Glued to the TV:
The Trading Activity of Distracted Investors

Joel PERESS and Daniel SCHMIDT*

December 24, 2014

ABSTRACT

We investigate how distraction affects the trading behavior of retail investors, and ultimately market liquidity. Exploiting episodes of sensational news exogenous to the stock market, we first document that investors stop trading altogether when they are distracted. We report further that these effects are more pronounced for more overconfident–i.e., single-male and active–investors, who are typically viewed as noise traders. We then exploit these sensational news events to study how shocks to noise trading affect the stock market at large and in particular its liquidity. Our results are most consistent with an adverse selection model of price impact, and are weakly supportive of inventory risk models.

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* Preliminary and incomplete, please do not cite without permission. Joel Peress is at INSEAD, Boulevard de Constance, 77300 Fontainebleau, France. Email: joel.peress@insead.edu. Daniel Schmidt is at HEC Paris, 1 rue de la Liberation, 78350 Jouy-en-Josas, France. Email: schmidt@hec.fr.
We are grateful to David Strömberg for sharing detailed news pressure data including headline information and to Terry Odean for providing the large discount brokerage data. We thank Thierry Foucault and Jacob Sagi for their valuable comments, as well as seminar participants at the Marshall School of Business. Joel Peress thanks the AXA Research Fund and the Institut Europlace de Finance for their financial support.

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 experienced a low as they avoided using bathrooms, and trading on the stock exchange fell off a cliff (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 affect the trading behavior of investors, and through their trades, financial markets. We first show that these events trigger sharp variations in retail trading, especially among those investors who behave as noise traders. We then exploit these exogenous variations to study the effect of retail (noise) trading on markets, with a particular focus on liquidity.

We track variations in investors' attention to the stock market, generated by sensational media reporting of news largely exogenous to economic fundamentals. These stories draw investors' attention, and crowd 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 Challenger space shuttle explosion. 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 U.S. disaster relief. We use it here as an instrument for retail 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 little 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 limited 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).

We also find that, conditional on trading, investors buy, but do not sell, fewer different stocks. This asymmetry is consistent with the notion that searching for stocks to buy requires more attention than choosing which stocks to sell from one's portfolio (Barber and Odean (2008)). Next, we study which investors are more distracted. Our findings suggest that overconfident–i.e., single-male, more active and money-losing–investors are more affected by distracting events. As these investors tend to trade too much, they actually benefit from inattention.

These findings lead us to conclude that we have identified events which primarily distract biased retail traders–investors that the literature regards as the archetypical noise traders. Consistent with this view, transaction data from the TAQ database displays a significant reduction in the volume of small trades (which are likely to come from retail traders) on distraction days, but not of large trades (which are likely to be institutional). Hence, we can exploit sensational news episodes to study how shocks to noise trading affect financial markets, and especially market liquidity.

This question is of fundamental importance because the literature has identified two *opposing* channels through which noise trading influences financial markets. On the one hand, models of adverse selection (e.g., Kyle (1985), Glosten and Milgrom (1985)) suggest that insiders exploit noise trades to conceal their own informed trades. When noise trading drops suddenly, market makers face a better informed order flow and compensate themselves by increasing price impact and/or bid-ask spreads. On the other hand, models of persistent noise or liquidity shocks (e.g., DeLong et al. (1990)) argue that, because arbitrage is limited, these shocks are a source of risk. Under this "noise trader risk" or "inventory risk" view, price impact and bid-ask spreads compensate market makers for bearing that risk. Accordingly, price impact and spreads should go down when noise traders are distracted.

We exploit distraction events to tease out which channel dominates in the U.S. stock market. While results for the overall market are weak, we find pronounced effects once we focus on subgroups of stocks with high retail ownership. These results are most consistent with an (extended) adverse selection model. Specifically, we find a significant reduction in share turnover in the bottom tercile of stocks in terms of firm size, stock price and institutional ownership, and this effect dissipates monotonically in the other terciles. Most importantly, we show that this reduction in turnover goes hand in hand with an *increase* in price impact (as proxied by the Amihud (2002) illiquidity ratio), which also vanishes monotonically for the other terciles. The increase in the Amihud ratio is consistent with adverse selection, but not with a noise trader risk. To further confirm that our results are driven by adverse selection, we sort stocks based on adjusted PIN (henceforth AdjPIN, Duarte and Young (2009)), a refinement of the PIN adverse selection measure (Easley et al (2002)). We find that, on distraction days, both the Amihud ratio and bid-ask spreads are increased in the tercile of stocks with high AdjPIN, but not for stocks with low AdjPIN. These results again speak in favor of the adverse selection channel.

We also find evidence of a reduction in return volatility on high distraction days, which is similarly concentrated in the subgroup of stocks with high retail ownership. These results are consistent with inventory risk being priced, and they *cannot* be rationalized in the standard Kyle (1985) model with *risk-neutral* market makers. This is because with risk-neutral market makers, prices follow a martingale and noise shocks are fully absorbed, resulting in no price reversals. We show however that a simple extension of the Kyle (1985) model to the case of a risk-averse market maker (Subrahmanyam (1991), Kim (2014)) fits all our results. Specifically, the extension predicts that, on days with low noise trading, turnover and volatility are reduced, while price impact is increased – all of which we find.

Our paper makes four main contributions. First, we add to the growing empirical literature that assesses 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 variation in investors' attention that is largely exogenous to the stock market.

Second, thanks to this measure, we shed light on retail traders' decision making process. Specifically, by carefully comparing different measure of trading activity, we identify the steps in investors' decision process which are particularly demanding in terms of attention. Our findings suggest that it is the decision to trade and, conditional on trading, the selection of stocks to buy which consume the most attention (rather than the choice of the amount to trade). Thus, they are most consistent with models that assume a fixed attention costs (such as Merton (1987), Barber and Odean (2008)), and less consistent with models in which investors gradually curb their trading intensity as they pay less attention (e.g., Peng and Xiong 2006, Van Nieuwerburgh and Veldkamp, 2010).

Third, 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), they may actually benefit from being distracted. This insight relates to Hou, Peng and Xiong (2006). Using trading volume as a proxy for investor attention, they report that return momentum 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.

Finally, and most importantly, we contribute to the literature on the impact of noise trading in financial markets.[1] As argued above, our unique empirical setting allows us to contrast the two most popular models of price impact – adverse selection and inventory risk. To the best of our knowledge, we are the first to show that, in response to short-lived noise shocks such as those triggered by our distraction events, the adverse selection channel dominates the inventory risk channel. In this respect, our paper is related to recent work by Foucault et al. (2011) and Collin-Dufresne and Fos (2014). The former paper finds that, in response to a structural reform that increased the cost of retail trading for a subset of stocks on the French stock exchange, turnover, volatility and the Amihud ratio all declined–which is consistent with the inventory risk channel. The latter paper shows how informed traders strategically time their trades to occur on days with low price impact/transaction costs. This result is again inconsistent with standard adverse selection models as it suggests that periods of low price impact are periods of high informed trading. Our results offer important countervailing evidence against these conclusions. More broadly, they suggest that the question as to which channel is the dominant determinant of price impact deserves are more nuanced answer.

The balance of the paper is organized as follows. Section 1 reviews our methodology and data. Section 2 considers the effect of distraction on retail investors. Section 3 studies how these shocks to noise trading affect the stock market, in particular for subgroups of stocks predominantly held by retail investors. Section 4 presents robustness checks and discusses endogeneity issues. Section 5 concludes.

[1] See, for example, Kumar and Lee (2006), Dorn et al. (2008), Hvidkjaer (2008), Kaniel et al. (2008) and Barber et al. (2009).

I. Methodology and Data

A. Distracting Events

We identify our candidate events using the *news pressure* measure developed by Eisensee and Strömberg (2007). News pressure is defined as the median number of minutes that U.S. news broadcasts devote to the first three news segments. Eisensee and Strömberg (2007) 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 Strömberg, 2007, p. 207). We are grateful to David Strömberg for providing us with an updated time-series of daily news pressure covering the time period 1968 to 2013 that includes headline information.[2] Figure 2 provides a time-series plot of daily news pressure over the sample period. Daily news pressure oscillates around a mean of 8 minutes with occasional spikes of 10 minutes and more.

These spikes in daily news pressure are what interest us. Specifically, for each sample year, we select the 10% of business days with the highest news pressure as our candidate events. This leaves us with a list of 1,084 event-days. Next, we refine this list by filtering out events that may have had an impact on U.S. economic fundamentals. We do this because a piece of economic news constitutes a confounding event, which blurs any distraction effect. Moreover,

[2] The raw measure, without headline information, can be downloaded from David Strömberg's website (http://people.su.se/~dstro).

high-news pressure days with economic news are perhaps not distracting at all; rather, they may attract investors' attention to the financial market.

We first drop events when any of the first three news segments for any broadcast feature a headline containing keywords pertaining to the economy.[3] Second, we manually go over the remaining events and drop those that we believe could arguably have had an economic impact, regardless of how small we deem this impact to be. Whenever in doubt, we eliminate the event. We are left with a list of 510 event days over the period 1968 to 2013 which we feel confident to classify as non-economic (but potentially distracting). We call this list the *Distraction* events.

Our choice of keywords and manual filter is arguably subjective. Note, however, that any lapses with these filters (wrongly retaining events with economic news) will go against our findings. Indeed, economic news trigger *more* trading and *more* volatility, which is the opposite of what we expect under distraction. Moreover, we experiment with these filters, and we find very similar results (see section IV below).

[Insert Table 1 around here.]

Table 1 presents a partial list of our distraction events along with a short description of the day's major news headline. It lists the two distraction events with the highest news pressure for each year. Many stories in this list involve accidents (e.g., Challenger explosion, Minneapolis bridge collapse), terrorist attacks (e.g., Lockerbie plane bombing, Oklahoma City bombing, London bombing), assassination attempts (on, e.g., Reagan and the pope), shootings

[3] The keywords we use are: banking, bankruptcy, depression, economic, economy, election, equity, federal reserve, fed reserve, fed rate, finance, financial, interest rate, stock market, treasury, war.

(e.g., Littleton school shooting, Virginia Tech massacre, Tucson Arizona shooting), criminal court rulings (e.g., O.J. Simpson, John DeLorean, William Calley), celebrity deaths (e.g., Lady Diana funeral, Michael Jackson memorial service), military skirmishes (e.g., Grenada invasion, USS Stark incident, Iraq Fallujah uprising), natural disasters (e.g., Haiti earthquake, Oklahoma tornado) and political scandals (e.g., Watergate hearings, Iran-Contra scandal). In essence, we argue and test that popular interest and, in turn, media coverage for these events far exceeds their (arguably negligible) impact on the aggregate U.S. economy.

B. Other Data

To study the impact of our distraction events on retail traders, we employ disaggregated trades data from a large discount brokerage firm. This data is 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 on a given day is constant, which facilitates the comparison of trading intensities over time. One advantage of the disaggregated data is that it allows us to analyze *which* investors are more prone to be distracted. For example, we study the interaction of distraction with past trading profits and several proxies of investors' biasedness. The disadvantage is that we have a relatively short time period, forcing us to work with 61 distraction events.

We therefore complement our analysis with 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.[4] 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-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. 100 distraction events fall into this sample.

Finally, for the market analysis, we draw on data from CRSP over the whole period 1968 to 2013, allowing us to employ all 510 distraction events. We focus on common stocks (share codes 10 or 11). We describe our stock market variables in section IV below where we present results for the market-wide analysis.

C. Methodology

[4] 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.

We employ an event study methodology in our main analyses. Let X be an outcome variable of interest. In a first step, we purge any seasonal effects from this variable by regressing it on a set of dummy variables for calendar-month and day-of-the-week interacted by year. We carry out our analyses on the residuals from this regression. In that way, we can ensure that our results are not driven (or confounded) by seasonal patterns. If anything, our results strengthen when we do not make this adjustment.

We define abnormal X as the realization of (the residual of) X on the event date (t=0) minus its average over an estimation window. The estimation window comprises all trading days without economic news (according to the filters described above) in a window of 200 days centered on the event day. Thus, we compare distraction days with no economic news to non-distraction days also with no economic news. If we did not impose this restriction, we would compare non-economic days to fundamentally different days since the estimation window would contain a mix of both types of days. By employing the same economic news filter across distraction and non-distraction days, we ensure that any difference we find is attributable to the distracting event only. Formally:

$$\text{Abnormal X} = X_{t=0} - \text{Average } X_{0<|t|<101\ \&\ \text{non-economic}}$$

We use an estimation window that includes both the pre-event and the post-event period in order to neutralize any trend in the data. Results are unchanged if we use a pre-event window only. We test for the significance of abnormal X across events using a standard Patell (1976) test.

II. Distraction and Retail Trading

A. Analysis of retail trades

In this section, we study the effect of distraction on retail trading activity. In addition to setting the stage for the market-wide analysis to come, this analysis is valuable in its own right: because investors can only be distracted if they were attentive to begin with, our analysis here sheds light on their decision making process. In particular, by comparing distraction effects across different measures of retail trading activity, we can identify *precisely* which stages in the decision making process are most sensitive to attention constraints. Thus, our results are of interest to researchers aiming to develop a positive theory of attention allocation.

We study three different measures of trading activity at the household-day level – for buys and sells separately, and combined. First, we count the number of households trading on a given day. We take logarithms and label this variable *log(#households)*. Second, we count the number of different stocks that a household trades on a given day and take logarithms. This variable is denoted *log(#stocks*). Third, we measure the average trade size per household-stock trade, denoted *log($volume)*.

Our measures are intended to reflect different stages in investors' decision making process. log(#households) captures the decision whether or not to trade (extensive margin). Finding a distraction effect for this variable indicates that directing attention to the stock market and logging-into one's brokerage account, or calling up a broker requires a fixed amount of attention. log(#stocks) measures how much more attention is required for trading an additional stock, conditional on having traded at least once on that day. This variable primarily reflects investors' attention dedicated to *searching* for stocks to trade. Past research suggests that there might be a difference between buys and sells during this search phase simply because short-sale constraints make the choice set for sells much smaller than the one for buys (Barber and Odean, 2008). Finally, models of rational attention choice predict that investors trade less aggressively when they possess less precise information (Verrecchia (1982), He and Wang, 1995; Vives, 1995; Van Nieuwerburgh and Veldkamp, 2010) – such as when they are distracted. According to this line of work, we expect to see a reduction in log($volume), the average dollar amount that is placed, conditional on trading a certain stock on a given day.

[Insert Table 2 around here.]

Table 2 displays event study results for the 61 distraction events that fall into the sample period for the retail data. For log($volume), we find a marginally significant negative effect for buys, but no significance for sells and total trades (columns (1), (2) and (4)). Thus, there is only weak evidence in favor of the rational attention view that households curb back their trade sizes in response to a distracting event (which should lower their signal precisions). log(#stocks) shows a strong dichotomy between buys and sells: conditional on trading, households buy 1.2% (p-value < 0.01) fewer distinct stocks on a distraction day, whereas they do not sell fewer distinct stocks (the difference is significant as shown column (3)). Even though the economic magnitude is rather small, this asymmetry suggests that the selection of stocks to *buy* requires particular attention, and is thus susceptible to attention shocks. This finding is consistent with Barber and Odean (2008), who argue that retail investors face a substantially larger choice set when they decide which stocks to buy. In contrast, because of short-sale constraints, the choice set for sells is limited to the small number of stocks currently held. Finally, log[#households] displays a strong distraction effect, almost symmetric across buys and sells: on average, there are 6 to 7% fewer households trading on a distraction day compared to the average day in the estimation window. This effect is highly statistically significant.

To sum up, distraction has a strong effect on the extensive margin (i.e., whether to trade or not), and a somewhat weaker effect on the number of different stocks that are bought, but no effect on the intensive margin (i.e., trade sizes). These results suggest that retail investors require attention for choosing which stocks to buy and for deciding whether or not to trade at all.

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". In unreported analyses, we find no evidence for catching up in the 5 trading days after the distracting event. If anything, it seems that households continue to be distracted from trading in those days, although the economic magnitude of the distraction effect is substantially reduced. This finding is consistent with the pattern displayed in Figure 1 for the O.J. Simpson trial: the trading flow plummets, then quickly reverts to its daily average but does not make up for the lost trades (i.e., there is no overshooting). Thus, the trades that households forego on a distraction day are "superfluous", in that they are not deemed important enough to be taken up once distraction subsides.

Next, we examine whether the distraction effect is stronger for more overconfident or more biased investors – investors that we regard as the archetypical noise traders. A priori it is unclear 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. Table 3 shows the results for log(#households).

[Insert Table 3 around here.]

Our first overconfidence proxy is gender. Barber and Odean (2001) document that men trade more frequently than women. We define a dummy variable, "single-male", which equals one for a single-male investor, and zero for a single-female investor. Investors living as couples are excluded as it is not clear which gender disposition would dominate for that household (see Barber and Odean (2001)). Table 3, row (1) shows that single-male investors are strongly distracted, whereas single-female investors are not (the difference between single-male and single-female is close to being significant).

In row (2), we check whether distraction is stronger for more active traders. To measure their propensity to trade, we sort households according to their average portfolio turnover over the sample period. Again, we find evidence for a strong distraction effect for the most active traders, but not for the least active traders. In row (3), we analyze whether distraction is stronger for households with a high portfolio concentration (as measured by the average Herfindahl index over monthly portfolio holdings). A concentrated portfolio foregoes benefits to diversification and indicates that the household has strong and presumably erroneous beliefs about the few stocks it chooses. Consequently, we expect a stronger distraction effect for such investors. Indeed, this is what we find (the difference between the high- and the low-concentration tercile is marginally significant).

In row (4), we look at dollar losses of investors. The intuition is simply that more biased investors should perform worse. Again, we find evidence of a stronger distraction effect for "more biased" investors: the difference between the high-losses and the low-losses terciles is negative significant. Finally, in row (5), we combine the measures of portfolio turnover and performance in order 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 who trade actively but perform poorly – are significantly distracted, whereas households that are less active and/or more successful are not distracted.

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 (Barber and Odean (2001)), these investors actually benefit from being distracted.

B. TAQ analysis

Because the retail data only captures a fraction of the retail investor population and covers a relatively short sample period, we conduct an event study for TAQ data covering the transactions in all stocks listed on NYSE/AMEX/Nasdaq from 1991 to 2001. Research has found that, until the decimalization in 2001, small trades are likely to stem from retail investors, whereas large trades come from institutions. Hence, we investigate here whether the distraction effect is stronger for small or large trades.

Table 4 shows the event study for the 100 distraction events that fall into this extended time period. Our measure of trading intensity is log($volume) aggregated over small and large trades, respectively. The table reveals that, on the day of a distracting event, trading volume stemming from small trades drops by 3.2% (p-value<0.05), whereas the reduction for large trades is less than 1% and not significant. Column (3) shows that the difference between the distraction effect for small and large trades is significant.

[Insert Table 4 around here.]

To sum up, results in this section confirm that retail investors, in particular the more active and overconfident ones, are strongly distracted on days with high news pressure. In contrast, large institutional trades are not affected. These findings lead us to view our distracting events as shocks to noise trades. In the next section, we study the impact of these shocks on the market, with a particular emphasis on liquidity.

III. Distraction and the Market

A. Hypotheses

Having identified shocks to noise trades, we begin by fleshing out the predictions drawn from two pivotal models of price impact. On one hand, adverse selection models à la Kyle (1985) and Glosten and Milgrom (1985) predict that price impact (e.g., Kyle's λ or bid-ask spreads) goes up when there is less noise trading. This occurs because on days with less noise trading, market makers face a more informative order flow and thus adjust prices more strongly in response to a trade of a given size. On the other hand, noise trader risk models à la DeLong et al. (1990, henceforth DSSW) – or, more generally, models in which risk-averse liquidity providers need to absorb demand shocks from noise traders (e.g., Campbell and Kyle (1993) and Campbell et al. (1993)) – predict that price impact is decreasing in the intensity of noise trading.[5] In these models, price impact compensates market makers for taking on *risky* inventory. Less noise trading implies lower inventory risk, leading market makers to require less compensation. Our setting provides the ideal testing ground to study which of the two

[5] In these models, noisy asset supply can be interpreted as either noise or liquidity trades – what matters is that both create inventory risk for market makers. We note, however, that the concentration of our results among "biased" retail traders (see section III) points more toward a noise trader interpretation. In what follows, we thus use the terms "noise trader risk" and "inventory risk" interchangeably.

channels – the *adverse selection channel* or the *noise trader risk channel* – dominates in response to shocks to noise trading triggered by distracting events.

While our focus is on liquidity and price impact (where the two channels yield opposing predictions), we also investigate how return volatility and autocorrelation react to a reduction in noise trading risk. Here, adverse selection and inventory risk are not necessarily in conflict. When demand shocks trigger price impact, as with the noise trader risk channel, such price impact will be transitory, hence resulting in *excess* volatility and negative return autocorrelation (for example, a positive demand shock from noise traders leads to a price increase which subsequently reverses, i.e. to a positive return followed by a negative return). To the extent that noise trader risk is reduced on distraction days, the inventory risk channel thus predicts lower volatility and less negative autocorrelation on such days. By contrast, in Kyle (1985)'s adverse selection model return volatility is independent of the standard deviation of noise trades. This feature, however, hinges on two critical assumptions, namely that the information structure is exogenous and that market makers are risk-neutral. Relaxing either assumption turns volatility into an increasing function of noise trader risk (at least over the short-term).[6] In particular, Appendix A outlines a Kyle-type model with a risk-averse market maker and shows how it leads to the following predictions: price impact (λ) increases, return volatility decreases and prices become more efficient (i.e., returns are less negatively autocorrelated) as the standard deviation of noise trades declines.

Finally, both the adverse selection and the noise trader risk channel predict a reduction in trading volume when there is less noise trading. Indeed, it is this reduction in noise trader

[6] See, among others, Subrahmanyam (1991) for an extension of Kyle (1985) to risk-averse market-makers, and Admati and Pfleiderer (1988) for an extension with endogenous entry of informed traders.

volume which *causes* market liquidity to change. Hence, one important aspect of our empirical analysis is to examine whether liquidity and volatility changes are larger for groups of stocks for which we find a larger distraction effect; i.e., for stocks predominantly held by retail investors.

B. Market-wide analysis

We start with a description of the variables used in this section. We winsorize the data at the 0.5% level on both tails and purge them from seasonal patterns as described above. Throughout our analysis, we focus on equally weighted averages across stocks of these data. Value-weighted averages yield weaker results, suggesting that our results are concentrated among smaller stocks–a point which we verify below. To assess the impact of our distraction events on stock market performance, we examine the (equally weighted) average market return on all stocks in CRSP (labeled *mkt return*) and its absolute value (labeled *abs mkt return*). For trading activity, we look at both the average of the logarithm of daily turnover (labeled *log(turnover)*), defined as the number of shares traded in a stock on a given day divided by the number of shares outstanding, and the logarithm of aggregate dollar volume (labeled *log($volume)*). As turnover can equal zero, we follow Llorente et al. (2002) and add a small constant, 0.0000025, to turnover before taking logs. Because turnover is scaled by a stock's market capitalization, it gives a larger weight to smaller stocks and we thus expect stronger effects for this measure.

Our two measures of price impact are the Amihud (2002) illiquidity ratio and the relative closing bid-ask spreads as reported in CRSP. Specifically, for each stock-day observation, the Amihud ratio equals the stock's absolute return divided by its dollar volume. Since this ratio is heavily skewed, we take its natural logarithm before averaging across stocks. Again, we add a small constant to the ratio, 0.00000001, before taking logs because it can equal zero.[7] The resulting measure is labeled *log(amihud)*. The spread measure is defined as the average of the closing bid minus ask divided by the midquote and labeled *bid-ask spread*.

Our volatility measures comprise the average stock-level absolute return (labeled *abs return*), the logarithm of the cross-sectional standard deviation of daily returns (labeled *return dispersion*) and the average of the logarithm of the ratio of the (stock-level) daily high to low prices (labeled *price range*). Finally, as a proxy for return autocorrelation, we use the sign of the product of a stock's returns on dates t and t+1, which we then average across stocks (labeled *autocorrelation*). This measure is positive (negative) when stock prices move in the same (opposite) directions on consecutive days.

[Insert Table 5 around here.]

Table 5 reports summary statistics for these measures. The first block shows the raw data before the seasonality-adjustment. For instance, we see that the average daily share turnover is 0.4%, implying that a firm changes hand entirely every year. This block also reveals that the raw Amihud measure is relatively skewed, with the 99th percentile being more than four standard deviations away from the mean, justifying our use of the logarithm. The second block shows the data after taking logs and the seasonality-adjustment-i.e., as they are used in our event study. Our measures appear well behaved: means (which are all zero after the seasonality-adjustment) and medians are well aligned and the 1st and 99th percentile are not off the chart. Inference based on the parametric Patell test thus appears suitable.

[7] The constant is chosen to make the distribution of the Amihud ratio closer to a normal. Our results are robust to alternative choices for this constant, including dropping it altogether.

[Insert Table 6 around here.]

Table 6 shows results for the market-wide event study. We first note the absence of any discernable effects on market index returns on distraction days. Indeed, any significant result here would call the non-economic nature of these events into question. Unfortunately, other results appear relatively weak. For example, abnormal average turnover is a negative 0.8% with a Patell statistic of -1.5. We do find some significant increases for Amihud, bid-ask spreads and return autocorrelation. These results are in line with the predictions from the adverse selection theory discussed earlier. Nonetheless, it appears that our distraction events are not impactful enough to show up for the average stock in the market. Therefore, we turn our attention to subgroups of stocks for which we expect stronger distraction effects–namely, stocks predominantly held by retail investors.

C. Sample splits

We begin by grouping stocks into terciles based on firm size (i.e., market capitalization). It is well documented that small stocks are held proportionately more by retail investors (e.g., Lee, Shleifer, and Thaler (1991)), so we expect results to be strongest for the bottom tercile of firms. As Table 7 reports, this is indeed what we find: average turnover in the bottom tercile is significantly reduced by approximately 2.1% on distraction days. The effect dissipates monotonically for the other terciles and the difference between the largest and smallest tercile is strongly significant. A similar pattern emerges for log($volume). The increase in the Amihud ratio is concentrated in the bottom tercile as well, where it equals 1.5% (with a p-value of 0.05 or lower). While results for spreads are not significant, the coefficients decline monotonically as with the Amihud ratio. Finally, return dispersion and price range also reveal a reduction in volatility among small stocks. In sum, though not significant for all measures, the results fit nicely with the predictions from an adverse selection model of price impact (as outlined in Appendix A). Importantly, the significant increase in the Amihud ratio implies that market makers for small stocks, which see the largest drop in noise trading, are more concerned about increased adverse selection than they are consoled with decreased inventory risk.

[Insert Table 7 around here.]

Next, we sort stocks on their price. Brandt et al (2010), among others, document that low-priced stocks are the natural habitat for retail investors, so we expect stronger results for stocks in this group. Table 8 confirms these expectations. In the low-price group, we again find a strongly significant reduction in turnover which goes hand in hand with a significant increase in the Amihud ratio. Spreads are also up, but not significantly so (though they are for the middle tercile). Results for return dispersion and price range indicate a reduction in volatility, while the results for autocorrelation are inconclusive. Taken together, our findings again favor the adverse selection channel over the inventory risk channel.

[Insert Table 8 around here.]

Having so far relied on indirect proxies for retail ownership, we exploit now institutional ownership data from 13(f) filings as a more direct measure. Section 13(f) of the Securities Exchange Act in 1975 requires institutional investment managers with more than $100 million of assets under management to disclose their holdings exceeding 10,000 shares or $-value 200,000. Thus, the fraction of shares not held by these institutions must either be held by smaller institutions or retail investors. Consequently, we expect stronger results for stocks in the low institutional ownership tercile. Since this data is only available from the early

1980's, our sample size is reduced to 324 events. Table 9 shows results consistent with our expectations: the bottom institutional ownership tercile sees a 2.4% reduction in turnover, a 7.7 basis points reduction in the price range (=2% with respect to the unconditional mean), an 1,5% increase in the Amihud ratio and a 3.3 basis points increase in bid-ask spreads (=1% with respect to the unconditional mean). All these effects are significant with a p-value of 0.05 or lower and thus support the predictions from an adverse selection model. We also find somewhat puzzling evidence of an increase in volatility (for absolute returns and, marginally, for price range) in the group of stocks with the highest institutional ownership. Such an effect is inconsistent with either theory.

[Insert Table 9 around here.]

In our last grouping exercise, we sort stocks directly on adverse selection. Specifically, we rely on a measure developed by Duarte and Young (2009), called AdjPIN, which we download from Duarte's website.[8] This measure, a refinement of the PIN measure developed by Easley et al. (2002), captures a stock's adverse selection risk. The data is available from 1983 to 2004, limiting our sample to 241 distraction events. The results, shown in Table 10, are again consistent with an adverse selection interpretation: while the drop in trading volume in the top AdjPIN group just falls short of being significant,[9] the effects on the Amihud ratio and bid-ask spreads are highly significant in that group: they are increased by 1.4% and 5% (= 16bp (Table 10)/335bp (Table 5)), respectively. In contrast, the bottom AdjPIN tercile shows no effect on liquidity whatsoever. These results lead us to conclude that market makers' adverse

[8] Available at: http://www.owlnet.rice.edu/~jd10/publications.htm.

[9] The fact that results for trading activity are weaker compared to before is perhaps not surprising. After all, we have now sorted stocks based on an adverse selection proxy, which need not be related to retail ownership.

selection concerns are driving our results. We also note that, for the middle tercile, there is again evidence of an increase in volatility, for which we have no explanation.

[Insert Table 10 around here.]

IV. Robustness

In this section, we check the robustness of our results and address endogeneity concerns.

A. Robustness of Event List

As described in Section I, we selected 510 non-economic events from 1,084 high-news pressure days based on arguably subjective filters. In unreported analyses, we experimented with these filters and found our results to be robust. Specifically, we formed two alternative event lists, one which does not use any manual filter but imposes automatic keyword filters (resulting in 535 events), and another which imposes a very conservative manual filter (resulting in 354 events). Both event lists yield a significant decrease in turnover and range and a significant increase in the Amihud ratio for stocks in the bottom terciles by firm size, stock price and institutional ownership.[10] When we sort stocks by AdjPIN, we also find a significant increase in bid-ask spreads with both lists.

Another concern is event clustering: occasionally, two distraction events are only a few days apart. For example, the two most newsworthy events in 1986 occurred on January 28 and 29 and dealt with the Challenger space shuttle explosion (Table 1). So far, we have treated such events as independent. In Table 11, we repeat our main analyses while restricting the sample to *distinct* distraction events that are at least 5 business days apart (i.e., at least one full

[10] With the smaller event list, the drop in turnover in the bottom size tercile is only marginally significant.

calendar week elapses between any two events). Note that this is a conservative approach that throws away all the information contained in an event close to another even if their correlation is low. Though this procedure leaves us with only 361 events, our main results continue to hold: for the subgroup of stocks with high retail ownership (as proxied by firm size, stock price or institutional ownership), we find a significant decrease in turnover and price range and a significant increase in Amihud. Stocks with high adverse selection risk (as proxied by AdjPIN) experience a significant increase in bid-ask spreads (with the increase in Amihud being borderline significant). We conclude that our findings survive this conservative approach of dealing with event clustering.

[Insert Table 11 around here.]

B. Endogeneity

We admit that news pressure, our selection criterion for candidate distraction events, is potentially endogenous to the stock market. There are two facets to this endogeneity and we argue that only one of them can be consistent with our results.

First, news pressure may be particularly high on days with important economic news, to the extent that TV news broadcasts devote considerable time to this news. In that case, the patterns we document for the market are not caused by investors' distraction as we claim but are a direct consequence of economic events. The economic filters we impose are an attempt to mitigate this concern. According to these filters, roughly half of high-news pressure days are classified as non-economic (this fraction is similar to the fraction of economic-news days measured over the whole sample period, i.e., regardless of whether or not news pressure is high). Hence, many events received extensive media coverage while having, as we believe, a negligible impact on the economy. The O.J. Simpson verdict on October 3, 1995, is exemplary in that respect. We acknowledge, however, that it is impossible to guarantee that none of our events had an impact on the U.S. economy. But such occurrences should only bias the results *against* finding any distraction effect, because economic news typically trigger *more rather than less* turnover and volatility. Indeed, when we run an event study on the set of high-news pressure days which we classified as economic, we find a significant increase in both trading volume and return volatility on those days. In a similar vein, it should not be surprising that we find somewhat confounded results when we conduct an event study for all 1,084 high-news pressure events (regardless of whether they are economic or not).[11] Put differently, many of the events in our list have both a distracting and an attention-attracting component to them. For example, when U.S. troops invaded Grenada in 1983, investors might have been led to reflect on the economic impact of this intervention. At the same time, sensational news coverage of military skirmishes might have drawn their minds away from the stock market. Our identification strategy essentially draws on the discrepancy between exuberant news coverage and fundamental newsworthiness. Distraction effects, such as documented here, prevail when the former outweighs the latter.

Second, news pressure may be endogeneous to the stock market, not because it is particularly high on days with important economic news, but quite the contrary, because it is particularly high on days with *little* economic news. Indeed, TV news broadcasts may devote considerable time to economically irrelevant stories precisely because they have nothing newsworthy to report about the economy. Here, the concern is reverse causality: a quiet stock market generates high news pressure (rather than high news pressure affecting the market). This alternative explanation is consistent

[11] These results are contained in Appendix B. They show that our main results continue to hold for this broad event list. However, we also find evidence of an increase in the volatility of the market return (we also find increases in volatility for other measures when we look at the middle and top terciles of stocks by firm size, stock price and institutional ownership), which is likely due to confounding economic news. Since it is therefore less clear whether the increases in price impact and spread for these events come from distraction, we prefer to focus on the events filtered for non-economic news.

with our finding that trading activity and volatility are reduced when news pressure is high. We make two counterarguments. First, by excluding economic-news days from the estimation window, our event study approach ensures that we *compare high-news pressure days without economic news to other days without economic news*. Hence, our results are not driven by an implicit sorting on the absence of economic news. Second, we conduct a placebo analysis on days that have no economic news (as in the main analysis) and on which news pressure is in the *bottom* decile for the respective year (rather than in the top decile as in the main analysis). If the reverse causality argument were correct, days with low news pressure should feature lots of economic news. We would then expect these days to display heightened trading activity and volatility. The results of this placebo exercise, shown in Table 12, indicate no such effect. To sum up, our results are driven by positive spikes in news pressure unrelated to the economy. In other words, they are driven by distracting events.

[Insert Table 12 around here.]

V. Conclusion

We exploit episodes of sensational news, which, we argue, are largely exogenous to the economy to study how retail investors, and in turn the stock market, are affected. We find that distracted retail investors 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 further show that the effect of distraction is more pronounced for overconfident–i.e., single-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 findings suggest that the sensational news events we identify generate shocks to retail (noise) trading. This allows us to shed light on the impact of noise trading in financial markets, and in particular on market liquidity. This question is of interest because the literature ascribes two opposing roles to noise trading: On the one hand, noise trades allow informed investors to conceal their trades. Under this adverse selection view, less noise leads to an increase in price impact and bid-ask spreads. On the other hand, when market makers are risk-averse and arbitrage is limited, noise trades create risk to their inventory. Under this inventory risk channel, less noise implies less risk and thus predicts a reduction in price impact and spreads. Our empirical setting offers a unique way of teasing out which one of the two channels dominates in the U.S. stock market. All in all, our results favor the adverse selection channel and thus suggest that market makers are more concerned with trading against insiders than they are with trading against noise traders.

Our research is only a first attempt to dissect the role of attention for investors' trading behavior and, in turn, stock market outcomes. 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 sorted into five size groups. Small (large) trades are those in the bottom (top) quintile. The horizontal axis labels 5-minute intervals starting from 9:30 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.

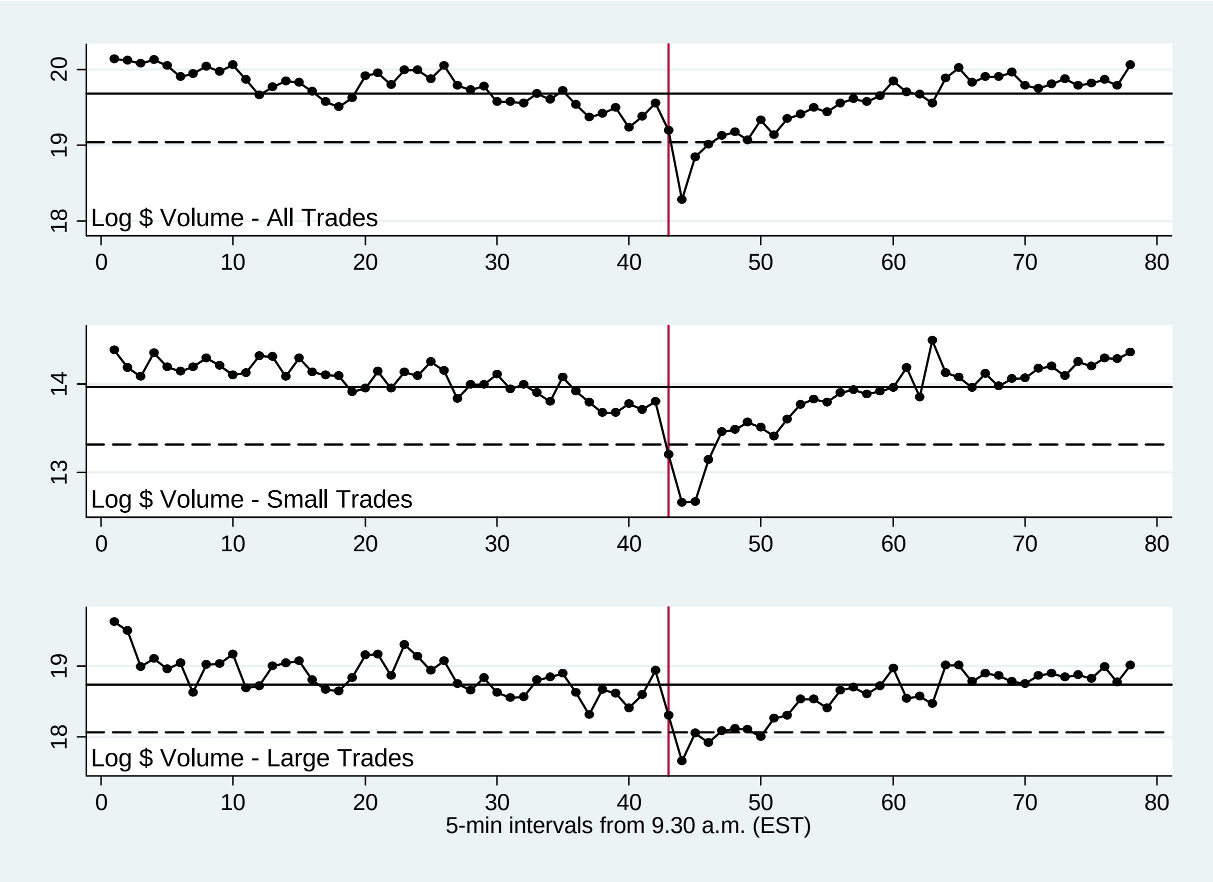

Figure 2: Daily news pressure and distraction events

The blue line in this figure shows daily news pressure over the period 1968 to 2013. The red dots mark a subset of the distraction events that we use in this paper. Specifically, they consist of days on which news pressure is the highest in a given year and which have survived our two-step filter process for excluding potential economic news (see data section).

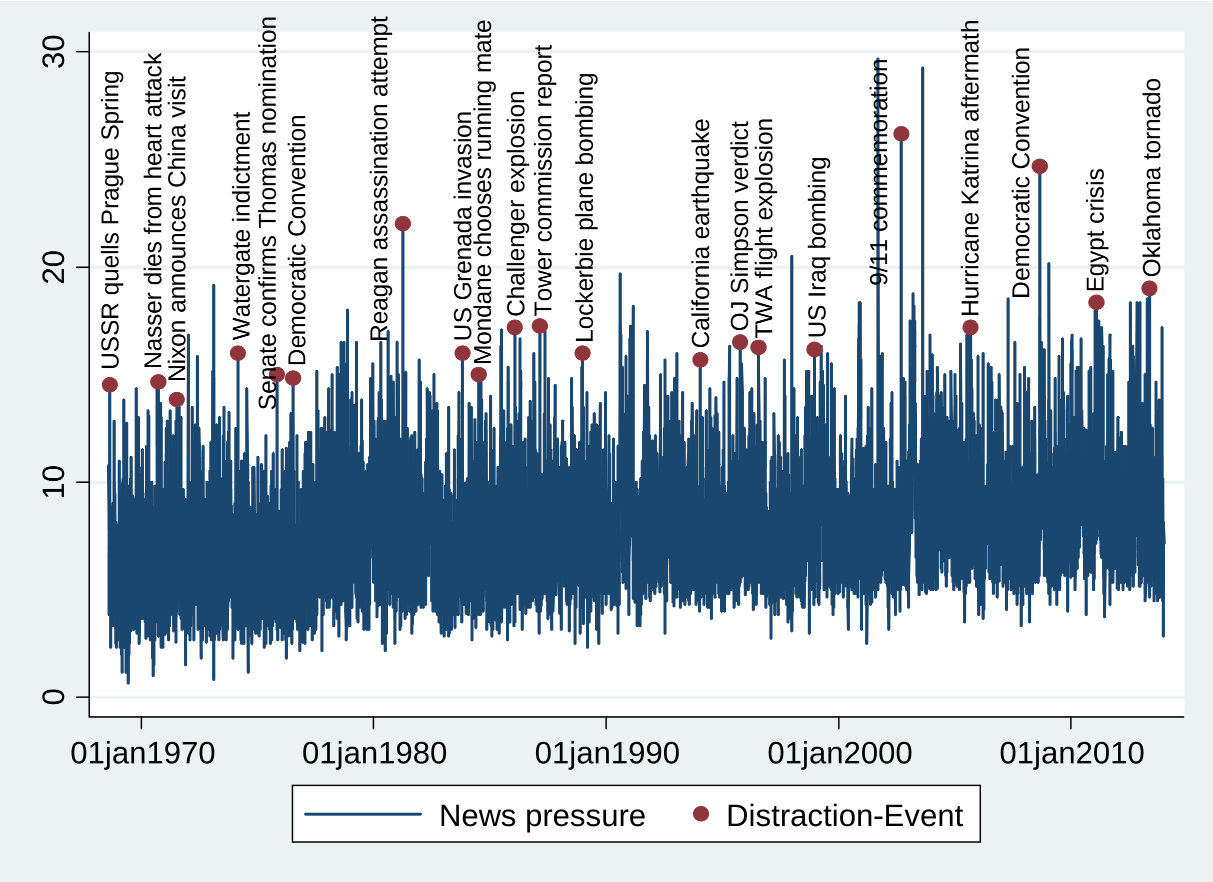

Table 1: Distraction events and household sample

This table provides a partial list of the distraction events used in this paper. For each year, we show the dates of the two distraction events with the highest news pressure (that have passed our economic filters) together with a short description of the accompanying news story.

Year	Date	Description	Date	Description
1968	Aug 22	USSR invasion of Czechoslovakia	Nov 1	Vietnam bombing halt
1969	Mar 28	Eisenhower death	Nov 20	Apollo 12 color film from moon
1970	Sep 28	Gamal Abdel Nasser death	Sep 9	Dawson's Field hijackings
1971	Jul 16	Nixon announces China visit	Apr 1	William Calley verdict
1972	Mar 6	Senate questions ITT settlement	May 2	Hoover death
1973	Jan 24	Vietnam ceasefire aftermath	Jul 26	Watergate hearings
1974	Mar 1	Watergate indictments	Feb 13	Solzhenitsyn deportation
1975	Nov 3	Rockefeller decides not to run for VP	May 14	South Vietnam evacuation plans
1976	Jul 13	Democratic Convention	Jun 9	Democratic presidential primaries
1977	Oct 18	West German plane hijacking	Mar 11	Hanafi Siege in Washington, DC
1978	Sep 19	Camp David Accords aftermath	Apr 18	Senate passes Panama Canal treaty
1979	Feb 14	U.S. embassy incident in Tehran	Jan 16	Iranian revolution, Shah flees
1980	Dec 26	Iran hostage crisis	Aug 11	Democratic Convention
1981	Mar 30	Reagan assassination attempt	May 13	Pope assassination attempt
1982	Sep 20	Lebanon massacre	Jun 8	Israel Lebanon invasion
1983	Oct 25	Grenada invasion aftermath	Oct 26	Grenada invasion aftermath
1984	Jul 12	Mondale chooses running mate	Aug 16	John DeLorean verdict
1985	Oct 8	Achille Lauro hijacking	Oct 11	Achille Lauro hijacking aftermath
1986	Jan 28	Challenger explosion	Jan 29	Challenger explosion aftermath
1987	Feb 26	Tower commission report	May 18	USS Stark incident in Persian Gulf
1988	Dec 22	Lockerbie plane bombing	Jul 5	Attorney General Meese resigns
1989	Jan 4	Libyan planes downed	Jul 3	Supreme Court abortion ruling
1990	Aug 8	Address on Iraq’s invasion of Kuwait	Aug 16	Persian Gulf crisis talks
1991	Oct 15	Senate confirms Thomas nomination	Jan 10	Preparations for Iraq invasion
1992	May 1	Los Angeles riots	Dec 8	US special forces enter Somalia
1993	Apr 20	Waco sect compound fire	Sep 13	Oslo Accords officially signed
1994	Jan 17	Northridge earthquake	Jan 18	Northridge earthquake aftermath
1995	Oct 3	O. J. Simpson verdict	Apr 20	Oklahoma City bombing
1996	Jul 18	TWA flight explosion	Nov 5	Presidential election aftermath
1997	Sep 5	Princess Diana’s funeral	Mar 27	Heaven’s Gate sect mass suicide
1998	Dec 16	Iraq missile attack	Dec 18	Clinton impeachment house debate
1999	Mar 25	NATO bombing of Yugoslavia	Apr 23	Littleton school shooting
2000	Nov 22	Presidential election aftermath	Dec 11	Florida recount, legal battles
2001	Oct 12	Anthrax letter attacks	Jun 11	Timothy McVeigh execution
2002	Sep 11	9/11 commemoration	Oct 24	Hurricane Lili
2003	Oct 27	California wildfires	--	n/a
2004	Apr 7	Iraq Fallujah uprising	Apr 8	9/11 commission hearing
2005	Sep 1	Hurricane Katrina aftermath	Jul 7	London bombing
2006	Jan 4	Sago coal mine explosion	Jul 13	Israel Lebanon conflict
2007	Apr 17	Virginia Tech massacre	Aug 2	Minneapolis bridge collapse
2008	Aug 27	Democratic Convention	Nov 3	Presidential election one day before
2009	Dec 28	Northwest Airlines bombing attempt	Jul 7	Michael Jackson memorial service
2010	Jan 15	Haiti earthquake	Mar 22	Health Care reform passed
2011	Jan 31	Egypt crisis	Jan 10	Tucson Arizona shooting
2012	Dec 14	Connecticut school shooting	Jul 20	Aurora movie theatre massacre
2013	May 20	Oklahoma tornado	May 21	Oklahoma tornado aftermath

Table 2: Distracting events and retail trading – retail traders' analysis

This table reports event-study results for different measures of retail trading activity on the 61 distraction event-days that fall into the sample period of the retail brokerage data (1991 to 1996). Log($volume) is the average across stocks and then across investors of the logarithm of dollar volume. Log(#stocks) is the average across investors of the logarithm of the number of different stocks traded. Log(#households) is the logarithm of the number of households trading. The estimation period includes all trading days without economic news within a 100-day window around the event-date. Columns (1) and (2) focus on buys and sells, respectively. Column (3) tests for the difference between buys and sells. Column (4) examines total trades (the sum of buys and sells). Below each average, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Buys	(2) Sells	(3) Difference	(4) Total trades
Log($volume)	-0.0231*	-0.0146	-0.0085	-0.0184
	(-1.69)	(-1.05)	(-0.20)	(-1.43)
Log(#stocks)	-0.0121***	0.0002	-0.0123*	-0.0095**
	(-2.81)	(0.27)	(-2.01)	(-2.37)
Log(#households)	-0.0613***	-0.0695**	0.0082	-0.0601***
	(-3.19)	(-2.56)	(0.26)	(-3.26)
N	61	61	61	61

Table 3: Distracting events and retail trading – sample splits by household characteristics

This table reports event-study results for retail trading activity of different groups of investors on the 61 distraction event-days that fall into the Odean sample period. Log(#households) is the logarithm of the number of households trading. The estimation period includes all trading days without economic news within a 100-day window around the event-date. In row (1), investors are split into single-female (column (1)) and single-male (column (2)), respectively. For the other rows, investors are split into terciles based on the variable indicated in the row caption. Column (4) tests for the difference between tercile 3 and tercile 1 (or single-males and single-females for row 1). PF turnover is the household's average portfolio turnover. PF concentration is the household's average portfolio concentration (measured by the Herfindahl index). PF losses are the household's total dollar losses. GK-proxy is the overconfidence proxy proposed by Goetzmann and Kumar (2008) based on the interaction of portfolio turnover and inverse profits. Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Total trades	(2) Total trades	(3) Total trades	(4) Difference
1) Single-male	Dummy=0	Dummy=1		
Log(#households)	0.0235	-0.1054***		-0.1205
	(0.12)	(-3.73)		(-1.48)
2) PF turnover	Tercile 1	Tercile 2	Tercile 3	
Log(#households)	-0.0193	-0.0551**	-0.0645***	-0.0453
	(-0.65)	(-2.23)	(-3.46)	(-0.70)
3) PF concentration	Tercile 1	Tercile 2	Tercile 3	
Log(#households)	-0.0447**	-0.0680***	-0.0863***	-0.0416*
	(-2.25)	(-3.06)	(-3.64)	(-1.94)
4) PF losses	Tercile 1	Tercile 2	Tercile 3	
Log(#households)	-0.0570***	-0.0277	-0.1049***	-0.0479***
	(-2.90)	(-1.43)	(-4.42)	(-2.90)
5) GK-proxy	Tercile 1	Tercile 2	Tercile 3	
Log(#households)	0.0454	-0.0675**	-0.0764***	-0.1072
	(0.60)	(-2.08)	(-3.54)	(-1.51)
N	61	61	61	61

Table 4: Distracting events and retail trading – TAQ analysis

This table reports event-study results for transactions data from the TAQ database for the period 1991 to 2001 (when decimalization rendered trade size ineffective as a proxy for retail trades). Trades are classified into small trades and large trades based on a procedure described in Hvidkjaer (2006) (see Section I). Log($volume) is the logarithm of the dollar volume aggregated over small trades (column (1)) and large trades (column (2)), respectively. The estimation period includes all trading days without economic news within a 100-day window around the event-date. Column (3) tests for the difference between small and large trades. Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Small trades	(2) Large trades	(3) Difference
Log($volume)	-3.153**	-0.990	-2.163**
	(-2.40)	(-0.99)	(-2.10)
N	100	100	100

Table 5: Descriptive Statistics for Market Variables

This table reports descriptive statistics for our stock market data. Mkt return is the equal-weighted average market return (in bp) and abs mkt return is its absolute value (in bp). Turnover is the equal-weighted average of share turnover (i.e., the ratio of dollar volume to market capitalization; in bp). Log(turnover) is the equal-weighted average of the logarithm of share turnover (in %). $volume is the aggregate daily dollar volume (in $mn). Log($volume) is the logarithm of dollar volume (in %). Amihud is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume; multiplied by 1,000,000 for visibility). Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (in %). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close (in bp). Abs return is the equal-weighted average of the absolute raw return (in bp). Return dispersion is the logarithm of the cross-sectional standard deviation of returns (in bp). Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices (in %). Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day (in %). The first block shows statistics for the raw measures (after winsorizing; and before taking logs for turnover, dollar volume and Amihud). The second block shows statistics after the data has been seasonality-adjusted by regressing the raw variables on a set of dummy variables for each month/year and day-of-week/year pair (see Section I).

	mean	median	sd	p1	p25	p75	p99
1) Raw Variables							
Mkt return	3.756	8.899	96.43	-273.755	-37.968	50.803	260.553
Abs mkt return	65.62	45.649	70.756	0.786	20.814	85.467	342.591
Turnover	41.379	34.765	26.422	6.919	18.226	60.78	107.191
$Volume	38,701	8,595	50,494	284	1,098	71,261	175,987
Amihud	3.014	2.058	2.966	0.281	1.031	4.074	15.221
Bid-ask spread	335.342	334.286	222.801	55.3	106.789	500.419	903.835
Return dispersion	-327.303	-334.062	32.821	-379.806	-354.771	-299.942	-248.901
Abs return	232.073	211.215	77.562	140.784	174.203	273.232	500.044
Price range	3.668	3.355	1.417	1.857	2.66	4.32	8.769
Auto-correlation	-4.308	-5.411	13.729	-39.29	-12.193	2.179	38.728
2) Seasonality-adjusted Variables							
Mkt return	0	2.14	90.557	-252.198	-41.488	41.58	253.633
Abs mkt return	0	-7.802	57.204	-120.92	-30.975	23.142	190.352
Log(turnover)	0	-0.542	14.91	-39.028	-7.547	7.275	42.469
Log($volume)	0	0.082	14.805	-43.855	-7.274	7.901	37.051
Log(amihud)	0	-0.022	1.812	-5.035	-0.83	0.81	5.057
Bid-ask spread	0	-0.432	14.405	-35.228	-4.62	4.068	35.044
Return dispersion	0	-1.041	10.781	-21.772	-6.347	4.773	36.31
Abs return	0	-3.289	35.22	-76.544	-14.106	8.497	130.005
Price range	0	-0.029	0.467	-1.133	-0.179	0.133	1.524
Auto-correlation	0	-0.489	12.353	-35.985	-5.67	5.055	38.966

Table 6: Market-wide Event Study

This table reports event-study results for the 510 distraction events that fall into the period 1968 to 2013. The estimation period includes all trading days without economic news within a 100-day window around the event-date. Mkt return is the equal-weighted average market return and abs mkt return is its absolute value. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

(1) Mkt return	(2) Abs mkt return
-2.054	-0.784
(-0.82)	(0.44)
510	510

(3) Log(turnover)	(4) Log($volume)	(5) Log(amihud)	(6) Bid-ask spread
-0.835	-0.361	0.063*	1.219**
(-1.47)	(-0.56)	(1.72)	(2.23)
510	510	510	323

(7) Abs return	(8) Return dispersion	(9) Price range	(10) Auto-correlation
1.643	-0.800*	-0.022	0.934*
(1.10)	(-1.70)	(-0.41)	(1.78)
510	510	510	509

Table 7: Sample Split by Firm Size

This table reports event-study results for the 510 distraction events that fall into the period 1968 to 2013. The estimation period includes all trading days without economic news within a 100-day window around the event-date. Stocks are sorted into three terciles based on their market capitalization at the end of the last trading day prior to the event. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Column (1)-(3) show results for terciles 1-3, respectively. Column (4) tests for the difference between tercile 1 and tercile 3. Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Tercile 1	(2) Tercile 2	(3) Tercile 3	(4) Difference
Log(turnover)	-2.134***	-1.110	0.690	-2.800***
	(-3.27)	(-1.46)	(0.96)	(-3.49)
Log($volume)	-2.216**	-0.846	0.836	-3.052***
	(-2.16)	(-1.21)	(1.07)	(-2.76)
Log(amihud)	1.452**	1.010***	-0.854	2.306**
	(2.37)	(2.97)	(-1.05)	(2.39)
Bid-ask spread	3.267	1.250*	-2.143	5.152
	(1.39)	(1.72)	(-0.94)	(1.35)
Abs return	-1.806	-0.522	0.108	-1.914**
	(-1.18)	(1.17)	(1.33)	(-1.99)
Return dispersion	-1.245*	-0.552	-0.230	-1.014
	(-1.83)	(-0.90)	(-0.16)	(-1.01)
Price range	-0.064***	-0.010	0.009*	-0.073***
	(-3.03)	(0.38)	(1.91)	(-4.17)
Auto-correlation	0.593	1.108*	1.078	-0.485
	(1.44)	(1.73)	(1.20)	(-0.22)

Table 8: Sample Split by Stock Price

This table reports event-study results for the 510 distraction events that fall into the period 1968 to 2013. The estimation period includes all trading days without economic news within a 100-day window around the event-date. Stocks are sorted into three terciles based on their closing price on the last trading day prior to the event. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Column (1)-(3) show results for terciles 1-3, respectively. Column (4) tests for the difference between tercile 1 and tercile 3. Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Tercile 1	(2) Tercile 2	(3) Tercile 3	(4) Difference
Log(turnover)	-2.392***	-0.886	0.779	-3.171***
	(-3.47)	(-1.27)	(1.13)	(-3.90)
Log($volume)	-1.558*	-1.017	0.495	-2.054**
	(-1.79)	(-1.16)	(0.75)	(-2.00)
Log(amihud)	1.771***	0.604*	-0.908	2.678***
	(3.04)	(1.79)	(-1.00)	(3.12)
Bid-ask spread	1.049	2.762**	-1.153	2.353
	(0.95)	(2.03)	(-0.44)	(1.01)
Abs return	-1.328	-0.783	-0.169	-1.159
	(-0.51)	(0.80)	(1.22)	(-1.37)
Return dispersion	-1.153*	-0.679	-0.188	-1.014
	(-1.79)	(-0.84)	(-0.09)	(-0.93)
Price range	-0.052**	-0.015	0.004*	-0.056***
	(-2.37)	(0.24)	(1.75)	(-3.33)
Auto-correlation	0.636	1.057**	1.115	-0.480
	(1.15)	(2.13)	(1.35)	(-0.57)

Table 9: Sample Split by Institutional Holdings

This table reports event-study results for the 324 distraction events that fall into the period 1981 to 2013, for which we have institutional holdings data from 13(f). The estimation period includes all trading days without economic news within a 100-day window around the event-date. Stocks are sorted into three terciles based on the fraction of institutional ownership at the end of the quarter prior to the event. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Column (1)-(3) show results for terciles 1-3, respectively. Column (4) tests for the difference between tercile 1 and tercile 3. Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Tercile 1	(2) Tercile 2	(3) Tercile 3	(4) Difference
Log(turnover)	-2.435***	-1.323*	0.235	-2.650***
	(-3.41)	(-1.69)	(0.34)	(-3.30)
Log($volume)	-1.747*	-0.499	0.257	-2.015**
	(-1.73)	(-0.63)	(0.34)	(-2.45)
Log(amihud)	1.492***	1.303***	0.105	1.358
	(2.83)	(3.41)	(-1.04)	(1.45)
Bid-ask spread	3.323**	1.126	-1.281	4.406
	(2.16)	(1.58)	(-0.05)	(1.53)
Abs return	-2.047	0.187*	1.308**	-3.442***
	(-0.85)	(1.89)	(2.44)	(-2.93)
Return dispersion	-0.329	-0.928	0.091	-0.445
	(-0.12)	(-1.30)	(-0.41)	(-0.11)
Price range	-0.077***	-0.023	0.004*	-0.082***
	(-3.34)	(-0.19)	(1.78)	(-4.92)
Auto-correlation	0.408	1.454**	1.561	-1.163
	(0.87)	(2.16)	(1.45)	(-1.40)

Table 10: Sample Split by AdjPIN

This table reports event-study results for the 241 distraction events that fall into the period 1984 to 2005, for which we have AdjPIN data (downloaded from http://www.owlnet.rice.edu/~jd10/publications.htm). The estimation period includes all trading days without economic news within a 100-day window around the event-date. Stocks are sorted into three terciles based on AdjPIN at the end of the year prior to the event. AdjPIN, developed by Duarte and Young (2009), measures a stock's adverse selection risk. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Column (1)-(3) show results for terciles 3-1, respectively (note the reversed order for ease of comparison to the other tables). Column (4) tests for the difference between tercile 3 and tercile 1. Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Tercile 3	(2) Tercile 2	(3) Tercile 1	(4) Difference
Log(turnover)	-1.364	-0.487	-0.384	0.981
	(-1.26)	(-0.53)	(-0.38)	(1.08)
Log($volume)	-2.407	-0.064	0.538	2.945**
	(-1.51)	(-0.11)	(0.67)	(-2.01)
Log(amihud)	1.397**	1.438***	-0.007	-1.404
	(2.09)	(3.45)	(0.47)	(1.51)
Bid-ask spread	16.146***	-1.801	-6.027	-26.036***
	(3.03)	(0.66)	(-0.14)	(-2.93)
Abs return	1.243	3.144***	1.829*	0.586
	(1.14)	(2.86)	(1.89)	(1.20)
Return dispersion	1.157	1.284	-0.326	-1.483
	(1.22)	(1.49)	(-0.04)	(-0.95)
Price range	-0.017	0.032**	0.027*	0.045***
	(-0.85)	(1.97)	(1.70)	(-3.26)
Auto-correlation	0.408	0.368	0.414	-0.208
	(0.91)	(0.53)	(0.63)	(-0.07)

Table 11: Robustness for Distraction Events at least 5 Trading Days Apart

This table reports event-study results for the 361 distinct distraction events that are at least 5 trading days apart. The estimation period includes all trading days without economic news within a 100-day window around the event-date. Mkt return is the equal-weighted average market return and abs mkt return is its absolute value. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership (limited to 222 events due to lack of data). Column (5) shows results for the stocks in the top tercile in terms of AdjPIN (limited to 167 events due to lack of data). Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Overall	(2) Firm Size Tercile 1	(3) Stock Price Tercile 1	(4) Inst. Holdings Tercile 1	(5) AdjPIN Tercile 3
Mkt return	-2.034	n/a	n/a	n/a	n/a
	(-0.76)				
Abs mkt return	-0.904	n/a	n/a	n/a	n/a
	(0.12)				
Log(turnover)	-1.029*	-2.323***	-2.609***	-2.705***	-1.079
	(-1.73)	(-3.10)	(-3.22)	(-3.38)	(-1.10)
Log($volume)	-0.720	-2.627**	-1.711	-1.793	-0.862
	(-1.04)	(-2.16)	(-1.60)	(-1.54)	(-0.55)
Log(amihud)	0.065	1.631**	1.935**	1.276**	1.074
	(1.15)	(2.05)	(2.57)	(2.01)	(1.29)
Bid-ask spread	0.333	3.261	0.223	2.847	13.120**
	(0.74)	(1.04)	(0.48)	(1.52)	(2.35)
Abs return	-0.009	-1.844	-1.051	-2.565	1.051
	(-0.28)	(-1.06)	(-0.24)	(-1.06)	(0.87)
Return dispersion	-0.903*	-1.161	-1.178	-0.564	1.580
	(-1.68)	(-1.48)	(-1.58)	(-0.06)	(1.48)
Price range	-0.035	-0.072***	-0.062**	-0.091***	-0.023
	(-1.27)	(-2.80)	(-2.45)	(-3.52)	(-0.96)
Auto-correlation	0.658	0.496	0.397	0.171	0.090
	(1.08)	(1.00)	(0.49)	(0.39)	(0.24)

Table 12: Placebo Test for Non-Economic Days with Lowest Newspressure

This table reports event-study results for 514 placebo events (i.e., days without economic news with newspressure being in the bottom decile for the year). The estimation period includes all trading days without economic news within a 100-day window around the event-date. Mkt return is the equal-weighted average market return and abs mkt return is its absolute value. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership (limited to 222 events due to lack of data). Column (5) shows results for the stocks in the top tercile in terms of AdjPIN (limited to 167 events due to lack of data). Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Overall	(2) Firm Size Tercile 1	(3) Stock Price Tercile 1	(4) Inst. Holdings Tercile 1	(5) AdjPIN Tercile 3
Mkt return	3.224 (1.13)	n/a	n/a	n/a	n/a
Abs mkt return	0.413 (-0.08)	n/a	n/a	n/a	n/a
Log(turnover)	-0.242 (-0.54)	0.140 (0.13)	0.119 (-0.02)	0.190 (0.29)	-0.243 (-0.11)
Log($volume)	-0.860 (-1.53)	0.119 (0.50)	-0.463 (-0.29)	-0.092 (0.03)	-1.023 (-1.01)
Log(amihud)	-0.008 (0.35)	-0.156 (-0.11)	-0.142 (0.03)	0.226 (0.39)	-0.042 (-0.01)
Bid-ask spread	-0.699 (0.37)	-2.208 (-0.82)	-0.788 (-0.59)	-1.325 (-0.82)	-4.418 (-0.93)
Abs return	0.001 (-0.06)	0.077 (0.34)	-0.002 (0.29)	0.266 (0.29)	-0.247 (0.08)
Return dispersion	-0.230 (-0.36)	-0.318 (-0.45)	0.027 (0.25)	-0.135 (0.42)	-0.907 (-0.90)
Price range	0.003 (0.13)	0.008 (0.60)	0.005 (0.44)	0.009 (0.65)	0.004 (0.63)
Auto-correlation	-0.431 (-0.55)	-0.031 (0.09)	-0.069 (-0.12)	0.152 (0.72)	0.207 (0.40)

Appendix A: Model of informed trading with a risk-averse market maker

In this appendix, we derive our empirical predictions in a model of informed trading à la Kyle (1985) with a risk-averse market maker. For brevity, we here focus on a static model and take some liberty when interpreting its predictions in a dynamic context. Importantly, however, the results derived below do not hinge on this simplification. See Kim (2014) for a dynamic version of the model (in discrete time).

Our model is a simplified version of Subrahmanyam (1991). Let the final dividend be θ. There is one risk-neutral informed insider who observes θ before submitting a market order x. Market makers compete for order flow $\omega = x + s$, where s is noise trades. Let θ and s be i.i.d. normal with mean zero and variances σ_θ and σ_s, respectively.

Deviating from Kyle (1985), we assume market makers have CARA-utility with risk-aversion coefficient γ. We further assume that a single market maker takes on the entire order flow. In equilibrium, his expected utility from making the market must equal his "autarky" utility, which we normalize to 0 without loss of generality. Written in mean-variance form, this condition becomes:

$$E[U_m] = E[-\omega(\theta - p)|\omega] - \frac{\gamma}{2}\mathrm{Var}[-\omega(\theta - p)|\omega] = 0$$

Conjecturing a linear pricing rule, $p = \lambda\omega$, and plugging into the expected utility condition, yields:

$$\lambda = \frac{E[\theta|\omega]}{\omega} + \frac{\gamma}{2}\mathrm{Var}[\theta|\omega]$$

The first term in this expression is the standard Kyle result for a risk-neutral market maker; the second term is the novel effect of risk aversion. Given λ, we can find the insider's optimal trading strategy $x = \beta\theta$.

Subrahmanyam (1991) proves that in this setting the trading game has a unique Nash equilibrium in linear strategies. Following Kim (2014), we have:

$$\lambda = \sqrt{\frac{\sigma_\theta}{\sigma_s}}\left(\frac{\gamma\sqrt{\sigma_\theta\sigma_s} + \sqrt{4 + \gamma^2\sigma_\theta\sigma_s}}{4}\right)$$
$$\beta = \sqrt{\frac{\sigma_s}{\sigma_\theta}}\left(\frac{-\gamma\sqrt{\sigma_\theta\sigma_s} + \sqrt{4 + \gamma^2\sigma_\theta\sigma_s}}{2}\right)$$

Note first that setting $\gamma = 0$ brings us back to Kyle (1985). Risk aversion induces an extra component into λ. As a consequence, λ is non-zero even when there is no informed trading ($\beta = 0$ implies $\lambda = \frac{\gamma}{2}\sigma_\theta$).

Mapping our empirical setting into the model, the distraction events correspond to a decrease in the standard deviation of noise trades, σ_s. This delivers the following predictions.

Prediction 1: Less noise trading results in lower trading volume

Proof: Expected trading volume $E(|\omega|)$ is proportional to $\beta\sigma_\theta + \sigma_s$, which is increasing in σ_s.

Prediction 2: Less noise trading leads to a decrease in liquidity (λ increases)

Proof: Can be seen directly from the equilibrium formula for λ. Intuition: Two opposing forces weigh on λ. On the one hand, a lower σ_s implies that the market maker faces a higher adverse selection risk, inducing him to increase λ as in Kyle (1985). On the other hand, a lower σ_s reduces the liquidity risk borne by the market maker, allowing him to charge a lower λ. It turns out that in this model the former effect always outweighs the latter, such that a reduction in σ_s unambiguously predicts an increase in λ.

Prediction 3: Less noise trading leads to a decrease in return volatility

Proof: Stretching a little the static interpretation, we can think about two return periods in our model. The first-period return captures any price update from the prior, $r_1 \equiv p$. The second-period return captures the resolution of remaining uncertainty, $r_2 \equiv \theta - p$. Short-term volatility is defined as $\mathrm{Var}[r_1]$ and long-term (or total) volatility is defined as $\mathrm{Var}[r_1] + \mathrm{Var}[r_2]$. To prove the result, note first that $\lambda\beta = \frac{1}{2}$. It is then easy to show that $\mathrm{Var}[r_1] = \mathrm{Var}[r_2] = \frac{1}{4}\sigma_\theta + \lambda^2\sigma_s$. The last term $\lambda^2\sigma_s$ can be written as $\frac{1}{4}\sigma_\theta\delta$, where δ can be shown to be greater than 1 and increasing in σ_s for all $\gamma > 0$. Intuition: the inventory-risk component of λ leads to transient price impact, thereby causing volatility. Less noise trading means less inventory risk and hence less volatility.

Prediction 4: Less noise trading leads to less price reversal

Proof: $\mathrm{Cov}[r_1, r_2] = \frac{1}{4}\sigma_\theta - \lambda^2\sigma_s = \frac{1}{4}\sigma_\theta(1-\delta)$. Recalling that $\delta > 1$ for $\gamma > 0$, we have the result that returns are negatively autocorrelated, $\mathrm{Cov}[r_1, r_2] < 0$. Moreover, since δ is increasing in σ_s, the return autocorrelation is increasing (becomes less negative) when noise trading goes down. Intuition: Price reversals are caused by the transient price impact of noise trades. Hence, when there are less noise trades, price reversal goes down.

Appendix B: Event Study for all Top10%-News Pressure Events

This table reports event-study results for the 1,084 top 10% news pressure events (i.e., all days in which news pressure is in the top tercile of the respective year; regardless of whether the news event is classified as economic or not). The estimation period includes all trading days within a 100-day window around the event-date. Mkt return is the equal-weighted average market return and abs mkt return is its absolute value. Log(turnover) is the equal-weighted average of the logarithm of share turnover (i.e., the ratio of dollar volume to market capitalization). Log($volume) is the logarithm of aggregate dollar volume. Log(amihud) is the equal-weighted average of the Amihud illiquidity ratio (i.e., absolute return divided by dollar volume). Bid-ask spread is the equal-weighted average of the relative bid-ask spread at market close. Abs return is the equal-weighted average of the absolute raw return. Return dispersion is the logarithm of the cross-sectional standard deviation of returns. Price range is the equal-weighted average of the logarithm of the ratio of daily high- to low-prices. Auto-correlation is the equal-weighted average of the sign of the product of the returns on the event day and the next trading day. Column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership (limited to 222 events due to lack of data). Column (5) shows results for the stocks in the top tercile in terms of AdjPIN (limited to 167 events due to lack of data). Below each number, we show the z-statistic of the parametric Patell (1976) test in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

	(1) Overall	(2) Firm Size Tercile 1	(3) Stock Price Tercile 1	(4) Inst. Holdings Tercile 1	(5) AdjPIN Tercile 3
Mkt return	-4.965 (-1.02)	n/a	n/a	n/a	n/a
Abs mkt return	4.2633*** (2.92)	n/a	n/a	n/a	n/a
Log(turnover)	-0.686 (-1.38)	-1.825*** (-3.71)	-2.048*** (-3.67)	-1.707*** (-3.12)	-1.059 (-1.51)
Log($volume)	-0.067 (-0.14)	-1.049* (-1.78)	-1.117 (-1.38)	-0.672 (0.98)	0.885 (0.16)
Log(amihud)	0.104*** (2.92)	1.060** (2.29)	1.357*** (3.07)	1.173*** (2.92)	1.054** (2.22)
Bid-ask spread	1.523*** (3.03)	4.203** (2.13)	2.675* (1.72)	3.851** (2.57)	23.796*** (3.51)
Abs return	0.844 (1.44)	-1.160 (-1.45)	-0.524 (0.44)	0.082 (-0.16)	2.051 (0.98)
Return dispersion	-0.771*** (-2.69)	-1.406*** (-3.63)	-1.277*** (-3.31)	-0.468 (-0.49)	0.133 (0.07)
Price range	0.011 (0.81)	-0.052*** (-3.01)	-0.034** (-2.13)	-0.023** (-2.16)	-0.007 (1.56)
Auto-correlation	-0.104 (-0.14)	-0.002 (-0.33)	-0.013 (-0.73)	-0.268 (-1.08)	-0.212 (-0.70)