Glued to the TV: Distracted Noise Traders and Stock Market Liquidity

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We study the impact of noise traders' limited attention on financial markets. We exploit episodes of sensational news (exogenous to the market) that distract noise traders. On "distraction days", trading activity, liquidity, and volatility decrease, and prices reverse less among stocks owned predominantly by noise traders. These outcomes contrast sharply with those that result from the inattention of informed speculators and market makers. Our paper establishes that noise traders contribute to liquidity by mitigating adverse selection risk, and thus complements research that identifies noise trading as a main driver of inventory risk.

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The literature on limited attention in financial markets focuses on informed agents—speculators and market makers—and on the speed at which they impound public information into stock prices. Less is known about how attention might affect a third, yet equally important, group of agents: noise traders. By trading stocks for reasons unrelated to stock fundamentals, noise traders allow speculators to profit from their information, and market makers to recoup losses from trading with speculators. As summarized by Fisher Black in his Presidential Address: "Noise makes financial markets possible" (Black, 1986, p. 530). In this paper we aim to improve our understanding of how noise traders' (in)attention affects financial markets. Toward that end, we consider events that distract noise traders and trace out their consequences. We find that, when noise traders are distracted from trading, liquidity and volatility decrease and prices reverse less. These effects conform to what theory predicts.

There are two main challenges to identifying the effect of noise traders' attention on markets. First, events that draw attention to stocks are typically associated with material news about stocks' fundamentals. It is then unclear whether any observed pattern is caused by the attention itself or instead by the news. Second, many attention-grabbing events affect investors at large and not just noise traders. We overcome these problems by exploiting events that (a) divert, rather than attract, investors' attention and (b) are especially appealing to irrational, biased, or sensation-seeking investors. Specifically, we identify episodes of sensational news that are exogenous to the stock market and temporarily distract traders. A vivid example of such an event is the murder trial verdict in the case of football and movie star O. J. Simpson on 3 October 1995. Millions interrupted what they were doing to hear 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 relevant for our purpose, and as shown by Figure 1, trading volume on the New York Stock Exchange (NYSE) plunged 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 dramatic for small and large trades, suggesting that both retail and institutional traders were distracted. Because the O. J. Simpson trial was unrelated to the economy, such an episode speaks to a causal effect of (in)attention on the stock market. Moreover, a detailed analysis of who is distracted by sensational news demonstrates that it mainly affects noise traders.

[[Insert Figure 1 about here]]

To create a sample of such distraction events, we use 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 days belonging to the highest decile. We then parse through the headlines of news segments covered in the broadcasts and retain only those 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 drew the attention of US households. Our final sample contains 532 days (distraction events) over the period from 1968 to 2013.

The first step in our analysis is to check that these news stories actually divert noise traders' attention away from the stock market. Detailed trading records of households (from a large discount broker) and of institutions (from Abel Noser Solutions, a.k.a. ANcerno) confirm that trading volume drops on distraction days—by 6.5% and 4%, respectively—before reverting to normal on the following day. Consistently with this decline, transactions data from the Trades and Quotes (TAQ) database reveal a reduction in the volume of small trades (which are likely to involve retail traders) and large trades (which are likely to involve institutions), although the reduction is statistically significant only for small trades. To assess whether noise traders in particular are distracted, we take advantage of our detailed trading data and construct several proxies for investors' "biasedness": the extent to which they make losses from trading, churn their portfolios, under-diversify, trade stocks covered in the media and, for households only, gender. These factors are all related to the tendency of traders to be sensation seeking, overconfident, or sensitive to media coverage. We find that, among both households and institutions, the more "biased" investors are more prone to distraction. In contrast, investors who consistently profit from trading are unaffected by sensational news events. These observations suggest that the sensational news episodes studied in this paper primarily distract noise traders. We therefore exploit those episodes to study how short-lived changes to noise trading affect financial markets.

The next step in our analysis is to examine how the U.S. stock market behaves on sensational news days (i.e., when noise traders are inattentive). Although we find weak results for the overall market, we uncover pronounced effects when focusing on subgroups of stocks with high retail ownership—stocks in which noise trading is expected to be more pronounced (e.g., Lee et al, 1991). At the outset, we check that trading activity declines 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 is consistent with noise trading being less important for those stocks.

For liquidity, we build several proxies using both CRSP daily data (closing bid–ask spreads and the illiquidity ratio of Amihud, 2002) and TAQ intraday data (average bid–ask, effective, and realized spreads; price impact; absolute trade imbalance; Kyle's lambda). We find that nearly all proxies in the bottom terciles 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 and test methodologies (i.e., parametric vs. 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.

Next we turn to examining the behavior of volatility and price reversals on distraction days. As our proxy for volatility we use the absolute value of close-to-close returns, the daily high-to-low ratio of prices (obtained from CRSP), and the standard deviation of intraday returns (using TAQ data). We measure price reversals as the average autocovariance of intraday returns. Again we find a reduction (of 3%) in volatility and a weakening (of 4%) in price reversals in the bottom terciles, which dissipate monotonically as we move away from stocks with high levels of retail ownership. In sum: among stocks owned predominantly by individual investors, distraction days are associated with reduced liquidity, volatility, and price reversals. Cross-sectional tests confirm that distraction events that see a greater decline in trading also exhibit a more pronounced reduction in these three variables, thus establishing that these distraction effects are all related.

We demonstrate theoretically that these findings—the reduction (on distraction days) in trading activity, volatility, price reversals, and liquidity for stocks with high retail ownership—can be attributed to a common shock: a reduction in noise trading. Indeed, when noise traders exit the market, market makers face worse adverse selection because they are then at greater risk of being "picked off" by informed speculators; hence liquidity drops. The concurrent reduction in volatility and in price reversals is also consistent with a drop in noise trading, 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, that it becomes 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. We make further use of our model to derive predictions from distracting other categories of agents (namely, informed speculators and market makers) and find that these predictions are not borne out by the evidence.[1]

Our findings on liquidity contrast with those of Foucault et al. (2011), who report an improvement following a reform that discouraged retail (noise) trading on the French stock exchange. They explain their findings by noting that the reform, because it permanently dampened noise trading and therefore volatility, reduced the inventory risk faced by market makers—that is, the risk associated with the future unwinding of their inventory. Our model rationalizes this divergence by considering a drop in noise trading that is transitory (in line with our experiment) and whose effect on inventory risk is therefore negligible. Noise trading matters instead through its (immediate) effect on adverse selection risk, which implies that a reduction in noise trading lowers liquidity (in line with what our data show). In other words, isolating the effect of noise trading on adverse selection requires fluctuations in noise trading that are sufficiently short lived to not affect future volatility. We argue that the short-lived distraction shocks studied here are ideally suited for this purpose.

We strengthen the causal interpretation of our results by discussing, and ultimately dismissing, two important endogeneity concerns. The first is that high-news pressure

[1] Our parsimonious model makes distinct predictions for market outcomes as a function of the attention paid by different categories of agents: speculators, market makers, and noise traders. These predictions are summarized in Table 4.

events might contain some economic news despite our filtering attempts. We address this concern in several ways. First, we show that our results are unchanged after removing firms operating in sectors that are plausibly the most economically affected by an event (e.g., firms in the construction or insurance sectors for natural disasters). Second, we point out that our results—namely, a decline in trading activity and volatility that is especially pronounced for small stocks—are at odds with the footprints of economic news. Indeed, such news is usually associated with surges in trading activity and volatility (see e.g. Ederington and Lee, 1993), especially among large stocks, which are known to lead small stocks in terms of price discovery (see e.g. Lo and MacKinlay, 1990; McQueen et al., 1996).

In view of this discussion, the second endogeneity concern, reverse causality, seems more relevant. Indeed, newscasts may devote more time to an economically irrelevant story (implying that news pressure is high) because they have nothing newsworthy to report about the economy, which would then coincide with low trading and volatility. We dismiss this concern on several grounds, including a placebo test and an analysis of firm-specific news on distraction days. The most direct counterargument is the previously mentioned spike in TV viewership observed on high-news pressure days. Indeed, one cannot reasonably argue that news broadcasters would rather report economic news when viewers evidently crave these sensational stories.

In a final step, we study how distraction effects have changed over time. Indeed, equity markets have seen profound changes—in terms of both investor composition and the institutional environment—over the four decades spanned by our data. It is not clear a priori what to expect. On the one hand, distraction effects may dissipate as retail (noise) traders are gradually replaced by institutional (noise) traders that are less prone to distraction. On the other hand, today's most active traders—algorithmic and especially high-frequency traders—interact with noise traders in ways that may exacerbate distraction effects. Analyzing the data over two subperiods, 1968–2000 and 2001–2013, reveals contrasting patterns across variables.[2] In the later subperiod we find that distraction effects on trading activity, volatility, and price reversals are considerably amplified whereas those effects on liquidity are attenuated. A straightforward

[2] We use year 2001 to split the sample period because major structural changes occurred around that time: decimalization in 2001, market fragmentation following the SEC's Regulation of Exchanges and Alternative Trading Systems (ATS) in 1998 and its 2005 Regulation National Market System (NMS), the so-called digital revolution, and the advent of algorithmic trading.

explanation of the attenuating effect on liquidity is the aforementioned decline in retail trading. For volatility, price reversals and trading activity, in contrast, the amplification appears to be related to the advent of algorithmic trading.

Indeed, we sort stocks in the post-2001 period on their intensity of algorithmic trading using data from the SEC's Market Information Data Analytics System (MIDAS). We find that the distraction effects for trading activity, volatility, and price reversals (among small stocks) are more pronounced for the stocks that are traded more intensively by algorithms. There is some (albeit weak) evidence that the distraction effect on liquidity is actually smaller for these stocks. These findings are consistent with the time patterns discussed above. We speculate that technological advances—including improvements in hardware (e.g., computing power, custom-designed chips, ultra-fast communication lines) and in software (e.g., pattern recognition algorithms, "Big Data", artificial intelligence)—as well as new business practices (e.g., co-location, access to exchanges' proprietary data feeds) have made it easier to detect and anticipate noise trades. These changes have allowed agency algorithms to improve the timing of their informed trades (i.e., to trade when noise trading surges) and have also, perhaps more controversially, allowed high-frequency traders to take advantage of noise traders by front-running their orders.[3]

Our paper contributes to several strands of research. First, it adds to the growing literature on limited attention in financial markets. This literature focuses largely on informed traders and the speed at which they impound public information into prices (see e.g. Cohen and Frazzini, 2008; DellaVigna and Pollet, 2009; Hirshleifer et al., 2009),[4] and, to a lesser extent, on market makers (Corwin and Coughenour, 2008; Chakrabarty and Moulton, 2012). Our main contribution in this context is to study noise traders, specifically, how their trading contributes to liquidity, volatility, and price efficiency. A few papers (e.g., Barber and Odean, 2008; Da et al., 2011) study retail investors' attention to stocks. These authors exploit attention-grabbing events (as captured, for example, by

3 Buy-side institutions (see Section V) employ agency algorithms to minimize the price impact of their trades. For example, the activist shareholders analyzed by Collin-Dufresne and Fos (2015) strategically time their informed trades to occur when they anticipate more active noise trading (such as when volume on the S&P 500 stock index is abnormally high). The attenuation we report for the effect of distraction on liquidity is consistent with Collin-Dufresne and Fos's finding of a negative relation between measures of adverse selection and informed trading. High-frequency traders' controversial behavior served as the basis of Michael Lewis's (2014) *Flash Boys* and inspired the launch of IEX, a purposely slowed-down trading platform.

4 In Internet Appendix B.1, we show that our distraction events do *not* affect the speed with which earnings news is incorporated into stock prices, suggesting that they do not distract rational investors. This is consistent with our argument that sensational news events primarily affect noise traders.

extreme returns, high trading volume, media coverage, high Google search volume) to uncover trading and return patterns that are consistent with retail buying pressure; however, they do not examine volatility or liquidity. Moreover, such research is subject to the criticism that these events are confounded by economic news. We thus make an important methodological contribution by showing how distracting events can be fruitfully exploited to study the causal consequences of short-term fluctuations in noise traders' attention. More broadly, our findings illustrate the general point that the impact of attention ultimately depends on who is (in)attentive (see also Ben-Rephael et al., 2017).

Our paper's second main contribution is to the literature on the determinants of liquidity. Microstructure theory has identified two opposing channels through which noise traders affect liquidity. On the one hand, adverse selection models (e.g., Glosten and Milgrom, 1985; Kyle, 1985) demonstrate that insiders exploit noise trades to conceal their informed trades. When noise trading lessens, market makers face more risk of being adversely selected and seek compensation by increasing spreads and/or price impact. On the other hand, inventory risk models (e.g., Ho and Stoll, 1981; Grossman and Miller, 1988) emphasize that market makers are concerned about fluctuations in their inventory's value, as might be triggered by future noise trading shocks. From this perspective, a reduction in noise trading improves liquidity. How liquidity is ultimately shaped by noise trading therefore remains an open question—and one that is hard to answer empirically because noise trading is endogenous and could itself be a function of liquidity.[5]

So far, the evidence has relied on structural estimations (e.g., the "probability of informed trading" (PIN) model" of Easley et al., 1996) or on laboratory experiments (e.g., Bloomfield et al. 2009). Only two papers offer causal evidence drawn from quasi-natural experiments, namely Greene and Smart (1999) and Foucault et al. (2011), who exploit changes in noise trading triggered by, respectively, analyst recommendations published in the press, and a stock market reform. But because these experiments entail long-lasting changes to noise trading, their findings on liquidity accentuate the inventory risk channel. This is striking in Foucault et al. (2011) where the drop in the intensity of noise trading

5 For instance, Grullon et al. (2004) document that firms that spend more on advertising have more individual stockholders and are also more liquid; however, it remains unclear whether these investors cause or instead are attracted by the improved liquidity. Likewise, there is evidence that retail investors are drawn to volatile stocks—either because such 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).

is permanent; hence the reduction in inventory cost is so large that it swamps any adverse selection effect and thus results in a liquidity improvement.[6] In contrast, our single-day decline in the intensity of noise trading leads to no detectable reduction in inventory cost but does lead to reduced liquidity because adverse selection now dominates.[7] Overall, our findings identify the importance of the adverse selection channel, the bedrock of a large literature on trading under asymmetric information; they also help reconcile prior conflicting evidence by emphasizing that the duration of noise trading shocks varies significantly across settings.

Our third contribution is to describe how attention interacts with behavioral biases and, thereby, to offer 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 more "biased" (e.g., unskilled, overconfident, sensation-seeking) investors are more prone to distraction—and so their performance actually improves when they watch TV instead of trading.

Finally, 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 (data limitations prevent us from drawing clear-cut conclusions for institutional traders). More specifically, for retail investors 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 this paper is organized as follows. Section I reviews our data and methodology, and Section II considers the effect of distraction on retail and institutional investors. In

6 In similar vein, an old literature on stock splits consistently documents that these events attract retail investors and are associated with an increase in stock return volatility and bid-ask spreads (e.g., Copeland, 1979; Conroy et al., 1990). Although there is some disagreement on the interpretation of these findings (e.g., Schultz, 2000; Easley et al., 2001), it is noteworthy that they are largely consistent with the inventory risk channel.

7 In the middle of this spectrum lies the paper of Greene and Smart (1999), who describe an increase in noise trading intensity that can last from ten days to several weeks. In their setup, the adverse selection and inventory cost channels balance each other and there is thus only a weak effect on overall liquidity. Moreover, their experiment consists of one-sided shocks to noise trading (i.e., increased buying—but not selling—by noise traders), and, to the extent that these shocks are known to market makers, may not affect the adverse selection risk they face.

Section III we study how distraction shocks affect the stock market—in particular, the stocks held predominantly by noise traders. Section IV presents robustness checks and discusses endogeneity issues, and in Section V we investigate how distraction effects have changed with the advent of algorithmic trading. Section VI concludes. The paper's Internet Appendix presents the details of our model along with 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 U.S. 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).[8] 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 news broadcasts cover important economic news—which, rather than distract, actually draw attention to the stock market. We dismiss this concern on three grounds.

First, economic news would bias our results *against* finding a distraction effect. Indeed, a large literature documents that stock returns are orders of magnitude more variable on days with economic news (see e.g. Cutler et al., 1989; Ederington and Lee, 1993). 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

[8] 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/).

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. Moreover, the impact of economic news should be felt most strongly for large stocks (which are known to lead small stocks in terms of price discovery; see e.g. Lo and MacKinlay, 1990; McQueen et al., 1996; Hou and Moskowitz, 2005), whereas our distraction effects primarily affect small stocks.

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.[9] 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),[10] assassination attempts (on President 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

[9] The keywords are: 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.

[10] 9/11 does not enter our sample because stock exchanges remained closed from 11 September to 17 September, 2001.

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.[11] 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.

An important prerequisite for the distraction hypothesis is that our events absorb the attention of potential investors (and thereby reduce the attention available for trading in the stock market).[12] 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 (from which the news pressure variable is calculated) rises on distraction days.[13] 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.[14] Thus we find strong evidence that US residents are "glued to the TV" on distraction days. We next describe the other data sources and explain our econometric methodology.

B. Other Data

We employ three different datasets to study the effect of distraction events on traders. The first source comprises about 1.9 million common stock trades executed by 78,000

[11] 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 (see Internet Appendix C.4). 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.

[12] To be clear, we do not claim that investors are distracted from trading *because* they are watching evening news broadcasts. Rather, we use these broadcasts to identify news stories that draw investors' attention throughout the trading day. Figure 3 below is consistent with this interpretation: investors trade less on distraction days, but not on the day after, which would have been the case if the broadcast itself—since it is aired after trading hours—had distracted investors.

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

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

households at a large discount brokerage house between January 1991 and November 1996 (for details, see Barber and Odean, 2000). 66 distraction events occur during that period. Our second source is data on institutional trades from Abel Noser Solutions, commonly known as ANcerno.[15] These data cover institutional stock transactions for 835 asset managers from 1999 to mid-2011—a period for which we have 99 distraction events. Though the dataset does not allow us to track individual funds, it includes an identifier for the management company of the fund executing the trade, enabling us to follow management companies over time. The advantage of these two disaggregated datasets is that they allow us to determine which investors are more prone to distraction.

Our third data source on 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.[16] Although these data sets do not reveal traders' identities, they do allow us to distinguish between small and large trades.[17] 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 to improve the accuracy of liquidity measures.[18] 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

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15 Ancerno Ltd. is the former name of Abel Noser Solutions. Puckett and Yan (2011) provide more information about this dataset.

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

17 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.

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

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.[19] 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 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.[20]

19 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.

20 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.

II. Distraction and Noise Trading

A. Overall analysis of retail and institutional trades

Here we study the effect of distraction on trading activity. In addition to setting the stage for the marketwide investigation to follow, this analysis is valuable in its own right: 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, we compare distraction effects across different measures of trading activity so as to identify *precisely* which stages in that process are most sensitive to attention constraints. Our results should thus be of interest to researchers working on the development of a positive theory of attention allocation.

We construct four measures of trading activity—which pertain to buys, sells, and their sum—for the retail and institutional data sets. The first measure, *log($volume)*, is obtained by aggregating the dollar value of all transactions on a given day and then taking logarithms. The remaining measures capture components of this aggregate measure. Our second measure, *log(avg trade size)*, is the average (log) trade size (in dollars) per investor and stock, conditional on trading. The third measure, *log(#stocks)*, is the average number of distinct stocks traded, again conditional on trading; it is defined as the (equal-weighted) average of the (logarithm of the) number of different stocks traded on a given day by an investor with at least one trade on that day. Our final measure, *log(#investors)*, is the (log) number of investors trading on a given day.

These last three measures are intended to reflect different stages in an investor's decision-making process. The variable *log(#investors)* captures the decision of whether or not to trade (i.e., the extensive margin). A drop in this variable on distraction days would indicate that the process of 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 to *search for* and trade additional stocks conditional on having traded at least once on that day. Past research suggests that, for underdiversified and short-sale–constrained retail investors, buys require more attention than sells during this phase because their choice set for buys is much larger than that for sells (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, distraction days should be associated with a reduction in the average trade size conditional on trading on a given day, or in *log(avg trade size)*.

[[Insert Table 2 about here]]

Panel A of Table 2 reports results using our retail brokerage data, for which there are 66 distraction events.[21] Dollar trading volume (*log($volume)*) is reduced by about 6.5% ($p < 0.05$) on distraction days, almost symmetrically across buys and sells. Breaking up this effect, we find a statistically significant drop in all three components of volume. However, the observed effect on the intensive margin is considerably weaker than that on the extensive margin: average trade size and number of distinct stocks traded both decline by less than 2% whereas the number of trading retail investors falls by 5%. We note that, in contrast to the other measures, the reduction in *log(#stocks)* is significantly greater for buys than for sells. Taken together, these findings are more consistent with models assuming a fixed attention cost for accessing the stock market than with models in which distraction reduces the (perceived) precision of retail investors' information. Our results are consistent also 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.

Panel B of Table 2 reports the results of a similar analysis conducted on institutional trades.[22] Again we find a significant drop in trading volume ($p < 0.05$), but its magnitude (about 4%) is smaller than for retail investors. Breaking up this effect yields results that are more nuanced than those for retail investors: although all three components exhibit negative estimates, none is consistently significant. In particular, the evidence at the extensive margin (i.e., for *log(#investors)*) is less compelling for institutional than for retail investors. This might be explained by professional investors facing a lower attention fixed cost for trading, or by the ANcerno data not identifying investors with enough precision. Indeed, the data identify only the management company (e.g., the fund

[21] To minimize the impact of structural breaks in the time series of the number of households covered in the data, we focus on households that report portfolio holdings for at least four of the six sample years. For the *log(#investors)* measure, we follow Barber and Odean (2002) in focusing on the trades of 12,743 households with holdings throughout the entire sample period.

[22] Because we do not have portfolio holdings data for institutions, we cannot restrict our analysis—as we did with retail investors—to institutional investors that report holdings persistently over the sample period. We have experimented with alternative filters (e.g., requiring institutions to trade at least once per month for a majority of the sample period) and obtained results that are similar to those reported here.

family); hence some fund families—Fidelity is an extreme example—appear to trade almost continuously over the sample period.

[[Insert Figure 3 about here]]

A natural question is whether investors eventually execute the trades that they missed while distracted—that is, whether they "catch up" on their trading. To answer this question, in Figure 3 we plot investors' abnormal trading activity in event time. We use the trading measures that produce the most reliable results in Table 2: *log(#investors)* for retail investors and *log($volume)* for institutions. In neither data set do we find any evidence of abnormal trading in the five trading days that precede or follow a distracting event; the only significant effect occurs on the distraction day itself. Thus, the figure confirms that our distraction events cause shocks to investors' trading activity that are short-lived. It also suggests that the trades forgone on distraction days are superfluous in the sense that they do not cause investors to trade more once the distraction subsides. Such trades are more likely to be speculative ones executed by sensation-seeking investors (Dorn and Sengmueller; 2009; Grinblatt and Keloharju, 2009; Gao and Lin, 2014) than to be liquidity trades motivated by a surplus or shortage of cash. Next we provide further evidence consistent with this interpretation.

B. Which retail and institutional investors are more distracted?

Having established that investors trade less on distraction days, we now seek to identify which investor types are more distractible. For that purpose, we sort investors on the extent to which they are biased and/or make losses (or forgo profits) from trading.

Motivated by past research, we employ six proxies to measure investors' biasedness. The first proxy, gender, is motivated by Barber and Odean's (2001) finding that men trade more frequently than women but earn lower returns. This pattern can be attributed to overconfidence—since many studies in psychology demonstrate that men are more overconfident than women—or to the pleasure derived from trading (e.g., the excitement of gambling; see Dorn and Sengmueller; 2009; Grinblatt and Keloharju, 2009; Gao and Lin, 2014). We define a dummy variable, *single-male*, which is set equal to 1 for a single male investor or to 0 for a single female investor; we focus on single households because they are likely to display starker differences (Barber and Odean, 2001). Information on gender is available in the retail data set only.

Our second proxy is portfolio concentration, which we measure as the average Herfindahl index over monthly portfolio holdings for retail investors and over monthly trading intensities for institutions. An investor who holds a concentrated portfolio forgoes the benefits of diversification, which indicates either that she has strong—and possibly ill-placed—faith in her few selected stocks or that she is seeking highly skewed (lottery-like) portfolio returns. Our third proxy is trading intensity, measured as an investor's average trading volume over the sample period; this metric builds on past evidence that investors trade too much (Barber and Odean, 2000; Kelley and Tetlock, 2013). Our fourth proxy is investment performance as measured by portfolio losses for individuals or by trading losses for institutions (since we don't observe their portfolio holdings). The rationale here is that investors who are more overconfident or more sensation seeking should perform worse. For our fifth proxy, we follow Goetzmann and Kumar (2008) and combine portfolio turnover and performance in order to capture the notion that overconfident or sensation-seeking investors underperform *because* they trade too much. Specifically, we multiply their portfolio turnover rank by their losses rank, and so a higher product corresponds to more overconfident or sensation-seeking investors.

Finally, we conjecture that investors with a habit of buying "glitter" stocks—that is, stocks that grab their attention (Barber and Odean, 2008)—are more prone to distraction. To measure this propensity, for each investor we calculate the fraction of buy decisions that occur on days when the purchased stock is covered in the media (specifically, in at least one of the four main U.S. newspapers: *New York Times*, the *Wall Street Journal*, the *Washington Post*, and *USA Today*). Our argument is that investors who react strongly to such (stale) newspaper coverage are also more attracted to sensational news stories and so should generate a larger distraction effect. Moreover, Fang et al. (2014) document that institutional investors more prone to buying media-covered stocks perform worse, which is consistent with them behaving like noise traders.

For each of these proxies, we split our sample of investors into halves and then carry out the event study separately on each subsample. We conduct the analysis on both the individual and institutional transactions data sets while focusing on the most reliable respective trade measures: *log(#investors)* for individuals and *log($volume)* for institutions. The results are reported in Table 3 and reveal that, regardless of which proxy is used, investors classified as more biased—be they individuals or institutions—trade less on sensational news days. The difference across groups is economically sizable: for 8 of 11 proxies, the distraction effect in the top group is more than twice its size in the bottom group; and the difference across groups is statistically significant in five cases.

[[Insert Table 3 about here]]

Altogether, these results suggest that the sensational news events studied in this paper primarily affect noise traders; that is, sensation-seeking, overconfident, or media-sensitive retail and institutional investors are more likely to be distracted from trading. It is ironic that, to the extent these investors trade too much because of their overconfidence (Barber and Odean, 2001), they actually *benefit* from being distracted. This finding offers a more nuanced view of inattention: it need not be detrimental (as is commonly assumed in the literature) because inattention—when it interacts with behavioral biases—may benefit the trader.

C. TAQ Analysis

Our results so far indicate that both retail and institutional noise traders are distracted. How strongly distraction affects the overall populations of retail and institutional investors then depends on the proportion of noise traders within each group.

Table 2, which reported a decline in trading volume one third larger for retail than for institutional investors, already hinted that distractible noise traders are more prominent among retail investors. The difference between the two investor types might actually be even larger since prior evidence suggests that the ANcerno dataset underrepresents skilled institutions. For instance, Jame (2017) and Choi et al. (2016) document no outperformance for the average hedge fund in ANcerno, whereas there is evidence of skill in the broader population (Kosowski et al., 2007; for a survey, see Agarwal et al., 2015). To the extent that ANcerno investors are less skilled than the average institution, they may also be more prone to distraction (Fang et al., 2014).

Here we present additional evidence that retail investors are more susceptible to distraction than are institutional investors. More specifically, we conduct an event study using TAQ data for all transactions involving stocks listed on NYSE/AMEX/Nasdaq from 1991 to 2000. The advantage of these data is that they cover all transactions and thereby offer a broad view of the market. A shortcoming is that they do not include traders' identities. Yet prior research has found that, until decimalization in 2001, small trades were most likely to be executed by retail investors and large trades by institutions

(Hvidkjaer, 2008; Barber et al., 2009). We accordingly investigate how distraction effects vary with trade size.

Panel C of Table 2 reports results for the 105 distraction events that occurred during the period 1991–2000. Our measure of trading intensity, *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 the volume due to large trades declines only by a statistically insignificant 0.7%. Column (3) shows that there is a significant difference—between small and large trades—in the distraction effect. This suggests that distractible noise traders account for a larger share of retail trading (as proxied by small trade volume) than of institutional trading (as proxied by large trade volume). For the stock market analysis to come, we therefore expect distraction effects to be more pronounced for stocks with high retail ownership.

III. Distraction and the Market

A. Hypotheses

Having established that noise traders 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, liquidity, volatility, and return auto-covariance which are summarized in Table 4.

[[Insert Table 4 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), returns become less volatile and their auto-covariance grows (is less negative).

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 market makers face higher adverse selection risk , which induces them to decrease liquidity. On the other hand, a lower variance reduces inventory risk, allowing market makers to charge a lower risk premium and thus improve liquidity. It turns out that the former effect outweighs the latter, 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 market makers need 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 market makers are concerned about fluctuations in the value of his inventory caused by *future* noise trading.[23] 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, return volatility and auto-covariance are driven by the inventory risk component of liquidity because that component leads to transient price impact.[24] Less noise trading means fewer temporary shocks to prices, which reduces volatility ad price reversals.

Distracted Insiders. 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 and auto-covariance 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 and auto-covariance are, 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.

Distracted Market Makers. If market makers are distracted (as modeled by a decrease in their signal precision), then trading volume declines, liquidity worsens (higher Kyle's

23 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.

24 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).

lambda), returns become more volatile and their auto-covariance declines (is more negative).

The market makers' signal represents their interpretation of public information.[25] As their signal becomes less precise, market makers assign more weight to the information conveyed by the order flow and less to their 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, she has more trading opportunities since she enjoys a bigger information advantage over market makers. The former effect dominates the latter and so the net effect is a decline in trading volume. Return volatility is magnified by the higher price impact in the trading period. Likewise, the return auto-covariance is more negative, that is, prices reverse more. These effects are dampened but not overturned by the insider's reduced trading aggressiveness.

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 insider being distracted. Evidence of a decrease in volatility and of an increase in return auto-covariance further suggests that noise traders are more distracted than market makers. Treating our distraction events as a natural experiment, we are thus able to tease out which type of investors is most affected by sensational news.

B. Marketwide Analysis

We start with a brief description of the variables used in this section.[26] 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

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[25] This signal is revealed to the insider through the prevailing mid-quote (i.e., price), so that the insider knows everything market makers know before deciding how much to trade.

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

number of shares traded in a stock on a given day divided by the number of shares outstanding,[27] 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).[28]

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.[29] This measure, denoted *log(amihud)*, is computed from CRSP data 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) argue that this measure captures the intuition of the PIN measure introduced by Easley et al. (2002), while having 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 comprises *realized spread*, which is the part of the effective spread that accrues to market makers as compensation for providing liquidity.

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27 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.

28 In the paper, we show results for TAQ-based spread measures that are equal-weighted across trades. In Internet Appendix C.3, we document very similar results for share-weighted and dollar volume-weighted spread measures.

29 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.

Finally, we investigate the impact of distraction on three measures of return volatility and on return auto-covariance. Two of the volatility measures—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 thus available throughout our study period. The remaining two measures are the intraday standard deviation of stock returns (*intraday volatility*) and the intraday auto-covariance of stock returns (*intraday auto-covariance*), both calculated from intraday returns obtained from TAQ.

[[Insert Table 5 around here]]

Table 5 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 they 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 6 around here]]

Table 6 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 for which noise trading is more pronounced; that is, stocks predominantly held by retail investors (see Subsection II.C above).

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 (which we draw from firms' 13(f) filings). For brevity, we only show the sample split results for firm size—those for stock price and institutional ownership are relegated to Internet Appendix C.1 and C.2, respectively.

It is well documented (e.g., Lee et al., 1991) that small stocks are held proportionately more by retail noise traders, so we expect results to be strongest for the bottom tercile in terms of firm size. As Panel A of Table 7 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 7 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 5). 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 statistically insignificant pattern, is observed. The return auto-covariance is significantly increased for small firms, but unchanged for large ones, implying that small firms have less inefficient (i.e., less negatively auto-correlated) prices on distraction days.

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.

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 4). The increase in realized spreads further suggests that, for small stocks, liquidity provision is also reduced. Additional analysis, presented in Internet Appendix B.6, reveals that this effect is driven by contrarian traders, rather than specialist market makers, being distracted. Experimental evidence suggests that uninformed investors often behave as "contrarian noise traders" (Bloomfield et al., 2009), so it may well be that that the distracted noise traders and distracted contrarian traders are one and the same. In any case, this effect appears to be small relative to the reduction in noise trading, as our results (and in particular the drop in return volatility) are collectively inconsistent with only liquidity providers being distracted.

In Internet Appendix C.1 and C.2, we sort stocks based on price and institutional ownership derived from 13(f) filings. Low-priced stocks and stocks with low institutional ownership are predominantly held by retail investors (e.g., Brandt et al., 2010). We therefore expect—and find—stronger results for such stocks: in the lowest terciles in terms of price (Table C.1) and institutional ownership (Table C.2), we find a reduction in trading activity, volatility, and liquidity, as well as an increase in return auto-covariance. These changes are typically statistically significant and tend to abate monotonically in the other terciles. For most measures, the difference between the top and bottom terciles is also significant.

D. Cross-sectional Test

The results from our three sample splits paint a consistent picture: on distraction days, stocks with high levels of retail ownership experience a reduction in trading activity, volatility, price reversals, and liquidity, whereas stocks with low retail ownership are unaffected. Our model demonstrates that these findings can all be attributed to a common shock: a reduction in noise trading. This interpretation further implies that distraction events that display a larger drop in trading should also exhibit a more pronounced reduction in volatility, price reversals and liquidity.

In this subsection, we test this prediction by regressing abnormal volatility, return autocovariance and liquidity on abnormal trading activity in the cross-section of distraction events. The results are shown in Table 8. For all measures of volatility, we find a strong positive relation to (abnormal) turnover (from CRSP) in the subsamples of firms with low capitalization, stock price and institutional ownership. This shows that distraction events with a larger drop in (i.e., more negative) turnover experience a larger drop in (i.e., more negative) volatility as well. Similarly, we obtain statistically negative coefficients when we regress liquidity measures on turnover, suggesting that events with a larger drop in trading see a larger increase in spreads/illiquidity. Replacing share turnover with either small TAQ trades, the number of retail traders from the brokerage dataset, or institutional trading volume from the Ancerno dataset yields similar but statistically weaker results, owing to the smaller number of observations for these shorter time series (see Table B.5 in the Internet Appendix).

[[Insert Table 8 around here]]

Overall, these results establish that our findings for trading activity, volatility, price reversals and liquidity are all interconnected. They strengthen our interpretation, derived from the model, that all of these effects are caused by a reduction in noise trading.

IV. Robustness and Endogeneity

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.

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 C.4 of the Internet Appendix, 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; the only exception is the return auto-covariance, which yields slightly weaker results). Both trading activity and volatility decline significantly in the bottom terciles of firm size, stock price, and institutional ownership. 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 noise traders and thereby affects the stocks in which they are most active.

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 C.5 of the Internet Appendix, 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 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, as well as an increase in return auto-covariance. Hence we conclude that our findings are robust to event clustering.

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 find that news pressure is only weakly related to indicators of business activity, newspaper sentiment, or macroeconomic news releases (see Internet Appendix B.2). We also check that our event study results are virtually unchanged after removing stocks operating in sectors that might be affected by certain types of events (e.g., firms in construction or insurance for events involving natural disasters and firms in regulated industries for political events; see Internet Appendix C.6). 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 is inconsistent two aspects of our results. The first is that we only find small, low-priced, and low-institutional ownership stocks to be affected. This observation does not fit with the well-established fact that big stocks lead smaller ones in terms of price discovery (e.g., Lo and MacKinlay 1990, McQueen, et al. 1996); if our distraction events were about economic news, one would expect big stocks to respond first. Second and most importantly, economic news should bias our results, if anything, against finding a distraction effect because economic news triggers more (rather than less) turnover and volatility.[30] 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 that trading activity and volatility are low when news pressure is high. We make four 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-*

30 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.

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 (macro-)economic news. Third, using different proxies for the amount of firm-specific news, we find no evidence that our distraction days exhibit fewer (or more) firm-specific news than other days (see Table B.4 of the Internet Appendix). Fourth, 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 C.7 of the Internet Appendix, 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.

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.[31] One may thus wonder whether our results could be explained (or confounded) by shocks to investor sentiment.[32] In our view, there are three 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 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.

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31 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.

32 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.

V. Distracted Noise Traders and Algorithmic Trading

Our distraction events span more than four decades—a period that has seen profound changes both in the composition of the investor population and in the institutional environment. In this section, we first study whether and, if so, how distraction effects have changed over time; we then examine the interaction between these effects and algorithmic trading.

A. Distraction effects over time

Equity markets changed drastically over our sample period, especially at the turn of the millennium under the combined effects of deregulation (decimalization in 2001; market fragmentation following Regulation ATS in 1998 and Regulation NMS in 2005) and technological progress (the "digital revolution" and algorithmic trading). The population of traders also evolved. Retail investors, who directly owned 57% of the stock market in 1991, saw their share slide to 37% by 2007 (Rydqvist et al., 2014) with a concomitant decline in their share of trading (Chordia et al., 2011).

The net outcome of these changes is not clear. On the one hand, one may expect distraction effects to dissipate over time as retail investors—the most natural candidates for the role of noise traders—withdraw from the market.[33] On the other hand, algorithmic traders—and chief among them, high-frequency traders—have come to dominate trading; according to a 2010 report by the SEC, algorithmic traders accounted for more than half of the trading volume in US equity markets in 2009. We shall argue that these traders interact with noise traders in ways that may exacerbate distraction effects. In any case, noise trading is not likely to vanish completely given that the proportion of retail ownership remains sizable among small and low-priced stocks.[34] Equally important is our documenting that institutional noise traders are distracted as well, although to a lesser degree (see Section II).

In order to study the impact of such structural changes on our findings, we conduct the event study separately over the two subperiods 1968–2000 and 2001–2013. The results reported in Table 9 reveal contrasting patterns across variables. For trading activity,

[33] Using different methodologies and data sources, several authors argue that the intensity of noise trading has declined over time. Bai et al. (2016) document an increase in stock price informativeness. Chordia et al. (2011) report that prices conform more closely to random walks in (then) recent years, which the authors interpret as evidence of greater efficiency. French (2008) estimates that spending on price discovery has risen as a share of GDP.

[34] For instance, we estimate that, in the bottom size tercile, the average fraction of institutional ownership remains below 30% at the end of our sample period despite its steady increase in recent decades.

volatility, and price reversals, the impact of distraction is substantially *amplified* in the later subperiod; for example, the effect increases threefold, from −1.7% to −4.8%, for turnover in the bottom size tercile. Similar increases are observed for the return autocovariance and in volatility metrics, and most of these changes are statistically significant. In contrast, the liquidity effect is *attenuated* in the most recent period: except for the Amihud measure, all liquidity variables exhibit a reduction (that is often statistically significant) in the distraction effect's strength.[35]

[[Insert Table 9 about here]]

A straightforward explanation for the weakening effect on liquidity is the aforementioned decline in retail trading: the impact of distraction diminishes as more distraction-prone (retail) investors are gradually replaced with less distraction-prone (institutional) investors; see Section II. But what might explain the strengthening of the effect for volatility, price reversals, and trading activity? We next offer evidence suggesting that this amplification is related to the advent of algorithmic trading.

B. Distraction effects and algorithmic trading

We speculate that the amplification of the distraction effects for volatility, price reversals, and trading activity in the post-2001 period may result from noise traders interacting with algorithmic traders. Indeed, technological advances—improvements in both hardware (e.g., computing power, custom-designed chips, ultra-fast communication lines) and software (e.g., pattern recognition algorithms, "Big Data", artificial intelligence)—and new business practices (e.g., colocation, access to exchanges' proprietary data feeds), have made it easier to detect and anticipate noise trades. These changes have contributed to the development of two types of algorithmic trading.[36]

35 These subperiod results might raise the concern that distinct subsets of events affect different variables; i.e., that some events impact only volume, while others impact only volatility or liquidity. Results of the cross-sectional tests in Section III.D show that this concern is not warranted because they demonstrate that events associated with a larger decline in share turnover tend to be associated with larger declines in volatility and liquidity as well. Hence the diverging time trends we document suggest that the market response to distraction events has evolved in different ways for volume, liquidity, and volatility; this evolution is presumably the consequence of changes in the investor population and/or the institutional environment.

36 Algorithmic trading is "the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission" (Hendershott et al., 2011). High-frequency trading is a subset of algorithmic trading in which execution times amount to milliseconds or less.

The first, *agency algorithms*, are ones that buy-side institutions use to minimize the price impact of their trades, given a target portfolio.[37] An example of such investors are the activist-shareholders analyzed by Collin-Dufresne and Fos (2015). These shareholders strategically time their informed trades (later disclosed in their SEC Schedule 13D filings) to occur when they anticipate more active noise trading, such as when volume on the S&P 500 market index is abnormally high. With the development of these agency algorithms, the decline in noise trading on days of sensational news prompts a more severe reduction in informed trades. The consequence for volume and volatility is an amplification during the later subperiod (since, as is well known, informed trades generate volatility over the short run); for liquidity, in contrast, the consequence is an attenuation because there is then less adverse selection. This attenuation is consistent with the empirical evidence presented in Collin-Dufresne and Fos (2015) and Kacperczyk and Pagnotta (2017), who document that adverse selection measures recently fail to detect the presence of informed trading in the stock market.

The second type of algorithmic trading that has emerged over the past 15 years is *high-frequency trading*. What characterizes such trading is the speed (on the order of milliseconds and faster) with which orders are placed and modified. It has been argued that high-frequency traders take advantage of slow traders by front-running their orders, and noise traders are presumed to be especially slow.[38] Indeed, high-frequency trading firms pay retail brokers hundreds of millions of dollars each year for the right to execute their customers' orders—a practice that has drawn the SEC's scrutiny.[39] In the best-seller *Flash Boys*, Lewis (2014) alleges that such fees are paid because retail orders are, "from the point of view of high-frequency traders, easy kill" (p. 180); in other words, they are easy to front-run. As a prominent example, in 2017 the SEC fined Citadel—a high-frequency trading firm responsible for handling approximately 35% of the total US retail trading volume—for using an algorithm that executed retail orders at less favorable, "stale" prices while covering these trades at the better prices indicated by proprietary

37 Hasbrouck and Saar (2013, p. 652) note that "agency algorithms have been in existence for about two decades, but the last 10 years have witnessed a dramatic increase in their appeal due to decimalization (in 2001) and increased fragmentation in the U.S. equity markets."

38 For studies of high-frequency trading around institutional orders, see Tong (2015), Korajczyk and Murphy (2017), and van Kervel and Menkveld (2017). We are not aware of a corresponding study for retail orders.

39 In 2014, the SEC began to probe brokerage firms about how retail customers' orders are routed, executed, and filled. This investigation resulted in a number of settlements involving brokers such as Barclays, Credit Suisse, and Deutsche Bank; it culminated in the January 2017 settlement with Citadel.

data feeds purchased from exchanges—a practice that essentially amounted to front-running.

Although we are not aware of a model that captures front-running of order flow by high-frequency traders, Foucault et al. (2016) make related predictions. These authors develop a dynamic model in which a fast speculator (i.e., a high-frequency trader) has advanced access to incoming public information. In addition to his usual trading on long-term fundamentals, this speculator trades on short-run price changes predicted by his advance knowledge of the news. Foucault et al. show that such news-based trading constitutes the bulk of a speculator's trading activity, which explains why trading volume has soared with the advent of algorithmic trading.[40] We hypothesize that a similar multiplier effect obtains under a variant of the model in which the fast speculator has advance information about imminent noise trades (i.e., rather than about news). Hence this speculator, by trading on short-run price changes predicted by his information about the incoming order flow, amplifies trading volume. Therefore, a decline in noise trading—as can be triggered by distracting sensational news—reduces trading volume by more than the forgone noise trades because the fast speculator scales back his front-running trades.

These considerations prompt us to investigate whether and how noise trading interacts with algorithmic trading in the post-2001 period. To this end, we examine whether the distraction effects on volume, volatility, and price reversals are more pronounced for stocks with more algorithmic trading. We focus on stocks in the bottom size tercile[41]—which display significant distraction effects—and further sort these stocks on their intensity of algorithmic trading as measured using data from MIDAS. Following Weller (2017), we employ four proxies for algorithmic trading: the *oddlot volume ratio*, or the fraction of volume of trades involving fewer than 100 shares; the *trade-to-order volume ratio*, which is equal to the executed trading volume divided by the total order volume; the *cancel-to-trade ratio*, or the number of full or partial cancellations divided by the number of trades; and the *average trade size*, which is the number of shares traded

40 Foucault at al. (2016) assume risk-neutral market makers, so their model makes no predictions concerning volatility.

41 Results are similar when we double-sort stocks on price or on the fraction of institutional ownership (i.e., instead of on size).

divided by the number of trades.[42] For brevity, we collapse these four proxies into a single algorithmic trading index by first standardizing them (so that each proxy has a mean of 0 and a standard deviation of 1) and then taking the average across all four.[43] Because low values for the trade-to-order ratio and the average trade size are associated with more algorithmic trading, these two proxies are inverted before constructing the index. Hence a high value of our index indicates more algorithmic trading.

[[Insert Table 10 about here]]

Table 10 presents event study results after sorting small stocks into terciles based on our algorithmic trading index. We find that, for the 112 distraction events occurring in the post-2001 period, the distraction effects for trading activity, volatility, and price reversals (among small stocks) are more pronounced for stocks with a high intensity of algorithmic trading (i.e., stocks in the top tercile) than for stocks with a low intensity. For both trading activity and the price range, the difference between the stocks subject to low versus high levels of algorithmic trading is statistically significant. In contrast, the distraction effects for liquidity are not amplified among high–algorithmic trading stocks. There is even some (weak) evidence that these effects are actually dampened: the difference across terciles is negative, though not significantly so, for six of eight liquidity measures. These findings suggest that the heightened distraction effects for volume, volatility, and price reversals that we find for the post-2001 period (and report in Table 9) are driven mainly by stocks characterized by a high level of algorithmic trading. In addition, our results are consistent with the attenuated liquidity effect observed after 2001—given that high–algorithmic trading stocks also exhibit signs of a diminished effect on liquidity.

In short: despite a decline in direct retail trading, the distraction effects of sensational news events do not simply dissipate over time. Our evidence is consistent with two (non-exclusive) explanations. The first is that retail noise traders have simply been replaced by institutional noise traders, who are likewise prone to distraction (see Section II). The second explanation is that, in a world of "robot" investors, noise traders interact with

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[42] These measures were not available until 2013. However, we find that stock rankings based on these algorithmic trading proxies are highly persistent. For instance, a stock ranked in the top tercile of the average oddlot volume ratio in 2013 remains in the top tercile in 2014 with a probability of about 90%. We therefore treat the algorithmic trading proxies as static characteristics and so implicitly assume that a stock's ranking relative to all other stocks does not change over time.

[43] In Internet Appendix C.8, we present the results for each individual algorithmic trading proxy. These results closely resemble those obtained using our index.

algorithmic traders in ways that exacerbate their overall trading impact—at least in terms of trading activity and volatility.

VI. Conclusion

This paper studies how noise traders' limited attention affects the stock market. We exploit episodes of sensational news that is exogenous to the stock market and that distracts noise traders among retail and institutional investors; then we assess how the consequent investor distraction affects market outcomes. We find that distraction days are associated with reduced trading activity, volatility, and liquidity among stocks for which noise trading is expected to be more pronounced—that is, stocks with a small market capitalization, low share price, and/or low level of institutional ownership. We rationalize these findings in a parsimonious model that extends Kyle (1985) to incorporate market makers' concern for inventory risk.

Our findings have important implications for the literature on liquidity. In particular, they confirm that liquidity deteriorates in response to short-lived reductions in the intensity of noise trading—just as predicted by theories of adverse selection (e.g., Glosten and Milgrom, 1985; Kyle, 1985)—and thus provide countervailing evidence to research documenting a liquidity improvement after a permanent reduction in the intensity of retail (noise) trading (Foucault et al., 2011). We reconcile these seemingly inconsistent results by noting that adverse selection and inventory risk are affected differently depending on the persistence of shocks to the intensity of noise trading: inventory concerns loom large when such shocks are persistent (as in Foucault et al.), but adverse selection dominates when they are not persistent (as in the case of our distraction shocks).

Finally, our results highlight that the importance of noise trading may not have declined in recent years—that is, notwithstanding the downward trend in direct retail ownership. We offer two possible explanations. First, retail noise traders may simply have been replaced by institutional ones. Second, noise traders may interact with algorithmic traders in ways that magnify their impact. Indeed, we find that distraction effects for trading activity and volatility (but not for liquidity) have become stronger in recent years among stocks with a large presence of algorithmic traders. Since algorithmic traders are unlikely to be distracted themselves, this finding suggests that such interaction effects could be important. We look forward to seeing more work along these lines.

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

This figure shows the value of aggregate trading volume (in logs) on the New York Stock Exchange on October 3, 1995, the day the verdict of O.J. Simpson's murder trial was announced. The top, middle and bottom panels display trading volume for, respectively, all, small and, large trades. Trades are sorted into five size groups. Small (large) trades are those in the bottom (top) quintile. The horizontal axis labels 5-minute intervals starting from 9:30 a.m. EST. The vertical line marks the announcement time (10 a.m. PST or 1 p.m. EST). The solid horizontal line indicates the average (log) trading volume during that day (excluding the period from 10.00 to 10.10 am) for the trade size category displayed in the panel. The dashed horizontal line indicates the 5% confidence bound (1.96 times the standard deviation of (log) trading volume during the day). Data for this figure comes from TAQ.

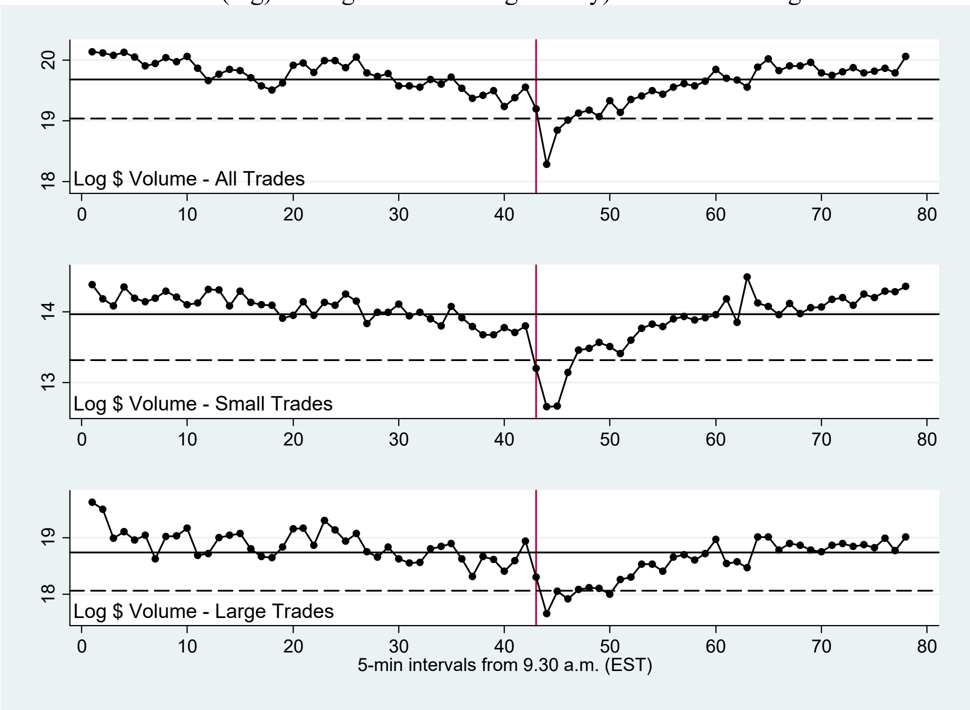


Figure 2: Daily News Pressure and Distraction Events

The blue line 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).

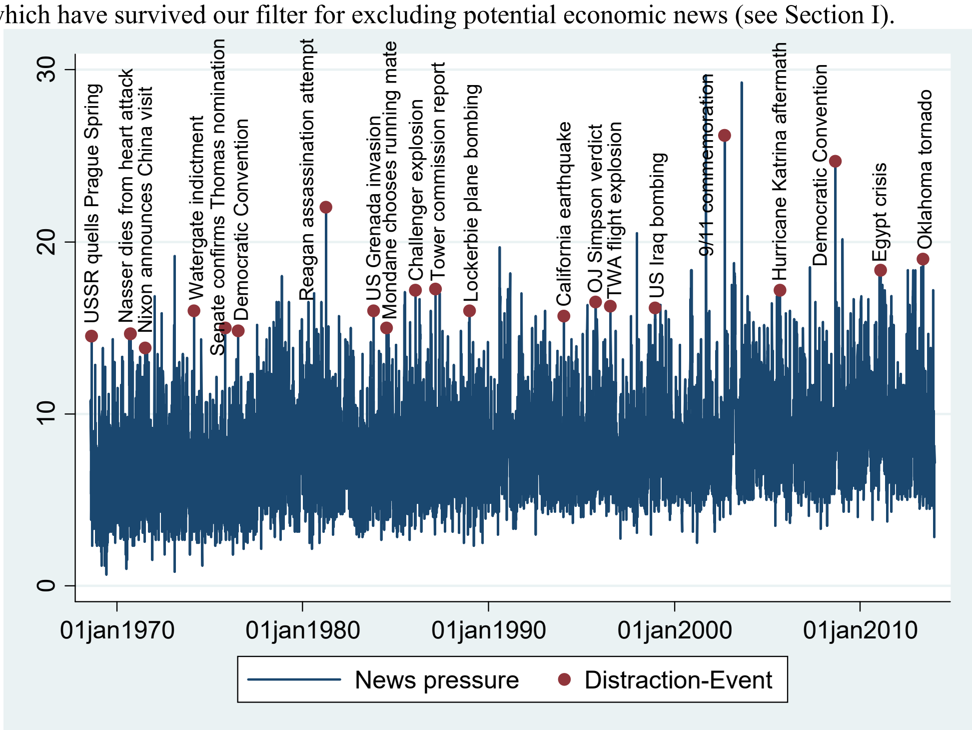
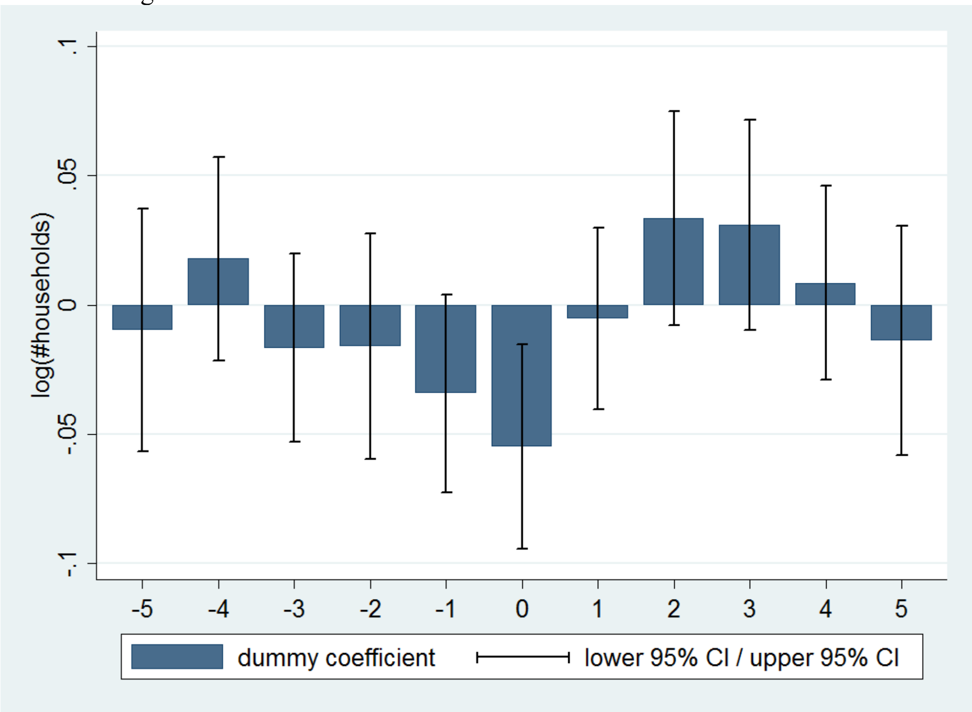


Figure 3: Distraction Effect on Retail and Institutional Trading in Event Time

This graph shows the coefficient estimates and their confidence intervals from regressing measures of (de-seasonalized and de-trended) retail and institutional trading on a set of event-time dummies. In Panel A, the dependent variable is the logarithm of number of households trading in the retail brokerage data. In Panel B, the dependent variable is the logarithm of the aggregated trade volume in the institutional trade data. In both panels, 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.

Panel A: Retail Brokerage Data



Panel B: Institutional Trade Data

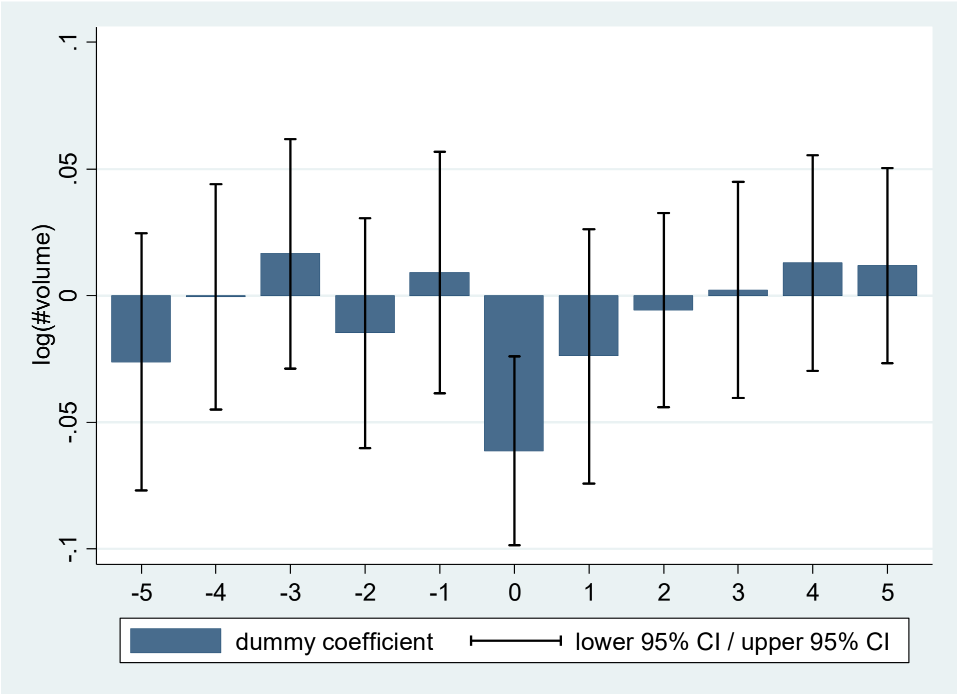


Table 1: Distraction Events

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) CNN viewership (total day)		(2) 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 and Institutional Trading

This table reports event-study results for 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 the institutional trade data over the period 1999-2011 (99 distraction events). Panel C shows the results for the ISSM/TAQ transaction data over the period 1991-2000 (105 distraction events). In Panels A and B, *Log($volume)* is the logarithm of dollar volume aggregated over all sample investors. *Log(avg trade size)* is the average across stocks and then across investors of the logarithm of the dollar trade size. *Log(#stocks)* is the average across investors of the logarithm of the number of different stocks traded. *Log(#investors*) is the logarithm of the number of investors trading. In Panel C, *Log($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 Panels A and B, 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 C, 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)	-0.073		-0.056		-0.018		-0.065	
	(-2.442)	**	(-1.649)		(-0.912)		(-2.221)	**
	[-2.635]	***	[-1.134]		[-0.476]		[-2.035]	**
Log(avg trade size)	-0.017		-0.025		0.008		-0.019	
	(-1.593)		(-1.526)		(0.111)		(-1.868)	*
	[-1.690]	*	[-1.255]		[0.789]		[-1.664]	*
Log(#stocks)	-0.010		0.003		-0.013		-0.007	
	(-2.480)	**	(0.841)		(-2.378)	**	(-2.625)	**
	[-2.622]	***	[0.885]		[-2.405]	**	[-2.782]	***
Log(#investors)	-0.0539		-0.0574		0.0034		-0.0508	
	(-2.857)	***	(-2.061)	**	(-0.714)		(-2.609)	**
	[-2.693]	***	[-2.067]	**	[0.214]		[-2.431]	**
N	66		66		66		66	

Panel B: Institutional Trade Data

	(1) Buys		(2) Sells		(3) Difference		(4) Total trades	
Log($volume)	-0.040		-0.044		0.003		-0.042	
	(-2.261)	**	(-1.967)	*	(-0.266)		(-2.293)	**
	[-1.832]	*	[-1.871]	*	[0.600]		[-2.049]	**
Log(avg trade size)	-0.019		-0.012		-0.007		-0.017	
	(-2.014)	**	(-1.211)		(-0.572)		(-2.066)	**
	[-1.892]	*	[-0.880]		[-0.848]		[-1.354]	
Log(#stocks)	-0.014		-0.004		-0.009		-0.014	
	(-1.590)		(-0.458)		(-0.858)		(-1.360)	
	[-1.759]	*	[-0.789]		[-1.044]		[-1.532]	
Log(#investors)	-0.0026		-0.0144		0.0118		-0.0056	
	(-0.385)		(-2.796)	***	(2.363)	**	(-1.465)	
	[0.436]		[-2.105]	**	[2.171]	**	[-0.332]	
N	99		99		99		99	

Panel C: 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: Distracting Events and Noise Traders

This table reports event-study results for the trading activity by different groups of investors. Panel A shows the results for the logarithm of the number of households trading in the discount brokerage data over the period 1991-1996 (66 distraction events). Panel B shows the results for the logarithm of the aggregated dollar volume in the institutional trade data over the period 1999-2011 (99 distraction events). For each event, the estimation period includes all trading days without economic news within a 200-day window centered on the event-date. Each row in Panels A and B represents a different sample split. In row [1], investors are split into single-females (column (1)) and single-males (column (2)) [only available for Panel A]. 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 investor's average portfolio concentration (measured by the Herfindahl index). *PF volume* is the investor's average portfolio volume. *PF losses* are the investor'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. *Glitter-proxy* is the investor's average propensity to buy stocks covered in the media. 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) Total trades		(2) Total trades		(3) Difference	
1) Gender	Single-female		Single-male		Difference	
Log(#investors)	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(#investors)	-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(#investors)	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(#investors)	-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(#investors)	0.001		-0.053		-0.054	
	(0.016)		(-2.196)	**	(-2.294)	**
	[0.533]		[-1.830]	*	[-1.319]	
6) Glitter-proxy	Low		High		Difference	
Log(#investors)	-0.028		-0.056		-0.028	
	(-1.328)		(-2.389)	**	(-0.869)	
	[-0.763]		[-2.003]	**	[-1.089]	
N	66		66		66	

Panel B: Institutional Trade Data

	(1) Total trades		(2) Total trades		(3) Difference	
1) Gender	Single-female		Single-male		Difference	
Log($volume)	N/A		N/A		N/A	
2) PF concentration	Low		High		Difference	
Log($volume)	-0.042		-0.049		-0.007	
	(-1.447)		(-2.222)	**	(-0.441)	
	[-1.358]		[-1.860]	*	[-0.552]	
3) PF volume	Low		High		Difference	
Log($volume)	0.017		-0.043		-0.059	
	(0.416)		(-2.309)	**	(-2.147)	**
	[-0.136]		[-2.119]	**	[-1.009]	
4) PF losses	Low		High		Difference	
Log($volume)	-0.017		-0.056		-0.039	
	(-0.923)		(-2.518)	**	(-1.345)	
	[-0.391]		[-2.325]	**	[-1.864]	*
5) GK-proxy	Low		High		Difference	
Log($volume)	-0.018		-0.044		-0.025	
	(-0.431)		(-2.365)	**	(-1.487)	
	[-1.449]		[-2.223]	**	[-0.014]	
6) Glitter-proxy	Low		High		Difference	
Log($volume)	-0.041		-0.062		-0.022	
	(-1.686)	*	(-2.350)	**	(-0.950)	
	[-1.282]		[-2.815]	***	[-1.036]	
N	99		99		99	

Table 4: Predictions from a Model of 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, return volatility and auto-covariance are displayed under each of these three interpretations.

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

Table 5: 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 one-hour intervals (in pp). *Intraday auto-covariance* is the average auto-covariance of intraday returns over one-hour intervals (multiplied by 10,000 for visibility). *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
Intraday auto-covariance	-0.205	-0.155	0.151	-0.761	-0.23	-0.124	-0.065
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
Intraday auto-covariance	0.000	0.003	0.078	-0.253	-0.013	0.020	0.188
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 6: 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)	(2)	(3)
Mkt return	Log(turnover)	Log($volume)
-0.022	-0.009	-0.012
(-0.903)	(-1.182)	(-1.527)
[-1.229]	[-1.116]	[-1.506]
532	532	532

(4)	(5)	(6)	(7)
Abs return	Price range	Intraday volatility	Intraday auto-covariance
-0.003	-0.013	-0.009	0.005
(1.009)	(0.446)	(-0.644)	(0.170)
[-1.575]	[-0.785]	[-1.328]	[1.879] *
532	532	206	206

(8)	(9)	(10)	(11)
Closing bid-ask spread	Average bid-ask spread	Effective spread	Realized spread
0.012	0.000	0.009	0.008
(2.395) **	(1.421)	(1.483)	(1.757) *
[2.196] **	[0.045]	[1.469]	[1.331]
335	206	206	206

(12)	(13)	(14)	(15)
Log(amihud)	Price impact	Absolute trade imbalance	Lambda
0.009	0.002	0.15	0.002
(2.689) ***	(0.887)	(1.891) *	(2.017) **
[1.314]	[0.719]	[1.584]	[2.415] **
532	206	206	206

Table 7: 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*	-0.010		-0.005		-0.001		0.009	
		(-3.071)	***	(-1.143)		(0.701)		(3.176)	***
		[-4.209]	***	[-2.785]	***	[0.639]		[3.914]	***
Intraday auto-covariance	*206*	0.008		0.005		0.004		-0.004	
		(2.282)	**	(0.071)		(-0.52)		(-2.366)	**
		[3.073]	***	[1.624]		[0.616]		[-1.642]	

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 8: Cross-sectional Regressions across Distraction Events

This table reports estimates from cross-sectional regressions of abnormal volatility, return auto-autocovariance and liquidity measures on abnormal (log of) turnover (from CRSP) in the cross-section of distraction events. For dependent variables from CRSP, we have 532 distraction events in the period 1968 to 2013. For dependent variables from TAQ, we have 206 distraction events in the period 1993 to 2013. Abnormal measures are calculated as described in Subsection I.C; that is, as the realization of the variable on the event-date minus its average in the estimation period (trading days without economic news within a 200-day window centered on the event-date). All variables are defined in the Appendix. Each cell shows the regression coefficient obtained for regressing the independent variable on the dependent variable. Column (1) shows results for stocks in the bottom tercile in terms of firm size. Column (2) shows results for stocks in the bottom tercile in terms of stock price. Column (3) shows results for stocks in the bottom tercile in terms of institutional ownership. Below each number, we show the t-statistic based on Huber-White standard errors corrected for heteroscedasticity. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Dependent Variable	*N*	(1) Firm Size Tercile 1	(2) Stock Price Tercile 1	(3) Inst. Holdings Tercile 1
Volatility				
Abs. return	*532*	0.702***	0.718***	0.831***
		(6.03)	(6.11)	(5.98)
Price range	*532*	2.064***	1.952***	1.982***
		(21.06)	(20.16)	(15.85)
Intraday volatility	*206*	0.284***	0.251***	0.292***
		(11.42)	(9.55)	(11.80)
Intraday auto-covariance	*206*	-0.061*	-0.036	-0.073*
		(-1.78)	(-0.84)	(-1.76)
Liquidity - overall				
Closing bid-ask spread	*335*	-0.569***	-0.517***	-0.278***
		(-4.46)	(-3.76)	(-3.18)
Average bid-ask spread	*206*	-0.695***	-0.608***	-0.486***
		(-4.87)	(-4.62)	(-4.40)
Effective spread	*206*	-44.89***	-38.59***	-32.99***
		(-2.92)	(-3.14)	(-2.82)
Liquidity - adverse selection				
Log(amihud)	*532*	-0.430***	-0.376***	-0.392***
		(-7.27)	(-6.44)	(-8.36)
Price impact	*206*	-0.057	-0.052	-0.027
		(-1.25)	(-1.17)	(-0.69)
Absolute trade imbalance	*206*	-10.73***	-9.118***	-8.790***
		(-8.31)	(-9.57)	(-7.33)
Lambda	*206*	-6.140***	-6.533***	-4.022**
		(-3.05)	(-3.03)	(-2.35)
Liquidity - inventory costs				
Realized spread	*206*	-0.469***	-0.395***	-0.354***
		(-2.70)	(-3.01)	(-2.71)

Table 9: Event Study Before and After the Advent of Algorithmic Trading

This table reports event-study results carried out over two subperiods: 1968-2000 (420 distraction events) and 2001-2013 (112 distraction events), when algorithmic trading gained prominence. 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 return volatility and autocovariance; Panel B shows the results for liquidity. All variables are defined in the Appendix. Columns (1) to (3) show results for stocks in the bottom tercile in terms of firm size. Columns (4) to (6) show results for stocks in the bottom tercile in terms of stock price. Columns (7) to (9) show results for stocks in the bottom tercile in terms of institutional ownership (limited to 351 events over the full period 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

	Firm Size Tercile 1			Stock Price Tercile 1			Inst. Holdings Tercile 1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1968-2000	2001-2013	Difference	1968-2000	2001-2013	Difference	1968-2000	2001-2013	Difference
Trading activity									
Log(turnover)	-0.017	-0.048	-0.030	-0.021	-0.046	-0.025	-0.016	-0.050	-0.034
	(-1.96) *	(-3.65) ***	(-1.71) *	(-2.20) **	(-3.48) ***	(-1.37)	(-1.37)	(-4.07) ***	(-1.64)
	[-2.49] **	[-3.41] ***	[-1.96] *	[-2.71] ***	[-3.37] ***	[-1.47]	[-0.79]	[-3.84] ***	[-2.79] ***
Log($volume)	-0.021	-0.051	-0.029	-0.026	-0.053	-0.026	-0.021	-0.051	-0.030
	(-2.42) **	(-3.54) ***	(-1.46)	(-2.63) ***	(-3.35) ***	(-1.15)	(-1.69) *	(-3.83) ***	(-1.31)
	[-2.85] ***	[-3.49] ***	[-1.86] *	[-3.06] ***	[-3.20] ***	[-1.42]	[-1.30]	[-3.59] ***	[-2.38] **
Volatility									
Abs return	0.005	-0.061	-0.067	0.010	-0.056	-0.066	0.023	-0.084	-0.107
	(0.68)	(-1.58)	(-1.83) *	(0.86)	(-0.98)	(-1.38)	(1.11)	(-1.76) *	(-2.13) **
	[-0.69]	[-1.93] *	[-1.79] *	[-0.68]	[-1.73] *	[-1.53]	[0.82]	[-2.65] ***	[-2.92] ***
Price range	-0.043	-0.150	-0.107	-0.022	-0.121	-0.099	0.002	-0.161	-0.163
	(-1.84) *	(-2.37) **	(-1.36)	(-0.62)	(-1.63)	(-1.30)	(-0.19)	(-2.46) **	(-1.89) *
	[-2.54] **	[-3.31] ***	[-1.84] *	[-1.48]	[-2.89] ***	[-1.86] *	[0.21]	[-3.61] ***	[-3.37] ***
Intraday	-0.011	-0.029	-0.018	-0.008	-0.024	-0.017	-0.004	-0.029	-0.025
volatility	(-1.68) *	(-3.74) ***	(-0.86)	(-1.46)	(-2.87) ***	(-0.76)	(-0.95)	(-3.53) ***	(-1.40)
	[-1.58]	[-4.21] ***	[-1.92] *	[-1.17]	[-3.70] ***	[-1.93] *	[-0.98]	[-4.11] ***	[-2.42] **
Intraday auto-	0.003	0.013	0.010	0.000	0.009	0.009	0.001	0.014	0.013
covariance	(1.24)	(1.93) *	(0.48)	(0.72)	(0.80)	(0.05)	(0.24)	(2.06) **	(1.26)
	[1.41]	[2.89] ***	[0.93]	[1.24]	[1.68] *	[0.65]	[1.13]	[2.90] ***	[1.43]

Panel B: Liquidity

	Firm Size Tercile 1			Stock Price Tercile 1			Inst. Holdings Tercile 1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1968-2000	2001-2013	Difference	1968-2000	2001-2013	Difference	1968-2000	2001-2013	Difference
Liquidity - overall									
Closing bid-ask	0.077	0.030	-0.047	0.078	0.016	-0.062	0.062	0.010	-0.052
spread	(4.52) ***	(0.91)	(-1.83) *	(4.35) ***	(0.42)	(-2.14) **	(5.06) ***	(0.50)	(-2.53) **
	[4.02] ***	[-0.01]	[-2.14] **	[3.88] ***	[0.21]	[-1.98] **	[4.46] ***	[-0.25]	[-2.71] ***
Average bid-ask	0.085	0.006	-0.079	0.083	-0.012	-0.095	0.069	-0.003	-0.072
spread	(2.70) ***	(1.03)	(-1.37)	(2.82) ***	(0.83)	(-1.53)	(2.79) ***	(0.85)	(-1.65)
	[3.10] ***	[-0.99]	[-2.99] ***	[3.26] ***	[-1.68] *	[-3.50] ***	[3.29] ***	[-1.07]	[-3.17] ***
Effective spread	0.055	0.033	-0.022	0.059	0.024	-0.035	0.045	0.021	-0.025
	(1.72) *	(1.56)	(-0.10)	(2.17) **	(1.21)	(-0.54)	(1.72) *	(1.31)	(-0.37)
	[1.93] *	[0.60]	[-0.81]	[2.71] ***	[0.52]	[-1.56]	[2.18] **	[0.43]	[-1.19]
Liquidity - adverse selection									
Log(amihud)	0.023	0.031	0.008	0.026	0.028	0.002	0.024	0.027	0.003
	(2.33) **	(2.21) **	(0.97)	(2.89) ***	(1.76) *	(0.28)	(3.07) ***	(2.19) **	(0.19)
	[1.85] *	[1.93] *	[0.67]	[2.59] **	[1.94] *	[0.28]	[3.20] ***	[1.75] *	[-0.22]
Price impact	0.016	0.004	-0.012	0.015	0.003	-0.012	0.014	0.002	-0.011
	(2.36) **	(-0.07)	(-1.94) *	(2.30) **	(-0.23)	(-1.97) *	(2.39) **	(-0.06)	(-1.94) *
	[2.04] **	[-0.14]	[-1.52]	[1.79] *	[-0.44]	[-1.56]	[1.97] **	[-0.71]	[-1.69] *
Absolute trade	0.485	0.346	-0.139	0.554	0.196	-0.357	0.508	0.295	-0.213
imbalance	(1.86) *	(1.98) *	(-0.60)	(2.30) **	(0.97)	(-1.37)	(2.03) **	(2.04) **	(-0.72)
	[1.87] *	[1.78] *	[-0.25]	[2.62] ***	[1.09]	[-1.48]	[1.99] **	[1.89] *	[-0.41]
Lambda	0.011	0.008	-0.003	0.011	0.007	-0.004	0.009	0.004	-0.005
	(3.07) ***	(1.22)	(-1.44)	(3.85) ***	(1.20)	(-1.90) *	(3.23) ***	(0.87)	(-1.66) *
	[2.92] ***	[1.62]	[-1.54]	[3.56] ***	[1.54]	[-1.79] *	[3.11] ***	[1.18]	[-1.75] *
Liquidity - inventory costs									
Realized spread	0.048	0.029	-0.019	0.049	0.019	-0.030	0.040	0.018	-0.022
	(1.59)	(2.03) **	(0.16)	(2.05) **	(1.80) *	(-0.29)	(1.73) *	(1.61)	(-0.33)
	[1.84] *	[1.13]	[-0.61]	[2.29] **	[1.08]	[-1.28]	[2.06] **	[0.89]	[-1.07]

Table 10: Sample Split for Small Stocks by Algorithmic Trading Index

This table reports event-study results for the tercile of small stocks for the 112 distraction events that fall into the post-2001 period that is marked by the advent of algorithmic trading. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. Small stocks are sorted into three terciles based on an algorithmic trading proxy constructed from MIDAS data (see Subsection V.B for details). All variables are defined in the Appendix. Column (4) tests for the difference between tercile 1 and tercile 3, respectively. 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

		Algorithmic Trading Intensity Index							
		(1)		(2)		(3)		(4)	
	N	Tercile 1		Tercile 2		Tercile 3		Difference	
Trading activity									
Log(turnover)	*112*	-0.037		-0.056		-0.059		-0.022	
		(-1.832)	*	(-4.009)	***	(-4.421)	***	(-2.079)	**
		[-1.887]	*	[-3.635]	***	[-4.053]	***	[-1.843]	*
Log($volume)	*112*	-0.044		-0.059		-0.060		-0.017	
		(-1.962)	*	(-3.825)	***	(-4.307)	***	(-1.846)	*
		[-2.07]	**	[-3.536]	***	[-4.003]	***	[-1.324]	
Volatility									
Abs return	*112*	-0.039		-0.076		-0.090		-0.051	
		(-1.083)		(-2.186)	**	(-2.206)	**	(-1.478)	
		[-0.848]		[-2.610]	***	[-2.352]	**	[-1.536]	
Price range	*112*	-0.080		-0.140		-0.223		-0.143	
		(-1.111)		(-2.439)	**	(-3.583)	***	(-2.669)	***
		[-1.031]		[-2.807]	***	[-4.021]	***	[-2.392]	**
Intraday volatility	*112*	-0.02		-0.027		-0.035		-0.016	
		(-2.150)	**	(-3.372)	***	(-3.749)	***	(-0.927)	
		[-2.241]	**	[-3.452]	***	[-3.699]	***	[-1.295]	
Intraday autocovariance	*112*	0.008		0.012		0.018		0.01	
		(1.157)		(1.694)	*	(2.379)	**	(0.800)	
		[1.727]	*	[1.573]		[2.293]	**	[0.589]	

Panel B: Liquidity

		Algorithmic Trading Intensity Index			
		(1)	(2)	(3)	(4)
	N	Tercile 1	Tercile 2	Tercile 3	Difference
Liquidity - overall					
Closing bid-ask spread	*112*	0.039	0.008	0.036	-0.003
		(1.260)	(-0.074)	(1.781) *	(0.735)
		[0.836]	[0.090]	[0.589]	[-0.142]
Average bid-ask spread	*112*	0.001	-0.009	0.035	0.035
		(1.055)	(0.641)	(1.752) *	(1.178)
		[-1.524]	[-1.251]	[0.197]	[1.385]
Effective spread	*112*	0.057	0.026	0.038	-0.020
		(1.722) *	(1.414)	(2.168) **	(0.626)
		[1.669] *	[0.990]	[0.883]	[-0.264]
Liquidity - adverse selection					
Log(amihud)	*112*	0.035	0.037	0.031	-0.005
		(1.928) *	(2.045) **	(1.725) *	(0.010)
		[1.983] **	[1.652] *	[0.923]	[-0.337]
Price impact	*112*	0.009	-0.011	0.001	-0.008
		(0.302)	(-1.850) *	(-0.084)	(-0.308)
		[0.081]	[-2.029] **	[-0.282]	[-0.044]
Absolute trade imbalance	*112*	0.75	0.257	0.658	-0.092
		(2.933) ***	(0.916)	(2.209) **	(-0.433)
		[3.141] ***	[0.827]	[2.645] ***	[-0.195]
Lambda	*112*	0.806	0.734	1.247	0.440
		(0.960)	(1.127)	(1.096)	(0.102)
		[1.176]	[1.623]	[1.019]	[0.099]
Liquidity - inventory costs					
Realized spread	*112*	0.041	0.038	0.034	-0.007
		(1.908) *	(2.693) ***	(1.639)	(0.154)
		[1.722] *	[2.206] **	[0.874]	[-0.212]

Appendix: Variable Definitions

Variable name	Data source	Explanation
Trading measures		
Log($volume)	Discount broker/ANcerno	Natural logarithm of the total dollar volume traded in a given stock by all sample households/inst. Investors.
Log(avg trade size)	Discount broker/ANcerno	Natural logarithm of the average dollar volume traded in a given stock by a household/inst. investor (conditional on trading at least one stock), averaged across investors.
Log(#stocks)	Discount broker/ANcerno	Natural logarithm of the number of distinct stocks traded by a household/inst. investor (conditional on trading at least one stock), averaged across investors.
Log(#investors)	Discount broker/ANcerno	Natural logarithm of the total number of households/inst. investors trading at least one stock.
TAQ small vs. large trades		
Log($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 one-hour intervals during the trading day (excluding the opening half hour). [Scaled by 100.]
Intraday auto-covariance	TAQ	Equal-weighted average of the standard deviation of stock returns over one-hour intervals during the trading day (excluding the opening half hour). [Scaled by 10,000.]

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.]