Abstract

In a dynamic model of information acquisition, we show that higher economic uncertainty causes investors to rationally allocate more attention to firm-specific information. The data lend support to this theoretical observation. We show that corporate earnings announced on days with important business and economics news tend to have stronger announcement-window reactions and weaker post-earnings announcement drift. These effects are concentrated in firms with lower institutional ownership, as the theory predicts. Overall, these findings suggest that economic uncertainty attracts investor attention to the stock market and improves price discovery.

JEL classification: G14; G41; M41.

Keywords: Economic uncertainty; Business and economics news; Earnings announcements; Investor attention; Post-earnings announcement drift.
1 Introduction

Due to cognitive resource constraints, investors can neglect value relevant information and may not incorporate all available information into prices. Indeed, extant research has shown that extraneous and unrelated events, such as the March Madness college basketball tournament, can distract investor attention away from corporate announcements (Drake, Gee, and Thornock, 2016), and that fund alphas are lower when the fund managers are affected by marital events (Lu, Ray, and Teo, 2016). DellaVigna and Pollet (2009) and Louis and Sun (2010) document a muted market reaction to Friday earnings or merger announcements. Hirshleifer, Lim, and Teoh (2009) find that the trading volume and stock price reactions to earnings announcements are weaker when earnings are released on days with many competing earnings announcements. Overall, these studies suggest that investors are often prone to distraction by irrelevant news events and neglect value relevant information, which attenuates short-term reactions to firm-specific news.

In this paper, we test the limited investor attention theory from a different perspective. Instead of focusing on irrelevant news events, we study investors’ attention behavior when the public news relates to business and economic developments, and the arrival of news is associated with higher economic uncertainty. In a dynamic model of information acquisition, building on Grossman and Stiglitz (1980), we show that greater economic uncertainty on days with big business and economic news induces greater investor attention to firm-specific information (earnings announcements). When economic uncertainty increases, firm-specific information becomes more valuable, and investors optimally allocate more attention to it. Investors, therefore, are more likely to search for and discover firm-specific information during days with big business and economic news and higher economic uncertainty (hereafter “big news” days). Conversely, investor attention is optimally weaker on days with extraneous and unrelated events, when economic uncertainty is likely to be low.

An immediate testable implication of the theory is that higher investor attention to firm-specific information should increase the overall price reaction to earnings information on big news days relative to other days. Heightened price reaction, in turn, should also generate a weaker post-earnings announcement drift. Moreover, the heightened price reaction should take place only if the earnings-specific information is not yet fully reflected into the share price. Thus, the price reaction to earnings information on big news days relative to other days should be weaker for firms with more informative stock prices (e.g., firms with a higher level of institutional ownership). Intuitively, a more informative stock price lowers investors’ incentive to search for information (Grossman and Stiglitz, 1980).

We test the implications of these theoretical results, focusing on whether and to what ex-
tent the arrival of systematic information affects price responses to earnings announcements. As a first step, we build a dataset of national news events using the Pew Research Center’s News Coverage Index (NCI). The NCI is a database of news stories in major media outlets including television, print, radio, and Internet sources, and provides information about story topics and coverage length (i.e., seconds for television and radio, and number of words for newspapers and websites). NCI data is available from January 2007 to May 2012, with over 200,000 stories appearing during this period. From the NCI, we create daily subject-specific indices of news coverage for news related to business/economics, government/politics, and entertainment/other. Each news index identifies the importance of daily subject-specific events based on coverage of specific stories. We use both the breadth of coverage (i.e., the number of news outlets covering a particular story) and the depth of coverage (i.e., the within-outlet time or space devoted to the story) in constructing our daily indices.

The NCI has several features that make it suitable for analyzing the effects of big news. First, the NCI provides comprehensive coverage of stories from major news outlets, not just the business press. Second, the news events it captures are unscheduled, in contrast to tightly scheduled announcements of macroeconomic policy or estimates (e.g., unemployment, inflation, or FOMC rate setting) or earnings announcements. The unscheduled nature of the events in the NCI mitigates concerns about firms selecting when to make their earnings announcements based on other news anticipated to come out simultaneously or firms with particular announcement dates systematically differing from other firms. Thus, these types of selection or omitted variables issues are less likely to confound inferences based on the NCI. Third, the stories covered in the NCI tend not to be about specific firms, mitigating concerns about the news coming out through other channels or being selectively disclosed by firms, as can be the case with press releases. Fourth, unlike other data sources (e.g., the Vanderbilt Television News Archive), the NCI provides extensive coding of the major topics addressed in each news story based on classification by disinterested human coders, whose coding is likely to match classifications made by market participants.

Supporting the importance of the information related to big news events, we first show that our business/economic news index is significantly related to absolute market-level returns after controlling for potential year and day-of-week effects. We also find that big business/economic news events are significantly associated with greater market turnover, higher bid-ask spreads, and greater expected volatility as reflected in the VIX, even after controlling for contemporaneous raw and absolute market returns. Overall, these results suggest that big business/economic news events provide value-relevant information, which drives trade, and their arrival is associated with higher economic uncertainty. News indices related to government/politics and entertainment/other events, in contrast, are not
significantly related to market-wide returns, volatility, or liquidity indicators.

We next examine how big news events affect market reactions to firm-specific information. We find evidence consistent with big business/economic news events driving investors to be attentive to the information contained in earnings announcements. In particular, we find that the market reacts more strongly to earnings news on days with big business/economic news. Furthermore, there is less post-earnings announcement drift following earnings released on big-news days than following earnings released on other days. Finally, the price reaction to earnings surprises vary with the investor base. We find that the incremental price reaction to earnings surprises is weaker for firms with a high fraction of shares held by institutional investors. These results hold after including various firm-specific control variables, day-of-the-week fixed effects, and interactions between these variables and the earnings surprise.

Our evidence therefore suggests that investors respond more strongly to earnings announcements on days with important economy-wide news. On these days, firm-specific news has a stronger association with current returns and a weaker association with future returns, suggesting that investors impound firm-specific information into stock price faster, in line with the predictions of the theory. In contrast, big news events in the “other” category are distracting. For firms announcing earnings on other big news event days, the market reactions to earnings surprises are dampened, which is consistent with findings of prior studies (e.g., Hirshleifer et al., 2009; Drake et al., 2016) on the distracting effect of irrelevant news on investor attention. Further supporting our thesis that investors rationally allocate their attention, investors’ heightened attention yields a weaker price reaction to earnings announcements when there is greater institutional ownership (i.e., when the stock price is more informative). Similarly, Hirshleifer et al. (2009) find that firms with more institutional ownership have earnings announcement returns less susceptible to the distracting effect of the concurrent earnings announcements they focus on.

Overall, these findings support our theoretical result that heightened economic uncertainty causes investors to optimally seek out more firm-specific information on days with important economy-wide information. Investors, therefore, allocate more attention to value relevant information when they find it optimal. The flip side of this result is that on days characterized by lower economic uncertainty investors’ incentive to search for information should be lower. Hence, it is not clear that investors are “distracted” by extraneous and unrelated events, if these events are observed on days with lower economic uncertainty.

The paper proceeds as follows. The next section reviews related literature. Section 3 builds a theoretical model of rational attention allocation and develops testable predictions. Section 4 details the construction of the news indices and presents results from empirical analyses. Section 5 concludes.
2 Related literature

Our study contributes to the literature on limited investor attention. Prior studies provide evidence that exogenous events that are likely unrelated to a firm’s underlying fundamentals can distract investor attention away from earnings announcements. Our findings related to news in the “other” category provide additional support to these claims. More importantly, however, we show that exogenous and often unscheduled events can also attract investor attention to earnings announcements when they relate to economic or business activity. In other words, we add to this literature by providing evidence that the nature of the events that are covered by the media have a significant effect on whether the news distracts or attracts attention to earnings announcements.

Our paper is also related to studies examining market reactions to macroeconomic news and firm-specific news. In the former stream, Jones, Lamont, and Lumsdaine (1998) show that U.S. Treasury Bond returns are affected by announcements of employment and inflation statistics. Boyd, Hu, and Jagannathan (2005) show that unemployment news has differential effects on market returns in contractionary and expansionary periods. Savor and Wilson (2013, 2014) show that market returns and returns to riskier firms (where risk is captured by CAPM beta) tend to be higher on days with scheduled announcements of inflation, unemployment, and interest rate news. Eisensee and Strömberg (2007), focusing on government policy rather than market response, find that natural disaster relief efforts get less government attention if the disasters are concurrent with other news-attracting events, such as the Olympics. We add to this literature by constructing news indices based on different topics and examining market reactions to the changes in these indices. In this respect, our study is similar in spirit to that by Baker, Bloom, and Davis (2016), who develop an index of economic policy uncertainty based on the frequency of phrases related to economic uncertainty appearing in news articles, and show that their index is associated with events relevant to fiscal policy (e.g., elections and wars) as well as firm-specific stock volatility and declines in economy-wide investment, employment, and output.

Our study provides new measures of news intensity for different categories of news. Extant studies have examined the price impact of media attention (e.g., Barber and Odean, 2007; Tetlock, 2010), macroeconomic announcements (e.g., Chen, Jiang, and Zhu, 2017; Savor and Wilson, 2013, 2014), and other one-time or periodic events (e.g., Edmans, Garcia, and Norli, 2007; Kaplanski and Levy, 2010). Other studies have used linguistic methods to quantify the tone of news (i.e., positive or negative). For instance, Tetlock, Saar-Tsechansky, and Macskassy (2008) show that the fraction of negative words in news articles contain information that is not contained in analyst report data; similarly, Demers and Vega (2008)
use textual analysis to show that optimistic language in earnings announcements is associated with more positive post-earnings announcement drift. We construct a daily metric of news intensity that takes into account the content and significance of news stories in different categories and provides a basis to compare the effect of different categories of news on prices.

Finally, in our theory investors are active learners (Veldkamp, 2011) and exercise control over purchasing information. Active learning has a long tradition in economics and finance, including seminal papers by Grossman and Stiglitz (1980) and Sims (1998, 2003). Alternative theoretical models feature choice between signals (e.g., Van Nieuwerburgh and Veldkamp, 2009, 2010). Another alternative is that news events that are out of the ordinary help investors better predict the future, and thus it is optimal to be more attentive in the same time. Andrei and Hasler (2019) develop this hypothesis in a dynamic model of costly information acquisition, and find empirical support for it.

3 A dynamic model of rational attention allocation

We develop a dynamic model of trading where all investors are exposed to a firm’s announcement about next period’s earnings. We assume that paying attention to this signal is costly. As a result, only a fraction of investors will choose to observe the signal. We demonstrate that this fraction varies with the degree of uncertainty in the economy.

3.1 Setup

We adopt the dynamic structure from DellaVigna and Pollet (2009), which we modify in two ways. First, we insert fluctuations in uncertainty; this allows us to study investors’ reaction to earnings information for different levels of economic uncertainty. Second, we let investors optimally decide whether to be attentive or not to earnings announcements.

Consider an overlapping-generations economy populated by a continuum of investors, indexed by $i \in [0, 1]$. A new generation of investors is born every period. At the beginning of the period (at time $t$), investors make trading and information acquisition decisions, and they consume their final wealth at the end of the period (at time $t+1$). Investors trade a riskless asset and a risky asset. The riskless asset is in infinitely elastic supply and pays a gross interest rate of $R_f > 1$ per period. The risky asset (the firm) has price $P_t$ and pays a risky dividend per period,

$$D_{t+1} = F + f_{t+1} + e_t,$$  \hfill (1)

which has three components: a long-term mean $F > 0$; a systematic component, $f_{t+1} \sim$
and a firm-specific component, $e_t \sim N(0, \sigma^2_e)$. The firm-specific component is announced by the firm at the beginning of the period (at time $t$), and thus can be interpreted as an earnings announcement.

The long-term mean $F$ is common knowledge to all investors. The variance of $f_{t+1}$, $\sigma^2_{f,t}$, is time-varying. At the beginning of each trading date, $\sigma^2_{f,t}$ takes one of $K \geq 2$ possible values, indexed by $k \in \{1, \ldots, K\}$. We denote the probability of the event $\sigma_{f,t} = \sigma_{f,k}$ by $\pi_k$.

At the beginning of period $t$, all investors observe the level of uncertainty, $\sigma^2_{f,t}$, together with a public signal about the economy:

$$G_t = f_{t+1} + \eta_t,$$

where $\eta_t \sim N(0, \sigma^2_{\eta})$. At the same time, each investor $i$ chooses whether to be attentive to the earnings announcement $e_t$. We adopt this information choice from Grossman and Stiglitz (1980), and we denote investor’s decision by the variable $L^i$: if investor $i$ decides to be attentive to the firm’s announcement, then $L^i = 1$; otherwise, $L^i = 0$.

We assume that each investor $i$ has expected utility

$$U^i = E^i_t \left[ -e^{-\gamma(W^i_{t+1} - cL^i)} \right],$$

where $\gamma$ is the risk aversion coefficient, $W^i_{t+1}$ is the wealth at the end of each period, and $cL^i$ represents the monetary cost of paying attention to the earnings announcement. The information cost parameter $c$ is positive and small.

Investors who decide to become informed about firm’s earnings perfectly observe $e_t$. We refer to them as $I$ investors, and to the investors who decide to remain uninformed as $U$ investors. (Notice, however, that $U$ investors will still be able to partially infer $e_t$ from the equilibrium price, as we will describe below.) After the information choice is made, investors chose optimal portfolios:

$$q^i_t = \frac{E^i_t[P_{t+1} + D_{t+1}] - R_f P_t}{\gamma Var^i_t[P_{t+1} + D_{t+1}]}, \quad \text{for } i \in \{I, U\},$$

where the superscript $i$ in $E^i_t[\cdot]$ and $Var^i_t[\cdot]$ reads “under the information set of investor $i$.”

The risky asset is in random supply, $x_t \sim N(0, \sigma^2_x)$, and it is drawn identically and independently across periods. Random supply prevents the price from perfectly revealing $e_t$ (Grossman and Stiglitz, 1980); it also prevents agents from refusing to trade (Milgrom and Stokey, 1982). Letting $\lambda_t$ be the equilibrium proportion of $I$ investors, the price of the risky
asset is determined by the market clearing condition:

\[ \lambda_t q_t^I + (1 - \lambda_t) q_t^U = x_t. \quad (5) \]

### 3.2 Equilibrium

As is customary in noisy rational expectations models, we conjecture a linear form for the equilibrium price, with time-varying coefficients:

\[ P_t = \frac{F}{R_f - 1} + \beta_t G_t + \alpha_t e_t - \xi_t x_t. \quad (6) \]

For an uninformed investor who does not pay attention to \( e_t \), the price partially reveals \( e_t \) for free (as long as \( \alpha_t \neq 0 \)). More precisely, one can transform the equilibrium price into an informationally equivalent signal about \( e_t \):

\[ \hat{P}_t \equiv \frac{P_t - F/(R_f - 1) - \beta_t G_t}{\alpha_t} = e_t - \frac{\xi_t}{\alpha_t} x_t. \quad (7) \]

The optimal portfolio choice (4) holds for both the informed and uninformed investors. The difference between the two is the information set of each investor type. The information set of \( I \) investors is \( \{ e_t, G_t, \hat{P}_t \} \), whereas the information set of \( U \) investors is \( \{ G_t, \hat{P}_t \} \).

Defining the dollar excess return from \( t \) to \( t + 1 \) as \( R_{t+1} \equiv P_{t+1} + D_{t+1} - R_f P_t \), an application of the Projection Theorem (see Appendix A.1) yields \( I \) investors’ asset demand:

\[ q_t^I = \frac{1}{\gamma \text{Var}^I_t[R_{t+1}]} \left( \frac{R_f}{R_f - 1} F + \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_e^2} G_t + e_t - R_f \hat{P}_t \right), \quad (8) \]

and \( U \) investors’ asset demand:

\[ q_t^U = \frac{1}{\gamma \text{Var}^U_t[R_{t+1}]} \left( \frac{R_f}{R_f - 1} F + \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_e^2} G_t + \frac{\sigma_e^2}{\sigma_e^2 + \xi_t^2 \sigma_x^2 / \alpha_t^2} \hat{P}_t - R_f P_t \right). \quad (9) \]

There are two main differences between the asset demands \( q_t^I \) and \( q_t^U \). First, \( U \) investors use the price signal to learn about \( e_t \): when they observe a high price signal, they increase their demand of the asset. The second difference is that, on average, when expected returns are positive \( I \) agents demand more, because their conditional variance of future returns is lower: \( \text{Var}^I_t[R_{t+1}] < \text{Var}^U_t[R_{t+1}] \).

Adding the two demand expressions (8) and (9) weighted by \( \lambda_t \) and \( 1 - \lambda_t \), and setting the total equal to \( x_t \) yields the market clearing condition (5). The coefficients \( \beta_t, \alpha_t, \) and
\( \xi_t \) are then determined by matching coefficients.\(^1\) Proposition 1, whose proof is provided in Appendix A.1, characterizes these equilibrium coefficients.

**Proposition 1.** In equilibrium, the price coefficients \( \beta_t \), \( \alpha_t \), and \( \xi_t \) are given by

\[
\beta_t = \frac{\sigma_{f,t}^2}{R_f(\sigma_{f,t}^2 + \sigma_{\eta}^2)}, \quad \alpha_t = \frac{1}{R_f} \left( 1 - \frac{1 - \lambda_t}{1 + \sigma_t^2(\gamma\sigma_x \sqrt{\Pi_t + \Pi_t})} \right), \quad \text{and} \quad \xi_t = \frac{\alpha_t}{\sigma_x \sqrt{\Pi_t}},
\]

(10)

where \( \Pi_t \) represents the price informativeness (i.e., the capacity of the price to reveal \( e_t \) to uninformed investors),

\[
\Pi_t \equiv \frac{\alpha_t^2}{\sigma_x^2 \xi_t^2} = \frac{\lambda_t^2}{\gamma^2 \text{Var}[R_{t+1}]^2 \sigma_x^2}.
\]

(11)

Price informativeness increases with the fraction of informed investors: when more investors observe \( e_t \), their aggregate demand comprises a large share of the total demand, increasing the information content of the price. Furthermore, price informativeness decreases when investors are more risk averse; when the variance of future returns is large; or when supply shocks are more volatile. In each one of these situations, investors place less aggressive orders, which in turn decreases the information content of the price. Furthermore, as we show in Appendix A.1, \( \text{Var}[R_{t+1}] \) can be written as

\[
\text{Var}[R_{t+1}] = \frac{\sigma_{f,t}^2 \sigma_{\eta}^2}{\sigma_{f,t}^2 + \sigma_{\eta}^2} + \text{Var}[P_{t+1}],
\]

(12)

where the variance of the future price, \( \text{Var}[P_{t+1}] \), does not depend on time or on investors’ type (intuitively, the information that investors have at \( t \) becomes irrelevant at \( t + 1 \); furthermore, at any time \( t \) investors face the same probability distribution over future values of \( \sigma_{f,t+1} \)). Thus, the variance of future returns, as perceived by \( I \) investors, is strictly increasing in the economy-wide uncertainty \( \sigma_{f,t} \). As a result, *ceteris paribus*, price informativeness decreases with economic uncertainty. In this model, however, investors are free to choose their information set, meaning that \( \lambda_t \) will also move with uncertainty.

Our aim is to measure the overall effect of uncertainty shocks on prices informativeness, and hence on the price coefficients in Proposition 1. In a first step, we analyze how investors’ demand for information is affected by fluctuations in economic uncertainty.

\(^1\)Dynamic models of trading of this type have multiple equilibria. More precisely, a model with \( N \) risky assets has \( 2^N \) equilibria (e.g. Banerjee, 2011; Andrei, 2018), and thus in this model there are two equilibria: a low volatility equilibrium and a high volatility equilibrium. The intuition presented here holds in both equilibria.
3.3 Demand for information

In equilibrium, each investor must be indifferent between observing $e_t$ or not. As in Grossman and Stiglitz (1980), this indifference condition yields (see Appendix A.2):

$$\sqrt{\frac{\text{Var}_t^U[R_{t+1}]}{\text{Var}_t^I[R_{t+1}]} = e^{\gamma c}}.$$ (13)

The left hand side measures the benefit of observing $e_t$; the right hand side measures the cost. The benefit of observing $e_t$ is always larger than one and increases in the ratio of return variance without the information to return variance with information. Further decomposing $\text{Var}_t^U[R_{t+1}] = \text{Var}_t^I[R_{t+1}] + \text{Var}_t^U[e_t]$ and replacing it above yields a simple tradeoff between the benefit and the cost of observing $e_t$:

$$\frac{\sigma_e^2/\text{Var}_t^I[R_{t+1}]}{1 + \Pi_t \sigma_e^2} = e^{2\gamma c} - 1.$$ (14)

An increase in uncertainty—as measured by an increase in $\sigma_{f,t}$ and therefore an increase in $\text{Var}_t^I[R_{t+1}]$—has two effects on the benefit of observing $e_t$. First, it reduces the ratio $\sigma_e^2/\text{Var}_t^I[R_{t+1}]$. This ratio measures the relative share of earnings uncertainty in the overall uncertainty perceived by informed investors. A smaller ratio means less gains from learning. Thus, higher economic uncertainty decreases the incentive to learn $e_t$, which leads to less information acquisition, or to a lower $\lambda_t$.

A second effect arises in the denominator on the left hand side of (14): when uncertainty increases, the price becomes less informative, and thus $\Pi_t$ decreases (as shown in Eq. 11). As argued by Grossman and Stiglitz (1980), less informative prices increase the incentive to acquire information—investors learn less from the price and thus the value of information increases, yielding a higher $\lambda_t$. Overall, the change in $\lambda_t$ caused by an increase in uncertainty depends on the balance between these two effects.

The price informativeness effect—the increase in $\lambda_t$ due to a decrease in price informativeness caused by higher uncertainty—is the effect that dominates for lower levels of uncertainty. To see this, the following proposition provides a direct link between the equilibrium fraction of $I$ investors and the level of uncertainty (the proof is provided in Appendix A.2).

**Proposition 2.** In equilibrium, the fraction $\lambda_t$ of investors who decide to pay attention to the earnings announcement solves the following implicit equation:

$$\lambda_t^2 = \gamma^2 \sigma_e^2 \text{Var}_t^I[R_{t+1}] \left( \frac{1}{e^{2\gamma c} - 1} - \frac{\text{Var}_t^I[R_{t+1}]}{\sigma_e^2} \right).$$ (15)
Equation (15) is implicit because $\lambda_t$ and $\text{Var}_t^I[R_{t+1}]$ are jointly determined in equilibrium. Nevertheless, it allows us to analyze the effect of higher uncertainty on the information choice of investors. The right-hand side of (15) is a quadratic function of $\text{Var}_t^I[R_{t+1}]$, with two distinct zeros: $\text{Var}_t^I[R_{t+1}] = 0$ and $\text{Var}_t^I[R_{t+1}] = \sigma_e^2/(e^{2\gamma_c} - 1)$. The curved line in Figure 1 depicts the square root of this function. As the plot shows, $\lambda_t$ reaches a (theoretical) maximum when

$$\frac{\text{Var}_t^I[R_{t+1}]}{\sigma_e^2} = \frac{1}{2(e^{2\gamma_c} - 1)}. \quad (16)$$

The plot further shows that $\lambda_t$ increases at first, until it reaches 100% (dot labeled A on the plot). A further increase in uncertainty beyond this point keeps the equilibrium level of $\lambda_t$ at 100%. Once $\lambda_t$ reaches its (theoretical) maximum value, a further increase in uncertainty dominates the potential gains of learning about earnings. Beyond this point, $\lambda_t$ decreases, and at the dot labeled B it gets below 100%. In this case, the ratio $\sigma_e^2/\text{Var}_t^I[R_{t+1}]$ is small enough that an increasingly large number of investors find no use in paying attention to the earnings announcement.
Although this latter effect is an interesting theoretical result, it is unlikely to take place when the cost of observing $e_t$ is low. With earnings-related information being relatively cheap and accessible, the cost of being attentive to earnings announcement is most likely small. Thus, the maximum obtained in Eq. (16) is not easily reached.\footnote{For instance, if $\gamma = 3$ and $c = 0.01$, the right hand side is larger than 8. This means that the uncertainty of future returns perceived by informed investors should be at least 8 times larger than the uncertainty of earnings in order to obtain a decrease in $\lambda_t$.} Although we do not exclude this possibility, the effects that we document in our empirical section are mostly consistent with a small information cost.

### 3.4 Response to earnings announcement and testable implications

We analyze the impact of fluctuations in uncertainty on the equilibrium price. Our main object of interest is the earnings response coefficient (ERC) $\alpha_t$. As can be seen from Proposition 1, $\alpha_t$ is strictly increasing in the proportion $\lambda_t$ of $I$ investors (both directly through the numerator in (10) and indirectly through an increase in price informativeness). More precisely, the coefficient $\alpha_t$ goes from 0 (when $\lambda_t = 0$) to a maximum of $1/R$ (when $\lambda_t = 1$). This is illustrated in Figure 2, where the two curves that increase from 0 to $1/R$ depict the coefficient $\alpha_t$ as a function of $\lambda_t$, for two different levels of uncertainty.

The plot further shows that, keeping $\lambda_t$ constant, an increase in uncertainty unambiguously lowers $\alpha_t$. This is in line with Proposition 1: more uncertainty leads to less aggressive trading from informed investors, which decreases price informativeness and in turn decreases $\alpha_t$. Indeed, the dashed curve that increases from 0 to $1/R$ remains below the solid curve at all interior points. Considering an hypothetical equilibrium value depicted with the dot labeled A, the spike in uncertainty pushes $\alpha_t$ towards the dot labeled B. However, as elaborated in the previous section, higher uncertainty also leads to lower price informativeness, which gives investors a stronger incentive to learn about the earnings announcement, and in turn increases $\lambda_t$. This increases the coefficient $\alpha_t$ and is illustrated in the plot with a move from B to C. A large enough increase in $\lambda_t$ can push $\alpha_t$ to a level higher than before.

It is important to emphasize that $\lambda_t$ is not the only parameter that can change $\alpha_t$ once uncertainty increases. But in our model $\lambda_t$ is the only moving parameter; the risk aversion $\gamma$, the earnings volatility $\sigma_e$, and the volatility of noise trading $\sigma_x$ are all constant (if anything, an increase in uncertainty is likely associated with an increase in any of these parameters, which would further decrease $\alpha_t$). We have therefore formulated a clear theoretical prediction: if investors are more attentive to earnings announcements on high uncertainty days, then we should observe a stronger $\alpha_t$ coefficient on those days. Furthermore, if the price is more responsive to the earnings announcement, then we should also observe a weaker
Figure 2: **Investor attention and the earnings response coefficient** $\alpha_t$

This figure plots the earnings response coefficient (ERC) $\alpha_t$ as a function of the fraction of investors, $\lambda_t$. The two curves (solid and dashed) plot the ERC for a low and high level of uncertainty $\sigma_{f,t}$, respectively. In both cases, the ERC increases from 0 to $1/R$, but the ERC is lower when uncertainty increases. The move from the dot labeled A to B represents the effect on the ERC of an increase in uncertainty, and the move from B to C represents the effect of an increase in $\lambda_t$ caused by the increase in uncertainty.

To test the above theoretical predictions, we follow DellaVigna and Pollet (2009) and build measures of the immediate and the delayed response of the stock price to the earnings announcement. The immediate response to the signal $e_t$ is defined as

$$\mathbb{E}_t[IR_t] \equiv R_t - \mathbb{E}_{t-1}[R_t] - (D_t - \mathbb{E}_{t-1}[D_t]),$$

and the delayed response is

$$\mathbb{E}_t[DR_{t+1}] \equiv \mathbb{E}_t[R_{t+1}] - \mathbb{E}_{t-1}[R_{t+1}].$$

In the context of our model, as in DellaVigna and Pollet (2009), the immediate response $\mathbb{E}_t[IR_t]$ is a linear function of the earnings announcement $e_t$ with slope coefficient $\alpha_t$, and the delayed response $\mathbb{E}_t[DR_{t+1}]$ is a linear function of the earnings announcement with slope coefficient $1 - R_f\alpha_t$. This yields two testable predictions: (i) if investors are more attentive
to earnings announcements on high uncertainty days, we should observe a stronger earnings response coefficient $\alpha_t$; and (ii) more investor attention to earnings announcements on high uncertainty days should yield a weaker post-earnings announcement drift.

A third and more subtle theoretical prediction results from what Grossman and Stiglitz call the “fundamental conflict between the efficiency with which markets spread information and the incentives to acquire information” (Grossman and Stiglitz, 1980, p. 405). When the fraction $\lambda_t$ of $I$ investors is large, the price system transmits a lot of information about $e_t$ to $U$ investors. Hence, when $\lambda_t$ is large, the incentive to become informed is low—in the extreme case when the price perfectly reveals $e_t$ all traders desire to be uninformed. The implication of this fundamental conflict is that we should observe a lower increase in the ERC for firms that are held mostly by informed investors, e.g., firms with a high fraction of shares held by institutional investors.

4 Empirical analyses

We structure our empirical work in three parts. First, we construct daily news indices, which we classify in three broad categories: business/economics; government/politics; and entertainment/other. Our category of interest is business/economics, but we also present results for the two other categories. Second, we compute measures of market activity and of market reaction to earnings announcements. Third, we directly test the hypotheses developed in Section 3.4. Overall, we find empirical support for our conjecture that investors pay more attention to firm-specific information on days with important business/economic news and heightened economic uncertainty.

4.1 Construction of the news indices

We first construct daily indices based on news coverage to capture the importance of attention-grabbing events. The underlying idea behind the indices is that the importance of a story or event will be reflected in the degree of journalists’ coverage. Bigger stories will be covered by multiple news outlets, and the coverage will tend to be more extensive, as reflected in coverage time for TV and radio broadcasts and length of articles for written pieces appearing online and in newspapers.

The data used for construction of the big news indices comes from the Pew Research Center’s Project for Excellence in Journalism’s News Coverage Index (NCI). The construction of the NCI begins with a survey of news coverage each day. The survey categorizes coverage from broadcast television news programs, newspapers, popular news websites, cable news,
and radio. The unit of observation in the NCI is the “Story” (capitalized). Each Story represents a piece of coverage on a specific day from a specific news source. For example, the ABC Evening News story on February 11, 2010 from 5:31 to 5:35pm on former President Bill Clinton’s health represents one Story. The CBS Evening News coverage of the same topic on the same evening represents a different Story observation, and coverage in a newspaper or on a website would represent yet another observation.³

Each Story in the NCI is coded according to its Source (i.e., which newspaper, TV or radio broadcast, or website), Broad Story Topic (26 potential categories), Big Story Code (approximately 1,200 categories), date, and approximate time of broadcast, if relevant.⁴ The NCI coverage began on January 1, 2007, and ended in May 2012. We use a five-full-year period of coverage from 1/1/2007 through 12/31/2011 in order to ensure that periodic events taking place earlier in the year are not overrepresented in the sample. We retain all Stories that have a valid Broad Story Topic and are featured in national newspapers, broadcast television, or websites during trading days, as identified in CRSP.⁵ We retain only the most prominent Stories from each source. These are the first Stories in television programs, the top right Stories in newspapers, and the topmost or biggest-headline Stories on websites. In order to ensure that the news in our sample relates to significant events, we retain a Story in our sample only if there are at least four other Stories with the same Big Story Code on the same day.

We then sort Stories into three categories based on the Broad Story Topics provided in the NCI: business/economics; government/politics; and entertainment/other. We identify business/economics news as those in NCI Broad Story Topics 7 and 8 or Big Story Code 862 (Economy), government/politics news as NCI Broad Story Topics 1, 2, 3, 4, and 25 and entertainment/other news as all other Stories.⁶

We choose government/politics and entertainment/other categories to ensure that the top quintile of the news index for each category contains only days with positive news coverage. Our indices are calculated within each category. For each category on each date, we calculate

³See www.journalism.org/news_index_methodology/99/ for a comprehensive description of the data.
⁴Examples of Big Story Codes as numbered in the NCI include: 497) Emmy awards; 820) congressional election results; 909) Lance Armstrong, Tour de France; 1184) Toyota accelerator recall; 1297) AOL buys Huffington Post.
⁵We drop Stories from cable news and radio, as their top stories often feature opinion or editorial content.
⁶Broad Story Topics as numbered in the NCI, with the number of days with big news Stories in square brackets, are: 1) government agencies, legislatures [230]; 2) campaigns, elections, politics [225]; 3) defense, military (domestic) [22]; 4) court, legal system [16]; 5) crime [72]; 6) domestic terrorism [43]; 7) business [154]; 8) economy, economics [284]; 9) environment [27]; 10) development, sprawl [9]; 11) transportation [24]; 12) education [10]; 13) religion [7]; 14) health, medicine [56]; 15) science, technology [6]; 16) race, gender, gay issues [13]; 17) immigration [3]; 18) additional domestic affairs [53]; 19) disasters, accidents [151]; 20) celebrity, entertainment [11]; 21) lifestyle [22]; 22) sports [11]; 23) media [16]; 24) U.S. miscellaneous [30]; 25) U.S. foreign affairs [226]; 26) foreign, non-U.S [207].
the mean duration in seconds for TV news Stories and the mean number of words for online and newspaper Stories. Since missing category-date values for mean words or mean duration imply that there were no stories that satisfied our cutoffs, missing values are set to zero. For each category, we standardize the duration- and word-means so that each time series is mean zero and unit variance. The standardized mean duration and mean words for a category-date are averaged to form the daily category indices: BE News (business/economics), GOV News (government/politics), and OTHER News (entertainment/other).

In our sample, the highest values for the BE News index occurred when: President Obama gave a speech in favor of the American Recovery and Reinvestment Act, a mid-recession stimulus package (January 8, 2009); General Motors filed for bankruptcy (June 1, 2009); and the federal government seized Washington Mutual and brokered its sale to JPMorgan Chase (September 26, 2008). The days with the highest GOV News index values capture Obama’s speech at the UN charging Iran with concealing its nuclear weapons program (September 25, 2009); the Fort Hood shooting (November 6, 2009); and the leak of over 250,000 classified diplomatic cables from U.S. embassies by WikiLeaks (November 29, 2010). The days with the highest OTHER News index values capture: the royal wedding of Kate Middleton and Prince William (April 29, 2011); the death of Senator Ted Kennedy (August 26, 2009); and the Japan earthquake and tsunami (3/11/2011).

4.2 Variable definitions, summary statistics, and validation

In our analyses of the effects of public news and economic uncertainty on the stock market, we examine the relation between the news indices and daily measures of market activity. Our measure of daily market returns is the market factor returns, MKT, and its absolute value, |MKT|, taken from Ken French’s website. Our measures of aggregate price protection and illiquidity are ILLIQ, the log of the value-weighted Amihud (2002) firm-level illiquidity measure, calculated as $10^6$ times a stock’s absolute return divided by a stock’s dollar volume, and SPREAD, which is the log of the value-weighted daily bid-ask spread, calculated as a stock’s ask price minus bid price divided by the midpoint. To examine trading activity, we focus on TURN, the log of value-weighted average turnover, calculated as shares traded divided by shares outstanding$^7$ and VOL, the log of total market volume. Importantly, we also examine the association between our big news indices and closing values of the VIX, which is an option-based measure of expected S&P 500 volatility that proxies for forward-looking stock market uncertainty, risk, or volatility.

$^7$NASDAQ turnover is corrected for multiple-counting by multiplying the turnover measure by 0.62, following Anderson and Dyl (2005).
For our analyses of market reaction to earnings announcements taking place on big business and economics news events days, we measure earnings surprise, SUE, following Livnat and Mendenhall (2006) as:

\[
SUE_{i,t} = \frac{X_{i,t} - \mathbb{E}[X_{i,t}]}{P_{i,t}}
\]

where \(i\) denotes firm, \(t\) denotes quarter, \(X_{i,t}\) are IBES reported actual earnings, \(\mathbb{E}[X_{i,t}]\) are expected earnings, the median of the most recent individual analysts’ forecasts issued in the 90 days before the earnings announcement date, and \(P_{i,t}\) is the share price at the end of quarter \(t\).

Daily excess returns are calculated each day as the raw CRSP-reported returns minus the return to the CRSP value-weighted market index. Earnings announcement returns, EARET, used for earnings response coefficient (ERC) tests are calculated as the compounded excess returns from the day of the earnings announcement through the day after (2-day window). Post-earnings announcement returns used for examining drift (PEAD) are compounded from two days after the earnings announcement date through the 7th, 30th, 61st, and 90th day after the earnings announcement. The ERC windows were chosen to capture market reactions to post-close earnings announcements on day \(t+1\). The PEAD window was chosen based on Hirshleifer et al. (2009) and earlier work on PEAD (e.g., Bernard and Thomas, 1989). As in prior studies, we use SUE deciles based on calendar-quarter sorts rather than raw values when SUE is an independent variable.

In our analyses of market reactions to earnings announcements we use the following variables as controls, following prior literature (e.g., Hirshleifer et al., 2009): the market value of equity on the day of the earnings announcement, Size; the ratio of book value of equity to the market value of equity at the end of the quarter for which earnings are announced, Book-to-Market; earnings persistence based on estimated quarter-to-quarter autocorrelation, EPersistence; institutional ownership as a fraction of total shares outstanding at the end of the quarter for which the earnings are announced, IO; earnings volatility, EVOL; the reporting lag measured as the number of days from quarter end to the earnings announcement, ERepLag; number of analysts following the firm defined as the number of analysts making forecasts up to 90 days before the earnings announcement, #Estimates; average share turnover over the preceding year, TURN; an indicator variable for negative earnings, Loss; the number of other firms announcing earnings on the same day, #Announcements; and day-of-week indicators. We provide detailed definitions of each of these variables in Appendix A.3.

In Table 1, we provide descriptive statistics for the variables used in the analyses. We
report statistics for the variables used in the daily market-level tests and for the variables used in the firm-quarter analyses of earnings announcement returns separately. Since all news indices are standardized and in most of the days there is only one type of major news event, each news index is right-skewed with a mean of zero and a negative median.

(Insert Table 1 about here)

In order to validate that our topical news indices capture big news events and that different categories of news have different effects on the markets—in particular, that big/business news events are associated with higher economic uncertainty—we begin our analyses by examining whether the three topical news indices are associated with absolute market returns and trading activity. We regress each of the market-based proxies on the news indices, and indicators for year and day-of-week. For the market activity indicators (ILLIQ, SPREAD, TURN, VOL, and VIX), we also include controls for signed and absolute market returns (MKT and |MKT|). Estimates from these regressions are presented in Table 2. The BE News index is positive and statistically significantly associated with absolute market returns, while the OTHER News and GOV News indices are not. Furthermore, days with higher BE News have lower liquidity (i.e., higher illiquidity and bid-ask spreads), greater turnover, and higher volume.

(Insert Table 2 about here)

Most important, the daily closing value of the VIX is strongly positively associated with the BE News index, suggesting that indeed days with high BE News are associated with greater expected market volatility and therefore with greater uncertainty. Furthermore, there is no significant relationship between the VIX and the OTHER News and GOV News indices. The results in Table 2 overall validate the BE News index as capturing news events that have significant impacts on the stock market and market activity.

4.3 The impact of economic uncertainty on investor attention

As elaborated in Section 3.4, our main tests related to investor attention allocation focus on the relation between economic uncertainty and market reactions to firm-specific information. We focus on quarterly earnings announcements as the source of firm-specific information and examine price reactions around earnings announcements as well as drift following announcements. Our analyses examine how big news—and in particular BE News—interacts with firm-specific news in the price formation process. We generally focus on the association between market-adjusted stock returns from various windows and the earnings surprise, our news indices, the interaction between news and the earnings surprise, and a set of controls.
We interact each of these controls with our earnings surprise variable to mitigate concerns that the coefficient on our interaction of interest is driven by a correlated omitted interaction.

To test the hypotheses developed in Section 3.4, we estimate the following regression at the firm-quarter level:

\[
EARET_{it} = c_0 + c_1 \times SUE_{it} + c_2 \times \text{News}_t + c_3 \times SUE_{it} \times \text{News} + X_{it} + u_{it},
\]  

where \( X_{it} \) represents a set of controls and \( \text{News} \) stands for each one of the 3 news categories built in Section 4.1 above.

We present results for announcement-window returns in Table 3. Returns around earnings announcements are highly positively associated across all specifications with the earnings surprise. We focus on interactions between our news indices and the earnings surprise (that is, on the coefficient \( c_3 \) in the specification above), using both our raw news indices and indicators for top-quintile news index scores.\(^8\)

Results in Table 3 suggest that only BE News and OTHER News are associated with differential market responses to earnings surprises, i.e., different earnings response coefficients. Specifically, the results in Table 3 suggest the association between earnings surprises and returns is stronger on days with high BE News, and there is some support for the relation being weaker on days with high OTHER News. We interpret this as providing modest evidence of a distraction effect of OTHER News, in that earnings releases on days with other news receive less attention. BE News, in contrast, appears to attract attention to earnings announcements, as predicted by our theoretical model. Overall, the most compelling evidence is that the positive effect of an earnings surprise on excess announcement returns is strengthened when the announcement occurs on a day with big BE News and higher economic uncertainty.

(Insert Table 3 about here)

If indeed investors are more attentive to earnings announcements on days with big BE News and higher economic uncertainty, then we should expect a weaker subsequent post-earnings-announcement drift (PEAD). The rationale for this is that with stronger investor attention, the information content of firms’ earnings should be quickly incorporated into prices. Indeed, our theoretical model predicts that the delayed response is a linear function of the earnings announcement with a slope coefficient that is decreasing in investor attention. In Table 4 we present results of our PEAD tests. Results suggest that earnings

---

\(^8\)The main effect of BE News (OTHER News) on earnings announcement returns is negative (positive), indicating that earnings announced on days with BE (other) newsworthy events tend to have more negative (positive) returns, independent of the earnings surprise.
announced on days with concurrent big business/economic news experience less drift over post-earnings announcement days. There is strong evidence of this over the seven-day period, and some evidence for the 60-day period. This, when combined with the result in Table 3, suggests that investors react to earnings announcement information more quickly when the announcements occur on days with big business/economic news. Associations between PEAD and both GOV News and OTHER News indices, which are not reported for the sake of brevity, are not statistically significant over any of the windows examined.⁹

(Insert Table 4 about here)

Last, we examine whether big business and economics news events have a differential impact depending on firms’ investor base. In particular, we compare our findings on the impact of big business and economic news on earnings announcements between firms with high and low institutional ownership (i.e., the percentage of shares owned by institutions at the end of the quarter for which the earnings are announced). As elaborated in Section 3.4, the impact on the earnings response coefficient on days with BE news should be weaker for firms with higher institutional ownership. The share of informed investors is likely higher for these firms, increasing the informativeness of their stock price. This, in turn, should decrease the incentive to acquire information (Grossman and Stiglitz, 1980).

Table 5 reports results from the analyses where we interact institutional ownership (IO) with BE News and SUE deciles. We standardize IO for this regression to be mean-zero and unit-variance, which allows the coefficients on the variables without the IO interaction to be comparable with those in Table 4. The first column of Table 5 shows that the triple interaction term (SUE Decile * BE News * IO) has a negative coefficient, suggesting that the incremental market reaction to earnings surprises on high BE News days is weaker when there is greater institutional ownership. This is in line with the theoretical prediction that firms with higher price informativeness should experience a comparatively weaker reaction to earnings announcements. Furthermore, the remaining columns in Table 5 show the impact of institutional investor on the results from the PEAD analysis. Here we find insignificant coefficients in all windows. This suggests that institutional ownership has little incremental impact on the effect of BE News on PEAD.

(Insert Table 5 about here)

Overall, the results from Tables 3, 4, and 5 provide support to the conjecture that higher economic uncertainty on BE News heightens investor attention to earnings announcements. As predicted by the theoretical model, the earnings response coefficient (ERC) is higher on

⁹Results for the other news indices are available from the authors.
days with important business/economic news. Moreover, the increase in ERC is weaker for firms with high institutional ownership, further supporting the theory. In sum, the data suggest that investors pay more attention to firm-specific information on days with big BE news and high economic uncertainty.

5 Conclusion

In this paper, we provide theoretical and empirical support for the idea that heightened economic uncertainty can cause investors to rationally allocate more attention to firm-specific information. Our theoretical predictions come from a dynamic model of information choice in the presence of both systematic and firm-specific signals, and where investors can learn from market prices. Empirically, we begin by constructing novel topic-specific indicators for important events covered extensively by media outlets. We call these big news events, and build daily indices that cover big news related to business and the economy, government, and events that fall into neither of the aforementioned categories (other). We show that days with big news/economic events tend to have greater economic uncertainty, larger absolute market returns, greater price protection, and more trading despite lower liquidity. Big news events related to government or falling into the “other” category, in contrast, seem to be ignored by the market in aggregate.

In our main tests of market reactions to earnings announcements on big news days relative to other days, we find that business/economic news tends to attract attention to earnings announcements, while other news tends to be mildly distracting. Specifically, market reactions to earnings announcements tend to be stronger and followed by less post-earnings announcement drift when the earnings announcements fall on days with big business/economic news. For earnings announcements falling on days with big “other” news, the market reaction to the earnings announcement is attenuated relative to other days, although we find no differential drift pattern. We also find that the impact of big business/economics news is attenuated for firms with greater institutional investor ownership. Overall, these results are consistent with a model of information choice (Grossman and Stiglitz, 1980). In line with the prediction of our theory, investors are more attentive to firm-specific information on days with big business/economic news and higher economic uncertainty.

An important implication of our results is that the nature of the underlying event is the key factor in determining whether a big news event is distracting or attention-inducing. The distraction effect is consistent with prior studies showing that contemporaneous events such as other firms’ earnings announcements reduce market reactions to earnings announcements. The attention-inducing effect that we document, in contrast, is new to the literature, and
suggests that investors are not only prone to distraction, but also more attentive when they find it optimal.
References


A Appendix

A.1 Proof of Proposition 1

We start by describing the learning of $I$ and $U$ investors. $I$ investors observe \{\(e_t, G_t, \hat{P}_t\)\} but not \(f_{t+1}\). Thus, one can write

\[
\begin{bmatrix}
  f_{t+1} \\
  G_t \\
  \eta_t
\end{bmatrix} =
\begin{bmatrix}
  1 & 0 & 0 \\
  0 & 1 & 0 \\
  0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
  f_{t+1} \\
  e_t \\
  \eta_t
\end{bmatrix}.
\]  

(A.1)

We will apply the Projection Theorem, which we state here for convenience.

**Projection Theorem.** Consider the n-dimensional normal random variable

\[
\begin{bmatrix}
  \theta \\
  s
\end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix}
  \mu_\theta \\
  \mu_s
\end{bmatrix}, \begin{bmatrix}
  \Sigma_{\theta,\theta} & \Sigma_{\theta,s} \\
  \Sigma_{s,\theta} & \Sigma_{s,s}
\end{bmatrix}\right).
\]  

(A.2)

Provided \(\Sigma_{s,s}\) is non-singular, the conditional density of \(\theta\) given \(s\) is normal with conditional mean and conditional variance-covariance matrix:

\[
\mathbb{E}[\theta|s] = \mu_\theta + \Sigma_{\theta,s}\Sigma_{s,s}^{-1}(s - \mu_s) \\
\text{Var}[\theta|s] = \Sigma_{\theta,\theta} - \Sigma_{\theta,s}\Sigma_{s,s}^{-1}\Sigma_{s,\theta}.
\]  

(A.3, A.4)

This yields

\[
\mathbb{E}_I[f_{t+1}|e_t] = \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2} G_t \\
\text{Var}_I[f_{t+1}|e_t] = \frac{\sigma_\eta^2 \sigma_f^2}{\sigma_{f,t}^2 + \sigma_\eta^2}.
\]  

(A.5, A.6)

\(U\) investors observe \{\(G_t, \hat{P}_t\)\} but not \(f_{t+1}\) and \(e_t\). Thus, one can write

\[
\begin{bmatrix}
  f_{t+1} \\
  e_t \\
  G_t \\
  \hat{P}_t
\end{bmatrix} =
\begin{bmatrix}
  1 & 0 & 0 & 0 \\
  0 & 1 & 0 & 0 \\
  0 & 0 & 1 & 1 \\
  0 & 0 & 0 & -\xi_t / \alpha_t
\end{bmatrix}
\begin{bmatrix}
  f_{t+1} \\
  e_t \\
  \eta_t \\
  x_t
\end{bmatrix}.
\]  

(A.7)

This yields

\[
\mathbb{E}_U[f_{t+1}|e_t] = \left[\frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2} G_t \bigg| \frac{\sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} \hat{P}_t\right]
\]  

(A.8)

and

\[
\text{Var}_U[f_{t+1}|e_t] = \left[\frac{\sigma_{f,t}^2 \sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} \frac{\sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} \frac{\sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} \frac{\sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} \right].
\]  

(A.9)
Both $I$ and $U$ investors form expectations about $P_{t+1} + D_{t+1}$:

$$P_{t+1} + D_{t+1} = \frac{R_f}{R_f - 1} F + f_{t+1} + e_t + \beta_{t+1} G_{t+1} + \alpha_{t+1} e_{t+1} - \xi_{t+1} x_{t+1}.$$  \hfill (A.10)

For $I$ investors:

$$\mathbb{E}_I^t[P_{t+1} + D_{t+1}] = \frac{R_f}{R_f - 1} F + \frac{\sigma^2_{f,t}}{\sigma^2_{f,t} + \sigma^2_{\eta}} G_t + \frac{\sigma^2_e}{\sigma^2_e + \sigma^2_{\xi} / \alpha_t^2} \tilde{P}_t$$ \hfill (A.11)

$$\text{Var}_I^t[P_{t+1} + D_{t+1}] = \frac{\sigma^2_{f,t} \sigma^2_{\eta}}{\sigma^2_{f,t} + \sigma^2_{\eta}} + \sum_{k=1}^{K} \pi_k (\beta^2_{k,t+1} \sigma^2_{f,k} + \beta^2_{k,t+1} \sigma^2_{\eta} + \alpha^2_{k,t+1} \sigma^2_{e} + \xi^2_{k,t+1} \sigma^2_{\xi}) \cdot$$ \hfill (A.12)

In Eq. (A.12), $\pi_k$ represents the probability that $\sigma_{f,t+1} = \sigma_{f,k}$, and the term $\text{Var}[P_{t+1}]$ represents the variance of the future price. This variance is the same for $I$ and $U$ investors, and it does not change over time (the information that investors have at $t$ becomes irrelevant at $t+1$; furthermore, at any time $t$ investors face the same probability distribution over future values of $\sigma_{f,t+1}$, and thus over the values of the price coefficients at time $t+1$).

For $U$ investors:

$$\mathbb{E}_U^t[P_{t+1} + D_{t+1}] = \frac{R_f}{R_f - 1} F + \frac{\sigma^2_{f,t}}{\sigma^2_{f,t} + \sigma^2_{\eta}} G_t + \frac{\sigma^2_e}{\sigma^2_e + \sigma^2_{\xi} / \alpha_t^2} \tilde{P}_t$$ \hfill (A.13)

$$\text{Var}_U^t[P_{t+1} + D_{t+1}] = \frac{\sigma^2_{f,t} \sigma^2_{\eta}}{\sigma^2_{f,t} + \sigma^2_{\eta}} + \frac{\sigma^2_e \sigma^2_{\xi} / \alpha_t^2}{\sigma^2_e + \sigma^2_{\xi} / \alpha_t^2} + \text{Var}[P_{t+1}].$$ \hfill (A.14)

Imposing the market clearing condition (5) then yields the undetermined coefficients as in Eq. (10) of Proposition 1.

A.2 Proof of Proposition 2

In order to solve for the equilibrium share of $I$ investors, we need to compute expected utilities for both investor types, then impose that each individual investor must be indifferent between learning $e_t$ or not learning.

Without loss of generality, we will assume zero initial wealth for all investors. Replacing the asset demand into the expected utility of an uninformed investor yields

$$U^U = -\mathbb{E}_I^U \left[ e^{-\gamma q_{t}^U R_{t+1}} \right] = -\mathbb{E}_I^U \left[ e^{-\frac{q_{t}^U[R_{t+1}]}{\text{Var}_I^U[R_{t+1}]} R_{t+1}} \right] = -e^{-\frac{1}{2} \frac{q_{t}^U[R_{t+1}]}{\text{Var}_I^U[R_{t+1}]}}.$$ \hfill (A.15)

Similarly, for an informed investor,

$$U^I = -e^{\gamma c} e^{-\frac{1}{2} \frac{q_{t}^I[R_{t+1}]}{\text{Var}_I^U[R_{t+1}]}}.$$ \hfill (A.16)

For an uninformed investor, $\mathbb{E}_I^U[R_{t+1}]$ is a random variable with mean $\mathbb{E}_I^U[R_{t+1}]$ (by the law of iterated expectations) and variance $\text{Var}_I^U[e_t]$. We will take an expectation of (A.16) over the realizations of $e_t$. To do so, we use the following standard result from multivariate normal calculus (see, e.g., Veldkamp, 2011, p. 102).
Lemma 1. Consider a random vector \( z \sim N(0, \Sigma) \). Then,

\[
E \left[ e^{z'Fz + G'z + H} \right] = |I - 2\Sigma F|^{-\frac{1}{2}} e^\frac{1}{2} e_2^1G'(I - 2\Sigma F)^{-1}\Sigma G + H.
\]

Applying the above Lemma, we obtain

\[
E \left[ -e^{\gamma c e^{-\frac{1}{2} \frac{\xi^2_t}{\text{Var}_t[R_{t+1}]}}} \right] = U e^{\gamma c} \sqrt{\frac{\text{Var}_t[R_{t+1}] + \text{Var}_t[e_t]}{\text{Var}_t[R_{t+1}]}}.
\]  \hspace{1cm} (A.17)

Imposing the indifference condition that the expected utility in (A.15) equals the expected utility in (A.17) yields

\[
\sqrt{\frac{\text{Var}_t[R_{t+1}] + \text{Var}_t[e_t]}{\text{Var}_t[R_{t+1}]}} = e^{\gamma c},
\]  \hspace{1cm} (A.18)

which is Eq. (13) in the text.

From Eqs. (A.12) and (A.14) we obtain

\[
\text{Var}_t[e_t] = \frac{\sigma_e^2 \sigma_z^2 \xi_t^2 / \alpha_t^2}{\sigma_e^2 + \sigma_z^2 \xi_t^2 / \alpha_t^2} = \frac{\sigma_e^2}{1 + \Pi_t \sigma_e^2},
\]  \hspace{1cm} (A.19)

which can be replaced in Eq. (A.18) to obtain Eq. (14) in the text:

\[
\frac{\sigma_e^2 / \text{Var}_t[R_{t+1}]}{1 + \Pi_t \sigma_e^2} = e^{2\gamma c} - 1.
\]  \hspace{1cm} (A.20)

Proposition 2 results from replacing \( \Pi_t \) from Eq. (11) above and solving for \( \lambda_t^2 \). \( \Box \)
### A.3 Variable definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BE News</td>
<td>Daily index for news associated with business and economic events, identified by broad Story topic codes 7 and 8 or big Story code 862 (Economy). Source: Pew Research Center’s News Coverage Index.</td>
</tr>
<tr>
<td>GOV News</td>
<td>Daily index for news associated with government-related events, identified by broad Story topic codes 1, 2, 3, 4, and 25. Source: Pew Research Center’s News Coverage Index.</td>
</tr>
<tr>
<td>OTHER News</td>
<td>Daily index for news associated with events not classified as business, economic, or government-related events. Source: Pew Research Center’s News Coverage Index.</td>
</tr>
<tr>
<td>MKT</td>
<td>Daily market return factor based on excess returns to the market portfolio over the risk-free rate. Source: Kenneth French’s website.</td>
</tr>
<tr>
<td></td>
<td>Absolute value of MKT.</td>
</tr>
<tr>
<td>ILLIQ</td>
<td>Amihud (2002) firm-level daily illiquidity measure, calculated as 106 times a stock’s daily absolute return divided by a stock’s dollar volume. Value-weighted illiquidity used when calculated at the market level. Source: CRSP.</td>
</tr>
<tr>
<td>SPREAD</td>
<td>Log of daily bid-ask spread, calculated as a stock’s ask price minus bid price divided by the midpoint. Value-weighted spreads used when calculated at the market level. Source: CRSP.</td>
</tr>
<tr>
<td>TURN</td>
<td>Log of daily turnover, calculated as daily shares traded divided by shares outstanding. Value-weighted turnover used when calculated at the market level. Source: CRSP.</td>
</tr>
<tr>
<td>VOL</td>
<td>Log of total daily trading volume at the firm or market level. Source: CRSP.</td>
</tr>
<tr>
<td>VIX</td>
<td>Daily closing value of VIX. Source: CRSP.</td>
</tr>
<tr>
<td>SUE</td>
<td>Earnings surprise relative to analyst consensus forecasts deflated by quarter-end share price. Source: IBES, CRSP. When ranks are used, they are calculated across same-quarter announcements.</td>
</tr>
<tr>
<td>EARET</td>
<td>Compound excess stock return over the value-weighted index for earnings announcement date and 1 day after. Source: CRSP.</td>
</tr>
<tr>
<td>PEADx</td>
<td>Compound excess stock return over the value-weighted index from 2 days after the earnings announcement to x days after. Source: CRSP.</td>
</tr>
<tr>
<td>Size</td>
<td>Market value of equity on the earnings announcement date. Source: CRSP.</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>Book to market ratio at end of quarter for which earnings are announced. Source: Compustat.</td>
</tr>
<tr>
<td>EPersistence</td>
<td>Earnings persistence based on AR(1) regression with at least 4, up to 16 quarterly earnings. Source: Compustat.</td>
</tr>
<tr>
<td>IO</td>
<td>Institutional ownership as a fraction of total shares outstanding. Source: Thomson-Reuters 13F Data, CRSP.</td>
</tr>
<tr>
<td>EVOL</td>
<td>Standard deviation of seasonally differenced quarterly earnings. Source: Compustat.</td>
</tr>
<tr>
<td>ERepLag</td>
<td>Number of days from quarter-end to earnings announcement. Source: Compustat.</td>
</tr>
<tr>
<td>#Estimates</td>
<td>Number of analysts forecasting in the 90 days prior to the earnings announcement. Source: IBES.</td>
</tr>
<tr>
<td>Turn</td>
<td>Average monthly turnover for the 12 months preceding the earnings announcement. Source: CRSP.</td>
</tr>
<tr>
<td>Loss</td>
<td>Indicator for negative earnings. Source: Compustat.</td>
</tr>
<tr>
<td>#Announcements</td>
<td>Number of concurrent earnings announcements. Source: Compustat, IBES.</td>
</tr>
</tbody>
</table>
## Tables

Table 1: **Descriptive Statistics.**

This table reports descriptive statistics for the samples used in daily market-level analyses and analyses of returns around earnings announcements. Detailed definitions of all variables are available in Appendix A.3.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variables used in daily market-level analyses:</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BE News</td>
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<td>0.916</td>
<td>-0.461</td>
<td>-0.461</td>
<td>-0.461</td>
</tr>
<tr>
<td>GOV News</td>
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<td>0.000</td>
<td>0.919</td>
<td>-0.569</td>
<td>-0.569</td>
<td>0.588</td>
</tr>
<tr>
<td>OTHER News</td>
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<td>-0.629</td>
<td>0.737</td>
</tr>
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<td>MKT</td>
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<td>0.017</td>
<td>-0.007</td>
<td>0.001</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>MKT</td>
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<td>0.011</td>
<td>0.013</td>
<td>0.003</td>
<td>0.007</td>
</tr>
<tr>
<td>ILLIQ</td>
<td>1,247</td>
<td>-6.247</td>
<td>0.598</td>
<td>-6.693</td>
<td>-6.334</td>
<td>-5.953</td>
</tr>
<tr>
<td>SPREAD</td>
<td>1,247</td>
<td>-7.310</td>
<td>0.601</td>
<td>-7.779</td>
<td>-7.486</td>
<td>-6.930</td>
</tr>
<tr>
<td>TURN</td>
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<td>2.679</td>
<td>0.239</td>
<td>2.531</td>
<td>2.653</td>
<td>2.815</td>
</tr>
<tr>
<td>VOL</td>
<td>1,247</td>
<td>21.921</td>
<td>0.285</td>
<td>21.747</td>
<td>21.918</td>
<td>22.095</td>
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<tr>
<td>VIX</td>
<td>1,247</td>
<td>25.728</td>
<td>11.316</td>
<td>18.310</td>
<td>23.050</td>
<td>29.030</td>
</tr>
<tr>
<td><strong>Variables used in analyses around earnings announcement:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BE News</td>
<td>30,540</td>
<td>0.049</td>
<td>0.940</td>
<td>-0.461</td>
<td>-0.461</td>
<td>0.317</td>
</tr>
<tr>
<td>GOV News</td>
<td>30,540</td>
<td>0.120</td>
<td>0.991</td>
<td>-0.569</td>
<td>-0.569</td>
<td>1.098</td>
</tr>
<tr>
<td>OTHER News</td>
<td>30,540</td>
<td>-0.048</td>
<td>0.885</td>
<td>-0.629</td>
<td>-0.629</td>
<td>0.598</td>
</tr>
<tr>
<td>SUE Decile</td>
<td>30,540</td>
<td>5.568</td>
<td>2.812</td>
<td>3.000</td>
<td>6.000</td>
<td>8.000</td>
</tr>
<tr>
<td>EARET</td>
<td>30,540</td>
<td>0.004</td>
<td>0.088</td>
<td>-0.038</td>
<td>0.002</td>
<td>0.047</td>
</tr>
<tr>
<td>PEAD7</td>
<td>30,532</td>
<td>0.001</td>
<td>0.066</td>
<td>-0.030</td>
<td>-0.001</td>
<td>0.029</td>
</tr>
<tr>
<td>PEAD30</td>
<td>30,444</td>
<td>0.005</td>
<td>0.132</td>
<td>-0.058</td>
<td>-0.001</td>
<td>0.060</td>
</tr>
<tr>
<td>PEAD61</td>
<td>30,293</td>
<td>0.012</td>
<td>0.203</td>
<td>-0.086</td>
<td>0.001</td>
<td>0.090</td>
</tr>
<tr>
<td>PEAD90</td>
<td>30,152</td>
<td>0.014</td>
<td>0.256</td>
<td>-0.115</td>
<td>-0.002</td>
<td>0.117</td>
</tr>
<tr>
<td>Size</td>
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<td>8091.290</td>
<td>24340.590</td>
<td>687.123</td>
<td>1774.830</td>
<td>5247.280</td>
</tr>
<tr>
<td>Book-to-Market</td>
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<td>0.613</td>
<td>0.559</td>
<td>0.311</td>
<td>0.497</td>
<td>0.760</td>
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<tr>
<td>EPersistence</td>
<td>30,540</td>
<td>0.034</td>
<td>16.622</td>
<td>-0.015</td>
<td>0.191</td>
<td>0.455</td>
</tr>
<tr>
<td>IO</td>
<td>30,540</td>
<td>0.787</td>
<td>0.177</td>
<td>0.687</td>
<td>0.817</td>
<td>0.923</td>
</tr>
<tr>
<td>EVOL</td>
<td>30,540</td>
<td>6.774</td>
<td>364.514</td>
<td>0.152</td>
<td>0.341</td>
<td>0.786</td>
</tr>
<tr>
<td>ERepLag</td>
<td>30,540</td>
<td>30.855</td>
<td>12.103</td>
<td>24.000</td>
<td>29.000</td>
<td>36.000</td>
</tr>
<tr>
<td>#Estimates</td>
<td>30,540</td>
<td>7.786</td>
<td>6.121</td>
<td>3.000</td>
<td>6.000</td>
<td>11.000</td>
</tr>
<tr>
<td>Turn</td>
<td>30,540</td>
<td>0.265</td>
<td>0.189</td>
<td>0.146</td>
<td>0.215</td>
<td>0.326</td>
</tr>
<tr>
<td>Loss</td>
<td>30,540</td>
<td>0.160</td>
<td>0.366</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>#Announcements</td>
<td>30,540</td>
<td>106.824</td>
<td>66.553</td>
<td>50.000</td>
<td>100.000</td>
<td>160.000</td>
</tr>
</tbody>
</table>
Table 2: **Big News and Aggregate Market-Indicators.**
This table presents results from regressions of daily market-based indicators (\(\text{[MKT]}, \text{ILLIQ}, \text{SPREAD}, \text{TURN}, \text{VOL}\)) on the daily news indices and controls for daily value-weighted market returns and absolute returns, year effects, and day-of-week effects. Detailed definitions of all variables are available in Appendix A.3. All coefficients and standard errors are multiplied by 100. White heteroscedasticity-robust standard errors are reported below coefficient estimates. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(\text{[MKT]})</th>
<th>ILLIQ</th>
<th>SPREAD</th>
<th>TURN</th>
<th>VOL</th>
<th>VIX</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BE News</strong></td>
<td>0.43***</td>
<td>6.687***</td>
<td>10.182***</td>
<td>3.505***</td>
<td>6.016***</td>
<td>282.361***</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(1.658)</td>
<td>(1.522)</td>
<td>(0.824)</td>
<td>(0.888)</td>
<td>(37.930)</td>
</tr>
<tr>
<td><strong>GOV News</strong></td>
<td>0.003</td>
<td>-0.165</td>
<td>-1.144</td>
<td>-0.938*</td>
<td>-0.936</td>
<td>23.984</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(1.334)</td>
<td>(1.136)</td>
<td>(0.567)</td>
<td>(0.628)</td>
<td>(28.434)</td>
</tr>
<tr>
<td><strong>Other News</strong></td>
<td>0.009</td>
<td>-1.143</td>
<td>0.071</td>
<td>0.241</td>
<td>0.963</td>
<td>34.562</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(1.278)</td>
<td>(1.079)</td>
<td>(0.647)</td>
<td>(0.680)</td>
<td>(24.470)</td>
</tr>
<tr>
<td><strong>MKT</strong></td>
<td>-109.094</td>
<td>-98.183</td>
<td>-24.611</td>
<td>-49.029</td>
<td>-6199.758</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(76.213)</td>
<td>(64.121)</td>
<td>(35.488)</td>
<td>(36.016)</td>
<td>(1820.799)</td>
<td></td>
</tr>
<tr>
<td><strong>[MKT]</strong></td>
<td>1550.767***</td>
<td>1119.568***</td>
<td>608.128***</td>
<td>702.570***</td>
<td>37605.154***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(112.706)</td>
<td>(96.486)</td>
<td>(54.990)</td>
<td>(55.684)</td>
<td>(2534.001)</td>
<td></td>
</tr>
<tr>
<td><strong>Year FE</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Day-of-week FE</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Number of obs.</strong></td>
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<td>1,247</td>
<td>1,247</td>
<td>1,247</td>
<td>1,247</td>
<td>1,247</td>
</tr>
<tr>
<td><strong>R-square</strong></td>
<td>0.174</td>
<td>0.58</td>
<td>0.683</td>
<td>0.336</td>
<td>0.461</td>
<td>0.523</td>
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</table>
Table 3: **Big News and Earnings Announcement Returns**.
This table presents results of regressions of earnings announcement returns (EARET) on earnings surprise deciles based on quarterly sorts interacted with the news deciles and indicators for top-quintile news index days. Control variables include: Size, Book-to-Market, EPersistence, IO, EVOL, ERepLag, #Estimates, Turn, Loss, #Announcements, day-of-week indicators, and each of these interacted with SUE Decile. Detailed definitions of all variables are available in Appendix A.3. Standard errors for the coefficients are clustered by date. All coefficients and standard errors are multiplied by 100. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Raw News Index Scores</th>
<th>News Index Top Quintile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BE News</td>
<td>GOV News</td>
</tr>
<tr>
<td>SUE Decile</td>
<td>1.08***</td>
<td>1.08***</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>News Index</td>
<td>-0.54***</td>
<td>-0.18</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>SUE Decile * News Index</td>
<td>0.09***</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Controls interacted with SUE Decile</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Date-clustered SE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of obs.</td>
<td>30,540</td>
<td>30,540</td>
</tr>
<tr>
<td>R-square</td>
<td>0.14</td>
<td>0.14</td>
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</table>
Table 4: Business and Economics News and Post-Earnings Announcement Drift. This table presents results of regressions of post-earnings announcement returns (PEAD) on earnings surprise deciles based on quarterly sorts interacted with the BE News index. Control variables include: Size, Book-to-Market, EPersistence, IO, EVOL, ERepLag, #Estimates, Turn, Loss, #Announcements. Detailed definitions of all variables are available in Appendix A.3. Standard errors for the coefficients are clustered by date. All coefficients and standard errors are multiplied by 100. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dep. Variable:</th>
<th>PEAD7</th>
<th>PEAD30</th>
<th>PEAD61</th>
<th>PEAD90</th>
</tr>
</thead>
<tbody>
<tr>
<td>SUE Decile</td>
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<td>1.01***</td>
<td>1.36***</td>
<td>1.17**</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.33)</td>
<td>(0.47)</td>
<td>(0.55)</td>
</tr>
<tr>
<td>BE News</td>
<td>0.32*</td>
<td>0.14</td>
<td>1.88***</td>
<td>1.51*</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.40)</td>
<td>(0.68)</td>
<td>(0.80)</td>
</tr>
<tr>
<td>SUE Decile*BE News</td>
<td>-0.07***</td>
<td>-0.07</td>
<td>-0.15*</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Controls interacted with SUE decile</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Date-clustered SE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of obs.</td>
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<td>30,445</td>
<td>30,294</td>
<td>30,153</td>
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<tr>
<td>R-square</td>
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<td>0.02</td>
<td>0.02</td>
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</table>
Table 5: The Effect of BE News on Institutional and Retail Investor Attention.  
This table presents results of regressions of announcement-window and post-earnings announcement excess returns on earnings surprise deciles based on quarterly sorts interacted with the BE News index and the fraction of shares held by institutions (IO). In the regressions, IO is standardized to be mean-zero and unit-variance. Control variables include: Size, Book-to-Market, EPersistence, EVOL, ERepLag, #Estimates, Turn, Loss, #Announcements. Detailed definitions of all variables are available in Appendix A.3. Standard errors for the coefficients are clustered by date. All coefficients and standard errors are multiplied by 100. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dep. Variable</th>
<th>EARET</th>
<th>PEAD7</th>
<th>PEAD30</th>
<th>PEAD61</th>
<th>PEAD90</th>
</tr>
</thead>
<tbody>
<tr>
<td>SUE Decile</td>
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<td>0.33***</td>
<td>0.81***</td>
<td>1.09***</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.27)</td>
<td>(0.40)</td>
<td>(0.45)</td>
</tr>
<tr>
<td>BE News</td>
<td>-0.54***</td>
<td>0.32*</td>
<td>0.13</td>
<td>1.87***</td>
<td>1.50*</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.19)</td>
<td>(0.39)</td>
<td>(0.68)</td>
<td>(0.80)</td>
</tr>
<tr>
<td>SUE Decile * BE News</td>
<td>0.09***</td>
<td>-0.07***</td>
<td>-0.07</td>
<td>-0.15*</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>IO</td>
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<td>-0.01</td>
<td>0.19</td>
<td>-0.20</td>
<td>0.29</td>
</tr>
<tr>
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<td>(0.13)</td>
<td>(0.14)</td>
<td>(0.28)</td>
<td>(0.40)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>SUE Decile * IO</td>
<td>0.09***</td>
<td>-0.01</td>
<td>-0.05</td>
<td>-0.05</td>
<td>-0.13*</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.04)</td>
<td>(0.06)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>BE News * IO</td>
<td>0.32**</td>
<td>0.00</td>
<td>-0.15</td>
<td>-0.27</td>
<td>0.32</td>
</tr>
<tr>
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<td>(0.17)</td>
<td>(0.42)</td>
<td>(0.60)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>SUE Decile * BE News * IO</td>
<td>-0.06**</td>
<td>0.00</td>
<td>0.03</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.11)</td>
</tr>
</tbody>
</table>

Controls interacted with SUE decile  Yes    Yes    Yes    Yes    Yes
Date-clustered SE                  Yes    Yes    Yes    Yes    Yes
Number of obs.                     30,540  30,533  30,445  30,294  30,153
R-Square                            0.142  0.009  0.018  0.024  0.017