Economic Uncertainty and Investor Attention

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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. Higher uncertainty weakens the informativeness of stock prices, which increases investors' incentive to search for information. The model yields clear testable predictions that we take to the data. We show that corporate earnings announced on days with higher economic uncertainty are associated with larger increases in SEC EDGAR queries, stronger earnings response coefficients, and weaker post-earnings announcement drift. Overall, these findings suggest that economic uncertainty attracts investor attention to firm-specific information and improves price discovery around earnings announcements.

JEL classification: G14; G41; M41.

Keywords: Investor attention; Economic uncertainty; Firm-specific news; Earnings announcements.

1 Introduction

The limited investor attention theory (Hirshleifer and Teoh, 2003; DellaVigna and Pollet, 2009) posits that due to cognitive resource constraints, investors can neglect value relevant information and may not incorporate all available information into prices. Ample evidence supports this theory. Hirshleifer, Lim, and Teoh (2009), for instance, show that stock price reactions to earnings announcements are weaker when earnings are released on days with many competing earnings announcements. Other studies document a muted market reaction to Friday earnings or merger announcements (DellaVigna and Pollet, 2009; Louis and Sun, 2010), or distraction effects caused by extraneous and unrelated events, such as the March Madness college basketball tournament or marital transitions (Drake, Gee, and Thornock, 2016; Lu, Ray, and Teo, 2016). Overall, these studies support the notion that investors are prone to distraction by irrelevant news events and neglect value relevant information, which attenuates short-term reactions to firm-specific news.

The above studies have focused mainly on events unrelated to economic fundamentals. Relatively little is known, however, about investors' attention behavior during economically important events, which are associated with increased economic uncertainty. In this paper, we fill this gap by examining the theoretical link between economic uncertainty and investor attention. In a dynamic model of information acquisition, building on Grossman and Stiglitz (1980), we show that higher economic uncertainty induces greater investor attention to firm-specific information. 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 higher economic uncertainty. Conversely, investor attention is optimally weaker on days with irrelevant news events, when economic uncertainty is low.

The channel through which investor attention to firm specific information increases with economic uncertainty is price informativeness. In the model, the equilibrium asset price conveys information from the informed to the uninformed investors. When economic uncertainty is high, price informativeness weakens, which increases the incentive of the uninformed investors to become informed. Although higher economic uncertainty may also decrease the benefit from acquiring information, the price informativeness effect dominates, except when economic uncertainty is implausibly high. Thus, investor attention to firm-specific information increases with economic uncertainty.

The model yields several testable predictions. First, greater investor attention to firm-specific information implies that price efficiency should be higher on days with higher economic uncertainty than on other days. Stated differently, stock prices should incorporate

firm-specific information faster on the day of its announcement when economic uncertainty is high. Furthermore, days with higher economic uncertainty should be associated with stronger demand for firm-specific information.

To test these theoretical predictions, 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 a daily subject-specific index of news coverage for news related to business/economics. This 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 index.

We first show that our business/economic news index is significantly associated with market-wide measures that plausibly capture economic uncertainty, including expected volatility as reflected in the VIX, the Equity Market Uncertainty and the Economic Policy Uncertainty indices from Baker, Bloom, and Davis's Economic Policy Uncertainty website (Baker, Bloom, and Davis, 2016), bid-ask spreads, absolute returns and market turnover.

We next examine how economic uncertainty uncertainty affects market reactions to firm-specific information. We find evidence consistent with higher economic uncertainty driving investors to be attentive to the information contained in earnings announcements. In particular, we show that investors' search for information, measured by the number of access queries to company-specific filings on the SEC EDGAR website, intensifies when aggregate uncertainty is higher. Furthermore, we find that the market reacts more strongly to earnings news on days with higher economic uncertainty. Finally, there is less post-earnings announcement drift following earnings released on high uncertainty days than following earnings released on other days. 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 study contributes to the literature on limited investor attention. Prior research on this topic primarily focuses on providing empirical evidence on the effect of irrelevant or distracting exogenous news on investor attention (e.g. Hirshleifer et al., 2009; Drake et al., 2016). We add to this research by providing a theoretical basis for the effect of *relevant* exogenous events on investor attention. The empirical findings support our theoretical result that heightened economic uncertainty causes investors to optimally seek out more firm-

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specific information on days with important economy-wide information. Investors, therefore, allocate more attention to value relevant information when they find it optimal. In this respect, our study demonstrates a flip side to the research on the limited attention theory.

In our theory, investors are active learners and exercise control over purchasing information. Active learning has a long tradition in economics and finance, starting with seminal papers by Grossman and Stiglitz (1980) and Sims (1998, 2003).[1] Models of information choice can explain the home bias puzzle (Van Nieuwerburgh and Veldkamp, 2009), investment and attention allocation behavior (Van Nieuwerburgh and Veldkamp, 2010; Andrei and Hasler, 2019), the attention allocation of mutual fund managers (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016), or the comovement of asset returns (Peng and Xiong, 2006; Veldkamp, 2006). We contribute to this literature by studying how fluctuations in economic uncertainty determine the attention behavior of rational investors.

We also add to the growing body of empirical literature that investigates the determinants of investor attention. Because attention is unobservable, several proxies have been proposed: trading volume or price limits (Gervais, Kaniel, and Mingelgrin, 2001; Li and Yu, 2012); news proxies (Yuan, 2015); volume of Google searches (Da, Engelberg, and Gao, 2011); logins to investment accounts (Karlsson, Loewenstein, and Seppi, 2009; Sicherman, Loewenstein, Seppi, and Utkus, 2015); or web browsing behavior within investors' brokerage domain (Gargano and Rossi, 2018). We proxy investor attention to firm-specific information by the number of SEC EDGAR logs of access to company-specific fillings, and provide evidence that attention to firm-specific information increases on days with greater economic uncertainty.

Finally, our paper relates to studies examining the stock price reactions to the interplay between 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. In a concurrent and complementary paper, Bonsall, Green, and Muller (2019) provide evidence of greater media coverage of earnings announcements when economic policy uncertainty is high. We add to this literature by examining changes in market reactions to firm-specific information based on the changes in

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[1]An extensive survey of this literature can be found in Veldkamp (2011).

a daily business/economics news index that we introduce. The index is similar in spirit to the one built by Baker et al. (2016) and is a daily metric of news intensity that takes into account the content and significance of news stories and provides a basis to examine the effect of news on prices.

The paper proceeds as follows. Section 2 introduces a theoretical model of rational attention allocation and develops testable predictions. Section 3 details our proxies for economic uncertainty and presents results from empirical analyses. Section 4 concludes.

2 Model

We develop a model of trading where all investors are exposed to a firm's announcement about future profitability. 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.

2.1 Static setup

We first develop the intuition behind our main result in a static model of information acquisition (Grossman and Stiglitz, 1980). In Section 2.2, we show that the same intuition holds in a fully dynamic setup, which we build in the spirit of DellaVigna and Pollet (2009). The role of the dynamic setup is to help us derive testable predictions that we will take to the data in Section 3.

Consider an economy populated by a continuum of investors, indexed by $i \in [0, 1]$. The economy has three dates $t \in \{0, 1, 2\}$. At $t = 0$, each investor makes an information acquisition decision that we will describe below. At $t = 1$, investors trade competitively in financial markets. At $t = 2$, financial assets' payoffs are realized and investors derive utility from consuming their terminal wealth.

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 an equilibrium price P_1 at $t = 1$ and pays a risky dividend at $t = 2$:

$$D_2 = F + f_2 + e_1. \tag{1}$$

The dividend has three components: a mean $F > 0$; a systematic component, $f_2 \sim N(0, \sigma_f^2)$; and a firm-specific component, $e_1 \sim N(0, \sigma_e^2)$. The firm-specific component is announced by the firm at $t = 1$, and thus can be interpreted as an earnings announcement.

The mean F is common knowledge to all investors at $t = 0$. The variance of the systematic component f_2, σ_f^2, and the variance of e_1, σ_e^2, are constant and known by investors at $t = 0$. Finally, f_2 and e_1 are independent.

At $t = 1$, all investors observe a public signal about the economy:

$$G_1 = f_2 + \eta_1, \tag{2}$$

where $\eta_1 \sim N(0, \sigma_\eta^2)$, drawn independently from f_2 and e_1.

At $t = 0$, each investor i chooses whether to be attentive to the earnings announcement e_1, which will be announced at $t = 1$. We adopt this information choice from Grossman and Stiglitz (1980), and we denote investor i's decision by the variable L_0^i: if investor i decides to be attentive to the firm's announcement, then $L_0^i = 1$; otherwise, $L_0^i = 0$.

We assume that each investor i starts with zero initial wealth and maximizes expected utility:[2]

$$U^i = \mathbb{E}_0^i \left[-e^{-\gamma(W_2^i - cL_0^i)} \right], \tag{3}$$

where γ is the risk aversion coefficient, W_2^i is investor i's wealth at $t = 2$, and cL_0^i represents the monetary cost of paying attention to the earnings announcement. The information cost parameter c is positive.

Investors who decide to become informed about the firm's earnings perfectly observe e_1 at $t = 1$. We refer to them as I investors, and to the investors who decide to remain uninformed as U investors. Notice, however, that U investors are still able to partially infer e_1 from the equilibrium price, as we will describe below. This tradeoff, between paying attention to firm-specific information or inferring information from the price for free, sets the theoretical basis of our argument.

At $t = 1$, investors choose optimal portfolios:

$$q_1^i = \frac{\mathbb{E}_1^i[D_2] - R_f P_1}{\gamma \operatorname{Var}_1^i[D_2]}, \quad \text{for } i \in \{I, U\}, \tag{4}$$

where the superscript i in $\mathbb{E}_1^i[\cdot]$ and $\operatorname{Var}_1^i[\cdot]$ reads "under the information set of investor i."

The risky asset is in random supply, $x_1 \sim N(0, \sigma_x^2)$, and it is drawn independently from f_2, e_1, and η_1. Random supply prevents the price from perfectly revealing e_1 (Grossman and Stiglitz, 1980); it also prevents agents from refusing to trade (Milgrom and Stokey, 1982). Letting λ_1 be the equilibrium proportion of I investors, the price of the risky asset is

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[2] The assumption of zero initial wealth is without loss of generality, because a CARA investor's demand for risky assets is independent of initial wealth.

determined by the market clearing condition:

$$\lambda_1 q_1^I + (1 - \lambda_1) q_1^U = x_1. \tag{5}$$

2.1.1 Equilibrium

As is customary in noisy rational expectations models, we conjecture a linear form for the equilibrium price:

$$P_1 = F/R_f + \beta_1 G_1 + \alpha_1 e_1 - \xi_1 x_1. \tag{6}$$

For an uninformed investor who does not pay attention to e_1, the price partially reveals e_1 for free (as long as $\alpha_1 \neq 0$). More precisely, one can transform the equilibrium price into an informationally equivalent signal about e_1:

$$\widehat{P}_1 \equiv \frac{P_1 - F/R_f - \beta_1 G_1}{\alpha_1} = e_1 - \frac{\xi_1}{\alpha_1} x_1. \tag{7}$$

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 $\{e_1, G_1, \widehat{P}_1\}$, whereas the information set of U investors is $\{G_1, \widehat{P}_1\}$. Defining the dollar excess return of the risky asset as $R_2^e \equiv D_2 - R_f P_1$, an application of the Projection Theorem (see Appendix A.1) yields I investors' asset demand:

$$q_1^I = \frac{1}{\gamma \operatorname{Var}_1^I[R_2^e]} \left(F + \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\eta^2} G_1 + e_1 - R_f P_1 \right), \tag{8}$$

and U investors' asset demand:

$$q_1^U = \frac{1}{\gamma \operatorname{Var}_1^U[R_2^e]} \left(F + \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\eta^2} G_1 + \frac{\sigma_e^2}{\sigma_e^2 + \xi_1^2 \sigma_x^2/\alpha_1^2} \widehat{P}_1 - R_f P_1 \right). \tag{9}$$

There are two main differences between the asset demands q_1^I and q_1^U. First, U investors use the price signal to learn about e_1: 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 investors demand more because their conditional variance of future returns is lower: $\operatorname{Var}_1^I[R_2^e] < \operatorname{Var}_1^U[R_2^e]$.

Adding the two demand expressions (8) and (9) weighted by λ_1 and $1 - \lambda_1$, and setting the total equal to x_1 yields the market clearing condition (5). The coefficients β_1, α_1, and ξ_1 are then determined by matching coefficients. Proposition 1, whose proof is provided in

Appendix A.1, characterizes these equilibrium coefficients.

Proposition 1. *In equilibrium, the price coefficients β_1, α_1, and ξ_1 are given by*

$$\beta_1 = \frac{\sigma_f^2}{R_f(\sigma_f^2 + \sigma_\eta^2)}, \quad \alpha_1 = \frac{1}{R_f}\left(1 - \frac{1 - \lambda_1}{1 + \Pi_1 + \gamma\sigma_x\sigma_e\sqrt{\Pi_1}}\right), \quad and \ \xi_1 = \frac{\sigma_e}{\sigma_x\sqrt{\Pi_1}}\alpha_1, \qquad (10)$$

where Π_1 represents the price informativeness, i.e., the capacity of the price to reveal e_1 to uninformed investors. More precisely, we define $\Pi_1 \in [0, \infty)$ as a strictly increasing function of the squared correlation coefficient between $\widehat{P}_1$ and e_1, ρ_1^2:

$$\Pi_1 \equiv \frac{\rho_1^2}{1 - \rho_1^2} = \frac{\lambda_1^2\sigma_e^2}{\gamma^2 \operatorname{Var}_1^I[R_2^e]^2\sigma_x^2}. \qquad (11)$$

Price informativeness increases with the fraction of informed investors: when more investors observe e_1, their aggregate demand comprises a large share of the total demand, increasing the information content of the price. Moreover, 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 informativeness of price. Furthermore, as we show in Appendix A.1, $\operatorname{Var}_1^I[R_2^e]$ can be written as

$$\operatorname{Var}_1^I[R_2^e] = \frac{\sigma_\eta^2}{1 + \sigma_\eta^2/\sigma_f^2}, \qquad (12)$$

Thus, the variance of future returns, as perceived by I investors, is strictly increasing in the economy-wide uncertainty σ_f^2. As a result, *ceteris paribus*, price informativeness decreases with economic uncertainty.

Notice, however, that investors are free to choose their information set, meaning that λ_1 endogenously depends on σ_f^2. Since our aim is to measure the overall effect of uncertainty on the price coefficients in Proposition 1, we need to understand how investors' demand for information is driven by economic uncertainty.

2.1.2 Demand for information

In equilibrium, each investor must be indifferent between observing e_1 or not. As in Grossman and Stiglitz (1980), this indifference condition yields (see Appendix A.2):

$$\sqrt{\frac{\operatorname{Var}_1^U[R_2^e]}{\operatorname{Var}_1^I[R_2^e]}} = e^{\gamma c}. \qquad (13)$$

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The left hand side measures the benefit of observing e_1; the right hand side measures the cost. The benefit of observing e_1 is always larger than one and increases in the ratio of return variance without the information to return variance with information. Further decomposing $\text{Var}_1^U[R_2^e] = \text{Var}_2^I[R_2^e] + \text{Var}_1^U[e_1]$ and replacing it above yields a simple tradeoff between the benefit and cost of observing e_1:

$$\frac{\sigma_e^2 / \text{Var}_1^I[R_2^e]}{1 + \Pi_1} = e^{2\gamma c} - 1. \tag{14}$$

An increase in uncertainty—as measured by an increase in σ_f^2 and therefore an increase in $\text{Var}_1^I[R_2^e]$—has two effects on the benefit of observing e_1. First, it reduces the ratio $\sigma_e^2 / \text{Var}_1^I[R_2^e]$. This ratio measures the the quality of informed investors' information (Grossman and Stiglitz, 1980). A smaller ratio means less gains from learning. Thus, higher economic uncertainty *decreases* the incentive to learn e_1, which leads to less information acquisition, or to a lower λ_1.

A second effect arises in the denominator on the left hand side of (14): when uncertainty increases, the price becomes less informative, and thus Π_1 decreases (as shown in Eq. 11). As demonstrated by Grossman and Stiglitz (1980), a less informative price *increases* the incentive to acquire information—because investors learn less from the price, the value of information increases, yielding a higher λ_1.

Overall, the change in λ_1 caused by an increase in uncertainty depends on the balance between the above effects. The price informativeness effect—the increase in λ_1 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 (see Appendix A.2 for the proof).

Proposition 2. *In equilibrium, the fraction λ_1 of investors who decide to pay attention to the earnings announcement solves the following implicit equation:*

$$\lambda_1^2 = \gamma^2 \sigma_x^2 \text{Var}_1^I[R_2^e] \left(\frac{1}{e^{2\gamma c} - 1} - \frac{\text{Var}_1^I[R_2^e]}{\sigma_e^2} \right). \tag{15}$$

Equation (15) is implicit because λ_1 and $\text{Var}_1^I[R_2^e]$ 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 $\text{Var}_1^I[R_2^e]$, with two distinct zeros: $\text{Var}_1^I[R_2^e] = 0$ and $\text{Var}_1^I[R_2^e] = \sigma_e^2 / (e^{2\gamma c} - 1)$. The curved line in Figure 1 depicts the
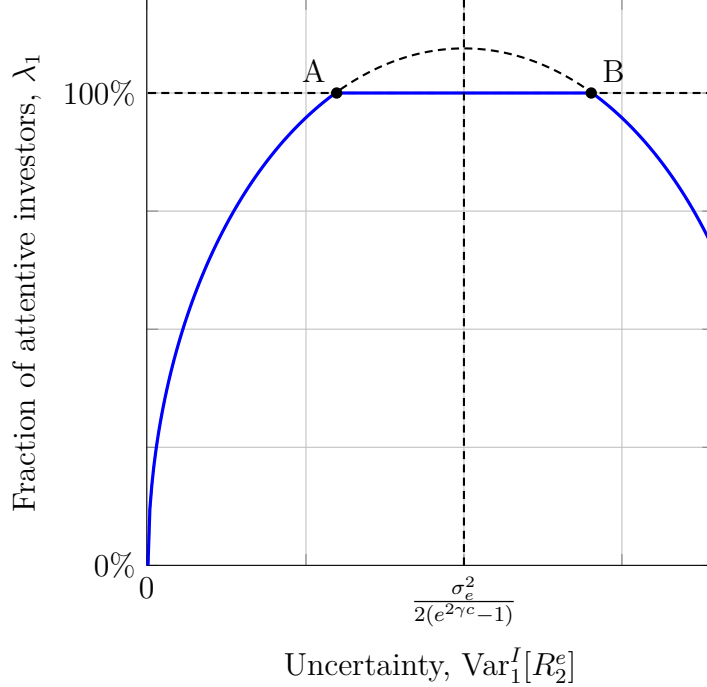
Figure 1: **Uncertainty and investor attention to earnings information**
This figure plots the equilibrium fraction of I investors, λ_1, as a function of the uncertainty about future returns perceived by I investors, $\mathrm{Var}_1^I[R_2^e]$ (Proposition 2). The curve reaches a maximum at $\mathrm{Var}_1^I[R_2^e] = \sigma_e^2/(2(e^{2\gamma c} - 1))$. The fraction λ_1 is capped below at 0% and above at 100%. Hence, between the dots labeled A and B, all investors are informed.

square root of this function. As the plot shows, λ_1 reaches a (theoretical) maximum when

$$\frac{\mathrm{Var}_1^I[R_2^e]}{\sigma_e^2} = \frac{1}{2(e^{2\gamma c} - 1)}. \tag{16}$$

The plot further shows that λ_1 increases at first, until it reaches 100% (dot labeled A on the plot).[3] A further increase in uncertainty beyond this point keeps the equilibrium level of λ_1 at 100%. Once λ_1 reaches its (theoretical) maximum value, a further increase in uncertainty dominates the potential gains of learning about earnings. Beyond this point, λ_1 decreases, and at the dot labeled B it gets below 100%. In this case, the quality of informed investors' information $\sigma_e^2/\mathrm{Var}_1^I[R_2^e]$ 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_1 is low. With earnings-related information being relatively cheap and accessible, the cost of being attentive to earnings announcements is most likely small.

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[3]If the cost of being attentive to firm-specific information is sufficiently large, the maximum proportion of attentive investors may not necessarily reach 100%.

Thus, the maximum obtained in Eq. (16) is not easily reached.[4] We do not exclude this possibility, but the effects that we document in our empirical section are mostly consistent with a small information cost.

2.1.3 Response to firm-specific information

Our main object of interest is the price response to firm-specific information, α_1. As can be seen from Proposition 1, α_1 is strictly increasing in the proportion λ_1 of I investors (both directly through the numerator in (10) and indirectly through an increase in price informativeness in the denominator). More precisely, the coefficient α_1 goes from 0 (when $\lambda_1 = 0$) to a maximum of $1/R_f$ (when $\lambda_1 = 1$). This is illustrated in Figure 2, where the two curves that increase from 0 to $1/R_f$ depict the coefficient α_1 as a function of λ_1, for two different levels of uncertainty.

The plot further shows that, keeping λ_1 constant, an increase in uncertainty unambiguously lowers α_1, in line with Proposition 1: more uncertainty leads to less aggressive trading from informed investors, which decreases price informativeness and in turn decreases α_1. Indeed, the dashed curve that increases from 0 to $1/R_f$ remains below the solid curve at all interior points. Considering a hypothetical equilibrium value depicted with the dot labeled A, a higher level of uncertainty pushes α_1 towards the dot labeled B. However, as shown 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 λ_1. This increases the coefficient α_1 and is illustrated in the plot with a move from B to C. A large enough increase in λ_1 can push α_1 to a level higher than before.

It is important to emphasize that λ_1 is not the only parameter that can change α_1. Other market-wide parameters that can affect α_1 are the risk aversion γ and the volatility of noise trading σ_x. Nevertheless, an increase in any of these parameters would *decrease* α_1.[5] Thus, we would need a lower risk aversion parameter and/or less volatile noise trading (both are unlikely to occur during high uncertainty days) in order to obtain a higher α_1. We have therefore formulated a clear theoretical prediction: if investors are more attentive to earnings announcements when economic uncertainty is high, then we should observe a stronger price response to earnings announcements (i.e., higher α_1).

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[4]For instance, if $\gamma = 3$ and $c = 0.001$ (i.e., the cost of information is 0.1% of final wealth), the right hand side is larger than 80. This means that the uncertainty of future returns perceived by *informed* investors should be at least 80 times larger than the uncertainty of earnings in order to obtain a decrease in λ_1. Blankespoor, deHaan, and Zhu (2018) show that earnings announcements with accompanying algorithmic coverage by the Associated Press were associated with greater trading volume and liquidity, consistent with a positive cost of attention to earnings announcements being lowered by such automated coverage.

[5]After replacing price informativeness from (11) in α_1 from (10), one can differentiate α_1 with respect to γ and σ_x. Both derivatives are negative. Thus, α_1 decreases in γ and in σ_x.
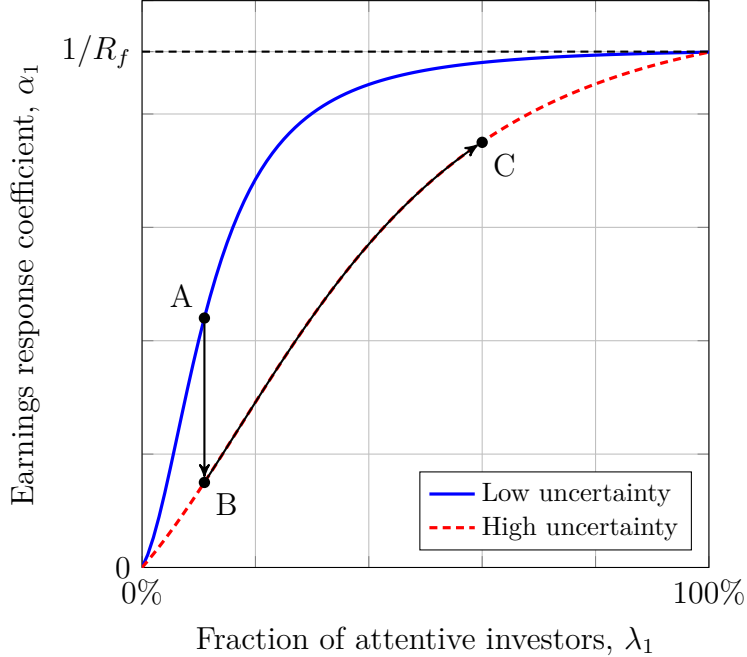
Figure 2: **Investor attention and the earnings response coefficient α_1**
This figure plots the earnings response coefficient (ERC) α_1 as a function of the fraction of I investors, λ_1. The two curves (solid and dashed) plot the ERC for a low and high level of uncertainty σ_f, respectively. In both cases, the ERC increases from 0 to $1/R_f$, but the ERC is lower when uncertainty is high. 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 λ_1 caused by the increase in uncertainty.

We now formalize this intuition in a dynamic model of trading with fluctuating economic uncertainty. The dynamic model allows us to build testable theoretical predictions.

2.2 Dynamic setup and testable predictions

We adopt the dynamic structure from DellaVigna and Pollet (2009), which we modify in two ways. First, we insert fluctuations in economic uncertainty. Second, as in the static model, we let investors optimally decide whether to be attentive or not to firm's announcements.

The dynamic setup consists of an overlapping-generations economy in which a new generation of investors is born every period. We refer to the generation of investors that is born at time t as *generation t*. Each generation is present in the economy for three dates and makes information acquisition and trading decisions sequentially, as in the static model. Focusing on generation $t-1$, each investor $i \in [0,1]$ in this generation makes an information choice between $t-1$ and t, then trades to take positions in securities at t, and consumes final wealth at $t+1$. As such, generation $t-1$ investors liquidate their holdings at time $t+1$
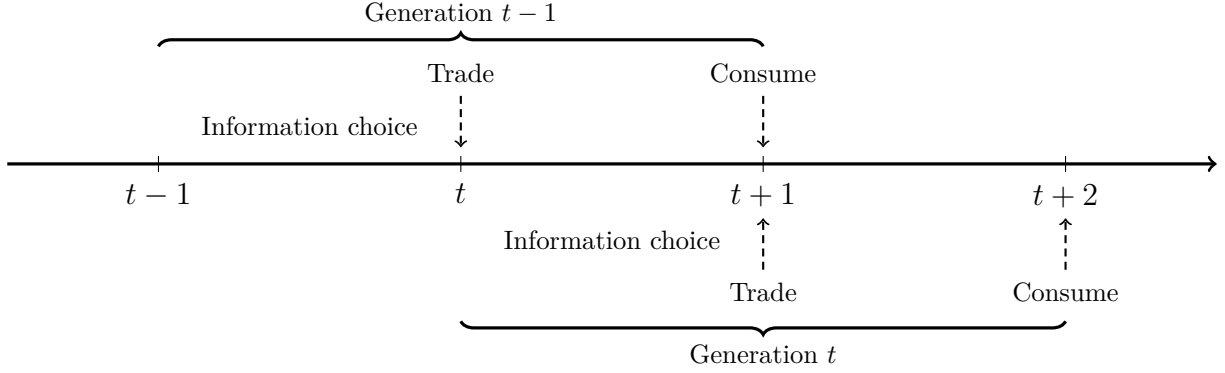
Figure 3: **Overlapping generations economy**

by selling them at market prices to generation t investors. Figure 3 shows a timeline.

As in the static model, 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 pays a risky dividend per period,

$$D_{t+1} = F + f_{t+1} + e_t, \tag{17}$$

which has three components: a long-term mean $F > 0$; a systematic component, $f_{t+1} \sim N(0, \sigma_{f,t}^2)$; and a firm-specific component, $e_t \sim N(0, \sigma_e^2)$.

The main difference with the static model is that we allow for the variance of f_{t+1}, $\sigma_{f,t}^2$, to be time-varying. More precisely, we assume that $\sigma_{f,t}^2$ takes one of $K \geq 2$ possible values, indexed by $k \in \{1, ..., K\}$, and we denote the probability of the event $\sigma_{f,t} = \sigma_{f,k}$ by π_k. Furthermore, $\sigma_{f,t}^2$ is observable to generation $t - 1$ investors, who make an information choice between $t - 1$ and t and subsequently trade in the market at t. One could assume, for instance, that $\sigma_{f,t}^2$ is revealed at time $t - \varepsilon$, where ε is very small (e.g., a fraction of a second). This assumption preserves the sequentiality of the information acquisition and trading decisions as in Grossman and Stiglitz (1980).

Investors who trade in the market at time t observe a public signal about the economy, $G_t = f_{t+1} + \eta_t$, where $\eta_t \sim N(0, \sigma_\eta^2)$. Furthermore, each investor $i \in [0, 1]$ of generation $t - 1$ starts with zero initial wealth and maximizes expected utility:

$$U_{t-1}^i = \mathbb{E}_{t-1}^i \left[-e^{-\gamma(W_{t+1}^i - cL_{t-\varepsilon}^i)} \right], \tag{18}$$

where $W_{t+1}^i \equiv q_t^i(D_{t+1} + P_{t+1} - R_f P_t) \equiv q_t^i R_{t+1}^e$ is investor i's terminal wealth, and γ, c, and $L_{t-\varepsilon}^i$ are defined as before.

The equilibrium in this dynamic model follows the same steps as in the static model. We

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refer the reader to Appendix A.3 for details. Two differences with the static model are worth mentioning here. First, 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. Our theoretical results hold in both equilibria. The second difference is that the future price P_{t+1} is an additional random variable in investors' portfolio choice problem at time t. Because the distribution of future prices is non-Gaussian (due to variation in $\sigma_{f,t+1}^2$), the equilibrium cannot be solved in closed form. Consequently, we resort to the approximation proposed by Vayanos and Weill (2008) and Gârleanu (2009). This approximation preserves risk aversion towards diffusion risks, while inducing risk neutrality towards future changes in $\sigma_{f,t+1}^2$. It allows us to restore the linearity of the model and to solve for the equilibrium as in Proposition 3 below (see Appendix A.3 for a proof).[6]

Proposition 3. *In the dynamic setup, the equilibrium risky asset price takes the linear form*

$$P_t \simeq \frac{F}{R_f - 1} + \beta_t G_t + \alpha_t e_t - \xi_t x_t, \tag{19}$$

where the coefficients β_t, α_t, and ξ_t are given by

$$\beta_t = \frac{\sigma_{f,t}^2}{R_f(\sigma_{f,t}^2 + \sigma_\eta^2)}, \ \ \alpha_t = \frac{1}{R_f}\left(1 - \frac{1 - \lambda_t}{1 + \Pi_t + \gamma\sigma_x\sigma_e\sqrt{\Pi_t}}\right), \ \ and \ \xi_t = \frac{\sigma_e}{\sigma_x\sqrt{\Pi_t}}\alpha_t. \tag{20}$$

We define price informativeness $\Pi_t \in [0, \infty)$ as a strictly increasing function of the squared correlation coefficient between $\widehat{P}_t$ and e_t, ρ_t^2:

$$\Pi_t \equiv \frac{\rho_t^2}{1 - \rho_t^2} = \frac{\lambda_t^2 \sigma_e^2}{\gamma^2 \operatorname{Var}_t^I[R_{t+1}^e]^2 \sigma_x^2}. \tag{21}$$

I investors' asset demand is given by:

$$q_t^I = \frac{1}{\gamma \operatorname{Var}_t^I[R_{t+1}^e]}\left(\frac{R_f}{R_f - 1}F + \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2}G_t + e_t - R_f P_t\right), \tag{22}$$

and U investors' asset demand is given by:

$$q_t^U = \frac{1}{\gamma \operatorname{Var}_t^U[R_{t+1}^e]}\left(\frac{R_f}{R_f - 1}F + \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2}G_t + \frac{\sigma_e^2}{\sigma_e^2 + \xi_t^2\sigma_x^2/\alpha_t^2}\widehat{P}_t - R_f P_t\right). \tag{23}$$

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[6]In our case, the distribution of future prices is a *normal variance mixture* and remains symmetric, unimodal, and elliptical. Such features will likely improve the accuracy of the approximation.

$\text{Var}_t^I[R_{t+1}^e]$ *and* $\text{Var}_t^U[R_{t+1}^e]$ *are defined in Appendix A.3 and represent variances of future excess returns as perceived by I and U investors, respectively.*

The following corollary characterizes, in the dynamic model, the equilibrium fraction λ_t of investors who decide to pay attention to the earnings announcement.

Corollary 3.1. *In equilibrium, the fraction λ_t of investors who decide to pay attention to the earnings announcement solves the following implicit equation:*

$$\lambda_t^2 = \gamma^2 \sigma_x^2 \, \text{Var}_t^I[R_{t+1}^e] \left(\frac{1}{e^{2\gamma c} - 1} - \frac{\text{Var}_t^I[R_{t+1}^e]}{\sigma_e^2} \right). \tag{24}$$

We recover the same result as in the static model, whereby the proportion of informed investors is a hump-shaped function of uncertainty. As demonstrated in the static model, when the cost of being attentive is small, an increase in uncertainty weakens price informativeness, which in turn increases investors' incentive to acquire information. The proportion λ_t, thus, increases with economic uncertainty, except when economic uncertainty is implausibly high. This yields our first testable prediction: on days with higher economic uncertainty, we should observe higher investor attention to firm-specific information.

The dynamic setup allows us to develop two additional testable predictions. For this, we follow DellaVigna and Pollet (2009) and define measures of the immediate and the delayed response of the stock price to the earnings announcement.

Lemma 1. *The immediate response to the earnings announcement e_t is defined as*

$$\mathbb{E}_t[IR_t] \equiv R_t^e - \mathbb{E}_{t-1}[R_t^e] - (D_t - \mathbb{E}_{t-1}[D_t]) = \alpha_t e_t + \beta_t G_t - \xi_t x_t, \tag{25}$$

and the delayed response is

$$\mathbb{E}_t[DR_{t+1}] \equiv \mathbb{E}_t[R_{t+1}^e] - \mathbb{E}_{t-1}[R_{t+1}^e] = (1 - R_f \alpha_t) e_t - R_f \beta_t G_t + R_f \xi_t x_t. \tag{26}$$

In 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 α_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 additional testable predictions: (*i*) if investors are more attentive to earnings announcements on high uncertainty days, we should observe a stronger earnings response coefficient (ERC) α_t, and (*ii*) more investor attention to earnings announcements on high uncertainty days should yield a weaker post-earnings announcement drift.

3 Empirical analyses

In this section, we conduct empirical tests of the theoretical predictions we draw in Section 2.2. For these analyses, we first construct a new index to capture daily variation in economic uncertainty. We then use this index and alternative measures of economic uncertainty to test our predictions regarding the effect of aggregate uncertainty on investors' information acquisition, earnings response coefficients, and post-earnings announcement drifts.

3.1 Construction of the news-based uncertainty index

We first construct a daily uncertainty index based on business and economics news coverage to capture events that grab attention and increase economic uncertainty. The underlying idea behind the index 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 broadcasts and length of articles for written pieces appearing online and in newspapers.

The data used for construction of the business and economics news index comes from the Pew Research Center's Project for Excellence in Journalism's News Coverage Index (NCI). The NCI has several features that make it suitable for constructing a news-based macro-uncertainty index. 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.

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.[7]

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. 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.[8] In order to ensure that the news relates to significant events, we retain the most prominent Stories from each source and require that there are at least four other Stories with the same Big Story Code on the same day. We determine the most prominent Story as the first Stories in television programs, the top right Stories in newspapers and the topmost or biggest-headline Stories on websites. Finally, we identify business/economics news as those in NCI Broad Story Topics 7 and 8 or Big Story Code 862 (Economy).

To calculate our business/economics (BE) news index for each date, we first calculate 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. We then 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 BE News Index. 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 led for bankruptcy (June 1, 2009); and the federal government seized Washington Mutual and brokered its sale to JPMorgan Chase (September 26, 2008).[9]

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[7]See www.journalism.org/news_index_methodology/99/ for a comprehensive description of the data.

[8]We drop Stories from cable news and radio, as their top stories often feature opinion or editorial content.

[9]In untabulated analyses we also calculate indices based on Stories that are unrelated to business/economics (i.e., related to Government/elections or entertainment/other). Similar to prior studies we find that entertainment/other news have a mildly distracting effect on investors' attention to earnings announcements.

3.2 Variable definitions, summary statistics, and validation

Besides the Pew-based news index, we use three alternative proxies for daily uncertainty. The first is the Equity Market Uncertainty (EMU) Index from Baker, Bloom, and Davis's Economic Policy Uncertainty website. Similar to the BE News Index, EMU is based on daily news reports. Specifically, EMU is based on the daily counts of newspaper articles containing words related to uncertainty, the economy, and equity/stock markets or prices, scaled by total counts of all articles appearing in the same newspaper. The second measure we use is the daily closing value 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. Our third additional uncertainty measure is Baker, Bloom, and Davis's Economic Policy Uncertainty (EPU) Index, which is similar to the EMU but replaces equity/stock market terms with terms related to legislation, regulation, deficits, and government bodies.[10] The EPU and EMU indices largely capture the breadth of coverage, while our topic-based news indices largely capture the depth of coverage. As shown below, they are positively, but only modestly correlated.

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. We use CRSP value-weighted market returns, MKT, and its absolute value, |MKT|. 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[11] and VOL, the log of total market volume.

To capture investor search for information, we exploit the download logs provided by the SEC's EDGAR website.[12] EDGAR provides a central location for investors to access forms filed by public companies, and provides logs of download/access activity to interested researchers. We use the company-day sum of downloads or search volume, LESV, as a search-driven proxy for investor attention.

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

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[10]The EMU and EPU data sets are described and downloadable at www.policyuncertainty.com/.

[11]NASDAQ turnover is corrected for multiple-counting by multiplying the turnover measure by 0.62, following Anderson and Dyl (2005).

[12]Available at www.sec.gov/dera/data/edgar-log-file-data-set.html.

and Mendenhall (2006) as:

$$\text{SUE}_{i,t} = \frac{X_{i,t} - \mathbb{E}[X_{i,t}]}{P_{i,t}} \tag{27}$$

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 windows were 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; analyst following defined as the number of analysts making forecasts up to 90 days before the earnings announcement, #Estimates; average monthly share turnover over the preceding 12 months, TURN; an indicator variable for negative earnings, Loss; the number of other firms announcing earnings on the same day, #Announcements; year indicators; and day-of-week indicators. We provide detailed definitions of each of these variables in Appendix A.4.

In Table 1, we provide descriptive statistics for the variables used the firm-quarter analyses of earnings announcement returns. Since the BE News Index is standardized and on many days there is no major news event, the index is right skewed with a mean of zero and

a negative median.

(Insert Table 1 about here)

In order to validate that our BE News Index captures higher economic uncertainty, we begin our analyses by examining whether the BE News Index is associated with other proxies for uncertainty and market activity. In Table 2, we present Pearson and Spearman correlations. The BE News index is positive and statistically significantly associated with the EMU and EPU indices, the VIX, and absolute market returns. 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)

Overall, the correlations in Table 2 suggest that days with high BE News are associated with greater uncertainty and expected market volatility. These correlations broadly validate the BE News Index as capturing news events that have significant impacts on the stock market and market activity via increases in uncertainty.

3.3 The impact of economic uncertainty on investor attention

As elaborated in Section 2.2, our main hypotheses relate to the effects of economic uncertainty on investor attention to firm-specific information, which we test for using EDGAR searches and market reactions around earnings announcements.

Our first set of tests examine whether aggregate uncertainty affects firm-specific search activity in and of itself. To address this, we exploit the SEC EDGAR logs of access to company-specific filings around quarterly earnings announcements. We estimate the following equation with the log of daily EDGAR search volume (LESV) as the dependent variable.

$$LESV_{it} = c_0 + c_1 \times \text{UV}_t + c_2 \times LESV_{it-1} + c_3 \times \text{SUE}_{it} + \gamma \cdot X_{it} + u_{it}, \qquad (28)$$

UV is the uncertainty variable proxy, which is one of BE News, EMU, VIX, or EPU. We also include the lagged dependent variable (LESV on the previous trading day), the SUE Decile, interactions between these, and the interaction between the SUE Decile and UV to control for differences in average search volume across firms and heterogeneous reactions to earnings surprises. Controls described above and their interactions with SUE Decile are also included.

The results in Table 3 provide strong evidence for more active searching for firm-specific information on days with higher BE News, EMU, VIX, and EPU indices, as all coefficients

of interest on these UV proxies are positive and statistically significant at the one percent level. The coefficient on each UV can be interpreted as the percent change in EDGAR search volume for a standard deviation change in the UV proxy. The coefficient on BE News, at 0.04, is roughly twice as large as the coefficients on the other UV proxies, which range from 0.018 to 0.023. This differential effect on attention may drive some of the heterogeneity in our later results on price responses around earnings announcements.

LESV is persistent, with a conditional autocorrelation coefficient of approximately 0.41. A potentially interesting result, though outside the scope of our theoretical prediction, is that there is little evidence for the magnitude of the earnings surprise being associated with search activity or the effect of macroeconomic uncertainty on firm-specific search activity.[13]

(Insert Table 3 about here)

Our next set of tests exploit the dynamic model's predictions regarding concurrent and delayed price reactions to firm-specific information. Again, we focus on quarterly earnings announcements as the source of firm-specific information and examine price reactions in the earnings announcement window as well as drift in post-announcement windows. Our analyses examine how economic uncertainty 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 index, 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 2.2, we estimate the the following regressions at the firm-quarter level:

$$Y_{it} = c_0 + c_1 \times \text{SUE}_{it} + c_2 \times \text{UV}_t + c_3 \times \text{SUE}_{it} * \text{UV} + \gamma \cdot X_{it} + u_{it}, \qquad (29)$$

where the dependent variable Y_{it} represents the announcement-window return EARET_{it} in a first specification and the post-earnings-announcement drift PEAD_{it+k} in a second specification. X_{it} represents a set of controls, and UV represents an uncertainty variable, i.e., the BE News Index, EMU, VIX, or EPU.

Table 4 presents results for the BE News Index as the UV proxy. The first column shows estimates for announcement-window returns. Returns around earnings announcements are highly positively associated with the earnings surprise. Focusing on the interactions between the BE News Index and the earnings surprise (that is, on the coefficient c_3 in the specification

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[13]Unreported analysis provides no significant evidence of an association between search activity and absolute earnings surprises (i.e., squared centered SUE Decile).

above), we find that economic uncertainty is associated with differential market responses to earnings surprises. Specifically, the results in the first column of Table 4 suggest the association between earnings surprises and stock returns is stronger on days with higher economic uncertainty. This is consistent with our Table 3 finding of economic uncertainty attracting attention to earnings announcements and the predictions of our theoretical model. In columns (2)-(5) we examine the relation between economic uncertainty and post earnings announcement drift. 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. Results suggest that earnings announced on days with higher economic uncertainty experience less drift over the seven days following the earnings announcement day ($p < 0.10$).[14] Although the coefficients of interest over the 30, 61, and 90-day windows are not individually statistically significant, they are all in the predicted negative direction. When combined with the result in the first column, the PEAD regression results suggest that investors react to earnings announcement information more quickly when the announcements occur on days with higher economic uncertainty.

(Insert Table 4 about here)

Overall, the results from Table 4 provide support to the conjecture that higher economic uncertainty on BE News days heightens investor attention to earnings announcements. The data suggest that investors pay more attention to firm-specific information on days with big BE news and high economic uncertainty.

In Table 5, we re-estimate our earnings response and 7-day PEAD regressions using the more conventional measures of daily economic uncertainty, including the EMU Index, VIX, and EPU Index. Market responses to earnings announcements are consistently stronger on days with greater news-related uncertainty, and the coefficient of interest is significant in two of the three specifications (for EMU Index and VIX). We do not find, however, a significant reduction in short-term PEAD using these alternative measures. Hence, these results provide partial support to our theoretical predictions.

(Insert Table 5 about here)

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[14]The main coefficient on SUE Decile in Table 4 is insignificant, partly due to the inclusion of year indicators interacted with SUE Decile (not reported).

4 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 a novel business/economics news specific index for important events covered extensively by media outlets. We show that days with more business/economic news tend to have greater economic uncertainty, larger absolute market returns, greater price protection, and more trading despite lower liquidity.

In our main tests of market reactions to earnings announcements on days with higher aggregate uncertainty relative to other days, we find that high economic uncertainty tends to attract attention to earnings announcements. 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 high BE News Index values. Our earnings announcement results hold with alternative proxies, but our post-earnings announcement drift result is sensitive to the use of alternative measures of aggregate uncertainty. Using EDGAR search logs, we find greater search activity for firms that announce earnings on days with greater aggregate uncertainty. 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 higher economic uncertainty.

An important implication of our results is that the nature of the underlying event is a key factor in determining whether the 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.

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A Appendix

A.1 Proof of Proposition 1

We start by describing the learning of I and U investors. I investors observe $\{e_1, G_1, \widehat{P}_1\}$ but not f_2. Thus, one can write

$$\begin{bmatrix} f_2 \\ G_1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} f_2 \\ \eta_1 \end{bmatrix}. \tag{A.1}$$

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

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

$$\begin{bmatrix} \theta \\ s \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mu_\theta \\ \mu_s \end{bmatrix}, \begin{bmatrix} \Sigma_{\theta,\theta} & \Sigma_{\theta,s} \\ \Sigma_{s,\theta} & \Sigma_{s,s} \end{bmatrix} \right). \tag{A.2}$$

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

$$\mathbb{E}[\theta|s] = \mu_\theta + \Sigma_{\theta,s}\Sigma_{s,s}^{-1}(s - \mu_s) \tag{A.3}$$

$$\text{Var}[\theta|s] = \Sigma_{\theta,\theta} - \Sigma_{\theta,s}\Sigma_{s,s}^{-1}\Sigma_{s,\theta}. \tag{A.4}$$

This yields

$$\mathbb{E}_1^I[f_2] = \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\eta^2} G_1 \tag{A.5}$$

$$\text{Var}_1^I[f_2] = \frac{\sigma_f^2 \sigma_\eta^2}{\sigma_f^2 + \sigma_\eta^2}. \tag{A.6}$$

U investors observe $\{G_1, \widehat{P}_1\}$ but not f_2 and e_1. Thus, one can write

$$\begin{bmatrix} f_2 \\ e_1 \\ G_1 \\ \widehat{P}_1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & -\frac{\xi_1}{\alpha_1} \end{bmatrix} \begin{bmatrix} f_2 \\ e_1 \\ \eta_1 \\ x_1 \end{bmatrix}. \tag{A.7}$$

This yields

$$\mathbb{E}_1^U \begin{bmatrix} f_2 \\ e_1 \end{bmatrix} = \begin{bmatrix} \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\eta^2} G_1 \\ \frac{\sigma_e^2}{\sigma_e^2 + \sigma_x^2 \xi_1^2/\alpha_1^2} \widehat{P}_1 \end{bmatrix} \tag{A.8}$$

and

$$\text{Var}_1^U \begin{bmatrix} f_2 \\ e_1 \end{bmatrix} = \begin{bmatrix} \frac{\sigma_f^2 \sigma_\eta^2}{\sigma_f^2 + \sigma_\eta^2} & 0 \\ 0 & \frac{\sigma_e^2 \sigma_x^2 \xi_1^2}{\sigma_e^2 \alpha_1^2 + \sigma_x^2 \xi_1^2} \end{bmatrix}. \tag{A.9}$$

Both I and U investors form expectations about D_2. For I investors:

$$\mathbb{E}_1^I[D_2] = F + \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\eta^2} G_1 + e_1 \tag{A.10}$$

$$\text{Var}_1^I[D_2] = \frac{\sigma_f^2 \sigma_\eta^2}{\sigma_f^2 + \sigma_\eta^2}. \tag{A.11}$$

For U investors:

$$\mathbb{E}_1^U[D_2] = F + \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\eta^2} G_1 + \frac{\sigma_e^2}{\sigma_e^2 + \sigma_x^2 \xi_1^2 / \alpha_1^2} \widehat{P}_1 \tag{A.12}$$

$$\text{Var}_1^U[D_2] = \frac{\sigma_f^2 \sigma_\eta^2}{\sigma_f^2 + \sigma_\eta^2} + \frac{\sigma_e^2 \sigma_x^2 \xi_1^2}{\sigma_e^2 \alpha_1^2 + \sigma_x^2 \xi_1^2} \tag{A.13}$$

$$= \text{Var}_1^I[D_2] + \text{Var}_1^U[e_1]. \tag{A.14}$$

Imposing the market clearing condition (5) then yields the undetermined coefficients β_1, α_1, and ξ_1 as functions of $\text{Var}_1^I[R_2^e] \equiv \text{Var}_1^I[D_2]$. This yields a simple relationship between α_1 and ξ_1:

$$\frac{\alpha_1}{\xi_1} = \frac{\lambda_1}{\gamma \, \text{Var}_1^I[R_2^e]}. \tag{A.15}$$

The correlation coefficient between $\widehat{P}_1$ and e_1 is given by

$$\rho_1 = \frac{\text{Cov}[\widehat{P}_1, e_1]}{\sigma_e \sqrt{\sigma_e^2 + \sigma_x^2 \xi_1^2 / \alpha_1^2}} = \frac{\sigma_e}{\sqrt{\sigma_e^2 + \sigma_x^2 \xi_1^2 / \alpha_1^2}}. \tag{A.16}$$

Define price informativeness as

$$\Pi_1 \equiv \frac{\rho_1^2}{1 - \rho_1^2} = \frac{\sigma_e^2 \alpha_1^2}{\sigma_x^2 \xi_1^2} = \frac{\lambda_1^2 \sigma_e^2}{\gamma^2 \, \text{Var}_1^I[R_2^e]^2 \sigma_x^2}, \tag{A.17}$$

where we have used (A.15) to obtain the last equality. Finally, straightforward but tedious algebra delivers the undetermined coefficients β_1, α_1, and ξ_1 as in Eq. (10) of Proposition 1. $\qquad\square$

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_1 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

$$U^U = -\mathbb{E}_1^U\left[e^{-\gamma q_1^U R_2^e}\right] = -\mathbb{E}_1^U\left[e^{-\frac{\mathbb{E}_1^U[R_2^e]}{\text{Var}_1^U[R_2^e]} R_2^e}\right] = -e^{-\frac{1}{2}\frac{\mathbb{E}_1^U[R_2^e]^2}{\text{Var}_1^U[R_2^e]}}. \tag{A.18}$$

Similarly, for an informed investor,

$$U^I = -e^{\gamma c} e^{-\frac{1}{2}\frac{\mathbb{E}_1^I[R_2^e]^2}{\text{Var}_1^I[R_2^e]}}. \tag{A.19}$$

For an uninformed investor, $\mathbb{E}_1^I[R_2^e]$ is a random variable with mean $\mathbb{E}_1^U[R_2^e]$ (by the law of iterated expectations) and variance $\mathrm{Var}_1^U[e_1]$. We will take an expectation of (A.19) over the realizations of e_1. To do so, we use the following standard result from multivariate normal calculus (see, e.g., Veldkamp, 2011, p. 102).

Lemma A2. *Consider a random vector $z \sim N(0, \Sigma)$. Then,*

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

Applying the above Lemma, we obtain

$$\mathbb{E}\left[-e^{\gamma c}e^{-\frac{1}{2}\frac{\mathbb{E}_1^I[R_2^e]^2}{\mathrm{Var}_1^I[R_2^e]}}\right] = U^U e^{\gamma c}\sqrt{\frac{\mathrm{Var}_1^I[R_2^e]}{\mathrm{Var}_1^I[R_2^e] + \mathrm{Var}_1^U[e_1]}}. \tag{A.20}$$

Imposing the indifference condition that the expected utility in (A.18) equals the expected utility in (A.20) yields

$$\sqrt{\frac{\mathrm{Var}_1^I[R_2^e] + \mathrm{Var}_1^U[e_1]}{\mathrm{Var}_1^I[R_2^e]}} = e^{\gamma c}, \tag{A.21}$$

which is Eq. (13) in the text.

From Eqs. (A.14) and (A.17) we obtain

$$\mathrm{Var}_1^U[e_1] = \frac{\sigma_e^2 \sigma_x^2 \xi_1^2}{\sigma_e^2 \alpha_1^2 + \sigma_x^2 \xi_1^2} = \frac{\sigma_e^2}{1 + \Pi_1}, \tag{A.22}$$

which can be replaced in Eq. (A.21) to obtain Eq. (14) in the text:

$$\frac{\sigma_e^2/\mathrm{Var}_1^I[R_2^e]}{1 + \Pi_1} = e^{2\gamma c} - 1. \tag{A.23}$$

This condition is equivalent with Eq. (19b) in Grossman and Stiglitz (1980). Finally, Proposition 2 results from replacing Π_1 from Eq. (A.17) above and solving for λ_1^2. □

A.3 Equilibrium and information choice in the dynamic model

I investors observe $\{e_t, G_t, \widehat{P}_t\}$ but not f_{t+1}. Thus, one can write

$$\begin{bmatrix} f_{t+1} \\ G_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} f_{t+1} \\ \eta_t \end{bmatrix}. \tag{A.24}$$

Applying the Projection Theorem yields

$$\mathbb{E}_t^I[f_{t+1}] = \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2}G_t \quad \text{and} \quad \mathrm{Var}_t^I[f_{t+1}] = \frac{\sigma_{f,t}^2 \sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2}. \tag{A.25}$$

U investors observe $\{G_t, \widehat{P}_t\}$ but not f_{t+1} and e_t. Normalize the prices signal as

$$\widehat{P}_t \equiv e_t - \frac{\xi_t}{\alpha_t}x_t, \tag{A.26}$$

and then write

$$\begin{bmatrix} f_{t+1} \\ e_t \\ G_t \\ \widehat{P}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & -\frac{\xi_t}{\alpha_t} \end{bmatrix} \begin{bmatrix} f_{t+1} \\ e_t \\ \eta_t \\ x_t \end{bmatrix}. \tag{A.27}$$

This yields

$$\mathbb{E}_t^U \begin{bmatrix} f_{t+1} \\ e_t \end{bmatrix} = \begin{bmatrix} \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2} G_t \\ \frac{\sigma_e^2}{\sigma_e^2 + \sigma_x^2 \xi_t^2 / \alpha_t^2} \widehat{P}_t \end{bmatrix} \quad \text{and} \quad \text{Var}_t^U \begin{bmatrix} f_{t+1} \\ e_t \end{bmatrix} = \begin{bmatrix} \frac{\sigma_{f,t}^2 \sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} & 0 \\ 0 & \frac{\sigma_e^2 \sigma_x^2 \xi_t^2}{\sigma_e^2 \alpha_t^2 + \sigma_x^2 \xi_t^2} \end{bmatrix}. \tag{A.28}$$

Both I and U investors form expectations about $P_{t+1} + D_{t+1}$:

$$P_{t+1} + D_{t+1} = \frac{R_f}{R_f - 1} F + f_{t+1} + e_t + \beta_{t+1} G_{t+1} + \alpha_{t+1} e_{t+1} - \xi_{t+1} x_{t+1}. \tag{A.29}$$

For I investors:

$$\mathbb{E}_t^I[P_{t+1} + D_{t+1}] = \frac{R_f}{R_f - 1} F + \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2} G_t + e_t \tag{A.30}$$

$$\text{Var}_t^I[P_{t+1} + D_{t+1}] = \frac{\sigma_{f,t}^2 \sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} + \underbrace{\sum_{k=1}^K \pi_k \left(\beta_{k,t+1}^2 \sigma_{f,k}^2 + \beta_{k,t+1}^2 \sigma_\eta^2 + \alpha_{k,t+1}^2 \sigma_e^2 + \xi_{k,t+1}^2 \sigma_x^2 \right)}_{\text{Var}[P_{t+1}] = \mathbb{E}[\text{Var}_t[P_{t+1}|\sigma_{f,t+1}=\sigma_{f,k}]] + \text{Var}[\mathbb{E}_t[P_{t+1}|\sigma_{f,t+1}=\sigma_{f,k}]]}. \tag{A.31}$$

In Eq. (A.31), π_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:

$$\mathbb{E}_t^U[P_{t+1} + D_{t+1}] = \frac{R_f}{R_f - 1} F + \frac{\sigma_{f,t}^2}{\sigma_{f,t}^2 + \sigma_\eta^2} G_t + \frac{\sigma_e^2}{\sigma_e^2 + \sigma_x^2 \xi_t^2 / \alpha_t^2} \widehat{P}_t \tag{A.32}$$

$$\text{Var}_t^U[P_{t+1} + D_{t+1}] = \frac{\sigma_{f,t}^2 \sigma_\eta^2}{\sigma_{f,t}^2 + \sigma_\eta^2} + \frac{\sigma_e^2 \sigma_x^2 \xi_t^2}{\sigma_e^2 \alpha_t^2 + \sigma_x^2 \xi_t^2} + \text{Var}[P_{t+1}] \tag{A.33}$$

$$= \text{Var}_t^I[P_{t+1} + D_{t+1}] + \underbrace{\frac{\sigma_e^2 \sigma_x^2 \xi_t^2}{\sigma_e^2 \alpha_t^2 + \sigma_x^2 \xi_t^2}}_{\text{Var}_t^U[e_t]}. \tag{A.34}$$

Consider now the portfolio choice problem of I investors:

$$\max_{q_t^I} \mathbb{E}_t^I \left[-e^{-\gamma q_t^I (P_{t+1} + D_{t+1} - R_f P_t)} \right]. \tag{A.35}$$

In the expectation above, the future price P_{t+1} is normally distributed *conditional* on the future

value of $\sigma_{f,t+1}^2$. One can therefore write the expectation as

$$\mathbb{E}_t^I\left[-e^{-\gamma q_t^I(P_{t+1}+D_{t+1}-R_fP_t)}\right] = \sum_{k=1}^K \pi_k\,\mathbb{E}_t^I\left[-e^{-\gamma q_t^I(P_{k,t+1}+D_{t+1}-R_fP_t)}\right], \tag{A.36}$$

where $P_{k,t+1}$ is the future price in the event that $\sigma_{f,t+1}^2 = \sigma_{f,k}^2$. Denoting by $R_{k,t+1}^e \equiv P_{k,t+1} + D_{t+1} - R_fP_t$, the expectation can be further written as

$$\mathbb{E}_t^I\left[-e^{-\gamma q_t^I(P_{t+1}+D_{t+1}-R_fP_t)}\right] = \sum_{k=1}^K \pi_k\left(-e^{-\gamma q_t^I\,\mathbb{E}_t^I[R_{k,t+1}^e]+\frac{1}{2}\gamma^2(q_t^I)^2\,\mathrm{Var}_t^I[R_{k,t+1}^e]}\right). \tag{A.37}$$

We now resort to an approximation of this function as in Vayanos and Weill (2008) and Gârleanu (2009). Economically, this approximation preserves risk aversion towards diffusion risks (i.e., risks created by normally distributed variables), but creates risk neutrality towards discrete jump risks (i.e., risks created by future changes in $\sigma_{f,t+1}^2$). This approximation is very accurate in our setting, particularly because $\mathbb{E}_t^I[P_{k,t+1}]$ is the same for all k, and thus the future distribution of prices remains symmetric, unimodal, and elliptical. First, define

$$\mathrm{Var}_t^I[R_{k,t+1}^e] \equiv \overline{\mathrm{Var}}_t^I[R_{k,t+1}^e]\frac{\bar{\gamma}}{\gamma} \tag{A.38}$$

where $\bar{\gamma}$ is a fixed parameter, and replace this above to obtain a function of γ:

$$f(\gamma) = \sum_{k=1}^K \pi_k\left[-e^{-\gamma q_t^I\,\mathbb{E}_t^I[R_{k,t+1}^e]+\frac{1}{2}\gamma(q_t^I)^2\overline{\mathrm{Var}}_t^I[R_{k,t+1}^e]\bar{\gamma}}\right] \tag{A.39}$$

The Taylor expansion of $f(\gamma)$ around zero is given by $f(\gamma) = f(0) + \gamma f'(0) + \mathcal{O}(\gamma)$, where $\mathcal{O}(\gamma)$ represents higher-order terms that go to zero faster than γ as $\gamma \to 0$. Therefore

$$f(\gamma) \approx -1 + \sum_{k=1}^K \pi_k\left[\gamma q_t^I\,\mathbb{E}_t^I[R_{k,t+1}^e] - \frac{1}{2}\gamma(q_t^I)^2\overline{\mathrm{Var}}_t^I[R_{k,t+1}^e]\bar{\gamma}\right] \tag{A.40}$$

$$= -1 + \sum_{k=1}^K \pi_k\left[\gamma q_t^I\,\mathbb{E}_t^I[R_{k,t+1}^e] - \frac{1}{2}\gamma^2(q_t^I)^2\,\mathrm{Var}_t^I[R_{k,t+1}^e]\right] \tag{A.41}$$

$$= -1 + \gamma q_t^I\,\mathbb{E}_t^I[R_{t+1}^e] - \frac{1}{2}\gamma^2(q_t^I)^2\,\mathrm{Var}_t^I[R_{t+1}^e]. \tag{A.42}$$

Taking first order condition with respect to q_t^I yields Eq. (22) in Proposition 3:

$$q_t^I = \frac{\mathbb{E}_t^I[R_{t+1}^e]}{\gamma\,\mathrm{Var}_t^I[R_{t+1}^e]}. \tag{A.43}$$

Similarly, we obtain the asset demand for U investors, i.e., Eq. (23) in Proposition 3:

$$q_t^U = \frac{\mathbb{E}_t^U[R_{t+1}^e]}{\gamma\,\mathrm{Var}_t^U[R_{t+1}^e]}. \tag{A.44}$$

Imposing the market clearing condition (5) then yields the undetermined coefficients β_t, α_t,

and ξ_t as functions of $\text{Var}_t^I[R_{t+1}]$. This yields a simple relationship between α_t and ξ_t:

$$\frac{\alpha_t}{\xi_t} = \frac{\lambda_t}{\gamma \, \text{Var}_t^I[R_{t+1}^e]}. \tag{A.45}$$

The correlation coefficient between $\widehat{P}_t$ and e_t is given by

$$\rho_t = \frac{\text{Cov}[\widehat{P}_t, e_t]}{\sigma_e \sqrt{\sigma_e^2 + \sigma_x^2 \xi_t^2 / \alpha_t^2}} = \frac{\sigma_e}{\sqrt{\sigma_e^2 + \sigma_x^2 \xi_t^2 / \alpha_t^2}}. \tag{A.46}$$

We define price informativeness as in the static model:

$$\Pi_t \equiv \frac{\rho_t^2}{1 - \rho_t^2} = \frac{\sigma_e^2 \alpha_t^2}{\sigma_x^2 \xi_t^2} = \frac{\lambda_t^2 \sigma_e^2}{\gamma^2 \, \text{Var}_t^I[R_{t+1}^e]^2 \sigma_x^2}, \tag{A.47}$$

where we have used (A.45) to obtain the last equality. Finally, straightforward but tedious algebra delivers the undetermined coefficients β_t, α_t, and ξ_t as in Eq. (10), which completes the proof of Proposition 3.

We now solve for the equilibrium λ_t in the dynamic model. The approximated expected utility of U investors, after replacement of the optimal portfolio choice (A.44), is

$$U_t^U = -1 + \gamma \frac{\mathbb{E}_t^U[R_{t+1}^e]}{\gamma \, \text{Var}_t^U[R_{t+1}^e]} \mathbb{E}_t^U[R_{t+1}^e] - \frac{1}{2} \gamma^2 \left(\frac{\mathbb{E}_t^U[R_{t+1}^e]}{\gamma \, \text{Var}_t^U[R_{t+1}^e]} \right)^2 \text{Var}_t^U[R_{t+1}^e] \tag{A.48}$$

$$= \frac{1}{2} \frac{\mathbb{E}_t^U[R_{t+1}^e]^2}{\text{Var}_t^U[R_{t+1}^e]} - 1 \approx -e^{-\frac{1}{2} \frac{\mathbb{E}_t^U[R_{t+1}^e]^2}{\text{Var}_t^U[R_{t+1}^e]}}. \tag{A.49}$$

where we have used the approximation $x - 1 \approx -e^{-x}$. This approximation restores the expected utility in exponential form and is highly accurate when $\mathbb{E}_t^U[R_{t+1}^e]^2/(2 \, \text{Var}_t^U[R_{t+1}^e])$ is small, which is likely to be the case ($\mathbb{E}_t^U[R_{t+1}^e]^2/\text{Var}_t^U[R_{t+1}^e]$ represents the squared Sharpe ratio of the stock from the perspective of uninformed investors).

Similarly, for an informed investor,

$$U_t^I \approx -e^{\gamma c} e^{-\frac{1}{2} \frac{\mathbb{E}_t^I[R_{t+1}^e]^2}{\text{Var}_t^I[R_{t+1}^e]}}. \tag{A.50}$$

For an uninformed investor, $\mathbb{E}_t^I[R_{t+1}^e]$ is a normally distributed random variable with mean $\mathbb{E}_t^U[R_{t+1}^e]$ (by the law of iterated expectations) and variance $\text{Var}_t^U[e_t]$. Taking expectation of (A.50) over the realizations of e_t and applying Lemma A2 yields

$$\mathbb{E}\left[-e^{\gamma c} e^{-\frac{1}{2} \frac{\mathbb{E}_t^I[R_{t+1}^e]^2}{\text{Var}_t^I[R_{t+1}^e]}} \right] = U^U e^{\gamma c} \sqrt{\frac{\text{Var}_t^I[R_{t+1}^e]}{\text{Var}_t^I[R_{t+1}^e] + \text{Var}_t^U[e_t]}}, \tag{A.51}$$

which leads to the indifference condition

$$\frac{\sigma_e^2 / \text{Var}_t^I[R_{t+1}^e]}{1 + \Pi_t} = e^{2\gamma c} - 1. \tag{A.52}$$

Finally, Corollary 3.1 results from replacing Π_t from Eq. (A.47) above and solving for λ_t^2.

A.4 Variable definitions

Variable	Description
BE News	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 (NCI).
EMU Index	Equity market uncertainty index, a daily news-based index of uncertainty related to the equity markets. Source: Baker, Bloom, and Davis' Economic Policy Uncertainty website (BBM).
EPU Index	Daily Economic policy uncertainty index. Source: BBM.
LESV	Log daily number of downloads (search volume) of company's filings from SEC EDGAR. Source: SEC.
MKT	Daily value-weighted market return. Source: CRSP.
|MKT|	Absolute value of MKT.
ILLIQ	Amihud (2002) firm-level daily illiquidity measure, calculated as 10^6 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.
SPREAD	Log of value-weighted daily bid-ask spread (market-wide measure), calculated as a stock's ask price minus bid price divided by the midpoint. Source: CRSP.
TURN	Log of value-weighted daily turnover (market-wide measure), calculated as daily shares traded divided by shares outstanding. Source: CRSP.
VOL	Log of total daily trading volume at the firm or market level. Source: CRSP.
VIX	Daily closing value of VIX. Source: CRSP.
SUE	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.
EARET	Compound excess stock return over the value-weighted index for earnings announcement date and 1 day after. Source: CRSP.
PEADx	Compound excess stock return over the value-weighted index from 2 days after the earnings announcement to x days after. Source: CRSP.
Size	Market value of equity on the earnings announcement date. Source: CRSP.
Book-to-Market	Book to market ratio at end of quarter for which earnings are announced. Source: Compustat.
EPersistence	Earnings persistence based on AR(1) regression with at least 4, up to 16 quarterly earnings. Source: Compustat.
IO	Institutional ownership as a fraction of total shares outstanding. Source: Thomson-Reuters 13F Data, CRSP.
EVOL	Standard deviation of seasonally differenced quarterly earnings. Source: Compustat.
ERepLag	Number of days from quarter-end to earnings announcement. Source: Compustat.
#Estimates	Number of analysts forecasting in the 90 days prior to the earnings announcement. Source: IBES.
Turn	Average monthly turnover for the 12 months preceding the earnings announcement. Source: CRSP.
Loss	Indicator for negative earnings. Source: Compustat.
#Announcements	Number of concurrent earnings announcements. Source: Compustat, IBES.

Tables

Table 1: **Descriptive Statistics.**
This table reports descriptive statistics for the sample used in analyses of returns around earnings announcements. Detailed definitions of all variables are available in Appendix A.4.

Variable	N	Mean	Std. Dev.	25%	50%	75%
BE News	32,769	0.049	0.940	-0.461	-0.461	0.317
SUE Decile	32,769	5.564	2.805	3.000	6.000	8.000
EMU Index	32,769	59.631	84.913	17.460	33.380	71.520
VIX	32,769	25.422	11.825	18.530	22.630	27.660
EPU Index	32,769	128.216	86.896	69.280	104.340	163.490
LESV	31,752	5.561	1.140	4.779	5.591	6.335
EARET	32,769	0.004	0.089	-0.039	0.002	0.047
PEAD7	32,760	0.001	0.067	-0.030	-0.001	0.029
PEAD30	32,667	0.006	0.134	-0.059	-0.001	0.061
PEAD61	32,513	0.012	0.205	-0.087	0.001	0.091
PEAD90	32,365	0.014	0.258	-0.117	-0.003	0.119
Size ($M)	32,769	7589.700	23478.270	613.982	1608.060	4792.070
Book-to-Market	32,769	0.616	0.561	0.310	0.498	0.766
EPersistence	32,769	0.084	16.038	-0.016	0.215	0.521
IO	32,769	0.769	0.207	0.669	0.811	0.923
EVOL	32,769	6.575	343.198	0.146	0.343	0.804
ERepLag	32,769	30.879	10.392	24.000	29.000	36.000
#Estimates	32,769	7.909	6.249	3.000	6.000	11.000
Turn	32,769	26.026	18.599	14.273	21.252	32.100
Loss	32,769	0.171	0.377	0.000	0.000	0.000
#Announcements	32,769	108.621	68.913	48.000	102.000	165.000

Table 2: **Correlations.**

This table presents Spearman (Pearson) correlations above (below) the diagonal for daily measures of news indices, uncertainty proxies, and market activity measures. N indicates the number of daily observations available since 1995. Detailed definitions of all variables are available in Appendix A.4. All correlations are significant at the 5 percent level, except those indicated in bold.

#	Variable	N	1	2	3	4	5	6	7	8	9	10	11
1	BE News	1,247		0.323	0.462	0.403	0.072	**-0.052**	0.346	0.359	0.283	0.326	0.391
2	EMU Index	6,042	0.252		0.396	0.353	-0.058	-0.090	0.310	0.271	0.229	-0.052	-0.070
3	VIX	6,037	0.373	0.437		0.383	**0.000**	-0.130	0.550	0.368	0.248	0.220	0.154
4	EPU Index	6,042	0.375	0.298	0.278		0.134	**0.010**	0.229	0.064	-0.062	0.214	0.247
5	LESV (log-sum)	3,619	0.100	-0.168	-0.113	0.130		**-0.003**	**-0.009**	-0.305	-0.403	0.081	0.314
6	MKT (VW)	6,042	**-0.032**	-0.045	-0.100	**0.020**	**-0.008**		-0.041	-0.032	**-0.011**	-0.026	-0.026
7	|MKT|	6,042	0.217	0.199	0.419	0.116	-0.068	-0.041		0.200	0.130	0.266	0.188
8	ILLIQ (VW)	6,042	0.274	0.422	0.509	**0.020**	-0.706	**-0.014**	0.220		0.626	-0.469	-0.648
9	SPREAD (VW)	6,042	0.121	0.376	0.455	-0.098	-0.863	**-0.010**	0.163	0.899		-0.544	-0.628
10	TURN (VW)	6,042	0.264	-0.182	**0.013**	0.200	0.101	**-0.005**	0.130	-0.575	-0.610		0.868
11	VOL (log-sum)	6,042	0.377	-0.156	0.072	0.307	0.303	**-0.016**	0.124	-0.588	-0.672	0.948	

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Table 3: **EDGAR searches around earnings announcements.**
This table presents results of regressions of announcement-window EDGAR searches on daily news and uncertainty proxies. Earnings surprise deciles based on quarterly sorts are included and interacted with each of the measures of uncertainty. All variables are standardized to be mean-zero and unit-variance. Control variables include: Size, Book-to-Market, EPersistence, EVOL, ERepLag, #Estimates, Turn, Loss, #Announcements, year indicators, and day-of-week indicators. All controls are interacted with SUE Decile. Detailed definitions of all variables are available in Appendix A.4. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

Dep. Var.	Log of EDGAR Search Volume (LESV)			
Param.\Uncertainty Var.	BE News	EMU	VIX	EPU
Uncertainty Var. (UV)	0.040***	0.023***	0.018***	0.022***
	(0.008)	(0.008)	(0.006)	(0.006)
lag(Dep. Var)	0.410***	0.414***	0.415***	0.414***
	(0.007)	(0.012)	(0.012)	(0.012)
SUE Decile	0.006	0.012	0.010	0.011
	(0.012)	(0.012)	(0.012)	(0.012)
SUE Decile * UV	0.000	0.002	-0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.002)
SUE Decile * lag(Dep. Var)	-0.011*	-0.003	-0.004	-0.003
	(0.006)	(0.004)	(0.004)	(0.004)
Controls	Yes	Yes	Yes	Yes
Controls * SUE Decile	Yes	Yes	Yes	Yes
Date-clustered SE	Yes	Yes	Yes	Yes
N	31,521	82,566	82,561	82,566
R-Square	0.568	0.791	0.791	0.792

Table 4: **Business and Economics News and Price Reaction to News**
This table presents results of regressions of earnings announcement returns (EARET) and
post-earnings announcement returns (PEAD) on earnings surprise deciles based on quar-
terly sorts interacted with the BE News Index. All variables are standardized to be mean-
zero and unit-variance. Control variables include: Size, Book-to-Market, EPersistence, IO,
EVOL, ERepLag, #Estimates, Turn, Loss, #Announcements, year indicators, day-of-week
indicators, and each of these interacted with SUE Decile. Detailed definitions of all variables
are available in Appendix A.4. 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.

Param.\Dep. Var.	(1) EARET	(2) PEAD7	(3) PEAD30	(4) PEAD61	(5) PEAD90
SUE Decile	2.395***	0.193	0.669	1.189	0.092
	(0.241)	(0.199)	(0.447)	(0.753)	(0.800)
BE News Index	-0.073	-0.075	-0.266*	0.656**	0.523*
	(0.083)	(0.100)	(0.151)	(0.259)	(0.291)
SUE Decile * BE News Index	0.170**	-0.123*	-0.137	-0.273	-0.006
	(0.079)	(0.065)	(0.154)	(0.244)	(0.284)
Controls	Yes	Yes	Yes	Yes	Yes
Controls * SUE Decile	Yes	Yes	Yes	Yes	Yes
Date-clustered SE	Yes	Yes	Yes	Yes	Yes
Number of obs.	32,769	32,761	32,668	32,514	32,366
R-Square	0.146	0.014	0.024	0.032	0.026

Table 5: **Alternative measures of news-driven uncertainty.**
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 each of the three following alternative measures of news-driven uncertainty: EMU Index, VIX, and EPU Index. All variables are standardized to be mean-zero and unit-variance. Control variables include: Size, Book-to-Market, EPersistence, EVOL, ERepLag, #Estimates, Turn, Loss, #Announcements, year indicators, and day-of-week indicators. All controls are interacted with SUE Decile. Detailed definitions of all variables are available in Appendix A.4. 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.

Uncertainty Proxy	EMU Index		VIX		EPU Index	
Param.\Dep. Var.	EARET	PEAD7	EARET	PEAD7	EARET	PEAD7
SUE Decile	2.393***	0.037	2.386***	0.045	2.369***	0.046
	(0.269)	(0.152)	(0.270)	(0.152)	(0.269)	(0.152)
Uncertainty Proxy	-0.059*	-0.004	-0.128**	0.024	-0.023	-0.037
	(0.031)	(0.032)	(0.055)	(0.072)	(0.033)	(0.037)
SUE Decile * Uncertainty Proxy	0.066**	-0.012	0.181***	0.038	0.032	0.010
	(0.032)	(0.026)	(0.055)	(0.049)	(0.031)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls * SUE Decile	Yes	Yes	Yes	Yes	Yes	Yes
Date-clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
N	157,869	157,827	157,827	157,785	157,869	157,827
R-Square	0.108	0.010	0.108	0.010	0.108	0.010