# Glued to the TV:
# Distracted Retail Investors and Stock Market Liquidity

*Joel PERESS & Daniel SCHMIDT*

19 July 2016

We study the causal effect of retail trading on stock market liquidity. We exploit episodes of sensational news (exogenous to the market) that distract retail investors. On "distraction days" we find that trading activity, liquidity, and volatility all decline among stocks owned predominantly by retail investors. These findings, complemented by additional tests, establish that retail investors contribute to liquidity by serving both as noise traders and as liquidity providers. They also identify adverse selection as an important driver of illiquidity, thereby countervailing recent work that assigns a leading role to inventory risk or questions the usefulness of adverse selection measures.

---

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 discount brokerage data. We thank Thierry Foucault, Marcin Kacperczyk, Yigitcan Karabulut, Maria Kasch, Asaf Manela, Paolo Pasquariello, Joshua Pollet (the AFA discussant), Jacob Sagi, and Paolo Sodini for their valuable comments as well as seminar/conference participants at the AFA, EFA, 7th Erasmus Liquidity Conference, ESSFM Gerzensee, 2015 European Conference on Household Finance, UC Berkeley, the Marshall School of Business, the Frankfurt School of Management and Finance, the University of Lugano, the University of Paris-Dauphine, and Warwick Business School. Joel Peress thanks the AXA Research Fund and the Institut Europlace de Finance for their financial support.

In this paper, we test for whether retail trading is a determinant of stock liquidity. The test sheds light on two important issues. First, it contributes to our understanding of what drives stock liquidity. Recent evidence questions whether standard measures of liquidity actually capture the presence of adverse selection. For instance, such measures do not appear to be negatively associated with the occurrence of informed trades (Collin-Dufresne and Fos, 2015; Kacperczyk and Pagnotta, 2016); nor do they seem to be positively associated with the occurrence of noise trades (Foucault et al., 2011). Second, our test helps explain the role of retail trading in financial markets. The literature has reported conflicting effects of retail traders on liquidity, arguing both that they stabilize markets by taking contrarian positions (Kaniel et al., 2008; Kaniel et al., 2012; Kelley and Tetlock, 2013) and that they *de*-stabilize markets by trading on noise (Foucault et al., 2011). Today, individual investors directly hold nearly a third of the US stock market's capitalization (despite a steady decline in this share since World War II) and hold far greater shares in other countries—for example, 81% in China.[1]

Identifying the effect of retail investors on liquidity is challenging because retail trading activity in a stock is endogenous and could itself be a function of the stocks' liquidity. For instance, there is evidence that retail investors are drawn to volatile stocks—either because these stocks grab their attention (Barber and Odean, 2008) or because these investors prefer stocks with lottery-type payoffs (Kumar, 2009)—and that volatile stocks tend to be illiquid (Benston and Hagerman, 1974; Chordia et al., 2000; Hameed et al., 2010).

We overcome this problem by identifying variations in retail trading activity that are exogenous to the stock market. These variations are generated by sensational news that temporarily distract individual traders. A vivid example of such news is the trial verdict against football and movie star O.J. Simpson on 3 October 1995. Millions 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, and water usage plummeted as they postponed using bathrooms (Dershowitz, 2004). More

[1] "Myth of China's retail investors understates large players' role," *Financial Times*, 13 July 2015; "An equity investor's guide to the Flow of Funds Accounts," *Goldman Sachs Report*, 11 March 2013. See also Gompers and Metrick (2001) and Bennett et al. (2003) for the United States and Rydqvist et al. (2014) for other developed countries.

relevant for our purpose and as shown by Figure 1, trading volume on the New York Stock Exchange (NYSE) plummeted by 41% in the first five minutes after the announcement—and by another 76% in the next five minutes—before abruptly recovering. The swing in trading activity was especially dramatic for small trades, the hallmark of retail traders. Because the O.J. Simpson trial is unrelated to the economy, such an episode speaks to a causal effect of retail trading on the stock market.

[[ Insert Figure 1 about here ]]

We create a sample of such *distraction events* and show that they trigger sharp variations in retail trading, which we exploit to study the effect of retail trading on the stock market's liquidity and volatility. An important feature of our shocks is that they last just one day. This feature distinguishes our approach from previous work, which has focused on long-lived or even permanent changes in retail trading, and enables our linking the results more tightly to theory that identifies adverse selection as an important driver of illiquidity (e.g., Glosten and Milgrom, 1985; Kyle, 1985). Our evidence demonstrates that retail traders contribute to liquidity by acting as noise traders and market makers, and that their *absence* from the market leads to an increase in standard measures of adverse selection, as predicted by the theory.

We identify episodes of highly sensational media reporting thanks to a variable, constructed by Eisensee and Strömberg (2007), called *news pressure*. This variable measures the median number of minutes that US news broadcasts devote to the first three news segments. For example, the O.J. Simpson trial verdict received 16½ minutes of air time, the highest value for that year. Every year, we sort days into news pressure deciles and identify those belonging to the highest decile. We then parse through the headlines of news segments covered in the broadcasts and retain only the days for which the sensational news is plausibly exogenous to the economy. Examples of such distracting news include the O.J. Simpson trial verdict, the Cessna plane crashing on the White House lawn, and the *Challenger* space shuttle explosion. Data on TV viewership confirm that these events draw the attention of US households. Our final sample contains 532 days (distraction events) over the period from 1968 to 2013.

We conjecture that these news stories divert individual investors' attention away from the stock market. Detailed trading data from a large discount broker confirm that fewer retail traders participate in the market on distraction days: their propensity to trade drops by 5% but is back to normal on the following day. Consistent with this decline, transactions data from the Trades and Quotes (TAQ) database reveal a significant reduction in the volume of small trades (which are likely to involve retail traders) but not of large trades (which are likely to involve institutions). We therefore conclude that the events we have identified distract mainly retail traders and hence that we can exploit sensational news episodes to study how short-lived changes to retail trading affect financial markets.

The next step is to study how the US stock market behaves on distraction days. While we find weak results for the overall market, we uncover pronounced effects when focusing on subgroups of stocks with high retail ownership. At the outset, we check that trading activity weakens significantly in the bottom tercile of stocks in terms of firm size, stock price, and institutional ownership—three variables that are negatively correlated with retail ownership. In these groups, share turnover and the dollar value of trades decline significantly (by about 3%). This effect dissipates monotonically in the other terciles, which again confirms our interpretation of retail investor-based distraction.

As regards liquidity, we build several proxies using both CRSP daily data (the illiquidity ratio of Amihud, 2002, and closing bid-ask spreads) and TAQ intraday data (average bid-ask, effective, and realized spreads; price impact; absolute trade imbalance; Kyle's lambda). We find virtually all proxies in the bottom terciles to increase by 1% to 6% on distraction days; for instance, spreads increase by 3%. These effects are economically modest but are commensurate with the drop in trading activity we report. They are statistically significant and robust across liquidity proxies, sorting variables, and test methodologies (parametric versus nonparametric). Moreover, the effects are concentrated in stocks with high levels of retail ownership and abate monotonically in the other terciles, conforming to the patterns we observe for trading activity. We emphasize that increases occur for measures of adverse selection (illiquidity ratio, price impact, absolute trade imbalance, Kyle's lambda) and also for a measure of inventory cost (realized spread).

The final step in our approach is to examine the behavior of volatility on distraction days. We proxy for volatility using the absolute value of close-to-close returns and with the daily high-to-low ratio of prices (obtained from CRSP); we also measure volatility (using intraday TAQ data) as the standard deviation of five-minute returns during the day. Again we find a drop of about 3% in the bottom terciles, which dissipates monotonically as we move away from stocks with high levels of retail ownership. In summary, among stocks owned predominantly by individual investors, liquidity and volatility *both decline* on distraction days; and these declines are accompanied by a reduction in trading activity.

We interpret the increase in measures of adverse selection as evidence that retail investors behave as noise traders. Indeed, their exit from the market leaves market makers at a greater risk of being picked off by informed speculators. To evaluate this interpretation, we take a closer look at which households in our brokerage dataset are distracted. We find that overconfident investors—who tend to be single-male, more active, and more likely to lose money—are prone to be distracted. In contrast, investors who consistently profit from trading are unaffected by sensational news events. These results are consistent with the interpretation that individuals pulling out of the market on distraction days are primarily noise traders.

The concurrent reduction in volatility is also consistent with retail investors behaving as noise traders, provided that inventory risk is priced. Such risk is not priced in the standard Kyle (1985) model with risk-neutral market makers, but we show, in a simple extension of the model, that it *is* priced when market makers are risk averse (cf. Subrahmanyam, 1991). Intuitively, risk-averse market makers dislike variation in the value of their stock inventory and therefore charge a premium for inventory risk, which in turn induces price reversals and excess volatility. Our simple model therefore predicts—and the data confirm—that trading activity, liquidity, and volatility are all low on days with weak noise trading.

One piece of evidence—the increase in realized spreads, a proxy for inventory costs—suggests that our noise trading interpretation does not tell the full story. Indeed, according to models of inventory risk (e.g., Stoll, 1978; Ho and Stoll, 1981), liquidity should, if anything, *improve* because a decline in noise trading renders the market makers' inventory safer. In our context, however, the short duration of distraction shocks sharply reduces the inventory risk channel's relevance. The increase in realized spreads is instead explained by noting that retail investors behave both as noise traders and as market makers (Kaniel et al., 2008; Kaniel et al., 2012; Kelley and Tetlock, 2013). So on distraction days, retail traders not only demand less liquidity but also supply less liquidity.

In order to evaluate this explanation empirically, we examine the number of households in our brokerage data set that engage in contrarian trades. Such trades—purchases (resp. sells) made on days when a stock's return is negative (resp. positive)—are likely to be liquidity-providing limit orders (Barber et al., 2009). We find that the number of contrarian households drops significantly (by about 5%) even among stocks characterized by *low* levels of retail ownership, where the drop cannot be explained by a contemporaneous reduction in trading activity driven by market orders. Thus retail traders indeed seem to supply less liquidity on distraction days, leading the realized spread to increase among high-retail ownership stocks.[2]

In short, our evidence shows that retail traders contribute to liquidity by acting both as noise traders and as market makers, and that their brief absence from the market leads to an increase in standard measures of adverse selection and inventory cost.

Our paper contributes to several strands of research. First, it adds to the literature on the determinants of liquidity. Recent papers have cast doubt on whether standard measures of liquidity are able to detect the presence of adverse selection; Collin-Dufresne and Fos (2015) and Kacperczyk and Pagnotta (2016) find that such measures do *not* decrease when informed investors trade. Evidence on how they respond to noise trades is mixed. Greene and Smart (1999) document that an increase in noise trading, as triggered by analyst recommendations published in the press, has no bearing on overall liquidity. In contrast, Foucault et al. (2011) report improved liquidity following a reform that discouraged retail trading on the French stock exchange. Finally, we find evidence of worse liquidity on distraction days.

---

[2] Because retail trades are outnumbered by institutional trades in big stocks, reduced liquidity provision by retail traders has no discernible effect on these stocks' liquidity.

These conflicting results can be reconciled by noting that (a) liquidity is shaped both by adverse selection and by inventory cost and (b) the latter's effect varies considerably across these experiments. Inventory cost is driven by market makers' concerns about fluctuations in the value of their portfolio and so is determined by their expectation of *future* return volatility, which is itself an increasing function of the intensity of (future) noise trading. The longer this intensity is expected to remain low, the sharper the decline in the (current) cost of inventory. At one extreme, Foucault et al. (2011) consider a permanent drop in the intensity of noise trading and hence find reduced inventory cost; the reduction is so large that it swamps any adverse selection effect and thus results in a liquidity improvement. At the other extreme, our single-day decline in the intensity of noise trading leads to no detectable reduction in inventory cost and, because adverse selection now dominates, to reduced liquidity.[3] Overall, our findings help make sense of prior conflicting evidence; they also support theoretical predictions about how standard measures of liquidity "should" respond to a short-lived change in noise trading intensity.

The paper's second main contribution is to the literature that studies the effect of retail trading on stock returns. For example, Brandt et al. (2010) attribute declining idiosyncratic volatility—as first reported by Campbell et al. (2001)—to retail investors' trading behavior. Grullon et al. (2004) document that firms that spend more on advertising have more individual stockholders and are also more liquid. Kaniel et al. (2008) and Kaniel et al. (2012) find that that individual investors earn a liquidity premium from making contrarian trades, especially around earnings announcements. These papers uncover important facts, but causal inferences are hampered by a lack of clean identification: instead of causing volatility or liquidity, retail traders may simply be attracted by volatile or illiquid stocks. Indeed, Barber and Odean (2008) report that individual investors are more likely to trade stocks exhibiting extreme returns, and Kumar (2009) finds that they prefer lottery-type stocks. This identification problem extends to liquidity because, in the data, liquidity is negatively associated with volatility (see e.g. Benston and Hagerman, 1974; Chordia et al., 2000, for cross-sectional evidence; and Hameed et al., 2010, for time-series evidence). Exceptions are the papers by Greene

[3] In the middle of this spectrum lies the paper by Greene and Smart (1999), which describes a shift in noise trading intensity that can last from ten days to several weeks. In their setup, the two channels—adverse selection and inventory cost—exactly offset each other and thereby keep liquidity constant.

and Smart (1999) and Foucault et al. (2011), but their findings (as described previously) differ with regard to liquidity.

Finally, we make five contributions to the growing literature on limited attention in financial markets (see e.g. Cohen and Frazzini, 2008; Corwin and Coughenour, 2008; DellaVigna and Pollet, 2009; Hirshleifer et al., 2009; Da et al., 2011). The first of these contributions is methodological: we demonstrate how sensational news can be fruitfully exploited to study the causal consequences of short-term fluctuations in investors' attention. Second, we apply this methodology to identify the implications—for liquidity and volatility—of marketwide inattention. One finding of interest is that the implications of investor *in*attention are not simply the reverse of the implications of investor attention. In particular: whereas attention-grabbing events have been found to affect returns (see Yuan, 2015, for evidence that selling pressure depresses returns at the market level; see Da et al., 2011, for evidence that buying pressure inflates returns at the stock level), retail investor distraction leads to a *nondirectional* drop in trading activity and so does not result in any price pressure effect. Third, we derive, in a parsimonious model, distinctive predictions for market outcomes as a function of the attention paid by different categories of agents (insiders, market makers, and noise traders)—predictions that allow us to tease out who is most prone to distraction.

Our fourth contribution to the attention literature is to describe how distraction interacts with behavioral biases, thereby offering a more nuanced view of attention: rather than being invariably good, attention can be bad for investors who trade too much (Odean, 1999). Indeed, we find that overconfident investors are more prone to distraction—hence their performance actually improves when they watch TV instead of trading. Last but not least, by studying the effect of distraction on different measures of trading activity, we shed light on the role that attention plays in the decision-making process of a retail trader. More specifically, we document that distraction has a strong negative effect on the extensive margin (i.e., whether or not to trade) but not on the intensive margin (i.e., how much to trade). These findings are difficult to reconcile with models in which investors gradually curb their trading intensity as they pay less attention (Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2010); however, they are consistent with models that assume a fixed attention cost for accessing the stock market (Merton, 1987; Abel et al., 2007; Chien et al., 2012; Abel et al., 2013).

The rest of the paper is organized as follows. Section I reviews our data and methodology. Section II considers the effect of distraction on retail investors. Section III studies how these shocks to retail trading affect the stock market—in particular, for subgroups of stocks held predominantly by retail investors. Section IV presents robustness checks and discusses endogeneity issues, and Section V investigates which types of retail traders are distracted. Section VI concludes. The internet appendix features the details of our model as well as some additional results.

## I. Data and Methodology

*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 US news broadcasts devote to the first three news segments, and the authors 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).[4] 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.

[[ Insert Figure 2 about here ]]

We focus on these spikes in daily news pressure. In particular, for each sample year we select the 10% of business days with the highest news pressure as our candidate events. This procedure yields an initial list of 1,084 event-days. One might object that news pressure could be high because of news broadcasts covering important economic news—

4 We are grateful to David Strömberg for providing us with an updated time series of daily news pressure that covers the 1968–2013 period and includes headline information. The raw measure—that is, without headline information—can be downloaded from David Strömberg's website (http://perseus.iies.su.se/~dstro/).

which, rather than distracting investors, could instead draw their attention to the stock market. We dismiss this concern on three grounds.

First and foremost, economic news would bias our results *against* finding a distraction effect. Indeed, a large literature has documented that stock returns are orders of magnitude more variable on days with economic news (see e.g. Cutler et al., 1989; Boudoukh et al., 2013). In contrast, we expect (and find) less return volatility under our distraction hypothesis. Similarly, public news typically coincides with large increases in trading activity, which are attributed to increases in disagreement and/or differences in information processing speeds among market participants (Hong and Stein, 2007; Foucault et al., 2016). As with volatility, we again expect (and find) the opposite effect under distraction.

Second, a correlation analysis indicates that macroeconomic news releases, business activity indicators, and investor sentiment together explain but a small fraction of the variation in news pressure (see Internet Appendix B.2). Hence it appears that news pressure is driven by sensational stories that are mostly orthogonal to news about future cash flows and discount rates (i.e., the economically important news).

Finally, to err on the conservative side, we exclude high-news pressure days on which the headlines of any of our selected broadcasters' top three news segments contain at least one word from our list of economic keywords.[5] We are left with a list of 532 event-days from 1968 to 2013 that we are confident in classifying as both noneconomic and potentially distracting. These are the *distraction events* used in our analyses.

[[ Insert Table 1 around here ]]

In Table 1, Panel B presents a partial list of these events along with a short description of the day's major news headline. It lists the top two distraction events by news pressure for each year. The stories in this list involve accidents (for example, the *Challenger* explosion, the Minneapolis bridge collapse), terrorist attacks (Lockerbie plane bombing, Oklahoma City bombing, London bombing),[6] assassination attempts (on President

[5] The keywords: banking, bankruptcy, default, depression, economic, economy, election, employment, equity, federal reserve, fed reserve, fed rate, finance, financial, inflation, interest rate, recession, stock market, treasury, war.

[6] 9/11 does not enter our sample because stock exchanges remained closed from 11 September to 17 September, 2001.

Reagan, on Pope John Paul II), shootings (Littleton school shooting, Virginia Tech massacre, Tucson shooting), criminal court rulings (O.J. Simpson, John DeLorean, William Calley), celebrity deaths (Lady Diana, Michael Jackson), military skirmishes (Grenada invasion, USS Stark incident, Iraq Fallujah uprising), natural disasters (Haiti earthquake, Oklahoma tornado), and political scandals (Watergate hearings, Iran-Contra scandal). In essence, our list collects news stories that captured national headlines but had an arguably negligible effect on the US economy. Robustness tests (see Section IV) show that our results are sensitive neither to the inclusion (or exclusion) of any particular event nor to the specific keywords employed as filters.[7] In that section we also address the concern that many of the events on our list have a negative connotation and may therefore proxy investor sentiment rather than investor distraction.

An important prerequisite for the distraction hypothesis is that our events absorb the attention of retail households (and thereby reduce the attention available for trading in the stock market). We directly test the first part of this statement using television viewership data purchased from Nielsen Research for the 1992–2013 subperiod. More specifically, we conduct an event study to determine whether television viewership during the 6:30–7:00 p.m. news broadcasts by ABC, CBS, and NBC (i.e., those from which the news pressure variable is calculated) rises on distraction days.[8] To ensure that any viewership increase is not confined to after-trading hours, we complement this measure with the average daily viewership of CNN, a dedicated news channel. Panel A of Table 1 reports the results. The viewership for CNN (column (1)) and for other broadcasts' news programming (column (2)) are, respectively, 34% and 3% higher on distraction days—an effect that is highly significant both economically and statistically.[9] Thus we find strong evidence that US residents are "glued to the TV" on distraction days. Before turning to the

[7] Moreover, we obtain strongly similar results when we use all the top 10% news pressure days—that is, regardless of whether or not some broadcast mentions an economic keyword. This outcome is consistent with the weak correlation we find between news pressure and economic news. It therefore seems that the stories receiving substantial news coverage on television broadcasts *differ* from the stories that should matter to stock market investors.

[8] Our event study methodology is explained in Section I.C.

[9] The difference in these economic magnitudes may reflect households switching to CNN in order to follow the news event in real time; these viewers may then be less likely to (also) watch the evening news broadcasts on any of the other three channels.

trading activity of these retail investors, we describe our other data sources and explain our econometric methodology.

*B. Other Data*

We employ two different data sources to study the effect of distraction events on retail traders. The first source comprises about 1.9 million common stock trades from a large discount brokerage house between January 1991 and November 1996 (for details, see Barber and Odean, 2000). As in Barber and Odean (2002), we focus on the trades of 12,743 households that had portfolio holdings throughout the sample period. Thus we hold constant the number of households that can trade on any given day, which facilitates the comparison of trading intensities over time. The advantage of these disaggregated data is that they allow us to analyze which particular investors are more prone to distraction; the disadvantage is that they cover a relatively short time period, forcing us to work with only 66 distraction events. Our second data source on retail trades consists of aggregated transactions in all NYSE/AMEX/Nasdaq stocks; these are obtained from the Institute for the Study of Security Markets (ISSM) and Trades and Quotes (TAQ) databases.[10] Although these data sets do not reveal traders' identities, they do allow us to distinguish between small and large trades.[11] Small trades were an effective proxy for retail trading until the early 2000s, when order splitting by institutions became popular (Lee and Radhakrishna, 2000; Barber et al., 2009; Hvidkjaer, 2008). For this reason, we limit our analysis of aggregated transactions data to the period 1991–2000, during which 105 distraction events occurred.

We obtain stock market data from two sources. First, we use daily data from CRSP covering the entire period from 1968 to 2013 (532 distraction events). Second, we again employ TAQ data but this time for the period from 1993 to 2013 (206 distraction events). We apply the filters and adjustments described by Holden and Jacobsen (2014) for dealing with withdrawn or canceled quotes, and we use their interpolated time technique

---

[10] We thank Søren Hvidkjaer for sharing the aggregated ISSM and TAQ volume data, broken down by trade size, for the period 1991–2000.

[11] Our size classification follows that described in Hvidkjaer (2006). Namely, we sort stocks into quintiles based on NYSE/AMEX firm-size cutoff points and use the following small-trade (large-trade) cutoff 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.

to improve the accuracy of liquidity measures.[12] All TAQ trades are signed using the Lee and Ready (1991) algorithm. Throughout our analyses, we focus on common stocks (share codes 10 or 11) and exclude penny stocks (closing price < \$1). We describe our stock market variables in Section III, where we also present results for the marketwide analysis.

*C. Methodology*

We start by purging any seasonal effects from all time-series variables (e.g., stock market data, brokerage trading volume, TV viewership) by regressing them on a set of dummy variables for years, calendar months, and days of the week (where the latter two are allowed to vary by year). We carry out our analyses on the residuals from these regressions, which ensures that the results are neither driven nor confounded by seasonal patterns.

Our event study approach works as follows. Let $X$ be an outcome variable of interest. We define *abnormal* $X$ as the realization of $X$ on the event date ($t = 0$) minus its average over an estimation window. The estimation window consists of all trading days without economic news (according to the filter described previously) in a 200-day window that is centered on the event day.[13] In this way we compare distraction days with no economic news to nondistraction days that are also without economic news. Employing the same economic news filter across distraction and nondistraction days ensures that any difference we find can be attributed only to the distracting event. Formally:

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

Our estimation window includes both the pre-event and the post-event periods—in order to neutralize any trend in the data—although results are unchanged if the window includes only the pre-event period. For variables related to stock market outcomes, we first calculate abnormal $X$ at the stock level and then calculate the equal-weighted average over the portfolio of interest (e.g., the entire market or stocks in the bottom tercile of

[12] The code for making these adjustments is available on Craig W. Holden's web page (http://kelley.iu.edu/cholden/).

[13] This choice of estimation window is motivated by our finding that effects of distraction events are so short-lived that they do not extend beyond the event date itself. Introducing a small gap between the event date and the estimation window leaves our results unchanged.

institutional ownership) for each event date. We test for the significance of abnormal $X$ across events using the parametric Boehmer-Musumeci-Poulsen $t$-test (Boehmer et al., 1991), or BMP for short, as well as a nonparametric rank test.[14]

## 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 marketwide analysis to follow, this analysis is valuable in its own right. That is: because investors can be distracted only if they were attentive to begin with, the 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 that process are most sensitive to attention constraints. Our results should therefore be of interest to researchers working on the development of a positive theory of attention allocation.

We study three different measures of trading activity for buys, sells, and combined. First we count the number of households trading on a given day and then take logarithms; we label this variable *log(#households)*. Our second variable is the equal-weighted average of the (logarithm of the) number of distinct stocks traded by a household with at least one trade. This variable is denoted *log(#stocks)* and captures the average number of distinct stocks traded conditional on trading. Our third variable is the average (log) trade size, in dollars, per household and stock; this is the *log($volume)* variable, which is also defined conditional on trading.

Our measures are intended to reflect different stages in an investor's decision-making process. *log(#households)* captures the decision of whether or not to trade (extensive margin). Finding a distraction effect involving this variable indicates that directing attention to the stock market and transacting (which involves logging into one's brokerage account or calling up a broker) requires a fixed amount of attention, as in the models of Merton (1987), Abel et al. (2007, 2013) and Chien et al. (2012). The *log(#stocks)* variable reflects how much more attention is required for *searching* and

[14] The BMP $t$-test builds on the Patell (1976) $t$-test but does not require the former's assumption of no event-induced variance. Because the BMP test may not perform well when the outcome variable's distribution departs markedly from normal, we complement our inference with a nonparametric rank test.

trading additional stocks conditional on having traded at least once on that day. Past research suggests that buys require more attention than sells during this phase because underdiversification coupled with short-sale constraints makes the choice set for sells much smaller than that for buys (Barber and Odean, 2008). Finally, models of rational attention predict that investors trade less aggressively when the information they possess is less precise (e.g., Verrecchia, 1982; Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2010)—as would be the case if investors were distracted. On this account, we should expect a reduction in *log($volume)*, the average trade size conditional on trading on a given day.

[[ Insert Table 2 around here ]]

In Table 2, Panel A reports results for the 66 distraction events that occur during the period for which we have brokerage data. We see a decline in *log(#households)* that is highly statistically significant and almost symmetric between buys and sells: on average, there are from 5% to 6% ($p < 0.01$) fewer households trading on a distraction day than on an average day in the estimation window. This result offers support to models that assume a fixed attention cost for accessing the stock market. For *log(#stocks)* we find that households buy 1.3% ($p < 0.01$) fewer distinct stocks on a distraction day—although they do not sell fewer distinct stocks (the difference is significant; see column (3)). Even though economically small, this finding is consistent with Barber and Odean (2008), who argue that the choice set of retail investors looking to buy is much larger than their choice set for sells (which short-sale constraints limit to the small number of stocks currently held). Finally, we find a negative but statistically insignificant effect of distraction on *log($volume)*. So conditional on trading, it seems that households do *not* scale down their trades in response to a distraction event. To the extent that distraction events reduce the precision of households' information, this finding is not consistent with the rational attention view, according to which less well-informed agents ought to trade less aggressively.

[[ Insert Figure 3 about here ]]

A natural question to ask is whether distracted households eventually execute the trades that they missed—that is, whether retail investors "catch up" on their trading. We address this question in Figure 3, which plots, in event time, the change in the number of retail investors actually trading. We find no significant evidence for catching up in the five trading days after a distracting event. Indeed, the only significant effect occurs on the distraction day itself, confirming the view that these events are short-lived shocks to retail participation. Moreover, the trades forgone on distraction days appear to be superfluous in that they don't cause households to trade more once the distraction subsides.

*B. TAQ Analysis*

Because the brokerage data cover only a fraction of the retail investor population and a relatively short sample period, we also conduct an event study using TAQ data for all transactions in stocks listed on NYSE/AMEX/Nasdaq from 1991 to 2001. Prior research has found that, until decimalization in 2001, small trades were likely made by retail investors whereas large trades were nearly always made by institutions. We accordingly investigate how the distraction effect varies with trade size.

In Panel B of Table 2 we report results for the 105 distraction events that occur during this period. Our measure of trading intensity, denoted *log($volume)*, is the (log of the) value of trades aggregated over small and large trades, respectively. On a distraction day, trading volume due to small trades declines by 2% ($p < 0.1$) whereas large trades decline only by a statistically insignificant 0.7%. Column (3) shows that the difference in the distraction effect—between small and large trades—is significant.

The results described in this section indicate that distraction has a strong effect at the extensive margin (i.e., on whether or not to trade), a somewhat weaker effect on the number of different stocks purchased, and no effect on trade size. The distraction effect is manifest in the aggregate volume of small trades, which are likely due to retail investors; in contrast, large (institutional) trades are not affected.[15]

[15] See Internet Appendix B.1 for additional evidence that institutional investors are not distracted by sensational events. We show there that our distraction events do *not* affect the speed with which earnings news is incorporated into stock prices. Using direct proxies for institutional and retail attention at the stock level, Ben-Rephael et al. (2016) find that only the former contributes to price discovery upon earnings news. Using different proxies of inattention, DellaVigna and Pollet (2009), Hirshleifer et al. (2009) and Peress (2008) also report evidence of underreaction to earnings news. We conclude that, in contrast to these studies, our events specifically capture *retail* inattention.

## III. Distraction and the Market

*A. Hypotheses*

Having established that retail investors trade less on distraction days, we now investigate the implications for the stock market. To guide the empirical analysis, we present the predictions made by an extension of the Kyle (1985) model; see Internet Appendix A for details. While the model is based on adverse selection, we introduce an inventory concern by making market makers risk averse. As a result, this extended model captures two important sources of illiquidity identified in the microstructure literature: adverse selection (Glosten and Milgrom, 1985; Kyle, 1985) and inventory risk (Stoll, 1978; Ho and Stoll, 1980; Ho and Stoll, 1981; Grossman and Miller, 1988).

Our model features three categories of agents—noise traders, informed speculators (a.k.a. insiders), and market makers—and is designed to study the implications of distracting agents in each category. The three cases deliver distinct sets of predictions for trading volume, liquidity, and volatility, which are summarized in Table 3.

[[ Insert Table 3 around here ]]

*Distracted Noise Traders*. If noise traders are distracted (as modeled by a reduction in the variance of noise trading) then trading volume declines, liquidity worsens (higher Kyle's lambda), and returns become less volatile. Intuitively, trading volume declines not only because there are fewer noise trades but also because speculators, who try to conceal their information, scale back their trades.

Two opposing forces affect liquidity. On the one hand, a lower variance of noise trades implies that the market maker faces a higher risk of adverse selection, which induces him to decrease liquidity. On the other hand, a lower variance reduces inventory risk, allowing the market maker to charge a lower risk premium and thus improve liquidity. It turns out that the former effect always outweighs the latter, such so that a reduction in the variance of noise trades unambiguously leads to reduced liquidity. This is because, in our model, noise shocks affect how much inventory the market maker needs to take on but do *not* affect the difficulty of unwinding this inventory going forward. In that respect our approach differs crucially from classic models of inventory risk (Ho and Stoll, 1980; Ho and Stoll, 1981; Grossman and Miller, 1988; Hendershott and Menkveld, 2014), where the market maker is concerned about fluctuations in the value of his inventory caused by *future* noise trading.[16] It is precisely this feature that makes our model well suited for deriving implications of such short-lived distraction shocks as studied in this paper.

Finally, volatility is driven by the inventory risk component of liquidity because that component leads to transient price impact.[17] Less noise trading means fewer temporary shocks to prices, which dampens volatility.

<u>*Distracted Insiders*</u>. If informed speculators are distracted (as modeled by a decrease in their signal precision), then trading volume declines and liquidity improves (lower Kyle's lambda). The effect on return volatility is ambiguous.

Intuitively, speculators trade less aggressively when they are less well informed. This reduces expected trading volume and also the order flow's informativeness, thereby weakening its price impact (improving liquidity). Volatility is, on the one hand, dampened by the weaker price impact, but on the other hand, amplified by the higher signal noise embedded in insiders' trades. The net effect is ambiguous.

<u>*Distracted Market Makers*</u>. If market makers are distracted (as modeled by a decrease in their signal precision), then trading volume declines, liquidity worsens (higher Kyle's lambda), and returns become more volatile.

As his signal becomes less precise, the market maker assigns more weight to the information conveyed by the order flow and less to his own signal, which leads to greater price impact. Thus liquidity worsens as adverse selection risk intensifies. Trading volume is shaped by two opposing forces. On the one hand, the insider scales back her trades as liquidity deteriorates. On the other hand, her trades grow more extreme as her signal deviates more from that of the market maker. The former effect dominates the latter and so the net effect is a decline in trading volume. Volatility is magnified by the higher price impact in the trading period. This increase in volatility is dampened but not reversed by the insider's reduced trading aggressiveness.

16 See Foucault et al. (2011), who exploit a quasi-permanent change in retail activity that resulted from a regulation change affecting the French stock market, for a test of this standard intuition about inventory risk.

17 In contrast, the adverse selection component of liquidity is *not* associated with volatility because it changes only the timing of when uncertainty is resolved (see Kyle, 1985).

To summarize: we expect trading volume to be reduced in all three cases. A worsening of liquidity speaks in favor of noise traders and/or market makers being distracted, but is inconsistent with the notion of distracted speculators. Evidence of a decline in volatility further suggests that noise traders are more distracted than market makers. Treating our distraction events as a natural experiment, the following analysis enables teasing out the causal effect of retail traders' inattention on financial markets.

*B. Marketwide Analysis*

We start with a brief description of the variables used in this section.[18] We winsorize the data at the 0.5% level in both tails and then purge them of seasonal patterns (as described previously). Throughout our analysis, we focus on equally weighted averages across stocks. Value-weighted averages yield weaker results, which suggests that our findings are concentrated among smaller stocks (we shall verify this later). To assess the effect of distraction events on stock market performance, we examine the (equal-weighted) average market return on all stocks in CRSP (denoted *mkt return*). For trading activity, we look at both the average of daily (log) 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,[19] and the (log) aggregate dollar volume (denoted *log($volume)*).

We use several measures of liquidity, which are broadly classified into three groups. The first group encompasses measures that reflect both adverse selection and inventory risk. It includes quoted bid-ask spreads (*closing bid-ask spread* from CRSP, available as of November 1982, and daily *average bid-ask spread* from TAQ; both are measured relative to the mid-quote) as well as *effective spreads* (i.e., the percentage increase in the ratio of transaction price over the prevailing mid-quote prior to the transaction; from TAQ).

The second group consists of four measures of adverse selection. The first of these is the Amihud (2002) illiquidity ratio, defined as the (log) of the stock's absolute return divided by its dollar volume.[20] This measure, denoted *log(amihud)*, is computed from CRSP data

[18] The Appendix gives detailed definitions of all the variables used in our study.

[19] Because turnover can be zero, we follow Llorente et al. (2002) and add a small constant (0.00000255) before taking logs. Our results are robust to alternative choices for this constant, including dropping it altogether.

[20] Because this ratio can be zero, we add a small constant (0.00000001) before taking logs. The constant is chosen so as to make the Amihud ratio's distribution closer to a normal. Our results are robust to alternative choices for this constant, including dropping it altogether.

and therefore available for the entire sample period. Goyenko et al. (2009) show that it does a good job of capturing adverse selection. The second measure is *price impact*, defined as the percentage change in the mid-quote from before to five minutes after the transaction. The third measure is the *absolute trade imbalance*. Easley et al. (2008) and Kaul et al. (2008) show that this measure, which is an alternative to the "probability of informed trading" (PIN) measure introduced by Easley et al. (2002), has the advantage of being computable at the daily frequency. Our fourth adverse selection measure, *lambda*, is the slope coefficient from a regression of stock returns on signed order flow over five-minute intervals; it can be interpreted as the cost of demanding a certain amount of liquidity over five minutes. The last three of these measures all require high-frequency TAQ data, so they are available for only a subset of our distraction events.

The third group of our liquidity measures captures noninformational sources of illiquidity, such as inventory or order-handling costs. This group includes *realized spread*, which is the part of the effective spread that accrues to market makers as compensation for providing liquidity.

Finally, we investigate the impact of distraction on three measures of return volatility. Two of these—the average stock-level absolute return (*abs return*) and the logarithm of the ratio of daily high and low prices (*price range*)—are computed from CRSP data and so are available throughout our study period. The last of these measures is the intraday standard deviation of stock returns over five-minute intervals, *intraday volatility*, and requires TAQ data.

[[ Insert Table 4 around here ]]

Table 4 reports summary statistics for all of our measures. Panel A shows the raw data before the seasonality adjustment. For instance, the average daily share turnover is 0.57%, which implies that a firm entirely changes hands more than once each year. Stock prices vary by 2.4% over a day and by 0.3% over five minutes; quoted spreads average about 2%–3%. The effective spread is somewhat lower: only 1.3%, of which 70% (resp., 30%) is accounted for by the realized spread (resp., the price impact). These magnitudes are in line with reports in the previous literature (e.g., Goyenko et al., 2009). Panel B of the table displays the data after we take logs and adjust for seasonality—in other words, as the data are used in our event study. These measures appear to be well behaved: means (which are all zero after the seasonality adjustment) and medians are well aligned, and neither the 1st nor the 99th percentile is off the chart. We therefore conclude that it is reasonable to base inferences on the parametric BMP test.

[[ Insert Table 5 around here ]]

Table 5 reports results for the marketwide event study. We first note that distraction days have no discernable effects on market returns. This is reassuring since any effect on returns would cast doubt on the presumed noneconomic nature of these events. Other results are relatively weak. For example, dollar volume and turnover decline by 1.2% and 1% (respectively), with $t$-statistics of −1.2 and −1.5. We uncover some significant increases—in closing bid-ask spreads, Amihud illiquidity ratio, and lambda—that are suggestive of an increase in adverse selection risk on distraction days. This being said, most of our measures show insignificant changes for the average stock in our sample. Hence we turn our attention to stocks for which we expect stronger distraction effects: stocks predominantly held by retail investors.

*C. Sample Splits*

We sort stocks into terciles based on three common proxies for retail ownership: the firm's size (market capitalization), its stock price, and the fraction of institutional ownership; the latter is drawn from firms' 13(f) filings. We start with firm size. It is well documented (e.g., Lee et al., 1991) that small stocks are held proportionately more by retail investors, so we expect results to be strongest for the bottom tercile of firms. As Panel A of Table 6 reports, this is indeed what we find: in the lowest tercile, turnover is significantly reduced (by 2.4%) on distraction days. There is no such effect for stocks in the top tercile and the *difference* between the highest and lowest terciles is strongly significant. A similar pattern emerges for trading volume.

[[ Insert Table 6 around here ]]

Small stocks also experience a drop in volatility: both the price range and intraday volatility are significantly reduced by roughly 2%–3% on distraction days (relative to their unconditional mean, see Table 4). For the largest firms, volatility is unchanged (except for the price range, which exhibits a marginally significant increase according to the parametric BMP test though not according to the nonparametric rank test). The difference between the bottom and top tercile is highly statistically significant. For absolute returns, a similar but not statistically significant pattern is observed.

Panel B displays our findings for liquidity: all measures are significantly increased for small stocks (with the exception of price impact, where the increase is only marginally significant) but are unchanged for large stocks. The difference is significant (again with the exception of price impact). In terms of economic magnitude, the largest effect is observed for lambda—the regression-based price impact measure. Among small stocks, this measure increases by 13% relative to its unconditional mean, which indicates that demanding liquidity has become substantially more costly. For small stocks, the increase in our spread measures ranges from 2% (for average quoted spreads) to 4% (for realized spreads). The Amihud illiquidity ratio and the absolute trade imbalance rise by 2.4% and 1.3%, respectively.

Overall, our results are strongest in the bottom size tercile and dissipate monotonically in the other groups. Taken together, they are in line with the "distracted noise trader" hypothesis we developed previously (cf. Table 3). The increase in realized spreads further suggests that, for small stocks, liquidity provision is reduced—an observation to which we return in Section V.

Next, we sort stocks in terms of their price. Brandt et al. (2010), among others, document that low-priced stocks are the natural habitat of retail investors. We therefore expect stronger results for such stocks. Table 7 confirms this expectation: in the lowest stock-price tercile, we find a significant reduction (of about 3%) in trading activity that coincides with a significant decline in volatility (Panel A). As before, there is strong evidence for a decrease in liquidity (Panel B). In particular, bid-ask spreads and proxies for adverse selection risk are significantly increased among low-priced stocks (with the exception of price impact—for which the increase is insignificant, with a $t$-statistic of 1.5). In contrast, high-priced stocks are mostly unaffected by distraction days and the difference between low- and high-priced stocks is typically significant.

[[ Insert Table 7 around here ]]

So far, we have relied on indirect proxies for retail ownership. We now measure it directly using institutional ownership data derived from 13(f) filings. In the Securities Exchange Act of 1975, section 13(f) requires institutional investment managers with more than $100 million in assets under management to disclose any holdings that exceed 10,000 shares or $200,000 in value. It follows that the fraction of shares *not* held by these institutions must be held either by smaller institutions or by retail investors, hence we expect stronger results for stocks in the lowest tercile of institutional ownership. Because this data is available only from the early 1980s, our sample is reduced to 351 events.

[[ Insert Table 8 around here ]]

Our results for institutional ownership, which are reported in Table 8, are consistent with those obtained from sorting stocks on market capitalization and share price. In the lowest tercile of such ownership, trading activity, return volatility (Panel A) and liquidity (Panel B) all decline. In particular, the stocks in that tercile experience a 3% reduction in turnover, a 3% reduction in intraday volatility, and a 2%–4% increase in spreads. All these changes are significant at the 5% level (except for price impact, where the increase is only marginally significant) and abate monotonically in the other terciles. For most measures, the difference between the top and bottom terciles is also significant.

The results from our three sample splits paint a consistent picture: on distraction days, stocks with high levels of retail ownership see reduced trading activity, volatility, and liquidity, whereas stocks with low retail ownership are unaffected. These findings confirm our intuition that sensational news events distract retail traders but have little effect on institutional investors. Tying the results to our model predictions, we conclude that distraction mainly causes a reduction in noise trading (though there is evidence of some decline in liquidity provision).

## IV. Robustness

In this section we check the robustness of our results to the choice of keywords used to distill the event list, and also to event clustering. In addition, we address endogeneity concerns and discuss an alternative explanation based on investor sentiment.

*A. Robustness of Results to the Event List*

As described in Section I, we used a list of economic keywords to filter 1,084 high-news pressure days down to a set of 532. In unreported analyses, we find that our results are robust to changes in the event list. For example, we check that our results are not driven by a few outlier events. We also experiment with a manual filter, since some events may have economic relevance even though no economic keyword appears in the headline (e.g., political party conventions, where economic policy agendas are announced and presidential candidates are determined). Results are strongly similar to those obtained with the arguably less subjective keyword filter.

[[ Insert Table 9 around here ]]

The fact that specific keywords do not alter our results leads us to conclude that, despite all their differences, most high-news pressure days are very much alike: they feature sensational news stories that have little bearing on the economy. This conjecture is confirmed in Table 9, which uses all 1,084 high-news pressure days and reports even stronger results (owing to the increased statistical power from doubling the number of events). Both trading activity and volatility decline significantly in the bottom terciles of firm size, stock price, and institutional ownership.[21] All adverse selection measures increase significantly—including price impact, which was only marginally significant before. Realized spreads also increase. Taken together, these results confirm that high news pressure distracts retail traders and thereby affects the stocks they own.

*B. Robustness of Results to Event Clustering*

Given that some distraction events are separated by only a few days, the clustering of events over time may have led us to overstate the statistical significance of our findings. According to Table 1, for example, the two most newsworthy days in 1986 (28 and 29 January) each concerned the *Challenger* space shuttle explosion. Until now, we have treated such events as independent. In Table 10, we repeat our main analyses while restricting the sample to *distinct* distraction events, defined as events that occur at least five business days (one full calendar week) apart. This approach is conservative because

[21] To save space, in Table 9 we report results for these terciles only. Results in the other terciles remain largely insignificant, as before, although now there is slightly stronger evidence for increased volatility in the top terciles (perhaps because some economic news crept into our sample).

it discards all the information contained in an event that is close to a previous one. Although only 370 events survive this requirement, our main results still obtain: stocks with high retail ownership (as proxied by firm size, by stock price, or by institutional ownership) experience a significant decrease in trading activity, volatility, and liquidity. Hence we conclude that our findings are robust to event clustering.

[[ Insert Table 10 around here ]]

*C. Endogeneity*

We acknowledge that news pressure—the criterion by which we select candidate distraction events—could be endogenous to the stock market. There are two facets of this endogeneity, but we argue that only one of them can be consistent with our results.

The first facet of endogeneity is that news pressure is elevated on days with important *economic* news. In that case, the patterns we document for the market are caused by the economic news itself—rather than by investors' distraction, as we claim. The economic filters we impose are an attempt to mitigate this concern. Moreover, we found that news pressure is only weakly related to indicators of business activity, newspaper sentiment, or macroeconomic news releases (see Internet Appendix B.2). Yet we acknowledge that it is impossible to guarantee that none of the events on our list affect the US economy. We emphasize, however, that this concern, if anything, biases our results *against* finding any distraction effect because economic news triggers more (rather than less) turnover and volatility.[22] In essence, our identification strategy draws on the discrepancy between the exuberant *news coverage* and the fundamental *newsworthiness* of a media story. Distraction effects, such as those that we document, prevail when the former outweighs the latter.

The second endogeneity concern is reverse causality: news pressure may be especially 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. This explanation is consistent with our finding

[22] In Internet Appendix B.3, we confirm this intuition by conducting event studies for two different lists of economic events. First, we examine 37 high–news pressure days on which the stock market is the topic of a news segment (these days are filtered out from the list of distraction events thanks to our "stock market" keyword). Second, we look at scheduled meetings of the Federal Open Market Committee, which are among the most anticipated recurring macroeconomic news events. For both these lists, we find a strong increase in trading volume and volatility.

that trading activity and volatility are low when news pressure is high. We make three counterarguments. First, if high news pressure is in fact caused by the absence of newsworthy material on high-news pressure days, then we should expect to find lower TV viewership on those days. Hence this explanation is difficult to reconcile with the surge in TV viewership documented in Table 1. Second, 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*. This means that our results cannot be driven by an implicit sorting on the absence of economic news. Third, we conduct a placebo analysis on *low*-news pressure days. In this analysis, events consist of days with no economic news (just as in the main analysis) but on which news pressure is in the lowest decile for the year (rather than in the highest decile, as in the main analysis). If the reverse causality argument were correct, days with low news pressure would feature lots of economic news; we should then expect these days to display heightened trading activity and volatility. The results of this placebo exercise, reported in Table 11, indicate no such effect. In short, our results are driven by positive spikes in news pressure unrelated to the economy—that is, by distracting events.

[[ Insert Table 11 around here ]]

*D. Alternative Explanation Based on Investor Sentiment*

Many of the distraction events in our sample carry a negative connotation because they pertain to natural disasters, terrorist attacks, accidents, or celebrity deaths.[23] Hence the question arises of whether our results could be explained (or confounded) by shocks to investor sentiment.[24] In our view, there are two reasons why this is unlikely. First, a negative shock to sentiment should be associated with a significantly negative return. Although we do observe a negative sign for the abnormal market return on distraction days (see Table 5, Panel A), this effect is both economically small and statistically insignificant. Second, Garcia (2013) reports that both positive and negative shocks to

[23] This tendency is confirmed in the correlation analysis of Internet Appendix B.2, where we show that the negative tone of stock market columns in the *New York Times* is significantly negatively correlated with news pressure (although the economic magnitude of this correlation is small).

[24] Several papers study the effect of investor sentiment on stock returns. See, for example, Saunders (1993), Hirshleifer and Shumway (2003), Kamstra et al. (2003), and Edmans et al. (2007) for studies on exogenous mood variables pertaining to weather, lunar phases, or sports results; see Tetlock (2007) and Garcia (2013), among others, for studies on sentiment extracted from newspaper columns.

investor sentiment lead to a surge in trading activity—yet we observe the exact opposite on distraction days. Finally, we manually split our distraction sample into positive/neutral and negative events but failed to find a significantly lower return for the negative events (results available upon request). We conclude that the sensational news stories in our sample are at most remotely related to investor sentiment.

## V. Who Is Distracted?

So far, our results—specifically, increased adverse selection and reduced volatility—suggest that noise traders are the ones who are distracted. One piece of evidence—the increase in realized spreads—further suggests that liquidity provision is also affected. In this section, we shed light on who is distracted.

### *A. Noise Traders*

We return to the brokerage data set studied in Section II and take a closer look at which households are distracted. We examine whether the distraction effect is stronger for more overconfident investors—that is, investors who are commonly regarded as noise traders. In Table 12, we carry out the event study for the number of households trading, *log(#households)*, on groups of households sorted on the extent of their overconfidence.

[[ Insert Table 12 around here ]]

Our first proxy for overconfidence is gender. Many studies in psychology demonstrate that men are more overconfident than women. In finance, Barber and Odean (2001) document that men trade more frequently than women, which hurts their performance. We define a dummy variable, *single_male*, which is set equal to 1 for a single male investor and to 0 for a single female investor; we focus on single households because Barber and Odean (2001) find the most pronounced differences among them. Row [1] of Table 12 shows that male investors are strongly distracted whereas female investors are not (the difference between the groups is significant).

In row [2] we check for whether or not distraction is greater for households with a high portfolio concentration (as measured by the average Herfindahl index over monthly portfolio holdings). A household that holds a concentrated portfolio forgoes the benefits of diversification, which indicates that it has strong—and likely ill-placed—faith in the few stocks it chooses. We find that households with an above-median portfolio concentration are twice as likely to be distracted as those with a below-median concentration; however, this difference is not statistically significant. In row [3] of the table, we check for whether or not the distraction effect is stronger for more active traders. To measure their propensity to trade, we sort households according to their average trading volume over the sample period. The evidence again reveals a strong distraction effect for the most active traders but not for the least active ones; the difference is statistically significant.

In row [4], we proxy for households' overconfidence via their investment performance measured as dollar losses (since investors who are more overconfident perform worse). Much as with the other proxies, households with above-median losses are twice as likely to be distracted as those with below-median losses (though the difference is not significant). Finally, in row [5] we combine our 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 the (inverse) rank of portfolio profits. We find that households that score high on this measure—namely, active traders performing poorly—are significantly distracted whereas households that are less active and/or more skilled are not distracted; again the difference is significant.

Altogether, these results demonstrate that overconfident/biased investors are more likely to be distracted from trading. Ironically, since these investors trade too much (Barber and Odean, 2001), they actually *benefit* from being distracted. This result offers a more nuanced view of inattention: it need not be detrimental (as is commonly assumed in the literature) because inattention—when interacting with behavioral biases—may benefit the trader.

*B. Liquidity Providers*

While the increase in adverse selection that we document—recall that the Amihud illiquidity ratio, the price impact, the absolute trade imbalance, and lambda all rise—is consistent with a decline in the variance of noise trading, the increase in realized spread is not.[25] One interpretation of this finding is that both the demand for liquidity and the provision of liquidity fall on distraction days.[26] That is, retail traders might not only demand less liquidity (noise traders are distracted) but also supply less liquidity. Indeed, several studies have documented that retail investors often trade in a contrarian fashion (i.e., buying/selling when prices fall/rise) and thereby provide liquidity to institutions (Kaniel et al., 2008). Alternatively, distracted professional market makers (specialists) may be responsible for the reduction in liquidity supply.

To assess the effect of distraction on liquidity provision, it would be ideal to study whether the supply of limit orders changes on distraction days. Unfortunately, none of our data sources contains information on order types. Given these data limitations, we tackle this question indirectly by devising two empirical tests that shed light on which type of liquidity providers are distracted: retail investors or (specialist) market makers.

The first test, whose results are presented in Panel A of Table 13, exploits the intraday frequency of quote updates (measured every five minutes), which captures the quote-processing activity of market makers (i.e., quote cancellations and updates). According to the panel's first row, the fraction of five-minute intervals with no quote change (referred to as *zero-return* intervals) increases sharply for stocks with high retail ownership, while no such effect is discernible for low-retail ownership stocks (not reported). This increase may be due to market makers being distracted from updating their quotes, but it could also be due to there being fewer market-moving trades.

To sort out these interpretations, we decompose the fraction of zero-return intervals into (a) the fraction of intervals with no trade and (b) the fraction of intervals with zero return conditional on there being no trade. We expect the latter measure to track closely the attention paid by specialist market makers, as we surmise that these agents are the ones

25 In fact, models of inventory risk (e.g., Ho and Stoll, 1980; Ho and Stoll, 1981; Grossman and Miller, 1988) predict that a reduction in noise trading reduces the inventory risk of market makers and so should yield greater liquidity. Due to the short-lived nature of our shocks, we don't expect this inventory risk channel to matter much here (see also Section III.A).

26 Our model allow us to rule out the possibility that *only* liquidity providers are distracted. Specifically, if market makers alone are distracted then our model predicts lower trading volume, less liquidity, and *higher* volatility. Since we find that event days reduce volatility, we can reject this hypothesis. We therefore reason that both the demand and supply of liquidity fall on distraction days and that the volatility effect of the drop in liquidity demand dominates the corresponding effect with respect to supply. After all, we found the distraction effect to be most pronounced for biased retail investors, which suggests that liquidity demand (noise trading) may be more affected than liquidity provision.

most responsible for canceling and updating quotes in the absence of trading. Indeed, Linnainmaa (2010) finds that retail traders rarely cancel or update limit orders after submitting them. The last two rows of Panel A give the results of this decomposition. The fraction of five-minute intervals with no trade strongly increases on distraction days for high-retail ownership stocks whereas the fraction of zero-return intervals conditional on no trade is not affected (with the exception of low-priced stocks, where the rank test shows a marginally significant increase). This finding suggests that professional market makers are not distracted and hence that retail investors are responsible for the reduced liquidity provision on distraction days.

[[ Insert Table 13 around here ]]

Our second test corroborates this result. Here, we look at contrarian trades executed by retail investors—in other words, at trades that actually supply liquidity to the market. Following Barber et al. (2009), we define as "contrarian" all buys (resp. sells) made on days when the stock's return is negative (resp. positive). We are interested in whether fewer households make contrarian trades on distraction days. One problem with this approach is that we cannot be sure that a drop in contrarian trades actually reflects reduced liquidity provision; it might simply be explained by there being fewer trades overall. For this reason, we focus our analysis on contrarian retail trades in stocks that experience no decline in overall trading activity. Thus we analyze stocks in the top tercile in terms of market capitalization, stock price, and institutional ownership (see Tables 6–8). A decline in contrarian trades for these stocks must come from retail investors providing less liquidity, presumably because they are distracted. Panel B of Table 13 presents the results of this test. The number of contrarian households drops significantly across all three sorting variables, and the decline of about 5% is similar to that reported in Table 2 (which considered all trades in all stocks). This finding suggests that retail traders indeed supply less liquidity on distraction days, which explains why the realized spread increases among high-retail ownership stocks.

Overall, we find that, on distraction days, both the demand for liquidity—coming from noise traders—and the supply of liquidity are reduced. The latter effect is driven by retail liquidity providers, rather than specialist market makers, being distracted.

## VI. Conclusion

This paper studies the causal effect of retail trading on stock market liquidity. We exploit episodes of sensational news exogenous to the stock market that distracts retail investors from trading. On distraction days, trading activity, volatility and liquidity (both its adverse selection and inventory risk components) decrease among stocks owned predominantly by retail investors. Together with evidence that overconfident investors—in particular, those who are male, relatively more active, and likely to have lost money—are more prone to being distracted, our results support the notion that retail investors behave as noise traders. The rise in inventory costs suggests that retail investors also serve as market makers. We conclude that retail traders contribute to liquidity by acting both as noise traders and as liquidity providers.

Among other contributions, our findings have important implications for the research on liquidity. First, they confirm that liquidity measures actually respond to short-lived changes in the intensities of noise trading and market making, just as predicted by theories of adverse selection (e.g., Glosten and Milgrom, 1985; Kyle, 1985), and thus provide countervailing evidence to recent work that questions the usefulness of these measures (Collin-Dufresne and Fos, 2015; Kacperczyk and Pagnotta, 2016). Second, we reconcile seemingly inconsistent results reported in the literature. We start from the insight that the components of liquidity are affected differently by long- and short-lived shocks to the intensity of noise trading: inventory concerns loom large when market makers face long-lasting changes to noise trading, which explains why Foucault et al. (2011) find a liquidity improvement in response to a permanent reduction in the intensity of retail trading. In contrast, inventory risk is hardly affected when the drop in noise trading is short-lived—as with our distraction shocks—which leads adverse selection to dominate and hence liquidity to worsen. More broadly, our results suggest that the question of what determines liquidity merits a more nuanced answer—one that, for example, depends on both the nature and persistence of changes to the stock market landscape. By solving a dynamic Kyle (1985) model under a general stochastic process for noise trading, Collin-Dufresne and Fos (2016) take an important step in this direction. We look forward to seeing more work in this area.

## REFERENCES


Abel, Andrew B., Janice C. Eberly, and Stavros Panageas, 2007, Optimal inattention to the stock market, *American Economic Review* 97, 244–249.

Abel, Andrew B., Janice C. Eberly, and Stavros Panageas, 2013, Optimal inattention to the stock market with information costs and transactions costs, *Econometrica* 81, 1455–1481.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Aruoba, S. Borağan, Francis X. Diebold, and Chiara Scotti, 2009, Real-time measurement of business conditions, Journal of Business and Economic Statistics 27, 417–427.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2016, Measuring economic policy uncertainty, Working paper.

Barber, Brad, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

Barber, Brad, and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–92.

Barber, Brad, and Terrance Odean, 2002, Online investors: Do the slow die first?, *Review of Financial Studies* 15, 455–89.

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

Barber, Brad, and Terrance Odean, and N. Zhu, 2009, Do retail trades move markets? *Review of Financial Studies* 22, 151–186.

Barber, Brad, Terrance Odean, and Ning Zhu, 2009, Systematic noise, *Journal of Financial Markets* 22, 547–569.

Bennett, James A., Richard W. Sias, and Laura T. Starks, 2003, Greener pastures and the impact of dynamic institutional preferences, *Review of Financial Studies* 16, 1203–1238.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen, 2016, It depends on where you search: A comparison of institutional and retail attention, Working paper.

Benston, George, Robert L. Hagerman, 1974, Determinants of bid-asked spreads in the over-the-counter market, *Journal of Financial Economics* 1, 353–364.

Boehmer, Ekkehart, Jim Musumeci, and Annette B. Poulsen, 1991, Event-study methodology under conditions of event-induced variance, *Journal of Financial Economics* 30, 253–272.

Boudoukh, Jacob, Ronen Feldman, Shimon Kogan, and Matthew P. Richardson, 2013, Which news moves stock prices? A textual analysis, Working paper.

Brandt, Michael W., Alon Brav, John R. Graham, and Alok Kumar, 2010, The idiosyncratic volatility puzzle: Time trend or speculative episodes?, *Review of Financial Studies* 23, 863–899.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 1–43.

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

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3–28.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *Journal of Finance* 63, 1977–2011.

Collin-Dufresne, Pierre, and Vyacheslav Fos, 2015, Do prices reveal the presence of informed trading? *Journal of Finance* 70, 1555–1582.

Collin-Dufresne, Pierre, and Vyacheslav Fos, 2016, Insider trading, stochastic liquidity, and equilibrium prices, *Econometrica*, forthcoming.

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

Cutler, David M., James M. Poterba, and Lawrence H. Summers, 1989, What moves stock prices? *Journal of Portfolio Management* 15, 4–12.

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

DellaVigna, Stefano, and Joshua Pollet, 2009, Investor inattention, firm reaction, and Friday earnings announcements, *Journal of Finance* 64, 709–749.

Dershowitz, Alan M., 2004, America on trial: inside the legal battles that transformed our nation (Grand Central Publishing, New York City, NY).

Easley, David, Robert Engle, Maureen O'Hara, and Liuren Wu, 2008, Time-varying arrival rates of informed and uninformed trades, *Journal of Financial Econometrics* 6, 171–207.

Easley, David, Søren Hvidkjaer, and Maureen O'Hara, 2002, Is information risk a determinant of asset returns? *Journal of Finance* 57, 2185–2221.

Edmans, Alex, Diego Garcia, and Oyvind Norli, 2007, Sports sentiment and stock returns, *Journal of Finance* 62, 1967–1998.

Eisensee, Thomas, and David Strömberg, 2007, News droughts, news floods, and U.S. disaster relief, *Quarterly Journal of Economics* 122, 693–728.

Foucault, Thierry, Johan Hombert, and Ioanid Roşu, 2016, News trading and speed, *Journal of Finance* 71, 335–382.

Foucault, Thierry, David Sraer, and David Thesmar, 2011, Individual investors and volatility, *Journal of Finance* 66, 1369–1406.

Garcia, Diego, 2013, Sentiment during recessions, *Journal of Finance* 68, 1267–1300.

Glosten, Lawrence, and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Gompers, Paul A., and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229–359.

Goyenko, Ruslan Y., Craig W. Holden, and Charles A. Trzcinka, 2009, Do liquidity measures measure liquidity? *Journal of Financial Economics* 92, 153–181.

Greene, Jason, and Scott Smart, 1999, Liquidity provision and noise trading: Evidence from the "Investment Dartboard" column, *Journal of Finance* 54, 1885–1899.

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and market structure, *Journal of Finance* 43, 617–633.

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

Hameed, Allaudeen, Wenjin Kang, and S. Viswanathan, 2010, Stock market declines and liquidity, *Journal of Finance* 65, 257–293.

Hendershott, Terrence, and Albert J. Menkveld, 2014, Price pressures, *Journal of Financial Economics* 114, 405–423.

Hirshleifer, David, Sonya S. Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *Journal of Finance* 64, 2289–2235.

Hirshleifer, David, and Tyler Shumway, 2003, Good day sunshine: Stock returns and the weather, *Journal of Finance* 58, 1009–1023.

Ho, Thomas, and Hans R. Stoll, 1980, On dealer markets under competition, *Journal of Finance* 35, 259–267.

Ho, Thomas, and Hans R. Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47–73.

Holden, Craig W., and Stacey Jacobsen, 2014, Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions, *Journal of Finance* 69, 1747–1785.

Hong, Harrison, and Jeremy C. Stein, 2007, Disagreement and the stock market, *Journal of Economic Perspectives* 21, 109–128.

Hvidkjaer, Søren, 2006, A trade-based analysis of momentum, *Review of Financial Studies* 19, 457–491.

Hvidkjaer, Søren, 2008, Small trades and the cross-section of stock returns, *Review of Financial Studies* 21, 1123–1151.

Kacperczyk, Marcin, and Emiliano Pagnotta, 2016, Chasing prive information, Working paper.

Kamstra, Mark J., Lisa A. Kramer, and Maurice D. Levi, 2003, Winter blues: A SAD stock market cycle, *American Economic Review* 93, 324–343.

Kaniel, Ron, Shuming Liu, Gideon Saar, and Sheridan Titman, 2012, Investor trading and return patterns around earnings announcements, *Journal of Finance* 67, 639–680.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual investor trading and stock returns, *Journal of Finance* 63, 273–310.

Kaul, Gautam, Qin Lei, and Noah Stoffman, 2008, AIMing at PIN: Order flow, information, and liquidity, Working paper.

Kelley, Eric K., and Paul C. Tetlock, 2013, How wise are crowds? Insights from retail orders and stock returns, *Journal of Finance* 68, 1229–1265.

Kim, Daejin, 2014, Thee essays on market microstructure, Dissertation.

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

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.

Lee, Charles M.C., and Balkrishna Radhakrishna, 2000, Inferring investor behavior: Evidence from TORQ data, *Journal of Financial Markets* 3, 83–111.

Lee, Charles M.C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.

Lee, Charles M.C., Andrei Shleifer, and Richard Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle, *Journal of Finance* 46, 75–109.

Linnainmaa, Juhani T., 2010, Do limit orders alter inferences about investor performance and behavior? *Journal of Finance* 65, 1473–1506.

Llorente, Guillermo, Roni Michaely, Gideon Saar, and Jiang Wang, 2002, Dynamic volume-return relation of individual stocks, *Review of Financial Studies* 15, 1005–1047.

Lucca, David O., and Emanuel Moench, 2015, The pre-FOMC announcement drift, *Journal of Finance* 70, 329–371.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483–510.

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

Patell, James M., 1976, Corporate forecasts of earnings per share and stock price behavior: Empirical tests, *Journal of Accounting Research* 14, 246–276.

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

Peress, Joel, 2008, Media coverage and investors' attention to earnings announcements, Working paper, INSEAD.

Rydqvist, Kristian, Joshua Spizman, and Ilya Strebulaev, 2014, Government policy and ownership of equity securities, *Journal of Financial Economics* 111, 70–85.

Saunders, Edward M., 1993, Stock prices and Wall Street weather, *American Economic Review* 83, 1337–1345.

Stoll, Hans R., 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133–1151.

Subrahmanyam, Avanidhar, 1991, Risk aversion, market liquidity, and price efficiency, *Review of Financial Studies* 4, 417–441.

Tetlock, Paul C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139–1168.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2010, Information acquisition and under-diversification, *Review of Economic Studies* 77, 779–805.

Verrecchia, Robert E., 1982, Information acquisition in a noisy rational expectations economy, *Econometrica* 50, 1415–1430.

Yuan, Yu, 2015, Market-wide attention, trading, and stock returns, *Journal of Financial Economics* 116, 548-564.

**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.

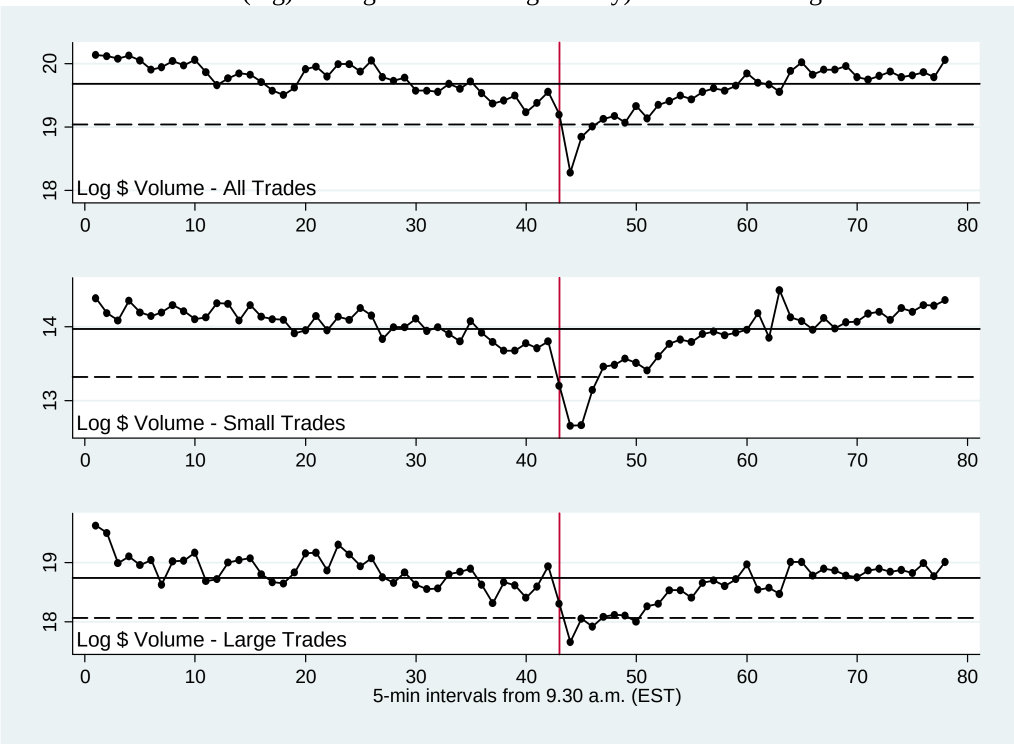


**Figure 2: Daily News Pressure and Distraction Events**

The blue line 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 filter for excluding potential economic news (see Section I).

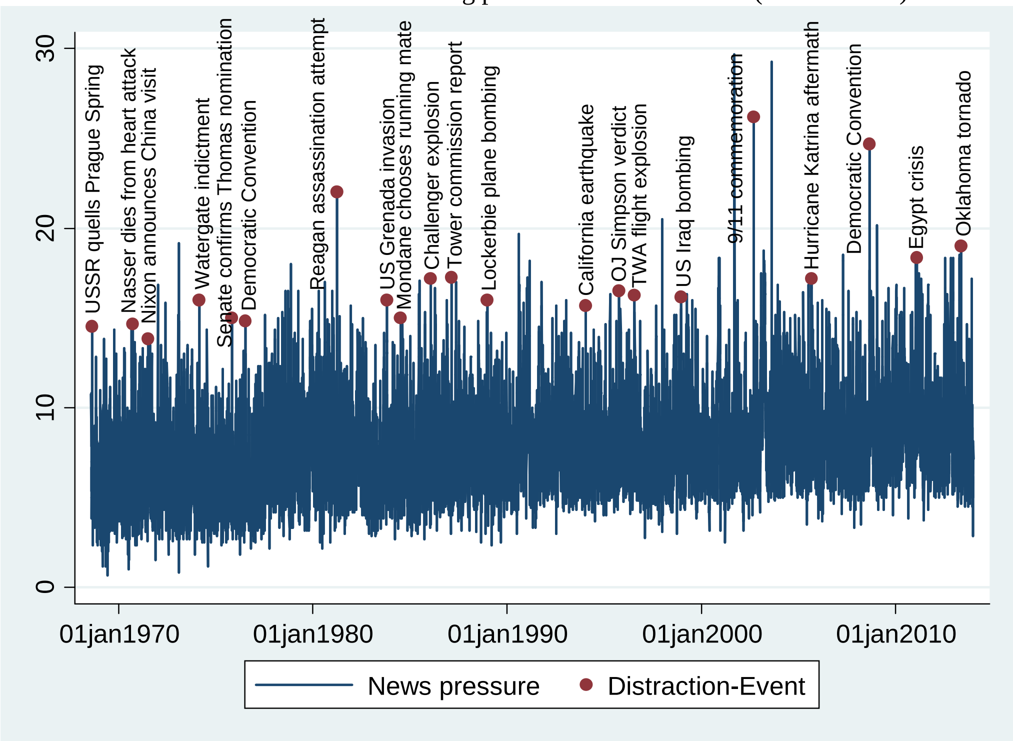
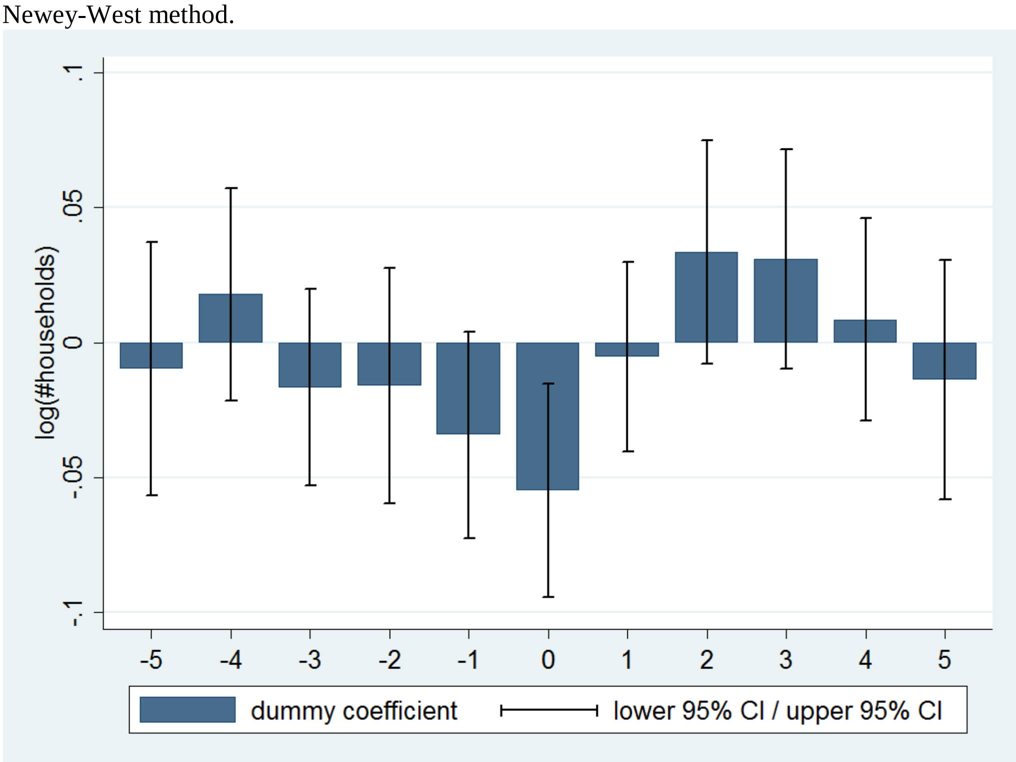



**Figure 3: Distraction Effect on Retail Trading in Event Time**

This graph shows the coefficient estimates and their confidence intervals from regressing (de-seasonalized and de-trended) logarithm of number of households trading (using data from the discount broker) on a set of event-time dummies. For instance, the bar at 0 represents the coefficient estimate on a dummy variable indicating distraction days; the bar at -1 is the coefficient estimate on a dummy variable indicating trading days one day prior to distraction days; etc. Confidence bars are based on standard errors adjusted for auto-correlation up to 3 lags with the Newey-West method.



## Table 1: Distraction Events

In Panel A, we show event study results for TV viewership over the period 1991-2013 (216 distraction events) using data from Nielsen Research. The estimation period includes all trading days without economic news within a 200-day window centered on the distraction event. Column (1) shows the abnormal value of the logarithm of average daily CNN viewership (scaled by the number of U.S. households). Column (2) shows the abnormal value of the logarithm of average 6:30-7:00 pm news broadcasts viewership for ABC, CBS, and NBC. Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively. In Panel B, we provide 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 survived our economic news filter) together with a short description of the accompanying news story.

Panel A: TV Viewership on Distraction Events

| (1) | | (2) | |
|---|---|---|---|
| CNN viewership (total day) | | ABC, CBS, NBC viewership (6:30-7:00pm) | |
| 0.339 | | 0.031 | |
| (12.9119) | *** | (5.8892) | *** |
| [10.3916] | *** | [4.7097] | *** |
| 216 | | 216 | |

Panel B: Two Highest News Pressure Events (without economic keyword in their headline) per Year

| 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 | Jun 17 | TWA847 hijacking |
| 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 | Aug 14 | Northeast blackout | Oct 27 | California wildfires |
| 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: Distraction Events and Retail Trading

This table reports event-study results for retail trading activity on distraction days. Panel A shows the results for the discount brokerage data over the period 1991-1996 (66 distraction events). Panel B shows the results for ISSM/TAQ transaction data over the period 1991-2000 (105 distraction events). In Panel A, *Log($volume)* is the average across stocks and then across investors of the logarithm of dollar volume of trade. *Log(#stocks)* is the average across investors of the logarithm of the number of different stocks traded. *Log(#households*) is the logarithm of the number of households trading. In Panel B, *Log($volume)* is the logarithm of aggregated dollar volume of trade in the respective trade size group. Trades are classified into small trades and large trades based on a procedure described in Hvidkjaer (2006). The estimation period includes all trading days without economic news within a 200-day window centered on the distraction event. In Panel A, 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). In Panel B, columns (1) and (2) show the results for small and large trades, respectively. Column (3) tests for the difference between small and large trades. Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Discount Brokerage Data

| | (1) Buys | | (2) Sells | | (3) Difference | | (4) Total trades | |
|---|---|---|---|---|---|---|---|---|
| Log($volume) | -0.024 | | -0.013 | | -0.011 | | -0.017 | |
| | (-1.624) | | (-0.869) | | (-0.489) | | (-1.341) | |
| | [-1.869] | * | [-0.712] | | [-0.086] | | [-1.575] | |
| Log(#stocks) | -0.011 | | 0.002 | | -0.012 | | -0.008 | |
| | (-2.572) | ** | (0.484) | | (-2.043) | ** | (-2.039) | ** |
| | [-2.546] | ** | [-0.061] | | [-1.734] | * | [-2.118] | ** |
| Log(#households) | -0.054 | | -0.057 | | 0.003 | | -0.051 | |
| | (-2.857) | *** | (-2.061) | ** | (-0.714) | | (-2.609) | ** |
| | [-2.693] | *** | [-2.067] | ** | [0.214] | | [-2.431] | ** |
| *N* | 66 | | 66 | | 66 | | 66 | |

Panel B: Aggregated ISSM/TAQ Data

| | (1) Small trades | | (2) Large trades | | (3) Difference | |
|---|---|---|---|---|---|---|
| Log($volume) | -0.0203 | | -0.0072 | | 0.0132 | |
| | (-1.822) | * | (-0.451) | | (2.072) | ** |
| | [-2.201] | ** | [-0.321] | | [1.680] | * |
| | 105 | | 105 | | 105 | |

**Table 3: Predictions from a Model of Informed Trading with a Risk-Averse Market Maker**

This table summarizes the implications of distracting one of the three types of agents in a model of informed trading à la Kyle (1985), in which a risk-averse market maker receives a signal about the final dividend. Noise traders being distracted is modelled as a decrease in the variance of noise trades. The insider being distracted is modelled as an increase in the variance of her signal. The market maker being distracted is modelled as an increase in the variance of his signal. Implications for trading volume, liquidity, and return volatility are displayed under each of these three interpretations.

| | | Trading volume | Liquidity | Return volatility |
|---|---|---|---|---|
| Who is distracted in the model? | [1] Noise traders | Reduced | Reduced | Reduced |
| | [2] Insider | Reduced | Increased | Ambiguous |
| | [3] Market maker | Reduced | Reduced | Increased |
| What we find in the data | | Reduced | Reduced | Reduced |

**Table 4: Descriptive Statistics for Market Variables**

This table reports descriptive statistics for our stock market data. All variables are equal-weighted across stocks. *Mkt return* is the average market return (in percentage points, denoted pp; i.e., multiplied by 100). *Turnover* is the average of share turnover (i.e., the ratio of dollar volume to market capitalization; in pp). *$volume* is the average daily dollar volume (in $mn). *Log(turnover)* and *log($volume)* are averages of the natural logarithms of these measures. *Abs return* is the average of the absolute raw return (in pp). *Price range* is the average of the logarithm of the ratio of daily high-price over low-price (in pp). *Intraday volatility* is the average of the standard deviation of intraday returns over 5-minute intervals (in pp). *Closing bid-ask spread* is the average of the relative bid-ask spread at market close (in pp). *Average bid-ask spread* is the average of the mean daily relative bid-ask spread (in pp). *Effective spread* is the average relative difference between the transaction price and the mid-quote prior to the transaction (in pp). *Amihud* is the 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 average of the natural logarithm of the Amihud illiquidity ratio. *Price impact* is the average relative difference between the mid-quote 5 minutes after and prior to the transaction (in pp). *Absolute trade imbalance* is the average of the absolute value of (dollar volume of) buys minus sells over buys plus sells (in pp). *Lambda* is the average slope coefficient of regressing returns on order flow over 5-minute intervals (multiplied by 10,000 for visibility). *Realized spread* is the average relative difference between the mid-quote 5 minutes after the transaction and the transaction price (in pp). All variables are defined in detail in the Appendix. Panel A shows statistics for the raw measures (after winsorizing; and before taking logs for turnover, dollar volume and Amihud). Panel B 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).

Panel A: Raw Variables

| | mean | median | sd | p1 | p25 | p75 | p99 |
|---|---|---|---|---|---|---|---|
| Mkt Return | 0.056 | 0.117 | 1.011 | -2.934 | -0.350 | 0.527 | 2.821 |
| *Trading activity* | | | | | | | |
| Turnover | 0.566 | 0.547 | 0.239 | 0.199 | 0.357 | 0.737 | 1.165 |
| $Volume | 13.397 | 7.113 | 13.227 | 0.986 | 2.077 | 24.085 | 45.345 |
| *Volatility* | | | | | | | |
| Abs return | 2.358 | 2.267 | 0.777 | 1.312 | 1.814 | 2.676 | 5.044 |
| Price range | 3.934 | 3.766 | 1.250 | 2.401 | 3.073 | 4.312 | 8.581 |
| Intraday Volatility | 0.298 | 0.278 | 0.090 | 0.194 | 0.235 | 0.332 | 0.629 |
| *Liquidity - overall* | | | | | | | |
| Closing bid-ask spread | 2.687 | 2.835 | 1.835 | 0.439 | 0.760 | 4.130 | 6.967 |
| Average bid-ask spread | 1.783 | 1.436 | 0.980 | 0.556 | 0.873 | 2.710 | 3.614 |
| Effective spread | 1.284 | 1.040 | 0.687 | 0.427 | 0.637 | 2.001 | 2.516 |
| *Liquidity - adverse selection* | | | | | | | |
| Amihud | 1.433 | 1.287 | 1.052 | 0.153 | 0.502 | 2.013 | 4.556 |
| Price impact | 0.387 | 0.387 | 0.148 | 0.154 | 0.270 | 0.480 | 0.765 |
| Absolute trade imbalance | 31.098 | 29.639 | 9.489 | 17.637 | 21.508 | 40.253 | 46.965 |
| Lambda | 0.072 | 0.070 | 0.040 | 0.005 | 0.042 | 0.095 | 0.181 |
| *Liquidity - inventory costs* | | | | | | | |
| Realized spread | 0.927 | 0.629 | 0.585 | 0.249 | 0.403 | 1.491 | 2.023 |

Panel B: Seasonality-Adjusted Variables

| | mean | median | sd | p1 | p25 | p75 | p99 |
|---|---|---|---|---|---|---|---|
| Mkt Return | 0.000 | 0.028 | 0.965 | -2.748 | -0.407 | 0.425 | 2.658 |
| *Trading activity* | | | | | | | |
| Log(turnover) | -0.001 | -0.004 | 0.144 | -0.437 | -0.068 | 0.068 | 0.402 |
| Log($volume) | -0.001 | -0.004 | 0.135 | -0.383 | -0.066 | 0.065 | 0.375 |
| *Volatility* | | | | | | | |
| Abs return | -0.001 | -0.032 | 0.391 | -0.889 | -0.149 | 0.088 | 1.428 |
| Price range | -0.002 | -0.029 | 0.493 | -1.206 | -0.184 | 0.133 | 1.587 |
| Intraday Volatility | 0.000 | -0.003 | 0.036 | -0.081 | -0.014 | 0.009 | 0.135 |
| *Liquidity - overall* | | | | | | | |
| Closing bid-ask spread | 0.000 | 0.000 | 0.005 | -0.012 | -0.002 | 0.001 | 0.016 |
| Average bid-ask spread | -0.001 | -0.010 | 0.191 | -0.287 | -0.055 | 0.030 | 0.425 |
| Effective spread | -0.001 | -0.004 | 0.081 | -0.205 | -0.029 | 0.023 | 0.251 |
| *Liquidity - adverse selection* | | | | | | | |
| Log(Amihud) | 0.000 | -0.005 | 0.070 | -0.157 | -0.039 | 0.033 | 0.208 |
| Price impact | 0.000 | -0.002 | 0.031 | -0.079 | -0.014 | 0.011 | 0.106 |
| Absolute trade imbalance | 0.006 | -0.046 | 1.136 | -2.363 | -0.606 | 0.518 | 4.210 |
| Lambda | 0.000 | 0.000 | 0.008 | -0.023 | -0.003 | 0.003 | 0.028 |
| *Liquidity - inventory costs* | | | | | | | |
| Realized spread | -0.001 | -0.003 | 0.067 | -0.164 | -0.025 | 0.019 | 0.185 |

## Table 5: Market-Wide Event Study

This table reports (equal-weighted) market-wide event-study results for the 532 distraction events that fall into the period 1968 to 2013. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. All variables are defined in the Appendix. Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, the z-statistic for the non-parametric rank test in square brackets, and the number of events for which the particular variable is available. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

| (1) Mkt return | (2) Log(turnover) | (3) Log($volume) |
|---|---|---|
| -0.022 | -0.009 | -0.012 |
| (-0.9033) | (-1.1816) | (-1.5272) |
| [-1.2294] | [-1.1158] | [-1.5062] |
| 532 | 532 | 532 |

| (4) Abs return | (5) Price range | (6) Return volatility |
|---|---|---|
| -0.003 | -0.013 | -0.005 |
| (1.0089) | (0.4455) | (-0.8645) |
| [-1.5748] | [-0.7848] | [-2.096] ** |
| 532 | 532 | 206 |

| (7) Closing bid-ask spread | (8) Average bid-ask spread | (9) Effective spread | (10) Realized spread |
|---|---|---|---|
| 0.012 | 0.000 | 0.009 | 0.008 |
| (2.3951) ** | (1.4208) | (1.4829) | (1.7566) * |
| [2.1985] ** | [0.0449] | [1.4691] | [1.3314] |
| 335 | 206 | 206 | 206 |

| (11) Log(amihud) | (12) Price impact | (13) Absolute trade imbalance | (14) Lambda |
|---|---|---|---|
| 0.009 | 0.002 | 0.150 | 0.002 |
| (2.6885) *** | (0.8865) | (1.8913) * | (2.0166) ** |
| [1.314] | [0.7185] | [1.5835] | [2.4147] ** |
| 532 | 206 | 206 | 206 |

## Table 6: Sample Split by Firm Size

This table reports event-study results for the 532 distraction events that fall into the period 1968 to 2013. The estimation period includes all trading days without economic news within a 200-day window centered on 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. All variables are defined in the Appendix. 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 t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

| | *N* | (1) Tercile 1 | | (2) Tercile 2 | | (3) Tercile 3 | | (4) Difference | |
|---|---|---|---|---|---|---|---|---|---|
| *Trading activity* | | | | | | | | | |
| Log(turnover) | *532* | -0.024 | | -0.014 | | 0.002 | | 0.026 | |
| | | (-3.174) | *** | (-1.511) | | (0.4049) | | (3.454) | *** |
| | | [-3.806] | *** | [-1.857] | * | [0.996] | | [4.257] | *** |
| Log($volume) | *532* | -0.028 | | -0.017 | | -0.001 | | 0.027 | |
| | | (-3.582) | *** | (-1.801) | * | (0.042) | | (3.604) | *** |
| | | [-4.138] | *** | [-2.143] | ** | [0.593] | | [4.290] | *** |
| *Volatility* | | | | | | | | | |
| Abs return | *532* | -0.009 | | -0.007 | | 0.007 | | 0.016 | |
| | | (-0.197) | | (0.445) | | (1.603) | | (1.897) | * |
| | | [-1.566] | | [-2.380] | ** | [-0.848] | | [0.991] | |
| Price range | *532* | -0.065 | | -0.016 | | 0.011 | | 0.076 | |
| | | (-2.743) | *** | (0.116) | | (1.922) | * | (4.358) | *** |
| | | [-3.748] | *** | [-1.452] | | [0.768] | | [4.665] | *** |
| Intraday Volatility | *206* | -0.0103 | | -0.0053 | | -0.0009 | | 0.0094 | |
| | | (-3.071) | *** | (-1.143) | | (0.701) | | (3.176) | *** |
| | | [-4.209] | *** | [-2.785] | *** | [0.639] | | [3.914] | *** |

Panel B: Liquidity

| | N | (1) Tercile 1 | (2) Tercile 2 | (3) Tercile 3 | (4) Difference |
|---|---|---|---|---|---|
| *Liquidity - overall* | | | | | |
| Closing bid-ask spread | *335* | 0.061 | 0.012 | -0.015 | -0.076 |
| | | (4.171)*** | (1.622) | (-0.448) | (-3.277)*** |
| | | [3.522]*** | [1.510] | [0.124] | [-3.436]*** |
| Average bid-ask spread | *206* | 0.042 | -0.002 | -0.021 | -0.063 |
| | | (2.607)*** | (0.943) | (-0.952) | (-2.229)** |
| | | [1.377] | [-0.500] | [-1.906]* | [-1.891]* |
| Effective spread | *206* | 0.043 | 0.014 | -0.013 | -0.056 |
| | | (2.301)** | (1.773)* | (0.211) | (-1.411) |
| | | [1.803]* | [1.845]* | [-0.819] | [-2.258]** |
| *Liquidity - adverse selection* | | | | | |
| Log(amihud) | *532* | 0.024 | 0.015 | -0.001 | -0.025 |
| | | (3.104)*** | (2.752)*** | (0.331) | (-2.154)** |
| | | [2.508]** | [1.680]* | [-0.748] | [-2.869]*** |
| Price impact | *206* | 0.010 | 0.003 | -0.003 | -0.012 |
| | | (1.677)* | (0.875) | (-0.009) | (-1.240) |
| | | [1.273] | [0.109] | [-0.009] | [-1.693]* |
| Absolute trade imbalance | *206* | 0.409 | 0.257 | -0.063 | -0.472 |
| | | (2.671)*** | (2.131)** | (-0.692) | (-2.992)*** |
| | | [2.581]*** | [1.712]* | [-1.630] | [-2.896]*** |
| Lambda | *206* | 0.009 | 0.004 | -0.001 | -0.010 |
| | | (2.968)*** | (1.899)* | (-0.450) | (-2.237)** |
| | | [3.288]*** | [2.414]** | [-0.249] | [-3.372]*** |
| *Liquidity - inventory costs* | | | | | |
| Realized spread | *206* | 0.037 | 0.011 | -0.010 | -0.047 |
| | | (2.575)** | (1.763)* | (-0.147) | (-1.854)* |
| | | [2.159]** | [1.299] | [-0.698] | [-2.270]** |

## Table 7: Sample Split by Stock Price

This table reports event-study results for the 532 distraction events that fall into the period 1968 to 2013. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. Stocks are sorted into three terciles based on their closing price on the last trading day prior to the event. All variables are defined in the Appendix. 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 t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

| | *N* | (1) Tercile 1 | | (2) Tercile 2 | | (3) Tercile 3 | | (4) Difference | |
|---|---|---|---|---|---|---|---|---|---|
| *Trading activity* | | | | | | | | | |
| Log(turnover) | *532* | -0.027 | | -0.013 | | 0.005 | | 0.031 | |
| | | (-3.308) | *** | (-1.531) | | (0.767) | | (4.126) | *** |
| | | [-3.880] | *** | [-1.673] | * | [1.298] | | [5.136] | *** |
| Log($volume) | *532* | -0.032 | | -0.016 | | 0.002 | | 0.034 | |
| | | (-3.682) | *** | (-1.820) | * | (0.475) | | (4.283) | *** |
| | | [-4.199] | *** | [-2.001] | ** | [0.949] | | [5.273] | *** |
| *Volatility* | | | | | | | | | |
| Abs return | *532* | -0.004 | | -0.003 | | 0.001 | | 0.006 | |
| | | (0.234) | | (0.798) | | (1.272) | | (1.179) | |
| | | [-1.438] | | [-1.856] | * | [-1.008] | | [1.078] | |
| Price range | *532* | -0.043 | | -0.017 | | 0.006 | | 0.049 | |
| | | (-1.349) | | (0.191) | | (1.772) | * | (3.168) | *** |
| | | [-2.617] | *** | [-1.280] | | [0.983] | | [3.775] | *** |
| Intraday Volatility | *206* | -0.0081 | | -0.0054 | | -0.0021 | | 0.006 | |
| | | (-2.394) | ** | (-0.698) | | (0.446) | | (2.875) | *** |
| | | [-3.425] | *** | [-2.499] | ** | [0.193] | | [3.290] | *** |

Panel B: Liquidity

| | *N* | (1) Tercile 1 | | (2) Tercile 2 | | (3) Tercile 3 | | (4) Difference | |
|---|---|---|---|---|---|---|---|---|---|
| *Liquidity - overall* | | | | | | | | | |
| Closing bid-ask spread | *335* | 0.057 | | 0.011 | | -0.016 | | -0.073 | |
| | | (3.748) | *** | (2.068) | ** | (-0.877) | | (-3.391) | *** |
| | | [3.307] | *** | [2.382] | ** | [-0.081] | | [-3.692] | *** |
| Average bid-ask spread | *206* | 0.0317 | | 0.0016 | | -0.0184 | | -0.0501 | |
| | | (2.512) | ** | (1.549) | | (-0.966) | | (-2.328) | ** |
| | | [1.026] | | [0.470] | | [-1.756] | * | [-1.624] | |
| Effective spread | *206* | 0.0401 | | 0.0118 | | -0.011 | | -0.0511 | |
| | | (2.281) | ** | (2.221) | ** | (0.139) | | (-1.474) | |
| | | [2.267] | ** | [2.047] | ** | [-0.787] | | [-2.661] | *** |
| *Liquidity - adverse selection* | | | | | | | | | |
| Log(amihud) | *532* | 0.026 | | 0.014 | | -0.004 | | -0.030 | |
| | | (3.381) | *** | (2.994) | *** | (-0.357) | | (-3.077) | *** |
| | | [3.174] | *** | [1.811] | * | [-1.045] | | [-3.892] | *** |
| Price impact | *206* | 0.008 | | 0.003 | | -0.002 | | -0.010 | |
| | | (1.495) | | (1.247) | | (-0.186) | | (-1.330) | |
| | | [1.028] | | [0.575] | | [-0.207] | | [-1.351] | |
| Absolute trade imbalance | *206* | 0.360 | | 0.173 | | 0.004 | | -0.356 | |
| | | (2.383) | ** | (1.856) | * | (-0.009) | | (-2.075) | ** |
| | | [2.642] | *** | [1.340] | | [-0.508] | | [-2.756] | *** |
| Lambda | *206* | 0.009 | | 0.002 | | -0.001 | | -0.010 | |
| | | (3.395) | *** | (1.612) | | (-0.793) | | (-2.889) | *** |
| | | [3.540] | *** | [1.700] | * | [-0.917] | | [-3.838] | *** |
| *Liquidity - inventory costs* | | | | | | | | | |
| Realized spread | *206* | 0.0328 | | 0.0094 | | -0.0083 | | -0.041 | |
| | | (2.717) | *** | (1.898) | * | (-0.325) | | (-2.072) | ** |
| | | [2.369] | ** | [1.838] | * | [-0.728] | | [-2.501] | ** |

**Table 8: Sample Split by Institutional Holdings**

This table reports event-study results for the 351 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 200-day window centered on 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. All variables are defined in the Appendix. 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 t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Liquidity

| | *N* | (1) Tercile 1 | | (2) Tercile 2 | | (3) Tercile 3 | | (4) Difference | |
|---|---|---|---|---|---|---|---|---|---|
| *Trading activity* | | | | | | | | | |
| Log(turnover) | *351* | -0.027 | | -0.012 | | 0.001 | | 0.028 | |
| | | (-2.936) | *** | (-1.242) | | (0.203) | | (3.779) | *** |
| | | [-2.894] | *** | [-0.853] | | [0.965] | | [4.151] | *** |
| Log($volume) | *351* | -0.031 | | -0.017 | | -0.004 | | 0.027 | |
| | | (-3.145) | *** | (-1.572) | | (-0.293) | | (3.654) | *** |
| | | [-3.160] | *** | [-1.342] | | [0.387] | | [4.274] | *** |
| *Volatility* | | | | | | | | | |
| Abs return | *351* | -0.011 | | 0.009 | | 0.016 | | 0.027 | |
| | | (-0.153) | | (1.699) | * | (2.110) | ** | (2.624) | *** |
| | | [-0.999] | | [0.169] | | [0.264] | | [1.211] | |
| Price range | *351* | -0.050 | | -0.010 | | 0.011 | | 0.061 | |
| | | (-1.522) | | (0.394) | | (1.878) | * | (3.824) | *** |
| | | [-2.003] | ** | [-0.359] | | [0.690] | | [3.125] | *** |
| Intraday Volatility | *206* | -0.0095 | | -0.0039 | | -0.0023 | | 0.0072 | |
| | | (-2.542) | ** | (-0.514) | | (0.123) | | (2.684) | *** |
| | | [-4.154] | *** | [-1.857] | * | [-0.228] | | [3.329] | *** |

Panel B: Liquidity

| | *N* | (1) Tercile 1 | | (2) Tercile 2 | | (3) Tercile 3 | | (4) Difference | |
|---|---|---|---|---|---|---|---|---|---|
| *Liquidity - overall* | | | | | | | | | |
| Closing bid-ask spread | *335* | 0.045 | | 0.010 | | -0.011 | | -0.056 | |
| | | (4.394) | *** | (1.596) | | (-0.301) | | (-3.543) | *** |
| | | [3.615] | *** | [1.646] | * | [0.430] | | [-3.798] | *** |
| Average bid-ask spread | *206* | 0.0297 | | 0.0006 | | -0.0204 | | -0.0501 | |
| | | (2.586) | ** | (1.116) | | (-0.746) | | (-2.264) | ** |
| | | [1.427] | | [-0.337] | | [-2.037] | ** | [-1.999] | ** |
| Effective spread | *206* | 0.0321 | | 0.0149 | | -0.0096 | | -0.0417 | |
| | | (2.123) | ** | (2.070) | ** | (0.244) | | (-1.347) | |
| | | [1.873] | * | [2.418] | ** | [-0.297] | | [-2.278] | ** |
| *Liquidity - adverse selection* | | | | | | | | | |
| Log(amihud) | *351* | 0.025 | | 0.016 | | 0.003 | | -0.022 | |
| | | (3.772) | *** | (3.025) | *** | (1.134) | | (-2.222) | ** |
| | | [3.600] | *** | [2.278] | ** | [0.736] | | [-3.583] | *** |
| Price impact | *206* | 0.008 | | 0.003 | | -0.002 | | -0.010 | |
| | | (1.695) | * | (0.797) | | (0.139) | | (-1.232) | |
| | | [0.912] | | [0.685] | | [0.075] | | [-1.200] | |
| Absolute trade imbalance | *206* | 0.392 | | 0.152 | | 0.013 | | -0.379 | |
| | | (2.843) | *** | (1.506) | | (0.266) | | (-2.524) | ** |
| | | [2.774] | *** | [1.231] | | [-0.647] | | [-2.941] | *** |
| Lambda | *206* | 0.006 | | 0.003 | | -0.001 | | -0.007 | |
| | | (2.736) | *** | (2.052) | ** | (-0.198) | | (-2.106) | ** |
| | | [3.012] | *** | [2.255] | ** | [0.198] | | [-3.146] | *** |
| *Liquidity - inventory costs* | | | | | | | | | |
| Realized spread | *206* | 0.0276 | | 0.0107 | | -0.0069 | | -0.0346 | |
| | | (2.362) | ** | (2.067) | ** | (0.131) | | (-1.639) | |
| | | [2.091] | ** | [2.063] | ** | [-0.052] | | [-2.361] | ** |

**Table 9: 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 decile for the respective year; regardless of whether the news event is classified as economic or not). The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity and volatility; Panel B shows the results for liquidity. All variables are defined in the Appendix. 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 768 events due to lack of data). Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

| | *N* | (1) Overall | | (2) Firm Size Tercile 1 | | (3) Stock Price Tercile 1 | | (4) Inst. Holdings Tercile 1 | |
|---|---|---|---|---|---|---|---|---|---|
| Market return | *1084* | -0.044 | | -0.041 | | -0.045 | | -0.040 | |
| | | (-0.689) | | (-1.122) | | (-0.824) | | (-0.333) | |
| | | [-0.606] | | [-0.932] | | [-0.739] | | [0.241] | |
| *Trading activity* | | | | | | | | | |
| Log(turnover) | *1084* | -0.009 | | -0.024 | | -0.026 | | -0.022 | |
| | | (-1.642) | | (-4.405) | *** | (-4.41) | *** | (-3.628) | *** |
| | | [-2.776] | *** | [-6.376] | *** | [-6.222] | *** | [-4.822] | *** |
| Log($volume) | *1084* | -0.012 | | -0.029 | | -0.034 | | -0.027 | |
| | | (-2.362) | ** | (-5.103) | *** | (-5.249) | *** | (-4.132) | *** |
| | | [-3.302] | *** | [-6.888] | *** | [-6.801] | *** | [-5.259] | *** |
| *Volatility* | | | | | | | | | |
| Abs return | *1084* | 0.012 | | -0.006 | | 0.011 | | 0.011 | |
| | | (1.303) | | (-0.563) | | (0.571) | | (0.571) | |
| | | [-4.593] | *** | [-4.115] | *** | [-2.838] | *** | [-2.838] | *** |
| Price range | *1084* | 0.016 | | -0.051 | | -0.018 | | -0.012 | |
| | | (1.170) | | (-3.127) | *** | (-1.144) | | (-1.019) | |
| | | [-2.770] | *** | [-6.233] | *** | [-5.198] | *** | [-3.937] | *** |
| Intraday Volatility | *504* | 0.000 | | -0.005 | | -0.002 | | -0.004 | |
| | | (0.658) | | (-2.674) | *** | (-1.101) | | (-1.788) | * |
| | | [-2.382] | ** | [-5.379] | *** | [-4.572] | *** | [-5.102] | *** |

Panel B: Liquidity

| | *N* | (1) Overall | | (2) Firm Size Tercile 1 | | (3) Stock Price Tercile 1 | | (4) Inst. Holdings Tercile 1 | |
|---|---|---|---|---|---|---|---|---|---|
| *Liquidity - overall* | | | | | | | | | |
| Closing bid-ask spread | *743* | 0.020 | | 0.064 | | 0.072 | | 0.050 | |
| | | (3.528) | *** | (5.177) | *** | (5.197) | *** | (5.444) | *** |
| | | [1.593] | | [3.071] | *** | [3.422] | *** | [3.180] | *** |
| Average bid-ask spread | *504* | 0.014 | | 0.049 | | 0.048 | | 0.039 | |
| | | (1.923) | * | (3.975) | *** | (3.313) | *** | (3.802) | *** |
| | | [0.500] | | [1.903] | * | [1.543] | | [1.727] | * |
| Effective spread | *504* | 0.018 | | 0.051 | | 0.052 | | 0.042 | |
| | | (4.080) | *** | (4.593) | *** | (4.417) | *** | (4.643) | *** |
| | | [3.008] | *** | [3.261] | *** | [3.685] | *** | [3.436] | *** |
| *Liquidity - adverse selection* | | | | | | | | | |
| Log(amihud) | *1084* | 0.010 | | 0.022 | | 0.027 | | 0.025 | |
| | | (3.765) | *** | (4.116) | *** | (4.875) | *** | (4.955) | *** |
| | | [1.668] | * | [3.363] | *** | [4.237] | *** | [4.235] | *** |
| Price impact | *504* | 0.005 | | 0.013 | | 0.014 | | 0.011 | |
| | | (2.706) | *** | (2.919) | *** | (3.023) | *** | (3.203) | *** |
| | | [1.870] | * | [2.179] | ** | [2.331] | ** | [2.326] | ** |
| Absolute trade imbalance | *504* | 0.150 | | 0.433 | | 0.390 | | 0.376 | |
| | | (2.408) | ** | (4.228) | *** | (3.885) | *** | (4.112) | *** |
| | | [2.224] | ** | [4.339] | *** | [4.236] | *** | [4.110] | *** |
| Lambda | *504* | 0.002 | | 0.011 | | 0.009 | | 0.007 | |
| | | (3.078) | *** | (4.007) | *** | (3.997) | *** | (3.606) | *** |
| | | [3.428] | *** | [3.872] | *** | [3.925] | *** | [3.618] | *** |
| *Liquidity - inventory costs* | | | | | | | | | |
| Realized spread | *504* | 0.014 | | 0.039 | | 0.038 | | 0.032 | |
| | | (3.739) | *** | (4.696) | *** | (4.499) | *** | (4.514) | *** |
| | | [2.711] | *** | [3.110] | *** | [3.396] | *** | [3.317] | *** |

## Table 10: Robustness Check Using Distraction Events at Least 5 Trading Days Apart

This table reports event-study results for the 370 distraction events that are at least 5 trading days apart. The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity and volatility; Panel B shows the results for liquidity. All variables are defined in the Appendix. 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 238 events due to lack of data). Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

| | *N* | (1) Overall | (2) Firm Size Tercile 1 | (3) Stock Price Tercile 1 | (4) Inst. Holdings Tercile 1 |
|---|---|---|---|---|---|
| *Trading activity* | | | | | |
| Log(turnover) | *370* | -0.011 | -0.029 | -0.032 | -0.029 |
| | | (-1.288) | (-3.16)*** | (-3.228)*** | (-2.659)*** |
| | | [-0.99] | [-3.762]*** | [-3.685]*** | [-2.533]** |
| Log($volume) | *370* | -0.014 | -0.033 | -0.037 | -0.033 |
| | | (-1.515) | (-3.484)*** | (-3.447)*** | (-2.765)*** |
| | | [-1.323] | [-3.975]*** | [-3.866]*** | [-2.629]*** |
| *Volatility* | | | | | |
| Abs return | *370* | -0.007 | -0.017 | -0.008 | -0.023 |
| | | (0.375) | (-0.632) | (0.020) | (-0.83) |
| | | [-1.964]* | [-1.763]* | [-1.407] | [-1.783]* |
| Price range | *370* | -0.025 | -0.078 | -0.061 | -0.062 |
| | | (-0.409) | (-2.409)** | (-1.799)* | (-1.789)* |
| | | [-1.211] | [-3.389]*** | [-2.763]*** | [-2.069]** |
| Intraday Volatility | *141* | -0.006 | -0.009 | -0.007 | -0.008 |
| | | (-1.587) | (-2.384)** | (-2.195)** | (-2.463)** |
| | | [-1.629] | [-2.736]*** | [-2.226]** | [-2.763]*** |

Panel B: Liquidity

| | *N* | (1) Overall | | (2) Firm Size Tercile 1 | | (3) Stock Price Tercile 1 | | (4) Inst. Holdings Tercile 1 | |
|---|---|---|---|---|---|---|---|---|---|
| *Liquidity - overall* | | | | | | | | | |
| Closing bid-ask spread | *227* | 0.008 | | 0.059 | | 0.056 | | 0.043 | |
| | | (1.102) | | (2.919) | *** | (2.767) | *** | (3.194) | *** |
| | | [0.952] | | [2.441] | ** | [2.465] | ** | [2.253] | ** |
| Average bid-ask spread | *141* | -0.001 | | 0.047 | | 0.036 | | 0.031 | |
| | | (0.996) | | (2.609) | ** | (2.292) | ** | (2.304) | ** |
| | | [-0.186] | | [1.038] | | [0.742] | | [0.983] | |
| Effective spread | *141* | 0.01 | | 0.052 | | 0.047 | | 0.034 | |
| | | (1.069) | | (2.32) | ** | (2.097) | ** | (1.73) | * |
| | | [1.149] | | [1.734] | * | [1.989] | ** | [1.382] | |
| *Liquidity - adverse selection* | | | | | | | | | |
| Log(amihud) | *370* | 0.008 | | 0.023 | | 0.030 | | 0.022 | |
| | | (1.951) | * | (2.199) | ** | (2.915) | *** | (2.655) | *** |
| | | [0.657] | | [1.845] | * | [2.682] | *** | [2.588] | ** |
| Price impact | *141* | 0.001 | | 0.009 | | 0.008 | | 0.005 | |
| | | (0.138) | | (1.073) | | (0.953) | | (0.743) | |
| | | [0.232] | | [0.732] | | [0.571] | | [0.351] | |
| Absolute trade imbalance | *141* | 0.16 | | 0.362 | | 0.331 | | 0.344 | |
| | | (1.622) | | (1.966) | * | (1.908) | * | (2.188) | ** |
| | | [1.077] | | [1.717] | * | [1.845] | * | [1.88] | * |
| Lambda | *141* | 0.002 | | 0.011 | | 0.010 | | 0.007 | |
| | | (1.191) | | (2.514) | ** | (2.592) | ** | (2.183) | ** |
| | | [2.016] | ** | [2.746] | *** | [2.88] | *** | [2.569] | ** |
| *Liquidity - inventory costs* | | | | | | | | | |
| Realized spread | *141* | 0.009 | | 0.047 | | 0.041 | | 0.032 | |
| | | (1.597) | | (2.838) | *** | (2.753) | *** | (2.272) | ** |
| | | [1.164] | | [2.039] | ** | [2.158] | ** | [1.697] | * |

**Table 11: Placebo Test for Non-Economic Days with Lowest News Pressure**

This table reports event-study results for 506 placebo events (i.e., days on which news pressure is in the bottom decile for the year and which survived our filter for excluding potential economic news). The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity and volatility; Panel B shows the results for liquidity. All variables are defined in the Appendix. 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 360 events due to lack of data). Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

| | *N* | (1) Overall | (2) Firm Size Tercile 1 | (3) Stock Price Tercile 1 | (4) Inst. Holdings Tercile 1 |
|---|---|---|---|---|---|
| Market return | *506* | 0.039 | 0.025 | 0.044 | 0.022 |
| | | (1.312) | (0.592) | (1.292) | (0.491) |
| | | [1.597] | [1.078] | [1.553] | [0.804] |
| *Trading activity* | | | | | |
| Log(turnover) | *506* | -0.002 | -0.003 | -0.003 | -0.001 |
| | | (-0.520) | (-0.366) | (-0.390) | (-0.021) |
| | | [0.243] | [-0.535] | [-1.019] | [-0.062] |
| Log($volume) | *506* | -0.003 | -0.008 | -0.008 | -0.005 |
| | | (-0.639) | (-1.072) | (-0.928) | (-0.546) |
| | | [-0.054] | [-1.743] * | [-2.002] ** | [-0.814] |
| *Volatility* | | | | | |
| Abs return | *506* | 0.003 | 0.009 | 0.007 | 0.004 |
| | | (-0.137) | (0.968) | (0.732) | (0.462) |
| | | [-1.276] | [1.250] | [0.443] | [0.886] |
| Price range | *506* | 0.003 | 0.006 | 0.008 | 0.003 |
| | | (-0.076) | (0.796) | (0.760) | (0.466) |
| | | [-0.146] | [0.259] | [-0.318] | [0.557] |
| Intraday Volatility | *213* | 0.003 | 0.004 | 0.003 | 0.005 |
| | | (0.890) | (1.044) | (0.943) | (1.263) |
| | | [-0.107] | [-0.604] | [-0.809] | [-0.391] |

Panel B: Liquidity

| | *N* | (1) Overall | (2) Firm Size Tercile 1 | (3) Stock Price Tercile 1 | (4) Inst. Holdings Tercile 1 |
|---|---|---|---|---|---|
| *Liquidity - overall* | | | | | |
| Closing bid-ask spread | *353* | 0.008 | 0.011 | 0.008 | 0.002 |
| | | (1.102) | (0.723) | (1.090) | (0.382) |
| | | [0.952] | [0.366] | [0.507] | [0.102] |
| Average bid-ask spread | *213* | 0.026 | 0.034 | 0.043 | 0.029 |
| | | (1.571) | (1.186) | (1.302) | (1.208) |
| | | [-0.453] | [-0.681] | [-0.529] | [-0.651] |
| Effective spread | *213* | 0.009 | 0.012 | 0.013 | 0.008 |
| | | (1.689) * | (1.065) | (1.305) | (0.739) |
| | | [1.390] | [0.725] | [1.043] | [0.401] |
| *Liquidity - adverse selection* | | | | | |
| Log(amihud) | *506* | -0.002 | 0.009 | 0.006 | 0.004 |
| | | (0.322) | (1.263) | (0.943) | (0.706) |
| | | [-0.347] | [1.135] | [0.951] | [0.734] |
| Price impact | *213* | -0.002 | -0.003 | -0.001 | -0.004 |
| | | (-0.697) | (-1.143) | (-0.419) | (-1.537) |
| | | [-2.211] ** | [-1.764] * | [-1.325] | [-2.369] ** |
| Absolute trade imbalance | *213* | 0.119 | 0.197 | 0.174 | 0.112 |
| | | (1.217) | (1.188) | (1.149) | (0.744) |
| | | [0.334] | [1.140] | [0.910] | [0.345] |
| Lambda | *213* | 0.000 | 0.003 | 0.001 | 0.001 |
| | | (-0.183) | (1.002) | (0.464) | (0.484) |
| | | [0.099] | [0.957] | [0.369] | [0.149] |
| *Liquidity - inventory costs* | | | | | |
| Realized spread | *213* | 0.010 | 0.013 | 0.014 | 0.011 |
| | | (2.382) ** | (1.113) | (1.349) | (1.108) |
| | | [2.388] ** | [1.069] | [1.586] | [1.174] |

## Table 12: Distracting Events and Noise Traders

This table reports event-study results for the retail trading activity of different groups of investors using discount brokerage data over the period 1991-1996 (66 distraction events). *Log(#households)* is the logarithm of the number of households trading. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. In row [1], investors are split into single-females (column (1)) and single-males (column (2)). In the other rows, investors are split in halves based on the variable indicated in the row label. Column (3) tests for the difference between above-median investors (column (2)) and below-median investors (column (1)) (or single-males and single-females for row 1). *PF concentration* is the household's average portfolio concentration (measured by the Herfindahl index). *PF volume* is the household's average portfolio volume. *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 t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

| | (1) Total trades | (2) Total trades | (3) Difference |
|---|---|---|---|
| [1] Gender | Single-female | Single-male | Difference |
| Log(#households) | 0.036 | -0.093 | -0.119 |
| | (0.315) | (-2.790) *** | (-2.532) ** |
| | [1.384] | [-1.964] ** | [-1.804] * |
| [2] PF concentration | Low | High | Difference |
| Log(#households) | -0.034 | -0.066 | -0.032 |
| | (-1.778) * | (-2.671) *** | (-0.908) |
| | [-1.306] | [-2.258] ** | [-0.866] |
| [3] PF volume | Low | High | Difference |
| Log(#households) | 0.001 | -0.049 | -0.051 |
| | (0.022) | (-2.482) ** | (-2.274) ** |
| | [0.361] | [-2.047] ** | [-1.313] |
| [4] PF losses | Low | High | Difference |
| Log(#households) | -0.036 | -0.068 | -0.032 |
| | (-1.935) * | (-2.364) ** | (-0.880) |
| | [-1.115] | [-2.380] ** | [-1.217] |
| [5] GK-proxy | Low | High | Difference |
| Log(#households) | 0.001 | -0.053 | -0.054 |
| | (0.016) | (-2.196) ** | (-2.294) ** |
| | [0.533] | [-1.830] * | [-1.319] |
| *N* | 66 | 66 | 66 |

## Table 13: Distraction Events and Liquidity Provision

This table reports event-study results for two tests of liquidity provision. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. In Panel A, we look at three measures of "market quality" constructed from TAQ data (covering 206 events). *Fraction of 0-return intervals* is the (equal-weighted) average of the fraction of 5-minute intervals without mid-quote change over all 5-minuate intervals with valid mid-quotes. *Fraction of intervals with no trade* is the (equal-weighted) average of the fraction of 5-minute intervals with zero trading volume over all 5-minuate intervals with valid mid-quotes. *Fraction of 0-return intervals among intervals with no trade* is the (equal-weighted) average of the fraction of 5-minute intervals with zero trading volume and no mid-quote change over all 5-minuate intervals with zero trading volume. 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. In Panel B, we look at the logarithm of the number of households engaging in contrarian trades (i.e., buying stocks with a negative return and vice versa) in the discount brokerage data (covering 66 events). Column (1) shows results for the overall market. Column (2) shows results for stocks in the top tercile in terms of firm size. Column (3) shows results for stocks in the top tercile in terms of stock price. Column (4) shows results for stocks in the top tercile in terms of institutional ownership. Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Fraction of Zero-Return Intervals

| | *N* | (1) Overall | (2) Firm Size Tercile 1 | (3) Stock Price Tercile 1 | (4) Inst. Holdings Tercile 1 |
|---|---|---|---|---|---|
| Fraction of 0-return intervals | *206* | 0.133 | 0.278 | 0.337 | 0.265 |
| | | (1.093) | (2.511)** | (2.819)*** | (2.237)** |
| | | [1.193] | [3.109]*** | [3.484]*** | [3.135]*** |
| Fraction of intervals with no trade | *206* | 0.217 | 0.273 | 0.408 | 0.331 |
| | | (1.932)* | (2.637)*** | (3.449)*** | (3.097)*** |
| | | [1.949]* | [2.794]*** | [3.832]*** | [3.699]*** |
| Fraction of 0-return intervals among intervals with no trade | *206* | -0.097 | 0.082 | 0.123 | 0.0568 |
| | | (0.048) | (1.014) | (1.517) | (1.058) |
| | | [-0.061] | [0.658] | [1.749]* | [0.866] |

Panel B: Contrarian Trades by Retail Investors

| | *N* | (1) Overall | (2) Firm Size Tercile 3 | (3) Stock Price Tercile 3 | (4) Inst. Holdings Tercile 3 |
|---|---|---|---|---|---|
| Log(#households) with contrarian trades | *66* | -0.055 | -0.051 | -0.056 | -0.071 |
| | | (-2.498)** | (-2.280)** | (-2.392)** | (-3.174)*** |
| | | [-2.067]** | [-2.067]** | [-2.341]** | [-3.006]*** |

## Appendix: Variable Definitions

| Variable name | Data source | Explanation |
|---|---|---|
| ***Household measures*** | | |
| Log(#stocks) | Discount broker | Natural logarithm of the number of distinct stocks traded by a household (conditional on trading at least one stock), averaged across households. |
| Log($volume) | Discount broker | Natural logarithm of the average dollar volume traded in a given stock by a household (conditional on trading at least one stock), averaged across households. |
| Log(#households) | Discount broker | Natural logarithm of the total number of households trading at least one stock. |
| ***TAQ small vs. large trades*** | | |
| Log($volume) | TAQ | Natural logarithm of the total dollar volume of either small or large trades. The classification into small and large trades follows Hvidkjaer (2006). That is, stocks are first sorted into quintiles based on NYSE/AMEX firm-size cut-off points. The following small- (large-) trade cut-off points are then used 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. |
| ***Stock market variables*** | | |
| Mkt return | CRSP | Equal-weighted average return of all sample stocks. Sample stocks are all stocks with CRSP share code 10 or 11 and a stock price above $1. [Scaled by 100.] |
| Turnover | CRSP | Equal-weighted average of the ratio of dollar volume over the stock's market capitalization on the previous trading day. [Scaled by 100.] |
| Log(turnover) | CRSP | Equal-weighted average of the natural logarithm of 0.00000255 (following Llorente et al., 2002) plus the ratio of dollar volume over the stock's market capitalization on the previous trading day. |
| $Volume | CRSP | Equal-weighted average of the total dollar volume. [In $millions.] |
| Log($volume) | CRSP | Equal-weighted average of the natural logarithm of total dollar volume. |
| Abs return | CRSP | Equal-weighted average of the absolute value of stock return. [Scaled by 100.] |
| Price range | CRSP | Equal-weighted average of the natural logarithm of the ratio of daily high- to low-prices. [Scaled by 100.] |
| Intraday volatility | TAQ | Equal-weighted average of the standard deviation of stock returns over 5-minute intervals during the trading day (excluding the opening half hour). [Scaled by 100.] |
| Closing bid-ask spread | CRSP | Equal-weighted average of the closing bid-ask spread taken from CRSP. The bid-ask spread is defined as $2 * (Ask - Bid)/(Ask + Bid)$. [Scaled by 100.] |
| Average bid-ask spread | TAQ | Equal-weighted average of the average bid-ask spread during the trading day (excluding the first half hour). The bid-ask spread is defined as $2 * (Ask - Bid)/(Ask + Bid)$. [Scaled by 100.] |
| Effective spread | TAQ | Equal-weighted average of the average effective spread during the trading day (excluding the first half hour). For each transaction, the |

| | | |
|---|---|---|
| | | effective spread is defined as $2 * \lvert TransactionPrice - Midpoint \rvert / Midpoint$, where $Midpoint = (Ask + Bid)/2$ valid 1 second before the transaction. [Scaled by 100.] |
| Amihud | CRSP | Equal-weighted average of the ratio of the absolute value of stock return over dollar volume. [Scaled by 1,000,000.] |
| Log(amihud) | CRSP | Equal-weighted average of the natural logarithm of 0.00000001 plus the ratio of the absolute value of stock return over dollar volume. |
| Price impact | TAQ | Equal-weighted average of the average price impact during the trading day (excluding the first half hour). For each transaction, the price impact is defined as $2 * (Midpoint5 - Midpoint)/Midpoint5$, where $Midpoint = (Ask + Bid)/2$ valid 1 second before the transaction and $Midpoint5 = (Ask + Bid)/2$ valid 5 minutes after the transaction. [Scaled by 100.] |
| Absolute trade imbalance | TAQ | Equal-weighted average of the ratio of the absolute value of trade imbalance, defined as dollar volume of buys minus dollar volume of sells, over the total dollar volume. Trades are signed using the Lee and Ready (1991) algorithm. [Scaled by 100.] |
| Lambda | TAQ | Equal-weighted average of the coefficient obtained from regressing returns over 5-minute intervals (calculated from bid-ask midpoints) on $S$, where $S$ equals the sum over all transactions in that 5-minute interval of $I_{Buy/Sell}\sqrt{\$volume}$ and $I_{Buy/Sell} = 1$ for a buy transaction and $I_{Buy/Sell} = -1$ for a sell transaction and $\$volume$ is the dollar volume of the transaction. Trades are signed using the Lee and Ready (1991) algorithm. [Scaled by 10,000.] |
| Realized spread | TAQ | Equal-weighted average of the average realized spread during the trading day (excluding the first half hour). For each transaction, the realized spread is defined as $2 * I_{Buy/Sell} * (TransactionPrice - Midpoint5)/Midpoint5$, where $I_{Buy/Sell} = 1$ for a buy transaction and $I_{Buy/Sell} = -1$ for a sell transaction and $Midpoint5 = (Ask + Bid)/2$ valid 5 minutes after the transaction. Trades are signed using the Lee and Ready (1991) algorithm. [Scaled by 100.] |

# Internet Appendix to

# "Glued to the TV: Distracted Retail Investors and Stock Market Liquidity"

*Joel PERESS & Daniel SCHMIDT*

19 July 2016

## Internet Appendix A: The Implications of Distraction in a Model of Informed Trading with a Risk-Averse Market Maker

In this appendix, we derive our empirical predictions—for trading volume, liquidity and volatility—in a model of informed trading à la Kyle (1985) with risk-averse market makers and an imperfectly informed insider. For brevity, we focus on a static model and take some liberty when interpreting its predictions in a dynamic context. See Kim (2014) for a dynamic version of the model (in discrete time) with risk-averse market makers and a perfectly informed insider. Our setup allows us to work out the implications from distracting noise traders, informed speculators, and market makers. They are summarized in Table 3.

There is one risky asset with a final dividend $\theta$, three periods, denoted 1 , 2 and 3, and three categories of agents, namely a market maker (referred to as 'he'), an insider (or speculator, referred to as 'she'), and noise traders. In period 1, the market maker observes a noisy signal about $\theta$, $s' = \theta + \varepsilon'$, and equates the price of the asset, $p_1$, to his expectation of the dividend. No trading takes place in period 1. In period 2, the risk-neutral informed insider observes a noisy signal about $\theta$, $s = \theta + \varepsilon$ and submits a market order $x$. The total order flow is given by $\omega = x + z$ , where $z$ represents noise trades. The random variables $\theta, \varepsilon, \varepsilon'$ and $z$ are uncorrelated with one another and normally distributed with mean zero and variances $\sigma_\theta$, $\sigma_\varepsilon$, $\sigma_{\varepsilon'}$ and $\sigma_z$, respectively. The riskfree rate is normalized to zero.

We assume that the market-making sector is competitive and is characterized by a "representative" market-maker who takes on the entire order flow. Our main deviation from Kyle (1985) is that we assume the market maker has CARA-utility with risk-aversion coefficient $\gamma$. In each period, his expected utility from making the market must equal his "autarky" utility, which we normalize to zero without loss of generality.

In period 1, the market maker sets a price equal to his expectation of the final dividend given his signal $s'$:[1]

$$p_1 = E[\theta|s'] = \frac{1}{h\sigma_{\varepsilon'}} s' \quad \text{where} \quad h \equiv \frac{1}{\mathrm{Var}[\theta|s']} = \frac{1}{\sigma_\theta} + \frac{1}{\sigma_{\varepsilon'}}.$$

In period 2, the equilibrium condition can be written in mean-variance form as:

$$E[U_m] = E[-\omega(\theta - p_2)|\omega, s'] - \frac{\gamma}{2}\mathrm{Var}[-\omega(\theta - p_2)|\omega, s'] = 0,$$

which implies:

$$p_2 = E[\theta|\omega, s'] + \frac{\gamma}{2}\mathrm{Var}[\theta|\omega, s']\omega.$$

The first term in this expression is the market maker's prediction of the final dividend. It captures the impact of adverse selection as in the standard Kyle model with a risk-neutral market maker. The second term reflects the impact of inventory risk, specifically the compensation required by a risk averse market maker for bearing that risk.

Liquidity

[1] This assumption can be micro-founded by noting that the market maker will update his quote, $p_1$, to avoid being picked off by other market makers. Indeed, one can think of $p_1$ as the mid-quote in the limit order book. If the market maker does not set this mid-quote equal to his conditional expectation of the dividend, another market maker with the same information has an incentive to submit marketable limit orders (or market orders) to take advantage of this stale quote.

We conjecture a linear pricing rule, $p_2 = \lambda\omega + \delta s'$, and a linear trading strategy, $x = \beta s + \beta' s'$. For the market maker, observing $\omega = x + z = \beta s + \beta' s' + z$ together with $s'$, is equivalent to observing $\omega' \equiv z + s/\beta$ and $s'$. Thus, we can express the price as $p_2 = E[\theta|\omega', s'] + \frac{\gamma}{2}\mathrm{Var}[\theta|\omega', s']\omega$. From Bayes rule,

$$E[\theta|\omega', s'] = \frac{1}{h'(\sigma_\varepsilon + \sigma_z/\beta^2)}\omega' + \frac{1}{h'\sigma_{\varepsilon'}}s', \text{ where } \frac{1}{\mathrm{Var}[\theta|\omega', s']} = h + \frac{1}{\sigma_\varepsilon + \sigma_z/\beta^2} \equiv h'.$$

Rearranging these expressions yields $p_2 = \lambda\omega + p_1$ where

(1)
$$\lambda = \frac{\beta + \frac{\gamma}{2}(\beta^2\sigma_\varepsilon + \sigma_z)}{\beta^2 + h(\beta^2\sigma_\varepsilon + \sigma_z)}.$$

Given $\lambda$, we solve for the insider's optimal trading strategy, $x = \beta s + \beta' s'$, by maximizing her expected profit conditional on her signal, $E[(\theta - p_2)x|p_1, s]$. The insider's first-order condition yields $x = \frac{E[\theta|p_1,s] - p_1}{2\lambda}$ where $E[\theta|p_1, s] = \frac{\sigma_\varepsilon h}{1+\sigma_\varepsilon h}p_1 + \frac{1}{1+\sigma_\varepsilon h}s$. It follows that $x = \beta(s - p_1)$ where

(2)
$$\beta = \frac{1}{2\lambda(1+\sigma_\varepsilon h)}.$$

Substituting into this equation the expression for $\lambda$ in Equation (1) yields a cubic equation in $\beta$:

(3)
$$\gamma\sigma_\varepsilon\beta^3 + \beta^2 + \gamma\sigma_z\beta = \frac{\sigma_z h}{1+\sigma_\varepsilon h}.$$

We confirm that setting $\sigma_{\varepsilon'}$ to infinity and $\gamma = \sigma_\varepsilon = 0$ delivers the classic Kyle (1985) formulas, $\beta = \sqrt{\frac{\sigma_z}{\sigma_\theta}}$ and $\lambda = \frac{1}{2}\sqrt{\frac{\sigma_\theta}{\sigma_z}}$. We also confirm that our results match those derived in Subrahmanyam (1991) in which the market maker is risk averse but does not receive a signal about the dividend.[2]

Compared to the classic Kyle (1985) model, risk aversion adds an extra component to $\lambda$. It is clearly seen by making the insider uninformed (setting $\sigma_\varepsilon$ to infinity), thereby eliminating all adverse selection. Though this case implies $\beta = 0$, $\lambda$ is non-zero. Specifically, $\lambda = \frac{\gamma}{2h}$, where the market maker's risk aversion and fundamental risk (captured by $h$, the precision of their information based on the prior and their signal $s$') jointly determine how he is compensated for bearing inventory risk. In short, $\lambda$ is non-zero even in the absence of informed trading, as long as the market maker is averse to risk.

We compute next trading volume and volatility.

Trading volume

Expected trading volume can by proxied by $TV \equiv E(|\omega|) = 2/\pi\sqrt{Var(\omega)}$, where $Var(\omega) = Var(x + z) = Var(\beta(s - p_1) + z) = Var\left(\beta(\theta + \varepsilon - \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')) + z\right) = \beta^2\left(\frac{1}{h} + \sigma_\varepsilon\right) + \sigma_z$. Hence,

2 Indeed, when $\sigma_{\varepsilon'}$ is infinite, Equations (1) to (3) become, respectively, $\lambda = \frac{\sigma_\theta\left(\beta + \frac{\gamma}{2}(\beta^2\sigma_\varepsilon + \sigma_z)\right)}{\beta^2(\sigma_\theta + \sigma_\varepsilon) + \sigma_z}$, $\beta = \frac{\sigma_\theta}{2\lambda(\sigma_\theta + \sigma_\varepsilon)}$, and $\gamma\sigma_\varepsilon\beta^3 + \beta^2 + \gamma\sigma_z\beta = \frac{\sigma_z}{\sigma_\theta + \sigma_\varepsilon}$. The first equation correspond to Equation (15) in Subrahmanyam (1991).

(4) $$TV = 2/\pi\sqrt{\beta^2(1/h + \sigma_\varepsilon) + \sigma_z}.$$

Return volatility

Stretching a little the static interpretation, we can think of returns being realized over three distinct periods. The first-period return captures any price update from the prior to period 1 when the market maker receives his signal, $r_1 \equiv p_1 - 0 = p_1$. The second-period return reflects the impact of the insider's trades, $r_2 \equiv p_2 - p_1 = \lambda\omega$. Finally, the third-period return captures the resolution of remaining uncertainty, $r_3 \equiv \theta - p_2 = \theta - \lambda\omega - p_1$. The total return volatility in our model is given by $VOL \equiv \mathrm{Var}[r_1] + \mathrm{Var}[r_2] + \mathrm{Var}[r_3]$. Substituting into this equation the expressions for the returns and expanding implies

$$VOL = 2\mathrm{Var}[p_1] + 2\mathrm{Var}[\lambda\omega] + \sigma_\theta - 2\mathrm{Cov}[\theta, \lambda\omega] - 2\mathrm{Cov}[\theta, p_1] + 2\mathrm{Cov}[\lambda\omega, p_1].$$

We compute in turn each term in this expression: $\mathrm{Var}[p_1] = (\sigma_\theta + \sigma_{\varepsilon'})/h^2/\sigma_{\varepsilon'}{}^2 = \sigma_\theta/h/\sigma_{\varepsilon'}$; $\mathrm{Var}[\lambda\omega] = \lambda^2\mathrm{Var}[\beta(s - p_1) + z] = \lambda^2\beta^2\mathrm{Var}[s - p_1] + \lambda^2\sigma_z = \lambda^2\beta^2\left(\frac{1}{h} + \sigma_\varepsilon\right) + \lambda^2\sigma_z$, given that $\mathrm{Var}[s - p_1] = \frac{1}{h} + \sigma_\varepsilon$ ; $\mathrm{Cov}[\theta, \lambda\omega] = \mathrm{Cov}\left[\theta, \lambda(\beta(\theta + \varepsilon - \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')) + z)\right] = \lambda\beta(1 - \frac{1}{h\sigma_{\varepsilon'}})\sigma_\theta = \lambda\beta/h$ ; $\mathrm{Cov}[\theta, p_1] = \mathrm{Cov}\left[\theta, \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')\right] = \sigma_\theta/h/\sigma_{\varepsilon'}$ ; $\mathrm{Cov}[\lambda\omega, p_1] = \mathrm{Cov}\left[\lambda\left(\beta\left(\theta + \varepsilon - \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')\right) + z\right), \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')\right] = \lambda\beta\left(1 - \frac{1}{h\sigma_{\varepsilon'}}\right)\frac{\sigma_\theta}{h\sigma_{\varepsilon'}} - \lambda\beta\frac{\sigma_\theta}{h^2\sigma_{\varepsilon'}} = 0.$ It follows that $VOL = \sigma_\theta - \frac{1}{2h(1 + h\sigma_\varepsilon)} + 2\lambda^2\sigma_z$. Alternative expressions for volatility can be derived from this expression by using Equation (2) to substitute out $\lambda$:

(5) $$VOL = \sigma_\theta - \frac{1}{2h(1 + h\sigma_\varepsilon)} + \frac{\sigma_z}{2\beta^2(1 + \sigma_\varepsilon h)^2},$$

And, by noting that, from Equation (3), $\gamma\sigma_\varepsilon\beta^3 + \gamma\sigma_z\beta = -\beta^2 + \frac{\sigma_z h}{1 + \sigma_\varepsilon h}$:

(6) $$VOL = \sigma_\theta + \gamma\lambda(\beta^2\sigma_\varepsilon + \sigma_z)/h.$$

As this expression shows, volatility equals $\sigma_\theta$ when the market maker is risk neutral ($\gamma = 0$) as in the classic Kyle (1985) model. It also makes clear that volatility is amplified by his inventory concern.

To establish a mapping from the model to our empirical analysis, we interpret our events as distracting any of the three types of agents in the model. First, noise traders being distracted corresponds to a decrease in the variance of noise trades, $\sigma_z$. We note that our model is well suited to capture the short-term variations in noise trading that our distraction events induce. Indeed, the market maker does not expect his inventory to be any more or less difficult to unwind since the market will be "back to normal" within a few days. Second, the insider being distracted corresponds to an increase in the variance of her signal error, $\sigma_\varepsilon$. Finally, the market maker being distracted corresponds to an increase in the variance of his signal error, $\sigma_{\varepsilon'}$.[3] We work out the implications for expected trading volume, liquidity (the inverse of the price impact

[3] Alternatively, we can model distraction on the part of the market maker as an increase in his risk aversion. Indeed, a distracted market marker perceives his future payout as more uncertain, effectively making him more risk averse today. This approach yields predictions that are identical to those obtained here (proofs available upon request).

parameter, $\lambda$), and return volatility under each of these three interpretations of distraction shocks. They are summarized in Table 3.

<u>Distracted noise traders</u>: *A lower variance of noise trading results in lower trading volume, worse liquidity (λ higher) and lower return volatility.*

Proof:

- Liquidity. Applying the implicit-function theorem to Equation (3) yields $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_z} = \frac{1}{\mathrm{g}(\beta)}\left(\frac{h}{1+\sigma_\varepsilon h} - \gamma\beta\right)$ where $\mathrm{g}(\beta) \equiv 3\gamma\sigma_\varepsilon\beta^2 + 2\beta + \gamma\sigma_z \geq 0$. To sign the term in brackets, let $f(\beta) \equiv \gamma\sigma_\varepsilon\beta^3 + \beta^2 + \gamma\sigma_z\beta - \frac{\sigma_z h}{1+\sigma_\varepsilon h}$. Note that Equation (3) defines a root of the function $f$. This function is increasing in β (note that $f'(\beta) = g(\beta) \geq 0$), with $f(0) = -\frac{\sigma_z h}{1+\sigma_\varepsilon h} < 0$ and $f\left(\frac{h}{\gamma(1+\sigma_\varepsilon h)}\right) = \frac{\sigma_\varepsilon h^2}{\gamma^2(1+\sigma_\varepsilon h)^2} + \frac{h^2}{\gamma^2(1+\sigma_\varepsilon h)^2} > 0$, which proves the existence of a unique equilibrium β (root of $f$) on the positive line, and moreover, that $\beta \leq \frac{h}{\gamma(1+\sigma_\varepsilon h)}$. As a result, the numerator of $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_z}$ is positive and $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_z} \geq 0$. Differentiating Equation (2) with respect to $\sigma_z$ yields $\frac{\mathrm{d}\lambda}{\mathrm{d}\sigma_z} = -\frac{\lambda}{\beta}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_z} \leq 0$.
- Trading volume. From Equation (4), trading volume is increasing in $\sigma_z$ since $\beta$ is.
- Return volatility. From Equation (5), the impact of $\sigma_z$ on volatility depends on the sign of $\frac{\mathrm{d}(\sigma_z/\beta^2)}{\mathrm{d}\sigma_z} = \frac{\sigma_z}{\beta}\left(\frac{1}{\beta^2} - \frac{2}{\beta}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_z}\right)$. Substituting in the expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_z}$ and rearranging using Equation (3) yields $\frac{\mathrm{d}VOL}{\mathrm{d}\sigma_z} = \frac{\gamma(\sigma_\varepsilon\beta^2+\sigma_z)}{\sigma_z g(\beta)} \geq 0$.

Intuition:

- Two opposing forces weigh on $\lambda$. On the one hand, a lower variance of noise trades, $\sigma_z$, implies that the market maker faces more adverse selection risk, inducing him to increase $\lambda$ as in Kyle (1985). On the other hand, a lower $\sigma_z$ reduces the inventory risk he bears, allowing him to charge a lower risk premium and reduce $\lambda$. Because noise trading has no long term impact (the stock's liquidation value is $\theta$ regardless of the level of noise $z$ in the trading period), the latter effect outweighs the former, such that a reduction in $\sigma_z$ unambiguously leads to an increase in $\lambda$.
- Trading volume drops when the variance of noise trades decreases, not only because noise trades weaken but also because insiders who try to conceal their information scale back their trades (smaller β).
- The adverse-selection component of $\lambda$ is not associated with (total) volatility as it only changes the timing of the resolution of uncertainty. In contrast, the inventory-risk component of $\lambda$ leads to transient price impact, thereby causing volatility. Less noise trading means fewer non-fundamental shocks to the order flow, and hence to the price, which dampens volatility.

<u>Distracted insiders</u>: *A higher variance of the insider's signal error results in lower trading volume and improved liquidity (λ lower). The impact on return volatility is ambiguous.*

Proof:

We proceed in a manner similar to the case of noise traders.

- Liquidity. The implicit-function theorem applied to Equation (3) yields $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_\varepsilon} = -\frac{\gamma\beta^3+\sigma_z h^2/(1+\sigma_\varepsilon h)^2}{g(\beta)} \leq 0$. Differentiating Equation (2) with respect to $\sigma_\varepsilon$ yields $\frac{\mathrm{d}\lambda}{\mathrm{d}\sigma_\varepsilon} = -\frac{\lambda h}{1+\sigma_\varepsilon h} - \frac{\lambda}{\beta}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_\varepsilon}$. Substituting in the above expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_\varepsilon}$ implies $\frac{\mathrm{d}\lambda}{\mathrm{d}\sigma_\varepsilon} = \frac{1}{\beta g(\beta)}(\gamma\beta^3 + \frac{\sigma_z h^2}{(1+\sigma_\varepsilon h)^2} - \frac{\beta g(\beta) h}{1+\sigma_\varepsilon h}) \leq 0$. To sign this expression, note that $\beta \leq \frac{h}{\gamma(1+\sigma_\varepsilon h)}$ implies that $\gamma\beta^3 + \frac{\sigma_z h^2}{(1+\sigma_\varepsilon h)^2} \leq \frac{3\gamma\sigma_\varepsilon h}{1+\sigma_\varepsilon h}\beta^3 + \frac{\gamma\beta\sigma_z h}{1+\sigma_\varepsilon h} \leq \frac{\beta g(\beta) h}{1+\sigma_\varepsilon h}$ in the numerator.
- Trading volume. From Equation (4), the impact of $\sigma_\varepsilon$ on trading volume depends on the sign of $\frac{\mathrm{d}\ln(\beta^2(1/h+\sigma_\varepsilon)}{\mathrm{d}\sigma_\varepsilon} = \frac{2}{\beta}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_\varepsilon} + \frac{h}{1+\sigma_\varepsilon h} = \frac{2}{\beta g(\beta)}(-\gamma\beta^3 - \frac{\sigma_z h^2}{(1+\sigma_\varepsilon h)^2}\frac{h\beta g(\beta)}{2(1+\sigma_\varepsilon h)})$ after substituting in the expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_\varepsilon}$ and rearranging. To sign this expression note first that Equation (3) leads to $g(\beta) = \gamma\sigma_\varepsilon\beta^3 - \gamma\sigma_z\beta + 2\frac{\sigma_z h}{1+\sigma_\varepsilon h}$ , and second, that $f\left(\sqrt{\frac{\sigma_z h}{1+\sigma_\varepsilon h}}\right) = \gamma\sigma_\varepsilon(\frac{\sigma_z h}{1+\sigma_\varepsilon h})^{3/2} + \gamma\sigma_z\sqrt{\frac{\sigma_z h}{1+\sigma_\varepsilon h}} > 0$, which implies that $\beta \leq \sqrt{\frac{\sigma_z h}{1+\sigma_\varepsilon h}}$ and as a result that $\beta^2\sigma_\varepsilon \leq \sigma_z$. It follows that $\frac{\mathrm{d}\ln(\beta^2(1/h+\sigma_\varepsilon)}{\mathrm{d}\sigma_\varepsilon} \leq 0$ and that trading volume is decreasing in $\sigma_\varepsilon$.
- Return volatility. The sign of $\frac{\mathrm{d}VOL}{\mathrm{d}\sigma_\varepsilon}$ depends on the model parameters.

Intuition:

- The insider trades less aggressively when she is less well informed (smaller $\beta$), reducing expected trading volume and the informativeness of the order flow, thereby weakening its price impact (improved liquidity).
- Volatility is, on the one hand, dampened by the lower price impact, but on the other hand, amplified by the higher noisiness of the insider's trades. The net effect is ambiguous.

*Distracted market maker: A higher variance of the market maker's signal error results in less trading volume, worse liquidity (λ higher) and higher return volatility.*

Proof:

We proceed in a manner similar to the previous two cases.

- Liquidity. The implicit-function theorem applied to Equation (3) yields $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}} = -\frac{\sigma_z}{g(\beta)(1+\sigma_\varepsilon h)^2(\sigma_{\varepsilon'})^2} \leq 0$. That is, $\beta$ decreases in $\sigma_{\varepsilon'}$. Equation (2) implies that $\lambda\beta$ increases in $\sigma_{\varepsilon'}$ so $\lambda$ must increase in $\sigma_{\varepsilon'}$.
- Trading volume. From Equation (4), the impact of $\sigma_{\varepsilon'}$ on trading volume depends on the sign of $\frac{\mathrm{d}\ln(\beta^2(1/h+\sigma_\varepsilon)}{\mathrm{d}\sigma_{\varepsilon'}} = \frac{2}{\beta}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}} + \frac{1}{(1+\sigma_\varepsilon h)h(\sigma_{\varepsilon'})^2} = \frac{\gamma\beta(\sigma_{\varepsilon'})^2}{g(\beta)(1+\sigma_\varepsilon h)h}(\beta^2\sigma_\varepsilon - \sigma_z)$ after substituting in the expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}}$, using Equation (3) and rearranging. This expression is negative because $\beta^2\sigma_\varepsilon \leq \sigma_z$, as shown above. It follows that trading volume is decreasing in $\sigma_{\varepsilon'}$.

- Return volatility. From Equation (4), it suffices that $(\beta^2\sigma_\varepsilon + \sigma_Z)/h$ increases in $\sigma_{\varepsilon\prime}$ for volatility to increase in $\sigma_{\varepsilon\prime}$, since we already established that $\lambda$ increases in $\sigma_{\varepsilon\prime}$. $\frac{\mathrm{dln}((\beta^2\sigma_\varepsilon+\sigma_Z)/h)}{\mathrm{d}\sigma_{\varepsilon\prime}} = (\frac{1}{\mathrm{h}} - \frac{2\beta\sigma_\varepsilon}{\beta^2\sigma_\varepsilon+\sigma_Z}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon\prime}})\ \frac{1}{(\sigma_{\varepsilon\prime})^2}$. Substituting in the expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon\prime}}$ and rearranging shows that the expression in brackets is positive, and therefore that volatility is increasing in $\sigma_{\varepsilon\prime}$.

Intuition:

- As his signal becomes less precise, the market maker assigns more weight to the information conveyed by the order flow and less to his signal, leading to higher price impact. That is, liquidity worsens as adverse selection risk intensifies.
- Trading volume is shaped by two opposing forces. On the one hand, the insider scales back her trades (smaller $\beta$) as liquidity deteriorates. On the other hand, her trades grow more extreme as her signal deviates more from that of the market maker (higher $Var[s - p_1]$). The former effect dominates the later so the net effect is a decrease in trading volume.
- Volatility is magnified by the higher price impact in the trading period. This increase is dampened but not overturned by the insider's reduced aggressiveness (smaller $\beta$).

## Internet Appendix B: Additional Results

### B.1: Distraction Events and Earnings Announcements

In this subsection, we check whether distraction affects the speed of incorporation of earnings news. Using direct stock-level proxies for institutional and retail investors' attention, Ben-Rephael et al. (2016) find that the former but not the latter drives price discovery around earnings announcements. Peress (2008) shows that media coverage of announcements reduces the tendency for stock prices to underreact to earnings news; that is, he observes a weaker immediate response and stronger subsequent drift for media-covered announcements. DellaVigna and Pollet (2009) were the first to proxy marketwide inattention by distractions unrelated to the stock market; they compare announcements made on Friday—when investors are distracted by the upcoming weekend—to those made on other weekdays, and report more underreaction for the former. In similar vein, Hirshleifer et al. (2009) argue that earnings announcements compete for investors' limited information-processing capacity; they expect and find more underreaction on days with many announcements. Despite their methodological differences, all these papers provide evidence for a delayed incorporation of earnings news when investors' attention is low. All in all, these results suggest that the very investors responsible for a timely incorporation of earnings news—presumably sophisticated institutions with fast access to news—suffer from attention constraints.

In this context, it is natural to ask whether our distraction events lead to similar effects. We expect them not to, since we have argued that our events primarily affect retail investors (and especially noise traders) and Ben-Rephael et al. (2016) suggest that these investors do not contribute much to the price discovery upon earnings news. The results, shown in Table A.1, confirm this intuition. The variables definitions and regression details are provided in the table header. The interaction coefficient of the earnings surprise decile with our distraction dummy is neither significant for the immediate stock price response (Panel A), nor for the post-announcement drift (Panel B). Taken together, these results suggest that the price discovery of earnings news is not different on distraction days. For comparison, the table also reproduces the results from DellaVigna and Pollet (2009) and Hirshleifer et al. (2009). They show that the immediate stock price response is muted both on Friday and on days with many concurrent announcements (Panel A). At the same time, the post-announcement drift is more pronounced on these days (though not significantly so for Fridays, Panel B).

## Table A.1: Distraction Events and Earnings Announcements

This table shows results for regressions of the kind $CAR_{it} = \alpha_i + \alpha_t + \beta_1 * DS_{it} + \beta_2 * DS_{it} * InattentionProxy_t + \boldsymbol{\beta} * \mathbf{X}_{it} + \varepsilon_{it}$ for the sample of earnings announcements with complete data over the period 1995 to 2012. In Panel A, the dependent variable is CAR[0,1]; in Panel B, it is CAR[2,61], where the windows designate trading days relative to the announcement date. DS is the earnings surprise decile (1[low] to 10[high]), where the earnings surprise is measured as the actual number of earnings per share minus the median earnings per share forecast issued in the last 30 calendar days before the announcement, scaled by the stock price 5 trading days before the announcement. The inattention proxy is either a dummy flagging our distraction events, a dummy for Fridays (following DellaVigna and Pollet, 2009), or the natural logarithm of the number of earnings announcements on the same day [de-meaned over the sample period] (following Hirshleifer et al., 2009). There are 9,098 earnings announcement that fall on a distraction event, representing 4.25% of the announcements in our sample. As in Hirshleifer et al. (2009), CARs are computed as the difference between the buy-and-hold return of the announcing firm and that of a size and book-to-market matching portfolio. X is a vector of control variables that includes firm size (natural logarithm of total assets), leverage ratio, market-to-book ratio, firm age (number of years since first appearance in Compustat), analyst coverage (natural logarithm of the number of analysts following the firm), and reporting lag (number of days between the announcement and the date of the last fiscal quarter end). When controls are included, they are also interacted with earnings surprise deciles. All regressions include firm and earnings announcement date fixed effects. Standard errors are double-clustered by firm and earnings announcement date. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: CAR[0,1]

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| DS | 0.0076*** | 0.0085*** | 0.0077*** | 0.0085*** | 0.0076*** | 0.0087*** | 0.0077*** | 0.0075*** |
| | (66.87) | (19.54) | (66.28) | (19.64) | (67.99) | (20.09) | (66.36) | (17.34) |
| DS*Distraction Events | -0.0005 | -0.0005 | | | | | -0.0005 | -0.0005 |
| | (-1.25) | (-1.11) | | | | | (-1.37) | (-1.17) |
| DS*Friday | | | -0.0014*** | -0.0013*** | | | -0.0018*** | -0.0018*** |
| | | | (-4.26) | (-3.86) | | | (-5.40) | (-5.25) |
| DS*log(#EAs) | | | | | -0.0003*** | -0.0005*** | -0.0005*** | -0.0005*** |
| | | | | | (-2.66) | (-4.09) | (-3.86) | (-4.03) |
| Firm & Date FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 193,660 | 187,354 | 193,660 | 187,354 | 193,654 | 187,348 | 193,654 | 187,348 |
| Adj. $R^2$ | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |

Panel B: CAR[2,61]

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| DS | 0.0028*** | 0.0075*** | 0.0027*** | 0.0074*** | 0.0027*** | 0.0069*** | 0.0027*** | 0.0047*** |
| | (10.28) | (5.50) | (9.86) | (5.43) | (10.21) | (5.08) | (9.56) | (3.43) |
| DS*Distraction | -0.0017 | -0.0018 | | | | | -0.0017 | -0.0017 |
| Events | (-1.45) | (-1.52) | | | | | (-1.45) | (-1.47) |
| DS*Friday | | | -0.0001 | -0.0002 | | | 0.0012 | 0.0009 |
| | | | (-0.10) | (-0.19) | | | (1.15) | (0.87) |
| DS*log(#EAs) | | | | | 0.0013*** | 0.0010*** | 0.0014*** | 0.0013*** |
| | | | | | (4.58) | (3.35) | (4.66) | (4.21) |
| Firm & Date FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 192,568 | 186,303 | 192,568 | 186,303 | 192,562 | 186,297 | 192,562 | 186,297 |
| Adj. $R^2$ | 0.04 | 0.06 | 0.04 | 0.06 | 0.05 | 0.06 | 0.05 | 0.06 |

## B.2: News Pressure, Economic News and Sentiment

In this subsection, we analyse how news pressure—the variable which defines our distraction events—is related to measures of economic activity and media sentiment. We do this by regressing de-seasonalized and de-trended news pressure on several indicators of economic activity, macroeconomic news releases and media sentiment. The overall message of this exercise is that news pressure is only weakly correlated with any of these measures.

The results are shown in Table A.2. All the variables and regression details are described in the table header. Here, we just summarize the results. In particular, the table shows that, even though some correlations are statistically significant, the economic magnitude of these correlations is consistently small. For instance, our most comprehensive model—which uses six different indicators for media sentiment/business activity to explain the variation in news pressure—still shows an R2-statistic of less than 0.5% (column (7)). Looking at individual indicators, the biggest economic effect is found for FOMC meetings (on FOMC days, news pressure is reduced by up to 13% of its standard deviation), but is statistically insignificant. In terms of statistical significance, news pressure is most closely associated with sentiment, but the economic magnitude of this correlation is weak (a one-standard deviation increase in NYT sentiment leads to an increase in news pressure of 3% of its standard deviation). Bearing in mind that our distraction events are days on which news pressure is about two standard deviations higher than its unconditional mean, we can rule out, given such weak correlations, that days with large shocks to sentiment and/or economic activity systematically enter our sample of distraction events.

## Table A.2: Correlation Analysis between News Pressure and Economic Indicators

This table shows results for time-series regressions of newspressure on a number of different news indexes. *NYT sentiment* is a measure of negative tone in two daily New York Times newspaper columns ("Financial Markets" and "Topics on Wall Street"). Negative tone in these columns is measured as the number of negative workds minues the number of positive words, over all words. See Garcia (2013) for details. *ADS index* is the Aruoba et al. (2009) "real-time" index of business activity that aggregates information from changes in the yield curve term premium, initial claims for unemployment insurance, employees on non-agricultural payrolls and real GDP. See Aruoba et al. (2009) for details. *BBD index* is the Baker et al. (2016) measure of economic policy uncertainty distilled from newspaper coverage. See Baker et al. (2016) for details. All these variables, including newspressure, have been de-trended and de-seasonalized using the same methodology as employed for our variables in the main analyses (that is, they have been regressed on month and day-of-week dummies). To ease interpretation of the magnitude of the results, they have further been standardized. *CPI release* is a dummy that takes the value one on a day in which the CPI was released, and zero otherwise. Employment release is a dummy that takes the value one on a day in which employment statistics were released, and zero otherwise. *FOMC release* is a dummy that takes the value one on a day in which FOMC meetings were held. Standard errors are Newey-West adjusted allowing for 10 lags of auto-correlation. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| NYT sentiment | 0.0330** | | | | | | 0.0463** |
| | (3.06) | | | | | | (2.59) |
| ADS index | | -0.0335** | | | | | -0.0412 |
| | | (-2.89) | | | | | (-1.03) |
| BBD index | | | 0.0253* | | | | 0.0147 |
| | | | (2.16) | | | | (0.75) |
| CPI release | | | | -0.0585 | | | -0.0653 |
| | | | | (-1.43) | | | (-0.86) |
| Employment release | | | | | -0.0319 | | -0.0274 |
| | | | | | (-0.83) | | (-0.36) |
| FOMC release | | | | | | -0.1174 | -0.1287 |
| | | | | | | (-1.67) | (-1.42) |
| Observations | 9,420 | 15,393 | 10,448 | 15,751 | 15,751 | 7,180 | 3,020 |
| $R^2$ | 0.0012 | 0.0011 | 0.0006 | 0.0001 | 0.0000 | 0.0003 | 0.0048 |
| Adjusted $R^2$ | 0.0011 | 0.0011 | 0.0006 | 0.0001 | 0.0000 | 0.0002 | 0.0028 |

## B.3 Event Study around Economic News

In this subsection, we show event study results for two sets of economic events. First, we examine 37 high-news pressure days on which the stock market is the topic of a news segment (these days obviously do not belong to our list of distraction events, because they were filtered out thanks to the keyword "stock market"). To be more precise, we look at high-news pressure days on which the expression "stock market" but not "stock market report" is mentioned in a headline. The latter occurs on 175 days, and seems to reflect routine news coverage of that day's stock market movements (as we don't find peculiar market movements on these days). Second, we show event study results for scheduled meetings of the Federal Open Market Committee (FOMC). The press conference following these meetings (as of 1994, at around 2:15pm Eastern Time) is arguably the most anticipated macroeconomic announcement by market commentators, investors and analysts alike. The variables definitions and regression details are provided in the header of Table A.3. Panel A, shows the results for the first list. We find a significant drop in returns, a surge in trading volume and a strong increase in volatility. The negative return indicates that stock market crashes feature in this sample of events. For the FOMC announcements (Panel B), we find a significantly positive market return, and again a sharp rise in trading activity and volatility. The return effect reflects the pre-FOMC announcement drift documented by Lucca and Moench (2013).

Thus, even if both sets of economic news events affect returns differently, they share two important features: they are associated with sharp increases in trading volume and volatility. As we have argued, these market outcomes are radically different from those observed on our distraction days. As a result, we believe that our results cannot be explained by high news-pressure reflecting economic news.

## Table A.3: Market-wide Event Study for Economic News

This table reports (equal-weighted) market-wide event-study results for two distinct sets of economic news days. Panel A shows results for the first set, which comprises 37 high-news pressure days on which the words "stock market" were explicitly mentioned in the caption of a news segment (but not "stock market report", which seems to be a recurring news item that typically does not contain important stock market news). Panel B shows results for the second set, which comprises of FOMC announcement days (i.e., the day of the press release following a Federal Open Market Committee meeting). FOMC announcement dates are taken from Lucca and Moench (2013), complemented by information from https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. All variables are defined in the Appendix. Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, the z-statistic for the non-parametric rank test in square brackets, and the number of events for which the particular variable is available. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: High-news pressure days with explicit mention of the stock market

| (1) Mkt return | | (2) Log(turnover) | | (3) Log($volume) | |
|---|---|---|---|---|---|
| -1.015 | | 0.126 | | 0.121 | |
| (-2.313) | ** | (2.945) | *** | (2.942) | *** |
| [-1.365] | | [2.482] | ** | [2.225] | ** |
| 37 | | 37 | | 37 | |

| (4) Abs return | | (5) Price range | | (6) Return volatility | |
|---|---|---|---|---|---|
| 0.784 | | 1.093 | | 0.072 | |
| (2.735) | *** | (3.356) | *** | (2.099) | * |
| [2.180] | ** | [2.783] | *** | [1.870] | * |
| 37 | | 37 | | 17 | |

Panel B: FOMC announcement days

| (1) Mkt return | | (2) Log(turnover) | | (3) Log($volume) | |
|---|---|---|---|---|---|
| 0.231 | | 0.032 | | 0.034 | |
| (2.220) | ** | (2.946) | *** | (3.261) | *** |
| [2.487] | ** | [3.564] | *** | [3.544] | *** |
| 160 | | 160 | | 160 | |

| (4) Abs return | | (5) Price range | | (6) Return volatility | |
|---|---|---|---|---|---|
| 0.068 | | 0.107 | | 0.010 | |
| (1.760) | * | (2.851) | *** | (3.697) | *** |
| [0.642] | | [2.337] | ** | [4.041] | *** |
| 160 | | 160 | | 160 | |