifically, in each sample year, we identify the 5 weeks with the highest weekly news pressure – resulting in 30 weeks with potential distraction events over our six years of retail data. Table 1 Panel (a) lists these weeks along with a short description of the week's major news headline. Many of these events are unrelated to U.S. economic fundamentals (e.g., West Memphis Three murder, Black Hawk Down in Somalia, Cave of the Patriarchs massacre, O.J. Simpson trial). Other events – such as the beginning of the Desert Storm offensive during the Iraq War – could be correlated with macroeconomic conditions. The last column of Table 1 Panel (a) shows the standardized weekly market return relative to its sample distribution, labelled 'z-score'. This z-score is approximately normally distributed. Overall, four out of the 30 distraction events occur in weeks in which the market return was significantly different from zero at the 10% significance level (2 positive and 2 negative) – and the launch of the Desert Storm offensive is indeed the most significant event in our sample according to this metric. A proportion of 4/30=13% is roughly what would be expected by chance at the 10%-level. Thus, we conclude that our distraction events are no different from other weeks in terms of economic news, as proxied by the market return.

We deal with any remaining endogeneity concerns about our distraction events in multiple ways. First, to ensure we capture the distraction component of the news over and above its impact on fundamentals, we include proxies for stock market activity and macroeconomic conditions in all our regressions below.[2] Second, we provide a comprehensive set of robustness checks by, for example, dropping distraction weeks with extreme z-scores or by

[2] We are essentially relying on the fact that perceived newsworthiness does not vary one-to-one with macroeconomic news content. In other words, not all macroeconomic news are perceived as similarly newsworthy. For example, both FED announcements and the beginning of the Desert Storm offensive may have macroeconomic effects of comparable magnitude, yet the latter triggers much more news coverage and distraction.

dropping events that could have arguably affected the economy. Moreover, we test and confirm in Section III that there is no relation between high-news pressure weeks and CRSP market returns or volatility for an extended sample period for which we have the news pressure data.

[Insert Table 1 around here.]

B. Retail Trading Data

Our main data consist of trades and holdings of retail investors at a large discount brokerage firm. They are described in detail in Barber and Odean (2000) and contain approximately 1.9 million common stock trades between January 1991 and November 1996. We focus on the trades of 12,743 households with portfolio holdings throughout the sample period, as in Barber and Odean (2002). Thus, in our sample, the number of households that could have traded in any given week is constant, which facilitates the comparison of trading intensities across weeks. Trades are aggregated at the weekly frequency. We study three different measures of trading activity at the household-week level – for buys and sells separately, and combined. First, we define a dummy variable, henceforth called *trade dummy*, for whether or not a household trades during the week. This variable captures any distraction effect at the extensive margin. Second, we count the number of different stocks that a household trades in a given week and take logarithms. This variable is denoted *log(#stocks*). Third, we measure the average trade size, denoted *log($volume)*. For that purpose, we first estimate the value of trades as the number of shares bought or sold multiplied by the end-of-day price from CRSP.[3] Then, we compute the average over all trades executed by a household in a week and take

[3] We use the CRSP closing price so that the estimated trade values are not influenced by bid-ask spreads. Spreads would drive a wedge between the values of buys (which are transacted at the ask price), and sells (which are transacted at the bid price), which could vary with market conditions.

logarithms. Because the logarithm is only defined when a household actually trades, the last two measures capture the intensive margin effect of distraction on trade size and the number of stocks traded.

Table 1 Panel (b) presents descriptive statistics for our retail sample. In any week, the average household is likely to execute a buy, a sell, or any of the two with probabilities 3.9%, 3.1% and 6.0%, respectively. Conditional on trading, the mean (median) trade value is $13,790 ($5,750). On average, households pay $135 in commissions in each week with a trade, and an additional $95 to $183 in bid-ask spreads. The lower spread estimate assumes that households transact at the market's average bid-ask spread (estimated from CRSP daily high and low prices and the algorithm developed by Corwin and Schultz, 2012), whereas the higher spread estimate compares the actual transaction price to the CRSP closing price (as in Barber and Odean, 2000).[4] The lower estimate is more conservative, whereas the higher one reflects more accurately the actual transaction cost incurred by households –but is noisier as indicated by its higher standard deviation. Finally, we also report the average post-trade return difference between buy and sell transactions (PTBSD) for different holding periods, starting on the first Monday after the transactions. PTBSD is defined as the difference between the trade-weighted average return of buys and sells across households. Consistent with the results in Odean (1999), we see that the average household loses money from trading. For instance, stocks bought underperform stocks sold by approximately 0.6% over a 12-weeks horizon.

[4] Because transaction prices contain some outliers, we winsorize this spread estimate at the 1%-level.

C. Control Variables

Throughout our analysis, we control for changing economic conditions that could influence investors' trading behavior. We use the absolute value of the return on the market (*Abs. market return*) and the dollar value of all shares traded on the market (*Log(market volume)*), both collected from CRSP. We also use an index of business and economic conditions developed by Aruoba et al. (2009), denoted *ADS index*. The ADS index combines macroeconomic news such as weekly initial jobless claims, monthly payroll employment, industrial production, manufacturing and trade sales and quarterly real GDP. Importantly, the index is updated daily, and thus tracks economic conditions closely. We download the index from the website of the Federal Reserve Bank of Philadelphia and compute its weekly average.

II. Distraction and Trading in the Aggregate

We start our analysis with an inspection of the impact of distraction events on the aggregate stock market. We consider four variables that track various aspects of the stock market: the (value-weighted) return on the market, its absolute value, the average price range (the ratio of intra-day high to low prices, a measure of intra-day volatility), and the (logarithm of the) dollar trading volume. We regress these variables on the Distraction-Event dummy, and the ADS business conditions index to control for macroeconomic activity. To account for, respectively, seasonality and trends in trading behavior, we include month-in-year (i.e., Jan, Feb,…) and quarter fixed effects (i.e., Q1-1991, Q2-1991,…, Q1-1992,…), respectively. Note that quarter fixed effects subsume slow-moving business cycle indicators such as the NBER recession dummy. We use the Newey-West adjustment to standard errors to account for autocorrelations in the variables of up to three weeks.[5]

Panel (a) of Table 2 presents two sets of results. The regressions in Columns (1) to (4) are based on the full period for which news pressure is available (1968-2011), and those in Columns (5) to (8) on a subperiod corresponding to the analysis in Panel (b) of Table 2 (1991-2000). The coefficient estimates on the distraction dummy are not distinguishable from zero throughout the regressions, except in Column 8 where it is marginally significant. It indicates that trading volume drops by 5% in distraction weeks occurring between 1991 and 2000. The O.J. Simpson case in Figure 1 shows a dramatic decline in trading volume at the time of the verdict announcement, but trading recovers within 20 minutes, so average trading over the day is only moderately lower. Overall, we find no sign that distraction affects stock returns or their variability, but we uncover weak evidence that it reduces trading activity.

The O.J. Simpson case in Figure 1 suggests that the volume decline is more pronounced for small trades compared to large trades. To assess which types of investors are distracted from trading throughout our sample period, we turn to transaction data from the Trades and Quotes (TAQ) database. These data allow us to sort trades according to their size, thus separating trades initiated by individuals from those initiated by institutions.[6] Trades are classified as buyer- or seller-initiated using the Lee and Ready (1991) algorithm, and by size using a procedure described in Hvidkjaer (2006). The procedure sorts stocks into quintiles based on NYSE/AMEX firm-size cut-off points and uses the following small- (large-) trade cut-

[5] The first-order autocorrelation for our distraction events is around 17% and statistically significant. Second- and higher-order autocorrelations are below 10% and insignificant.
[6] Analyzing various transaction databases, including the one we use here, Lee and Radhakrishna (2000) and Barber, Odean and Zhu (2001) confirm that trade size is an effective proxy for identifying retail trades.

off points within firm-size quintiles: \$3,400 (\$6.800) for the smallest firms, \$4,800 (\$9.600), \$7,300 (\$14.600), \$10,300 (\$20,600) , and \$16,400 (32,800) for the largest firms. We then aggregate dollar buys, dollar sells and dollar trades (the sum of dollar buys and dollar sells) over the entire market in each week, separately for small and large trades. We thus produce three pairs of time series, namely for the value of small and large buys, of small and large sells, and of small and large trades.

Our data include all transactions in all stocks listed on NYSE/AMEX/Nasdaq from 1991 to present. However, order splitting strategies became prominent after decimalization was introduced in 2001, rendering the identification of retail trades ineffective (Hvidkjaer (2008)). For this reason, we limit our analysis of TAQ data to the period 1991 to 2001.

[Insert Table 2 around here.]

We regress the (log of the) buy, sell and trade series on the Distraction-Event dummy and control variables. As controls, we include, in addition to the ADS business conditions index, the logarithm of CRSP dollar volume and the absolute return of the value-weighted CRSP index. . Again, these controls are meant to soak up weekly changes in macroeconomic activity that could pollute the interpretation of high-news pressure weeks as distraction events. The results, displayed in Panel (b) of Table 2, reveal that small trades, be them buys or sells, all decline on high-distraction days. The magnitude of the decline is similar across buys and sells, ranging from 8.3% to 8.8% per week (with *t*-stats in excess of 3). Large trades are also affected, but less so. The coefficients on the Distraction-Event dummy for, respectively, large buys, sells, and trades are statistically significant with *t*-stats ranging from 1.58 to 2.10, and about half the magnitude obtained for small buys, sells, and trades. This asymmetry is confirmed by estimating the regressions with the (log of the) ratio of small to large buys, sells, and trades as dependent variables: the coefficients on the Distraction-Event dummy displayed in columns (3), (6) and (9) are all significantly negative and about the size of the coefficients obtained in the large buys, sells and trades regressions. These findings support the notion that our distraction events do not reflect economic news, or that, if they do, then our control variables are effective at controlling for these news. Indeed, a large literature shows that investors trade more, not less, in response to news (see, for instance, Tetlock, 2010, and also Harris and Raviv (1993) for a review of the early evidence,).

Overall, these results suggest that investors, particularly retail investors, trade less on high-distraction days. In the next section, we exploit data from a large brokerage to shed light on their behavior.

III. Distraction and Retail Trading

In this section, we turn to retail brokerage data to check, and refine our understanding of the effect of distraction on retail trading. Our analysis allows us to shed light on the following questions: Do retail investors continue to trade the same set of stocks but scale down the size of each stock transaction? Do they stop trading some stocks while they continue to trade others? Or do they give up trading altogether? All three scenarios are consistent with the drop we report in the aggregate TAQ analysis.

Answering these questions contributes to our understanding of limited attention. For example, rational attention models typically predict that investors trade less aggressively and focus on fewer stocks when their information becomes less precise (Verrecchia (1982), He and Wang, 1995; Vives, 1995; Van Nieuwerburgh and Veldkamp, 2010) – such as when they are distracted. On the other hand, if the effect is primarily at the extensive margin (i.e., the decision to trade or not), then this is more compatible with a model in which trading has a high fixed cost in terms of attention.

We now trace the trading behavior of retail investors during distraction events to study these questions. We start by regressing weekly aggregate measures of retail trading activity on our distraction event dummy in the time-series. We include the same control variables as in the TAQ analysis in Table 2 and adjust the standard errors in the same way.

[Insert Table 3 around here.]

Table 3 Panel (a) shows the results. In columns (1)-(3), we look at the average trade size conditional on a household trading. In columns (4)-(6), we look at the average number of (different) stocks traded by a household, again conditional on the household trading. Across all six columns, the coefficient estimate on the Distraction dummy is not distinguishable from zero, indicating that households who trade in high-distraction weeks trade the same number of stocks, and for the same value per stock. In columns (7)-(9), we check whether fewer households are trading. Here we find a statistically significant and economically meaningful effect. For example, Columns (7) and (8) imply that there are approx. 6% (8%) fewer households buying (selling) stock in a distraction week. Panel (b) confirms these results in a panel regression setting, in which we control for unobserved household characteristics with household fixed effects. We find that households do not trade smaller amounts or fewer stocks conditional on trading, but that their propensity to trade is significantly reduced by approx. 6.3% (=0.38%/5.96%) relative to the unconditional probability of trading in our sample (Column 9). To sum up, distraction has a strong effect on the extensive margin (i.e., whether to trade or not), but no effect on the intensive margin (i.e., trade sizes).

[Insert Table 4 around here.]

A natural question to ask is whether households who are distracted from trading eventually execute the trades that they have missed; that is, whether they "catch up". Table 4 investigates this question by including dummies for up to three weeks after a distraction event. As can be seen from both the time-series (Panel (a)) and panel results (Panel (b)), there is no evidence that households are more likely to trade or that they trade larger amounts in the weeks following a distraction week. If anything, it seems that households continue to be distracted from trading, particularly from buying, for the next couple of weeks. This finding is consistent with the pattern displayed in Figure 1 for the O.J. Simpson trial: the trading flow plummets, then quickly returns to its daily average but does not make up for the lost trades (i.e. there is no overshooting). This means that the trades that households forego in a distraction week are somewhat "superfluous", in that they are not deemed important enough to be taken up once distraction subsides. We return to this interpretation in Section V when we examine the performance of trades.

IV. Search vs. Execution

We think of the trading decision process as consisting of two stages. In the search stage, investors consider a subset of stocks for potential trading. In the execution stage, investors pull the trigger on stocks from the consideration set. Distraction may interfere with both stages: a distracted investor may not become aware of a stock that would have otherwise grabbed his attention (search stage), and/or he may forego trading in stocks that are already in his choice set (execution stage). Our results so far show that distraction disturbs the execution stage, because the reduction in trades is symmetric for buys and sells.

In this section, we investigate further how distraction affects trades. This analysis is an important step toward understanding how investors direct their attention – whether deliberately or passively. Indeed, there can only be distraction where there was attention to begin with. If an investor is distracted from trading a particular stock, he must have traded and paid attention to this stock before. We can thus use our distraction events to trace out investors' consideration sets.

To start with, we expect households to closely follow stocks that are already in their portfolio. They must have paid attention to them at the time of purchase, and, given their exposure, are more likely to continue to track their performance compared to other stocks in the market. Because currently-held stocks are more likely to be part of their consideration set, investors are more likely to trade them, and consequently, to be distracted from trading them. Putting it differently, stocks not currently held are not at risk of not being traded due to distraction, because they are not considered for trading in the first place. Accordingly, we test whether the distraction effect is stronger for buys of previously-held stocks compared to other stocks.[7]

To determine whether a stock that is bought was already in the household's portfolio, we construct weekly portfolios by combining monthly position statements available in our brokerage data with households' trades as follows. The portfolio in the first week of a month is set to the beginning-of-month portfolio. The portfolio in week n+1 of a month equals the week-n portfolio, adjusted for the trades executed during week n. Specifically, we add to (subtract from) week-n positions the number of shares purchased (sold) in that week. Our procedure makes two approximations. First, it ignores trades executed between the first day

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[7] Because households do not short-sell, there are almost no sells – and hence no distraction for sells – of stocks not previously held. We thus only conduct this analysis for buys.

of the month and the first Monday of the month. Second, it assumes that buys and sells happen at the end of the week.

[Insert Table 5 around here.]

Table 5 columns (1) and (2) show the results of this exercise. We see that distracted households are significantly less likely to buy stocks already in their portfolio, but not other stocks. As argued above, this suggests that portfolio stocks are on the household's radar screen, unlike other stocks.

Our next test concerns attention-grabbing or "glitter" stocks. Barber and Odean (2008) argue that stocks with abnormally high volume or absolute return attract investors' attention and are more likely to enter their consideration sets. We investigate whether distraction affects "glitter" and "non-glitter" stocks differently. We find that the distraction effect is more pronounced for attention-grabbing stocks compared to other stocks, again consistent with the idea that investors only trade stocks in their consideration set –so that non-glitter stocks cannot be subject to distraction. For instance, the number of households buying stocks with high abnormal volume drops by a significant 7% in a distraction week (Column (3)), whereas the drop is an insignificant 4% for a low-volume stocks (Column (4)). Similar results obtain when we split stocks based on absolute returns (Columns (5)-(6)).

Finally, Columns (7) to (10) consider the distraction effect on sells of glitter and non-glitter stocks. Because sold stocks were part of the portfolio and thus already in the consideration set, we do not expect sells to differ across glitter and non-glitter stocks. Our results confirm this intuition: the distraction effect is strong and of comparable magnitude for all sold stocks, regardless of their glitter status.

In sum, the results in this section support the view of a two-stage decision process: before trading, retail investors form a consideration set consisting of the stocks they follow (stocks already in their portfolio and stocks that grab their attention). Then they choose which stocks within the consideration set to trade. Distracting events disrupt the second stage (execution), conditional on stocks having passed the first stage (search).

V. Investor Distraction and Trading Profits

Having shown that some households abstain from trading when they are distracted, we examine how their trading performance is affected. Do they forego valuable trading opportunities, or do they avoid costly trading mistakes? Odean (1999) finds that the stocks retail investors buy underperform the stocks they sell. Moreover, Barber and Odean (2000) document that they trade too much –households who trade more frequently earn a lower return on average after accounting for transaction costs. Both findings suggest that distraction may actually be beneficial to retail investors: distracted traders escape losing trades and save on transaction costs.

Table 6 confirms this intuition. Column (1) of Panel (a) shows that the average percentage commissions do not change during a distraction event, implying that the total dollar commissions paid by investors decrease by about 7% (Column 2). Column (3) to (6) focus on the bid-ask spread component of transaction costs. In columns (3) and (4), we estimate spreads as the transaction price divided by the closing price on the day of the transaction minus one (and then multiplied by minus one for sells), following Barber and Odean (2000). We find a statistically insignificant reduction in the percentage and dollar spreads. This may not be surprising given that the descriptive statistics in Table 1 Panel (b) reveal that spreads based on actual transaction prices seem to relatively noisy. In columns (5) and (6), we estimate spreads from CRSP data rather than actual transaction prices. Specifically, we use the algorithm developed by Corwin and Schultz (2012) that relies on daily high and low prices. This approach essentially assumes that households transact at the average market bid/ask prices. Given that retail investors are likely to execute at less favorable quotes than professional investors, this estimate may be considered a lower bound on the actual transaction spread incurred by households in our sample. Measured in this way, the value of spreads paid is significantly reduced in a distraction week by about 11% (Column 6).

Taken together, the drops in commissions and spreads lead to a reduction in the dollar transaction costs incurred by households of about 9% (Columns 8 and 10). The drop is marginally significant for the noisy spread estimate based on actual transaction costs, and highly statistically significant for the spread estimate based on Corwin and Schultz (2012). This reduction translates into savings of approximately $281,000 per week out of total transaction costs of $3,122,000, or $22.1 per household and week.

Table 6 Panel (b) looks at the performance of trades executed in distraction weeks. Specifically, following Odean (1999) and Goetzmann and Kumar (2008), we define the post-trade buy-sell return difference (PTBSD) as the difference between the average return on buys and the average return on sells executed in the same week. Returns are computed over holding ranging from one to twelve weeks. Columns (2) to (5) show that PTBSD is significantly improved in the weeks following the distraction event. This pattern is confirmed in Columns (7) to (10), in which stock returns are first adjusted using the characteristic-based benchmark method of Daniel et al. (1997) (DGTW). The findings of Panel (b) thus indicate that distraction eliminates “bad” trades. They may explain why trades foregone in distraction weeks are not executed once distraction subsides, as reported in Table 5, to the extent that households do not believe strongly in them.

Together, our evidence suggests that distracted investors are underperformers. Their performance improves when they are distracted from trading for two reasons: first, they save on transaction costs; second, they avoid purchasing stocks that fall behind the ones they sell. This foreshadows our next set of results which relate investors' propensity to be distracted to their overconfidence.

VI. Distraction and Biases

Attention and behavioral biases are mostly studied separately in the literature. In this section, we put them together and examine how distraction interacts with overconfidence. Odean (1999) and Barber and Odean (2000) demonstrate that retail investors trade excessively; not only do they spend too much on transaction costs, but the stocks they sell also outperform those they buy. This fact is commonly interpreted as evidence for overconfidence. It is not clear a priori whether overconfident traders are more or less distracted than other traders. On one hand, they may be so convinced of their superior trading "abilities" that they do not stray away from trading. On the other hand, their bias may be associated with self-indulgence and a propensity to succumb to distractions.

To test which argument prevails, we interact our distraction event dummy with several proxies for overconfidence. An advantage of this test is that it exploits variations in overconfidence across households, and thus allows us to control for unobserved time fixed effects. To ensure that we are really capturing the effect of distraction, rather than a differential response to changes in macroeconomic conditions, we also interact all our control variables with overconfidence proxies. Note also that in this restrictive regression, static household characteristics as well as time-series variables (including our distraction-event dummy) are subsumed by household and time fixed effects. These variables will only matter through their interactions.

Table 7 presents the results of this analysis. In Column (1), we use gender as a proxy for overconfidence. Indeed, a large literature in psychology shows that men are more overconfident than women (see, for instance, Barber and Odean (2001) and the references therein). We interact the distraction event dummy with an indicator variable which equals one for men, and zero for women. The negative coefficient estimate on this interaction term indicates that males tend to be more easily distracted. Our data only features gender for 60% of the households, which may explain why the coefficient is only marginally significant.

In Column (2), we check whether distraction is stronger for more active traders. Barber and Odean (2001) document that men trade more frequently than women. To measure their propensity to trade, we sort households every week according to their portfolio turnover over the previous 12 months. Unlike gender, the resulting rank varies not only across households, but also over time. Again, we find evidence that more active traders are more distracted. The coefficient estimate on the interaction variable is negative with a *t*-stat in excess of three. In Column (3), we analyze whether distraction is stronger for households who have recently performed well. Every week, we sort households according to their portfolio return over the preceding 12 months, and use their rank as a proxy for overconfidence. The idea is that investors tend to attribute their past successes to skill, but to blame their past failures on bad luck. Thus, more successful traders grow overconfident (Daniel et al. (1998), Odean (1999), Gervais and Odean (2001)). The negative coefficient estimate on the interaction variable in Column (3), though not the significant, is consistent with this notion.

In Column (4), we examine whether a household's propensity to buy glitter stocks interacts with distraction. Intuitively, households that are drawn to attention-grabbing stocks may also be more easily distracted by sensational news. We measure a household's propensity to buy glitter stocks as the fraction of the household's purchases of glitter stocks (stocks with high abnormal volume) over all its purchases. We find that, indeed, households who buy mostly glitter stocks are significantly less likely to trade in a distraction week, compared to other households. That is, the propensity to favor glitter stocks (in the cross-section of stocks) goes hand in hand with the propensity to be distracted (over time). The flipside is that some households may be able to both trade non-glitter stocks, and do it in periods of distraction (consistent with Table 5 Column (2)). For them, our postulated two-stage decision process would not apply. We believe that the two-stage model is a good approximation for the average retail investors, though it is not universal.

In Columns (5) and (6), we employ two more direct proxies of overconfidence. We combine first the turnover and performance ranks defined above to capture the notion that overconfident investors underperform *because* they trade too much. Following Goetzmann and Kumar (2008), we interact the portfolio turnover rank with an inversed rank of portfolio profits. We find that households who score high on this measure – i.e. , households that trade actively but perform poorly – are more distracted compared to households that are less active and/or more successful. Column (6) repeats the analysis, but now we are interacting past trading activity with a rank of portfolio concentration (as measured by the Herfindahl index). A concentrated portfolio reveals that the household believes that it has an informational advantage in the few stocks it chooses. The negative coefficient estimate on the interaction variable confirms again that distraction is stronger for overconfident households.

Collectively, the results in this section document that overconfident, and more generally biased, investors are more likely to be distracted from trading. Given that trading harms their performance, these investors benefit from being distracted. Appendix A provides a back-of-the-envelope calculation that assesses the economic magnitude of this effect. We find that, for an overconfident household, being distracted from one of the five annual distraction events leads to an expected increase in portfolio net returns of 4.5%. This estimate can be considered as a lower bound on the benefits of distraction given that the events we identify are only a small fraction of all those that could distract the overconfident household.

VII. Robustness Checks

In our baseline results from Table 3, we had identified distraction events as those weeks in which news pressure is in the top decile of a given year. We now show that our key results from Table 3 are robust to alternative choices of measuring investor distraction.

As argued in Section II, some of the distraction events in our sample may be confounded by economic news. To ensure that our results capture distraction above and beyond such economic effects, we have controlled for stock market activity and macroeconomic news in our analyses. To further prove the robustness of our results, we now repeat the analysis while excluding some distraction weeks that are "suspicious". First, we let ourselves be guided by an objective criterion, the standardized return z-score shown in Table 1 Panel (a). We thus repeat the analysis while dropping those 4 weeks in which the marker return movement was marginally significant. Row 1 in Table 8 shows that the results are virtually unchanged: no evidence for the intensive margin of trade (i.e., average trade sizes), but a significant reduction in the number of households that are trading. In row 2, we manually drop 10 out of the 30 events that we believe could have affected the economy.[8] Results do not change much, despite the lower number of distraction events.

Next, we want to confirm that our results do not depend on the 10%-threshold for identifying our distraction events. In row 3, we repeat the analysis using a dummy to flag all weeks in which news pressure is in the top two deciles of each year, thus doubling the number of distraction weeks. The effect remains statistically significant but is slightly smaller (now between 4%-5%), which is to be expected given that we now include events that were less distracting. In row 4, we use the continuous measure of average news pressure instead of focusing on dummies for the most distracting weeks. Results are again consistent, with no effect on the intensive margin and a strong negative effect on the extensive margin of trade.

Finally, we return to our baseline definition of distracting events and examine whether the significance of our results could be inflated by the persistence of the dependent variables (i.e., investors' trades). A common way to deal with strong persistence is to include the lagged dependent variable on the right-hand-side as a control. For this robustness check, we drop the household fixed effects from the panel regressions to avoid the issue of inconsistently estimated standard errors that would otherwise occur in this context. Row 5 shows that our results remain robust.

VII. Conclusion

We investigate individual investors' trading process and show how it is affected by inattention. For that purpose, we exploit episodes of sensational news, which, we argue, are

[8] Specifically, we drop all events relating to the Iraq War (1, 2, 3, 4, 5), major political events (6, 9, 17) and major natural disasters (14, 16).

largely exogenous to the stock market. We find that investors, when distracted, do not reduce the size of their trades but stop trading altogether. These findings are consistent with a model of attention in which investors incur a fixed cost for deciding whether or not to trade and/or for accessing their brokerage account. They are less consistent with standard models of information acquisition in which inattentive investors adjust at the intensive margin how much information to gather.

We show further that this phenomenon is related to, but distinct from, investors' documented tendency to buy attention-grabbing stocks (Barber and Odean (2008)). In contrast to this tendency, distraction affects buys and sells symmetrically. We argue that the trading decision process consists of two successive stages, a search stage followed by an execution stage: in the search stage, investors consider a subset of stocks for potential trading; in the execution stage, investors pull the trigger on stocks from the consideration set. Most models focus on the search stage. Our analysis calls for models integrating both stages.

Finally, we report that the effect of distraction is more pronounced for more overconfident – i.e., male and active – investors. As these investors tend to trade too much, they actually benefit from inattention. Thus, we offer a more neutral perspective on attention than in the literature, which typically views attention as good and inattention as bad. We show that when investors are "misbehaving" (trading too much), their behavior may actually improve when they are distracted.

Our research is only a first attempt to dissect the role of attention in the trading process for retail investors. We look forward to seeing more work in this area.

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Figure 1: Trading Activity during the O.J. Simpson Trial Verdict

This figure shows the value of aggregate trading volume (in logs) on the New York Stock Exchange on October 3, 1995, the day the verdict of O.J. Simpson's murder trial was announced. The top, middle and bottom panels display trading volume for, respectively, all, small and, large trades. Trades are sorting into five size groups. Small (large) trades are those in the bottom (top) quintile. The horizontal axis labels 5-minute intervals starting from the opening of the market at 9 a.m. EST. The vertical line marks the announcement time (10 a.m. PST or 1 p.m. EST). The solid horizontal line indicates the average (log) trading volume during that day (excluding the period from 10.00 to 10.10 am) for the trade size category displayed in the panel. The dashed horizontal line indicates the 5% confidence bound (1.96 times the standard deviation of (log) trading volume during the day). Data for this figure comes from TAQ.

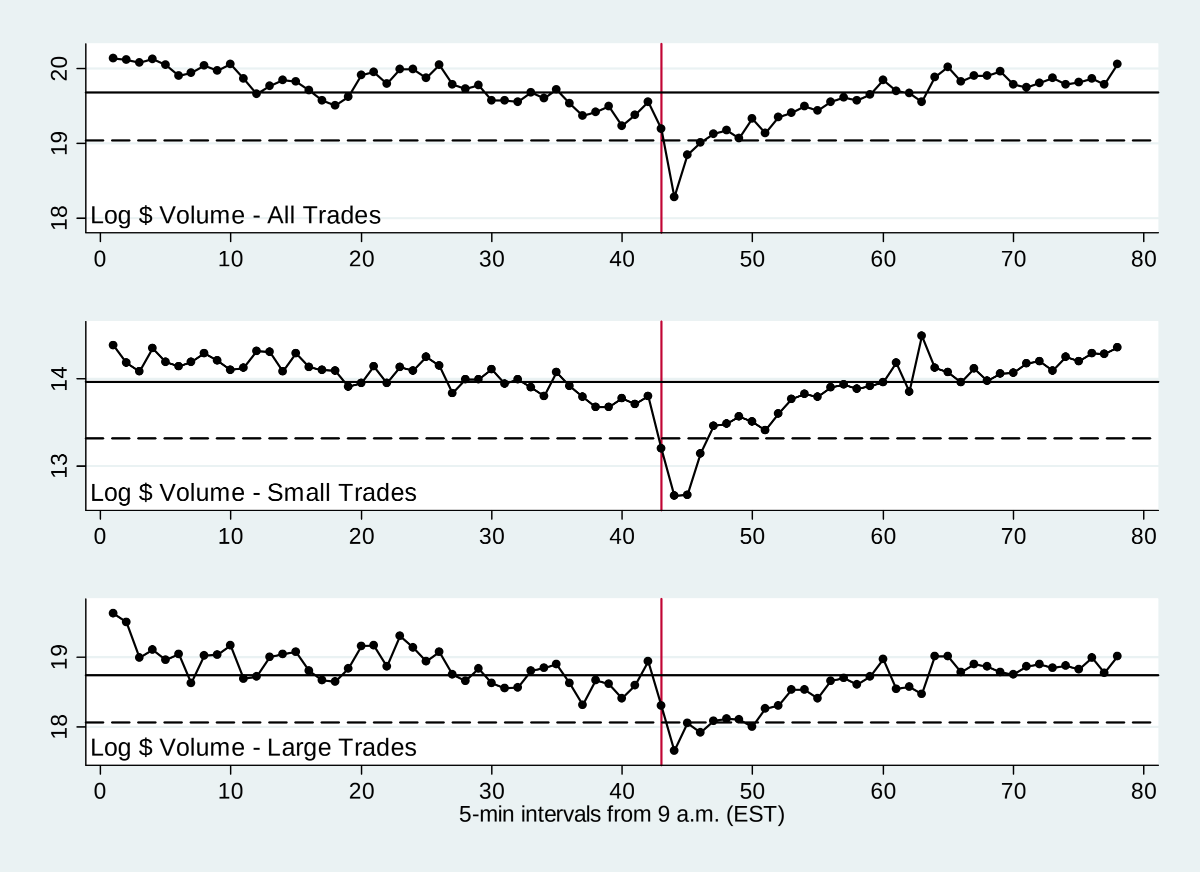

Figure 2: Average weekly news pressure and distraction events

The blue line in this figure shows the average weekly news pressure taken over business days between 1991 and 1996 – the sample period of the discount brokerage data. The red dots mark the weeks in which weekly news pressure is in the top decile of that year – i.e., the distraction events that we use in this paper. Daily news pressure can be downloaded at David Stroemberg's website: http://people.su.se/~dstro.

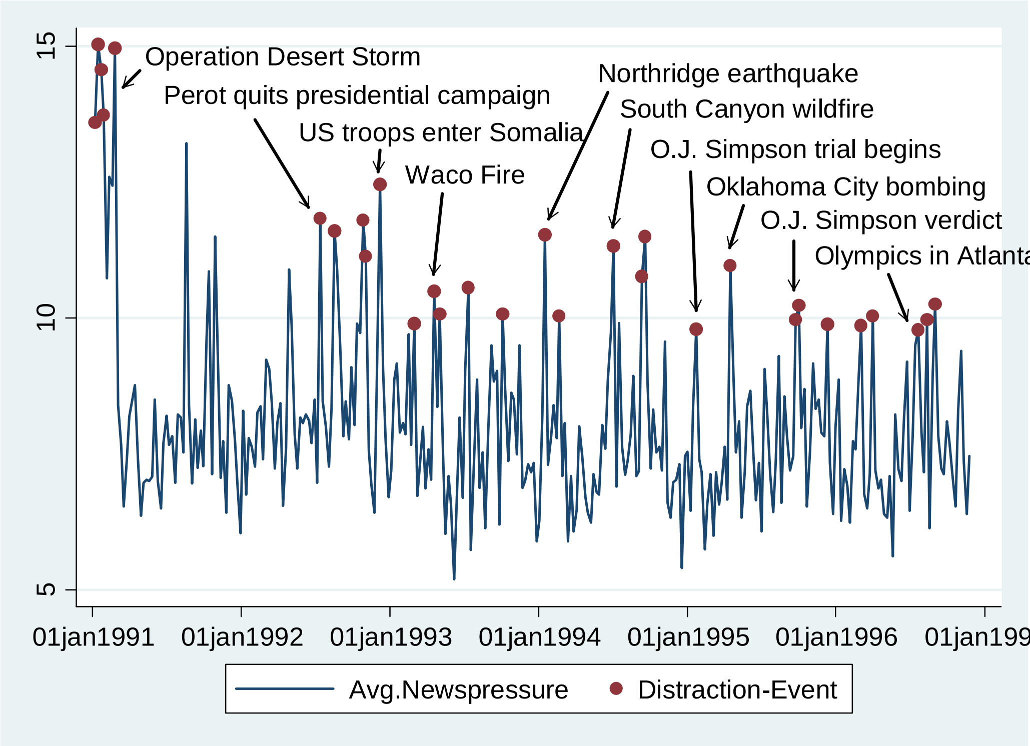

Table 1: Distraction events and household sample

Panel (a) lists the distraction events used in this paper and a corresponding description of the major headline of the week. The last column shows the Z-score corresponding to the weekly value-weighted CRSP return. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively. Panel (b) shows descriptive statistics for the balanced panel at the household-week level spanned by our sample of 12,743 households with portfolio holdings between January 1991 and November 1996. Blocks I, II and III report statistics for buys, sells, and all trades, respectively. Block IV shows the components of transaction costs in % and $: trade commissions and two different estimates of spreads, one based on actual transaction prices (denoted TR-PR) and one based on high-low CRSP prices (denoted HI-LO) using the algorithm developed by Corwin and Schultz (2012). Block V shows the average post-trade buy-sell return difference for holding periods of 1, 2, 4, 8, and 12 weeks, respectively.

Panel (a): List of distracting events

No	Week	Description	Z-score
1	07/01/91 – 11/01/91	US congress debates about Persian Gulf Crisis	-1.567
2	14/01/91 – 18/01/91	Gulf War: Operation Desert Storm begins	3.101***
3	21/01/91 – 25/01/91	Gulf War: Iraqi Scud missile hits Israel, which threatens to engage	1.063
4	28/01/91 – 01/02/91	Gulf War: Battle of Khafji	1.780*
5	25/02/91 – 01/03/91	Gulf War: Bush declares Kuwait liberated	0.817
6	13/07/92 – 17/07/92	Perot publicly quits presidential campaign	-0.007
7	17/08/92 – 21/08/92	Republican National Convention; Ruby Ridge incident	-1.039
8	26/10/92 – 30/10/92	Presidential election campaign draws to a close	0.727
9	02/11/92 – 06/11/92	Bill Clinton wins presidential election	-0.036
10	07/12/92 – 11/12/92	US troops enter South Somalia as part of a UN mission	-0.094
11	01/03/93 – 05/03/93	World Trade Center bomber Mohammad Salameh is captured	0.497
12	19/04/93 – 24/04/93	Siege of Branch Davidians compound in Waco, Texas, ends in fire	-1.836*
13	03/05/93 – 07/05/93	West Memphis Three murder as part of an alleged satanic ritual	0.498
14	12/07/93 – 16/07/93	Magnitude 7.8 earthquake hits Hokkaidō, Japan	-0.505
15	04/10/93 – 08/10/93	Battle of Mogadishu (“Black Hawk Down”)	-0.300
16	17/01/94 – 21/01/94	Northridge Earthquake hits San Fernando valley in Los Angeles	-0.230
17	21/02/94 – 25/02/94	Cave of the Patriarchs massacre in Hebron, West Bank	-0.568
18	04/07/94 – 08/07/94	South Canyon wildfire in Colorado	0.220
19	12/09/94 – 16/09/94	Cessna plane crashes onto White House lawn	0.343
20	19/09/94 – 24/09/94	US troops enter Haiti to restore democracy	-1.979**
21	23/01/95 – 27/01/95	O. J. Simpson trial begins	0.346
22	17/04/95 – 21/04/95	Oklahoma City bombing	-0.472
23	25/09/95 – 29/09/95	O. J. Simpson trial sent to jury	-0.045
24	02/10/95 – 06/10/95	O. J. Simpson is found not guilty	-0.862
25	11/12/95 – 15/12/95	Dayton Agreement ends Bosnian War	-0.693
26	04/03/96 – 08/03/96	Train derailment leads to evacuation of city of Weyauwega in Wisconsin	-1.341
27	01/04/96 – 05/04/96	Suspected "Unabomber" Theodore Kaczynski is arrested	0.822
28	22/07/96 – 26/07/96	Summer Olympics in Atlanta	-0.841
29	12/08/96 – 16/08/96	Republican National Convention	0.275
30	02/09/96 – 06/09/96	Cruise missile strikes on Iraq	0.015

Panel (b): Descriptive statistics for household sample

	Mean	Standard Dev.	1st Quartile	Median	3rd Quartile
I. Buys					
Uncond. Probability (in %)	3.94				
$-volume	10,354	33,347	2,525	4,830	9,875
#-stocks	1.43	1.06	1.00	1.00	1.00
II. Sells					
Uncond. Probability (in %)	3.12				
$-volume	13,392	44,321	2,897	5,813	12,688
#-stocks	1.44	1.13	1.00	1.00	1.00
III. All Trades					
Uncond. Probability (in %)	5.99				
$-volume	13,790	47,021	2,850	5,750	12,503
#-stocks	1.69	1.50	1.00	1.00	2.00
IV. Transaction costs					
%-commissions	2.05	3.84	0.86	1.40	2.32
%-spreads based on TR-PR	0.97	2.36	0.00	0.26	1.32
%-spreads based on HI-LO	0.60	0.89	0.20	0.38	0.70
$-commissions	150.40	192.92	55.00	99.00	165.45
$-spreads based on TR-PR	182.73	1523.24	0.00	12.50	112.50
$-spreads based on HI-LO	94.62	448.80	10.02	27.45	75.08
V. Post-trade buy-sell return difference (PTBSD)					
1-week	-0.0007	0.0761	-0.0379	0.0000	0.0371
2-weeks	-0.0011	0.1024	-0.0530	0.0000	0.0511
4-weeks	-0.0030	0.1424	-0.0770	0.0000	0.0706
8-weeks	-0.0046	0.2036	-0.1119	0.0000	0.1015
12-weeks	-0.0058	0.2517	-0.1386	0.0000	0.1251

Table 2: Distracting events and the stock market – analysis using CRSP and TAQ data

This table presents the effect of distracting events on the stocks market. Panel (a) reports time-series regressions of the value-weighted CRSP return [*Market return*], its absolute value [*Abs. market return*], the average price range (the ratio of intra-day high to low stock prices) [*Price range*], and the logarithm of the dollar trading volume [*Log(market volume)*], on the distraction-event dummy, and one control variable, the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. Panel (b) reports time-series regressions of small and large trades on the distraction-event dummy and three controls: the logarithm of total CRSP trading volume [*Log(market volume)*], the absolute value of the value-weighted CRSP return [*Abs. market return*] and the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. Trades data are obtained from TAQ and include all transactions in all stocks listed on NYSE/AMEX/Nasdaq over the period from 1991 to 2001 (panel (a)), and over the period from 1991 to 2006 (panel (b)). Trades are classified as buyer- or seller-initiated using the Lee and Ready (1991) algorithm, and by size using a procedure described in Hvidkjaer (2006) based on the following small- (large-) trade cut-off points within firm-size quintiles: $3,400 ($6.800) for the smallest firms, $4,800 ($9.600), $7,300 ($14.600), $10,300 ($20,600), and $16,400 (32,800) for the largest firms. Dollar buys, dollar sells and dollar trades (the sum of dollar buys and dollar sells) are aggregated over the entire market in each week, separately for small and large trades. In columns (1), (2) and (3), respectively, the dependent variable is the logarithm of aggregate dollar buy volume for, respectively, small buys, large buys and their difference. In columns (4), (5) and (6), respectively, the dependent variable is the logarithm of aggregate dollar sell volume for, respectively, small sells, large sells and their difference. In columns (7), (8) and (9), respectively, the dependent variable is the logarithm of aggregate dollar trade volume (the sum of buys and sells) for, respectively, small trades, large trades and their difference. All regressions include quarter and month-in-year fixed effects. Standard errors are robust to autocorrelation of up to three lags using the Newey-West correction. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel (a): CRSP-analysis

	1968-2011				1991-2000			
	(1) Market return	(2) Abs. market return	(3) Price range	(4) Log(market volume)	(5) Market return	(6) Abs. market return	(7) Price range	(8) Log(market volume)
Distraction-Event	-0.001	-0.000	0.000	-0.006	-0.001	-0.002	-0.001	-0.050*
	(-0.765)	(-0.063)	(0.738)	(-0.414)	(-0.288)	(-1.017)	(-0.604)	(-1.742)
ADS index	0.002	0.000	-0.000	0.043***	-0.007**	0.005*	0.001	-0.005
	(1.342)	(0.340)	(-0.229)	(3.278)	(-2.001)	(1.948)	(0.876)	(-0.165)
N	2,257	2,257	2,257	2,257	521	521	521	521
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel (b): TAQ-analysis (period: 1991-2000)

	Buys only			Sells only			All trades		
	(1) Log(Small)	(2) Log(Large)	(3) Log(S/L)	(4) Log(Small)	(5) Log(Large)	(6) Log(S/L)	(7) Log(Small)	(8) Log(Large)	(9) Log(S/L)
Distraction-Event	-0.088***	-0.053**	-0.041**	-0.083***	-0.041	-0.051***	-0.085***	-0.047*	-0.046***
	(-3.02)	(-2.10)	(-2.56)	(-3.19)	(-1.58)	(-3.37)	(-3.15)	(-1.86)	(-3.13)
Abs. market return	-0.241	1.645***	-1.732***	0.041	1.102**	-0.830**	-0.105	1.407***	-1.313***
	(-0.40)	(2.88)	(-3.95)	(0.07)	(2.07)	(-1.99)	(-0.18)	(2.68)	(-3.20)
ADS index	-0.052	-0.026	-0.027	-0.071*	-0.001	-0.072***	-0.062*	-0.014	-0.050**
	(-1.33)	(-0.82)	(-1.17)	(-1.93)	(-0.05)	(-2.68)	(-1.65)	(-0.48)	(-2.08)
Log(market volume)			-0.126***			-0.189***			-0.163***
			(-3.49)			(-3.71)			(-3.81)
N	522	522	522	522	522	522	522	522	522
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 3: Distracting events and retail trading

Panel (a) reports time-series regressions of retail trading activity on the distraction-event dummy and three controls: the logarithm of total CRSP trading volume [*Log(market volume)*], the absolute value of the value-weighted CRSP return [*Abs. market return*] and the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. In columns (1)-(3), the dependent variable is the logarithm of dollar trade volume averaged across trading investors. In columns (4)-(6), the dependent variable is the logarithm of the number of different stocks traded averaged across trading investors. In columns (4)-(6), the dependent variable is the logarithm of the number of trading households. All regressions include quarter and month-in-year fixed effects. Standard errors are robust to autocorrelation of up to three lags using the Newey-West correction. Panel (b) reports panel regressions on the distraction-event dummy and the same controls. In columns (1)-(3), the dependent variable is the logarithm of dollar trade volume at the household level. In columns (4)-(6), the dependent variable is the logarithm of the number of different stocks traded. In columns (4)-(6), the dependent variable is a dummy for whether the household is trading or not. All regressions include household, quarter and month-in-year fixed effects. Standard errors are panel-corrected allowing autocorrelation of up to three lags (Driscoll and Kraay, 1998). Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel (a): Time-series regressions

	Avg Log($volume)			Avg Log(#stocks)			Log(#HH trading)		
	(1) Buys	(2) Sells	(3) All Trades	(4) Buys	(5) Sells	(6) All Trades	(7) Buys	(8) Sells	(9) All Trades
Distraction-Event	0.0001	0.0199	0.0009	-0.0033	0.0025	-0.0064	-0.0557***	-0.0846***	-0.0632***
	(0.01)	(1.13)	(0.08)	(-0.63)	(0.40)	(-1.07)	(-2.80)	(-3.39)	(-3.86)
Log(market volume)	0.0599*	0.1483***	0.1576***	0.0694***	0.0459**	0.0988***	0.7159***	0.7869***	0.6762***
	(1.80)	(3.72)	(4.73)	(5.85)	(1.98)	(6.85)	(11.98)	(8.20)	(10.00)
Abs. market return	-0.2522	1.0448**	0.2279	0.5899***	0.5440*	0.3869*	-1.6822*	2.0415	0.3632
	(-0.43)	(2.11)	(0.47)	(2.89)	(1.74)	(1.68)	(-1.87)	(1.47)	(0.52)
ADS index	0.0091	-0.0022	-0.0084	-0.0163***	-0.0034	-0.0185***	-0.0004	-0.1352***	-0.0548**
	(0.63)	(-0.12)	(-0.63)	(-2.77)	(-0.45)	(-2.89)	(-0.01)	(-2.66)	(-2.28)
N	308	308	308	308	308	308	308	308	308
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel (b): Panel regressions

	Log($volume)			Log(#stocks)			Trade Dummy		
	(1) Buys	(2) Sells	(3) All Trades	(4) Buys	(5) Sells	(6) All Trades	(7) Buys	(8) Sells	(9) All Trades
Distraction-Event	-0.0007	0.0127	-0.0021	-0.0028	-0.0018	-0.0084*	-0.0022**	-0.0028***	-0.0038***
	(-0.10)	(1.09)	(-0.28)	(-0.66)	(-0.30)	(-1.75)	(-2.50)	(-3.76)	(-3.63)
Log(market volume)	0.0553**	0.1802***	0.1881***	0.0904***	0.0567***	0.1137***	0.0275***	0.0230***	0.0393***
	(2.56)	(5.98)	(8.06)	(7.50)	(3.12)	(6.86)	(11.27)	(7.62)	(11.45)
Abs. market return	-0.2542	0.7538**	0.0700	0.4558**	0.6981***	0.4124*	-0.0650*	0.0715*	0.0229
	(-0.80)	(2.03)	(0.22)	(2.43)	(2.61)	(1.80)	(-1.77)	(1.87)	(0.55)
ADS index	0.0166	0.0128	0.0019	-0.0138**	-0.0110	-0.0214***	-0.0003	-0.0046***	-0.0037***
	(1.52)	(0.92)	(0.19)	(-2.52)	(-1.63)	(-3.27)	(-0.21)	(-3.17)	(-2.82)
N	154,752	122,261	234,922	154,752	122,261	234,922	3,924,844	3,924,844	3,924,844
Household FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 4: Distracting events and subsequent retail trading

Panel (a) reports time-series regressions of retail trading activity on the distraction-event dummy, past-distraction-event dummies that flag the weeks 1, 2, and 3 after a distraction-event and three controls: the logarithm of total CRSP trading volume [*Log(market volume)*], the absolute value of the value-weighted CRSP return [*Abs. market return*] and the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. In columns (1)-(3), the dependent variable is the logarithm of dollar trade volume averaged across trading investors. In columns (4)-(6), the dependent variable is the logarithm of the number of different stocks traded averaged across trading investors. In columns (4)-(6), the dependent variable is the logarithm of the number of trading households. All regressions include quarter and month-in-year fixed effects. Standard errors are robust to autocorrelation of up to three lags using the Newey-West correction. Panel (b) reports panel regressions on the distraction-event and past distraction-events dummies and the same controls. In columns (1)-(3), the dependent variable is the logarithm of dollar trade volume at the household level. In columns (4)-(6), the dependent variable is the logarithm of the number of different stocks traded. In columns (4)-(6), the dependent variable is a dummy for whether the household is trading or not. All regressions include household, quarter and month-in-year fixed effects. Standard errors are panel-corrected allowing autocorrelation of up to three lags (Driscoll and Kraay, 1998). Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel (a): Time-series regressions

	Avg Log($vol)			Avg Log(#stocks)			Log(#HH trading)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Buys	Sells	All Trades	Buys	Sells	All Trades	Buys	Sells	All Trades
Distraction-Event	-0.0002	0.0158	-0.0003	-0.0021	0.0008	-0.0066	-0.0668***	-0.0864***	-0.0701***
	(-0.01)	(0.88)	(-0.02)	(-0.41)	(0.13)	(-1.13)	(-2.81)	(-3.44)	(-4.04)
Distraction-Event $_{-1}$	0.0045	-0.0323*	-0.0149	0.0033	-0.0054	-0.0012	-0.0162	-0.0410	-0.0258
	(0.33)	(-1.94)	(-0.96)	(0.79)	(-0.89)	(-0.28)	(-0.59)	(-1.56)	(-1.39)
Distraction-Event $_{-2}$	-0.0092	-0.0089	-0.0053	0.0055	-0.0072	-0.0008	-0.0534**	-0.0052	-0.0314
	(-0.66)	(-0.62)	(-0.41)	(1.16)	(-1.15)	(-0.17)	(-2.09)	(-0.17)	(-1.63)
Distraction-Event $_{-3}$	0.0071	-0.0249	-0.0037	0.0049	-0.0067	-0.0010	-0.0425**	-0.0075	-0.0262*
	(0.58)	(-1.44)	(-0.31)	(0.98)	(-1.30)	(-0.22)	(-2.11)	(-0.27)	(-1.66)
Log(market volume)	0.0610*	0.1528***	0.1607***	0.0686***	0.0471**	0.0990***	0.7209***	0.7945***	0.6822***
	(1.85)	(3.74)	(4.69)	(6.10)	(2.35)	(7.40)	(11.90)	(8.43)	(10.85)
Abs. market return	-0.2590	1.1361**	0.2850	0.5858***	0.5535*	0.3899*	-1.7002*	2.2042*	0.4208
	(-0.45)	(2.37)	(0.61)	(2.88)	(1.77)	(1.77)	(-1.83)	(1.73)	(0.58)
ADS index	0.0095	-0.0107	-0.0111	-0.0145**	-0.0061	-0.0189***	-0.0165	-0.1409***	-0.0659***
	(0.66)	(-0.60)	(-0.84)	(-2.41)	(-0.78)	(-3.03)	(-0.47)	(-3.04)	(-2.97)
N	308	308	308	308	308	308	308	308	308
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel (b): Panel regressions

	Log($vol)			Log(#stocks)			Trade Dummy		
	(1) Buys	(2) Sells	(3) All Trades	(4) Buys	(5) Sells	(6) All Trades	(7) Buys	(8) Sells	(9) All Trades
Distraction-Event	-0.0004	0.0102	-0.0031	-0.0026	-0.0030	-0.0094**	-0.0027***	-0.0028***	-0.0042***
	(-0.06)	(0.85)	(-0.43)	(-0.60)	(-0.52)	(-2.06)	(-3.05)	(-3.77)	(-4.20)
Distraction-Event $_{-1}$	0.0037	-0.0218*	-0.0142	0.0027	-0.0060	-0.0038	-0.0010	-0.0013	-0.0017
	(0.45)	(-1.84)	(-1.37)	(0.73)	(-1.24)	(-0.91)	(-0.93)	(-1.60)	(-1.62)
Distraction-Event $_{-2}$	-0.0042	-0.0090	-0.0062	0.0014	-0.0062	-0.0042	-0.0024**	-0.0002	-0.0021*
	(-0.56)	(-0.87)	(-0.73)	(0.32)	(-1.13)	(-0.77)	(-2.49)	(-0.17)	(-1.92)
Distraction-Event $_{-3}$	0.0065	-0.0071	-0.0001	-0.0000	-0.0025	-0.0035	-0.0017**	0.0000	-0.0014
	(0.97)	(-0.63)	(-0.01)	(-0.01)	(-0.54)	(-0.71)	(-2.19)	(0.03)	(-1.57)
Log(market volume)	0.0557**	0.1836***	0.1910***	0.0898***	0.0578***	0.1144***	0.0278***	0.0233***	0.0398***
	(2.57)	(6.12)	(8.04)	(7.30)	(3.14)	(6.86)	(11.13)	(7.60)	(11.13)
Abs. market return	-0.2573	0.8504**	0.1346	0.4445**	0.7251***	0.4248*	-0.0643*	0.0773**	0.0276
	(-0.81)	(2.39)	(0.45)	(2.34)	(2.71)	(1.87)	(-1.81)	(2.01)	(0.66)
ADS index	0.0175	0.0080	-0.0003	-0.0134**	-0.0129*	-0.0230***	-0.0010	-0.0048***	-0.0044***
	(1.59)	(0.59)	(-0.04)	(-2.45)	(-1.95)	(-3.61)	(-0.71)	(-3.20)	(-3.63)
N	154,752	122,261	234,922	154,752	122,261	234,922	392,4844	392,4844	392,4844
Household FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 5: Distracting events and retail trading – separating between different attention channels

Panel (a) reports time-series regressions of the logarithm of the number of trading households in different stocks on the distraction-event dummy and three controls: the logarithm of total CRSP trading volume [*Log(market volume)*], the absolute value of the value-weighted CRSP return [*Abs. market return*] and the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. Columns (1)-(2) distinguish between buys of stocks previously- and not-previously-held by the household. Columns (3)-(4) distinguish between buys of stocks with above and below median abnormal CRSP trading volume. Columns (5)-(6) distinguish between buys of stocks with above and below median absolute CRSP return. Columns (7)-(8) distinguish between sells of stocks with above and below median abnormal CRSP trading volume. Columns (9)-(10) distinguish between sells of stocks with above and below median absolute CRSP return. All regressions include quarter and month-in-year fixed effects. Standard errors are robust to autocorrelation of up to three lags using the Newey-West correction. Panel (b) reports panel regressions of the trade dummy for the same stock splits on the distraction-event dummy and the same controls. All regressions include household, quarter and month-in-year fixed effects. Standard errors are panel-corrected allowing autocorrelation of up to three lags (Driscoll and Kraay, 1998). Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel (a): Time-series regressions

Log(#HH doing…)	Buys of stocks previously held/not-held		Buys of stocks with high/low abn. volume		Buys of stocks with high/low abs. return		Sells of stocks with high/low abn. volume		Sells of stocks with high/low abs. return	
	(1) held	(2) not-held	(3) high	(4) low	(5) high	(6) low	(7) high	(8) low	(9) high	(10) low
Distraction-Event	-0.0441*	-0.0319	-0.0651**	-0.0422	-0.0662**	-0.0445	-0.0782***	-0.1020**	-0.0903***	-0.0745**
	(-1.91)	(-0.46)	(-2.33)	(-1.14)	(-2.01)	(-1.22)	(-3.60)	(-2.10)	(-2.80)	(-2.16)
Log(market volume)	0.7014***	1.3003***	0.8957***	0.5119***	0.8095***	0.6437***	0.9113***	0.6643***	0.8944***	0.7159***
	(11.40)	(9.58)	(11.64)	(7.62)	(10.52)	(7.24)	(9.24)	(5.65)	(8.75)	(6.49)
Abs. market return	-1.4422	-0.8342	-0.9322	-2.4254*	1.1086	-5.1240***	3.6877**	-0.1638	6.0865***	-2.7258*
	(-1.48)	(-0.39)	(-0.89)	(-1.66)	(0.97)	(-3.21)	(2.49)	(-0.09)	(3.50)	(-1.79)
ADS index	-0.0010	-0.0471	0.0375	-0.0578	-0.0073	0.0011	-0.0669	-0.2295***	-0.1032**	-0.1680***
	(-0.03)	(-0.53)	(0.72)	(-1.31)	(-0.17)	(0.03)	(-1.53)	(-3.69)	(-2.01)	(-3.37)
N	304	304	308	308	308	308	308	308	308	308
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel (b): Panel regressions

Trade Dummy for…	Buys of stocks previously held/not-held		Buys of stocks with high/low abn. volume		Buys of stocks with high/low abs. return		Sells of stocks with high/low abn. volume		Sells of stocks with high/low abs. return	
	(1) held	(2) not-held	(3) high	(4) low	(5) high	(6) low	(7) high	(8) low	(9) high	(10) low
Distraction-Event	-0.0017**	-0.0001	-0.0019***	-0.0006	-0.0016**	-0.0009	-0.0016***	-0.0015**	-0.0016***	-0.0014**
	(-2.00)	(-1.08)	(-2.82)	(-0.96)	(-2.19)	(-1.37)	(-4.28)	(-2.33)	(-3.29)	(-2.39)
Log(market volume)	0.0267***	0.0016***	0.0219***	0.0083***	0.0181***	0.0124***	0.0172***	0.0075***	0.0141***	0.0109***
	(10.59)	(8.61)	(10.05)	(7.74)	(9.61)	(7.19)	(8.73)	(4.33)	(7.45)	(5.76)
Abs. market return	-0.0540	-0.0014	-0.0269	-0.0367	0.0170	-0.0859***	0.0765***	0.0042	0.1094***	-0.0322
	(-1.43)	(-0.56)	(-0.97)	(-1.59)	(0.67)	(-2.90)	(2.89)	(0.18)	(3.77)	(-1.29)
ADS index	-0.0003	-0.0001	0.0003	-0.0009	-0.0006	-0.0000	-0.0019**	-0.0031***	-0.0017*	-0.0032***
	(-0.23)	(-1.28)	(0.23)	(-1.22)	(-0.54)	(-0.01)	(-1.98)	(-3.51)	(-1.83)	(-3.86)
N	3,873,872	3,873,872	3,924,844	3,924,844	3,924,844	3,924,844	3,924,844	3,924,844	3,924,844	3,924,844
Household FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 6: Distracting events and retail performance

Panel (a) reports time-series regressions of transaction costs on the distraction-event dummy and three controls: the logarithm of total CRSP trading volume [*Log(market volume)*], the absolute value of the value-weighted CRSP return [*Abs. market return*] and the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. Columns (1)-(2) show results for the average %-commission and the total $-commissions, respectively. Columns (3)-(4) show results for the average %-spread and the total $-spread based on actual transaction prices (denoted TR-PR), respectively. Columns (5)-(6) show results for the average %-spread and the total $-spread based on high-low prices (denoted HI-LO; based on the methodology developed by Corwin and Schultz, 2012), respectively. Columns (7)-(8) show results for the %-transaction costs and $-transaction costs when commissions are combined with spreads based on TR-PR. Columns (9)-(10) show results for the %-transaction costs and $-transaction costs when commissions are combined with spreads based on HI-LO. Panel (b) reports time-series regressions of cumulative post-trade buy-sell return differences (PTBSD) on the same controls. PTBSD is defined as the average future returns of buys minus the average future return of sells, of all the buys and sells for a given week. In columns (1)-(5), the dependent variable is the cumulative PTBSD for the next 1, 2, 4, 8, and 12 weeks, respectively. In columns (6)-(10), the dependent variable is the PTBSD after adjusting returns by the DGTW methodology for the next 1, 2, 4, 8, and 12 weeks, respectively. All regressions include quarter and month-in-year fixed effects. In Panel (a), standard errors are robust to autocorrelation of up to three lags. In Panel (b), standard errors are robust to autocorrelation of up to fifteen lags in order to mitigate mechanical autocorrelation induced by partly overlapping returns. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel (a): Time-series regressions for transaction costs

	Trade Commissions		Spreads based on TR-PR		Spreads based on HI-LO		Transaction Costs based on TR-PR		Transaction Costs based on HI-LO	
	(1) Avg. (%)	(2) Tot. Log($)	(3) Avg. (%)	(4) Tot. Log($)	(5) Avg. (%)	(6) Tot. Log($)	(7) Avg. (%)	(8) Tot. Log($)	(9) Avg. (%)	(10) Tot. Log($)
Distraction-Event	0.0001	-0.0708***	-0.0001	-0.1119	-0.0001	-0.1141**	0.0001	-0.0930*	0.0000	-0.0897***
	(0.36)	(-2.79)	(-0.14)	(-1.30)	(-0.94)	(-2.58)	(0.15)	(-1.65)	(0.07)	(-2.82)
Log(market volume)	-0.0028***	0.8643***	-0.0001	1.0966***	-0.0000	1.1606***	-0.0028**	0.9737***	-0.0028**	0.9788***
	(-2.99)	(11.30)	(-0.09)	(6.02)	(-0.02)	(11.24)	(-2.40)	(8.14)	(-2.41)	(11.75)
Abs. market return	-0.0050	0.9632	0.0061	2.4047	-0.0078*	-0.7603	0.0011	1.3149	-0.0128	0.2748
	(-0.43)	(0.95)	(0.55)	(0.77)	(-1.71)	(-0.47)	(0.08)	(0.64)	(-0.92)	(0.23)
ADS index	-0.0003	-0.0711**	-0.0003	-0.0400	-0.0001	-0.1086**	-0.0006	-0.0673	-0.0004	-0.0861**
	(-0.92)	(-2.31)	(-0.67)	(-0.43)	(-0.91)	(-2.01)	(-1.07)	(-1.09)	(-1.10)	(-2.33)
N	308	308	308	308	308	308	308	308	308	308
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel (b): Time-series regressions for post-trade buy-sell return difference

	Cumulative PTBSD					Cumulative DGTW-adj. PTBSD				
	(1) 1 week	(2) 2 weeks	(3) 4 weeks	(4) 8 weeks	(5) 12 weeks	(6) 1 week	(7) 2 weeks	(8) 4 weeks	(9) 8 weeks	(10) 12 weeks
Distraction-Event	0.0019	0.0032***	0.0057***	0.0112***	0.0086**	0.0017	0.0031***	0.0056***	0.0103**	0.0080**
	(1.14)	(2.70)	(2.65)	(2.60)	(2.26)	(0.97)	(2.65)	(2.83)	(2.56)	(2.39)
Log(market volume)	0.0092**	0.0118***	0.0053	0.0139*	0.0146	0.0085**	0.0116***	0.0057	0.0143**	0.0144*
	(2.45)	(3.11)	(0.89)	(1.88)	(1.50)	(2.37)	(3.02)	(1.03)	(2.08)	(1.69)
Abs. market return	0.0299	0.0188	0.1249	0.1014	0.0066	0.0072	-0.0333	0.0630	0.0322	-0.0564
	(0.59)	(0.25)	(1.02)	(0.50)	(0.03)	(0.14)	(-0.42)	(0.50)	(0.16)	(-0.28)
ADS index	0.0005	0.0007	-0.0017	0.0015	0.0052	0.0004	0.0005	-0.0019	0.0024	0.0061
	(0.32)	(0.23)	(-0.30)	(0.33)	(0.97)	(0.25)	(0.17)	(-0.38)	(0.58)	(1.21)
N	308	308	308	308	308	308	308	308	308	308
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month-in-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 7: Distraction events interacted with household characteristics

This Table reports panel regressions of the trade dummy on the distraction-event dummy interacted with different household characteristics and the interactions of the same characteristic with three controls : the logarithm of total CRSP trading volume [*Log(market volume)*], the absolute value of the value-weighted CRSP return [*Abs. market return*] and the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. All regressions include household and week fixed effects; the inclusion of the latter subsumes the distraction event dummy and any static household characteristics. In Column (1), the household characteristic is a male dummy, flagging households whose principal income earner is male. In Column (2), the characteristic is the population percentile in portfolio turnover, defined as dollar volume over dollar portfolio value, over the previous 12 months. In Column (3), the characteristic is the population percentile of gross portfolio profits over the previous 12 months. In Column (4), the characteristic is the "propensity to buy glitter", defined as the fraction of the number of buys of glitter-stocks (i.e., stocks with above median abnormal volume) over the number of all buys in our sample period. In Column (5), the characteristic is the product of the percentile of past turnover with one minus the percentile of past portfolio profits. Households who score high on this measure trade a lot while performing badly – i.e., they are likely to be overconfident (Goetzmann and Kumar 2008). In Column (6), the characteristic is the product of the percentile of past turnover with the percentile of past portfolio concentration. Households who score high on this measure trade a lot while having a highly concentrated portfolio, suggesting that they are overconfident. Standard errors are panel-corrected allowing autocorrelation of up to three lags (Driscoll and Kraay, 1998). Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Interaction with…	Household Characteristics			Proxies for Household Biasedness		
	(1)	(2)	(3)	(4)	(5)	(6)
	Male	Past Turnover	Past Profits	Propensity to buy Glitter	Past Turnover* Inverse Profits	Past Turnover* Concentration
Characteristics* Distraction-Event	-0.0018*	-0.0125***	-0.0023	-0.0053***	-0.0122***	-0.0097***
	(-1.91)	(-3.12)	(-1.28)	(-3.30)	(-2.72)	(-2.66)
Characteristics		-0.9036***	-0.3362***		-0.6849***	-0.7386***
		(-7.73)	(-4.75)		(-4.78)	(-6.27)
Characteristics* Log(market volume)	0.0068***	0.0373***	0.0143***	0.0143***	0.0271***	0.0301***
	(5.89)	(7.95)	(5.06)	(9.80)	(4.74)	(6.40)
Characteristics* Abs. market return	0.0898**	0.3935***	0.0216	0.0635	0.3801***	0.3509**
	(1.97)	(2.87)	(0.28)	(1.10)	(2.81)	(2.58)
Characteristics* ADS index	-0.0025***	-0.0248***	-0.0049**	-0.0060***	-0.0257***	-0.0232***
	(-2.58)	(-4.50)	(-2.24)	(-4.66)	(-4.18)	(-3.72)
N	2,448,908	3,678,119	3,727,332	3,153,304	3,678,119	3,076,816
Household FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y

Table 8: Distracting events and retail trading - robustness

This Table reports robustness checks for our baseline results reported in Table 3. For brevity, only the coefficient estimate of the respective distraction variable is reported. Columns (1)-(5) show the results of time-series regressions; columns (6)-(8) show the results for panel regressions. In columns (1)-(2), the dependent variables are the average logarithm of dollar volume and number of stocks traded. In columns (3)-(5), the dependent variables are the logarithm of the number of households that are buying, selling, and trading, respectively. In columns (6)-(8), the dependent variables are trade dummies for buys, sells, and all trades, respectively. All regressions include quarter and month-in-year fixed effects as well as three controls: the logarithm of total CRSP trading volume [*Log(market volume)*], the absolute value of the value-weighted CRSP return [*Abs. market return*] and the business and economics conditions index developed by Aruoba, Diebold and Scotti (2009) [*ADS index*]. The panel regressions also include household fixed effects, except for row 5. In row 1, the distraction event dummy excludes those 4 distraction weeks in which the CRSP market return was marginally significant (see Table 1 Panel (a)). In row 2, the distraction event dummy excludes 10 events that could have potentially had a direct impact on the economy. These dropped events are all events relating to the Iraq War (1, 2, 3, 4, 5), major political events (6, 9, 17) and major natural disasters (14, 16), where the numbers in parenthesis refer to the event number indicated in Table 1 Panel (a). In row 3, the distraction event dummy is extended to include all weeks in which news pressure was in the top two deciles. In row 4, the distraction event dummy is replaced by average news pressure directly. In row 5, we return to our distraction event dummy, but further include the lagged dependent variable as a control variable. In the time-series regressions, standard errors are robust to autocorrelation of up to three lags using the Newey-West correction. In the panel regressions, standard errors are panel-corrected allowing autocorrelation of up to three lags (Driscoll and Kraay, 1998). Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	Time-series regressions					Panel regressions		
	Log($vol)	Log(#stks)	Log(#HH trading)			Trade Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Trades	All Trades	Buys	Sells	All Trades	Buys	Sells	All Trades
1) Drop high z-score events	-0.0007	-0.0089	-0.0587**	-0.0723***	-0.0583***	-0.0023**	-0.0023***	-0.0033***
	(-0.05)	(-1.42)	(-2.55)	(-2.70)	(-3.28)	(-2.54)	(-2.98)	(-3.21)
2) Drop events with pot. economic impact	0.0048	-0.0081	-0.0413*	-0.0815***	-0.0539***	-0.0015*	-0.0023***	-0.0028**
	(0.33)	(-1.07)	(-1.83)	(-2.87)	(-2.76)	(-1.72)	(-2.94)	(-2.51)
3) Top 20% districation events	-0.0010	-0.0017	-0.0351*	-0.0595***	-0.0436***	-0.0012*	-0.0018***	-0.0024***
	(-0.11)	(-0.41)	(-1.88)	(-3.35)	(-3.19)	(-1.65)	(-3.46)	(-3.03)
4) Average news pressure	-0.0034	-0.0014	-0.0118**	-0.0246***	-0.0163***	-0.0004*	-0.0009***	-0.0010***
	(-1.41)	(-1.18)	(-2.03)	(-4.22)	(-3.73)	(-1.91)	(-4.26)	(-3.70)
5) Lagged dependent variable	0.0056	-0.0048	-0.0510**	-0.0626***	-0.0552***	-0.0020**	-0.0022***	-0.0030***
	(0.49)	(-0.81)	(-2.18)	(-2.72)	(-3.16)	(-2.26)	(-3.34)	(-2.96)

Appendix A: Back-of-the-envelope calculation for an overconfident household

In this Appendix, we present a back-of-the-envelope calculation to illustrate the benefits from distraction for an overconfident household. We consider a household who is in the top decile for the overconfidence proxy based on Past Turnover* Inverse Profits (see Table 7 Column 5) and we assume that this household finances his buys only from his sells. In other words, if the household trades $X, he has sold some position of value $X/2 to buy another position of value $X/2.

1)	**Characteristics of Overconfident Households**			
	median overconfidence score	0.5		
	PTBSD for 12 weeks	1.20%		
	median portfolio holdings	$29,233.00		
	median net return	3.20%		
	annual dollar profits	**$935.46**		
2)	**Savings from one Roundtrip Trade less**			
		in %	*avg. trade size*	*dollar savings*
	in transaction costs	2.80%	$16,147.00	$452.12
	in return (annualized; i.e. 4*PTBSD for 12 weeks)	4.80%	$8,073.50	$387.53
	total dollar savings	**$839.64**		
3)	**Reduction in Probability of Trading from 1 Distraction-Event**			
		in %		
	baseline reduction	0.38%	[Table 3 Panel (b) Column (9)]	
	further reduction from interaction	0.61%	[0.5 * Table 7 Column 5]	
	total reduction from one distraction	**1.00%**		
4)	**Annual Savings from Distraction**			
	total probability reduction from 5 distractions	5.00%		
	expected dollar savings from 5 distractions	**$41.98**		
	relative increase in net returns from 5 distractions	**4.49%**		