Economic Uncertainty and Investor Attention

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Abstract

This paper develops a multi-firm equilibrium model of information acquisition based on differences in firms’ characteristics. It is shown that higher market-level uncertainty crowds-in investor attention to firm-level earnings announcements. Increased investor attention magnifies the earnings response coefficients of all announcing firms, but stock prices react differently to the increase in attention (e.g., firms with higher systematic risk attract more investor attention and their prices react more to earnings announcements). The implications of the model for the cross section of firms are tested using data on firm-level attention and return measures around earnings announcements.

JEL classification: G14; G41; M41.

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1 Introduction

An important decision investors face in the process of building portfolios of assets is what information to collect. This decision is especially relevant in the information age, when the set of available signals and the context in which these signals are produced is constantly changing. In this paper, we study this decision and attempt to understand how investors’ attention to multiple firm-level signals is affected by the macroeconomic context. Our main focus is on the impact of economic uncertainty on investor attention.

We begin with a model of optimal attention allocation in a multi-firm economy in which a subset of firms provide earnings announcements that convey both systematic and idiosyncratic information. With costly information acquisition, as in Grossman and Stiglitz (1980), we show that investors’ attention to firm-level earnings announcements increases with the amount of economic uncertainty investors face. In turn, increased investor attention magnifies earnings response coefficients, which are defined as the firms’ price reactions to the earnings announcements.

Our main results show that firms’ stock prices react differently to the increase in attention. Earnings response coefficients increase incrementally more for firms that (i) have a stronger exposure to systematic risk; (ii) have more informative earnings announcements; (iii) have a more volatile idiosyncratic component in their earnings; (iv) have more noise trading; and (v) have lower information acquisition costs. The intuition behind all these five cases is that the benefit of collecting information outweighs its cost for these types of firms, which incentivizes investors to acquire information. Thus, heightened economic uncertainty attracts investors’ attention mainly to these types of firms, which in equilibrium generates our results.

Our results imply that higher economic uncertainty stimulates overall attention to firm-level news. In contrast, existing theoretical models suggest that investors tend to focus more on market-wide factors and less on firm-specific factors (Peng and Xiong, 2006), and that they are likely to pay more attention to market-wide factors during times of high uncertainty such as recessions (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016). These results are only seemingly contradictory with ours, for two main reasons. First, these studies build economies in which asset returns have a factor structure and investors acquire signals about factors. Instead, in our model the signals investors acquire are firm-level earnings announcements, which convey both systematic and idiosyncratic information. That earnings announcements convey systematic information is consistent with theoretical and empirical work by Savor and Wilson (2016) and Ben-Rephael, Carlin, Da, and Israelsen (2019). A further benefit of modeling earnings announcements as signals is that it allows us to directly test our theory using firm-level data and validate its cross-sectional predictions.
The second reason for the difference between our results and the literature is that prior studies assume that investors are attention-constrained or have behavioral biases, and thus their total attention allocation remains constant over time (e.g., Peng and Xiong, 2006). In contrast, in our model the total amount of attention increases with economic uncertainty. Recent empirical work seems to confirm this view: Hirshleifer and Sheng (2019) find higher earnings response coefficients and lower post-earnings-announcement drift for earnings announcements that immediately precede or coincide with major macroeconomic announcements (e.g., unemployment, inflation, or consumption). They interpret their results as consistent with an attention trigger effect, whereby macro news stimulates overall attention to the stock market, including firm-level news.\footnote{For additional empirical evidence that investors’ aggregate attention to the economy and individual stocks is time-varying, see Barber and Odean (2007), Da, Engelberg, and Gao (2011), Sicherman, Loewenstein, Seppi, and Utkus (2016), Fisher, Martineau, and Sheng (2017), and Gargano and Rossi (2018).}

Our model suggests a rational explanation to Hirshleifer and Sheng’s (2019) findings. Our contribution is to show that higher economic uncertainty crowds-in investor attention to firm-level earnings announcements, and that the stock price reaction to the increase in attention varies predictably with firm-specific factors. The model yields new predictions, which we test and confirm using data on firm-level attention and return measures around earnings announcements. We use the VIX as a time-varying measure of economic uncertainty and SEC EDGAR downloads to proxy for investor attention.\footnote{Several recent studies use EDGAR data to explore different issues in corporate finance and asset pricing: see Drake, Roulstone, and Thornock (2015), Chen, Cohen, Gurun, Lou, and Malloy (2020), Chen, Kelly, and Wu (2020), and Gao and Huang (2020), among others.} The results generally support our predictions. First, we find that investors pay more attention to firm-level information on high-VIX days. Second, we find that market reactions, as measured by earnings response coefficients (ERC), are greater for firms that announce on days with higher VIX, and we attribute this effect primarily to the increase in investors’ attention.

In cross-sectional analyses, we find that our ERC results are concentrated in firms with high CAPM beta, whose announcements are more likely to convey systematic information. We also find that the results are concentrated in subsamples with higher institutional ownership, idiosyncratic volatility, and prior share turnover (i.e., trading volume). We view these as consistent with theoretical predictions related to cross-sectional variation in the cost of acquiring information (captured by the number of institutional owners) and noise trade (captured by trading volume).

Our study adds to the literature on investor learning and attention allocation. Active learning has a long tradition in economics and finance, starting with seminal papers by Grossman and Stiglitz (1980) and Sims (1998, 2003). 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 et al., 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 and non-attention-constrained investors in a heterogeneous-firm economy.

Our study also contributes to the literature on the determinants of investor attention. Prior studies examine the negative effects of cognitive constraints and behavioral factors on investor attention (e.g., Hirshleifer, Lim, and Teoh, 2009; DellaVigna and Pollet, 2009; Louis and Sun, 2010; Lu, Ray, and Teo, 2016). In contrast to these studies, we focus on factors that bring investor attention to the stock market and provide a theoretical basis for analyzing them. Our empirical findings support our theoretical result that heightened economic uncertainty causes investors to optimally seek out more firm-level information and that the magnitude of this effect varies with firm characteristics. In a concurrent working paper, Hirshleifer and Sheng (2019) find that macroeconomic news triggers attention to firm-level news. While our empirical findings are consistent with their findings, we build a theory that focuses on economic uncertainty as the attention trigger, and analyze the cross-sectional implications of investors’ rational response to heightened uncertainty. Our results using EDGAR logs provide further support for our attention-based hypothesis.

Empirical studies have used various proxies for investor attention. Among these studies,
Sicherman et al. (2016) measure investor attention using online logins to defined-contribution retirement accounts. They find that investors’ attention to their personal portfolios is decreasing in the VIX. In our paper, investors choose to pay attention to earnings announcements rather than their personal wealth, which may explain the different empirical outcome. We show that the effects of economic uncertainty on investors’ attention and on price efficiency are stronger for firms with high institutional ownership, which suggests that institutional and retail investors respond differently to changes in economic uncertainty. Recent empirical evidence (Israeli, Kasznik, and Sridharan, 2020) supports the view that retail and institutional investors have different attention behaviors.

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.

An extensive survey of this literature can be found in Veldkamp (2011). Blankespoor, deHaan, and Marinovic (2020) review related literature on disclosure processing costs faced by capital market participants.

These include trading volume or price limits (Gervais, Kaniel, and Mingelgrin, 2001; Li and Yu, 2012); news proxies (Yuan, 2015); volume of Google searches (Da et al., 2011); logins to investment accounts (Karlsson, Loewenstein, and Seppi, 2009; Sicherman et al., 2016); web browsing behavior within investors’ brokerage domain (Gargano and Rossi, 2018); or Bloomberg terminal use (Ben-Rephael, Da, and Israelsen, 2017).
2 Model

We build on a static model of information acquisition (Grossman and Stiglitz, 1980), which we extend to multiple firms and multiple signals. We mainly focus on the impact of economic uncertainty on investors’ attention to firm-level information and on stock price responses to the earnings announcements.

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 $N$ risky assets indexed by $n \in \{1, ..., N\}$. The riskless asset is in infinitely elastic supply and pays a gross interest rate of 1 per period. Each risky asset (“firm”) has an equilibrium price $P_n$ at $t = 1$ and pays a risky dividend at $t = 2$:

$$D_n = \beta_n f + e_n.$$  

(1)

The payoff $D_n$ has a systematic component $f \sim \mathcal{N}(0, \sigma_f^2)$ and a firm-specific component, $e_n \sim \mathcal{N}(0, \sigma_{en}^2)$. The parameter $\beta_n$, which is heterogeneous across firms, dictates the exposure of firm $n$’s payoff to the systematic component. Firm-specific components are independent across firms, but we allow for variances $\sigma_{en}^2$ to vary in the cross section of firms. The variance of the systematic component $\sigma_f^2$ (to which we refer hereafter as the economic uncertainty), and the variance of $e_n$, $\sigma_{en}^2$, are constant and known by investors at $t = 0$. Finally, $f$ and $e_n$ are independent, $\forall n \in \{1, ..., N\}$.

Defining $\sigma_f$ as economic uncertainty is the simplest and most transparent way to obtain our theoretical results. Alternatively, one can assume the existence of public information about the systematic component $f$, and refer to the variance of this public information as economic uncertainty. This alternative specification delivers the same results, as we show in Appendix B. Formally, consider the public signal $G = f + g$, where $g \sim \mathcal{N}(0, \sigma_g^2)$ and define economic uncertainty as the uncertainty in this public signal, $\sigma_g^2$, instead of $\sigma_f^2$ as we do in our main model. This alternative framework is isomorphic to the model described below, but is unnecessarily complicated by the additional layer of learning induced by the public signal and by the presence of the public signal into the equilibrium prices.

Two firms make earnings announcements at $t = 1$. For ease of exposition, we assume that these two announcing firms are $a \in \{1, 2\}$. The earnings announcements convey information
about firms’ future dividends:

\[ E_a = D_a + \varepsilon_a, \quad \text{for } a \in \{1, 2\}, \]  

(2)

where the earnings noise shocks \( \varepsilon_a \) are independently distributed, \( \varepsilon_a \sim \mathcal{N}(0, \sigma_{\varepsilon_a}^2) \), and drawn independently from \( f \) and \( e_n, \forall n \in \{1, ..., N\} \).

At \( t = 0 \), each investor \( i \) chooses whether to be attentive to the earnings announcements. Each investor is free to choose whether to pay attention to \( E_1, E_2 \), neither, or both. We denote investor \( i \)’s decisions by the variables \( L_i^a, a \in \{1, 2\} \): if investor \( i \) decides to be attentive to firm \( a \)’s announcement, then \( L_i^a = 1 \); otherwise, \( L_i^a = 0 \).

Each investor \( i \) starts with zero initial wealth and maximizes expected utility:

\[ \mathbb{E}_0^i \left[ -e^{-\gamma(W^i - c_1L_i^1 - c_2L_i^2)} \right], \]  

(3)

where \( \gamma \) is the risk aversion coefficient, \( W^i \) is investor \( i \)’s wealth at \( t = 2 \), and \( c_aL_i^a \) is the monetary cost of paying attention to the announcement, for \( a \in \{1, 2\} \). The information cost parameters \( c_1 \) and \( c_2 \) are strictly positive for both firms.

There are potentially four types of investors: \( I_1 \) investors observing only \( E_1 \) (of mass \( \lambda_1 \geq 0 \)); \( I_2 \) investors observing only \( E_2 \) (of mass \( \lambda_2 \geq 0 \)); \( I_{12} \) investors observing both \( E_1 \) and \( E_2 \) (of mass \( \lambda_{12} \geq 0 \)); and uninformed investors \( U \). For the rest of the paper, we focus on the case where there will always be a positive mass of investors who decide to stay uninformed; that is, the information costs \( c_1 \) and \( c_2 \) are sufficiently large such that \( \lambda_1 + \lambda_2 + \lambda_{12} < 1 \). This assumption, made for simplicity, avoids scenarios in which all investors become informed about either \( E_1 \) or \( E_2 \). In reality, it is unlikely that every investor in the economy is informed.

At \( t = 1 \), investors choose optimal portfolios:

\[ q^i = \frac{1}{\gamma} \text{Var}^i[D]^{-1}(\mathbb{E}^i[D] - P), \quad \text{for } i \in \{I_1, I_2, I_{12}, U\}, \]  

(4)

where the superscript \( i \) in \( \mathbb{E}_1^i[\cdot] \) and \( \text{Var}_1^i[\cdot] \) reads “under the information set of investor \( i \).” \( D \) is the \( N \times 1 \) vector of asset payoffs, \( P \) is the \( N \times 1 \) vector of equilibrium prices, and \( \text{Var}^i[D] \) is the \( N \times N \) covariance matrix of assets’ payoffs, conditioned on investor \( i \)’s information set. Defining the vector of dollar excess return of the risky assets as \( R^e \equiv D - P \), the final wealth of investor \( i \) is then \( W^i = q^i R^e \).

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.

Throughout the paper, we will adopt the following notation: we use bold letters to indicate vectors and matrices, and letters in plain font to indicate univariate variables; we use subscripts to indicate individual assets, and superscripts to indicate individual investors.
Each risky asset \( n \) is in random supply \( x_n \sim \mathcal{N}(0, \sigma_{xn}^2) \). We denote by \( x \) the \( N \times 1 \) vector of asset supplies. Asset supplies \( x_n \) are independently distributed across firms and are drawn independently from \( f \) and the \( N \times 1 \) vector of firm-specific components \( e \). Random supplies prevent prices from perfectly revealing \( D_1 \) and \( D_2 \) (Grossman and Stiglitz, 1980), and also prevent investors from refusing to trade (Milgrom and Stokey, 1982). Consistent with much of the prior literature, we often interpret \( x_n \) as noise trade in stock \( n \).

Denoting by \( \lambda_U = 1 - \lambda_1 - \lambda_2 - \lambda_{12} \) the fraction of \( U \) investors, the prices of the risky assets are determined in equilibrium by the market-clearing condition:

\[
\lambda_1 q^{I_1} + \lambda_2 q^{I_2} + \lambda_{12} q^{I_{12}} + \lambda_U q^U = x. \tag{5}
\]

In our model, firms differ along multiple dimensions: exposure to systematic risk \( \beta_n \); firm-specific uncertainty \( \sigma_{en} \); variability of firm-level information \( \sigma_{ea} \); cost of acquiring information \( c_a \); and variability of supply noise \( \sigma_{xn} \). Each one of these dimensions will generate cross-sectional predictions. We further note that assuming two announcing firms is sufficient for characterizing our results in the simplest possible terms, but the model can be extended to \( J > 2 \) announcers.

### 2.1 Equilibrium

As is customary in noisy rational expectations models, prices take the linear form

\[
P = \alpha_1 E_1 + \alpha_2 E_2 - \xi x, \tag{6}
\]

where \( P \equiv [P_1, P_2, \cdots, P_N]' \), \( \alpha_1 \) and \( \alpha_2 \) are \( N \times 1 \) vectors, and \( \xi \) is a \( N \times N \) matrix.

Solving for the equilibrium price coefficients is not necessary in order to determine the equilibrium demand for information. Instead, it is sufficient to make the following conjecture, which will be verified in Proposition 3.\(^\text{7}\)

**Conjecture 1.** For every \( \lambda_1 \geq 0 \), \( \lambda_2 \geq 0 \) and \( \lambda_{12} \geq 0 \),

\[
\hat{P} \equiv \xi^{-1} P = \frac{\lambda_1 + \lambda_{12}}{\gamma \sigma_{e_1}^2} \iota_1 E_1 + \frac{\lambda_2 + \lambda_{12}}{\gamma \sigma_{e_2}^2} \iota_2 E_2 - x, \tag{7}
\]

where \( \hat{P} \equiv [\hat{P}_1, \hat{P}_2, \cdots, \hat{P}_N]' \) and \( \iota_1 \) (\( \iota_2 \)) is a standard basis vector with the first (second) component 1 and all other components 0.

This conjecture transforms the equilibrium prices into simple signals about \( E_1 \) and \( E_2 \). In equilibrium, all investors except \( I_{12} \) use prices to learn: \( I_1 \) investors use prices to learn about

\(^{7}\text{This conjecture is equivalent to Lemma 3.2 in Admati (1985).}\)
$E_2$; $I_2$ investors use prices to learn about $E_1$; and $U$ investors use prices to learn about $E_1$ and $E_2$. Accordingly, the information sets of investors are: $\mathcal{F}^{I_1} = \{E_1, \hat{P}_2\}$, $\mathcal{F}^{I_2} = \{E_2, \hat{P}_1\}$, $\mathcal{F}^{I_{12}} = \{E_1, E_2\}$, and $\mathcal{F}^U = \{\hat{P}_1, \hat{P}_2\}$. Although from the perspective of investors of types different than $I_{12}$ all prices are informative, the linear transformation (7) implies that the signals $\hat{P}_1$ and $\hat{P}_2$ are sufficient statistics for the information about $E_1$ and $E_2$ contained in all prices.

Before characterizing the information acquisition decision for each investor type, we define the following learning coefficients:

$$\ell^i_a = \begin{cases} 1 & \text{if investor } i \text{ observes } E_a \\ \frac{(\lambda_a + \lambda_{12})^2}{(\lambda_a + \lambda_{12})^2 + \gamma^2 \sigma^2_a} & \text{otherwise} \end{cases}, \text{ for } a \in \{1, 2\}, i \in \{I_1, I_2, I_{12}, U\}. \quad (8)$$

If investor $i$ observes the earnings announcement $E_a$, then the learning coefficient $\ell_a^i$ reaches its maximum value, 1. Without observing $E_a$, investor $i$ relies on prices to learn about it and $\ell_a^i < 1$. Prices are informative to the extent that someone buys the signal $E_a$, that is, if $\lambda_a + \lambda_{12} > 0$. In this case, $\ell_a^i$ increases with the fraction of informed investors (investors learn more from prices when a higher fraction of them pay attention to $E_a$), and decreases with the amount of noise in supply $\sigma_{sa}$ and the amount of noise in the earnings announcement $\sigma_{\varepsilon a}$ (investors learn less from prices when there is more noise in supply or when earnings announcements are noisier).

Investor $i$’s demand for information ultimately depends on the reduction in uncertainty achieved by observing new information. Because in our setup the vector of final payoffs $D$ is a multidimensional, normally distributed random variable, the reduction in uncertainty from observing new information is easily measured using the notion of entropy: under the information set of any investor $i \in \{I_1, I_2, I_{12}, U\}$, the vector $D$ has entropy

$$H^i[D] = \frac{N}{2} \ln(2\pi + 1) - \frac{1}{2} \ln(||\text{Var}^i[D]||). \quad (9)$$

From this definition, it follows that the uncertainty perceived by investor $i$ decreases with the determinant of the posterior precision matrix of $D$ (i.e., the inverse of the posterior covariance matrix $\text{Var}^i[D]$).

**Proposition 1.** The posterior precision matrix for each investor type $i \in \{I_1, I_2, I_{12}, U\}$ is

$$\tau^i \equiv \text{Var}^i[D]^{-1} = \text{Var}[D]^{-1} + \frac{\ell_1^i}{\sigma^2_{\varepsilon 1}} \tau_1^i + \frac{\ell_2^i}{\sigma^2_{\varepsilon 2}} \tau_2^i, \quad (10)$$
and, defining $\rho_{12} \equiv \text{Corr}[D_1, D_2]$, the determinant of $\tau^i$ is

$$|	au^i| = |\text{Var}[D]^{-1}| \left(1 + \frac{\text{Var}[D_1]}{\sigma_{e_1}^2} \ell_1^1 + \frac{\text{Var}[D_2]}{\sigma_{e_2}^2} \ell_2^1 + \frac{(1 - \rho_{12}^2) \text{Var}[D_1] \text{Var}[D_2]}{\sigma_{e_1}^2 \sigma_{e_2}^2} \ell_1^1 \ell_2^1\right),$$

where the following quantities are all increasing in economic uncertainty $\sigma_f$:

$$\text{Var}[D_a] = \beta_a^2 \sigma_f^2 + \sigma_{e_a}^2, \quad a \in \{1, 2\}$$

$$(1 - \rho_{12}^2) \text{Var}[D_1] \text{Var}[D_2] = \sigma_f^2 (\beta_1^2 \sigma_{e_2}^2 + \beta_2^2 \sigma_{e_1}^2) + \sigma_{e_1}^2 \sigma_{e_2}^2.$$  

An important result of Proposition 1 is that the heterogeneity in the determinants $|\tau^i|$, for $i \in \{I_1, I_2, I_{12}, U\}$, is exclusively driven by heterogeneity in the learning coefficients $\ell_a^i$. Because a higher determinant means less uncertainty (Eq. 9), the determinants $|\tau^i|$ provide a clear ranking of the informational distances between the four investor types. For instance, type $I_{12}$ investors have the highest $|\tau^i|$ because $\ell_1^{12} = \ell_2^{12} = 1$, whereas type $U$ investors have the lowest $|\tau^i|$.

The ranking in $|\tau^i|$ dictated by Proposition 1 allows for a simple characterization of the information market equilibrium. For ease of exposition, we assume hereafter that $c_1 = c_2 = c$. (We revisit the case of $c_1 \neq c_2$ at the end of the section.) Consider now an investor who decides whether or not to acquire one additional signal. To fix ideas, we denote this investor by $i_-$ before acquiring information and by $i_+$ after acquiring information. For instance, $i_-$ could be an investor of type $U$, and after acquiring the signal $E_1$ becomes type $i_+ = I_1$; or $i_-$ can be of type $I_1$, and after acquiring the signal $E_2$ becomes type $i_+ = I_{12}$.

**Proposition 2.** The investor $i_-$ changes type to $i_+$ if and only if

$$\frac{1}{2\gamma} \ln \left|\frac{\tau^{i+}}{\tau^{i-}}\right| > c.$$  

On the left hand side of (14), the benefit of acquiring information is the reduction in entropy from type $i_-$ to type $i_+$, divided by investor’s risk aversion, $(H^{i-}[D] - H^{i+}[D]) / \gamma$. Investor $i_-$ acquires information if and only if the benefit from the reduction in entropy (or uncertainty) achieved by observing information outweighs its cost. Risk aversion lowers the benefit of information: because more risk-averse investors trade less aggressively, they benefit less from learning.

The ratio $|\tau^{i+}| / |\tau^{i-}|$ in (14) is greatly simplified by means of Proposition 1: all the heterogeneity pertaining to non-announcing firms enters only in $|\text{Var}[D]^{-1}|$ and thus vanishes in the ratio. This makes the tradeoff faced by investor $i_-$ particularly transparent and intuitive. To analyze this tradeoff, we will focus on a simplified version where investors in
aggregate pay attention to one firm only (in other words, there is only one announcing firm). In this case, investor \( i_− \) changes type to \( i_+ \) if and only if

\[
1 + \frac{\text{Var}[D_a]}{\sigma^2_{\varepsilon a}} > e^{2\gamma c}.
\]  

(15)

The benefit of information increases with \( \text{Var}[D_a]/\sigma^2_{\varepsilon a} \), which measures the quality of informed investors’ information; decreases with the fraction of informed investors \( \lambda_a \), in which case prices are more informative and the signal \( E_a \) becomes less valuable; and increases with the amount of noise in supply \( \sigma_{xa} \), in which case prices are less informative and the signal \( E_a \) becomes more valuable (see also Grossman and Stiglitz, 1980, for similar tradeoffs).

The same tradeoffs are at play when there are two announcing firms instead of one, with the major difference that heterogeneity in firms characteristics (\( \beta_a, \sigma_{\varepsilon a}, \sigma_{ea}, \) and \( \sigma_{xa} \)) yields heterogeneous information choices across firms. We now characterize the information market equilibrium, accounting for these differences. Assumption 1 facilitates our discussion.

**Assumption 1.** The quality of informed investors’ information for firm 1 is greater than that for firm 2:

\[
\frac{\text{Var}[D_1]}{\sigma^2_{\varepsilon 1}} > \frac{\text{Var}[D_2]}{\sigma^2_{\varepsilon 2}}.
\]  

(16)

To have a higher quality of informed investors’ information, firm 1 must either have a relatively higher \( \beta_1 \) (a stronger exposure to systematic risk), a relatively lower \( \sigma_{\varepsilon 1} \) (a more informative signal), or a relatively higher \( \sigma_{ea} \) (stronger firm-specific uncertainty). In each of these situations, or in any combination of them that satisfies Assumption 1, the benefit of information is comparatively stronger for firm 1, which allows us to characterize the information market equilibrium as follows.

**Theorem 1.** Defining the scalar \( \kappa^*_1 \), strictly increasing in \( \sigma_f \),

\[
\kappa^*_1 \equiv \frac{1}{2\gamma} \ln \left( 1 + \frac{\text{Var}[D_1]}{\sigma^2_{\varepsilon 1}} \right) > 0,
\]  

(17)

there exists a unique positive value \( \kappa^*_2 \leq \kappa^*_1 \), strictly increasing in \( \sigma_f \), such that:

(A) If \( c \in [\kappa^*_1, \infty) \), then the cost of information is prohibitive and no investor finds it optimal to pay attention to the earnings announcements: \( \lambda_1 = \lambda_2 = \lambda_{12} = 0 \).

(B) If \( c \in [\kappa^*_2, \kappa^*_1) \), then investors pay attention only to the earnings announcement \( E_1 \): \( \lambda_1 > 0 \) and \( \lambda_2 = \lambda_{12} = 0 \).
(C) If $c \in (0, \kappa_2^*)$, then information is cheap enough so that investors pay attention to both announcements, but more investors pay attention to $E_1$, $\lambda_1 > \lambda_2 > 0$, and $\lambda_{12} = 0$.

Figure 1 illustrates the three equilibria of Theorem 1. For this illustration, we assume that firm 1 differs from firm 2 only through its exposure to systematic risk: $\beta_1 > \beta_2$, $\sigma_{e1} = \sigma_{e2}$, $\sigma_{e1} = \sigma_{e2}$. Differences in the other characteristics, which we discuss further below, deliver similar plots and the same intuition—see also Appendix A.3. The two lines in the figure depict the values $\kappa_1^*$ and $\kappa_2^*$ as functions of the economic uncertainty $\sigma_f$. The lines split the plot area into three regions, corresponding to the three cases in Theorem 1.

(Insert Figure 1 about here)

From Theorem 1, we note that in all cases $\lambda_1 \geq \lambda_2$, meaning that investors find the earnings announcement of firm 1 more valuable: in equilibrium, a larger fraction of investors pay attention to $E_1$. This is a logical result: $E_1$ is more informative about the systematic factor $f$ than $E_2$, and thus more useful in predicting the future returns of all firms in the economy. Thus, in this example investors behave as if they queue announcements based on their exposure to systematic risk. One can also understand this queueing result by fixing $\lambda_1 = \lambda_2 = 0$ and picking any investor $i$ in the economy: from Propositions 1 and 2, the benefit of observing $E_1$ is always larger than the benefit of observing $E_2$, and thus the investor will turn her attention first to firm 1. Frederickson and Zolotoy (2016) document a similar queuing result: investors devote more immediate attention to announcing firms that are comparatively more visible (i.e., larger firms, firms with more media coverage, with higher advertising expense, or with higher analyst coverage). In the case discussed here, attention queueing is based on firms’ exposure to the systematic factor $f$.

Furthermore, $\lambda_{12} = 0$ in all cases of Theorem 1, meaning that no investor finds it optimal to be attentive to both announcements. This equilibrium result arises because of diminishing returns to learning. Suppose an investor considers whether to pay attention to the earnings announcement $E_1$ (the same logic works for $E_2$). The type of this investor must necessarily be $U$ or $I_2$. According to Theorem 1, as long as $\lambda_U > 0$, it is always true that

$$\frac{|\tau_{I_1}|}{|\tau_U|} > \frac{|\tau_{I_12}|}{|\tau_{I_2}|}. \quad (18)$$

The benefit of learning is diminishing: once the investor observes the announcement $E_2$, the announcement $E_1$ becomes less valuable. Thus, no investor in equilibrium finds it optimal to pay attention to both announcements. Rather, investors prefer either to become specialized in one firm or to remain uninformed. The result that $\lambda_{12} = 0$ is clearly false, given that
investors often obtain information about multiple announcing firms.\(^8\) While this prediction of the model facilitates our characterization of the equilibria, it is not important for our results. It is a direct consequence of our assumption that there will always be a positive mass of investors who decide to stay uninformed, \(\lambda_U > 0\) (see discussion in Appendix A.3). If, on the contrary, the cost of information is low enough such that all the investors in the economy are informed, then one can obtain \(\lambda_{12} > 0\); such (trivial) equilibria would be situated in the extreme bottom of Figure 1. Furthermore, the assumption \(\lambda_U > 0\) is less likely to be satisfied with an increasing number of announcing firms, in which case one can more easily obtain positive masses of investors who get information about multiple earnings announcements.

In case (B) of Theorem 1, investors focus their attention only on the announcement of firm 1. An interesting situation that occurs in case (B) is a crowding-out equilibrium: the announcement \(E_1\) crowds out investors’ attention to \(E_2\). This occurs when the cost of information is above \(\kappa^*_2\) but below \(\kappa^*_3 \equiv \ln(1 + \text{Var}[D_2]/\sigma^2_{\varepsilon_2})/(2\gamma) < \kappa^*_1\). In this situation, the only reason investors are not attentive to firm’s 2 announcement is that firm 2 is not the sole announcer in the economy. A similar result has been described in the literature as the investor distraction hypothesis (Hirshleifer et al., 2009): when a greater number of announcements compete for investor attention, prices underreact to the new information.\(^9\) In our model, this result arises not because investors are distracted by the simultaneous announcements, but because the (higher \(\beta_a\)) firm announcement \(E_1\) decreases the benefit of observing \(E_2\) below its acquisition cost \(c\).

Assuming that firms differ through the noise in their signals, \(\sigma_{\varepsilon_1} < \sigma_{\varepsilon_2}\), yields the signal \(E_1\) more valuable for investors for the same reason as above: \(E_1\) is more informative about \(f\) than \(E_2\).Assuming that firms differ through the volatility of their firm-specific shocks, \(\sigma_{\varepsilon_1} > \sigma_{\varepsilon_2}\), yields the signal \(E_1\) more valuable for investors, but this time because \(E_1\) has a better signal-to-noise ratio in reducing the overall uncertainty about firm 1’s final payoff. In both cases, the same set of equilibria of Theorem 1 obtain, and the basic intuition from Figure 1 remains unchanged, as we show in Figure 6 of Appendix A.3.

We now aggregate investors’ demands in order to solve for equilibrium prices. Moving forward, we fix \(\lambda_{12} = 0\) as per Theorem 1. The weighted average precision matrix for the population of heterogeneously informed investors is defined as

\[\tau \equiv \lambda_1 \tau_{I_1} + \lambda_2 \tau_{I_2} + \lambda_U \tau^U.\] (19)

\(^8\)A similar specialization result arises when investors have an attention capacity constraint (Van Nieuwerburgh and Veldkamp, 2009, 2010). The existence of the capacity constraint often yields corner solutions. Here investors are free to increase their attention capacity by paying a financial cost \(c\), but once they have acquired one of the signals they do not find it optimal to acquire the other signal.

\(^9\)See also Hirshleifer and Teoh (2003); DellaVigna and Pollet (2009); Louis and Sun (2010); Drake, Gee, and Thornock (2016); Lu et al. (2016) for additional evidence on the distraction hypothesis.
Lemma 1. The weighted average precision is given by
\[ \tau = \text{Var}[D]^{-1} + [t_1 \ t_2] \begin{bmatrix} \pi_1(\lambda_1) & 0 \\ 0 & \pi_2(\lambda_2) \end{bmatrix} [t_1' \ t_2'], \] (20)
where \( \pi_a(\lambda_a) \) is a strictly increasing function of \( \lambda_a \):
\[ \pi_a(\lambda_a) = \frac{\lambda_a^2 + \lambda_a \gamma^2 \sigma_{x_a}^2 \sigma_{\varepsilon_a}^2}{\lambda_a^2 \sigma_{x_a}^2 + \gamma^2 \sigma_{x_a}^2 \sigma_{\varepsilon_a}^2}, \quad a \in \{1, 2\}. \] (21)

The functions \( \pi_1(\lambda_1) \) and \( \pi_2(\lambda_2) \) determine the aggregate precision gains from observing \( E_1 \) and \( E_2 \). Naturally, if no one pays attention to information, then \( \pi_1(\lambda_1) = \pi_2(\lambda_2) = 0 \) and the weighted average precision \( \tau \) equals the prior precision matrix \( \text{Var}[D]^{-1} \). A key property of the functions \( \pi_1(\lambda_1) \) and \( \pi_2(\lambda_2) \), which will be very useful shortly, is that they depend on the economic uncertainty \( \sigma_f \) only indirectly through \( \lambda_1 \) and \( \lambda_2 \).\(^\text{10}\)

Proposition 3. The equilibrium prices in this economy satisfy
\[ \tau P = \pi_1(\lambda_1)t_1E_1 + \pi_2(\lambda_2)t_2E_2 - \gamma \begin{bmatrix} \frac{\pi_1(\lambda_1)\sigma_{\varepsilon_1}^2}{\lambda_1} & 0 \\ 0 & \frac{\pi_2(\lambda_2)\sigma_{\varepsilon_2}^2}{\lambda_2} \\ \mathbf{0}_{N-2} & \mathbf{0}_{N-2} \end{bmatrix} \mathbf{0}_{N-2} \mathbf{I}_{N-2} \mathbf{x}, \] (22)
where \( \mathbf{I}_z \) is the identity matrix of dimension \( z \) and \( \mathbf{0}_z \) is a zero vector of size \( z \).

Proposition 3 allows us to analyze the earnings response coefficients, which measure the reactions of the equilibrium prices to the earnings announcements. They are given by \( \alpha_1 \) and \( \alpha_2 \) in the price conjecture (6). The following Corollary solves these coefficients and splits them into two categories, for announcing and non-announcing firms.

Corollary 3.1. The earnings response coefficients of the announcing firms are
\[ \text{ERC}_A = \mathbf{I}_2 - \left( \mathbf{I}_2 + \begin{bmatrix} \sigma_f^2 \beta_1^2 + \sigma_{\varepsilon_1}^2 \\ \sigma_f^2 \beta_1 \beta_2 \\ \sigma_f^2 \beta_2^2 + \sigma_{\varepsilon_2}^2 \end{bmatrix} \begin{bmatrix} \pi_1(\lambda_1) & 0 \\ 0 & \pi_2(\lambda_2) \end{bmatrix} \right)^{-1}. \] (23)

For any \( n \in \{3, \ldots, N\} \) and \( a \in \{1, 2\} \), the cross-earnings response coefficient \( \text{ERC}_{na} \) (the
\(^\text{10}\)The off-diagonal elements in the second term of equation (20) are zero, potentially suggesting that \( E_1 \) is uninformative about \( D_2 \) and that \( E_2 \) is uninformative about \( D_1 \). This seems odd given that \( D_1 \) and \( D_2 \) share a common systematic component. However, the precision matrix does not have the usual element-wise interpretation of the covariance matrix (e.g. the diagonal terms of the precision matrix are not asset-specific precisions). Inverting the precision matrix \( \tau \) would restore the common interpretation and would show that \( E_1 \) (\( E_2 \)) is indeed informative about \( D_2 \) (\( D_1 \)).
response of non-announcing firm $n$ to the earnings announcement $E_a$) is given by

$$ERC_{na} = \frac{\sigma_f^2}{\sigma_f^2(\sigma_{e2}^2\beta_1^2 + \sigma_{e1}^2\beta_2^2) + \sigma_{e1}^2\beta_n(\sigma_{e2}^2\beta_1 ERC_{1a} + \sigma_{e1}^2\beta_2 ERC_{2a})}.$$  

(24)

Our focus is on the earnings response coefficients of the announcing firms, $ERC_A$. They form a $2 \times 2$ matrix whose solution is provided in (23). $ERC_A$ is zero if $\lambda_1 = \lambda_2 = 0$. An important separation result helps us easily interpret $ERC_A$: as shown in Lemma 1, the last matrix in Eq. (23) does not directly depend on $\sigma_f$. Therefore, in the analysis that follows, we can separately assess the effects of an increase in economic uncertainty on $ERC_A$, and in particular the additional effect that arises from changes in investors’ attention.

The equilibrium prices of the non-announcing firms respond to the earnings announcements $E_1$ and $E_2$, as shown in (24). Although we do not focus our empirical work on these coefficients, it is worth mentioning here that they are non-zero only when the non-announcing firms have non-zero exposure to the systematic factor $f$. The stronger the exposure $\beta_n$, the greater the response of the non-announcing firm $n$ to $E_1$ and $E_2$. When Assumption 1 holds, $ERC_{2a}$ and $ERC_{2a}$ are stronger for $a = 1$, and Eq. (24) further shows that non-announcing firms respond more strongly to the earnings announcement of firm 1.

### 2.2 Testable implications

Our theoretical model has implications that can be tested empirically. The first result that emerges from Theorem 1 and Figure 1 is the effect of an increase in economic uncertainty on the information market equilibrium. Suppose uncertainty is low enough such that all investors are inattentive. This is the case (A), depicted with the hatched area in the plot. After an increase in economic uncertainty, the equilibrium moves to the right: depending on the cost of information and the magnitude of the increase in uncertainty, the new equilibrium can be anywhere from case (B) to case (C). In all cases, a positive fraction of investors become attentive, first to $E_1$ and, if the increase in uncertainty is sufficiently strong, to $E_2$. The main implication is that an increase in economic uncertainty activates investors’ attention to firm-level information, and that investors direct their attention to an increasing number of firms as uncertainty increases.

The previous implication refers to the number of firms: more announcing firms become the focus of investors’ attention as uncertainty increases. We now turn to the effect of an increase in uncertainty on the number of investors who pay attention to $E_1$ and $E_2$. The fractions $\lambda_1$ and $\lambda_2$ are not apparent from Figure 1, which shows only when these fractions are positive or zero. Therefore, we rely on Proposition 2 and Eq. (15) to understand how $\lambda_1$
and $\lambda_2$ vary with economic uncertainty.

In Eq. (15), the quality of informed investors’ information (measured by $\text{Var}[D_a]/\sigma^2_a$) always increases with economic uncertainty. When economic uncertainty increases, investors benefit more from observing the earnings announcement $E_a$. The key implication of our multiple asset economy is that the impact of economic uncertainty on the fraction of informed investors is heterogeneous across announcing firms, which in our model differ along five dimensions: $\beta_a$, $\sigma_{\epsilon a}$, $\sigma_{ea}$, $\sigma_{xa}$, and $c_a$.

The four panels of Figure 2 isolate the first four of the above dimensions one by one. In each case, the parameters of the announcing firms are kept equal except the ones in the titles of the panels. The solid (dashed) lines depict the fractions $\lambda_1$ ($\lambda_2$) of informed investors as functions of economic uncertainty. The dotted lines plot the difference $\lambda_1 - \lambda_2$. Confirming Eq. (15), the fractions $\lambda_1$ and $\lambda_2$ increase with $\sigma_f$. We also note that for low levels of economic uncertainty the fractions $\lambda_1$ and $\lambda_2$ are zero, which corresponds to case (A) of Theorem 1; furthermore, as uncertainty increases, the economy moves to case (B), and finally to case (C). The differences $\lambda_1 - \lambda_2$, depicted with the dotted lines, show that investors turn their attention first to firms that are more exposed to systematic risk ($\beta_1 > \beta_2$); firms that communicate more precise information ($\sigma_{\epsilon 1} < \sigma_{\epsilon 2}$); firms with greater firm-specific uncertainty ($\sigma_{ea 1} > \sigma_{ea 2}$); and firms with stronger noise in supply ($\sigma_{xa 1} > \sigma_{xa 2}$). However, as uncertainty further increases, these differences are not generally monotonic.

(Insert Figure 2 about here)

The intuition behind each one of these cases matches the intuition behind Theorem 1: the signals of firms with higher $\beta_a$, lower $\sigma_{\epsilon a}$, or higher $\sigma_{ea}$ are more informative and thus more desirable for investors. Regarding the latter case (noise in supply), the intuition stems from price informativeness: the equilibrium prices of firms with stronger noise in supply reveal less information to investors, which increases the ex-ante incentive to look for information (Grossman and Stiglitz, 1980). This yields a higher $\lambda_a$ for firms with higher $\sigma_{xa}$.

The increase in investors’ attention caused by an increase in uncertainty has additional cross-sectional implications for the response of prices to firm-level information. Consider the equilibrium price of announcing firm $a \in \{1, 2\}$,

$$P_a = \text{ERC}_{a1}E_1 + \text{ERC}_{a2}E_2 - \xi_{(a)}x,$$

where $\xi_{(a)}$ denotes the $a$-th row of matrix $\xi$, whose form is not important for the arguments made here. We mainly focus on the earnings response coefficients of announcing firms to their own announcements, $\text{ERC}_{11}$ and $\text{ERC}_{22}$. These are the two diagonal elements of the $2 \times 2$ matrix $\text{ERC}_A$ from Corollary 3.1. We plot them in the four panels of Figure 3. The
solid (dashed) lines depict the earnings response coefficients $ERC_{11}$ ($ERC_{22}$) as functions of economic uncertainty. The dotted lines plot the difference $ERC_{11} - ERC_{22}$. As in Figure 2, the parameters of the announcing firms are kept equal except the ones in the titles of the panels.

(Insert Figure 3 about here)

Earnings response coefficients increase with economic uncertainty. According to Corollary 3.1, the increase in attention caused by higher uncertainty magnifies the price reaction to firm specific news. This increases the earnings response coefficients, incrementally more for firms that observe a stronger increase in attention: firms with higher $\beta_a$, lower $\sigma_{ea}$, higher $\sigma_{ea}$, or higher $\sigma_{xa}$. The testable implication is that we should observe a stronger increase in the earnings response coefficients of announcing firms to their own announcements when investors pay more attention to firm-level information on high uncertainty days. Furthermore, Figure 3 offers additional cross-sectional implications: earning response coefficients should be incrementally stronger on high-uncertainty days for firms with higher $\beta_a$, lower $\sigma_{ea}$, higher $\sigma_{ea}$, or higher $\sigma_{xa}$. We note, however, that these differences are not generally monotonic: the Figure shows monotonic relations for $\beta_n$, $\sigma_{en}$, and $\sigma_{xn}$, but not for $\sigma_{en}$.

We now focus on the last parameter whose heterogeneity across firms can affect the cross section of price reactions to earnings. Specifically, announcing firms also differ in their information acquisition cost $c_a$. We have postponed the analysis of this case with the aim of simplifying the exposition of our results, starting from Proposition 2. Figure 4 shows how economic uncertainty affects investors’ attention and earnings response coefficients under the assumption of different information costs. For this illustration, we assume that $c_1 < c_2$. The left panel shows that investors’ attention to the announcement of firm 1 responds faster and stronger for firm 1 relative to firm 2 as uncertainty increases, and the right panel confirms this result for earnings response coefficients.

(Insert Figure 4 about here)

In our model, the fractions of attentive investors and the earnings response coefficients for each announcing firm are endogenously determined in equilibrium. In order to better understand the relation between attention and price reaction to news, we plot them in Figure 5 for different levels of economic uncertainty. For this illustration, we assume a higher exposure to systematic risk for firm 1, $\beta_1 > \beta_2$, but the results are similar in the other cases studied so far: $\sigma_{e1} < \sigma_{e2}$, $\sigma_{e1} > \sigma_{e2}$, $\sigma_{x1} > \sigma_{x2}$, or $c_1 < c_2$. Each dot is obtained for a different level of economic uncertainty, which is increasing from left to right. Both plots depict a clear positive relation between investor attention and earnings response coefficients, and this relation is stronger for the high-beta firm 1.
To summarize, the testable implications of our model with respect to the impact of economic uncertainty on investor attention and on the price reaction to firm-level news are: (i) when economic uncertainty increases, more announcing firms become the focus of investors’ attention, and more investors pay attention to each announcing firm; (ii) when economic uncertainty (investor attention) increase, earnings response coefficients are stronger for all announcing firms; and (iii) the increases in earnings response coefficients caused by higher economic uncertainty (investor attention) is incrementally stronger for firms with higher $\beta_a$, lower $\sigma_{ea}$, higher $\sigma_{ea}$, higher $\sigma_{xa}$, and lower $c_a$.

3 Empirical analyses

In this section, we conduct empirical tests of the theoretical predictions we draw in Section 2 regarding the effect of aggregate uncertainty on investors’ information acquisition and earnings response coefficients.

3.1 Variable definitions, summary statistics, and validation

We use the daily closing value of the VIX to capture time-varying uncertainty. The VIX is an option-based measure of expected S&P 500 volatility that proxies for forward-looking stock market uncertainty, risk, or volatility.

To capture investor search for information, we exploit the download logs provided by the SEC’s EDGAR website. EDGAR provides a central location for investors to access forms filed by public companies, and provides logs of download/access activity. We use the company-day total log of EDGAR search/download volume, ESV, as a search-driven proxy for investor attention. We also use the log of the number of downloads of a company’s filings from unique IP addresses, ESVU, to capture the extensive margin of investor search based on the number of investors accessing the firm’s filings. The EDGAR search logs are available from February 14, 2003 to June 30, 2017.\footnote{Available at www.sec.gov/dera/data/edgar-log-file-data-set.html.}

\footnote{EDGAR downloads may come from humans or from automated programs or robots (e.g., Ryans, 2017). We use all downloads for three reasons: 1) automated downloads may be used by services that provide information to investor clients; 2) automated downloads are programmed, and may be programmed to access EDGAR files conditional on other inputs to the program capturing, for instance, macroeconomic conditions; and 3) our use of year fixed effects in regressions controls for a secular trend of increasing robot downloads over time.}
For our analyses of market reactions to earnings announcements, we measure earnings surprise, SUE, following Livnat and Mendenhall (2006) as:

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

(26)

where \( i \) denotes firm, \( t \) denotes quarter, \( X_{i,t} \) are IBES reported actual earnings, \( E[X_{i,t}] \) are expected earnings, taken as the latest median forecast from the IBES summary file, and \( P_{i,t} \) is the share price at the end of quarter \( t \).\(^{13}\)

Daily excess returns are calculated each day as CRSP-reported returns adjusted for size decile.\(^{14}\) 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 (two-day window). 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): compound excess returns from ten to one days before the earnings announcement, PreRet; 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 quarterly earnings forecasts according to the IBES summary file, #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 C.

Our subsample analyses use partitions based on plausible proxies for the underlying constructs. Although the exposures of firms’ payoffs to the systematic factor \( f \) (the parameters \( \beta_n \)) are not perfectly observed in the data, they can be proxied by firms’ CAPM betas. More precisely, in our model firms that have larger exposures to \( f \) necessarily have higher market

\(^{13}\)The earnings surprise calculation follows WRDS guidance described in Dai (2020).

\(^{14}\)Our main results on earnings announcement window returns presented in Table 4 are robust to defining excess daily returns as firm-specific returns adjusted for either equal-weighted or value-weighted market returns.
We use Forecast Dispersion and Idiosyncratic Volatility as proxies for total earnings variance ($\text{Var} [\text{E}]$) in our model and firm-specific payoff variance ($\sigma_{ea}^2$).\(^{16}\) The volatility of noise trade ($\sigma_{ea}^2$) is reflected in share turnover (TURN), though we caution that turnover also captures other constructs, such as information asymmetry and disagreement. Finally, we split the sample on institutional ownership (IO) to capture variation in the cost to investors of acquiring information ($c_a$), as these costs are likely to be lower for institutional than retail owners. Appendix C provides detail on how these variables are constructed.

Our sample begins in 1995, as earnings announcement dates tended to be identified unreliably prior to 1995 (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009). We further limit our sample to firms for which we are able to calculate analyst forecast-based earnings surprises, firms with stock price greater than $5$, and firms with average monthly turnover in the past year no lower than $1$.\(^{17}\) The latter restrictions drop the smallest and least actively traded firms from the sample.

In Table 1, we provide descriptive statistics for the variables used in the regression tests. The unit of analysis is the quarterly earnings announcement (i.e., firm-quarter).

Table 2 provides correlations. All correlations except those in bold are significant at the five percent level. VIX is negatively correlated with EDGAR search volume measures, but these are raw correlations that do not correct for other factors, such as time factors affecting both VIX and EDGAR search volume (e.g., higher VIX and lower search in recessions). VIX is not generally significantly related to earnings announcement returns or earnings surprises, suggesting that macro uncertainty is not directly linked to firm-level earnings surprises.

3.2 Regression results

As elaborated in Section 2, our main hypotheses relate to the effects of economic uncertainty on investor attention to firm-level information, which we test for using EDGAR searches and market reactions around earnings announcements.

\(^{15}\)The computation of betas in our theoretical model is beyond the scope of this paper. See Andrei, Cujean, and Wilson (2020) for a discussion of the effect of private information on empiricist’s beta estimates and on the CAPM.

\(^{16}\)Note that Forecast Dispersion could be driven by variation and unpredictability in either earnings fundamentals ($\text{Var} [\text{D}] = \beta_d^2 \sigma_f^2 + \sigma_{ea}^2$) or earnings noise ($\sigma_{ea}^2$). As can be seen in a comparison of panels (b) and (c) of Figure 3, $\sigma_{ea}^2$ and $\sigma_{ea}^2$ have opposing effects on the relation between economic uncertainty and earnings response coefficients.

\(^{17}\)After dropping firms without forecast-based earnings surprises and with prices lower than $5$, less than 1% of the remaining firms have prior year turnover lower than 1.
Our first set of tests examine whether aggregate uncertainty affects firm-level 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 (ESV) and the log of daily EDGAR search volume from unique IP addresses (ESVU) as the dependent variables.

\[
\begin{align*}
\text{ESV(U)}_{it} &= c_0 + c_1 \times \text{VIX}_t + c_2 \times \text{ESV}_{it-1} \\
&+ c_3 \times \text{SUE}_it + c_4 \times \text{abs} (\text{SUE}_it) + \gamma \cdot X_{it} + u_{it},
\end{align*}
\]

We also include the lagged dependent variable (ESV on the previous earnings announcement), the standardized SUE Decile, and the absolute standardized SUE Decile to control for differences in average search volume across firms. We present results separately for ESV and ESVU.

The results in Table 3 provide strong evidence for more active searching for firm-level information on days with higher VIX, as the coefficients of interest on VIX are positive and statistically significant both for ESV and ESVU as dependent variables. The coefficients of interest can be interpreted as the approximate percent change in EDGAR search volume and unique EDGAR searchers for a standard deviation change in the VIX. A one standard deviation change in VIX is associated with a 1.9 (4.5) percent increase in the number of EDGAR searches (from unique IP addresses) for the announcer’s filings on the earnings announcement date. Lagged ESV and ESVU are significantly associated with announcement day searches, as are the signed and absolute earnings surprise deciles.

(Insert Table 3 about here)

Our next set of tests exploit the model’s predictions regarding price reactions to firm-level information. Again, we focus on quarterly earnings announcements as the source of firm-level information and examine price reactions in the earnings announcement window. Our analyses examine how economic uncertainty interacts with firm-level news in the price formation process. We focus on the association between size decile-adjusted stock returns in the two-day earnings announcement window and the earnings surprise, the VIX, the interaction between the VIX 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. Standard errors are clustered at the earnings announcement date level.

To test the hypotheses developed in Section 2, we estimate the following regressions at
the firm-quarter level:

\[
\text{EARET}_{it} = c_0 + c_1 \times \text{SUE}_{it} + c_2 \times \text{VIX}_t + c_3 \times \text{SUE}_{it} \times \text{VIX}_t + \gamma \cdot X_{it} + u_{it}, \quad \text{and}
\]

\[
\text{EARET}_{it} = c_0 + c_1 \times \text{SUE}_{it} + c_2 \times \text{ESVU}_t + c_3 \times \text{SUE}_{it} \times \text{ESVU}_t + \gamma \cdot X_{it} + u_{it},
\]

(28)

where the dependent variable EARET\(_{it}\) represents the announcement-window return and \(X_{it}\) represents a set of controls.

Column (a) of Table 4 reports our estimates of the first equation in (28). The coefficient on SUE decile is positive and significantly different from zero (0.287, \(p < 0.01\)), consistent with positive market responses to earnings surprises. Our main coefficient of interest, the interaction between VIX and SUE, is also positive and significantly different from zero (0.017, \(p < 0.01\)). We can infer from this that market responses to firm-level information are higher on days with greater uncertainty. Specifically, a one-standard deviation change in VIX yields an ERC that is approximately six percent higher than the average response to earnings surprises (6.1\% = \(\frac{0.017}{0.287}\)).

Columns (b) and (c) of Table 4 explore the mediating role of attention. In column (b), we replace VIX with ESVU. The sample shrinks considerably because EDGAR search data is available for a shorter window (2003-2017 relative to the earnings announcement sample from 1995 to 2020). Even with the smaller sample, however, the coefficient on ESVU*SUE is positive and significant (0.015, \(p < 0.01\)), consistent with earnings announcements that attract greater search volume to the firm’s SEC filings receiving stronger market reactions in the announcement window. In column (c), we include both VIX and ESVU as well as their interactions with SUE. The coefficients of interest are both positive, although the ESVU*SUE interaction (0.015, \(p < 0.01\)) is significant at a lower p-value than the VIX*SUE interaction (0.011, \(p < 0.10\)). Overall, the coefficient pattern is consistent with both a direct effect of VIX on market responses as well as an indirect effect that operates through investors’ attention allocation as reflected in EDGAR search activity.

(Insert Table 4 about here)

We estimate (28) in several subsamples to provide additional support for the theoretical predictions derived above. As shown in Figures 3 and 4, the effect of macroeconomic uncertainty on earnings response coefficients is not generally monotonic in the splitting variables: the plots show monotonic relations for \(\beta_n\), \(\sigma_{zn}\), and \(\sigma_{xn}\), but not for and \(\sigma_{en}\) and \(c_n\).

Table 5 presents estimates from these cross-sectional splits, where the variable of interest is the VIX*SUE interaction. For each subsample, we split announcing firms based on annual medians of: CAPM beta, Forecast dispersion, Idiosyncratic Volatility, trailing monthly share turnover (TURN), and institutional ownership (IO).
In the CAPM beta split subsamples, the coefficient of interest is mildly positive but not significantly different from zero for low-beta firms. In contrast, the coefficient for high-beta firms is positive and significantly different from both zero ($p < 0.01$) and the corresponding low-beta coefficient ($p < 0.05$). This is consistent with our result displayed in Figure 3, panel (a), that the effect of macro uncertainty on ERC’s is greater for firms with larger exposures to systematic risk.

(Insert Table 5 about here)

In the subsamples split on Forecast Dispersion and Idiosyncratic Volatility, the coefficients of interest are all positive and significantly different from zero ($0.010 - 0.020, p < 0.05$). However, they are not significantly different from each other, even though the coefficient in the high Idiosyncratic Volatility subsample is 70% larger than the coefficient in the low Idiosyncratic Volatility subsample ($0.017$ vs. $0.010$).

For the splits using share turnover to capture the expected magnitude of noise trade, $\sigma_{xa}$, the effects of macro uncertainty on ERCs are concentrated in subsamples with above-median TURN. The coefficient on VIX*SUE in the high-TURN sample ($0.026$) is positive and significantly different from both zero ($p < 0.01$) and the coefficient in the low-TURN sample ($0.05, p < 0.05$ for the test of difference in coefficients). This plausibly captures the predicted positive effect shown in Figure 3, panel (d), where the effect of macro uncertainty on ERCs is greater when the volatility of noise trade is larger. Similar to noise trade in our model, high turnover can make it difficult to infer fundamental information from price, which makes attention to earnings incrementally more valuable during periods of high uncertainty.

Our last subsample splits are based on institutional ownership (IO). Institutional owners can be expected to have lower information acquisition costs than retail investors. When choosing whether to pay attention to firm-level financial information, their alternative is generally to pay attention to a different financial signal or other job-related tasks (e.g., human resources, calling investors). In contrast, the alternative for retail investors is typically to pay attention to a primary job, family matter, hobby, or the back of their eyelids (i.e., sleep), which may carry greater opportunity costs. This suggests lower opportunity costs for professional institutional investors. Furthermore, institutional investors subscribe to services providing earnings information such as Bloomberg terminals, which can push earnings information to users, lowering the direct costs of information acquisition. Consistent with this interpretation and our prediction illustrated in Figure 4, panel (b), we find that the effect of macro uncertainty on ERC’s is concentrated in the high-IO subsample ($0.027, p < 0.01$), while the estimated effect for the low-IO subsample is insignificantly different from zero ($0.008, p > 0.10$). The difference in coefficients is significant at the ten percent level, sug-
suggesting that higher information acquisition costs reduce the effects of macro uncertainty on ERCs.

Table 6 re-estimates the regressions from Table 5 with ESVU replacing VIX, to provide evidence that the effects are attributable to attention rather than the VIX itself and other co-varying constructs, in line with Figure 5 from our theoretical analysis. Due to data constraints imposed by the use of EDGAR search logs, the sample sizes are cut roughly in half relative to Table 5. In general, the pattern is similar, albeit weaker, plausibly due to the smaller sample size. Interestingly, the results for the Forecast Dispersion and Idiosyncratic Volatility splits are stronger than those in Table 5, as the effect of ESVU on ERCs is concentrated in the high Forecast Dispersion (0.020, p < 0.05) and Idiosyncratic Volatility (0.021, p < 0.05) subsamples, consistent with greater uncertainty (Var[$D_a$]) leading to stronger relations between attention and ERCs. However, the coefficients of interest across the Forecast Dispersion and Idiosyncratic Volatility subsamples are not significantly different from each other (p = 0.14 and p = 0.18, respectively), so this can only be interpreted as mildly supportive evidence.

(Insert Table 6 about here)

4 Conclusion

This paper examines, both theoretically and empirically, the relation between economic uncertainty and investor attention to firm-level earnings announcements. In a multi-firm equilibrium model, we show that heightened economic uncertainty causes investors to rationally allocate more attention to firm-level information. Investors maximize the ratio of benefit to cost of acquiring information and accordingly pay incrementally more attention to earnings announcements of high-beta firms, as well as firms with more informative earnings announcements, higher idiosyncratic volatility of earnings, less informative prices, and lower information acquisition costs.

These predictions of the model are supported in the data. Using SEC EDGAR search traffic as our measure of investor attention to firm-level information, we find that on days with high economic uncertainty, as reflected in the VIX, investors pay more attention to firm-level earnings announcements. Our analysis of earnings response coefficients reveals that prices respond to news in earnings more strongly when there is greater economic uncertainty. In subsample analyses, we find that these results are concentrated in firms with high CAPM beta, higher institutional ownership, idiosyncratic volatility, and prior share turnover. We view these as consistent with our theoretical predictions related to cross-sectional variation in the benefit/cost ratio of information. We conclude that economic uncertainty is an important driver of investor attention to firm-level information and to earnings announcements.
References


Israeli, D., R. Kasznik, and S. A. Sridharan (2020). Unexpected distractions and investor attention to corporate announcements. *Available at SSRN 3057278*.


Appendix

A.1 Proof of Proposition 1

We denote $I$ as the identity matrix, $1$ as a vector of ones, and $0$ as a vector/matrix of zeros. These vectors and matrices are always assumed to have the conformable dimension, which we do not specify below in order to avoid overly cumbersome notation. The vectors $ι_1$ and $ι_2$ have been defined in the text (see Conjecture 1).

Learning for type $I_{12}$ investors

Type $I_{12}$ investors observe $E_1$ and $E_2$ and do not learn from prices. Write

$$
\begin{bmatrix}
D \\
E_1 \\
E_2
\end{bmatrix}
= \begin{bmatrix}
I \\
ι_1' \\
ι_2'
\end{bmatrix} D + \begin{bmatrix}
0 & 0 \\
1 & 0 \\
0 & 1
\end{bmatrix} \begin{bmatrix}
ε_1 \\
ε_2
\end{bmatrix},
$$

(A.1)

and thus

$$
\begin{bmatrix}
D \\
E_1 \\
E_2
\end{bmatrix} \sim N\left( \begin{bmatrix}
0 \\
0
\end{bmatrix}, \begin{bmatrix}
Var[D] & Var[D] [ι_1' ι_2'] \\
Var[D] [ι_1' ι_2'] & Var[D] [ι_1 ι_2] + \begin{bmatrix}
σ^2_{ε_1} & 0 \\
0 & σ^2_{ε_2}
\end{bmatrix}
\end{bmatrix} \right).
$$

(A.2)

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

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

$$
\begin{bmatrix}
θ \\
s
\end{bmatrix} \sim N\left( \begin{bmatrix}
μ_θ \\
μ_s
\end{bmatrix}, \begin{bmatrix}
Σ_{θ,θ} & Σ_{θ,s} \\
Σ_{s,θ} & Σ_{s,s}
\end{bmatrix} \right).
$$

(A.3)

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

$$
E[θ|s] = μ_θ + Σ_{θ,s} Σ_{s,s}^{-1} (s - μ_s)
$$

(A.4)

$$
Var[θ|s] = Σ_{θ,θ} - Σ_{θ,s} Σ_{s,s}^{-1} Σ_{s,θ}.
$$

(A.5)

Applied to (A.2), the Projection Theorem together with the Woodbury Matrix Identity imply:

$$
\text{Var}^{I_{12}}[D] = \text{Var}[D] - \text{Var}[D] [ι_1 ι_2] \begin{bmatrix}
ι_1' \\
ι_2'
\end{bmatrix} Var[D] [ι_1 ι_2] + \begin{bmatrix}
σ^2_{ε_1} & 0 \\
0 & σ^2_{ε_2}
\end{bmatrix}^{-1} \begin{bmatrix}
ι_1' \\
ι_2'
\end{bmatrix} Var[D]
$$

(A.6)

and thus we have obtained $τ^{I_{12}} \equiv \text{Var}^{I_{12}}[D]^{-1}$ as in Proposition 1. This simple form for $τ^{I_{12}}$ allows us to compute its determinant using the following special case of the Matrix Determinant Lemma:

Lemma A2. Let $s_1$ and $s_2$ be two non-zero scalars. Then

$$
\begin{bmatrix}
\text{Var}[D]^{-1} + [ι_1 ι_2] \begin{bmatrix}
s_1 & 0 \\
0 & s_2
\end{bmatrix} [ι_1' ι_2']
\end{bmatrix} =
\begin{bmatrix}
\text{Var}[D]^{-1} \times (1 + s_1 \text{Var}[D_1] + s_2 \text{Var}[D_2] + s_1 s_2 (1 - ρ_{12}^2) \text{Var}[D_1] \text{Var}[D_2])
\end{bmatrix}
$$

(A.8)

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Proof. The proof is an application of the Matrix Determinant Lemma:
\[
|A + UVV'| = |W^{-1} + V'A^{-1}U| \times |W| \times |A|, \tag{A.9}
\]
where
\[
A = \text{Var}[D]^{-1}, \quad U = [\tau_1 \tau_2], \quad W = \begin{bmatrix} s_1 & 0 \\ 0 & s_2 \end{bmatrix}, \quad V' = [\tau'_1 \tau'_2]. \tag{A.10}
\]
Replacing terms, we obtain
\[
W^{-1} + V'A^{-1}U = \begin{bmatrix} \text{Var}[D_1] + \frac{1}{s_1} & \text{Cov}[D_1, D_2] \\ \text{Cov}[D_1, D_2] & \text{Var}[D_2] + \frac{1}{s_2} \end{bmatrix} \tag{A.11}
\]
whose determinant is
\[
|W^{-1} + V'A^{-1}U| = \frac{1}{s_1 s_2} + \frac{\text{Var}[D_1]}{s_2} + \frac{\text{Var}[D_2]}{s_1} + (1 - \rho_{12}^2) \text{Var}[D_1] \text{Var}[D_2], \tag{A.12}
\]
which, replaced in (A.9) yields (A.8).

We can now apply Lemma A2 to compute the determinant of \(\tau_{12}^2\):
\[
|\tau_{12}^2| = |\text{Var}[D]|^{-1} \times \left( 1 + \frac{\text{Var}[D_1]}{\sigma_{\varepsilon_1}^2} + \frac{\text{Var}[D_2]}{\sigma_{\varepsilon_2}^2} + \frac{(1 - \rho_{12}^2) \text{Var}[D_1] \text{Var}[D_2]}{\sigma_{\varepsilon_1}^2 \sigma_{\varepsilon_2}^2} \right). \tag{A.13}
\]

Learning for type I investors

Type I investors observe \(E_1\) and use prices to learn about \(E_2\). According to Conjecture 1, the only informative price in this case is \(P_2\). Denote \(h_2 = \frac{\lambda_1 \lambda_{12}}{\gamma \sigma_{\varepsilon_2}^2}\) and write
\[
\begin{bmatrix} D \\ E_1 \\ P_2 \end{bmatrix} = \begin{bmatrix} I \\ \tau'_1 \\ h_2 \tau'_2 \end{bmatrix} D + \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & h_2 \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ 0 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ \tau'_2 \end{bmatrix}, \tag{A.14}
\]
and thus
\[
\begin{bmatrix} D \\ E_1 \\ P_2 \end{bmatrix} \sim N\left( \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \text{Var}[D] & \tau'_1 & \tau'_2 \\ \tau'_1 & \text{Var}[D] & \tau'_1 \\ \tau'_2 & \tau'_1 & \text{Var}[D] + \begin{bmatrix} \sigma_{\varepsilon_1}^2 & 0 \\ 0 & h_2^2 \sigma_{\varepsilon_2}^2 + \sigma_{\varepsilon_2}^2 \end{bmatrix} \end{bmatrix} \right), \tag{A.15}
\]
which, after applying the Projection Theorem and the Woodbury matrix identity leads to
\[
\text{Var}^{I_1}[D] = \left( \text{Var}[D]^{-1} + \frac{1}{\sigma_{\varepsilon_1}^2} \tau_1 \tau'_1 + \frac{h_2^2}{h_2^2 \sigma_{\varepsilon_2}^2 + \sigma_{\varepsilon_2}^2} \tau_2 \tau'_2 \right)^{-1}, \tag{A.16}
\]
\[
\text{Var}^{I_1}[D] = \left( \text{Var}[D]^{-1} + \frac{1}{\sigma_{\varepsilon_1}^2} \tau_1 \tau'_1 + \frac{\ell_{12}^I}{\sigma_{\varepsilon_2}^2} \tau_2 \tau'_2 \right)^{-1}, \tag{A.17}
\]
where \(\ell_{12}^I\) has been defined in (8). Apply Lemma A2 to compute the determinant of \(\tau_{I_1}\):
\[
|\tau_{I_1}| = |\text{Var}[D]|^{-1} \left( 1 + \frac{\text{Var}[D_1]}{\sigma_{\varepsilon_1}^2} \ell_{12}^I + \frac{\text{Var}[D_2]}{\sigma_{\varepsilon_2}^2} \ell_{12}^I + \frac{(1 - \rho_{12}^2) \text{Var}[D_1] \text{Var}[D_2]}{\sigma_{\varepsilon_1}^2 \sigma_{\varepsilon_2}^2} \ell_{12}^I \right). \tag{A.18}
\]
Learning for type $I_2$ investors and for type $U$ investors

Type $I_2$ investors observe $E_2$ and use prices to learn about $E_1$. According to Conjecture 1, the only informative price in this case is $\hat{P}_1$. Type $U$ investors learn only from prices. According to Conjecture 1, the only informative prices are $\hat{P}_1$ and $\hat{P}_2$. After following the same steps as above, we can write the posterior precision matrix for each investor type $i \in \{I_1, I_2, I_{12}, U\}$ as

$$\tau^i \equiv \text{Var}^i[D]^{-1} = \text{Var}[D]^{-1} + \frac{\ell_1^i}{\sigma_{z1}^2} \nu_1 \nu_1' + \frac{\ell_2^i}{\sigma_{z2}^2} \nu_2 \nu_2',$$

(A.19)
and the determinant of $\tau^i$ as

$$|\tau^i| = |\text{Var}[D]^{-1}| \left(1 + \frac{\text{Var}[D_1]}{\sigma_{z1}^2} \ell_1^i + \frac{\text{Var}[D_2]}{\sigma_{z2}^2} \ell_2^i + \frac{(1 - \rho_{12}^2) \text{Var}[D_1] \text{Var}[D_2]}{\sigma_{z1}^2 \sigma_{z2}^2} \ell_1^i \ell_2^i\right),$$

(A.20)

which completes the proof of Proposition 1.

## A.2 Proof of Proposition 2

Consider the general case $c_1 \neq c_2$. The expected utility of investor $i \in \{I_1, I_2, I_{12}, U\}$ at time 1 is:

$$U^i = E^i \left[-e^{-\gamma(W^i - c_1 L_1^i - c_2 L_2^i)}\right] = -e^{\gamma(c_1 L_1^i + c_2 L_2^i)} E^i \left[e^{-\gamma R'^e}\right].$$

(A.21)

Further replacing the optimal portfolio choice from Eq. (4) yields

$$U^i = -e^{\gamma(c_1 L_1^i + c_2 L_2^i)} E^i \left[e^{-\gamma R'^e} \text{Var}^i[D]^{-1} R^e\right]$$

(A.22)

$$= -e^{\gamma(c_1 L_1^i + c_2 L_2^i)} e^{-\frac{1}{2} E^i[R^e] \text{Var}[D]^{-1} E^i[R^e]},$$

(A.23)

Assume that an investor of type $i_-$ considers acquiring one additional signal and thus becoming type $i_+$. At time 1, from the perspective of investor $i_-$, $E^i_+ [R^e]$ is a random vector that depends on the additional signal. Denote this random vector by $z + m$, with mean $m$ and variance $\Sigma$ (in other words, $z$ has mean $0$ and variance $\Sigma$). By the law of iterated expectations,

$$m \equiv E^{i_-} [E^i_+ [R^e]] = E^{i_-} [R^e],$$

(A.24)
and by the law of total variance,

$$\Sigma \equiv \text{Var}^{i_-} [E^i_+ [R^e]] = \text{Var}^{i_-} [R^e] - \text{Var}^{i_+} [R^e].$$

(A.25)

Therefore, for investor $i_-$, $-\frac{1}{2} E^i_+ [R^e]' \text{Var}^{i_+} [R^e]^{-1} E^i_+ [R^e]$ (that is, the random exponent in (A.23), written for investor $i_+$) is a random scalar that can be written as:

$$-\frac{1}{2} E^i_+ [R^e]' \text{Var}^{i_+} [R^e]^{-1} E^i_+ [R^e] = -\frac{1}{2} (z + m)' (\text{Var}^{i_-} [R^e] - \Sigma)^{-1} (z + m)$$

(A.26)

$$= z' \left(-\frac{1}{2} (\text{Var}^{i_-} [R^e] - \Sigma)^{-1}\right) z + (m' (\text{Var}^{i_-} [R^e] - \Sigma)^{-1}) z + m' \left(-\frac{1}{2} (\text{Var}^{i_-} [R^e] - \Sigma)^{-1}\right) m.$$

(A.27)

To compute $E^{i_-} [U^{i_+}]$, we will apply the following Lemma (Veldkamp, 2011, p. 102):
Lemma A3. Consider a random vector \( z \sim \mathcal{N}(0, \Sigma) \). Then,

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

(A.28)

Compute first

\[
I - 2\Sigma F = I - 2\Sigma \left( -\frac{1}{2} \text{Var}^{i-}[R^c] - \Sigma \right)^{-1}
\]

(A.29)

\[
= I + \Sigma \text{Var}^{i-}[R^c] - \Sigma)^{-1}
\]

(A.30)

\[
= \text{Var}^{i-}[R^c](\text{Var}^{i-}[R^c] - \Sigma)^{-1},
\]

(A.31)

which, using (A.25), leads to the determinant in Lemma A3:

\[
|I - 2\Sigma F| = \left| \frac{\text{Var}^{i-}[R^c]}{\text{Var}^{i+}[R^c]} \right| = \left| \frac{\tau^i}{\tau^{-i}} \right|.
\]

(A.32)

The exponent in Lemma A3 is (define \( \Sigma^{i-} \equiv \text{Var}^{i-}[R^c] \) to simplify notation):

\[
\frac{1}{2} G' (I - 2\Sigma F)^{-1} \Sigma G + H
\]

(A.33)

\[
= \frac{1}{2} \left( -m' (\Sigma^{i-} - \Sigma)^{-1} \right) (\Sigma^{i-} - \Sigma) (\Sigma^{i-} - \Sigma)^{-1} \Sigma \left( -m' (\Sigma^{i-} - \Sigma)^{-1} \right)' - m' \frac{1}{2} (\Sigma^{i-} - \Sigma)^{-1} m
\]

(A.34)

\[
= \frac{1}{2} m' (\Sigma^{i-} - \Sigma)^{-1} \Sigma (\Sigma^{i-} - \Sigma)^{-1} m - \frac{1}{2} m' (\Sigma^{i-} - \Sigma)^{-1} m
\]

(A.35)

\[
= \frac{1}{2} m' \left( (\Sigma^{i-} - \Sigma)^{-1} \Sigma - I \right) (\Sigma^{i-} - \Sigma)^{-1} m
\]

(A.36)

\[
= -\frac{1}{2} m' (\Sigma^{i-} - \Sigma)^{-1} m
\]

(A.37)

\[
= -\frac{1}{2} E^{i-}[R^c]' \text{Var}^{i-}[R^c]^{-1} E^{i-}[R^c].
\]

(A.38)

We can therefore write

\[
E^{i-}[U^{i+}] = -e^{\gamma (c_1 L_{i1}^{1+} + c_2 L_{i2}^{1+})} E^{i-} \left[ e^{-\frac{1}{2} E^{i-}[R^c]' \text{Var}^{i-}[R^c]^{-1} E^{i-}[R^c]} \right]
\]

(A.39)

\[
= -e^{\gamma (c_1 L_{i1}^{1+} + c_2 L_{i2}^{1+})} \sqrt{\frac{\tau_{i^{-1}}}{\tau_{i^{+}}}} e^{-\frac{1}{2} E^{i-}[R^c]' \text{Var}^{i-}[R^c]^{-1} E^{i-}[R^c]}
\]

(A.40)

\[
= \frac{e^{\gamma (c_1 L_{i1}^{1+} + c_2 L_{i2}^{1+})}}{e^{\gamma (c_1 L_{i1}^{1-} + c_2 L_{i2}^{1-})}} \sqrt{\frac{\tau_{i^{-1}}}{\tau_{i^{+}}}} U^{i-}.
\]

(A.41)

where \( c_+ = c_1 \) or \( c_+ = c_2 \) depending on the signal that investor \( i_- \) decides to acquire. At time \( t = 0 \), investor \( i_- \) compares \( E_0[U^{i-}] \) with \( E_0[E^{i-}[U^{i+}]] \) and acquires the additional signal if and only if

\[
E_0[E^{i-}[U^{i+}]] > E_0[U^{i-}],
\]

(A.42)

which yields \( e^{\gamma c_+} \sqrt{\tau_{i^{-1}}/\tau_{i^{+}}} < 1 \) (the division by \( E_0[U^{i-}] < 0 \) flips the inequality sign). Thus,
We notice that

\[ \frac{1}{2\gamma} \ln \left| \frac{\tau^{i+}}{\tau^{i-}} \right| > c_+ , \]  

which completes the proof. Proposition 2 is a special case with \( c_1 = c_2 = c \).

### A.3 Proof of Theorem 1

We start by analyzing the tradeoffs of the uninformed investor. To ease notation, we define \( V_1 \equiv \text{Var}[D_1]/\sigma_{l_1}^2 \) and \( V_2 \equiv \text{Var}[D_2]/\sigma_{l_2}^2 \). Using the learning coefficients \( \ell_1 \) and \( \ell_2 \) from (8), which we do not index by investor type for notational simplicity, the following equations, which result directly from Propositions 1 and 2, state the indifference conditions for paying attention to \( E_1 \) and \( E_2 \):

\[
U \rightarrow I_1 : \quad \frac{1 + V_1 + V_2\ell_2 + (1 - \rho_{12}^2)V_1V_2\ell_2}{1 + V_1\ell_1 + V_2\ell_2 + (1 - \rho_{12}^2)V_1V_2\ell_1\ell_2} \triangleq B_{U \rightarrow I_1} \quad (A.44)
\]

\[
U \rightarrow I_2 : \quad \frac{1 + V_1\ell_1 + V_2\ell_2 + (1 - \rho_{12}^2)V_1V_2\ell_1\ell_2}{1 + V_1\ell_1 + V_2\ell_2 + (1 - \rho_{12}^2)V_1V_2\ell_1\ell_2} = e^{2\gamma c}. \quad (A.45)
\]

Since the learning coefficients \( \ell_1 \) and \( \ell_2 \) are smaller or equal to one, the left-hand sides of (A.44)-(A.45) are always greater or equal to 1. Furthermore, the benefit of learning \( E_1 \), \( B_{U \rightarrow I_1} \), always decreases with \( \ell_1 \): if more investors pay attention to \( E_1 \) (that is, if \( \ell_1 \) is higher), then prices are more informative and the signal \( E_1 \) is less valuable. In the same way, the benefit of learning \( E_2 \), \( B_{U \rightarrow I_2} \), always decreases with \( \ell_2 \). We thus recover here 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 indifference conditions (A.44)-(A.45) are satisfied, no investor finds it beneficial to pay attention simultaneously to \( E_1 \) and \( E_2 \), and thus \( \lambda_{12} = 0 \). Consider first a type \( I_1 \) investor. This investor pays attention to \( E_2 \) if an only if

\[
B_{I_1 \rightarrow I_{12}} \equiv \frac{1 + V_1 + V_2 + (1 - \rho_{12}^2)V_1V_2}{1 + V_1\ell_1 + V_2\ell_2 + (1 - \rho_{12}^2)V_1V_2\ell_1\ell_2} > e^{2\gamma c}. \quad (A.46)
\]

We notice that \( B_{I_1 \rightarrow I_{12}} \) is obtained by replacing \( \ell_1 = 1 \) in \( B_{U \rightarrow I_2} \). We also have:

\[
\frac{\partial B_{U \rightarrow I_2}}{\partial \ell_1} = -\frac{(1 - \ell_2)^2 V_1V_2}{(1 + V_1\ell_1 + V_2\ell_2 + (1 - \rho_{12}^2)V_1V_2\ell_1\ell_2)^2} \leq 0, \quad (A.47)
\]

which implies \( B_{I_1 \rightarrow I_{12}} < B_{U \rightarrow I_2} = e^{2\gamma c} \). Then the inequality (A.46) cannot hold, and thus a type \( I_1 \) investor will never find it optimal to pay attention to \( E_2 \). By the same logic, a type \( I_2 \) investor will never find it optimal to pay attention to \( E_1 \). Furthermore, \( B_{U \rightarrow I_{12}} = B_{U \rightarrow I_1} \times B_{I_1 \rightarrow I_{12}} < e^{4\gamma c} \) and thus, in equilibrium,

\[
\lambda_{12} = 0. \quad (A.48)
\]

We will now characterize the three cases of Theorem 1. We have shown above that \( \frac{\partial B_{U \rightarrow I_2}}{\partial \ell_1} \leq 0 \)
and \( \frac{\partial B_{U \rightarrow I_1}}{\partial \ell_2} \leq 0 \). It is a matter of algebra to further show that \( \frac{\partial B_{U \rightarrow I_1}}{\partial \ell_2} \leq 0 \) and \( \frac{\partial B_{U \rightarrow I_1}}{\partial \ell_1} \leq 0 \). Thus, the maximum possible benefit of learning \( E_1 \) is attained when \( \ell_1 = \ell_2 = 0 \) and equals \( 1 + V_1 \); and the maximum possible benefit of learning \( E_2 \) is attained when \( \ell_1 = \ell_2 = 0 \) and equals \( 1 + V_2 \). (Intuitively, the investor who reaps the highest benefit from information is the first investor who gets informed.) This implies an upper bound on \( c \), above which no investor finds it optimal to pay attention to firm-level information. Recalling that \( V_1 > V_2 \), this upper bound solves:

\[
e^{2\gamma c_1} = 1 + V_1,
\]

and therefore we have obtained \( \kappa_{1}^* = \ln(1 + \text{Var}[D_1]/\sigma_{z_1}^2)/(2\gamma) > 0 \) and case (A) of Theorem 1: if \( c \in [\kappa_{1}^*, \infty) \), then the cost of information is prohibitive and no investor finds it optimal to pay attention to the earnings announcements: \( \lambda_1 = \lambda_2 = \lambda_{12} = 0 \).

Assume now that \( c < \ln(1 + \text{Var}[D_1]/\sigma_{z_1}^2)/(2\gamma) \), in which case there is a strictly positive mass of investors attentive to \( E_1 \), or \( \ell_1 > 0 \). We solve for the threshold \( \kappa_{2}^* \leq \kappa_{1}^* \) such that \( \ell_2 = 0 \), that is, no investor pays attention to \( E_2 \). First, when \( \ell_2 = 0 \) the indifference condition (A.44) becomes:

\[
\frac{1 + V_1}{1 + V_1 \ell_1} = e^{2\gamma c},
\]

from which we obtain

\[
\ell_1 = \frac{1 + V_1 - e^{2\gamma c}}{V_1 e^{2\gamma c}} > 0.
\]

Replacing this in the indifference condition (A.45) and setting \( \ell_2 = 0 \) yields an equation for \( \kappa_{2}^* \):

\[
e^{2\gamma \kappa_{2}^*} = (1 + V_1) \frac{1 + V_2 - \rho_{12}^2 V_2}{1 + V_1 - \rho_{12}^2 V_2} < 1 + V_1.
\]

Comparing this equation with the equation (A.49) that determines \( \kappa_{1}^* \), \( V_1 > V_2 \) implies that \( \kappa_{2}^* \leq \kappa_{1}^* \). Furthermore, after replacement of terms and tedious algebra we obtain that \( \partial \kappa_{2}^* / \partial \gamma > 0 \). We have therefore obtained case (B) of Theorem 1: if \( c \in [\kappa_{2}^*, \kappa_{1}^*) \), then investors pay attention only to the earnings announcement \( E_1 \): \( \lambda_1 > 0 \) and \( \lambda_2 = \lambda_{12} = 0 \).

Equation (A.52) can also be written as

\[
e^{2\gamma \kappa_{2}^*} = (1 + V_2) - \frac{\rho_{12}^2 V_2 (V_1 - V_2)}{1 + V_1 - \rho_{12}^2 V_2} < 1 + V_2,
\]

and thus we notice that \( \kappa_{2}^* \) is smaller than the value \( \kappa_{3}^* \) that satisfies \( e^{2\gamma \kappa_{3}^*} = 1 + V_2 \). When the information cost is between \( \kappa_{2}^* \) and \( \kappa_{3}^* \), the announcement of firm 1 crowds out investors’ attention to the announcement of firm 2 (this is the *crowding-out equilibrium* to which we refer in the text).

When \( c < \kappa_{2}^* \), investors pay attention to both announcements, as in case (C) of Theorem 1: if \( c \in (0, \kappa_{2}^*) \), then information is cheap enough so that investors pay attention to both announcements, but more investors pay attention to \( E_1 \), \( \lambda_1 > \lambda_2 > 0 \), and \( \lambda_{12} = 0 \).

We also show that an equilibrium with \( \lambda_1 = \lambda_2 = 0 \) but \( \lambda_{12} > 0 \) cannot exist as long as \( \lambda_{U} > 0 \). Such an equilibrium would imply (we make here the argument in the general case \( c_1 \neq c_2 \)):

\[
\mathcal{B}_{U \rightarrow I_1} = \frac{1 + V_1 + V_2 \ell_2 + (1 - \rho_{12}^2) V_1 V_2 \ell_2}{1 + V_1 \ell_1 + V_2 \ell_2 + (1 - \rho_{12}^2) V_1 V_2 \ell_1 \ell_2} < e^{2\gamma c_1}
\]
Eq. (A.54) states that uninformed investors do not find it optimal to buy the signal $E_1$; Eq. (A.55) states that uninformed investors do not find it optimal to buy the signal $E_2$; Eq. (A.56) states that uninformed investors are indifferent between staying uninformed or buying both signals.

Dividing (A.56) by (A.54) yields

\[
\frac{B_{U\rightarrow I_{12}}}{B_{U\rightarrow I_1}} > e^{2\gamma c_2} \Rightarrow \frac{1 + V_1 + V_2 + (1 - \mu^2_{12})V_1V_2}{1 + V_1 + V_2 + (1 - \mu^2_{12})V_1V_2} > e^{2\gamma c_2}. \tag{A.57}
\]

and we know that $B_{I_1\rightarrow I_{12}} < B_{U\rightarrow I_2}$. Therefore, (A.55) cannot hold. Similarly, dividing (A.56) by (A.55) implies that (A.54) cannot hold. Thus, if $\lambda_U > 0$ then $\lambda_1 = \lambda_2 = 0, \lambda_{12} > 0$ cannot be an equilibrium. One can also rule out equilibria of the type $\lambda_1 = 0, \lambda_2 > 0, \lambda_{12} > 0$ and $\lambda_1 > 0, \lambda_2 = 0, \lambda_{12} > 0$. Thus, as long as there is a non-zero mass of uninformed investors in the economy, the only possible equilibria are cases (A), (B), and (C) from Theorem 1.

Figure 6 complements Figure 1 in the paper. It depicts the three equilibria of Theorem 1 when the announcing firms are heterogeneous with respect to $\sigma_{x\alpha}$ (panel a) or with respect to $\sigma_{e\alpha}$ (panel b), while keeping all the others parameters homogeneous across firms.

(Insert Figure 6 about here)

We note that heterogeneity in $\sigma_{x\alpha}$ is irrelevant for Theorem 1 (this heterogeneity affects the levels of $\lambda_1$ and $\lambda_2$ but not the endogenous thresholds $\kappa_1^*$ and $\kappa_2^*$). Finally, the case of heterogeneous information costs $c_\alpha$ is trivial: if $c_1 < c_2$, then investors pay attention first to $E_1$, and for high levels of uncertainty they pay attention both to $E_1$ and $E_2$. This completes the proof of Theorem 1. \hfill \qed

### A.4 Proof of Lemma 1

Lemma 1 results directly after writing $\tau^i$ for each investor type:

- **Type $I_1$:** $\tau^{I_1} = \text{Var}[D]^{-1} + \frac{1}{\sigma^2_{x_1}} \ell_1 t'_1 + \frac{\ell_2}{\sigma^2_{e_2}} \ell_2 t'_2$ \tag{A.58}
- **Type $I_2$:** $\tau^{I_2} = \text{Var}[D]^{-1} + \frac{\ell_1}{\sigma^2_{x_1}} \ell_1 t'_1 + \frac{1}{\sigma^2_{e_2}} t'_2$ \tag{A.59}
- **Type $U$:** $\tau^U = \text{Var}[D]^{-1} + \frac{\ell_1}{\sigma^2_{x_1}} \ell_1 t'_1 + \frac{\ell_2}{\sigma^2_{e_2}} t'_2$. \tag{A.60}

The weighted average precision is $\tau = \lambda_1 \tau^{I_1} + \lambda_2 \tau^{I_2} + (1 - \lambda_1 - \lambda_2) \tau^U$, which yields (20). \hfill \qed

### A.5 Proof of Proposition 3

We will use the market clearing condition to solve for the undetermined price coefficients:

\[
\lambda_1 \frac{\text{Var}[D]^{-1}}{\gamma} E^I_1[D] + \lambda_2 \frac{\text{Var}[D]^{-1}}{\gamma} E^I_2[D] + \lambda_U \frac{\text{Var}[D]^{-1}}{\gamma} E^U[D] - \frac{\tau}{\gamma} \mathbf{P} = \mathbf{x}. \tag{A.61}
\]
Using the Projection Theorem and \( h \equiv \frac{\lambda_1}{\gamma \sigma_{x2}^2} \) we can compute

\[
\text{Var}^I[D]^{-1} E^I[D] = \left( \text{Var}[D]^{-1} + [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{1}{h \sigma_{z}^2 + \sigma_{x2}^2} \end{bmatrix} \begin{bmatrix} \iota'_1 \\ h \iota'_2 \end{bmatrix} \right) \times \\
\times \text{Var}[D] [\iota_1 \ h \iota_2] \left( \begin{bmatrix} \iota'_1 \\ h \iota'_2 \end{bmatrix} \right) \text{Var}[D] \begin{bmatrix} [\iota_1 \ h \iota_2] + \begin{bmatrix} \sigma_{x1}^2 & 0 \\ 0 & h^2 \sigma_{z}^2 + \sigma_{x2}^2 \end{bmatrix} \end{bmatrix}^{-1} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix},
\]

which simplifies to

\[
\text{Var}^I[D]^{-1} E^I[D] = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{1}{h \sigma_{z}^2 + \sigma_{x2}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix}. \quad (A.63)
\]

The same reasoning leads to:

\[
\text{Var}^U[D]^{-1} E^U[D] = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} & 0 \\ 0 & \frac{1}{\sigma_{x2}^2} \end{bmatrix} \begin{bmatrix} \widehat{P}_1 \\ E_2 \end{bmatrix} = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \end{bmatrix} \begin{bmatrix} \widehat{P}_1 \\ E_2 \end{bmatrix}. \quad (A.65)
\]

Replacing Conjecture 1 into (A.63)-(A.65) yields:

\[
\text{Var}^I[D]^{-1} E^I[D] = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{1}{h \sigma_{z}^2 + \sigma_{x2}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_1}{\lambda_2^2 + \gamma^2 \sigma_{z}^2 \sigma_{x2}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} - \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \iota_1 \times_2 \iota_2 \quad (A.66)
\]

\[
\text{Var}^U[D]^{-1} E^U[D] = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{1}{h \sigma_{z}^2 + \sigma_{x2}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} \begin{bmatrix} \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} - \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} \iota_1 \times_1 \iota_2 \quad (A.67)
\]

\[
\text{Var}^U[D]^{-1} E^U[D] = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{1}{\sigma_{x1}^2} & 0 \\ 0 & \frac{1}{h \sigma_{z}^2 + \sigma_{x2}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} \begin{bmatrix} \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} = [\iota_1 \ h \iota_2] \begin{bmatrix} \frac{\gamma \lambda_1}{\lambda_1^2 + \gamma \sigma_{x2}^2 \sigma_{x1}^2} & 0 \\ 0 & \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \end{bmatrix} \begin{bmatrix} E_1 \\ \widehat{P}_2 \end{bmatrix} - \frac{\gamma \lambda_2}{\lambda_2^2 + \gamma^2 \sigma_{x2}^2 \sigma_{x1}^2} \iota_1 \times_2 \iota_2 \quad (A.68)
\]

We now go back to (A.61), which we write as

\[
\tau P = \lambda_1 \text{Var}^I[D]^{-1} E^I[D] + \lambda_2 \text{Var}^U[D]^{-1} E^U[D] + \lambda_1 \text{Var}^U[D]^{-1} E^U[D] - \gamma x, \quad (A.69)
\]

which, after replacement of (A.66)-(A.68) becomes

\[
\tau P = \pi_1(\lambda_1) \iota_1 E_1 + \pi_2(\lambda_2) \iota_2 E_2 - \gamma \begin{bmatrix} \pi_1(\lambda_1) \sigma_{x1}^2 & 0 \\ \lambda_1 & 0 \end{bmatrix} \begin{bmatrix} E_1 \\ \iota_2 E_2 \end{bmatrix} - \gamma \begin{bmatrix} 0 & \pi_2(\lambda_2) \sigma_{x2}^2 \\ \lambda_2 & 0 \end{bmatrix} \begin{bmatrix} 0 & \iota_2 E_2 \end{bmatrix} x, \quad (A.70)
\]
where the function $\pi_a(\lambda_a)$ is defined in Lemma 1. We can now verify Conjecture 1:

\[
\hat{P} = \frac{1}{\gamma} \left[ \begin{array}{ccc} \frac{\pi_1(\lambda_1)\sigma_{\epsilon_1}^2}{\lambda_1} & 0 & 0'_{N-2} \\ 0 & \frac{\pi_2(\lambda_2)\sigma_{\epsilon_2}^2}{\lambda_2} & 0'_{N-2} \\ 0'_{N-2} & 0_{N-2} & I_{N-2} \end{array} \right]^{-1} \left[ \pi_1(\lambda_1)\epsilon_1 E_1 + \pi_2(\lambda_2)\epsilon_2 E_2 \right] - x
\]

(A.71)

which completes the proof of Proposition 3.

\[\square\]

A.5.1 Proof of Corollary 3.1

Define first $\iota \equiv [\iota_1 \iota_2]$ and $\Pi \equiv \left[ \begin{array}{cc} \pi(\lambda_1) & 0 \\ 0 & \pi(\lambda_2) \end{array} \right]$. From (A.70), the earnings response coefficients for all assets are

\[\text{ERC} = \tau^{-1}\iota\Pi = (\text{Var}[D]^{-1} + \iota\Pi\iota')^{-1}\iota\Pi,\]  

(A.72)

and thus, using the Woodbury matrix identity:

\[\Pi\iota'\text{ERC} = \Pi - (\Pi^{-1} + \iota'\text{Var}[D]\iota)^{-1}.\]  

(A.73)

We recognize that $\iota'\text{ERC} = \text{ERC}_A$ and $\iota'\text{Var}[D]\iota = \text{Var}[D_A]$, where $D_A$ is the $2 \times 1$ vector of payoffs for the announcing firms. Thus, after multiplication with $\Pi^{-1}$, we obtain Eq. (23):

\[\text{ERC}_A = I - (I + \text{Var}[D_A]\Pi)^{-1}.\]  

(A.74)

Eq. (23) can also be written

\[\text{ERC}_A = I - (I - \text{Var}[D_A](I + \Pi\text{Var}[D_A])^{-1}\Pi) = \text{Var}[D_A](I + \Pi\text{Var}[D_A])^{-1}\Pi,\]  

(A.75)

and thus

\[\text{ERC}_A^{-1} = I + \Pi^{-1}\text{Var}[D_A]^{-1}.\]  

(A.76)

Using the above relation, we will obtain the earnings response coefficients for non-announcing firms. Start from

\[\text{ERC} \times \text{ERC}_A^{-1} = \left(\text{Var}[D]^{-1} + \iota\Pi\iota'\right)^{-1}\iota\Pi (I + \Pi^{-1}\text{Var}[D_A]^{-1}) \]

(A.77)

\[= \left[\text{Var}[D]\iota\Pi - \text{Var}[D]\iota(I^{-1} + \text{Var}[D_A])^{-1}\text{Var}[D_A]\Pi (I + \Pi^{-1}\text{Var}[D_A]^{-1})\right],\]  

(A.78)

which, after some matrix algebra, becomes

\[\text{ERC} \times \text{ERC}_A^{-1} = \text{Var}[D]\iota\text{Var}[D_A]^{-1}.\]  

(A.79)
Thus, the earnings response coefficients of non-announcing firms are

\[
\text{ERC}_{NA} = \frac{\sigma_f^2}{\sigma_f^2(\beta_1^2\sigma_{e1}^2 + \beta_2^2\sigma_{e2}^2) + \sigma_e^2\sigma_f^2} \left[ \begin{array}{c} \beta_3 \\ \vdots \\ \beta_N \end{array} \right]
\]

which is Eq. (24) in the text. This completes the proof of Corollary 3.1.

\[\Box\]

**B Alternative model specification**

Consider an alternative setup in which investors observe a public signal about \( f \):

\[ G = f + g, \quad \text{where } g \sim N(0, \sigma_g^2). \]  

(B.81)

and define \( \sigma_g \) as *economic uncertainty* (instead of \( \sigma_f \) as in the main model).

In this setup, prices take the form

\[ P = \varphi G + \alpha_1 E_1 + \alpha_2 E_2 - \xi x, \]  

(B.82)

and all the previous propositions, theorems, and corollaries hold by replacing \( \text{Var}[D] \) with \( \text{Var}[D|G] \):

\[
\text{Var}[D|G] = \begin{bmatrix}
\frac{\sigma_f^2 \sigma_e^2 \beta_1^2 + \sigma_e^2}{\sigma_f^2 + \sigma_g^2} & \frac{\sigma_f^2 \sigma_e^2 \beta_1 \beta_2}{\sigma_f^2 + \sigma_g^2} & \cdots & \frac{\sigma_f^2 \sigma_e^2 \beta_1 \beta_N}{\sigma_f^2 + \sigma_g^2} \\
\frac{\sigma_f^2 \sigma_e^2 \beta_2 \beta_1}{\sigma_f^2 + \sigma_g^2} & \frac{\sigma_f^2 \sigma_g^2 \beta_2^2}{\sigma_f^2 + \sigma_g^2} + \sigma_e^2 & \cdots & \frac{\sigma_f^2 \sigma_g^2 \beta_2 \beta_N}{\sigma_f^2 + \sigma_g^2} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\sigma_f^2 \sigma_e^2 \beta_N \beta_1}{\sigma_f^2 + \sigma_g^2} & \frac{\sigma_f^2 \sigma_e^2 \beta_N \beta_2}{\sigma_f^2 + \sigma_g^2} & \cdots & \frac{\sigma_f^2 \sigma_e^2 \beta_N \beta_N + \sigma_e^2}{\sigma_f^2 + \sigma_g^2}
\end{bmatrix}.
\]  

(B.83)

Panel (a) of Figure 7 depicts the three equilibria of Theorem 1 when \( \sigma_f \) is replaced with \( \sigma_g \) (compare with Figure 1). Panel (b) of Figure 7 depicts the equilibrium proportions of informed investors as functions of \( \sigma_g \) (compare with panel (a) of Figure 2).

(Insert Figure 7 about here)

This alternative model specification is therefore isomorphic to our main model (in the sense that \( \sigma_f^2 \sigma_g^2 / (\sigma_f^2 + \sigma_g^2) \) plays the role of \( \sigma_f^2 \) in the main model), but is unnecessarily complicated by the additional layer of learning induced by the public signal (Eq. B.83) and by the presence of the public signal into the equilibrium prices (Eq. B.82).
## Variable definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>Closing value of VIX. Source: CRSP.</td>
</tr>
<tr>
<td>ESV</td>
<td>Log daily number of EDGAR downloads (search volume) of the company’s filings from SEC EDGAR. Source: SEC.</td>
</tr>
<tr>
<td>ESVU</td>
<td>Log daily number of EDGAR downloads (search volume) of the company’s filings from unique IP addresses. Source: SEC.</td>
</tr>
<tr>
<td>EARET</td>
<td>Earnings announcement return. Compound excess return over the size decile portfolio for earnings announcement trading date and one trading day after. Source: CRSP.</td>
</tr>
<tr>
<td>SUE</td>
<td>Earnings surprise relative to analyst consensus forecasts deflated by quarter-end share price. When ranks are used, they are calculated across same-quarter announcements. Source: IBES, CRSP.</td>
</tr>
<tr>
<td>PreRet</td>
<td>Pre-earnings announcement returns. Compound excess return over the size decile portfolio for earnings announcement trading date -10 to -1 and 1 day after. Source: CRSP.</td>
</tr>
<tr>
<td>Size</td>
<td>Market value of equity on the earnings announcement date in $M. Source: CRSP.</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>Book to market ratio at the 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 over the prior 16 (at least 4) quarters. Source: Compustat.</td>
</tr>
<tr>
<td>ERepLag</td>
<td>Days from quarter-end to earnings announcement. Source: Compustat.</td>
</tr>
<tr>
<td>#Estimates</td>
<td>Number of analysts making quarterly earnings forecasts. Source: IBES Summary File.</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>
<tr>
<td>CAPM Beta</td>
<td>CAPM Beta estimated using the CRSP value-weighted return index for the 250 (at least 60) trading days prior to the earnings announcement. Source: CRSP</td>
</tr>
</tbody>
</table>


D  Figures and tables

Figure 1: Information market equilibrium
This figure depicts the three cases of Theorem 1. The two lines plot the values $\kappa_1^*$ and $\kappa_2^*$ as functions of the economic uncertainty $\sigma_f$, when $\beta_1 > \beta_2$, $\sigma_{e1} = \sigma_{e2}$, $\sigma_{\varepsilon1} = \sigma_{\varepsilon2}$, and $c_1 = c_2 = c$. 
Fractions of informed investors

(a) $\beta_1 > \beta_2$

(b) $\sigma_{e_1} < \sigma_{e_2}$

(c) $\sigma_{e_1} > \sigma_{e_2}$

(d) $\sigma_{x_1} > \sigma_{x_2}$

Figure 2: The impact of economic uncertainty on investor attention
This figure plots the fractions of attentive investors, $\lambda_1$ (solid lines) and $\lambda_2$ (dashed lines), as functions of economic uncertainty $\sigma_f$. The dotted lines plot the difference $\lambda_1 - \lambda_2$. Four cases are analyzed: different $\beta_a$, different $\sigma_{e_a}$, different $\sigma_{e_a}$, and different $\sigma_{x_a}$. 
Figure 3: The impact of economic uncertainty on earning response coefficients
This figure plots the earnings response coefficients of the announcing firms to their own announcements, ERC11 (solid lines) and ERC22 (dashed lines), as functions of economic uncertainty $\sigma_f$. The dotted lines plot the difference ERC11 − ERC22. Four cases are analyzed: different $\beta_a$, different $\sigma_{x_a}$, different $\sigma_{e_a}$, and different $\sigma_{x_a}$. 
Figure 4: The impact of economic uncertainty on investor attention and earnings response coefficients when information acquisition costs differ across firms
Panel (a) plots the fractions of attentive investors, $\lambda_1$ (solid lines) and $\lambda_2$ (dashed lines), as functions of economic uncertainty $\sigma_f$. Panel (b) plots the earnings response coefficients of the announcing firms to their own announcements, $\text{ERC}_{11}$ (solid lines) and $\text{ERC}_{22}$ (dashed lines), as functions of economic uncertainty $\sigma_f$. The dotted lines plot the differences $\lambda_1 - \lambda_2$ and $\text{ERC}_{11} - \text{ERC}_{22}$. Firms 1 and 2 are identical in all respects, except their information acquisition costs: $c_1 < c_2$.

Figure 5: Investor attention and earnings response coefficients
This figure plots the earnings response coefficients of the announcing firms to their own announcements versus the fraction of investors attentive to the earnings announcement, for firm 1 in panel (a) and firm 2 in panel (b). In both panels, the dots are obtained for different levels of economic uncertainty $\sigma_f$ (increasing from left to right). Firms 1 and 2 are identical in all respects, except their exposure to systematic risk: $\beta_1 > \beta_2$. 


Figure 6: **Information market equilibrium when the announcing firms differ with respect to** $\sigma_{ea}$ **and** $\sigma_{ea}$

This figure depicts the three cases of Theorem 1 when $\sigma_{e1} < \sigma_{e2}$ (panel a) and $\sigma_{e1} > \sigma_{e2}$ (panel b). In each case, the remaining parameters are homogeneous across firms 1 and 2.

Figure 7: **Information market equilibrium and proportions of informed investors in an alternative model with a public signal (Appendix B)**

Panel (a) depicts the three equilibria of Theorem 1 when $\sigma_f$ is replaced with $\sigma_g$ and $\beta_1 > \beta_2$ (compare with Figure 1). Panel (b) depicts the equilibrium proportions of informed investors as functions of $\sigma_g$ when $\beta_1 > \beta_2$ (compare with panel (a) of Figure 2). In each case, the remaining parameters are homogeneous across firms 1 and 2.
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 C.

<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>VIX</td>
<td>236,826</td>
<td>19.625</td>
<td>8.159</td>
<td>13.770</td>
<td>18.020</td>
<td>23.010</td>
</tr>
<tr>
<td>ESV</td>
<td>125,570</td>
<td>5.655</td>
<td>1.931</td>
<td>4.277</td>
<td>5.820</td>
<td>7.122</td>
</tr>
<tr>
<td>ESVU</td>
<td>125,570</td>
<td>4.048</td>
<td>1.396</td>
<td>3.045</td>
<td>4.205</td>
<td>5.187</td>
</tr>
<tr>
<td>EARET</td>
<td>237,416</td>
<td>0.001</td>
<td>0.080</td>
<td>-0.033</td>
<td>0.001</td>
<td>0.037</td>
</tr>
<tr>
<td>SUE Decile</td>
<td>237,416</td>
<td>5.535</td>
<td>2.706</td>
<td>3.000</td>
<td>6.000</td>
<td>8.000</td>
</tr>
<tr>
<td>PreRet</td>
<td>236,839</td>
<td>0.002</td>
<td>0.081</td>
<td>-0.035</td>
<td>-0.001</td>
<td>0.035</td>
</tr>
<tr>
<td>Size</td>
<td>236,862</td>
<td>5930.250</td>
<td>24719.650</td>
<td>281.568</td>
<td>850.259</td>
<td>2963.590</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>237,262</td>
<td>0.534</td>
<td>0.382</td>
<td>0.274</td>
<td>0.458</td>
<td>0.701</td>
</tr>
<tr>
<td>EPersistence</td>
<td>236,742</td>
<td>-0.032</td>
<td>26.319</td>
<td>-0.040</td>
<td>0.179</td>
<td>0.500</td>
</tr>
<tr>
<td>IO</td>
<td>227,911</td>
<td>0.633</td>
<td>2.276</td>
<td>0.430</td>
<td>0.666</td>
<td>0.842</td>
</tr>
<tr>
<td>EVOL</td>
<td>236,768</td>
<td>67.372</td>
<td>7108.010</td>
<td>0.116</td>
<td>0.272</td>
<td>0.654</td>
</tr>
<tr>
<td>ERepLag</td>
<td>237,416</td>
<td>30.747</td>
<td>13.644</td>
<td>22.000</td>
<td>28.000</td>
<td>37.000</td>
</tr>
<tr>
<td>#Estimates</td>
<td>237,416</td>
<td>7.784</td>
<td>6.567</td>
<td>3.000</td>
<td>6.000</td>
<td>11.000</td>
</tr>
<tr>
<td>TURN</td>
<td>237,416</td>
<td>17.439</td>
<td>17.591</td>
<td>6.932</td>
<td>12.824</td>
<td>22.116</td>
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<tr>
<td>Loss</td>
<td>237,416</td>
<td>0.194</td>
<td>0.395</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>#Announcements</td>
<td>237,416</td>
<td>149.190</td>
<td>92.937</td>
<td>72.000</td>
<td>136.000</td>
<td>221.000</td>
</tr>
</tbody>
</table>
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. Detailed definitions of all variables are available in Appendix C. All correlations are significant at the five percent level, except those indicated in bold.

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
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</thead>
<tbody>
<tr>
<td>VIX</td>
<td>-0.129</td>
<td>-0.143</td>
<td>0.004</td>
<td>0.005</td>
<td>-0.006</td>
<td>-0.123</td>
<td>0.079</td>
<td>0.029</td>
<td>-0.133</td>
<td>-0.047</td>
<td>-0.066</td>
<td>-0.061</td>
<td>-0.003</td>
<td>0.028</td>
<td>0.050</td>
<td></td>
</tr>
<tr>
<td>ESV</td>
<td>-0.074</td>
<td>0.958</td>
<td>-0.002</td>
<td>0.008</td>
<td>0.018</td>
<td>0.318</td>
<td>-0.047</td>
<td>-0.105</td>
<td>0.205</td>
<td>0.158</td>
<td>0.111</td>
<td>0.261</td>
<td>0.149</td>
<td>0.036</td>
<td>-0.097</td>
<td></td>
</tr>
<tr>
<td>ESVU</td>
<td>-0.074</td>
<td>0.957</td>
<td>-0.002</td>
<td>0.010</td>
<td>0.016</td>
<td>0.334</td>
<td>-0.062</td>
<td>-0.103</td>
<td>0.207</td>
<td>0.159</td>
<td>0.105</td>
<td>0.282</td>
<td>0.155</td>
<td>0.042</td>
<td>-0.076</td>
<td></td>
</tr>
<tr>
<td>EARET</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.002</td>
<td>0.316</td>
<td>-0.045</td>
<td>0.022</td>
<td>0.012</td>
<td>0.001</td>
<td>0.023</td>
<td>-0.023</td>
<td>-0.023</td>
<td>0.007</td>
<td>-0.015</td>
<td>-0.094</td>
<td>0.004</td>
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</tr>
<tr>
<td>SUE Decile</td>
<td>0.004</td>
<td>0.010</td>
<td>0.013</td>
<td>0.299</td>
<td>0.006</td>
<td>0.032</td>
<td>-0.009</td>
<td>0.004</td>
<td>0.035</td>
<td>0.030</td>
<td>-0.035</td>
<td>0.019</td>
<td>0.045</td>
<td>-0.146</td>
<td>0.025</td>
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</tr>
<tr>
<td>PreRet</td>
<td>-0.007</td>
<td>0.005</td>
<td>0.004</td>
<td>-0.043</td>
<td>0.097</td>
<td>0.052</td>
<td>-0.011</td>
<td>0.009</td>
<td>0.004</td>
<td>-0.018</td>
<td>-0.019</td>
<td>0.010</td>
<td>0.025</td>
<td>-0.050</td>
<td>-0.005</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>-0.039</td>
<td>0.178</td>
<td>0.207</td>
<td>0.001</td>
<td>0.001</td>
<td>0.005</td>
<td>-0.313</td>
<td>0.004</td>
<td>0.442</td>
<td>0.133</td>
<td>-0.143</td>
<td>0.746</td>
<td>0.274</td>
<td>-0.179</td>
<td>0.021</td>
<td></td>
</tr>
<tr>
<td>Book-to-Mkt</td>
<td>0.097</td>
<td>-0.011</td>
<td>-0.022</td>
<td>0.017</td>
<td>-0.018</td>
<td>-0.005</td>
<td>-0.104</td>
<td>-0.087</td>
<td>-0.114</td>
<td>0.198</td>
<td>0.023</td>
<td>-0.254</td>
<td>-0.216</td>
<td>-0.004</td>
<td>-0.020</td>
<td></td>
</tr>
<tr>
<td>EPersistence</td>
<td>0.004</td>
<td>0.006</td>
<td>0.006</td>
<td>0.000</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>-0.359</td>
<td>-0.096</td>
<td>0.049</td>
<td>0.068</td>
<td>-0.052</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td>IO</td>
<td>-0.007</td>
<td>0.016</td>
<td>0.015</td>
<td>0.000</td>
<td>0.002</td>
<td>-0.002</td>
<td>0.004</td>
<td>-0.008</td>
<td>0.000</td>
<td>0.192</td>
<td>0.093</td>
<td>0.465</td>
<td>0.508</td>
<td>-0.026</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>EVOL</td>
<td>0.005</td>
<td>-0.007</td>
<td>-0.007</td>
<td>-0.001</td>
<td>-0.003</td>
<td>0.001</td>
<td>-0.002</td>
<td>-0.008</td>
<td>0.000</td>
<td>0.000</td>
<td>0.163</td>
<td>0.083</td>
<td>0.195</td>
<td>0.196</td>
<td>0.012</td>
<td></td>
</tr>
<tr>
<td>ERepLag</td>
<td>-0.025</td>
<td>0.078</td>
<td>0.067</td>
<td>-0.022</td>
<td>-0.049</td>
<td>-0.019</td>
<td>-0.095</td>
<td>0.033</td>
<td>-0.009</td>
<td>0.004</td>
<td>0.005</td>
<td>-0.120</td>
<td>0.109</td>
<td>0.199</td>
<td>-0.171</td>
<td></td>
</tr>
<tr>
<td>#Estimates</td>
<td>-0.047</td>
<td>0.263</td>
<td>0.292</td>
<td>0.000</td>
<td>0.014</td>
<td>-0.004</td>
<td>0.400</td>
<td>-0.195</td>
<td>-0.001</td>
<td>0.043</td>
<td>-0.003</td>
<td>-0.139</td>
<td>0.453</td>
<td>-0.067</td>
<td>0.017</td>
<td></td>
</tr>
<tr>
<td>TURN</td>
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<td>0.103</td>
<td>0.113</td>
<td>-0.022</td>
<td>0.032</td>
<td>0.018</td>
<td>-0.026</td>
<td>-0.085</td>
<td>-0.003</td>
<td>0.037</td>
<td>0.004</td>
<td>0.041</td>
<td>0.298</td>
<td>0.156</td>
<td>-0.003</td>
<td></td>
</tr>
<tr>
<td>Loss</td>
<td>0.033</td>
<td>0.037</td>
<td>0.042</td>
<td>-0.091</td>
<td>-0.149</td>
<td>-0.040</td>
<td>-0.073</td>
<td>0.050</td>
<td>0.002</td>
<td>-0.004</td>
<td>0.016</td>
<td>0.185</td>
<td>-0.070</td>
<td>0.156</td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td>#Ann.</td>
<td>0.027</td>
<td>-0.108</td>
<td>-0.082</td>
<td>0.001</td>
<td>0.025</td>
<td>0.003</td>
<td>-0.026</td>
<td>-0.019</td>
<td>0.002</td>
<td>0.004</td>
<td>0.000</td>
<td>-0.225</td>
<td>-0.016</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
</tbody>
</table>
Table 3: **Investor attention around earnings announcements.**
This table presents results of regressions of announcement-window EDGAR searches on daily closing VIX and controls (Eq. 27). 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. Detailed definitions of all variables are available in Appendix C. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
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<tr>
<th>Dep. Var.</th>
<th>ESV</th>
<th>ESVU</th>
</tr>
</thead>
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<tr>
<td>VIX</td>
<td>0.019***</td>
<td>0.045***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>lag(Dep. Var.)</td>
<td>0.210***</td>
<td>0.499***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>SUE Decile</td>
<td>0.005***</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>abs(SUE Decile)</td>
<td>0.008***</td>
<td>0.021***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Size</td>
<td>0.052***</td>
<td>0.077***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>-0.009***</td>
<td>-0.016***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>EPersistence</td>
<td>-0.002</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>IO</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>EVOL</td>
<td>0.001</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>ERepLag</td>
<td>0.024***</td>
<td>0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>#Estimates</td>
<td>0.065***</td>
<td>0.088***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>TURN</td>
<td>0.027***</td>
<td>0.035***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Loss</td>
<td>-0.001</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>#Announcements</td>
<td>-0.034***</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Date-clustered SE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Day-of-week FE</td>
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<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>117,461</td>
<td>117,461</td>
</tr>
<tr>
<td>R-Square</td>
<td>0.799</td>
<td>0.828</td>
</tr>
</tbody>
</table>
Table 4: **Economic uncertainty, investor attention, and the price reaction to earnings announcements**

This table presents results of regressions of earnings announcement returns (EARET) on earnings surprise deciles interacted with the VIX (column a), with ESVU (column b), and with both the VIX and ESVU (column c) (Eq. 28). All variables are standardized to be mean-zero and unit-variance. Control variables include: PreRet, 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 C. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
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<tr>
<th>Dep. Var. = EARET during [0,1] window</th>
<th>(a)</th>
<th>(b)</th>
<th>(c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX*SUE Decile</td>
<td>0.017***</td>
<td>0.015***</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>ESVU*SUE Decile</td>
<td>0.015***</td>
<td>0.015***</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>SUE Decile</td>
<td>0.287***</td>
<td>0.328***</td>
<td>0.341***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.039)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>VIX</td>
<td>-0.013***</td>
<td>-0.015**</td>
<td>-0.015**</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>ESVU</td>
<td>-0.010**</td>
<td>-0.009</td>
<td>-0.009*</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>lag(ESVU)</td>
<td>-0.004</td>
<td>-0.005</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>lag(ESVU)*SUE Decile</td>
<td>-0.017***</td>
<td>-0.016***</td>
<td>-0.016***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>PreRet</td>
<td>-0.075***</td>
<td>-0.076***</td>
<td>-0.077***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>PreRet*SUE Decile</td>
<td>-0.013***</td>
<td>-0.014***</td>
<td>-0.013***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
</tbody>
</table>

Controls: Yes Yes Yes
Controls*SUE Decile: Yes Yes Yes
Date-clustered SE: Yes Yes Yes
Year and Day-of-week FE: Yes Yes Yes
N: 226,569 117,451 117,451
R-Square: 0.111 0.139 0.139

45
Table 5: Economic uncertainty and the price reaction to earnings announcements
This table presents results of regressions of earnings announcement returns (EARET) on earnings surprise deciles based on quarterly sorts interacted with the VIX. All variables are standardized to be mean-zero and unit-variance. Control variables include: PreRet, 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 C. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Sample:</th>
<th>Low CAPM Beta</th>
<th>High CAPM Beta</th>
<th>Low Forecast Dispersion</th>
<th>High Forecast Dispersion</th>
<th>Low Idiosync. Volatility</th>
<th>High Idiosync. Volatility</th>
<th>Low TURN</th>
<th>High TURN</th>
<th>Low IO High IO</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX*SUE Decile</td>
<td>0.007 (0.006)</td>
<td>0.025*** (0.007)</td>
<td>0.020*** (0.007)</td>
<td>0.020*** (0.007)</td>
<td>0.010** (0.005)</td>
<td>0.017*** (0.006)</td>
<td>0.005 (0.006)</td>
<td>0.026*** (0.008)</td>
<td>0.008 (0.005)</td>
</tr>
<tr>
<td>SUE Decile</td>
<td>0.290*** (0.027)</td>
<td>0.306*** (0.043)</td>
<td>0.328*** (0.038)</td>
<td>0.285*** (0.038)</td>
<td>0.274*** (0.025)</td>
<td>0.328*** (0.034)</td>
<td>0.411*** (0.030)</td>
<td>0.317*** (0.039)</td>
<td>0.277*** (0.033)</td>
</tr>
<tr>
<td>VIX</td>
<td>-0.013*** (0.005)</td>
<td>-0.012 (0.009)</td>
<td>-0.010** (0.005)</td>
<td>-0.019** (0.008)</td>
<td>-0.005 (0.005)</td>
<td>-0.020** (0.008)</td>
<td>-0.011** (0.006)</td>
<td>-0.016** (0.008)</td>
<td>-0.012** (0.006)</td>
</tr>
<tr>
<td>PreRet</td>
<td>-0.079*** (0.004)</td>
<td>-0.076*** (0.005)</td>
<td>-0.081*** (0.005)</td>
<td>-0.070*** (0.005)</td>
<td>-0.072*** (0.005)</td>
<td>-0.080*** (0.004)</td>
<td>-0.071*** (0.005)</td>
<td>-0.080*** (0.005)</td>
<td>-0.083*** (0.005)</td>
</tr>
<tr>
<td>PreRet*SUE Decile</td>
<td>-0.015*** (0.004)</td>
<td>-0.011*** (0.004)</td>
<td>-0.016*** (0.006)</td>
<td>-0.012*** (0.004)</td>
<td>-0.010** (0.004)</td>
<td>-0.015*** (0.003)</td>
<td>-0.018*** (0.004)</td>
<td>-0.011*** (0.004)</td>
<td>-0.010*** (0.003)</td>
</tr>
</tbody>
</table>

Controls Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes
Controls*SUE Decile Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes
Date-clustered SE Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes
Year and Day-of-week FE Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes
N 113,363 113,090 110,365 99,581 113,509 112,944 113,404 113,165 113,234 113,335
R-Square 0.122 0.107 0.120 0.110 0.124 0.114 0.140 0.102 0.115 0.110
Table 6: **Investor attention and the price reaction to earnings announcements**

This table presents results of regressions of earnings announcement returns (EARET) on earnings surprise deciles based on quarterly sorts interacted with ESVU. All variables are standardized to be mean-zero and unit-variance. Control variables include: PreRet, 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 C. Standard errors for the coefficients are clustered by date.

∗∗∗, ∗∗, and ∗ indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dep. Var. = Earnings announcement returns during [0,1] window</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subsamples: based on Within-year-of-earnings-announcement Median splits on announcing firm characteristics</td>
</tr>
<tr>
<td>Sample:</td>
</tr>
<tr>
<td>ESVU*SUE Decile</td>
</tr>
<tr>
<td>(0.007)</td>
</tr>
<tr>
<td>SUE Decile</td>
</tr>
<tr>
<td>(0.051)</td>
</tr>
<tr>
<td>ESVU</td>
</tr>
<tr>
<td>(0.006)</td>
</tr>
<tr>
<td>lag(ESVU)</td>
</tr>
<tr>
<td>(0.006)</td>
</tr>
<tr>
<td>lag(ESVU)*SUE Decile</td>
</tr>
<tr>
<td>(0.007)</td>
</tr>
<tr>
<td>PreRet</td>
</tr>
<tr>
<td>(0.007)</td>
</tr>
<tr>
<td>PreRet*SUE Decile</td>
</tr>
<tr>
<td>(0.007)</td>
</tr>
<tr>
<td>Controls</td>
</tr>
<tr>
<td>Controls*SUE Decile</td>
</tr>
<tr>
<td>Date-clustered SE</td>
</tr>
<tr>
<td>Year and Day-of-week FE</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>R-Square</td>
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</table>