Internet Appendix to

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

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

In this appendix, we derive our empirical predictions—for trading volume, liquidity, volatility, and return auto-covariance—in a model of informed trading à la Kyle (1985) with risk-averse market makers and an imperfectly informed insider. For brevity, we focus on a static model and take some liberty when interpreting its predictions in a dynamic context. See Kim (2014) for a dynamic version of the model (in discrete time) with risk-averse market makers and a perfectly informed insider. Our setup allows us to work out the implications from distracting noise traders, informed speculators, and market makers. They are summarized in Table 4.

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

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

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

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

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

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

which implies:

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

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

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

Liquidity

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

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

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

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

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

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

Substituting into this equation the expression for λ in Equation (1) yields a cubic equation in β:

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

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

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

We next compute trading volume and volatility.

Trading volume

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

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

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

Return volatility

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

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

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

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

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

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

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

Return auto-covariance

As with volatility, we define the total return auto-covariance in our model as $COV \equiv \mathrm{Cov}[r_1,r_2] + \mathrm{Cov}[r_2,r_3]$. Substituting into this equation the expressions for the returns and expanding yields

$$COV = \mathrm{Cov}[\theta,\lambda\omega] - \mathrm{Var}[\lambda\omega] - \mathrm{Cov}[\lambda\omega,p_1].$$

Each of these terms have been computed above. Substituting their expressions leads to:

(7) $$COV = -\frac{1}{2}VOL + \frac{\sigma_\theta}{2}.$$

Given that $VOL \geq \sigma_\theta$, $COV \leq 0$. In words, returns are negatively auto-correlated, or equivalently, prices tend to reverse.

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

A.1: Distracted Noise Traders

A lower variance of noise trading results in lower trading volume, worse liquidity (λ higher), lower return volatility and higher return auto-covariance.

Proof:

- Liquidity. Applying the implicit-function theorem to Equation (3) yields $\frac{d\beta}{d\sigma_z} = \frac{1}{g(\beta)}\left(\frac{h}{1+\sigma_\varepsilon h} - \gamma\beta\right)$ where $g(\beta) \equiv 3\gamma\sigma_\varepsilon\beta^2 + 2\beta + \gamma\sigma_z \geq 0$. To sign the term in brackets, let $f(\beta) \equiv \gamma\sigma_\varepsilon\beta^3 + \beta^2 + \gamma\sigma_z\beta - \frac{\sigma_z h}{1+\sigma_\varepsilon h}$. Note that Equation (3) defines a root of the function f. This function is increasing in β (note that $f'(\beta) = g(\beta) \geq 0$), with $f(0) = -\frac{\sigma_z h}{1+\sigma_\varepsilon h} < 0$ and $f\left(\frac{h}{\gamma(1+\sigma_\varepsilon h)}\right) = \frac{\sigma_\varepsilon h^2}{\gamma^2(1+\sigma_\varepsilon h)^2} + \frac{h^2}{\gamma^2(1+\sigma_\varepsilon h)^2} > 0$, which proves the existence of a unique equilibrium β (root of f) on the positive line, and moreover, that $\beta \leq \frac{h}{\gamma(1+\sigma_\varepsilon h)}$. As a result, the numerator of $\frac{d\beta}{d\sigma_z}$ is positive and $\frac{d\beta}{d\sigma_z} \geq 0$. Differentiating Equation (2) with respect to σ_z yields $\frac{d\lambda}{d\sigma_z} = -\frac{\lambda}{\beta}\frac{d\beta}{d\sigma_z} \leq 0$.
- Trading volume. From Equation (4), trading volume is increasing in σ_z since β is.
- Return volatility. From Equation (5), the impact of σ_z on volatility depends on the sign of $\frac{d(\sigma_z/\beta^2)}{d\sigma_z} = \frac{\sigma_z}{\beta}\left(\frac{1}{\beta^2} - \frac{2}{\beta}\frac{d\beta}{d\sigma_z}\right)$. Substituting in the expression for $\frac{d\beta}{d\sigma_z}$ and rearranging using Equation (3) yields $\frac{dVOL}{d\sigma_z} = \frac{\gamma(\sigma_\varepsilon\beta^2+\sigma_z)}{\sigma_z g(\beta)} \geq 0$.
- Return auto-covariance. From Equation (7), autocovariance is decreasing in σ_z since volatility is increasing.

Intuition:

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

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

A.2: Distracted Insiders

A higher variance of the insider's signal error results in lower trading volume and improved liquidity (λ lower). The impact on return volatility is ambiguous.

Proof:

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

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

Intuition:

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

A.3: Distracted Market Maker

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

Proof:

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

- Liquidity. The implicit-function theorem applied to Equation (3) yields $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}} = -\frac{\sigma_Z}{g(\beta)(1+\sigma_\varepsilon h)^2(\sigma_{\varepsilon'})^2} \leq 0$. That is, β decreases in $\sigma_{\varepsilon'}$. Equation (2) implies that $\lambda\beta$ increases in $\sigma_{\varepsilon'}$ so λ must increase in $\sigma_{\varepsilon'}$.
- Trading volume. From Equation (4), the impact of $\sigma_{\varepsilon'}$ on trading volume depends on the sign of $\frac{\mathrm{d}\ln(\beta^2(1/h+\sigma_\varepsilon)}{\mathrm{d}\sigma_{\varepsilon'}} = \frac{2}{\beta}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}} + \frac{1}{(1+\sigma_\varepsilon h)h(\sigma_{\varepsilon'})^2} = \frac{\gamma\beta\left(\sigma_{\varepsilon'}\right)^2}{g(\beta)(1+\sigma_\varepsilon h)h}(\beta^2\sigma_\varepsilon - \sigma_Z)$ after substituting in the expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}}$, using Equation (3) and rearranging. This expression is negative because $\beta^2\sigma_\varepsilon \leq \sigma_Z$, as shown above. It follows that trading volume is decreasing in $\sigma_{\varepsilon'}$.
- Return volatility. From Equation (4), it suffices that $(\beta^2\sigma_\varepsilon + \sigma_Z)/h$ increases in $\sigma_{\varepsilon'}$ for volatility to increase in $\sigma_{\varepsilon'}$, since we already established that λ increases in $\sigma_{\varepsilon'}$. $\frac{\mathrm{d}\ln((\beta^2\sigma_\varepsilon+\sigma_Z)/h)}{\mathrm{d}\sigma_{\varepsilon'}} = (\frac{1}{\mathrm{h}} - \frac{2\beta\sigma_\varepsilon}{\beta^2\sigma_\varepsilon+\sigma_Z}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}})\frac{1}{(\sigma_{\varepsilon'})^2}$. Substituting in the expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}}$ and rearranging shows that the expression in brackets is positive, and therefore that volatility is increasing in $\sigma_{\varepsilon'}$.
- Return auto-covariance. From Equation (7), autocovariance is decreasing in $\sigma_{\varepsilon'}$ since volatility is increasing.

Intuition:

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

Internet Appendix B: Additional Results

B.1: Distraction Events and Earnings Announcements

In this subsection, we check whether distraction affects the speed of incorporation of earnings news. Using direct stock-level proxies for institutional and retail investors' attention, Ben-Rephael et al. (2017) find that the former but not the latter drives price discovery around earnings announcements. DellaVigna and Pollet (2009) were the first to proxy for marketwide inattention with distractions unrelated to the stock market; they compare announcements made on Friday—when investors are distracted by the upcoming weekend—to those made on other weekdays, and report more underreaction for the former. Hirshleifer et al. (2009) find more underreaction on days with many earnings announcements, as announcements compete for investors' limited information-processing capacity. Peress (2008) reports that media coverage of announcements reduces the underreaction. Despite their methodological differences, all these papers provide evidence for a delayed incorporation of earnings news when investors' attention is low, which materializes through a weaker immediate price response and a stronger subsequent price drift for lower-attention announcements. These results suggest that the very investors responsible for a timely incorporation of earnings news—presumably sophisticated institutions with fast access to news—suffer from attention constraints.

In this context, it is natural to ask whether our distraction events lead to similar effects. We expect them not to, since we have argued that our events primarily affect retail investors (and especially noise traders) and Ben-Rephael et al. (2017) suggest that these investors do not contribute much to the price discovery upon earnings news. The results, shown in Table B.1, confirm this expectation. The variables' definitions and regression details are provided in the table header. The interaction coefficient of the earnings surprise decile with our distraction dummy is neither significant for the immediate stock price response (Panel A), nor for the post-announcement drift (Panel B). Taken together, these results suggest that price discovery pertaining to earnings news is not different on distraction days from other days. They lend support to our story that sensational news events mainly affect noise traders, rather than those responsible for the timely incorporation of *public* news such as smart investors and professional market makers.

As a comparison, the table also reproduces the results from DellaVigna and Pollet (2009) and Hirshleifer et al. (2009). They show that the immediate stock price response is muted both on Friday and on days with many concurrent announcements (Panel A). In contrast, the post-announcement drift is more pronounced on these days (though not significantly so for Fridays in Panel B, which might be caused by the inclusion of firm fixed-effects in the regression; see Michaely et al., 2016).

Table B.1: Distraction Events and Earnings Announcements

This table shows results for regressions of the kind $CAR_{it} = \alpha_i + \alpha_t + \beta_1{*}DS_{it} + \beta_2{*}DS_{it}{*}InattentionProxy_t + \boldsymbol{\beta}{*}\mathbf{X}_{it} + \varepsilon_{it}$ for the sample of earnings announcements with complete data over the period 1995 to 2012. CAR denotes the cumulative abnormal return, and The subscripts *i* and *t* denote a firm and a day, respectively. In Panel A, the dependent variable is CAR[0,1]; in Panel B, it is CAR[2,61], where the windows designate trading days relative to the announcement date. DS is the earnings surprise decile (1[low] to 10[high]), where the earnings surprise is measured as the actual earnings per share minus the median earnings per share forecast issued in the last 30 calendar days before the announcement, scaled by the stock price 5 trading days before the announcement. The inattention proxy is either a dummy flagging our distraction events (columns 1, 2, 7 and 8), a dummy for Fridays (following DellaVigna and Pollet, 2009) (columns 3, 4, 7 and 8), or the natural logarithm of the number of earnings announced on the same day [de-meaned over the sample period] (following Hirshleifer et al., 2009) (columns 5 to 8). There are 9,098 earnings announcement that fall on a distraction event, representing 4.25% of the announcements in our sample. As in Hirshleifer et al. (2009), CARs are computed as the difference between the buy-and-hold return of the announcing firm and that of a size and book-to-market matching portfolio. X is a vector of control variables that includes firm size (natural logarithm of total assets), leverage ratio, market-to-book ratio, firm age (number of years since first appearance in Compustat), analyst coverage (natural logarithm of the number of analysts following the firm), and reporting lag (number of days between the announcement and the date of the last fiscal quarter end). When controls are included, they are also interacted with earnings surprise deciles. All regressions include firm and earnings announcement-date fixed effects. Standard errors are double-clustered by firm and earnings announcement date. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: CAR[0,1]

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

Panel B: CAR[2,61]

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

B.2: News Pressure, Economic News and Sentiment

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

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

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

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

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

B.3: Event Study Around Economic News

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

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

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

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

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

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

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

Panel B: FOMC announcement days

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

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

B.4: Event Study for the Amount of Firm-specific News

One alternative explanation for our results is reverse causality: news pressure is high when there is little economic news to report. In this subsection, we assess this possibility directly by testing whether the amount of firm-specific news published on distraction days is significantly different from other days.

We employ four proxies for the amount of firm-specific news. The first is the number of (quarterly) earnings announcements, obtained from Compustat quarterly files. It covers our sample period almost entirely (1971 to 2013). The second proxy is the number of firms featured in any of the four major US newspapers over a 30-year period (1980 to 2010). These data are described in detail in Fang and Peress (2009); we have expanded the original dataset by adding both years and stocks. The last two proxies are the number of firms covered in news articles published in the Dow Jones and Thomson Reuters newswires. These datasets span only a small portion of our sample period (2000 to 2011 for the Dow Jones newswire, and 2005 to 2011 for the Thomson Reuters newswire), but, they offer the advantage of covering a very broad sample of stock (since considerably more firms are covered in newswires than in newspapers).

Table B.4 shows the event study results for these four firm-specific news measures. We find that none of them is significantly affected on distraction days. The only exception is the rank test for the number of earnings announcements, but it does not seem robust as the parametric test is far from significant. We conclude that there is no evidence that distraction days differ from other days in terms of the amount of firm-specific news.

Table B.4: Event Study for Firm-specific News

This table reports event-study results for the amount of firm-specific news disclosed on distraction days. Column (1) shows results for the abnormal value of the logarithm of (one plus) the number of firms announcing their earnings on a given day over the period 1971-2013. Column (2) shows the abnormal value of the logarithm of the number of firms covered in newspaper articles on a given day over the period 1980-2010. Column (3) shows the abnormal value of the logarithm of the number of firms featured in the Dow Jones newswire over the period 2000-2011. Column (4) shows the abnormal value of the logarithm of the number of firms featured in the Thomson Reuters newswire over the period 2005-2011. 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) Log of #EA	(2) Log of #Newspaper	(3) Log of #News in DJA	(4) Log of #News in TRA
0.031	0.002	-0.023	-0.0469
(1.443)	(-0.000)	(-1.459)	(-0.440)
[1.999] **	[0.843]	[-1.581]	[-0.181]
480	325	92	43

B.5: Cross-sectional Analysis of Distraction Events

In the paper, we show that distraction events with a larger drop in CRSP turnover also see a larger drop in volatility and liquidity, as well as a larger increase in return reversals. In this subsection, we show that we obtain similar results when we use the number of retail investors trading, institutional trading volume, or small TAQ trades.

Table B.5 shows the results. For comparison, the table also reports the results for CRSP turnover (which are also reported in Table 8 of the paper). Overall, the results paint a consistent picture: events that seem to have distracted investors more—as indicated by a larger drop in turnover, the number or retail investors trading, institutional trading volume, or the TAQ small trade volume—also witness a stronger drop in volatility and liquidity. Unsurprisingly, the results are strongest for CRSP turnover, which is available for the entire sample period. Nonetheless, our other measures of trading activity often deliver significant results and almost always go in the right direction (despite substantially reduced sample sizes).

At the top of Table B.5, we further show that distraction events with a larger surge in TV viewership see a more pronounced drop in trading activity. This suggests that events that attract more TV viewership are also those that are more distracting.

Table B.5: Cross-Sectional Analysis of Distraction Events

This table reports results from regressions of abnormal market variables (trading activity, volatility, liquidity) on either abnormal TV viewership or abnormal trading activity. The dependent variables are listed in the first column and include the abnormal market outcome variables reported in previous tables (trading activity, volatility, reversals, liquidity). The independent variables are listed in the second column, and include abnormal TV viewership, and abnormal trading activity (*Log(turnover),* the logarithm of the average of share turnover on the market obtained from CRSP); *Log(#households*), the logarithm of the number of households trading, obtained from the discount brokerage data over the period 1991-1996; and *Log(small TAQ trades),* logarithm of aggregated dollar volume of small trades, obtained from the ISSM/TAQ dataset over the period 1991-2000). Reported are the coefficient estimates from individual cross-sectional regressions. For example, Column (1) reports a coefficient estimate of -0.051 from regressing abnormal *Log(turnover)* on abnormal CNN viewership; likewise, it reports a coefficient estimate of 0.702 from regressing abnormal *Abs. return* on abnormal *Log(turnover)*. Abnormal variables are estimated using an event-study methodology, based on all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity, return volatility and autocovariance; Panel B shows the results for liquidity. All variables are defined in the Appendix. 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. T-statistic, based on Huber–White standard errors corrected for heteroscedasticity, are reported in parenthesis. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

Dependent Variable	Independent Variable	*N*	(1) Firm Size Tercile 1	(2) Stock Price Tercile 1	(3) Inst. Holdings Tercile 1
Trading activity					
Log(turnover)	CNN viewership	*216*	-0.051**	-0.057**	-0.033
			(-2.22)	(-2.45)	(-1.46)
	Evening ABC, CBS, NBC viewership	*216*	-0.253**	-0.235**	-0.191
			(-2.18)	(-2.03)	(-1.62)
Log($volume)	CNN viewership	*216*	-0.060**	-0.069***	-0.044*
			(-2.53)	(-2.77)	(-1.89)
	Evening ABC, CBS, NBC viewership	*216*	-0.290**	-0.287**	-0.237*
			(-2.42)	(-2.33)	(-1.97)
Volatility					
Abs. return	Log(turnover)	*532*	0.702***	0.718***	0.831***
			(6.03)	(6.11)	(5.98)
	Log(#households)	*66*	0.240	0.174	0.125
			(1.52)	(1.14)	(0.72)
	Log(inst. $vol.)	*99*	0.004	0.163	0.023
			(0.03)	(0.82)	(0.13)
	Log(small TAQ trades)	*106*	0.359*	0.439***	0.361**
			(1.68)	(2.70)	(2.56)
Price range	Log(turnover)	*532*	2.064***	1.952***	1.982***
			(21.06)	(20.16)	(15.85)
	Log(#households)	*66*	1.595***	1.514***	1.186**
			(3.41)	(3.31)	(2.62)
	Log(inst. $vol.)	*99*	0.234	0.669*	0.416
			(0.66)	(1.73)	(1.10)
	Log(small TAQ trades)	*106*	2.245***	2.204***	1.962***
			(8.16)	(8.97)	(9.24)
Intraday volatility	Log(turnover)	*206*	0.284***	0.251***	0.292***
			(11.42)	(9.55)	(11.80)
	Log(#households)	*54*	0.159**	0.183**	0.173***
			(2.12)	(2.61)	(2.70)
	Log(inst. $vol.)	*99*	0.037	0.110**	0.065
			(0.76)	(2.15)	(1.20)
	Log(small TAQ trades)	*94*	0.232***	0.250***	0.240***
			(4.83)	(6.06)	(6.73)
Intraday auto-covariance	Log(turnover)	*206*	-0.061*	-0.036	-0.073*
			(-1.78)	(-0.84)	(-1.76)
	Log(#households)	*54*	0.019	0.017	0.005
			(0.54)	(0.32)	(0.10)
	Log(inst. $vol.)	*99*	-0.016	-0.042	-0.034
			(-0.71)	(-1.25)	(-1.11)
	Log(small TAQ trades)	*94*	-0.004	0.015	-0.002
			(-0.07)	(0.22)	(-0.03)

Panel B: Liquidity

Dependent Variable	Independent Variable	*N*	(1) Firm Size Tercile 1	(2) Stock Price Tercile 1	(3) Inst. Holdings Tercile 1
Liquidity - overall					
Closing bid-ask spread	Log(turnover)	*335*	-0.569***	-0.517***	-0.278***
			(-4.46)	(-3.76)	(-3.18)
	Log(#households)	*66*	-0.669**	-0.737**	-0.503**
			(-2.57)	(-2.53)	(-2.43)
	Log(inst. $vol.)	*99*	0.169	0.121	0.151
			(1.00)	(0.89)	(1.17)
	Log(small TAQ trades)	106	-0.841***	-0.905***	-0.696***
			(-3.93)	(-3.50)	(-3.90)

(continued on next page)

Dependent Variable	Independent Variable	*N*	(1) Firm Size Tercile 1	(2) Stock Price Tercile 1	(3) Inst. Holdings Tercile 1
(continued from previous page)					
Liquidity - overall					
Average bid-ask spread	Log(turnover)	*206*	-0.695***	-0.608***	-0.486***
			(-4.87)	(-4.62)	(-4.40)
	Log(#households)	*54*	-0.508	-0.468*	-0.354
			(-1.62)	(-1.88)	(-1.60)
	Log(inst. $vol.)	*99*	-0.016	-0.010	-0.026
			(-0.09)	(-0.05)	(-0.18)
	Log(small TAQ trades)	94	-0.751***	-0.660***	-0.533***
			(-3.34)	(-4.03)	(-3.55)
Effective spread	Log(turnover)	*206*	-44.89***	-38.59***	-32.99***
			(-2.92)	(-3.14)	(-2.82)
	Log(#households)	*54*	-40.390	-33.470	-33.12
			(-1.19)	(-1.38)	(-1.41)
	Log(inst. $vol.)	*99*	3.146	0.730	1.576
			0.230	0.050	(0.14)
	Log(small TAQ trades)	94	-55.53*	-42.90*	-45.88**
			(-1.79)	(-1.98)	(-2.42)
Liquidity - adverse selection					
Log(amihud)	Log(turnover)	*532*	-0.430***	-0.376***	-0.392***
			(-7.27)	(-6.44)	(-8.36)
	Log(#households)	*66*	-0.382**	-0.412***	-0.352**
			(-2.48)	(-2.83)	(-2.39)
	Log(inst. $vol.)	*99*	-0.007	-0.038	-0.0533
			(-0.09)	(-0.45)	(-0.76)
	Log(small TAQ trades)	106	-0.586***	-0.586***	-0.570***
			(-6.60)	(-7.29)	(-7.84)
Price impact	Log(turnover)	*206*	-0.057	-0.052	-0.0268
			(-1.25)	(-1.17)	(-0.69)
	Log(#households)	*54*	-0.033	-0.015	-0.00921
			(-0.53)	(-0.35)	(-0.16)
	Log(inst. $vol.)	*99*	0.023	0.024	0.0204
			(0.49)	(0.51)	(0.53)
	Log(small TAQ trades)	94	-0.050	-0.050	-0.035
			(-0.57)	(-0.75)	(-0.53)
Absolute trade imbalance	Log(turnover)	*206*	-10.73***	-9.118***	-8.790***
			(-8.31)	(-9.57)	(-7.33)
	Log(#households)	*54*	-10.16**	-8.365***	-9.534***
			(-2.55)	(-2.70)	(-2.87)
	Log(inst. $vol.)	*99*	-1.501	-1.973	-2.002*
			(-1.19)	(-1.48)	(-1.81)
	Log(small TAQ trades)	94	-13.69***	-11.73***	-12.99***
			(-6.46)	(-9.31)	(-10.52)
Lambda	Log(turnover)	*206*	-6.140***	-6.533***	-4.022**
			(-3.05)	(-3.03)	(-2.35)
	Log(#households)	*54*	-0.590	-2.501	-0.588
			(-0.13)	(-1.18)	(-0.26)
	Log(inst. $vol.)	*99*	0.244	-1.006	0.482
			0.090	(-0.38)	(0.24)
	Log(small TAQ trades)	94	-3.323	-3.704*	-2.736
			(-1.21)	(-1.86)	(-1.32)
Liquidity - inventory costs					
Realized spread	Log(turnover)	*206*	-0.469***	-0.395***	-0.354***
			(-2.70)	(-3.01)	(-2.71)
	Log(#households)	*54*	-0.481	-0.428	-0.387
			(-1.21)	(-1.46)	(-1.35)
	Log(inst. $vol.)	*99*	0.036	0.006	0.024
			0.350	0.070	(0.30)
	Log(small TAQ trades)	*94*	-0.601	-0.489*	-0.481*
			(-1.55)	(-1.76)	(-1.86)

B.6 Who are the Distracted Liquidity Providers?

In the paper, we document that the realized spread, a measure of the inventory costs faced by market makers, increases on distraction days. This finding is not directly consistent with our main story: sensational news events causing a short-lived reduction in the intensity of noise trading.[4] Rather, it suggests that not only the demand for liquidity (from noise traders) but also the provision of liquidity falls on distraction days.[5] This raises the question of which type of liquidity providers are distracted: contrarian traders—e.g., Kaniel et al. (2008) document that retail investors often trade in a contrarian fashion (i.e., buy/sell when prices fall/rise)—or specialist market makers. In this subsection, we devise two tests that shed light on this question.

The first test looks at contrarian trades executed by retail and institutional investors—in other words, trades that supply liquidity to the market. We define as "contrarian" all buys (resp. sells) transacted at a price below (resp. above) the stock's benchmark price. This benchmark price is chosen as, in that order, (1) the volume-weighted average price (VWAP) calculated from TAQ, or (2) the average between the CRSP opening and closing prices, or (3) the CRSP closing price (since the opening price is not available before June 1992).[6] In unreported analysis, we find that distraction days see fewer contrarian trades for stocks in the bottom tercile in terms of market capitalization, stock price, and institutional ownership. However, since these stocks also experience a significant drop in total trading activity (see Table 7 in the paper and Tables C.1 and C.2 below), we cannot conclude from this evidence that contrarian traders choose to provide less liquidity. For this reason, we repeat our analysis for contrarian trades in stocks that experience *no* decline in overall trading activity, i.e., stocks in the *top* tercile in terms of market capitalization, stock price, and institutional ownership. A decline in contrarian trades for these stocks must reflect a drop in liquidity-supplying trades since liquidity-taking trades (noise trades) are unaffected. Panel A of Table B.6 presents the results of this test. Both the number of contrarian households and the volume of contrarian trades executed by institutions drop by, respectively, 5% and 3%. These finding suggests that contrarian traders appear to be distracted, explaining why the realized spread increases.[7]

Our second test, presented in Panel B of Table B.6, investigates whether specialist market makers are also distracted. To this end, we look at the frequency with which quotes are

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

5 Our findings for volatility and price reversals rule out the possibility that *only* liquidity providers are distracted. Indeed, our model predicts that, if market makers alone were distracted, then one would expect volatility and price reversals to intensify alongside the worsening of liquidity. We find the exact opposite. We therefore reason that both the demand and supply of liquidity fall on distraction days, and that the effects of the drop in liquidity demand on volatility and price reversals dominate the corresponding effects with respect to liquidity supply. After all, we found the distraction effect to be most pronounced for biased investors, suggesting that liquidity demand (noise trading) may be more affected than liquidity provision.

6 Our retail brokerage data do not include transaction times so we cannot identify passive trades by comparing trade prices to pre-trade quote midpoints. The institutional trades data include a time stamp but it has been recognized as unreliable (e.g., Choi et al., 2016). We obtain similar results when we define as "contrarian" all buys (resp. sells) made on days when the stock's return is negative (resp. positive) following Barber et al. (2009).

7 Note that contrarian and noise traders may even be one and the same. Indeed, Bloomfield et al. (2009) use a laboratory market to document that uninformed traders behave largely as "*contrarian noise traders*."

updated during the day (divided into five-minute intervals). The idea is that quote updates (and quote cancellations) in the order book are typically made by specialist market makers. Other traders may also submit limit orders, but they rarely update/cancel them, and so these limit orders only disappear from the book when they are hit by a trade.[8]

According to the panel's first row, the fraction of five-minute intervals with a quote change decreases sharply on distraction days for stocks with high retail ownership, whereas no such effect is discernible for low-retail ownership stocks (not reported). However, this decrease does not imply that distracted market makers fail to update their quotes as it could be caused by a decline in the number of price-moving trades. Indeed, when an incoming market order fills the current best quote in the book, the price jumps to the second-best quote and there appears to be a quote change. Given the decline in trading activity that we document, we expect such quote changes to be less frequent on distraction days.

To detect any lack of quote updates caused by inattentive specialist market makers, we decompose the fraction of intervals with quote changes into the product of: (a) the fraction of intervals with no trade (out of all intervals) and (b) the fraction of intervals with quote updates out of intervals with no trade. We surmise that the latter fraction closely tracks the attention paid by specialist market makers, as they are the ones responsible for canceling and updating quotes *in the absence of trading*. The last two rows of Panel B present the results of this decomposition. As expected, the fraction of five-minute intervals with no trade increases markedly on distraction days for high-retail ownership stocks. In contrast, the fraction of intervals with quote updates conditional on no-trade is not significantly affected (with the exception of low-priced stocks, where the rank test shows a marginally significant decrease). Moreover, as shown by the last row in Table B.6, this no-effect is significantly different from the unconditional drop in the fraction of intervals with quote change (again with the exception of low-priced stocks), showing that intervals without quote change behave very differently from the average interval. This suggests that specialist market makers, who monitor and update their quotes even in the absence of trading, are not distracted.

To conclude, this subsection finds that contrarian traders, but not specialist market makers, supply less liquidity on distraction days, explaining why we found an increased realized spread on these days.

[8] Consistent with this view, Linnainmaa (2010) finds that retail traders rarely cancel or update limit orders after submitting them.

Table B.6: Distraction Events and Liquidity Provision

This table reports event-study results for two tests of liquidity provision. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. In Panel A, we look at the logarithm of the number of households engaging in contrarian trades and at the logarithm of institutional dollar volume from contrarian trades (where contrarian trades are all buys (sells) transacted at a price below (above) the stock's benchmark price, defined as VWAP, or average between open and closing price, or closing price, in that order). In Panel B, we look at three measures of "market quality" constructed from TAQ data (covering 206 events). *Fraction of intervals with quote change* is the (equal-weighted) average of the fraction of 5-minute intervals with a mid-quote change over all 5-minute intervals with valid mid-quotes. *Fraction of intervals without trade* is the (equal-weighted) average of the fraction of 5-minute intervals with zero trading volume out of all 5-minute intervals with valid mid-quotes. *Fraction of intervals with quote change among intervals without trade* is the (equal-weighted) average of the fraction of 5-minute intervals without trading and with a mid-quote change out of all 5-minute intervals without trading. *Difference of fraction of intervals with quote change* is the difference between the fraction of intervals with quote change and the fraction of intervals with quote change among intervals without trade. In both panels, column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership. 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: Contrarian Trades by Retail and Institutional Investors

	N	(1) Overall		(2) Firm Size Tercile 3		(3) Stock Price Tercile 3		(4) Inst. Holdings Tercile 3	
Log(#households with contrarian trades)	*66*	-0.055		-0.056		-0.049		-0.064	
		(-2.498)	**	(-1.623)		(-1.077)		(-1.416)	
		[-2.067]	**	[-1.284]		[-0.834]		[-1.064]	
Log(#inst. volume from contrarian trades)	*99*	-0.035		-0.043		-0.042		-0.032	
		(-2.073)	**	(-2.310)	**	(-2.136)	**	(-1.770)	*
		[-1.354]		[-2.056]	**	[-2.070]	**	[-1.494]	

Panel B: Fraction of Intervals with Quote Changes

	N	(1) Overall		(2) Firm Size Tercile 1		(3) Stock Price Tercile 1		(4) Inst. Holdings Tercile 1	
Fraction of intervals with quote change	*206*	-0.133		-0.278		-0.337		-0.265	
		(-1.093)		(-2.511)	**	(-2.819)	***	(-2.237)	**
		[-1.193]		[-3.109]	***	[-3.484]	***	[-3.135]	***
Fraction of intervals without trade	*206*	0.217		0.273		0.408		0.331	
		(1.932)	*	(2.637)	***	(3.449)	***	(3.097)	***
		[1.949]	*	[2.794]	***	[3.832]	***	[3.699]	***
Fraction of intervals with quote change among intervals without trade	*206*	0.097		-0.082		-0.123		-0.057	
		(-0.048)		(-1.014)		(-1.517)		(-1.058)	
		[0.061]		[-0.658]		[-1.749]	*	[-0.866]	
Difference in fraction of intervals with quote change	*206*	-0.230		-0.196		-0.214		-0.208	
		(-1.325)		(-2.139)	**	(-1.532)		(-2.006)	**
		[-2.834]	***	[-3.565]	***	[-2.911]	***	[-4.050]	***

Internet Appendix C: Robustness Checks

C.1: Sample Split by Stock Price

In the paper, we report event study results after sorting stocks into terciles based on market capitalization as it is well known that small stocks are held predominantly by retail (noise) traders (see e.g. Lee et al., 1991). Here, we instead sort stocks based on their price, another commonly used proxy for retail ownership (see e.g. Brandt et al., 2010). Table C.1 below shows that—consistent with the results of the market capitalization split—distraction effects are economically pronounced and statistically significant in the low-price tercile, while being absent in the high-price tercile.

Specifically, for the stock-price tercile, we find a significant reduction (of about 3%) in trading activity that coincides with a significant decline in volatility (Panel A), as well as with a decrease in liquidity (Panel B). In particular, bid-ask spreads and proxies for adverse selection risk are significantly increased among low-priced stocks (with the exception of price impact—for which the increase is insignificant, with a t-statistic of 1.5). In contrast, high-priced stocks are unaffected on distraction days. As shown in the last column, the difference between low- and high-priced stocks is typically significant.

Table C.1: Sample Split by Stock Price

This table reports event-study results for the 532 distraction events that fall into the period 1968 to 2013. The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. Stocks are sorted into three terciles based on their closing price on the last trading day prior to the event. All variables are defined in the Appendix. Column (1)-(3) show results for terciles 1-3, respectively. Column (4) tests for the difference between tercile 1 and tercile 3. Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

	N	(1) Tercile 1	(2) Tercile 2	(3) Tercile 3	(4) Difference
Trading activity					
Log(turnover)	*532*	-0.027	-0.013	0.005	0.031
		(-3.308) ***	(-1.531)	(0.767)	(4.126) ***
		[-3.880] ***	[-1.673] *	[1.298]	[5.136] ***
Log($volume)	*532*	-0.032	-0.016	0.002	0.034
		(-3.682) ***	(-1.820) *	(0.475)	(4.283) ***
		[-4.199] ***	[-2.001] **	[0.949]	[5.273] ***
Volatility					
Abs return	*532*	-0.004	-0.003	0.001	0.006
		(0.234)	(0.798)	(1.272)	(1.179)
		[-1.438]	[-1.856] *	[-1.008]	[1.078]
Price range	*532*	-0.043	-0.017	0.006	0.049
		(-1.349)	(0.191)	(1.772) *	(3.168) ***
		[-2.617] ***	[-1.280]	[0.983]	[3.775] ***
Intraday volatility	*206*	-0.008	-0.005	-0.002	0.006
		(-2.394) **	(-0.698)	(0.446)	(2.875) ***
		[-3.425] ***	[-2.499] **	[0.193]	[3.290] ***
Intraday auto-covariance	*206*	0.005	0.006	0.006	0.002
		(1.079)	(-0.009)	(-0.06)	(-1.085)
		[2.039] **	[1.657] *	[0.789]	[-0.93]

Panel B: Liquidity

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

C.2: Sample Split by Institutional Ownership

In the paper, we report event study results after sorting stocks into terciles based on firm size as it is well known that small stocks are held predominantly by retail (noise) traders (see e.g. Lee et al., 1991). Here, we instead sort stocks based on institutional ownership data derived from 13(f) filings. In the Securities Exchange Act of 1975, section 13(f) requires institutional investment managers with more than $100 million in assets under management to disclose any holdings that exceed 10,000 shares or $200,000 in value. It follows that the fraction of shares not held by these institutions must be held either by smaller institutions or by retail investors, hence we expect stronger distraction effects for stocks in the lowest tercile of institutional ownership. Because this data is available only from the early 1980s, our sample is reduced to 351 events.

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

Table C.2: Sample Split by Institutional Holdings

This table reports event-study results for the 351 distraction events that fall into the period 1981 to 2013, for which we have institutional holdings data from 13(f). The estimation period includes all trading days without economic news within a 200-day window centered on the event-date. Stocks are sorted into three terciles based on the fraction of institutional ownership at the end of the quarter prior to the event. All variables are defined in the Appendix. Column (1)-(3) show results for terciles 1-3, respectively. Column (4) tests for the difference between tercile 1 and tercile 3. Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

		(1)		(2)		(3)		(4)	
	N	Tercile 1		Tercile 2		Tercile 3		Difference	
Trading activity									
Log(turnover)	*351*	-0.027		-0.012		0.001		0.028	
		(-2.936)	***	(-1.242)		(0.203)		(3.779)	***
		[-2.894]	***	[-0.853]		[0.965]		[4.151]	***
Log($volume)	*351*	-0.031		-0.017		-0.004		0.027	
		(-3.145)	***	(-1.572)		(-0.293)		(3.654)	***
		[-3.160]	***	[-1.342]		[0.387]		[4.274]	***
Volatility									
Abs return	*351*	-0.011		0.009		0.016		0.027	
		(-0.153)		(1.699)	*	(2.110)	**	(2.624)	***
		[-0.999]		[0.169]		[0.264]		[1.211]	
Price range	*351*	-0.050		-0.010		0.011		0.061	
		(-1.522)		(0.394)		(1.878)	*	(3.824)	***
		[-2.003]	**	[-0.359]		[0.690]		[3.125]	***
Intraday volatility	*206*	-0.010		-0.004		-0.002		0.007	
		(-2.542)	**	(-0.514)		(0.123)		(2.684)	***
		[-4.154]	***	[-1.857]	*	[-0.228]		[3.329]	***
Intraday auto-covariance	*206*	0.008		0.005		0.005		-0.003	
		(1.715)	*	(-0.025)		(-0.077)		(-1.721)	*
		[2.869]	***	[1.606]		[1.132]		[-1.142]	

Panel B: Liquidity

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

C.3: Alternative Weighting Schemes for Spread Measures

In the paper, we present results for equal-weighted spread measures (meaning that each trade is weighted equally). In Table C.3 below, we show that we obtain very similar results when we use instead *share-weighted and volume-weighted spread measures* (meaning that trades are weighted by the number of shares traded or the dollar value of trade, respectively).

Table C.3: Event Study Results for Share- and Volume-weighted Spread Measures

This table reports event-study results for share- and volume-weighted spread measures for the 206 distraction events that fall into the period 1993 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 (1) their market capitalization at the end of the last trading day prior to the event, (2) based on their closing price on the last trading day prior to the event, and (3) based on the fraction of institutional ownership at the end of the quarter prior to the event. All variables are defined in the Appendix. Columns (1)-(3) show results for share-weighted spread measures for terciles 1-3, respectively. Columns (5)-(7) show results for dollar volume-weighted spread measures for terciles 1-3, respectively. Columns (4) and (8) test for the differences between tercile 1 and tercile 3 for each spread measure. 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.

	Share-weighted				Volume-weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tercile 1	Tercile 2	Tercile 3	Difference	Tercile 1	Tercile 2	Tercile 3	Difference
(1) Tercile sorts by firm size								
Effective spread	0.048	0.013	-0.014	-0.062	0.048	0.013	-0.014	-0.062
	(2.741)***	(1.634)	(-0.169)	(-1.993)**	(2.748)***	(1.630)	(-0.169)	(-1.994)**
	[2.227]**	[1.371]	[-0.989]	[-2.686]***	[2.230]**	[1.373]	[-0.986]	[-2.686]***
Realized spread	0.038	0.007	-0.010	-0.048	0.038	0.007	-0.010	-0.048
	(2.613)**	(1.436)	(-0.44)	(-2.135)**	(2.635)***	(1.430)	(-0.440)	(-2.149)**
	[2.149]**	[0.520]	[-0.736]	[-2.417]**	[2.179]**	[0.521]	[-0.742]	[-2.426]**
Price impact	0.008	0.002	-0.004	-0.012	0.008	0.002	-0.004	-0.012
	(1.443)	(1.100)	(-0.153)	(-1.243)	(1.428)	(1.096)	(-0.152)	(-1.233)
	[1.285]	[0.008]	[-0.297]	[-1.580]	[1.249]	[0.011]	[-0.276]	[-1.579]
(2) Tercile sorts by stock price								
Effective spread	0.044	0.011	-0.012	-0.056	0.044	0.011	-0.012	-0.056
	(2.619)***	(2.074)**	(-0.234)	(-2.030)**	(2.625)***	(2.074)**	(-0.241)	(-2.035)**
	[2.562]**	[1.887]*	[-0.960]	[-3.184]***	[2.587]**	[1.879]*	[-0.947]	[-3.207]***
Realized spread	0.033	0.007	-0.009	-0.042	0.033	0.007	-0.009	-0.042
	(2.660)***	(1.423)	(-0.658)	(-2.344)**	(2.684)***	(1.429)	(-0.662)	(-2.363)**
	[2.327]**	[1.312]	[-1.080]	[-2.900]***	[2.386]**	[1.317]	[-1.089]	[-2.947]***
Price impact	0.006	0.003	-0.003	-0.009	0.006	0.003	-0.003	-0.009
	(1.044)	(1.428)	(-0.074)	(-0.938)	(1.026)	(1.427)	(-0.071)	(-0.921)
	[0.800]	[1.012]	[-0.435]	[-1.115]	[0.785]	[1.007]	[-0.429]	[-1.114]
(3) Tercile sorts by institutional holdings								
Effective spread	0.035	0.015	-0.011	-0.046	0.035	0.015	-0.011	-0.046
	(2.424)**	(2.142)**	(-0.094)	(-1.836)*	(2.435)**	(2.139)**	(-0.099)	(-1.845)*
	[2.282]**	[2.271]**	[-0.566]	[-2.898]***	[2.293]**	[2.266]**	[-0.588]	[-2.896]***
Realized spread	0.027	0.009	-0.009	-0.036	0.027	0.009	-0.008	-0.036
	(2.330)**	(1.693)*	(-0.420)	(-2.053)**	(2.365)**	(1.688)*	(-0.416)	(-2.077)**
	[1.980]**	[1.463]	[-0.560]	[-2.564]**	[2.029]**	[1.467]	[-0.583]	[-2.575]**
Price impact	0.006	0.002	-0.003	-0.008	0.005	0.002	-0.003	-0.008
	(1.344)	(1.034)	(0.250)	(-0.907)	(1.325)	(1.025)	(0.234)	(-0.904)
	[0.924]	[0.235]	[0.264]	[-1.057]	[0.899]	[0.224]	[0.232]	[-1.054]

C.4: No Filter for Economic News

In the paper, we mostly present results based on the 532 distraction events that are obtained from top 10% news pressure days after excluding days in which the news broadcast headlines contained an economic keyword. In Table C.4 below, we show that we obtain very similar results when we do *not* filter on economic keywords and use instead all top 10% news pressure days.

Table C.4: Event Study for all Top10%-News Pressure Events

This table reports event-study results for the 1,084 top-10% news pressure events (i.e., all days in which news pressure is in the top decile for the respective year; regardless of whether the news event is classified as economic or not). The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity and volatility; Panel B shows the results for liquidity. All variables are defined in the Appendix. Column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership (limited to 768 events due to lack of data). Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

	N	(1) Overall		(2) Firm Size Tercile 1		(3) Stock Price Tercile 1		(4) Inst. Holdings Tercile 1	
Market return	*1084*	-0.044		-0.041		-0.045		-0.040	
		(-0.689)		(-1.122)		(-0.824)		(-0.333)	
		[-0.606]		[-0.932]		[-0.739]		[0.241]	
Trading activity									
Log(turnover)	*1084*	-0.009		-0.024		-0.026		-0.022	
		(-1.642)		(-4.405)	***	(-4.41)	***	(-3.628)	***
		[-2.776]	***	[-6.376]	***	[-6.222]	***	[-4.822]	***
Log($volume)	*1084*	-0.012		-0.029		-0.034		-0.027	
		(-2.362)	**	(-5.103)	***	(-5.249)	***	(-4.132)	***
		[-3.302]	***	[-6.888]	***	[-6.801]	***	[-5.259]	***
Volatility									
Abs return	*1084*	0.012		-0.006		0.011		0.011	
		(1.303)		(-0.563)		(0.571)		(0.571)	
		[-4.593]	***	[-4.115]	***	[-2.838]	***	[-2.838]	***
Price range	*1084*	0.016		-0.051		-0.018		-0.012	
		(1.170)		(-3.127)	***	(-1.144)		(-1.019)	
		[-2.770]	***	[-6.233]	***	[-5.198]	***	[-3.937]	***
Intraday volatility	*504*	0.002		-0.010		-0.004		-0.007	
		(0.734)		(-2.813)	***	(-1.291)		(-1.979)	**
		[-2.023]	**	[-4.373]	***	[-3.705]	***	[-4.079]	***
Intraday auto-covariance	*504*	-0.004		0.003		0.005		0.004	
		(-0.485)		(1.593)		(1.404)		(1.217)	
		[1.465]		[4.166]	***	[2.946]	***	[3.867]	***

Panel B: Liquidity

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

C.5: Event Clustering

Many distraction events cluster in time. In order to check the robustness of our results to such clustering, we present in Table C.5 below event-study results based only on distraction events that are *more than 5 trading days apart* from one another.

Table C.5: Robustness Check Using Distraction Events at Least 5 Trading Days Apart

This table reports event-study results for the 370 distraction events that are at least 5 trading days apart. The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity and volatility; Panel B shows the results for liquidity. All variables are defined in the Appendix. Column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership (limited to 238 events due to lack of data). Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

	N	(1) Overall	(2) Firm Size Tercile 1	(3) Stock Price Tercile 1	(4) Inst. Holdings Tercile 1
Trading activity					
Log(turnover)	*370*	-0.011	-0.029	-0.032	-0.029
		(-1.288)	(-3.160) ***	(-3.228) ***	(-2.659) ***
		[-0.990]	[-3.762] ***	[-3.685] ***	[-2.533] **
Log($volume)	*370*	-0.014	-0.033	-0.037	-0.033
		(-1.515)	(-3.484) ***	(-3.447) ***	(-2.765) ***
		[-1.323]	[-3.975] ***	[-3.866] ***	[-2.629] ***
Volatility					
Abs return	*370*	-0.007	-0.017	-0.008	-0.023
		(0.375)	(-0.632)	(0.020)	(-0.83)
		[-1.964] *	[-1.763] *	[-1.407]	[-1.783] *
Price range	*370*	-0.025	-0.078	-0.061	-0.062
		(-0.409)	(-2.409) **	(-1.799) *	(-1.789) *
		[-1.211]	[-3.389] ***	[-2.763] ***	[-2.069] **
Intraday volatility	*141*	-0.014	-0.022	-0.019	-0.020
		(-1.615)	(-3.371) ***	(-3.284) ***	(-3.193) ***
		[-1.571]	[-3.510] ***	[-3.115] ***	[-3.374] ***
Intraday auto-covariance	*141*	0.004	0.008	0.003	0.007
		(-0.514)	(1.828) *	(0.505)	(1.231)
		[0.950]	[2.458] **	[1.248]	[2.032] **

Panel B: Liquidity

	N	(1) Overall		(2) Firm Size Tercile 1		(3) Stock Price Tercile 1		(4) Inst. Holdings Tercile 1	
Liquidity - overall									
Closing bid-ask spread	*227*	0.008		0.059		0.056		0.043	
		(1.102)		(2.919)	***	(2.767)	***	(3.194)	***
		[0.952]		[2.441]	**	[2.465]	**	[2.253]	**
Average bid-ask spread	*141*	-0.001		0.047		0.036		0.031	
		(0.996)		(2.609)	**	(2.292)	**	(2.304)	**
		[-0.186]		[1.038]		[0.742]		[0.983]	
Effective spread	*141*	0.01		0.052		0.047		0.034	
		(1.069)		(2.320)	**	(2.097)	**	(1.730)	*
		[1.149]		[1.734]	*	[1.989]	**	[1.382]	
Liquidity - adverse selection									
Log(amihud)	*370*	0.008		0.023		0.030		0.022	
		(1.951)	*	(2.199)	**	(2.915)	***	(2.655)	***
		[0.657]		[1.845]	*	[2.682]	***	[2.588]	**
Price impact	*141*	0.001		0.009		0.008		0.005	
		(0.138)		(1.073)		(0.953)		(0.743)	
		[0.232]		[0.732]		[0.571]		[0.351]	
Absolute trade imbalance	*141*	0.16		0.362		0.331		0.344	
		(1.622)		(1.966)	*	(1.908)	*	(2.188)	**
		[1.077]		[1.717]	*	[1.845]	*	[1.880]	*
Lambda	*141*	0.002		0.011		0.010		0.007	
		(1.191)		(2.514)	**	(2.592)	**	(2.183)	**
		[2.016]	**	[2.746]	***	[2.880]	***	[2.569]	**
Liquidity - inventory costs									
Realized spread	*141*	0.009		0.047		0.041		0.032	
		(1.597)		(2.838)	***	(2.753)	***	(2.272)	**
		[1.164]		[2.039]	**	[2.158]	**	[1.697]	*

C.6: Removing Potentially Related Sectors

One concern with our distraction events is that they still contain some economic news that could affect stock prices—at least for stocks in certain, potentially-related sectors. To mitigate this concern, we conduct a robustness check in which we remove firms operating in sectors that are potentially affected from certain types of events. Specifically, we remove all oil and transportation (including defense) stocks (Fama-French 17 industry classification codes 3 and 13) for distraction events involving accidents (e.g., plane crashes), foreign crisis, minor military action (recall that references to war are excluded due to the keywords), and terror attacks (affecting altogether 41% of distraction events). We further remove all construction and finance stocks (industry classification codes 8 and 16) for distraction events involving natural disasters (about 9% of distraction events). Finally, we remove stocks in heavily-regulated sectors—mining, oil, automobile, transportation and finance (industry codes 2, 3, 12, 13, 14 and 16)—for distraction events involving politics (about 35% of distraction events; recall that elections are excluded due to our keywords). The results, shown in Table C.6 below, show that these exclusions barely affect our results.

Table C.6: Event Study after removing stocks from potentially-related sectors

This table reports (equal-weighted) market-wide event-study results for the 532 distraction events that fall into the period 1968 to 2013—after removing stocks operating in sectors that are potentially affected from certain types of events; see explanation above. The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity and volatility; Panel B shows the results for liquidity. All variables are defined in the Appendix. Column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership (limited to 351 events due to lack of data). Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

	N	(1) Overall		(2) Firm Size Tercile 1		(3) Stock Price Tercile 1		(4) Inst. Holdings Tercile 1	
Trading activity									
Log(turnover)	*532*	-0.009		-0.023		-0.027		-0.027	
		(-1.206)		(-3.055)	***	(-3.299)	***	(-2.797)	***
		[-1.168]		[-3.838]	***	[-3.899]	***	[-2.898]	***
Log($volume)	*532*	-0.013		-0.028		-0.032		-0.033	
		(-1.559)		(-3.497)	***	(-3.759)	***	(-3.113)	***
		[-1.569]		[-4.189]	***	[-4.287]	***	[-3.235]	***
Volatility									
Abs return	*532*	-0.002		-0.007		-0.003		-0.007	
		(0.923)		(-0.195)		(0.239)		(-0.156)	
		[-1.441]		[-1.313]		[-1.364]		[-1.001]	
Price range	*532*	-0.011		-0.059		-0.040		-0.039	
		(0.479)		(-2.331)	**	(-1.224)		(-1.161)	
		[-0.642]		[-3.215]	***	[-2.323]	**	[-1.549]	
Intraday volatility	*206*	-0.009		-0.020		-0.017		-0.016	
		(-0.698)		(-3.639)	***	(-3.230)	***	(-2.915)	***
		[-1.473]		[-3.959]	***	[-3.584]	***	[-3.556]	***
Intraday auto-covariance	*206*	0.005		0.008		0.005		0.007	
		(0.316)		(2.081)	**	(1.153)		(1.665)	*
		[1.914]	*	[2.723]	***	[2.073]	**	[2.927]	***

Panel B: Liquidity

	N	(1) Overall		(2) Firm Size Tercile 1		(3) Stock Price Tercile 1		(4) Inst. Holdings Tercile 1	
Liquidity - overall									
Closing bid-ask spread	*335*	0.014		0.060		0.057		0.050	
		(2.514)	**	(4.202)	***	(3.709)	***	(4.556)	***
		[2.253]	**	[3.500]	***	[3.306]	***	[3.488]	***
Average bid-ask spread	*206*	0.002		0.044		0.034		0.033	
		(1.579)		(2.769)	***	(2.672)	***	(2.742)	***
		[0.189]		[1.282]		[1.085]		[1.407]	
Effective spread	*206*	0.011		0.049		0.043		0.037	
		(1.627)		(2.611)	**	(2.440)	**	(2.388)	**
		[1.787]	*	[2.366]	**	[2.512]	**	[2.167]	**
Liquidity - adverse selection									
Log(amihud)	*532*	0.010		0.023		0.025		0.025	
		(2.641)	***	(2.922)	***	(3.383)	***	(3.590)	***
		[1.306]		[2.395]	**	[2.951]	***	[3.191]	***
Price impact	*206*	0.002		0.008		0.007		0.006	
		(0.687)		(1.311)		(1.122)		(1.150)	
		[0.338]		[0.801]		[0.622]		[0.205]	
Absolute trade imbalance	*206*	0.162		0.444		0.387		0.410	
		(1.876)	*	(2.776)	***	(2.542)	**	(2.668)	***
		[1.620]		[2.775]	***	[2.944]	***	[2.723]	***
Lambda	*206*	0.178		0.937		0.936		0.692	
		(2.297)	**	(3.195)	***	(3.698)	***	(2.980)	***
		[2.715]	***	[3.456]	***	[3.845]	***	[3.317]	***
Liquidity - inventory costs									
Realized spread	*206*	0.010		0.044		0.037		0.034	
		(2.160)	**	(3.142)	***	(3.090)	***	(2.959)	***
		[1.983]	**	[2.742]	***	[2.731]	***	[2.850]	***

C.7: Placebo Test Based on Low News Pressure Events

A reverse causality argument is that high news pressure days might be days with *little* economic news. To address this concern, we present in Table C.7 below event-study results for 506 placebo events, defined as days on which news pressure is in the *bottom* decile for the year and which do not feature economic news (i.e., such that the news broadcast headlines do not contain any economic keyword). If news pressure is high because there is little economic news to report, then, conversely, days when news pressure is low should contain economic news. The results below show no sign of elevated trading activity or volatility, which typically accompany the revelation of news, thus alleviating concerns about reverse causality.

Table C.7: Placebo Test for Non-Economic Days with Lowest News Pressure

This table reports event-study results for 506 placebo events (i.e., days on which news pressure is in the bottom decile for the year and which survived our filter for excluding potential economic news). The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A shows the results for measures of trading activity and volatility; Panel B shows the results for liquidity. All variables are defined in the Appendix. Column (1) shows results for the overall market. Column (2) shows results for stocks in the bottom tercile in terms of firm size. Column (3) shows results for stocks in the bottom tercile in terms of stock price. Column (4) shows results for stocks in the bottom tercile in terms of institutional ownership (limited to 360 events due to lack of data). Below each number, we show the t-statistic for the parametric Boehmer, Musumeci, Poulsen (1991) test in parenthesis, and the z-statistic for the non-parametric rank test in square brackets. Statistical significance at the 1%, 5% and 10% level is indicated by ***, **, *, respectively.

Panel A: Trading Activity and Volatility

	N	(1) Overall	(2) Firm Size Tercile 1	(3) Stock Price Tercile 1	(4) Inst. Holdings Tercile 1
Market return	*506*	0.039	0.025	0.044	0.022
		(1.312)	(0.592)	(1.292)	(0.491)
		[1.597]	[1.078]	[1.553]	[0.804]
Trading activity					
Log(turnover)	*506*	-0.002	-0.003	-0.003	-0.001
		(-0.520)	(-0.366)	(-0.390)	(-0.021)
		[0.243]	[-0.535]	[-1.019]	[-0.062]
Log($volume)	*506*	-0.003	-0.008	-0.008	-0.005
		(-0.639)	(-1.072)	(-0.928)	(-0.546)
		[-0.054]	[-1.743] *	[-2.002] **	[-0.814]
Volatility					
Abs return	*506*	0.003	0.009	0.007	0.004
		(-0.137)	(0.968)	(0.732)	(0.462)
		[-1.276]	[1.250]	[0.443]	[0.886]
Price range	*506*	0.003	0.006	0.008	0.003
		(-0.076)	(0.796)	(0.760)	(0.466)
		[-0.146]	[0.259]	[-0.318]	[0.557]
Intraday volatility	*213*	0.006	0.004	0.003	0.006
		(0.921)	(1.225)	(0.941)	(1.689) *
		[-0.066]	[0.877]	[-0.127]	[1.101]
Intraday auto-covariance	*213*	-0.004	-0.002	-0.003	-0.003
		(-1.594)	(-1.45)	(-1.39)	(-1.511)
		[0.387]	[0.032]	[0.355]	[-0.091]

Panel B: Liquidity

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

C.8: Alternative Algorithmic Trading Proxies

In Subsection V.B of the paper, we document how distraction effects interact with the intensity of algorithmic trading in the post-2001 period. To measure this intensity, we use there an algorithmic trading index that summarizes the information from four algorithmic trading proxies gleaned from the SEC Market Information Data Analytics System (MIDAS): the oddlot volume ratio (i.e., the fraction of volume of trades involving less than 100 shares), the and the trade-to-order volume ratio (i.e., the fraction of the executed trading volume out of the total order volume), the cancel-to-trade ratio (i.e., the number of full or partial cancellations divided by the number of trades), and the average trade size (i.e., the number of shares traded divided by the number of trades). In Table C.8 below, we present event-study results for the bottom market capitalization tercile after further sorting stocks into terciles based on these four proxies individually. For better readability, we do not show the estimates for the middle tercile of these double-sorts. We invert the trade-to-order volume ratio and the average trade size so that high values for each proxy correspond to a high level of algorithmic trading. The results are similar to those based on the algorithmic trading index and displayed in the paper.

Table C.8: Sample Split by Algorithmic Trading Proxies for Small Stocks

This table reports event-study results for the tercile of small stocks for the 112 distraction events in the post-2001 period, the era 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 the oddlot-volume ratio (columns (1)-(2)), the order volume-to-trade ratio (columns (4)-(5)), the cancel-to-trade ratio (columns (7)-(8)), and the inverse trade size (columns (10)-(11)) [the middle tercile is not shown for brevity]. Stocks in tercile 3 are associated with a high level of algorithmic trading. All variables are defined in the Appendix. Columns (3), (6), (9) and (12) test 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

	Oddlot Volume Ratio			Order Volume to Trade Ratio			Cancel to Trade Ratio			Inverse Trade Size		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Tercile 1	Tercile 3	Difference	Tercile 1	Tercile 3	Difference	Tercile 1	Tercile 3	Difference	Tercile 1	Tercile 3	Difference
Trading activity												
Log(turnover)	-0.042	-0.062	-0.020	-0.042	-0.055	-0.013	-0.047	-0.055	-0.007	-0.044	-0.050	-0.006
	(-1.963) *	(-4.578) ***	(-2.130) **	(-2.174) **	(-4.142) ***	(-1.871) *	(-2.482) **	(-3.690) ***	(-0.934)	(-2.572) **	(-3.544) ***	(-0.713)
	[-2.090] **	[-4.027] ***	[-1.646]	[-2.253] **	[-3.745] ***	[-1.251]	[-2.572] **	[-3.635] ***	[-0.973]	[-2.401] **	[-3.228] ***	[-0.244]
Log($volume)	-0.050	-0.063	-0.013	-0.047	-0.056	-0.008	-0.055	-0.054	0.001	-0.047	-0.054	-0.007
	(-2.079) **	(-4.383) ***	(-1.865) *	(-2.156) **	(-3.982) ***	(-1.723) *	(-2.472) **	(-3.528) ***	(-0.752)	(-2.584) **	(-3.473) ***	(-0.696)
	[-2.305] **	[-3.826] ***	[-1.124]	[-2.273] **	[-3.675] ***	[-0.842]	[-2.572] **	[-3.524] ***	[-0.375]	[-2.473] **	[-3.170] ***	[-0.267]
Volatility												
Abs return	-0.068	-0.088	-0.020	-0.035	-0.100	-0.065	-0.065	-0.064	0.001	-0.048	-0.056	-0.008
	(-1.886) *	(-2.330) **	(-0.827)	(-0.974)	(-2.363) **	(-1.565)	(-1.406)	(-2.013) **	(-0.390)	(-1.347)	(-1.078)	(0.077)
	[-2.044] **	[-2.505] **	[-0.615]	[-0.935]	[-2.743] ***	[-1.649] *	[-1.971] **	[-2.116] **	[0.343]	[-1.019]	[-1.588]	[-0.090]
Price range	-0.105	-0.214	-0.109	-0.079	-0.199	-0.121	-0.108	-0.153	-0.045	-0.126	-0.157	-0.031
	(-1.453)	(-3.444) ***	(-2.000) **	(-1.163)	(-3.217) ***	(-2.408) **	(-1.289)	(-2.254) **	(-0.895)	(-1.920) *	(-2.222) **	(-0.376)
	[-1.634]	[-3.713] ***	[-2.128] **	[-1.034]	[-3.710] ***	[-2.488] **	[-2.305] **	[-2.645] ***	[-1.147]	[-2.096] **	[-3.086] ***	[-0.197]
Intraday volatility	-0.022	-0.036	-0.014	-0.017	-0.035	-0.018	-0.020	-0.030	-0.01	-0.025	-0.029	-0.004
	(-2.515) **	(-4.056) ***	(-0.760)	(-1.896) *	(-3.896) ***	(-1.627)	(-2.042) **	(-3.292) ***	(-0.836)	(-2.743) ***	(-3.179) ***	(0.111)
	[-2.468] **	[-3.722] ***	[-0.897]	[-2.073] **	[-3.806] ***	[-1.666] *	[-2.346] **	[-3.742] ***	[-0.772]	[-3.141] ***	[-3.452] ***	[-0.261]
Intraday Auto-	0.014	0.018	0.004	0.004	0.015	0.011	0.008	0.015	0.006	0.01	0.014	0.004
covariance	(1.731) *	(2.845) ***	(0.620)	(0.925)	(2.149) **	(0.932)	(1.064)	(1.920) *	(0.478)	(1.764) *	(1.651)	(-0.103)
	[1.919] *	[2.616] ***	[0.128]	[0.909]	[2.137] **	[0.996]	[1.231]	[2.262] **	[0.049]	[2.067] **	[1.559]	[0.839]

Panel B: Liquidity

	Oddlot Volume Ratio			Order Volume to Trade Ratio			Cancel to Trade Ratio			Inverse Trade Size		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Tercile 1	Tercile 3	Difference	Tercile 1	Tercile 3	Difference	Tercile 1	Tercile 3	Difference	Tercile 1	Tercile 3	Difference
Liquidity - overall												
Closing bid-ask	0.033	0.027	-0.006	0.029	0.027	-0.002	0.027	0.033	0.006	0.038	0.036	-0.002
spread	(0.815)	(1.197)	(0.485)	(1.085)	(1.344)	(0.449)	(0.915)	(1.400)	(0.481)	(1.812) *	(1.567)	(-0.003)
	[0.613]	[0.496]	[-0.354]	[0.830]	[0.479]	[-0.383]	[0.581]	[0.604]	[0.192]	[1.167]	[0.752]	[-0.308]
Average bid-ask	0.002	0.033	0.031	-0.015	0.032	0.047	-0.004	0.02	0.024	0.000	0.014	0.014
spread	(1.240)	(1.555)	(0.714)	(0.424)	(1.677) *	(1.641)	(1.032)	(1.175)	(0.163)	(1.138)	(1.479)	(0.641)
	[-1.449]	[0.255]	[1.330]	[-2.264] **	[0.255]	[2.111] **	[-2.163] **	[-0.241]	[1.132]	[-1.208]	[-0.531]	[0.244]
Effective spread	0.056	0.033	-0.023	0.042	0.034	-0.008	0.043	0.034	-0.009	0.029	0.043	0.014
	(1.994) **	(2.063) **	(0.203)	(1.175)	(1.904) *	(0.971)	(1.370)	(1.793) *	(0.310)	(1.455)	(2.329) **	(1.099)
	[1.977] **	[1.031]	[-0.604]	[0.769]	[0.949]	[0.412]	[0.769]	[0.813]	[-0.186]	[1.060]	[1.530]	[0.630]
Liquidity - adverse selection												
Log(amihud)	0.033	0.035	0.003	0.044	0.019	-0.025	0.035	0.034	-0.002	0.040	0.034	-0.006
	(1.843) *	(1.890) *	(0.307)	(2.357) **	(1.169)	(-1.081)	(1.524)	(2.174) **	(0.556)	(2.323) **	(1.642)	(-0.422)
	[1.864] *	[1.205]	[-0.215]	[2.320] **	[0.552]	[-1.385]	[1.446]	[1.425]	[0.221]	[2.192] **	[1.330]	[-0.909]
Price impact	0.001	0.003	0.002	0.004	-0.001	-0.005	0.004	-0.003	-0.007	0.002	0.007	0.005
	(-0.267)	(-0.215)	(0.032)	(-0.147)	(-0.443)	(-0.222)	(-0.112)	(-1.056)	(-0.739)	(-0.049)	(0.571)	(0.524)
	[-0.279]	[-0.247]	[0.250]	[0.212]	[-0.412]	[-0.531]	[-0.610]	[-0.453]	[-0.813]	[-0.496]	[0.694]	[0.267]
Absolute trade	0.479	0.606	0.128	0.542	0.667	0.125	0.441	0.589	0.148	0.728	0.448	-0.279
imbalance	(1.807) *	(1.820) *	(0.185)	(1.612)	(2.475) **	(0.821)	(1.724) *	(2.152) **	(0.357)	(2.907) ***	(1.901) *	(-0.785)
	[1.989] **	[2.227] **	[0.293]	[1.806] *	[2.430] **	[0.746]	[1.727] *	[2.111] **	[0.531]	[2.999] ***	[1.902] *	[-1.248]
Lambda	0.343	1.320	0.978	0.842	0.966	0.124	0.792	0.804	0.011	0.671	0.654	-0.017
	(0.239)	(1.380)	(0.898)	(1.248)	(0.873)	(-0.408)	(1.046)	(0.716)	(-0.282)	(0.894)	(1.305)	(0.320)
	[0.700]	[2.079] **	[1.202]	[1.571]	[1.016]	[-0.798]	[0.734]	[0.253]	[-0.314]	[0.851]	[1.338]	[0.154]
Liquidity - inventory costs												
Realized spread	0.047	0.034	-0.014	0.035	0.033	-0.001	0.030	0.039	0.009	0.026	0.030	0.005
	(2.594) **	(1.787) *	(-0.238)	(1.252)	(1.750) *	(0.749)	(2.013) **	(2.261) **	(0.504)	(2.291) **	(1.681) *	(-0.296)
	[2.572] **	[1.048]	[-0.441]	[0.917]	[1.266]	[0.563]	[1.513]	[1.629]	[0.450]	[1.370]	[1.385]	[0.165]

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