Internet Appendix to

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

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I. 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 autocovariance—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. These implications are summarized in Table IA.I below.

There is one risky asset with 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 risk-free 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.

Table IA.I

Predictions from a Model of Trading with a Risk-Averse Market Maker

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

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

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

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

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

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

which implies

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

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

Liquidity

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

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

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

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

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

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[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.

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

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. However, this case implies that $\beta = 0$, λ is nonzero. Specifically, $\lambda = \frac{\gamma}{2h}$, where the market maker's risk aversion and fundamental risk (captured by h, the precision of his information based on the prior and the signal s') jointly determine how he is compensated for bearing inventory risk. In short, λ is nonzero 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

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,

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

_Return volatility

Stretching the static interpretation a little, we can think of returns as 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 the expressions for the returns into this equation 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 in turn: $\mathrm{Var}[p_1] = (\sigma_\theta + \sigma_{\varepsilon'})/h^2/\sigma_{\varepsilon'}{}^2 = \sigma_\theta/h/\sigma_{\varepsilon'}$;

2 Indeed, when $\sigma_{\varepsilon'}$ is infinite, equations (IA.1) to (IA.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).

$\text{Var}[\lambda\omega] = \lambda^2\text{Var}[\beta(s - p_1) + z] = \lambda^{2\beta^2}\text{Var}[s - p_1] + \lambda^2\sigma_z = \lambda^{2\beta^2\left(\frac{1}{h}+\sigma_\varepsilon\right)} + \lambda^2\sigma_z$, again given that $\text{Var}[s - p_1] = \frac{1}{h} + \sigma_\varepsilon$; $\text{Cov}[\theta, \lambda\omega] = \text{Cov}\left[\theta, \lambda(\beta(\theta + \varepsilon - \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')) + z)\right] = \lambda\beta(1 - \frac{1}{h\sigma_{\varepsilon'}})\sigma_\theta = \lambda\beta/h$; $\text{Cov}[\theta, p_1] = \text{Cov}\left[\theta, \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')\right] = \sigma_\theta/h/\sigma_{\varepsilon'}$; $\text{Cov}[\lambda\omega, p_1] = \text{Cov}\left[\lambda\left(\beta\left(\theta + \varepsilon - \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')\right) + z\right), \frac{1}{h\sigma_{\varepsilon'}}(\theta + \varepsilon')\right] = \lambda\beta\left(1 - \frac{1}{h\sigma_{\varepsilon'}}\right)\frac{\sigma_\theta}{h\sigma_{\varepsilon'}} - \lambda\beta\frac{\sigma_\theta}{h^2\sigma_{\varepsilon'}} = 0.$

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 (IA.2) to substitute out λ

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

and by noting that, from equation (IA.3), $\gamma\sigma_\varepsilon\beta^3 + \gamma\sigma_z\beta = -\beta^2 + \frac{\sigma_z h}{1+\sigma_\varepsilon h}$,

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

As this expression shows, volatility equals σ_θ when the market maker is risk-neutral ($\gamma = 0$) as in the classic Kyle (1985) model. Equation (IA.6) also makes clear that volatility is amplified by the market marker's inventory concern.

Return autocovariance

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

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

Each of these terms is computed above. Substituting their expressions leads to

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

Given that $VOL \geq \sigma_\theta$, $COV \leq 0$, that is, returns are negatively autocorrelated, 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 variation 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 derive the implications for expected trading volume, liquidity (the inverse of the price

[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, which effectively makes him more risk-averse today. This approach yields predictions that are identical to those obtained here (proofs are available upon request).

impact parameter, λ), and return volatility under each of these three interpretations of distraction shocks. These implications are summarized in Table III in the main article.

A. Distracted Noise Traders

PROPOSITION 1: A lower variance of noise trading results in lower trading volume, lower liquidity (higher λ), lower return volatility, and higher return autocovariance.

Proof:

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

Intuition:

- 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 that 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 nonfundamental 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 autocovariance). Less noise trading therefore implies fewer such reversals, that is, a less negative return autocovariance

B. Distracted Insiders

PROPOSITION 2: A higher variance of the insider's signal error results in lower trading volume and higher liquidity (lower λ). 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 (IA.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 (IA.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 $\gamma\beta^3 + \frac{\sigma_z h^2}{(1+\sigma_\varepsilon h)^2} \leq \frac{3\gamma\sigma_\varepsilon h}{1+\sigma_\varepsilon h}\beta^3 + \frac{\gamma\beta\sigma_z h}{1+\sigma_\varepsilon h} \leq \frac{\beta g(\beta) h}{1+\sigma_\varepsilon h}$ in the numerator.
- Trading volume. From equation (IA.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 (IA.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 $\beta \leq \sqrt{\frac{\sigma_z h}{1+\sigma_\varepsilon h}}$ and as a result $\beta^2\sigma_\varepsilon \leq \sigma_z$. 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 autocovariance. 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 (higher liquidity).
- Volatility and autocovariance are dampened by the lower price impact but amplified by the elevated noisiness of the insider's trades. The net effect is ambiguous.

C. Distracted Market Maker

PROPOSITION 3: A higher variance of the market maker's signal error results in less trading volume, lo liquidity (higher λ), and higher return volatility.

Proof:

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

- Liquidity. The implicit-function theorem applied to equation (IA.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 (IA.2) implies that $\lambda\beta$ increases in $\sigma_{\varepsilon'}$ so λ must increase in $\sigma_{\varepsilon'}$.
- Trading volume. From equation (IA.4), the impact of $\sigma_{\varepsilon'}$ on trading volume depends on the sign of $\frac{\mathrm{d}\ln(\beta^2(1/h+\sigma_\varepsilon)}{\mathrm{d}\sigma_{\varepsilon'}} = \frac{2}{\beta}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}} + \frac{1}{(1+\sigma_\varepsilon h)h(\sigma_{\varepsilon'})^2} = \frac{\gamma\beta(\sigma_{\varepsilon'})^2}{g(\beta)(1+\sigma_\varepsilon h)h}(\beta^2\sigma_\varepsilon - \sigma_Z)$ after substituting in the expression for $\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}}$, using equation (IA.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 (IA.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 autocovariance. 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 latter, 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 autocovariance.

II. Descriptive Statistics and Robustness Checks

A. Descriptive Statistics

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

Table IA.II
Descriptive Statistics for Market Variables

This table reports descriptive statistics for our stock market data. All variables are equal-weighted across stocks. *Mkt return* is the average market return (in percentage points, denoted pp; that is, multiplied by 100). *Turnover* is the average of share turnover, i.e., the ratio of dollar volume to market capitalization (in pp). *$volume* is the average daily dollar volume (in $mn). *Log(turnover)* and *log($volume)* are averages of the natural logarithms of these measures. *Abs return* is the average of the absolute raw return (in pp). *Price range* is the average of the logarithm of the ratio of the daily high price over low price (in pp). *Intraday volatility* is the average of the standard deviation of intraday returns over one-hour intervals (in pp). *Intraday autocovariance* is the average autocovariance of intraday returns over one-hour intervals (multiplied by 10,000 for visibility). *Closing bid-ask spread* is the average of the relative bid-ask spread at market close (in pp). *Average bid-ask spread* is the average of the mean daily relative bid-ask spread (in pp). *Effective spread* is the average relative difference between the transaction price and the mid-quote prior to the transaction (in pp). *Amihud* is the average of the Amihud illiquidity ratio., i.e., the absolute return divided by dollar volume (multiplied by 1,000,000 for visibility). *Log(amihud)* is the average of the natural logarithm of the Amihud illiquidity ratio. *Price impact* is the average relative difference between the mid-quote five minutes after and prior to the transaction (in pp). *Absolute trade imbalance* is the average of the absolute value of (dollar volume of) buys minus sells over buys plus sells (in pp). *Lambda* is the average slope coefficient from regressing returns on order flow over five-minute intervals (multiplied by 1,000,000 for visibility). *Realized spread* is the average relative difference between the mid-quote five minutes after the transaction and the transaction price (in pp). All variables are defined in the Appendix. Panel A reports results for the raw measures (after winsorizing, and before taking logs for turnover, dollar volume, and Amihud). Panel B reports results after the data have been seasonality adjusted by regressing the raw variables on a set of dummy variables for each month/year and day-of-week/year pair (see Section II.C in the paper).

Panel A: Raw Variables

	mean	median	sd	p1	p25	p75	p99
Mkt Return	0.056	0.117	1.011	-2.934	-0.350	0.527	2.821
Trading activity							
Turnover	0.566	0.547	0.239	0.199	0.357	0.737	1.165
$volume	13.397	7.113	13.227	0.986	2.077	24.085	45.345
Volatility							
Abs return	2.358	2.267	0.777	1.312	1.814	2.676	5.044
Price range	3.934	3.766	1.250	2.401	3.073	4.312	8.581
Intraday volatility	0.298	0.278	0.090	0.194	0.235	0.332	0.629
Intraday autocovariance	-0.205	-0.155	0.151	-0.761	-0.23	-0.124	-0.065
Liquidity - overall							
Closing bid-ask spread	2.687	2.835	1.835	0.439	0.760	4.130	6.967
Average bid-ask spread	1.783	1.436	0.980	0.556	0.873	2.710	3.614
Effective spread	1.284	1.040	0.687	0.427	0.637	2.001	2.516
Liquidity - adverse selection							
Amihud	1.433	1.287	1.052	0.153	0.502	2.013	4.556
Price impact	0.387	0.387	0.148	0.154	0.270	0.480	0.765
Absolute trade imbalance	31.098	29.639	9.489	17.637	21.508	40.253	46.965
Lambda	7.196	6.982	4.046	0.542	4.213	9.538	18.114
Liquidity - inventory costs							
Realized spread	0.927	0.629	0.585	0.249	0.403	1.491	2.023

Panel B: Seasonality-Adjusted Variables

	mean	median	sd	p1	p25	p75	p99
Mkt Return	0.000	0.028	0.965	-2.748	-0.407	0.425	2.658
Trading activity							
Log(turnover)	-0.001	-0.004	0.144	-0.437	-0.068	0.068	0.402
Log($volume)	-0.001	-0.004	0.135	-0.383	-0.066	0.065	0.375
Volatility							
Abs return	-0.001	-0.032	0.391	-0.889	-0.149	0.088	1.428
Price range	-0.002	-0.029	0.493	-1.206	-0.184	0.133	1.587
Intraday volatility	0.000	-0.003	0.036	-0.081	-0.014	0.009	0.135
Intraday autocovariance	0.000	0.003	0.078	-0.253	-0.013	0.020	0.188
Liquidity - overall							
Closing bid-ask spread	0.000	0.000	0.005	-0.012	-0.002	0.001	0.016
Average bid-ask spread	-0.001	-0.010	0.191	-0.287	-0.055	0.030	0.425
Effective spread	-0.001	-0.004	0.081	-0.205	-0.029	0.023	0.251
Liquidity - adverse selection							
Log(Amihud)	0.000	-0.005	0.070	-0.157	-0.039	0.033	0.208
Price impact	0.000	-0.002	0.031	-0.079	-0.014	0.011	0.106
Absolute trade imbalance	0.006	-0.046	1.136	-2.363	-0.606	0.518	4.210
Lambda	-0.009	-0.039	0.838	-2.307	-0.340	0.263	2.792
Liquidity - inventory costs							
Realized spread	-0.001	-0.003	0.067	-0.164	-0.025	0.019	0.185

B. 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 for example Lee, Shleifer, and Thaler (1991)). Here, we instead sort stocks based on their price, another commonly used proxy for retail ownership (see for example Brandt et al. (2010)). Table IA.III shows that, consistent with the results of the market capitalization split, distraction effects are economically pronounced and statistically significant in the low-price tercile, but are 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 1.49). 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 IA.III
Sample Split by Stock Price

This table reports event-study results for the 551 distraction events in the period 1968 to 2014. 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. Columns (1) to (3) show results for terciles 1 to 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Trading Activity and Volatility

	N	(1) Tercile 1		(2) Tercile 2		(3) Tercile 3		(4) Difference	
Trading activity									
Log(turnover)	*551*	-0.025		-0.012		0.005		0.031	
		(-3.291)	***	(-1.462)		(0.826)		(4.158)	***
		[-3.822]	***	[-1.553]		[1.365]		[5.105]	***
Log($volume)	*551*	-0.030		-0.015		0.003		0.033	
		(-3.654)	***	(-1.762)	*	(0.514)		(4.280)	***
		[-4.131]	***	[-1.906]	*	[1.011]		[5.204]	***
Volatility									
Abs return	*551*	-0.001		0.000		0.005		0.006	
		(0.448)		(0.966)		(1.519)		(1.235)	
		[-1.252]		[-1.677]	*	[-0.772]		[1.198]	
Price range	*551*	-0.036		-0.010		0.013		0.048	
		(-1.012)		(0.498)		(2.132)	**	(3.264)	***
		[-2.390]	**	[-1.019]		[1.214]		[3.858]	***
Intraday volatility	*225*	-0.014		-0.007		0.001		0.015	
		(-2.596)	**	(-0.232)		(0.995)		(4.315)	***
		[-3.397]	***	[-1.344]		[0.197]		[3.615]	***
Intraday autocovariance	*225*	0.005		0.005		0.006		0.001	
		(1.206)		(0.078)		(0.001)		(-1.181)	
		[2.228]	**	[1.909]	*	[0.940]		[-1.162]	

Panel B: Liquidity

	N	(1) Tercile 1		(2) Tercile 2		(3) Tercile 3	(4) Difference	
Liquidity - overall								
Closing bid-ask spread	*354*	0.053		0.010		-0.015	-0.068	
		(3.408)	***	(2.013)	**	(-0.570)	(-2.894)	***
		[3.106]	***	[2.309]	**	[0.003]	[-3.503]	***
Average bid-ask spread	*225*	0.026		0.002		-0.016	-0.042	
		(2.393)	**	(1.588)		(-0.670)	(-2.033)	**
		[0.705]		[0.580]		[-1.396]	[-1.153]	
Effective spread	*225*	0.037		0.011		-0.009	-0.046	
		(2.200)	**	(2.535)	**	(0.751)	(-1.021)	
		[2.164]	**	[2.248]	**	[-0.313]	[-2.441]	**
Liquidity - adverse selection								
Log(amihud)	*551*	0.026		0.014		-0.003	-0.029	
		(3.496)	***	(3.120)	***	(0.039)	(-2.802)	***
		[3.288]	***	[1.897]	*	[-0.775]	[-3.858]	***
Price impact	*225*	0.008		0.003		-0.001	-0.009	
		(1.489)		(1.213)		(0.372)	(-0.869)	
		[0.992]		[0.545]		[0.259]	[-1.164]	
Absolute trade imbalance	*225*	0.298		0.140		-0.021	-0.319	
		(2.016)	**	(1.691)	*	(-0.237)	(-1.989)	**
		[2.236]	**	[1.065]		[-0.834]	[-2.649]	***
Lambda	*225*	0.804		0.197		-0.098	-0.902	
		(3.111)	***	(1.718)	*	(-0.629)	(-2.568)	**
		[3.345]	***	[1.779]	*	[-0.748]	[-3.639]	***
Liquidity - inventory costs								
Realized spread	*225*	0.030		0.009		-0.007	-0.037	
		(2.622)	***	(2.203)	**	(0.112)	(-1.708)	*
		[2.255]	**	[2.115]	**	[-0.367]	[-2.321]	**

C. 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 for example 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 by either smaller institutions or retail investors, and thus we expect stronger distraction effects for stocks in the lowest tercile of institutional ownership. Because these data are available only from the early 1980s, our sample is reduced to 370 events.

Our results for institutional ownership, reported in Table IA.IV, 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 autocovariance increases (Panel A). In particular, stocks in that tercile experience a 2.5% reduction in turnover, a 5% reduction in intraday volatility, and a 2% to 4% increase in spreads. All of these changes are significant at the 5% level (except for price impact, where the increase fails to be significant) and decrease monotonically in the other terciles. For most measures, the difference between the top and bottom terciles is also significant.

Table IA.IV
Sample Split by Institutional Holdings

This table reports event-study results for the 370 distraction events in the period 1981 to 2014, 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. Columns (1) to (3) show results for terciles 1 to 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Trading Activity and Volatility

		(1)		(2)		(3)		(4)	
	N	Tercile 1		Tercile 2		Tercile 3		Difference	
Trading activity									
Log(turnover)	*370*	-0.025		-0.011		0.002		0.027	
		(-2.909)	***	(-1.167)		(0.255)		(3.769)	***
		[-2.848]	***	[-0.715]		[1.040]		[4.076]	***
Log($volume)	*370*	-0.029		-0.015		-0.003		0.026	
		(-3.117)	***	(-1.509)		(-0.257)		(3.619)	***
		[-3.098]	***	[-1.187]		[0.454]		[4.174]	***
Volatility									
Abs return	*370*	-0.006		0.013		0.020		0.026	
		(0.131)		(1.905)	*	(2.296)	**	(2.554)	**
		[-0.803]		[0.360]		[0.463]		[1.238]	
Price range	*370*	-0.041		0.000		0.020		0.061	
		(-1.150)		(0.790)		(2.209)	**	(3.861)	***
		[-1.641]		[-0.031]		[0.910]		[3.226]	***
Intraday volatility	*225*	-0.015		-0.005		0.000		0.015	
		(-2.686)	***	(-0.047)		(0.700)		(3.966)	***
		[-3.493]	***	[-0.955]		[-0.217]		[2.450]	**
Intraday autocovariance	*225*	0.007		0.005		0.005		-0.003	
		(1.799)	*	(0.063)		(0.010)		(-1.757)	*
		[2.919]	***	[1.853]	*	[1.332]		[-1.282]	

Panel B: Liquidity

	N	(1) Tercile 1	(2) Tercile 2	(3) Tercile 3	(4) Difference
Liquidity - overall					
Closing bid-ask spread	*354*	0.042	0.010	-0.011	-0.053
		(4.089) ***	(1.571)	(-0.059)	(-3.119) ***
		[3.421] ***	[1.560]	[0.491]	[-3.620] ***
Average bid-ask spread	*225*	0.026	0.000	-0.018	-0.044
		(2.508) **	(1.104)	(-0.602)	(-2.110) **
		[1.213]	[-0.292]	[-1.744] *	[-1.652] *
Effective spread	*225*	0.030	0.014	-0.008	-0.038
		(2.148) **	(2.397) **	(0.820)	(-0.997)
		[1.818] *	[2.623] ***	[0.184]	[-2.113] **
Liquidity - adverse selection					
Log(amihud)	*370*	0.025	0.016	0.004	-0.021
		(3.842) ***	(3.288) ***	(1.457)	(-1.930) *
		[3.700] ***	[2.484] **	[1.039]	[-3.495] ***
Price impact	*225*	0.007	0.003	-0.001	-0.008
		(1.618)	(0.916)	(0.736)	(-0.658)
		[0.826]	[0.788]	[0.586]	[-0.970]
Absolute trade imbalance	*225*	0.333	0.120	-0.015	-0.348
		(2.502) **	(1.332)	(0.013)	(-2.445) **
		[2.452] **	[0.961]	[-1.051]	[-2.878] ***
Lambda	*225*	0.564	0.235	-0.047	-0.611
		(2.574) **	(1.894) *	(-0.035)	(-1.874) *
		[2.929] ***	[2.107] **	[0.331]	[-3.045] ***
Liquidity - inventory costs					
Realized spread	*225*	0.026	0.010	-0.006	-0.032
		(2.378) **	(2.420) **	(0.499)	(-1.387)
		[2.051] **	[2.334] **	[0.261]	[-2.256] **

D. Alternative Weighting Schemes for Spread Measures

In the paper, we present results for equal-weighted spread measures (i.e., that each trade is weighted equally). In Table IA.IV below, we show that similar results obtain when we instead use 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 IA.V

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 225 distraction events in the period 1993 to 2014. 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) their closing price on the last trading day prior to the event, and (3) the fraction of institutional ownership at the end of the quarter prior to the event. All variables are defined in the Appendix. Columns (1) to (3) show results for share-weighted spread measures for terciles 1 to 3, respectively. Columns (5) to (7) show results for dollar volume-weighted spread measures for terciles 1 to 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, 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
Tercile sorts by firm size								
Effective spread	0.044	0.012	-0.012	-0.056	0.044	0.012	-0.012	-0.056
	(2.542) **	(1.804) *	(0.112)	(-1.652)	(2.545) **	(1.796) *	(0.110)	(-1.652)
	[1.955] *	[1.420]	[-0.696]	[-2.363] **	[1.953] *	[1.419]	[-0.694]	[-2.355] **
Realized spread	0.034	0.007	-0.009	-0.043	0.034	0.007	-0.009	-0.043
	(2.450) **	(1.425)	(-0.206)	(-1.843) *	(2.466) **	(1.413)	(-0.209)	(-1.855) *
	[1.974] **	[0.466]	[-0.485]	[-2.200] **	[2.004] **	[0.464]	[-0.495]	[-2.210] **
Price impact	0.008	0.002	-0.003	-0.011	0.008	0.002	-0.003	-0.011
	(1.520)	(1.233)	(0.153)	(-1.070)	(1.506)	(1.228)	(0.151)	(-1.063)
	[1.333]	[0.075]	[0.074]	[-1.534]	[1.298]	[0.093]	[0.088]	[-1.532]
Tercile sorts by stock price								
Effective spread	0.039	0.011	-0.011	-0.050	0.039	0.011	-0.011	-0.050
	(2.416) **	(2.193) **	(0.151)	(-1.602)	(2.417) **	(2.189) **	(0.143)	(-1.605)
	[2.346] **	[1.962] *	[-0.610]	[-2.905] ***	[2.368] **	[1.950] *	[-0.602]	[-2.929] ***
Realized spread	0.029	0.007	-0.008	-0.037	0.029	0.007	-0.008	-0.037
	(2.384) **	(1.604)	(-0.387)	(-1.946) *	(2.402) **	(1.605)	(-0.392)	(-1.961) *
	[2.096] **	[1.455]	[-0.789]	[-2.568] **	[2.146] **	[1.453]	[-0.802]	[-2.611] ***
Price impact	0.006	0.003	-0.002	-0.008	0.006	0.003	-0.002	-0.008
	(1.150)	(1.517)	(0.234)	(-0.774)	(1.133)	(1.513)	(0.236)	(-0.759)
	[0.856]	[1.031]	[-0.131]	[-1.110]	[0.840]	[1.022]	[-0.130]	[-1.110]
Tercile sorts by institutional holdings								
Effective spread	0.032	0.014	-0.009	-0.041	0.032	0.014	-0.009	-0.041
	(2.315) **	(2.219) **	(0.153)	(-1.563)	(2.322) **	(2.212) **	(0.144)	(-1.571)
	[2.104] **	[2.334] **	[-0.284]	[-2.681] ***	[2.115] **	[2.321] **	[-0.303]	[-2.673] ***
Realized spread	0.024	0.009	-0.008	-0.032	0.025	0.009	-0.008	-0.032
	(2.163) **	(1.781) *	(-0.371)	(-1.856) *	(2.193) **	(1.771) *	(-0.370)	(-1.878) *
	[1.842] *	[1.568]	[-0.413]	[-2.354] **	[1.884] *	[1.567]	[-0.441]	[-2.354] **
Price impact	0.006	0.002	-0.002	-0.008	0.006	0.002	-0.002	-0.008
	(1.515)	(1.060)	(0.579)	(-0.770)	(1.498)	(1.047)	(0.561)	(-0.771)
	[1.060]	[0.218]	[0.636]	[-1.039]	[1.048]	[0.202]	[0.597]	[-1.047]

E. No Filter for Economic News

In the paper, we present results based on the 551 distraction events that are obtained from top 10% news pressure days after excluding days when the news broadcast headlines contained an economic keyword. In Table IA.VI, we show that similar results obtain when we do *not* filter on economic keywords and instead use all top 10% news pressure days.

IA.VI

Event Study for all Top10% News Pressure Events

This table reports event-study results for the 1,108 top-10% news pressure events (i.e., all days when news pressure is in the top decile for the respective year, regardless of whether the news event is classified as economic). The estimation period includes all trading days within a 200-day window centered on the event date. Panel A reports results for measures of trading activity and volatility; Panel B reprots 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, 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	*1108*	-0.041		-0.037		-0.039		-0.034	
		(-0.612)		(-0.956)		(-0.647)		(-0.163)	
		[-0.571]		[-0.775]		[-0.567]		[0.408]	
Trading activity									
Log(turnover)	*1108*	-0.008		-0.023		-0.025		-0.021	
		(-1.591)		(-4.426)	***	(-4.381)	***	(-3.619)	***
		[-2.711]	***	[-6.373]	***	[-6.161]	***	[-4.782]	***
Log($volume)	*1108*	-0.012		-0.029		-0.033		-0.026	
		(-2.316)	**	(-5.117)	***	(-5.201)	***	(-4.109)	***
		[-3.224]	***	[-6.867]	***	[-6.724]	***	[-5.196]	***
Volatility									
Abs return	*1108*	0.013		-0.005		0.009		0.012	
		(1.406)		(-0.502)		(0.739)		(0.708)	
		[-4.458]	***	[-4.080]	***	[-3.527]	***	[-2.731]	***
Price range	*1108*	0.019		-0.048		-0.014		-0.007	
		(1.462)		(-2.889)	***	(-0.845)		(-0.712)	
		[-2.552]	**	[-6.054]	***	[-5.016]	***	[-3.678]	***
Intraday volatility	*528*	0.003		-0.009		-0.003		-0.006	
		(1.001)		(-2.589)	**	(-1.038)		(-1.746)	*
		[-2.003]	**	[-4.230]	***	[-3.681]	***	[-3.976]	***
Intraday autocovariance	*528*	-0.004		0.003		-0.004		0.000	
		(-0.356)		(1.684)	*	(0.541)		(1.337)	
		[2.690]	***	[4.176]	***	[3.127]	***	[3.953]	***

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	*767*	0.019		0.062		0.070		0.048	
		(3.517)	***	(4.966)	***	(4.989)	***	(5.266)	***
		[1.570]		[2.960]	***	[3.297]	***	[3.061]	***
Average bid-ask spread	*528*	0.013		0.046		0.045		0.037	
		(1.957)	*	(3.914)	***	(3.234)	***	(3.774)	***
		[0.594]		[1.748]	*	[1.350]		[1.627]	
Effective spread	*528*	0.018		0.048		0.050		0.040	
		(4.300)	***	(4.497)	***	(4.330)	***	(4.637)	***
		[3.106]	***	[3.153]	***	[3.596]	***	[3.411]	***
Liquidity - adverse selection									
Log(amihud)	*1108*	0.010		0.022		0.027		0.024	
		(3.899)	***	(4.113)	***	(4.897)	***	(4.981)	***
		[1.770]	*	[3.378]	***	[4.258]	***	[4.274]	***
Price impact	*528*	0.005		0.012		0.013		0.011	
		(2.849)	***	(2.853)	***	(3.015)	***	(3.182)	***
		[1.952]	*	[2.132]	**	[2.307]	**	[2.322]	**
Absolute trade imbalance	*528*	0.129		0.396		0.353		0.341	
		(2.182)	**	(3.933)	***	(3.539)	***	(3.776)	***
		[1.866]	*	[4.057]	***	[3.859]	***	[3.791]	***
Lambda	*528*	0.200		1.037		0.854		0.662	
		(3.012)	***	(3.933)	***	(3.795)	***	(3.544)	***
		[3.356]	***	[3.805]	***	[3.776]	***	[3.571]	***
Liquidity - inventory costs									
Realized spread	*528*	0.013		0.038		0.037		0.031	
		(3.894)	***	(4.642)	***	(4.398)	***	(4.472)	***
		[2.808]	***	[3.065]	***	[3.311]	***	[3.285]	***

F. Event Clustering

Many distraction events cluster in time. To check the robustness of our results to such clustering, we present in Table IA.VII event-study results based only on distraction events that are more than five trading days apart from one another.

Table IA.VII
Robustness Check Using Distraction Events at Least Five Trading Days Apart

This table reports event-study results for the 382 distraction events that are at least five trading days apart. The estimation period includes all trading days within a 200-day window centered on the event-date. Panel A reports results for measures of trading activity and volatility; Panel B reports 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, 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)	*382*	-0.024		-0.035		-0.038		-0.033	
		(-2.581)	**	(-3.975)	***	(-4.074)	***	(-3.122)	***
		[-3.002]	***	[-4.627]	***	[-4.604]	***	[-3.234]	***
Log($volume)	*382*	-0.025		-0.037		-0.040		-0.034	
		(-2.615)	***	(-4.063)	***	(-4.020)	***	(-3.096)	***
		[-2.926]	***	[-4.539]	***	[-4.427]	***	[-3.002]	***
Volatility									
Abs return	*382*	-0.038		-0.035		-0.034		-0.041	
		(-1.129)		(-1.659)	*	(-1.069)		(-1.315)	
		[-4.074]	***	[-2.997]	***	[-2.903]	***	[-2.809]	***
Price range	*382*	-0.066		-0.107		-0.107		-0.093	
		(-1.760)	*	(-3.456)	***	(-3.069)	***	(-2.295)	**
		[-3.570]	***	[-4.843]	***	[-4.721]	***	[-3.253]	***
Intraday volatility	*153*	-0.010		-0.019		-0.016		-0.017	
		(-1.163)		(-3.103)	***	(-2.884)	***	(-2.852)	***
		[-1.332]		[-3.236]	***	[-2.924]	***	[-3.079]	***
Intraday autocovariance	*153*	0.003		0.007		0.003		0.007	
		(-0.558)		(1.613)	*	(0.474)		(1.156)	
		[1.006]		[2.254]	**	[1.296]		[1.994]	**

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	*239*	0.000	0.051	0.042	0.044
		(0.833)	(2.761) ***	(2.684) ***	(3.353) ***
		[0.163]	[1.745] *	[2.483] **	[2.791] ***
Average bid-ask spread	*153*	-0.001	0.042	0.031	0.028
		(0.993)	(2.555) **	(2.217) **	(2.273) **
		[-0.192]	[0.872]	[0.500]	[0.850]
Effective spread	*153*	0.010	0.048	0.044	0.033
		(1.365)	(2.374) **	(2.085) **	(1.861) *
		[1.263]	[1.719] *	[1.924] *	[1.429]
Liquidity - adverse selection					
Log(amihud)	*382*	0.005	0.021	0.024	0.019
		(1.383)	(2.548) **	(2.520) **	(2.383) **
		[0.149]	[2.223] **	[2.022] **	[2.127] **
Price impact	*153*	0.001	0.008	0.008	0.005
		(0.340)	(1.092)	(1.044)	(0.830)
		[0.389]	[0.724]	[0.626]	[0.403]
Absolute trade imbalance	*153*	0.133	0.327	0.293	0.307
		(1.501)	(1.877) *	(1.774) *	(2.037) **
		[0.855]	[1.602]	[1.658] *	[1.724] *
Lambda	*153*	0.145	0.963	0.912	0.648
		(0.827)	(2.144) **	(2.142) **	(1.816) *
		[1.768] *	[2.522] **	[2.582] **	[2.325] **
Liquidity - inventory costs					
Realized spread	*153*	0.009	0.044	0.038	0.030
		(1.758) *	(2.862) ***	(2.650) ***	(2.297) **
		[1.250]	[1.994] **	[2.021] **	[1.662] *

G. 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 by 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 terrorist attacks (together affecting 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 IA. below, show that these exclusions have little effect on our results.

Table IA.VIII
Event Study After Removing Stocks from Potentially Related Sectors

This table reports (equal-weighted) marketwide event-study results for the 551 distraction events that fall into the period 1968 to 2014—after removing stocks operating in sectors that are potentially affected by certain types of events; see the explanation above. The estimation period includes all trading days within a 200-day window centered on the event date. Panel A reports results for measures of trading activity and volatility; Panel B reports 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, 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)	*551*	-0.008	-0.023	-0.026	-0.026
		(-1.150)	(-3.078) ***	(-3.285) ***	(-2.774) ***
		[-1.049]	[-3.843] ***	[-3.838] ***	[-2.856] ***
Log($volume)	*551*	-0.012	-0.027	-0.031	-0.031
		(-1.509)	(-3.514) ***	(-3.724) ***	(-3.071) ***
		[-1.448]	[-4.174] ***	[-4.221] ***	[-3.166] ***
Volatility					
Abs return	*551*	0.001	-0.005	0.000	-0.003
		(1.129)	(0.017)	(0.457)	(0.136)
		[-1.198]	[-1.166]	[-1.173]	[-0.802]
Price range	*551*	-0.005	-0.053	-0.033	-0.031
		(0.804)	(-2.041) **	(-0.904)	(-0.810)
		[-0.389]	[-2.957] ***	[-2.068] **	[-1.206]
Intraday volatility	*225*	-0.006	-0.017	-0.014	-0.013
		(-0.288)	(-3.177) ***	(-2.711) ***	(-2.529) **
		[-1.321]	[-3.609] ***	[-3.429] ***	[-3.312] ***
Intraday autocovariance	*225*	0.005	0.008	0.005	0.007
		(0.434)	(2.086) **	(1.275)	(1.794) *
		[2.170] **	[2.695] ***	[2.233] **	[3.032] ***

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	*354*	0.013		0.056		0.053		0.046	
		(2.444)	**	(3.939)	***	(3.413)	***	(4.322)	***
		[2.116]	**	[3.348]	***	[3.117]	***	[3.328]	***
Average bid-ask spread	*225*	0.002		0.039		0.028		0.029	
		(1.560)		(2.672)	***	(2.549)	**	(2.663)	***
		[0.149]		[0.997]		[0.708]		[1.142]	
Effective spread	*225*	0.011		0.045		0.039		0.035	
		(1.885)	*	(2.549)	**	(2.320)	**	(2.415)	**
		[1.878]	*	[2.213]	**	[2.361]	**	[2.100]	**
Liquidity - adverse selection									
Log(amihud)	*551*	0.010		0.023		0.025		0.025	
		(2.856)	***	(3.004)	***	(3.503)	***	(3.657)	***
		[1.488]		[2.486]	**	[3.076]	***	[3.282]	***
Price impact	*225*	0.002		0.007		0.006		0.005	
		(0.778)		(1.120)		(1.041)		(1.033)	
		[0.372]		[0.620]		[0.506]		[0.054]	
Absolute trade imbalance	*225*	0.127		0.386		0.325		0.358	
		(1.658)	*	(2.522)	**	(2.185)	**	(2.430)	**
		[1.223]		[2.555]	**	[2.562]	**	[2.527]	**
Lambda	*225*	0.163		0.855		0.848		0.634	
		(2.226)	**	(3.026)	***	(3.373)	***	(2.845)	***
		[2.700]	***	[3.424]	***	[3.651]	***	[3.287]	***
Liquidity - inventory costs									
Realized spread	*225*	0.010		0.041		0.034		0.032	
		(2.395)	**	(3.185)	***	(2.962)	***	(2.981)	***
		[2.135]	**	[2.718]	***	[2.575]	**	[2.820]	***

H. 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, in Table IA.IX we present event-study results for 532 placebo events, defined as days on which news pressure is in the *bottom* decile for the year and that do not feature economic news (i.e., the news broadcast headlines do not contain any economic keyword). If news pressure is high because there is little economic news to report, then days when news pressure is low should contain economic news. The results show no sign of elevated trading activity or volatility, which typically accompany the revelation of news, and thus alleviate concerns about reverse causality.

Table IA.IX

Placebo Test for Noneconomic Days with Lowest News Pressure

This table reports event-study results for 532 placebo events (i.e., days when news pressure is in the bottom decile for the year and that survive our filter for excluding potential economic news) in the 1968 to 2014 period. The estimation period includes all trading days within a 200-day window centered on the event date. Panel A reports results for measures of trading activity and volatility; Panel B reports 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, 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	*532*	0.041	0.028	0.046	0.025
		(1.389)	(0.714)	(1.376)	(0.616)
		[1.749] *	[1.329]	[1.792] *	[1.100]
Trading activity					
Log(turnover)	*532*	-0.002	-0.002	-0.002	0.000
		(-0.542)	(-0.347)	(-0.353)	(0.016)
		[0.268]	[-0.584]	[-0.955]	[-0.024]
Log($volume)	*532*	-0.003	-0.008	-0.008	-0.005
		(-0.661)	(-1.104)	(-0.945)	(-0.548)
		[-0.053]	[-1.832] *	[-2.018] **	[-0.831]
Volatility					
Abs return	*532*	0.004	0.010	0.008	0.006
		(-0.037)	(1.034)	(0.820)	(0.546)
		[-1.146]	[1.271]	[0.457]	[0.853]
Price range	*532*	0.002	0.007	0.007	0.004
		(-0.127)	(0.836)	(0.742)	(0.492)
		[-0.120]	[0.253]	[-0.334]	[0.508]
Intraday volatility	*239*	0.004	0.002	0.002	0.005
		(0.725)	(0.972)	(0.763)	(1.458)
		[-0.464]	[0.437]	[-0.454]	[0.682]
Intraday autocovariance	*239*	-0.003	-0.002	-0.002	-0.003
		(-1.425)	(-1.346)	(-1.179)	(-1.393)
		[0.754]	[0.204]	[0.672]	[0.160]

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	*379*	0.003		0.010		0.007		0.002	
		(1.373)		(0.581)		(0.928)		(0.243)	
		[1.129]		[0.313]		[0.349]		[-0.002]	
Average bid-ask spread	*239*	0.018		0.023		0.031		0.020	
		(1.370)		(1.068)		(1.195)		(1.081)	
		[-1.649]	*	[-1.417]		[-1.41]		[-1.4]	
Effective spread	*239*	0.008		0.011		0.012		0.008	
		(1.530)		(1.082)		(1.329)		(0.724)	
		[1.214]		[0.786]		[1.098]		[0.444]	
Liquidity - adverse selection									
Log(amihud)	*532*	-0.001		0.009		0.006		0.004	
		(0.331)		(1.314)		(0.993)		(0.705)	
		[-0.323]		[1.206]		[1.013]		[0.726]	
Price impact	*239*	-0.002		-0.003		-0.001		-0.004	
		(-0.968)		(-1.257)		(-0.499)		(-1.685)	*
		[-2.429]	**	[-1.905]	*	[-1.435]		[-2.537]	**
Absolute trade imbalance	*239*	0.110		0.183		0.169		0.117	
		(1.194)		(1.218)		(1.196)		(0.866)	
		[0.102]		[1.070]		[0.864]		[0.423]	
Lambda	*239*	0.043		0.343		0.177		0.151	
		(1.063)		(2.150)	**	(1.597)		(1.692)	*
		[0.808]		[1.451]		[0.922]		[0.820]	
Liquidity - inventory costs									
Realized spread	*239*	0.009		0.012		0.013		0.010	
		(2.143)	**	(1.043)		(1.252)		(1.042)	
		[2.138]	**	[0.988]		[1.531]		[1.111]	

I.: Alternative Algorithmic Trading Proxy – MIDAS

In Section VI.C of the paper, we explore how distraction effects interact with algorithmic trading in the post-2007 period. To measure this intensity, we use the quote-to-trade ratio, a commonly used proxy for the intensity of algorithmic trading (see Hendershott, Jones, and Menkveld (2011), Conrad, Wahal, and Xiang (2015), Brogaard, Hendershott, and Riordan (2017), Roşu, Sojli, and Tham (2018)). Here we instead use an algorithmic trading index constructed from the SEC Market Information Data Analytics System (MIDAS). [4] Specifically, we construct an algorithmic trading index that summarizes the information from four algorithmic trading proxies available in MIDAS: the oddlot volume ratio (i.e., the fraction of volume of trades involving less than 100 shares), the trade-to-order volume ratio (i.e., the fraction of the executed trading volume of 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). We collapse these four proxies into a single algorithmic trading index by first standardizing them (so that each proxy has a mean of zero and a standard deviation of one) and then taking the average across all four. Because low values for the trade-to-order ratio and the average trade size are associated with more algorithmic trading, these two proxies are inverted before constructing the index. A high value of our index indicates more algorithmic trading.

In Table IA.X below, we present event-study results for the bottom market capitalization tercile after further sorting stocks into terciles based on the resulting algorithmic trading index. The results are similar to, albeit slightly weaker than, to those found for the quote-to-trade ratio reported in Table IX in the paper.

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

Table IA X
Sample Split for Small Stocks by Algorithmic Trading Index

This table reports event-study results for the tercile of small stocks for the 87 distraction events in the post-2007 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 an algorithmic trading proxy constructed from MIDAS data (see above for details). All variables are defined in the Appendix. 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Trading Activity and Volatility

		Algorithmic Trading Intensity Index							
		(1)		(2)		(3)		(4)	
	N	Tercile 1		Tercile 2		Tercile 3		Difference	
Trading activity									
Log(turnover)	*87*	-0.035		-0.042		-0.056		-0.021	
		(-1.904)	*	(-2.597)	***	(-3.109)	***	(-1.823)	*
		[-2.010]	**	[-2.467]	**	[-2.840]	***	[-1.707]	*
Log($volume)	*87*	-0.038		-0.048		-0.055		-0.017	
		(-1.919)	*	(-2.430)	**	(-2.886)	***	(-1.778)	*
		[-2.120]	**	[-2.332]	**	[-2.671]	***	[-1.541]	
Volatility									
Abs return	*87*	-0.032		-0.076		-0.096		-0.064	
		(-0.386)		(-1.561)		(-1.953)	*	(-1.935)	*
		[-0.478]		[-2.421]	**	[-2.137]	**	[-1.638]	
Price range	*87*	-0.101		-0.145		-0.194		-0.093	
		(-0.881)		(-1.769)	*	(-2.560)	**	(-1.802)	*
		[-1.558]		[-2.607]	***	[-2.688]	***	[-1.160]	
Intraday volatility	*87*	-0.022		-0.026		-0.034		-0.012	
		(-1.926)	*	(-2.469)	**	(-3.412)	***	(-0.725)	
		[-2.704]	***	[-2.865]	***	[-3.064]	***	[-0.567]	
Intraday autocovariance	*87*	0.011		0.017		0.018		0.007	
		(1.786)	*	(2.084)	**	(2.129)	**	(0.993)	
		[2.374]	**	[2.565]	**	[2.004]	**	[0.888]	

Panel B: Liquidity

		Algorithmic Trading Intensity Index			
		(1)	(2)	(3)	(4)
	N	Tercile 1	Tercile 2	Tercile 3	Difference
Liquidity - overall					
Closing bid-ask spread	*87*	0.006	-0.021	0.004	-0.002
		(0.115)	(-1.161)	(0.179)	(-0.074)
		[-0.466]	[-1.473]	[0.897]	[-0.377]
Average bid-ask spread	*87*	0.022	0.023	0.000	-0.021
		(1.322)	(1.200)	(0.523)	(-1.439)
		[1.211]	[1.035]	[-0.158]	[-1.105]
Effective spread	*87*	0.015	0.001	0.008	-0.007
		(1.240)	(0.257)	(0.749)	(-1.207)
		[1.281]	[-0.499]	[0.512]	[-1.495]
Liquidity - adverse selection					
Log(amihud)	*87*	0.036	0.039	0.010	-0.026
		(1.913) *	(2.045) **	(0.492)	(-1.332)
		[2.129] **	[1.862] *	[-0.220]	[-1.629]
Price impact	*87*	0.004	0.004	0.002	-0.002
		(0.349)	(0.481)	(0.123)	(-0.233)
		[0.330]	[0.538]	[0.343]	[-0.169]
Absolute trade imbalance	*87*	0.314	-0.070	0.177	-0.137
		(1.071)	(-0.442)	(0.453)	(-0.437)
		[1.756] *	[-0.402]	[0.741]	[-0.398]
Lambda	*87*	0.376	0.322	0.044	-0.332
		(0.542)	(1.148)	(0.056)	(-0.381)
		[0.914]	[1.731] *	[-0.296]	[-0.961]
Liquidity - inventory costs					
Realized spread	*87*	0.015	0.009	0.011	-0.005
		(1.616)	(0.982)	(0.519)	(-0.935)
		[1.356]	[0.406]	[0.212]	[-0.431]

I. Alternative Algorithmic Trading Proxy – Orthogonalized Price

In Subsection VI.C of the paper, we explore how distraction effects interact with algorithmic trading in the post-2007 period. To measure this intensity, we use the quote-to-trade ratio, a commonly used proxy for the intensity of algorithmic trading (see Hendershott, Jones, and Menkveld (2011), Conrad, Wahal, and Xiang (2015), Brogaard, Hendershott, and Riordan (2017), Roşu, Sojli, and Tham (2018)). Here we instead use the lagged stock price (from the end of the previous year), orthogonalized with respect to firm size (i.e., the residual from regressing stock price on the logarithm of market capitalization). Weller (2017) shows that this measure is a valid instrument for algorithmic trading activity: because of the minimum tick size of one cent imposed by SEC Rule 612 (the "sub-penny" rule), high-price stocks have a finer price grid, which advantages algorithms over humans for continually updating quotes.

In Table IA.XI below, we present event-study results for the bottom market capitalization tercile after further sorting stocks into terciles based on the orthogonalized price described above. The results are similar to those found for the quote-to-trade ratio reported in Table IX in the paper.

Table IA.XI
Sample Split for Small Stocks by Orthogonalized Price

This table reports event-study results for the tercile of small stocks for the 87 distraction events in the post-2007 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 orthogonalized price (see above for details). All variables are defined in the Appendix. 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Trading Activity and Volatility

		Orthogonalized Price							
		(1)		(2)		(3)		(4)	
	N	Tercile 1		Tercile 2		Tercile 3		Difference	
Trading activity									
Log(turnover)	*87*	-0.030		-0.046		-0.054		-0.024	
		(-1.751)	*	(-2.791)	***	(-3.233)	***	(-2.588)	**
		[-1.986]	**	[-2.586]	**	[-3.208]	***	[-2.429]	**
Log($volume)	*87*	-0.033		-0.045		-0.057		-0.024	
		(-1.846)	*	(-2.505)	**	(-4.448)	***	(-2.353)	**
		[-1.858]	*	[-2.391]	**	[-3.843]	***	[-2.247]	**
Volatility									
Abs return	*87*	-0.040		-0.082		-0.087		-0.047	
		(-1.125)		(-1.816)	*	(-1.889)	*	(-1.637)	
		[-1.045]		[-2.336]	**	[-2.365]	**	[-1.701]	*
Price range	*87*	-0.104		-0.175		-0.159		-0.055	
		(-1.007)		(-1.995)	**	(-2.061)	**	(-0.747)	
		[-1.740]	*	[-2.556]	**	[-1.803]	*	[-0.571]	
Intraday volatility	*87*	-0.020		-0.03		-0.039		-0.019	
		(-1.764)	*	(-2.881)	***	(-3.211)	***	(-2.200)	**
		[-2.671]	***	[-2.726]	***	[-3.132]	***	[-2.125]	**
Intraday autocovariance	*87*	0.014		0.014		0.017		0.003	
		(1.901)	*	(2.015)	**	(2.335)	**	(0.057)	
		[2.374]	**	[2.273]	**	[2.277]	**	[0.453]	

Panel B: Liquidity

	N	Orthogonalized Price (1) Tercile 1	(2) Tercile 2	(3) Tercile 3	(4) Difference
Liquidity - overall					
Closing bid-ask spread	*87*	0.048	-0.007	-0.018	-0.066
		(0.667)	(-0.621)	(-0.883)	(-1.503)
		[-0.051]	[-1.587]	[-1.388]	[-0.432]
Average bid-ask spread	*87*	0.042	-0.056	-0.068	-0.110
		(0.435)	(-1.856) *	(-1.625)	(-0.979)
		[1.342]	[-1.155]	[-1.799] *	[-1.608]
Effective spread	*87*	0.032	0.001	-0.004	-0.037
		(0.573)	(0.252)	(-0.504)	(-1.058)
		[0.072]	[-0.982]	[-1.147]	[-0.512]
Liquidity - adverse selection					
Log(amihud)	*87*	0.027	0.037	0.020	-0.007
		(1.361)	(2.212) **	(0.814)	(-0.585)
		[1.367]	[1.896] *	[0.698]	[-0.631]
Price impact	*87*	0.017	-0.003	-0.004	-0.021
		(1.015)	(-0.802)	(-0.865)	(-1.537)
		[1.913] *	[-0.842]	[-0.474]	[-1.346]
Absolute trade imbalance	*87*	0.121	0.250	-0.063	-0.184
		(0.379)	(0.689)	(-0.401)	(-0.611)
		[0.385]	[0.838]	[-0.186]	[-0.385]
Lambda	*87*	0.458	0.019	0.729	0.271
		(1.444)	(-1.046)	(1.222)	(0.446)
		[1.414]	[-0.131]	[1.062]	[1.095]
Liquidity - inventory costs					
Realized spread	*87*	0.017	0.010	-0.001	-0.018
		(0.047)	(1.094)	(-0.273)	(-0.255)
		[-0.216]	[0.140]	[-0.652]	[-0.072]

III. Additional Results

A. 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, Da and Israelsen (2017) find that the former but not the latter drive 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, Lim, and Teoh (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 of 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 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 argue that our events primarily affect noise traders and Ben-Rephael, Da and Israelsen (2017) suggest that these investors do not contribute much to price discovery upon earnings news. The results, shown in Table IA.XII, confirm this expectation. Variable definitions and regression details are provided in the table header. The interaction coefficient of the earnings surprise decile with our distraction dummy is not significant for either the immediate stock price response (Panel A) or 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. The results thus 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, Lim, and Teoh (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, Rubin, and Vedrashko (2016).

Table IA.XII
Distraction Events and Earnings Announcements

This table reports 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 the firm and 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 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 five 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, Lim, and Teoh (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, Lim, and Teoh (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 ***, **, and *, 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. News Pressure, Economic News, and Sentiment

In this subsection, we analyse how news pressure—the variable that defines that identify our distraction events—is related to measures of economic activity and media sentiment. We do so 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 IA.XIII. All of the variables and regression details are described in the table header. Here, we summarize the results. 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 of less than 0.5% (column (7)). Looking at individual indicators, the largest 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, given such weak correlations, we can rule out the possibility that days with large shocks to sentiment and/or economic activity systematically enter our sample of distraction events.

Table IA.XIII
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* (available for the period 1968 to 2005) 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* (available for the period 1968 to 2012) is the Aruoba, Diebold, and Scotti (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 nonagricultural payrolls, and real GDP. See Aruoba, Diebold, and Scotti (2009) for details. *BBD index* (available for the period 1985 to 2014) is the Baker, Bloom, and Davis (2016) measure of economic policy uncertainty distilled from newspaper coverage. See Baker, Bloom, and Davis (2016) for details. All of these variables, including news pressure, 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 been further standardized. *CPI release* (available for the period 1968 to 2014) is a dummy that takes the value of one on a day in which the CPI was released, and zero otherwise. *Employment release* (available for the period 1968 to 2014) is a dummy that takes the value of one on a day in which employment statistics were released, and zero otherwise. *FOMC release* (available for the period 1994 to 2014) is a dummy that takes the value of one on a day in which FOMC meetings were held. Standard errors are Newey-West adjusted allowing for 10 lags of autocorrelation. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NYT sentiment	0.0330**						0.0460**
	(3.06)						(2.60)
ADS index		-0.0335**					-0.0407
		(-2.89)					(-1.03)
BBD index			0.0251*				0.0141
			(2.25)				(0.74)
CPI release				-0.0600			-0.0641
				(-1.48)			(-0.85)
Employment release					-0.0278		-0.0199
					(-0.73)		(-0.27)
FOMC release						-0.1200	-0.1281
						(-1.73)	(-1.43)
Observations	9,420	15,393	11,139	17,182	17,182	8,611	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	0.000`	0.0028

C : Event Study Around Economic News

In this subsection, we report 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 do not belong to our list of distraction events because they were filtered out by the keyword "stock market"). More specifically, 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 do not find peculiar market movements on these days). Second, we report event-study results for scheduled meetings of the 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. Variable definitions and regression details are provided in the header of Table IA.XIV. Panel A reports 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 (2015).

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 IA.XIV
Marketwide Event Study for Economic News

This table reports (equal-weighted) marketwide event-study results for two distinct sets of economic news days. Panel A reports 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 reports results for the second set, which comprises FOMC announcement days (i.e., the day of the press release following FOMC meeting). FOMC announcement dates are taken from Lucca and Moench (2015), and 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, 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	

D. Event Study for the Amount of Firm-Specific News

An 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 2014). The second proxy is the number of firms featured in any of the four major U.S. 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 data set 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 data sets 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 stocks (since considerably more firms are covered in newswires than in newspapers).

Table IA.XV reports the event-study results for these four firm-specific news measures. We find that none of these measures 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 IA.XV
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 to 2014. 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 to 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 to 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 to 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

(1) Log of #EA	(2) Log of #Newspaper	(3) Log of #News in DJA	(4) Log of #News in TRA
0.029	0.002	-0.023	-0.0469
(1.414)	(-0.000)	(-1.459)	(-0.440)
[2.042] **	[0.843]	[-1.581]	[-0.181]
499	325	92	43

E. 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 IA.XVI shows the results. For comparison, the table also reports the results for CRSP turnover (which are also reported in Table VI 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 of retail investors trading, institutional trading volume, or 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 IA.XVI, 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 IA.XVI
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 to 1996; and *Log(small TAQ trades),* thelogarithm of the aggregated dollar volume of small trades, obtained from the ISSM/TAQ data set over the period 1991 to 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 0.718 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 reports the results for measures of trading activity, return volatility, and autocovariance; Panel B reports 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*-statistics, based on Huber–White standard errors corrected for heteroskedasticity, are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Trading Activity and Volatility

Dependent Variable	Independent Variable	(1) Firm Size Tercile 1	(2) Stock Price Tercile 1	(3) Inst. Holdings Tercile 1
Trading activity				
Log(turnover)	CNN viewership	-0.051**	-0.058**	-0.0327
		(-2.29)	(-2.59)	(-1.49)
	Evening ABC, CBS, NBC viewership	-0.215*	-0.218*	-0.162
		(-1.90)	(-1.96)	(-1.42)
Log($volume)	CNN viewership	-0.059**	-0.070***	-0.043*
		(-2.60)	(-2.92)	(-1.92)
	Evening ABC, CBS, NBC viewership	-0.258**	-0.276**	-0.213*
		(-2.22)	(-2.33)	(-1.83)
Volatility				
Abs return	Log(turnover)	0.718***	0.741***	0.869***
		(6.24)	(6.32)	(6.29)
	Log(#households)	0.240	0.174	0.125
		(1.52)	(1.14)	(0.72)
	Log(inst. dolvol.)	0.004	0.163	0.0234
		(0.03)	(0.82)	(0.13)
	Log(small TAQ trades)	0.359*	0.439***	0.361**
		(1.68)	(2.70)	(2.56)
Price range	Log(turnover)	2.053***	1.957***	1.982***
		(21.15)	(20.38)	(16.20)
	Log(#households)	1.595***	1.514***	1.186**
		(3.41)	(3.31)	(2.62)
	Log(inst. dolvol.)	0.234	0.669*	0.416
		(0.66)	(1.73)	(1.10)
	Log(small TAQ trades)	2.245***	2.204***	1.962***
		(8.16)	(8.97)	(9.24)
Intraday volatility	Log(turnover)	0.278***	0.253***	0.288***
		(11.42)	(9.68)	(12.09)
	Log(#households)	0.159**	0.183**	0.173***
		(2.12)	(2.61)	(2.70)
	Log(inst. dolvol.)	0.037	0.110**	0.0646
		(0.76)	(2.15)	(1.20)
	Log(small TAQ trades)	0.232***	0.250***	0.240***
		(4.83)	(6.06)	(6.73)
Return autocovariance	Log(turnover)	-0.057*	-0.030	-0.068*
		(-1.76)	(-0.74)	(-1.76)
	Log(#households)	0.019	0.017	0.005
		(0.54)	(0.32)	(0.10)
	Log(inst. dolvol.)	-0.016	-0.042	-0.034
		(-0.71)	(-1.25)	(-1.11)
	Log(small TAQ trades)	-0.004	0.015	-0.002
		(-0.07)	(0.22)	(-0.03)

Panel B: Liquidity

Dependent Variable	Independent Variable	(1) Firm Size Tercile 1	(2) Stock Price Tercile 1	(3) Inst. Holdings Tercile 1
Liquidity - overall				
Closing bid-ask spread	Log(turnover)	-0.556***	-0.510***	-0.274***
		(-4.49)	(-3.79)	(-3.21)
	Log(#households)	-0.669**	-0.737**	-0.503**
		(-2.57)	(-2.53)	(-2.43)
	Log(inst. dolvol.)	0.169	0.121	0.151
		(1.00)	(0.89)	(1.17)
	Log(small TAQ trades)	-0.841***	-0.905***	-0.696***
		(-3.93)	(-3.50)	(-3.90)
Average bid-ask spread	Log(turnover)	-0.675***	-0.600***	-0.474***
		(-4.90)	(-4.74)	(-4.48)
	Log(#households)	-0.508	-0.468*	-0.354
		(-1.62)	(-1.88)	(-1.60)
	Log(inst. dolvol.)	-0.016	-0.010	-0.026
		(-0.09)	(-0.05)	(-0.18)
	Log(small TAQ trades)	-0.751***	-0.660***	-0.533***
		(-3.34)	(-4.03)	(-3.55)
Effective spread	Log(turnover)	-44.45***	-38.56***	-32.69***
		(-3.04)	(-3.29)	(-2.94)
	Log(#households)	-40.390	-33.470	-33.12
		(-1.19)	(-1.38)	(-1.41)
	Log(inst. dolvol.)	3.146	0.730	1.576
		0.230	0.050	(0.14)
	Log(small TAQ trades)	-55.53*	-42.90*	-45.88**
		(-1.79)	(-1.98)	(-2.42)
Log(amihud)	Log(turnover)	-0.423***	-0.371***	-0.379***
		(-7.27)	(-6.43)	(-8.19)
	Log(#households)	-0.382**	-0.412***	-0.352**
		(-2.48)	(-2.83)	(-2.39)
	Log(inst. dolvol.)	-0.00664	-0.0381	-0.0533
		(-0.09)	(-0.45)	(-0.76)
	Log(small TAQ trades)	-0.586***	-0.586***	-0.570***
		(-6.60)	(-7.29)	(-7.84)
Price impact	Log(turnover)	-0.0545	-0.0509	-0.0249
		(-1.28)	(-1.21)	(-0.68)
	Log(#households)	-0.0326	-0.0154	-0.00921
		(-0.53)	(-0.35)	(-0.16)
	Log(inst. dolvol.)	0.0231	0.0243	0.0204
		(0.49)	(0.51)	(0.53)
	Log(small TAQ trades)	-0.0498	-0.0495	-0.035
		(-0.57)	(-0.75)	(-0.53)
Absolute trade imb.	Log(turnover)	-10.19***	-8.699***	-8.379***
		(-7.74)	(-8.79)	(-6.92)
	Log(#households)	-10.16**	-8.365***	-9.534***
		(-2.55)	(-2.70)	(-2.87)
	Log(inst. dolvol.)	-1.501	-1.973	-2.002*
		(-1.19)	(-1.48)	(-1.81)
	Log(small TAQ trades)	-13.69***	-11.73***	-12.99***
		(-6.46)	(-9.31)	(-10.52)
Lambda	Log(turnover)	-5.788***	-6.290***	-3.793**
		(-3.05)	(-3.09)	(-2.37)
	Log(#households)	-0.59	-2.501	-0.588
		(-0.13)	(-1.18)	(-0.26)
	Log(inst. dolvol.)	0.244	-1.006	0.482
		(0.09)	(-0.38)	(0.24)
	Log(small TAQ trades)	-3.323	-3.704*	-2.736
		(-1.21)	(-1.86)	(-1.32)
Realized spread	Log(turnover)	-0.462***	-0.390***	-0.351***
		(-2.79)	(-2.79)	(-3.11)
	Log(#households)	-0.481	-0.428	-0.387
		(-1.21)	(-1.46)	(-1.35)
	Log(inst. dolvol.)	0.0361	0.00634	0.024
		(0.35)	(0.07)	(0.30)
	Log(small TAQ trades)	-0.601	-0.489*	-0.481*
		(-1.55)	(-1.76)	(-1.86)

F. 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 that sensational news events cause a short-lived reduction in the intensity of noise trading. [5] Rather, it suggests that not only the demand for liquidity (from noise traders) but also the provision of liquidity falls on distraction days.[6] This raises the question of which type of liquidity providers are distracted: contrarian traders—e.g., Kaniel, Saar, and Titman (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 conduct 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 (sells) transacted at a price below (above) the stock's benchmark price. This benchmark price is chosen as, in order, (1) the volume-weighted average price (VWAP) calculated from TAQ, (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).[7] 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 V in the paper and Tables IA.III and IA.IV above), 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, that is, 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 IA.XVII presents the results of this test. Both the number of contrarian households and the volume of contrarian trades executed by institutions drop by 5% and 3%, respectively. These findings suggest that contrarian traders appear to be distracted, which explains why the realized spread increases.[8]

Our second test, presented in Panel B of Table IA.XVII, investigates whether specialist market makers are also distracted. To this end, we look at the frequency with which quotes are updated during the day (divided into five-minute intervals). The idea is

5 In fact, models of inventory risk (e.g., Ho and Stoll, (1980, 1981), Grossman and Miller (1988) predict that a reduction in noise trading reduces the inventory risk of market makers and thus 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).

6 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 the 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 find the distraction effect to be most pronounced for biased investors, suggesting that liquidity demand (noise trading) may be more affected than liquidity provision.

7 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 they have been deemed unreliable (e.g., Choi, Laibson, and Metrick (2016)). We obtain similar results when we define as "contrarian" all buys (sells) made on days when the stock's return is negative (positive) following Barber, Odean and Zhu (2009).

8 Note that contrarian and noise traders may even be one and the same. Indeed, Bloomfield, O'Hara, and Saar. (2009) use a laboratory market to document that uninformed traders behave largely as "*contrarian noise traders*."

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 disappear from the book only when they are hit by a trade.[9]

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 a 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, in the absence of trading as, they are the ones responsible for canceling and updating quotes. 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. Moreover, as shown by the last row in Table IA.XVII, this no-effect tends to be significantly different from the unconditional drop in the fraction of intervals with a quote change, showing that intervals without a 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, which explain why we find an increase in the realized spread on these days.

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

Table IA.XVII
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 the average between the 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 225 events). *Fraction of intervals with quote change* is the (equal-weighted) average of the fraction of five-minute intervals with a mid-quote change over all five-minute intervals with valid mid-quotes. *Fraction of intervals without trade* is the (equal-weighted) average of the fraction of five-minute intervals with zero trading volume out of all five-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 five-minute intervals without trading and with a mid-quote change out of all five-minute intervals without trading. *Difference of fraction of intervals with quote change* is the difference between the fraction of intervals with a quote change and the fraction of intervals with a 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, 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	*225*	-0.027	-0.181	-0.201	-0.155
		(-0.508)	(-1.677) *	(-1.882) *	(-1.355)
		[-0.389]	[-2.305] **	[-2.574] **	[-2.211] **
Fraction of intervals without trade	*225*	0.152	0.187	0.335	0.237
		(1.597)	(2.149) **	(3.071) ***	(2.544) **
		[1.355]	[2.038] **	[3.310] ***	[2.831] ***
Fraction of intervals with quote change among intervals without trade	*225*	0.239	0.014	-0.029	0.030
		(0.518)	(-0.328)	(-0.873)	(-0.479)
		[0.963]	[0.172]	[-0.874]	[-0.069]
Difference in fraction of intervals with quote change	*225*	-0.266	-0.195	-0.172	-0.185
		(-1.325)	(-2.031) **	(-1.310)	(-1.541)
		[-3.346] ***	[-3.429] ***	[-2.247] **	[-3.562] ***

G. Distraction Events and Average Trade Size

In Table II of the paper, we document that, apart from a sizable effect at the extensive margin (i.e., on the number of investors trading), distraction days also exhibit a modest reduction in the average trade size. This could reflect an intensive margin effect as predicted by theories of rational attention allocation (e.g., Verrecchia(1982), Peng and Xiong(2006), Van Nieuwerburgh and Veldkamp(2010)). Another possibility is that the reduction comes from a composition effect: when investors trading larger quantities on average are more likely to sit on the sidelines on distraction days, the average trade size goes down even when, conditional on trading, no investor trades less. In this subsection, we investigate whether there is such a composition effect.

To this end, we sort investors into two groups based on their average trade size over the sample period and study which group is more likely to abstain from trading on distraction days. The results, shown in Table IA.VXIII below, are consistent with an extensive margin effect, although they are not fully conclusive due to a lack of power. In particular, for both the discount brokerage (Panel A) and the institutional trade (Panel B) data, we find that trading activity (the number of retail investors trading in Panel A, and aggregated institutional dollar volume in Panel B) is reduced slightly more for the group of investors with above-median average trade size, although the difference with the below-median group is not significant (see row 2). Moreover, within the two trade size groups, average trade sizes are not significantly lower on distraction days (see row 1), implying that we cannot reject the null that there is no intensive margin effect. We acknowledge, however, that this no-result may be due to a lack of power, as the economic magnitudes of the estimates indicate a reduction in average trade size that is comparable to what we find for the full sample of investors.

In short, the results suggest that the modest reduction in the average trade size documented in Table II of the paper comes primarily from a shift in the composition of investors who keep trading on distraction days: investors who trade larger quantities on average tend to be slightly more distracted, which explains why the average trade size goes down on distraction days.

Table IA.XVIII
Distraction Events and Average Trade Size

This table reports event-study results for the trading activity of groups of investors sorted on their average trade size (measured in terms of dollar volume over the sample period). Panel A reports results for the equal-weighted average across investors of the logarithm of trade volume (row 1) and the logarithm of the number of households trading (row 2) in the discount brokerage data over the period 1991 to 1996 (66 distraction events). Panel B reports results for the equal-weighted average across investors of the logarithm of trade volume (row 1) and the logarithm of aggregated dollar volume (row 2) in the institutional trade data over the period 1999 to 2011 (99 distraction events). For each event, the estimation period includes all trading days without economic news within a 200-day window centered on the event date. Column (3) tests for the difference between above-median investors (column (2)) and below-median investors (column (1)). Below each number, we show the *t*-statistic for the parametric Boehmer, Musumeci, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Discount Brokerage Data

	(1) Total trades		(2) Total trades		(3) Difference
1) Avg trade size	Low		High		Difference
Log(trade size)	-0.014		-0.012		0.002
	(-1.337)		(-1.011)		(0.256)
	[-1.578]		[-1.290]		[0.079]
2) Avg trade size	Low		High		Difference
Log(#investors)	-0.043		-0.057		-0.014
	(-1.897)	*	(-2.450)	**	(-0.660)
	[-1.785]	*	[-2.010]	**	[-0.546]
N	66		66		66

Panel B: Institutional Trade Data

	(1) Total trades		(2) Total trades		(3) Difference
1) Avg trade size	Low		High		Difference
Log(trade size)	-0.016		-0.015		0.001
	(-1.612)		(-1.214)		(0.457)
	[-1.577]		[-0.723]		[0.031]
2) Avg trade size	Low		High		Difference
Log($volume)	-0.033		-0.051		-0.019
	(-1.447)		(-2.807)	***	(-0.954)
	[-0.824]		[-2.628]	***	[-1.019]
N	99		99		99

H. Distraction Events and Investor Sentiment

Many of the distraction events in our sample carry a negative connotation because they pertain to natural disasters, terrorist attacks, accidents, or celebrity deaths. One may thus wonder whether our results could be explained (or confounded) by shocks to investor sentiment. In our view, there are two reasons why this is unlikely. First, a negative shock to sentiment should be associated with a significantly negative return. Although we do observe a negative sign for the abnormal market return on distraction days (see Table IV of the paper), this effect is both economically small and statistically insignificant. Second, Garcia (2013) reports that both positive and negative shocks to investor sentiment lead to a surge in trading activity, yet we observe the exact opposite on distraction days.

In this subsection, we present additional evidence against a sentiment-based explanation by manually splitting our distraction sample into positive, neutral, and negative events and separately testing for the market return reaction in each of the three groups. Based on our manual classification, we identify 224 negative (mostly pertaining to natural disasters, terrorist attacks, accidents) and 60 positive (mostly pertaining to peace talks, hostage releases, or space missions) distraction events; the remaining 267 distraction events (mostly pertaining to political events such as party conventions) are sentiment-neutral.

Table IA.XIX below shows the average abnormal market returns on distraction days for different sentiment groups. Curiously, the market returns on positive-sentiment distraction days appear to be not positive, but even slightly more negative than those on negative-sentiment days. In any case, market returns are always far from being significant, making it unlikely that our distraction events represent shocks to investor sentiment.

Table IA.XIX
Distraction Events and Investor Sentiment

This table reports event-study results for (equal-weighted) market returns for the 551 distraction events in the period 1968 to 2014, after sorting distraction events into those with negative, neutral, or positive sentiment. 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, and Poulsen (1991) test in parentheses, and the z-statistic for the nonparametric rank test in square brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

(1)	(2)	(3)
Negative sentiment	Neutral sentiment	Positive sentiment
-0.092	0.038	-0.159
(-0.849)	(0.860)	(-1.015)
[-0.657]	[0.363]	[-1.296]
224	267	60

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