Internet Appendix to

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

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

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

There is one risky asset with a final dividend 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. The total order flow is given by $\omega = x + z$, where z represents noise trades. The random variables $\theta, \varepsilon, \varepsilon'$ and z are uncorrelated with one another and normally distributed with mean zero and variances σ_θ, σ_ε, $\sigma_{\varepsilon'}$ and σ_z, respectively. The riskfree rate is normalized to zero.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

We compute next trading volume and volatility.

Trading volume

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

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

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

Return volatility

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

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

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

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

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

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

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

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

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

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

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

Proof:

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

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

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

Proof:

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

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

Intuition:

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

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

Proof:

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

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

- Return volatility. From Equation (4), it suffices that $(\beta^2\sigma_\varepsilon + \sigma_Z)/h$ increases in $\sigma_{\varepsilon'}$ for volatility to increase in $\sigma_{\varepsilon'}$, since we already established that λ increases in $\sigma_{\varepsilon'}$. $\frac{\mathrm{dln}((\beta^2\sigma_\varepsilon+\sigma_Z)/h)}{\mathrm{d}\sigma_{\varepsilon'}} = (\frac{1}{\mathrm{h}} - \frac{2\beta\sigma_\varepsilon}{\beta^2\sigma_\varepsilon+\sigma_Z}\frac{\mathrm{d}\beta}{\mathrm{d}\sigma_{\varepsilon'}})\ \frac{1}{(\sigma_{\varepsilon'})^2}$. 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 $\sigma_{\varepsilon'}$.

Intuition:

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

Internet Appendix B: Additional Results

B.1: Distraction Events and Earnings Announcements

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

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

Table A.1: Distraction Events and Earnings Announcements

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

Panel A: CAR[0,1]

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

Panel B: CAR[2,61]

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

B.2: News Pressure, Economic News and Sentiment

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

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

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

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

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

B.3 Event Study around Economic News

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

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

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

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

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

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

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

Panel B: FOMC announcement days

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

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