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.

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1 Introduction

The limited investor attention theory posits that due to cognitive resource constraints, investors can neglect value relevant information and may not incorporate all available information into prices (Hirshleifer and Teoh, 2003; Peng, 2005). The theory's main premise is that attention-constrained investors need to prioritize which news events are the most important to be processed. Building on this premise, Peng and Xiong (2006) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) describe economies in which investors choose to be attentive to market-wide news or to firm-specific news, and show that investors tend to prioritize the former over the latter. These models offer powerful and intuitively simple predictions about what type of information should be incorporated into asset prices, and when. They play an important role in our understanding of the informational efficiency of security markets (e.g., Hayek, 1945; Fama, 1970).

Early empirical evidence supports this theory. Peng, Xiong, and Bollerslev (2007) show that an increase in market-wide uncertainty temporarily shifts investors' attention away from processing firm-specific information to market-level information. Hirshleifer, Lim, and Teoh (2009) show that stock price reactions to earnings announcements are weaker when earnings are released on days with many competing earnings announcements.[1] Kacperczyk et al. (2016) find that fund managers process information about aggregate news in recessions (when aggregate volatility and the price of risk are high) and idiosyncratic news in booms. Overall, these studies support the narrative that investors have a limited attention capacity, and that they view macro and firm-level news as attention substitutes.

Yet even as this literature continues to grow, new findings are challenging its narrative. Hirshleifer and Sheng (2021) find that macro-news announcements, in fact, trigger investors' attention to firm-level news: on days when macro-news announcements are released, firm-level information is processed more efficiently into the market.[2] Ben-Rephael, Carlin, Da, and Israelsen (2021) show that macro-news events increase information consumption on individual stocks. These recent findings point out to complementarities between micro news and macro news, and to the presence of information spillover effects—news from issuing firms may convey information about related firms and the general economy, and vice versa. To our knowledge, existing models of investor attention do not yet capture such information spillovers.

A second discrepancy between theory and data arises from Hirshleifer and Sheng (2021). Their findings suggest that macro news stimulates *overall* attention to the stock market.

[1]Other studies document a muted market reaction to Friday earnings or merger announcements (DellaVigna and Pollet, 2009; Louis and Sun, 2010), and also distraction effects caused by extraneous and unrelated events, such as the March Madness college basketball tournament or marital transitions (Drake, Gee, and Thornock, 2016; Lu, Ray, and Teo, 2016).

[2]Eberbach, Uhrig-Homburg, and Yu (2021) confirm the result using high-frequency options markets data.

This point is further confirmed by Chan and Marsh (2021), who show that leading earnings announcement days are times when investors' attention is high, and by Benamar, Foucault, and Vega (2021), who document an increase in information demand ahead of influential economic announcements.[3] It suggests that on a given day investors can potentially devote more or less attention to the economy (macro and micro news included). Instead, existing theories of attention allocation (e.g., Peng and Xiong, 2006; Kacperczyk et al., 2016) assume a constant attention capacity. This assumption is automatically placing investors in a box, where all their attention is focused on the economy alone, and the total amount of attention is not allowed to change with the state of the economy.

In this paper, we propose and test a model of optimal attention allocation in which firms provide earnings announcements that convey *both* systematic and idiosyncratic information. We allow the total amount of attention to depend endogenously on the state of the economy. The model borrows from the seminal work of Grossman and Stiglitz (1980), which we extend to a multi-firm economy with multiple earnings announcements. We attempt to address the following questions: how do investors decide to pay attention when multiple firms disclose their earnings? How does the level of uncertainty impact investors' attention behavior? How do asset prices respond to shifts in investors' attention caused by changes in uncertainty?

Understanding the reaction of investors' attention to changes in economic uncertainty and its subsequent impact on market efficiency is important for at least three reasons. First, it helps us better understand how markets incorporate firm-level information. Earnings announcements are among the most important disclosure events in financial markets.[4] They represent a wealth of information that is regularly communicated to market participants, and their processing by investors affects the market's informational efficiency and its ability to effectively allocate capital (Hayek, 1945; Fama, 1970). Second, it sheds light on the importance of processing costs and attention decisions in financial markets (Blankespoor, deHaan, and Marinovic, 2020), and their impact on asset pricing (Ben-Rephael et al., 2021; Chan and Marsh, 2021). Third, we know little about how economic uncertainty affects disclosure processing decisions. Uncertainty and its effects of the economy have been subject to much research over the past decades (e.g., Bloom, 2009; Jurado, Ludvigson, and Ng, 2015). Investors' attention response to uncertainty shocks play a key role in mitigating (or amplifying) the impairment of market efficiency caused by these shocks. It is thus important to link investors' demand for firm-level information to uncertainty fluctuations.

[3]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).

[4]In the United States alone, on average, hundreds of publicly-traded firms announce their earnings every day (Hirshleifer and Sheng, 2021). Chan and Marsh (2021) document that an average of 31 influential S&P 500 firms disclose their earnings on leading days. See also Moulton and Leow (2015).

The main premise of our model is that earnings announcements provide valuable information not only about the prospects of the issuing firms but also about the entire economy. This premise is consistent with arguments from Patton and Verardo (2012) and Savor and Wilson (2016). Patton and Verardo (2012) rationalize the finding that market betas of announcing firms are higher on the days around their announcements. Savor and Wilson (2016) propose an explanation for the finding that announcing firms earn a significant risk premium.[5] Both of these studies provide explanations that are consistent with the idea of information spillovers from the announcing firms to the aggregate economy. Along the same lines, Chan and Marsh (2021) provide evidence that the CAPM fits stock returns better on days when influential S&P 500 firms disclose earnings news, highlighting the importance of corporate earnings announcements for aggregate asset pricing.

The variable that drives investors' attention allocation decision in our model is *uncertainty*, which we define as investors' expected forecasting error conditional on information available at the time of the attention decision. This is the commonly adopted definition of uncertainty in the literature.[6] Our choice is consistent with the basic intuition that investors' learning and uncertainty go hand in hand—it is only natural to assume that investors condition their information choice on the level of economic uncertainty they face.

Several results emerge from the model. We first show that investors' attention to firm-level earnings announcements increases with the amount of uncertainty. In turn, increased investor attention magnifies earnings response coefficients (ERC*s*), which are defined as the firms' price reactions to the earnings announcements. Furthermore, the stock price reaction to the increase in attention varies predictably with firm-specific factors: ERC*s* 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.

We test and confirm the model's predictions 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.[7] 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 ERC*s* are greater for firms that

[5]See, e.g., Beaver (1968); Chari, Jagannathan, and Ofer (1988); Ball and Kothari (1991).

[6]See, among others, Van Nieuwerburgh and Veldkamp (2010), Andrei and Hasler (2015), Berger, Dew-Becker, and Giglio (2020), and Benamar et al. (2021).

[7]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.

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).

Thus, the main message of this paper is that heightened economic uncertainty motivates investors to increase their attention to firm-level information, which in turn improves price responsiveness. Our results stand in contrast to traditional models of attention allocation. Existing 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 et al., 2016). 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. Importantly, in our model the total amount of attention increases with economic uncertainty, whereas in previous work the total attention allocation remains constant over time. As previously discussed, the empirical literature offers compelling evidence that earnings announcements convey systematic information, and that investors' aggregate level of attention varies over time. Thus, our work highlights the importance of information spillovers and unrestricted attention capacity for theories of information acquisition.

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).[8] We contribute to this literature by studying how economic uncertainty determine the attention behavior of rational and non-attention-constrained investors in a heterogeneous-firm economy.

Goldstein and Yang (2015) show theoretically that multi-dimensional uncertainty (e.g., uncertainty about the technology of the firm and the demand of its products) creates strategic

[8]An extensive survey of this literature can be found in Veldkamp (2011). Blankespoor et al. (2020) review related literature on disclosure processing costs faced by capital market participants.

complementarities between differently informed traders: an increase in uncertainty in one dimension deters trading on information involving the other dimension. Our setting differs in that we study an economy in which firms are heterogeneously exposed to a single dimension of uncertainty. We show that an increase of uncertainty rises investors' attention towards firm-specific news. Our results corroborate with Benamar et al. (2021), who propose to use information demand as a new proxy for investors' uncertainty. They justify this proposal on the basis of a standard model of endogenous information acquisition, which predicts heightened attention in the face of greater uncertainty. Empirically, Chen et al. (2020) further confirm the view that information acquisition increases in more opaque environments. They find that sophisticated investors scale up information acquisition after an exogenous deterioration of the informational environment (i.e., a reduction in analyst coverage).

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 et al., 2009; DellaVigna and Pollet, 2009; Louis and Sun, 2010; Lu et al., 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. While our empirical findings are consistent with the attention-trigger effect documented by Hirshleifer and Sheng (2021), we build a theory that focuses on 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 theory of rational attention allocation.

It should be noted that the concept or rationality used in this paper does not imply market efficiency in the traditional sense. The traditional definition of semi-strong efficiency requires that *"current prices 'fully reflect' all obviously publicly available information."* (Fama, 1970, p. 404). Instead, in our model as in Grossman and Stiglitz (1980), costly information acquisition implies that firm disclosures are a form of costly private information rather than public information, and are not efficiently processed by financial markets (see Blankespoor et al., 2020, for a thorough discussion on this). However, investors in our model are rational, in the sense that they form expectations using Bayes' rule; they maximize expected utility; and they have common priors. Given this, our attention allocation model can be viewed as *"efficiently inefficient"* conditional on information processing frictions (Pedersen, 2015).[9]

[9] Vives (2010) offers additional examples of informationally inefficient outcomes seemingly inconsistent with rational expectations models—e.g., herding, price drifts, bubbles, and crashes—that can be explained without recourse to irrationality. Gabaix (2019) provides an in-depth review of the behavioral literature and enumerates specific psychological biases that may lead to investor inattention.

Empirical studies have used various proxies for investor attention.[10] 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, 2021) supports the view that retail and institutional investors have different attention behaviors.

2 Model

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 $t=2$:[11]

$$D_n = \beta_n f + e_n, \quad \text{for } n \in \{1,...,N\}. \tag{1}$$

The payoff D_n has a systematic component f and a firm-specific component e_n. The parameters β_n, which are heterogeneous across firms and known by investors, dictate the exposures of firms' payoffs to the systematic component. Without loss of generality, we assume that the average of β_n across firms is 1.

At $t=0$, all investors have a common information set $\mathcal{F}_0$ that consists of the prior

[10] 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).

[11] Throughout the paper, we will adopt the following notation: we use letters in plain font to indicate univariate variables and bold letters to indicate vectors and matrices; we use subscripts to indicate individual assets and superscripts to indicate individual investors. Appendix A.1 provides further details.

distributions of f and e_n:

$$f \sim \mathcal{N}(0, U^2) \tag{2}$$

$$e_n \sim \mathcal{N}(0, \sigma^2_{en}), \quad \text{for } n \in \{1, ..., N\}. \tag{3}$$

We allow for variances σ^2_{en} to vary in the cross section of firms. Firm-specific components e_n are independent across firms, and f and e_n are independent, $\forall n \in \{1, ..., N\}$.

For the rest of the paper, we refer to U as *uncertainty.* It represents investors' expected forecasting error conditional on information available at time 0, $U^2 \equiv \text{Var}[f|\mathcal{F}_0]$. As we will show below, in our model U is closely related to investors' uncertainty about the future return on the market, which helps us confront the theory with the data.

Defining U as uncertainty is the simplest way to derive theoretical predictions. Alternatively, we could be more specific about the information set $\mathcal{F}_0$, without any impact on the results. Assuming for instance that *before* time 0 investors hold the prior $f \sim \mathcal{N}(0, \sigma^2_f)$, and that at time 0 they observe public information about f under the form of a signal $G = f + g$ with $g \sim \mathcal{N}(0, \sigma^2_g)$, Bayesian updating implies

$$U^2 = \text{Var}[f|\mathcal{F}_0] = \frac{\sigma^2_f \sigma^2_g}{\sigma^2_f + \sigma^2_g}. \tag{4}$$

It is clear that a higher variance σ^2_f of the fundamental or a higher variance σ^2_g of the noise in public information increases investors' uncertainty at time 0. Thus, our results come through whether U measures uncertainty in macro fundamentals or if it captures noise in the available public information at time 0. We therefore avoid any additional layers of learning that takes place beforehand and keep our model agnostic about what determines U.[12]

A total of $A \leq N$ firms issue earnings announcements at $t = 1$. We denote the set of announcing firms by $\mathcal{A} = \{1, ..., A\}$. As in Teoh and Wong (1993), earnings announcements convey information about firms' future dividends:

$$E_a = D_a + \varepsilon_a, \quad \text{for } a \in \mathcal{A}, \tag{5}$$

where the earnings noise shocks ε_a are independently distributed, $\varepsilon_a \sim \mathcal{N}(0, \sigma^2_{\varepsilon a})$, and drawn independently from f and e_n, $\forall a \in \mathcal{A}$ and $\forall n \in \{1, ..., N\}$.

At $t = 0$, each investor i chooses whether to be attentive to the earnings announcements. Investor i is free to choose whether to pay attention to announcements made by any of the

[12]It is also possible that investors, facing increased uncertainty, acquire more information *before* the day of earnings announcements. We discuss this additional layer of information acquisition in Section 3.2 using a dynamic version of the model, and show that including this feature does not qualitatively change our results.

2^A possible subsets of $\mathcal{A}$. (The set of all subsets of $\mathcal{A}$ represents the *power set* of $\mathcal{A}$, or $\mathscr{P}(\mathcal{A})$, and includes the empty set $\emptyset$ and $\mathcal{A}$ itself.) Thus, there are potentially 2^A *types* of investors, indexed by $k \in \mathscr{P}(\mathcal{A})$. For instance, investors who choose to stay uninformed are of type $k = \emptyset$; investors who pay attention to all earnings announcements are of type $k = \mathcal{A}$. We use the indicator variable I_a^k, with $a \in \mathcal{A}$ and $k \in \mathscr{P}(\mathcal{A})$, to indicate type k investor's decision to pay attention to E_a: if $a \in k$, then $I_a^k = 1$; otherwise, $I_a^k = 0$.

Each investor starts with zero initial wealth and maximizes expected utility at time 0,

$$\max_{k \in \mathscr{P}(\mathcal{A})} \mathbb{E}_0 \left[\max_{\mathbf{q}^k} \mathbb{E}_1^k \left[-e^{-\gamma \left(W^k - c|k| \right)} \right] \right], \tag{6}$$

where $\mathbf{q}^k$ is the optimal portfolio of a type k investor and $|k|$ denotes the cardinality of the set k, or $|k| = \sum_{a \in \mathcal{A}} I_a^k$.

At time 0, investor i decides her type k, knowing that at time 1 she will choose an optimal portfolio based on the information set pertaining to the type k. The first optimization is a combinatorial discrete choice problem.[13] The second optimization is a standard Markowitz (1952) portfolio choice problem, where γ is the risk aversion coefficient, W^k is investor's final wealth at $t = 2$ (which depends on her type k), and c is the monetary cost of paying attention to one earnings announcement—e.g., an information-processing cost, or time and opportunity cost. The attention cost c is strictly positive and is the same across investors and across firms. We derive additional predictions in a model with heterogeneous costs across investors (e.g., retail versus institutional investors) in Section 3.

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

$$\mathbf{q}^k = \frac{1}{\gamma} \mathrm{Var}_1^k[\mathbf{D}]^{-1} (\mathbb{E}_1^k[\mathbf{D}] - \mathbf{P}), \quad \text{for } k \in \mathscr{P}(\mathcal{A}), \tag{7}$$

where the superscripts k in $\mathbb{E}_1^k[\cdot]$ and $\mathrm{Var}_1^k[\cdot]$ read "under the information set of a type k investor." $\mathbf{D}$ is the $N \times 1$ vector of asset payoffs, $\mathbf{P}$ is the $N \times 1$ vector of equilibrium prices, and $\mathrm{Var}_1^k[\mathbf{D}]$ is the $N \times N$ covariance matrix of assets' payoffs, conditioned on type k investor's information set. Defining the vector of dollar excess return of the risky assets as $\mathbf{R}^e \equiv \mathbf{D} - \mathbf{P}$, the final wealth of any investor type is then $W^k = (\mathbf{q}^k)'\mathbf{R}^e$.

We assume that an unmodeled group of agents trade for liquidity needs and/or for non-informational reasons. This is a common assumption in noisy rational expectations models, which ensures that equilibrium prices do not fully reveal investors' information. Consistent

[13] Examples of combinatorial discrete choice problems in economics include plant location problems, country selection by multinational firms, selection of which goods to produce, and many other situations in which economic agents make discrete binary choices. See Hu and Shi (2019) and Arkolakis, Eckert, and Shi (2021) for recent theoretical advances in this field.

with much of the prior literature, we often interpret liquidity trading as noise (Grossman and Stiglitz, 1980; He and Wang, 1995). We fix the total number of shares for all assets to $\mathbf{M}$ (hereafter the *market portfolio*), an equally-weighted vector whose elements are all equal to $1/N$. Liquidity traders have inelastic demands of $\mathbf{x}$ shares, where each element of $\mathbf{x}$ is normally and independently distributed, $x_n \sim \mathcal{N}(0, \sigma_{xn}^2)$; the remainder, $\mathbf{M} - \mathbf{x}$, is available for trade to informed investors.

The assumption of an equally-weighted market portfolio $\mathbf{M}$ does not have any bearing on our results, but is important for the interpretation of the results in terms that are empirically measurable. Notably, this definition implies that the future market return is $\mathbf{M}'\mathbf{R}^e$. It can then be shown that in a large economy (when $N \to \infty$) investors' prior uncertainty about the market portfolio is a multiple of U^2 (we provide this proof in Section 4.1) A consequence of this result is that our theoretical measure of uncertainty has a natural empirical counterpart in measures of implied volatility of the market (e.g., the CBOE Volatility index, or the VIX). Moreover, the market portfolio $\mathbf{M}$ will further allow us to establish in Section 4 a direct link between a firm's exposure β_n to the fundamental and the firm's equilibrium market beta.

Denoting by λ^k the fraction of type k investors, the prices of risky assets are determined in equilibrium by the market-clearing condition:

$$\sum_{k \in \mathscr{P}(\mathcal{A})} \lambda^k \mathbf{q}^k + \mathbf{x} = \mathbf{M}. \tag{8}$$

Before turning to the equilibrium analysis, we define the fraction of investors who observe the announcement E_a as

$$\Lambda_a \equiv \sum_{k \in \mathscr{P}(\mathcal{A})} \lambda^k I_a^k. \tag{9}$$

Importantly, in our model the attention capacity of investors is virtually unlimited, in the sense that there exists an equilibrium in which $\Lambda_a = 1 \ \forall a \in \mathcal{A}$, as we will describe below.

2.1 Equilibrium search for information

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

$$\mathbf{P} = \boldsymbol{\alpha}\mathbf{E} + \boldsymbol{\xi}\mathbf{x} - \boldsymbol{\zeta}\mathbf{M}, \tag{10}$$

where $\mathbf{E} \equiv [E_1, E_2, \cdots, E_A]'$, $\boldsymbol{\alpha}$ is a $N \times A$ matrix, and $\boldsymbol{\xi}$ and $\boldsymbol{\zeta}$ are $N \times N$ matrices.

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 (equivalent to Lemma 3.2 in Admati (1985)), which will be verified in Proposition 3.

Conjecture 1.

$$\widehat{\mathbf{P}} \equiv \boldsymbol{\xi}^{-1}(\mathbf{P} + \boldsymbol{\zeta}\mathbf{M}) = \sum_{a=1}^{A} \frac{\Lambda_a}{\gamma\sigma_{\varepsilon a}^2}\boldsymbol{\iota}_a E_a + \mathbf{x}, \tag{11}$$

where $\widehat{\mathbf{P}} \equiv [\widehat{P}_1, \widehat{P}_2, \cdots, \widehat{P}_N]'$ *and* $\boldsymbol{\iota}_a$ *is a standard basis vector of dimension* N *with all components equal to 0, except the* a*-th, which is 1.*

This conjecture transforms the equilibrium prices into simple signals about E_a, $a \in \mathcal{A}$. In equilibrium, all investors except the fully informed (of type $k = \mathcal{A}$) use prices to learn. Accordingly, the information sets of investors at time 1 are

$$\begin{cases} \mathcal{F}^k = \{E_a \mid a \in k\} \cup \widehat{\mathbf{P}} & \text{if } k \in \mathscr{P}(\mathcal{A}) \setminus \mathcal{A}, \\ \mathcal{F}^k = \{E_a \mid a \in \mathcal{A}\} & \text{if } k = \mathcal{A}. \end{cases} \tag{12}$$

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

$$\ell_a^k = I_a^k + (1 - I_a^k)\ell_a, \quad \text{where } \ell_a \equiv \frac{\Lambda_a^2}{\Lambda_a^2 + \gamma^2\sigma_{xa}^2\sigma_{\varepsilon a}^2}. \tag{13}$$

If a type k investor observes the earnings announcement E_a, then $I_a^k = 1$ and the learning coefficient ℓ_a^k reaches its maximum value, 1. Without observing E_a, $I_a^k = 0$ and the investor relies on prices to learn, which yields $\ell_a^k = \ell_a < 1$. Prices are informative about E_a to the extent that *someone* pays attention to the signal E_a, that is, if $\Lambda_a > 0$. In this case, ℓ_a 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 σ_{xa} 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).

Investors' demand for information ultimately depends on the reduction in uncertainty achieved by observing new information. Because in our setup the vector of final payoffs $\mathbf{D}$ is a multidimensional normally distributed random variable, the reduction in uncertainty from observing new information is conveniently measured using the notion of entropy: under the information set of any investor type $k \in \mathscr{P}(\mathcal{A})$, the vector $\mathbf{D}$ has entropy

$$H^k[\mathbf{D}] = \frac{N}{2}\ln(2\pi + 1) - \frac{1}{2}\ln(\det(\text{Var}_1^k[\mathbf{D}]^{-1})). \tag{14}$$

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

Proposition 1. *The posterior precision matrix for each investor type* $k \in \mathscr{P}(\mathcal{A})$ *is*

$$\boldsymbol{\tau}^k \equiv \text{Var}_1^k[\mathbf{D}]^{-1} = \text{Var}[\mathbf{D}]^{-1} + \sum_{a=1}^{A} \frac{\ell_a^k}{\sigma_{\varepsilon a}^2} \boldsymbol{\iota}_a \boldsymbol{\iota}_a', \tag{15}$$

and its determinant is given by

$$\det(\boldsymbol{\tau}^k) = \det(\text{Var}[\mathbf{D}]^{-1}) \left(\prod_{a=1}^{A} \frac{\ell_a^k \sigma_{ea}^2 + \sigma_{\varepsilon a}^2}{\sigma_{\varepsilon a}^2} \right) \left(1 + U^2 \sum_{a=1}^{A} \frac{\ell_a^k \beta_a^2}{\ell_a^k \sigma_{ea}^2 + \sigma_{\varepsilon a}^2} \right). \tag{16}$$

Proposition 1 shows how the heterogeneity in the learning coefficients ℓ_a^k across investors of different types $k \in \mathscr{P}(\mathcal{A})$ drives the heterogeneity in the determinants $\det(\boldsymbol{\tau}^k)$. Because a higher determinant means less uncertainty (Eq. 14), the determinants $\det(\boldsymbol{\tau}^k)$ provide a clear ranking of the informational distances between the 2^A investor types. For instance, the most informed investors (of type $\mathcal{A}$) have the highest $\det(\boldsymbol{\tau}^k)$ because $\ell_a^{\mathcal{A}} = 1, \ \forall a \in \mathcal{A}$, whereas the least informed investors (of type $\emptyset$) have the lowest $\det(\boldsymbol{\tau}^k)$.

The ranking in $\det(\boldsymbol{\tau}^k)$ dictated by Proposition 1 allows for a simple characterization of the information market equilibrium. Consider a type k investor who decides whether to migrate to any alternative type in $\mathscr{P}(\mathcal{A}) \setminus k$. The key quantity that regulates investor's decision is the *benefit-cost ratio*, which we define as

$$B_\emptyset^k \equiv \frac{\det(\boldsymbol{\tau}^k)}{\det(\boldsymbol{\tau}^\emptyset)} e^{-2\gamma c|k|}. \tag{17}$$

The ratio $\det(\boldsymbol{\tau}^k)/\det(\boldsymbol{\tau}^\emptyset)$ in $B_\emptyset^k$ measures the gain in precision obtained from observing the earnings announcements made by all the firms in the set k, whereas $e^{-2\gamma c|k|}$ measures the cost of paying attention to these announcements. With this benefit-cost ratio in hand, we can now formulate the following result.

Proposition 2. *A type* k *investor changes type from* k *to* $k' \in \mathscr{P}(\mathcal{A}) \setminus k$ *if and only if*

$$\frac{B_\emptyset^{k'}}{B_\emptyset^k} > 1 \quad \Longleftrightarrow \quad \frac{1}{2\gamma} \ln \frac{\det(\tau^{k'})}{\det(\tau^k)} > c(|k'| - |k|). \tag{18}$$

Assume, without loss of generality, that $|k'| - |k| > 0$. On the left hand side of (18), $\frac{1}{2\gamma} \ln \frac{\det(\tau^{k'})}{\det(\tau^k)}$ measures the benefit of migrating from k to k' as a reduction in entropy divided by investor's risk aversion, $(H^k[\mathbf{D}] - H^{k'}[\mathbf{D}])/\gamma$; the right hand side measures the attention cost. The type k investor changes type if and only if the benefit from the reduction in entropy achieved by becoming of type k' outweighs its cost. Note that risk aversion lowers the benefit of information: because more risk-averse investors trade less aggressively, they benefit less from paying attention to firm disclosures.

The ratio $\det(\tau^{k'})/\det(\tau^k)$ in (18) is greatly simplified by means of Proposition 1: all the heterogeneity pertaining to non-announcing firms enters only in $\det(\mathrm{Var}[\mathbf{D}]^{-1})$ and thus vanishes in the ratio. To gain further insight into this ratio, let us focus on a simplified version where investors in aggregate pay attention to one firm only (i.e., there is only one announcing firm). In this case, a type $\emptyset$ investor changes type to $\{a\}$ if and only if

$$\frac{1 + \frac{\mathrm{Var}[D_a]}{\sigma^2_{\varepsilon a}}}{1 + \frac{\mathrm{Var}[D_a]}{\sigma^2_{\varepsilon a}} \frac{\Lambda^2_a}{\Lambda^2_a + \gamma^2 \sigma^2_{xa} \sigma^2_{\varepsilon a}}} > e^{2\gamma c}. \tag{19}$$

On the left-hand side, the benefit of information increases with $\mathrm{Var}[D_a]/\sigma^2_{\varepsilon a}$, which measures the *quality of information* provided by the earnings announcement; decreases with the fraction of informed investors Λ_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 σ_{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 multiple announcing firms, with the major difference that heterogeneity in firms characteristics (β_a, $\sigma_{\varepsilon a}$, σ_{ea}, and σ_{xa}) yields heterogeneous information choices across firms. We will analyze this heterogeneity in Section 2.4, where we discuss the model's theoretical predictions, and continue to focus here on the information market equilibrium, which we characterize in the following theorem.

Theorem 1. *There exist two positive values $c_{min} < c_{max}$, strictly increasing in U, such that:*

(A) If $c \in [c_{max}, \infty)$, then the cost of information is prohibitive and no investor finds it optimal to pay attention to the earnings announcements: $\lambda^{\emptyset} = 1$.

(B) If $c \in (c_{min}, c_{max})$, then there exists a set $\{\lambda^k \mid k \in \mathscr{P}(\mathcal{A})\}$ such that, in equilibrium: $\sum_{k \in \mathscr{P}(\mathcal{A})} \lambda^k = 1$; $\lambda^{\emptyset} < 1$; $\lambda^{\mathcal{A}} < 1$; and the benefit-cost ratios $\{B^k_{\emptyset} \mid k \in \mathscr{P}(\mathcal{A})\}$ are determined such that for any pair $\{k, k'\} \in \mathscr{P}(\mathcal{A})$:

(i) If $\{\lambda^k > 0\} \wedge \{\lambda^{k'} > 0\}$, then $B^{k'}_{\emptyset}/B^k_{\emptyset} = 1$.

(ii) If $\{\lambda^k = 0\} \wedge \{\lambda^{k'} > 0\}$, then $B^{k'}_{\emptyset}/B^k_{\emptyset} \geq 1$.

Conditions (i) and (ii) are both necessary and sufficient for the stability of the information market equlibrium when $c \in (c_{min}, c_{max})$.

(C) If $c \in [0, c_{min}]$, then the cost of information is small enough such that all investors pay attention to all the earnings announcements: $\lambda^{\mathcal{A}} = 1$.

Cases (A) and (C) and are trivial equilibria in which the cost of information is either too high or too low. In these cases investors unanimously choose to remain uninformed or to pay attention to all earnings announcements. Case (B), which will be the focus our our analysis in Section 2.4, defines a set of conditions such that, in equilibrium, no investor can unilaterally improve their personal utility by changing their type.[14] We explain in Section 2.4 how investors arrive at this self-sustaining equilibrium, and describe an iterative algorithm which converges to equilibrium from any initial conditions $\{\lambda_0^k \mid k \in \mathscr{P}(\mathcal{A})\}$.

2.2 Equilibrium prices and earnings response coefficients

We now aggregate investors' demands in order to solve for equilibrium prices. Define first the weighted average precision matrix for the population of informed investors as

$$\boldsymbol{\tau} \equiv \sum_{k \in \mathscr{P}(\mathcal{A})} \lambda^k \boldsymbol{\tau}^k. \tag{20}$$

Lemma 1. *The weighted average precision is given by*

$$\boldsymbol{\tau} = \mathrm{Var}[\mathbf{D}]^{-1} + \begin{bmatrix} \mathrm{diag}[\pi_a(\Lambda_a) \mid a \in \mathcal{A}] & \mathbf{0}_{A \times (N-A)} \\ \mathbf{0}_{(N-A) \times A} & \mathbf{0}_{(N-A) \times (N-A)} \end{bmatrix}, \tag{21}$$

where each coefficient $\pi_a(\Lambda_a)$ is a strictly increasing function of Λ_a,

$$\pi_a(\Lambda_a) = \frac{\Lambda_a^2 + \Lambda_a \gamma^2 \sigma_{xa}^2 \sigma_{\varepsilon a}^2}{\Lambda_a^2 \sigma_{\varepsilon a}^2 + \gamma^2 \sigma_{xa}^2 \sigma_{\varepsilon a}^4}, \quad a \in \mathcal{A}, \tag{22}$$

and $\mathrm{diag}[y_j \mid j \in z]$ is a diagonal matrix with $\{y_j \mid j \in z\}$ on its diagonal.[15]

Each function $\pi_a(\Lambda_a)$ determines the aggregate precision gains from observing E_a. A key property of these functions, which will be very useful shortly, is that they depend on the

[14] Conditions (i) and (ii) can be conveniently grouped by means of a Kronecker product. Consider the column vector $\mathbf{B} = \{B_\emptyset^k \mid k \in \mathscr{P}(\mathcal{A})\}$ and let $\mathbf{B}^{-1}$ be its element-wise inverse. The Kronecker product $\mathbf{B}^{-1} \otimes \mathbf{B}'$, whose rows correspond to λ^k and columns to $\lambda^{k'}$, groups all the necessary elements. For example, if $\{\lambda^k > 0\} \wedge \{\lambda^{k'} > 0\}$, then the element (k, k') of $\mathbf{B}^{-1} \otimes \mathbf{B}'$ should equal 1.

[15] The off-diagonal elements in the second term of equation (21) are all zero, potentially suggesting that an earnings announcement E_a is only informative about D_a. This seems odd given that all final payoffs 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 $\boldsymbol{\tau}$ would restore the common interpretation and would show that any earnings announcement E_a is indeed informative about all firms' payoffs.

economic uncertainty U only *indirectly* through Λ_a.

Proposition 3. *The equilibrium prices in this economy satisfy*

$$\boldsymbol{\tau}\mathbf{P} = \sum_{a=1}^{A} \pi_a(\Lambda_a)\boldsymbol{\iota}_a E_a + \gamma \begin{bmatrix} \operatorname{diag}\left[\frac{\pi_a(\Lambda_a)\sigma_{\varepsilon a}^2}{\Lambda_a} \mid a \in \mathcal{A}\right] & \mathbf{0}_{A\times(N-A)} \\ \mathbf{0}_{(N-A)\times A} & \mathbf{I}_{N-A} \end{bmatrix} \mathbf{x} - \gamma\mathbf{M}, \tag{23}$$

where $\mathbf{I}_z$ is the identity matrix of dimension z.

The *earnings response coefficients* measure the reactions of the equilibrium prices to the earnings announcements. In a simpler model with a sole announcer (Teoh and Wong, 1993), the earnings response coefficient (ERC) is given by the coefficient of E_a in the equilibrium price. In our model with N firms and A announcers, the ERC*s* form the principal diagonal of the $N \times A$ matrix $\boldsymbol{\alpha}$ in the price conjecture (10). That is, the ERC*s* measure the price reactions of the announcing firms to their *own* announcements. Denoting by $\mathbf{D}_{\mathcal{A}}$ the final payoffs of all announcing firms, the following corollary solves for the ERC*s*.

Corollary 3.1. *The earnings response coefficients of the announcing firms are given by the diagonal of the $A \times A$ matrix $\boldsymbol{\alpha}_{\mathcal{A}}$, which solves:*

$$\boldsymbol{\alpha}_{\mathcal{A}} = \mathbf{I}_A - \left(\mathbf{I}_A + \operatorname{Var}[\mathbf{D}_{\mathcal{A}}] \operatorname{diag}[\pi_a(\Lambda_a) \mid a \in \mathcal{A}]\right)^{-1}. \tag{24}$$

The $A \times A$ matrix $\boldsymbol{\alpha}_{\mathcal{A}}$ is zero if $\Lambda_a = 0 \ \forall a \in \mathcal{A}$. An important *separation result* helps us interpret $\boldsymbol{\alpha}_{\mathcal{A}}$: as shown in Lemma 1, the coefficients $\pi_a(\Lambda_a)$ do not directly depend on U. Therefore, in the analysis that follows, we can separately assess the effects of an increase in economic uncertainty on the earnings response coefficients and, in particular, the additional effect that arises from changes in investors' attention.

2.3 Illustration

To illustrate how investors' search for information converges to a stable equilibrium, it is helpful to write the individual optimization problem (6) under a simpler form. Appendix A.7 shows that at time 0 each investor makes the following choice:

$$\max_{k \in \mathscr{P}(\mathcal{A})} \ln B_{\emptyset}^{k}, \tag{25}$$

where the benefit-cost ratios $B_{\emptyset}^{k}$ have been defined in (17).

A key property of the function $f(k) = \ln B_{\emptyset}^{k}$ is submodularity—the difference in the incremental value of $f(k)$ that one element a makes when added to the type k decreases as the size of k increases. Submodularity can be interpreted as a property of *diminishing returns*, and implies that an individual investor's incentive to become more informed (e.g., to increase her type from k to $k \cup \{a\}$) decreases with her current level of attention. Furthermore, we show in Appendix A.7 that a migration of a positive mass of investors from any type k to a different type k' decreases the relative attractiveness of type k' with respect to type k, i.e., decreases the fraction $B_{\emptyset}^{k'}/B_{\emptyset}^{k}$. This implies that an individual investor's incentive to chose k' over k decreases if in aggregate more investors chose k' over k. Hence we recover the Grossman and Stiglitz (1980) result that individual action and the aggregate of (others) individual actions are strategic substitutes.

Hu and Shi (2019) and Arkolakis et al. (2021) study submodular games and derive an evolutionary learning algorithm that reaches the equilibrium from any initial point. Starting from a set of initial values $\{\lambda_0^k > 0 \mid k \in \mathscr{P}(\mathcal{A})\}$ such that $\sum_k \lambda_0^k = 1$, the algorithm allows some small fraction of the population of investors of a given type k to revise their strategy as a best response to the current total population strategy. This process is iterated over all types until it converges to a self-sustaining equilibrium in which no investor changes strategy, as in Theorem 1. We relegate the details of this algorithm in Appendix A.7, and focus here on a numerical example, which we illustrate in Figure 1.

This numerical example considers an economy with three announcers, in which the announcing firms differ through their exposure to systematic risk, $\beta_1 > \beta_2 > \beta_3$, while other firm-level parameters are homogeneous across firms. (Differences in the other characteristics, which we discuss further below, deliver similar plots and the same intuition.) The parameters that we choose are provided in the caption of the figure. We emphasize that this example is only illustrative—in Section 4, we propose a more realistic calibration, with a larger number of firms and of announcers.

The dashed and solid lines in the figure depict the values c_{min} and c_{max}, respectively. The plot confirms the statements of Theorem 1 that (i) $c_{min} < c_{max}$ and (ii) both c_{min} and c_{max} increase with the amount of uncertainty U. When $c \leq c_{min}$, all investors in the economy are attentive to all earnings announcements, $\lambda^{\mathcal{A}} = 1$; when $c \geq c_{max}$, no investor pays attention to earnings announcements, $\lambda^{\emptyset} = 1$; when $c \in (c_{min}, c_{max})$, the two dotted lines that split the middle zone show that investors always find the earnings announcement of firm 1 most valuable—they pay attention to E_1 in cases (B1), (B2), and (B3)—whereas the earnings announcement of firm 3 least valuable—they pay attention to E_3 only in case (B3). Because $\beta_1 > \beta_2 > \beta_3$, E_1 is the most informative announcement about the systematic factor f, and thus investors turn their attention first to firm 1. Thus, in this equilibrium investors behave as if they queue announcements based on their exposure to systematic risk. Fredericksson and Zolotoy (2016) document a similar queuing result: investors devote more immediate attention

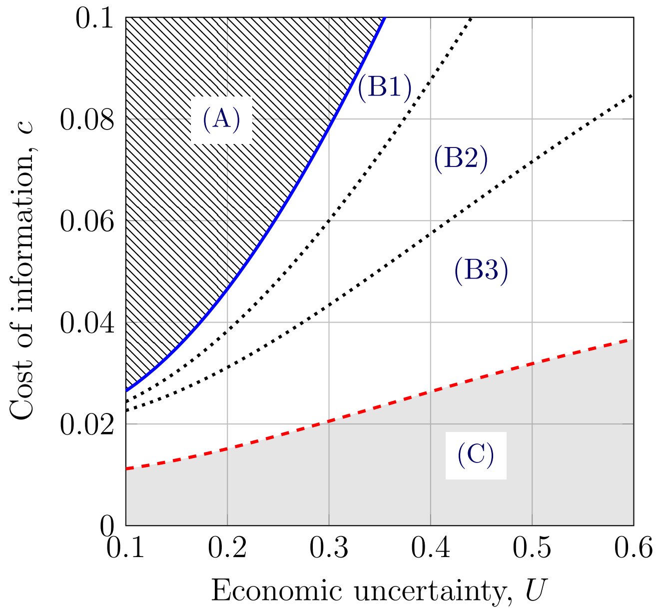

Figure 1: **Information market equilibrium**
This figure depicts the three cases of Theorem 1, (A), (B), and (C). We further split case (B) in theree sub-cases: (B1) $\Lambda_1 > 0, \Lambda_2 = \Lambda_3 = 0$, in which investors only pay attention to the announcement of firm 1; (B2) $\Lambda_1 > 0, \Lambda_2 > 0, \Lambda_3 = 0$, in which investors pay attention to the announcements of firms 1 and 2 but not 3; (B3) $\Lambda_1 > 0, \Lambda_2 > 0, \Lambda_3 > 0$, in which investors pay attention to the announcements of all firms. The calibration used for this illustration is: $\gamma = 1$, $\beta_1 = 1.2$, $\beta_2 = 1$, $\beta_3 = 0.8$, $\sigma_{e1} = \sigma_{e2} = \sigma_{e3} = 0.2$, $\sigma_{\varepsilon 1} = \sigma_{\varepsilon 2} = \sigma_{\varepsilon 3} = 1$, and $\sigma_{x1} = \sigma_{x2} = \sigma_{x3} = 1$.

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. Indeed, as we show in the next section, firm's exposure to the systematic factor yields a clear ranking of investors' attention across firms.

2.4 Testable implications

Building on the previous illustration, we will now derive several testable implications of the model. 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): a positive fraction of investors become attentive first to E_1 and, if the increase in uncertainty is sufficiently strong, to E_2 and ultimately to E_3. 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 the earnings announcements. The fractions Λ_a of investors who observe each earnings annoucement, defined in (9), are not apparent from Figure 1, which shows only when these fractions are positive or zero. We now analyze how these fractions vary with economic uncertainty.

Assume for simplicity that no investor in the economy observes the announcement of firm a, or $\Lambda_a = 0$. (This assumption is made only for ease of exposition and will not alter our results.) For a type k investor, the benefit of paying attention to E_a follows from (17):

$$\frac{\det(\boldsymbol{\tau}^{k\cup\{a\}})}{\det(\boldsymbol{\tau}^{k})} = 1 + \frac{1}{\sigma_{\varepsilon a}^2}\left(\sigma_{ea}^2 + \frac{\beta_a^2}{\frac{1}{U^2} + \sum_{\alpha=1,\ \alpha\neq a}^{A} \frac{\beta_\alpha^2 \ell_\alpha^k}{\ell_\alpha^k \sigma_{ej}^2 + \sigma_{\varepsilon\alpha}^2}}\right). \tag{26}$$

The first implication from (26) is that the benefit of paying attention to E_a stictly increases with economic uncertainty. This holds for all investor types and for all announcing firms. Moreover, the benefit of attention is higher for firms that have a stronger exposure β_a to the systematic component; a higher volatility σ_{ea} of their idiosyncratic component; and less noise in their announcement (a lower $\sigma_{\varepsilon a}$). Equation (26) also implies that the benefit of attention decreases with the amount of attention that investors pay to *other* earnings announcements, which is reflected in the summation term: if a large number of firms announce at the same time (if A is high), and if large fractions of investors are attentive their annoucements (if Λ_α are large, $\forall \alpha \neq a$), then prices are highly informative about f and paying attention to E_a becomes less valuable. 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.[16] In our model, this result arises not because investors are distracted by the simultaneous announcements, but because the benefit of attention diminishes with aggregate price informativeness.

Panel (a) of Figure 2 illustrates the impact of an increase in uncertainty in our calibrated economy with three announcers. The three lines depict the fractions of the population of investors attentive to each earnings announcement. This example assumes that $\beta_1 > \beta_2 > \beta_3$.

[16] See also Hirshleifer and Teoh (2003); DellaVigna and Pollet (2009); Louis and Sun (2010); Drake et al. (2016); Lu et al. (2016) for additional evidence on the distraction hypothesis.

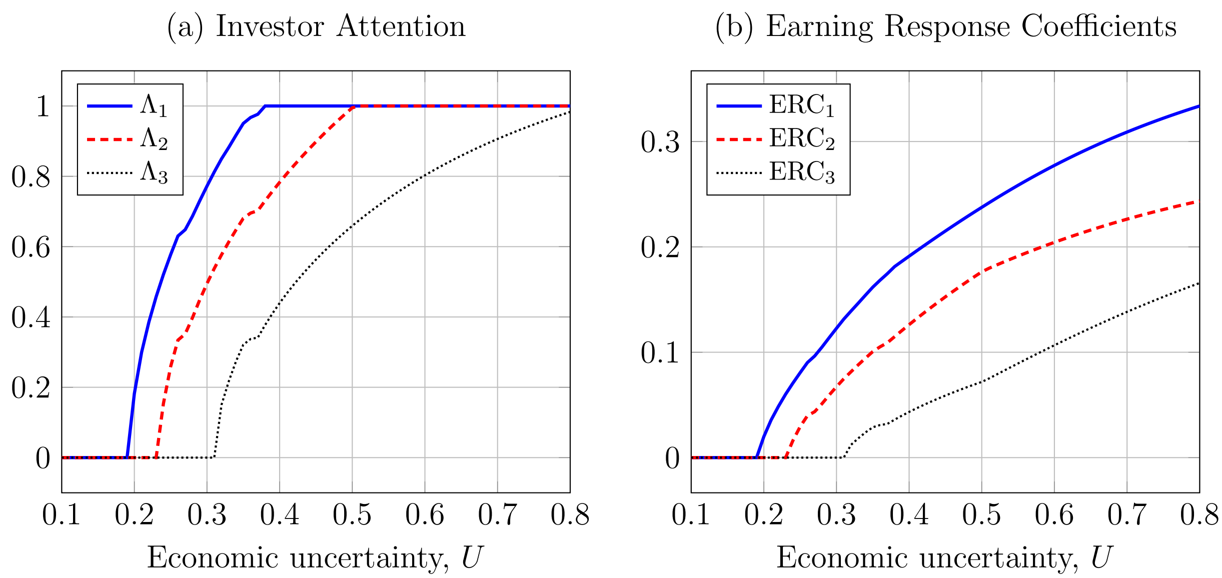

Figure 2: **The impact of economic uncertainty on investor attention and on ERC*s*** Panel (a) plots the fractions of attentive investors to each one of the three earnings announcements. Panel (b) plots the earnings response coefficients. In this economy, $\beta_1 > \beta_2 > \beta_3$, $c = 0.045$, and the rest of the calibration is provided in Figure 1.

Confirming Eq. (26), the fractions Λ_1, Λ_2, and Λ_3 increase with U. We note that for low levels of economic uncertainty the fractions Λ_a are all zero for $a \in \{1, 2, 3\}$, which corresponds to case (A) of Theorem 1. As uncertainty increases, the economy moves successively to all the subcases of (B), and ultimately to case (C).

The increase in investors' attention caused by an increase in uncertainty has additional implications for the response of prices to firm-level information. To gain more intuition, we write the ERC in an economy with a sole announcer (Corollary 3.1):

$$\mathrm{ERC}_a = 1 - \frac{1}{1 + (U^2\beta_a^2 + \sigma_{ea}^2)\pi_a(\Lambda_a)}. \tag{27}$$

The ERC increases with economic uncertainty, both directly through an increase in the variance of the firm's payoff $\mathrm{Var}[D_a]$, and indirectly, to an increase in investors' attention to the earnings announcement. Firms that have a stronger exposure β_a to the systematic systematic component, or a higher volatility σ_{ea} of their idiosyncratic component, should observe a stronger increase in their ERC as economic uncertainty increases. Panel (b) of Figure 2 revisits our economy with three announcers and confirms that the ERC*s* increase with economic uncertainty, and that firms with stronger exposure to the systematic components have higher ERC*s*.

Equation (27) implies that the ERC*s* are driven both by the exogenous increase in eco-

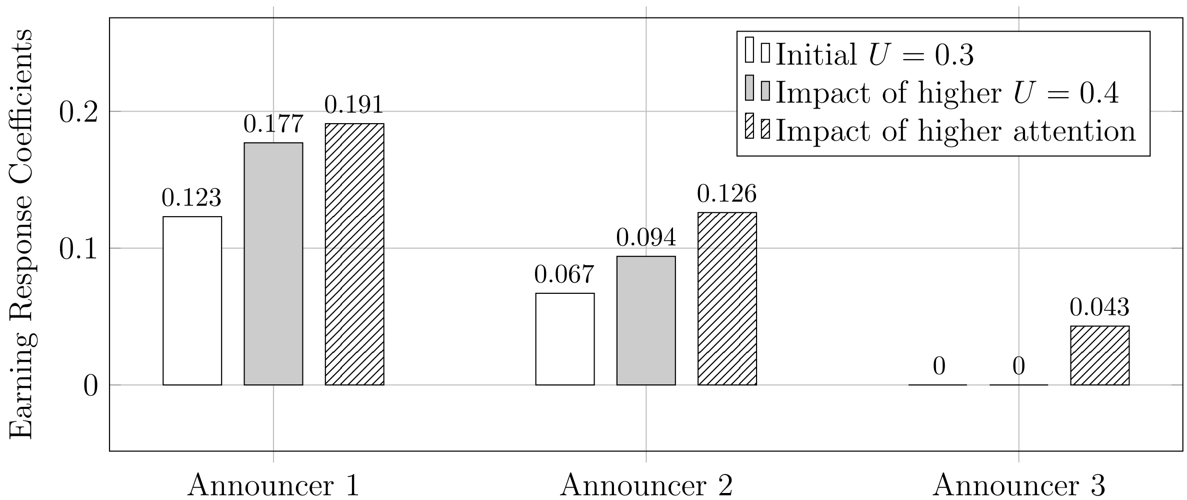

Figure 3: **The separate impact of an increase in uncertainty and an increase in investor attention on ERC*s***
This figure plots the successive changes in the ERC*s* of the announcing firms after an increase of economic uncertainty from 0.3 to 0.4. The grey bars plot the ERC*s* resulting exclusively from the increase in U. The hatched bars plot the final ERC*s*, including also the impact of the increase in investors' attention. In this economy, $\beta_1 > \beta_2 > \beta_3$, $c = 0.045$, and the rest of the calibration is provided in Figure 1.

nomic uncertainty and the endogenous increase in investors' attention. We disentangle these two effects in Figure 3. The impact on the ERC*s* of an increase in U is shown with the gray bars, whereas the additional impact of the increase in investors' attention is shown with the hatched bars, confirming the direct and indirect effects implied by (27). It is interesting to notice that in this example the ERC of the third announcer increases from zero to a positive value only through the indirect effect of an increase in attention.

Figures 2 and 3 depict results in an economy in which the three announcers have different exposures to the systematic component. We now turn to other dimensions of heterogeneity across firms, and summarize the results in Figure 4. Panels (a) and (d) analyze the case or announcing firms that differ through their volatility idiosyncratic shocks, $\sigma_{e1} > \sigma_{e2} > \sigma_{e3}$ (while all other parameters are constant across firms). Equations (26)-(27) imply that firms with higher σ_{ea} should observe stronger investor attention and stronger ERC*s* to their announcements. (The quality of information provided an earnings announcement, $\text{Var}[D_a]/\sigma^2_{\varepsilon a}$, is higher for firms with higher σ_{ea}, and thus after an increase in uncertainty investors turn their attention to those firms first.) Panels (a) and (d) confirm these effects, both for the fractions of informed investors and for the ERC*s*.

Assuming that firms differ through the noise in their signals, $\sigma_{\varepsilon 1} < \sigma_{\varepsilon 2} < \sigma_{\varepsilon 3}$, implies that the signal of firm 1 is more valuable for investors, for the same reason as above: E_1 is more

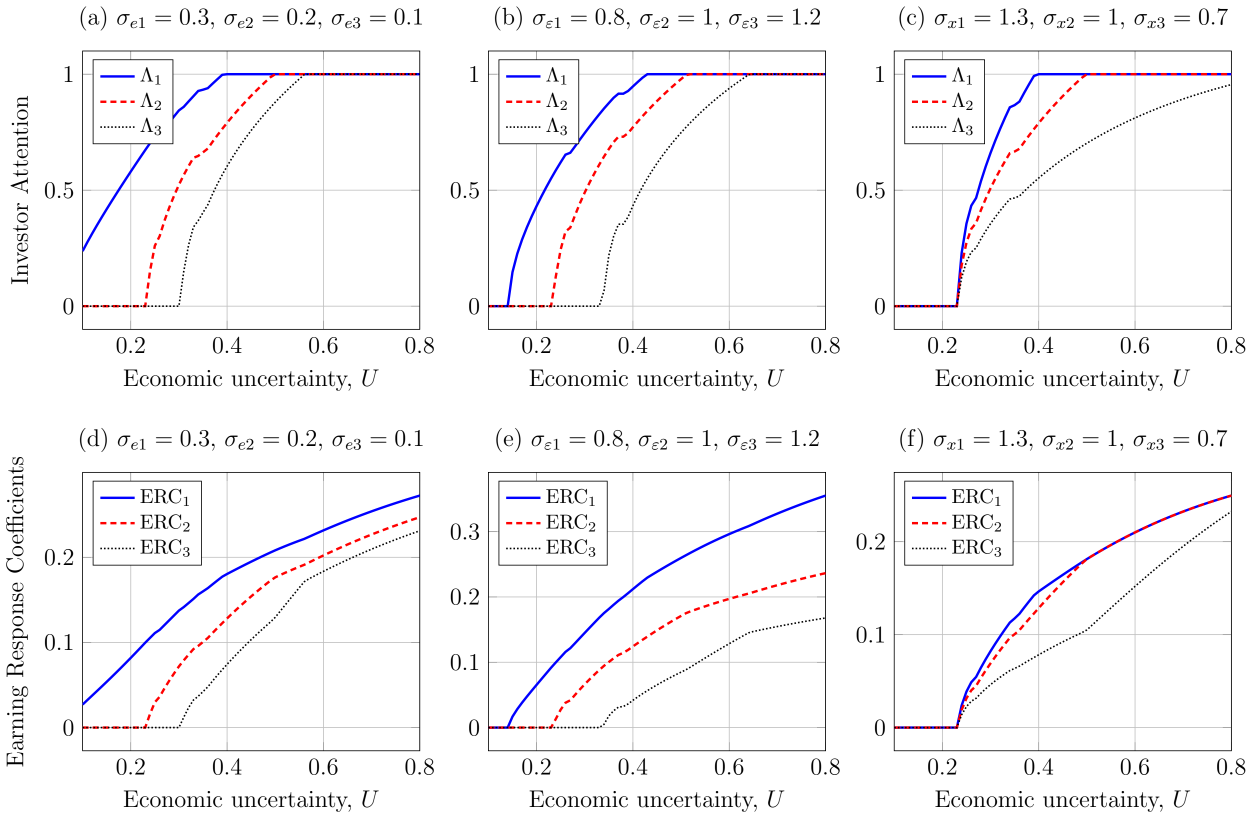

Figure 4: **The impact of economic uncertainty on investor attention and on ERC*s*** This figure plots the fractions of investors attentive to each earning announcement (above) and the ERC*s* (below), as functions of economic uncertainty, for different σ_{ea}, different $\sigma_{\varepsilon a}$, and different σ_{xa}. The rest of the calibration is provided in Figure 1, and $c = 0.045$.

informative about f than E_2, which itself is more informative than E_3. Panels (b) and (e) of Figure 4 illustrate this. Finally we also analyze the case of different noise in supply. Panels (c) and (f) consider an economy in which $\sigma_{x1} > \sigma_{x2} > \sigma_{x3}$ and show that after an increase in U investors turn their attention more to firm 1 and the ERC*s* are higher for firm 1. 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 (as in Grossman and Stiglitz, 1980). This yields a higher Λ_a for firms with higher σ_{xa}, and consequently a stronger ERC.

To summarize, the testable implications of our model with respect to the impact of economic uncertainty on investor attention and on the ERC*s* 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*) investors' incentives to pay attention to the earnings announcements decreases with the number of firms that announce their earnings simultaneously; (*iii*) when economic uncertainty (investor attention) increase, earnings response coefficients are stronger for all announcing firms; and (*iv*) the increases in earnings response coefficients caused by higher economic uncertainty (investor attention) is incrementally stronger for firms with higher β_a, higher σ_{ea}, lower $\sigma_{\varepsilon a}$, and higher σ_{xa}.

3 Extensions and additional implications

3.1 Heterogeneous attention costs

Our analysis so far has focused on an economy in which firms are heterogeneous but investors are identical before making their information acquisition and portfolio choice decisions. In reality, it is plausible to assume that investors have different information acquisition costs. For instance, 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.

To study the implications of heterogeneous information costs, we extend our model to two groups of investors, *institutional* and *retail* investors, with information costs $c_i < c_r$. This additional layer of heterogeneity requires re-writing the equilibrium conditions of Theorem 1 separately for each investor group. Importantly, $c_i < c_r$ implies that

$$B_{i,k}^{k\cup\{a\}} > B_{r,k}^{k\cup\{a\}}, \quad \forall k \in \mathscr{P}(\mathcal{A}) \text{ and } a \notin k, \tag{28}$$

where $B_{j,k}^{k\cup\{a\}} = \exp(-2\gamma c_j|k|)\det(\boldsymbol{\tau}^{k\cup\{a\}})/\det(\boldsymbol{\tau}^k)$ for $j \in \{i,r\}$. In words, paying attention to one extra announcement has a larger benefit for an institutional investor than for a retail investor. The condition (28), labeled "monotonicity in types" in Hu and Shi (2019), guarantees the existence of an equilibrium and ensures that the solution method described in Appendix A.7 reaches the equilibrium.

Figure 5 plots the attention of institutional (left) and retail (right) investors as functions of economic uncertainty. We use the same calibration with $\beta_1 > \beta_2 > \beta_3$ as in Figure 1, and split the population of investors into 50% institutional and 50% retail (other splits lead to similar result), and fix $c_i = 0.045$ and $c_r = 0.055$. The two panels clearly show that for any level of economic uncertainty larger fractions of institutional investors pay attention to the

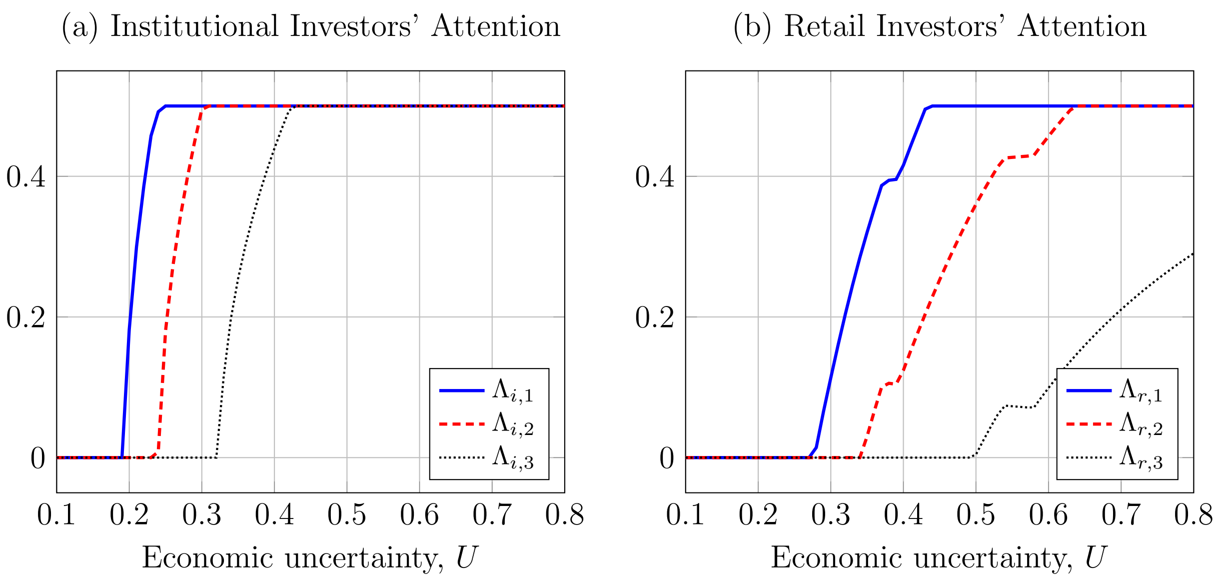

Figure 5: **The impact of economic uncertainty on investor attention in an economy with heterogeneous attention costs**
Each panel of the figure plots the fractions of attentive investors as functions of economic uncertainty, with institutional investors in panel (a) and retail investors in panel (b). In this economy, $\beta_1 > \beta_2 > \beta_3$, $c_i = 0.045$, $c_r = 0.055$, the fractions of institutional and retail investors are of equal size (50%), and the rest of the calibration is provided in Figure 1.

earnings announcements. Furthermore, the steeper lines in the left-hand side plot suggest that institutional investors respond faster to the increase in uncertainty than retail investors, confirming the intuition from (28) that institutional investors benefit comparatively more from increasing their attention.

An economy in which investors have different attention costs has further implications for the ERC*s*. As shown in (27), the ERC*s* increase with the amount of attention in the economy. This implies that the *investor base* of firms now has an impact on the ERC*s*: the ERC*s* for firms with high institutional ownership should show a stronger response to an increase in uncertainty, through the stronger increase in investors' attention. We will test this theoretical implication in Section 4.

3.2 Dynamic model

We have derived our main results under the simplifying assumption of a one-period economy. In this section, we show that the same comparative statics results with respect to economic uncertainty also hold in a dynamic economy.

The dynamic setup consists of an overlapping-generations economy in which a new generation of investors is born every period. We refer to the generation of investors that is born at

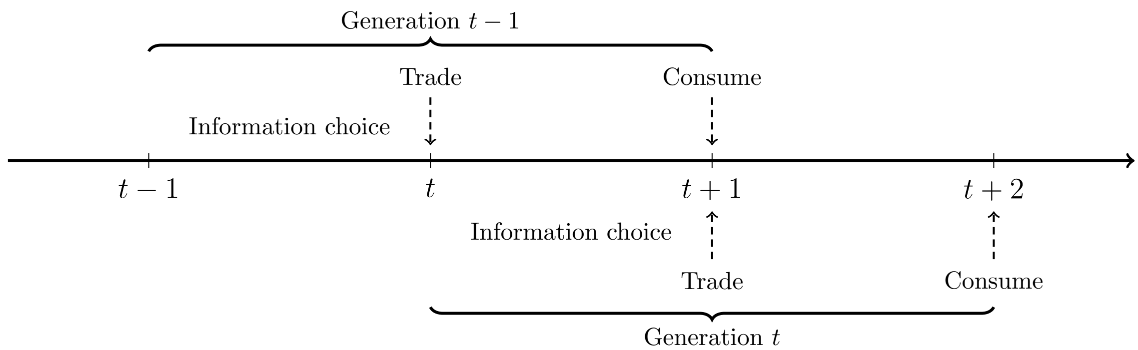

Figure 6: **Overlapping generations economy**

time t as *generation* t. Each generation is present in the economy for three dates and makes information acquisition and trading decisions sequentially, as in the static model. Focusing on generation $t-1$, each investor $i \in [0,1]$ in this generation makes an information choice between $t-1$ and t, then trades to take positions in securities at t, and consumes final wealth at $t+1$. As such, generation $t-1$ investors liquidate their holdings at time $t+1$ by selling them at market prices to generation t investors. Figure 6 shows the timeline.

Our main purpose is to understand how the dynamic feature of the economy impacts the results obtained in the previous section. For this purpose it is sufficient to assume that investors trade a single risky asset and a riskless asset. (Assuming multiple risky assets would considerably complicate the analysis without adding additional insights.) The riskless asset is in infinitely elastic supply and pays a gross interest rate of $R_f > 1$ per period. The risky asset pays a risky dividend per period,

$$D_{t+1} = \beta f_{t+1} + e_{t+1}, \tag{29}$$

which, as in (1), has two components: a systematic component, $f_{t+1} \sim \mathcal{N}(0, U^2)$, and a firm-specific component, $e_t \sim \mathcal{N}(0, \sigma_e^2)$.

At time t, the firm issues an earnings announcement,

$$E_t = D_{t+1} + \varepsilon_t, \tag{30}$$

with $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. We denote the investors who pay attention to E_t as I investors, and the ones who decide to remain uninformed as U investors. The indicator variable I^k takes the value 1 if $k = I$ and 0 if $k = U$. The cost of paying attention to E_t is $c > 0$.

Each investor $i \in [0,1]$ of generation $t-1$ starts with zero initial wealth and maximizes expected utility:

$$\max_{k\in\{I,U\}} \mathbb{E}_{t-1}\left[\max_{q_t^k} \mathbb{E}_t^k\left[-e^{-\gamma\left(W_{t+1}^k - cI^k\right)}\right]\right] \tag{31}$$

where $W_{t+1}^k \equiv q_t^k(D_{t+1} + P_{t+1} - R_f P_t) \equiv q_t^k R_{t+1}^e$ is type k investor's terminal wealth.

The supply of the risky asset is noisy and equals $M - x_t$, with x_t being independently and identically distributed, $x_t \sim \mathcal{N}(0, \sigma_x^2)$. We conjecture the following linear structure for the price, which is the dynamic equivalent of (10) from the static version of the model:

$$P_t = \alpha E_t + \xi x_t - \zeta M. \tag{32}$$

The equilibrium in this dynamic model follows the same steps as in the static model. We refer the reader to Appendix A.8 for details and proceed here to discuss the main results.[17]

Proposition 4. *(a) Investor i is attentive to the earnings announcement if and only if*

$$\frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^I[R_{t+1}^e]} > e^{2\gamma c}. \tag{33}$$

(b) The benefit of information, $\mathrm{Var}_t^U[R_{t+1}^e]/\,\mathrm{Var}_t^I[R_{t+1}^e]$, *increases in* $\mathrm{Var}_t[D_{t+1}] = \beta^2 U^2 + \sigma_e^2$.

We recover the same result as in the static model: the benefit of paying attention to E_t increases with economic uncertainty. Moreover, the benefit of attention is higher when β is higher and when the volatility σ_e of the idiosyncratic component is higher. Thus, in the dynamic model as in the static model, we should observe higher investor attention when economic uncertainty is high.

Proposition 5. *The earnings response coefficient in this economy is given by*

$$\mathrm{ERC}_t = \frac{w_t}{R_f}\frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}] + \sigma_\varepsilon^2} + \frac{1-w_t}{R_f}\frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}] + \sigma_\varepsilon^2/\ell_t}, \tag{34}$$

where $w_t \in [0,1]$, $\ell_t \in [0,1)$. *Both* w_t *and* ℓ_t *are increasing with the fraction* Λ_t *of investors who are paying attention to* E_t. *Thus, the ERC increases in* Λ_t.

Proposition 5 shows that in the dynamic model the ERC is a weighted average of price responses from different investors, with weights w_t on I investors and $1 - w_t$ on U investors

[17]Dynamic models of trading of this type have multiple equilibria. More precisely, a model with N risky assets has 2^N equilibria (e.g. Banerjee, 2011; Andrei, 2018), and thus in this model there are two equilibria: a low volatility equilibrium and a high volatility equilibrium. The theoretical results that we present here hold in both equilibria.

(see Appendix A.8 for an expression of w_t in Λ_t). This result mirrors Hirshleifer and Teoh (2003), where it is shown that the equilibrium price is a weighted average of beliefs of attentive and inattentive investors. The coefficient ℓ_t in (34) is the dynamic counterpart of the learning coefficient defined in (13) in the static model.

Two effects take place when economic uncertainty increases. The first, direct effect is the increase in both terms of (34) caused by a higher $\text{Var}_t[D_{t+1}]$. The second effect is endogenous and results from Proposition 4. The increase in economic uncertainty causes investor attention to rise and therefore both w_t and ℓ_t to increase. This, in turn, further increases the ERC. We thus recover the intuition from the static model, equation (27): the ERC increases with economic uncertainty, both directly through an increase in the variance of the firm's payoff $\text{Var}_t[D_{t+1}]$, and indirectly, to an increase in investors' attention. The two effects are stronger for firms with a higher β or a higher idiosyncratic volatility σ_e.

In both our static and dynamic setups, we have assumed that the attention of investors is to the earnings announcement itself, in line with the existing inattention literature.[18] Our choice was further motivated by a basic premise of the model, namely that earnings announcements convey valuable information about the macroeconomy, a notion that finds empirical support.[19] But in reality investors may also decide to scale up their information acquisition ahead of the earnings announcements—for instance, in our dynamic model investors may decide to acquire information *before* time t. Yet, Proposition 4 shows that the same attention tradeoff holds: regardless of prior information acquisition decisions, the benefit of paying attention to the earnings announcement increases with the uncertainty that investors face at time t. Moreover, as shown in Proposition 5, higher investor attention always increases w_t and ℓ_t, which in turn increase the ERC. Although investors' search for information beforehand may dampen the effect of an increase in uncertainty U on the conditional variance $\text{Var}_t[D_{t+1}]$, the indirect effect characterized by Proposition 5 still guarantees that more attention increases the earnings response coefficients.[20]

Finally, in keeping with the one-period version of the model, we have derived results in the dynamic model using comparative statics analysis. The alternative would be to assume a time-varying U, and then analyze the effects of this time variation in uncertainty on investors'

[18]See, among others, Hirshleifer and Teoh (2003); Hirshleifer et al. (2009); DellaVigna and Pollet (2009); Hirshleifer and Sheng (2021).

[19]See Patton and Verardo (2012) and Savor and Wilson (2016).

[20]Related to this, Benamar et al. (2021) use a standard endogenous information acquisition argument to show that heightened attention in the face of greater uncertainty is insufficient to fully neutralize the effect of uncertainty. Put differently, a higher uncertainty at time $t-1$ would result in a *higher* $\text{Var}_t[D_{t+1}]$, despite investors' heightened attention at $t-1$. The argument simply follows from the first-order condition in an information acquisition problem with convex attention costs: since the marginal cost of attention increases with attention, the effect of the increase in uncertainty on $\text{Var}_t[D_{t+1}]$ is only partially offset by investors' heightened attention. See Proposition 1 in Benamar et al. (2021) and the discussion that follows.

attention response and on the ERC. However, this alternative creates a non-linearity in the model—with time variation in U, the distribution of the future price P_{t+1} becomes non-Gaussian and thus the equilibrium cannot be solved in closed form. Solving this alternative model is beyond the scope of this study, but based on the good approximations developed in the literature it is likely to reach the same conclusions.[21]

4 Empirical analyses

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

4.1 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, and its direct counterpart in our model is U.[22]

To capture investor search for information, we exploit the download logs provided by the SEC's EDGAR website.[23] 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.[24] Transforming the ESV(U) in logs allows us to

[21]The solution proposed in the literature to this non-linearity is the approximation method developed by Vayanos and Weill (2008) and Gârleanu (2009). This approximation preserves risk aversion towards diffusion risks, while inducing risk neutrality towards future changes in U, in this way restoring linearity.

[22]Formally, denoting by $\boldsymbol{\beta}$ the vector of firms' exposures to f and by $\boldsymbol{\Sigma}_e$ the covariance matrix of firm-specific shocks, then investors' uncertainty at $t = 0$ about the future market return, $\mathrm{Var}[\mathbf{M}'\mathbf{R}^e|\mathcal{F}_0]$, equals $U^2\mathbf{M}'\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{M} + \mathbf{M}'\boldsymbol{\Sigma}_e\mathbf{M}$. Our assumptions of an equally weighted market portfolio and an average of 1 for firms' exposures to the systematic factor imply $\mathbf{M}'\boldsymbol{\beta} = 1$. Moreover, in the model the matrix of idiosyncratic shocks $\boldsymbol{\Sigma}_e$ is diagonal and its diagonal has a finite mean, thus $\lim_{N\to\infty} \mathbf{M}'\boldsymbol{\Sigma}_e\mathbf{M} = 0$ and $\mathrm{Var}[\mathbf{M}'\mathbf{R}^e|\mathcal{F}_0] = U^2$.

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

[24]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.

interpret changes in percentage terms. We also note that a change in ESV(U) is equivalent with a change in $\log \Lambda_a$ in our model.[25]

For our analyses of market reactions to earnings announcements, we measure earnings surprise, SUE, following Livnat and Mendenhall (2006) as:

$$\text{SUE}_{i,t} = \frac{X_{i,t} - \mathbb{E}[X_{i,t}]}{P_{i,t}}, \tag{35}$$

where i denotes firm, t denotes quarter, $X_{i,t}$ are IBES reported actual earnings, $\mathbb{E}[X_{i,t}]$ 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.[26]

Daily excess returns are calculated each day as CRSP-reported returns adjusted for size decile.[27] 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 B.

[25] In the model, Λ_a can be approximated with Q_a/Q, where Q is a very large number that measures the total population of investors and Q_a measures the number of investors who observe E_a. Hence, $\Delta \log \Lambda_a = \Delta \log Q_a$, and thus a change in $\log \Lambda_a$ is equivalent with a change in ESV(U).

[26] The earnings surprise calculation follows WRDS guidance described in Dai (2020).

[27] 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.

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 β_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 betas.[28] We use Forecast Dispersion and Idiosyncratic Volatility as proxies for total earnings variance ($\text{Var}[E_a]$ in our model) and firm-specific payoff variance (σ^2_{ea}).[29] The volatility of noise trade (σ^2_{xa}) 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 B 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.[30] 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).

(Insert Table 1 about here)

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.

(Insert Table 2 about here)

[28] One can see this link starting from the initial covariance matrix $\text{Var}[\mathbf{R}^e|\mathcal{F}_0] = U^2\boldsymbol{\beta}\boldsymbol{\beta}' + \boldsymbol{\Sigma}_e$ and then computing the vector of market betas as $\text{Var}[\mathbf{R}^e|\mathcal{F}_0]\mathbf{M}/(\mathbf{M}'\,\text{Var}[\mathbf{R}^e|\mathcal{F}_0]\mathbf{M})$. When $N \to \infty$, this vector converges to $\boldsymbol{\beta}$, which provides a direct link between firms' exposures to f and their market betas. See Andrei, Cujean, and Wilson (2020) and the references therein for a discussion of beta measurement in noisy rational expectations models, and Chan and Marsh (2021) for a discussion of the impact of investor attention on the market beta-return relation on earnings announcement days.

[29] Note that Forecast Dispersion could be driven by variation and unpredictability in either earnings fundamentals ($\text{Var}[D_a] = \beta_a^2\sigma_f^2 + \sigma^2_{ea}$) or earnings noise ($\sigma_{\varepsilon a}$). As can be seen in a comparison of panels (b) and (c) of Figure 4, σ^2_{ea} and $\sigma^2_{\varepsilon a}$ have opposing effects on the relation between economic uncertainty and earnings response coefficients.

[30] 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.

4.2 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.

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.

$$\begin{aligned} \text{ESV(U)}_{it} &= c_0 + c_1 \times \text{VIX}_t + c_2 \times \text{ESV}_{it-1} \\ &+ c_3 \times \text{SUE}_{it} + c_4 \times \text{abs}\left(\text{SUE}_{it}\right) + \gamma \cdot X_{it} + u_{it}, \end{aligned} \quad (36)$$

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)

Can our model generate quantitatively similar attention responses to changes in economic uncertainty? To answer this question, we build a more realistic calibration of the model. First, we match historical data on VIX: from January 1990 to June 2021, the VIX has averaged 20%, with a daily standard deviation of 8.1%; we standardize U using these values and define $\widehat{U} \equiv (U - 0.2)/0.081$. We further assume that the total number of firms in the economy, N, equals 3000,[31] and that between 10 and 50 firms announce their earnings on any trading day

[31] The Russell 3000 Index, which measures the performance of the largest 3000 US companies, represents approximately 98% of the investable US equity market.

(Chan and Marsh, 2021, Table 1). We use these parameters and the remaining calibration[32] to compute the response of $\log \Lambda_a$ to a change in $\widehat{U}$, or $\partial \log \Lambda_a / \partial \widehat{U}$.

Panel (a) of Figure 7 plots these responses in two cases: when 10 firms are announcing earnings (solid line) and when 50 firms are announcing (dashed line). On the horizontal axis we let U vary from 10% to 40%, while the vertical axis measures the sensitivity of $\log \Lambda_a$ to changes in $\widehat{U}$, consistent with the coefficient c_1 in (36) and in Table 3. The plot shows that our calibrated model can match the quantitative magnitudes from Table 3. Furthermore, the model also correctly implies a lower coefficient when the number of announcers is higher (in which case price informativeness is higher), in line with the negative coefficients for #Announcements obtained in Table 3. We discuss further below the implications of this calibration on the ERCs.

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:

$$
\begin{aligned}
\text{EARET}_{it} &= c_0 + c_1 \times \text{SUE}_{it} + c_2 \times \text{VIX}_t + c_3 \times \text{SUE}_{it} * \text{VIX}_t + \gamma \cdot X_{it} + u_{it}, \text{ and} \\
\text{EARET}_{it} &= c_0 + c_1 \times \text{SUE}_{it} + c_2 \times \text{ESVU}_t + c_3 \times \text{SUE}_{it} * \text{ESVU}_t + \gamma \cdot X_{it} + u_{it}, \qquad (37)
\end{aligned}
$$

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 (37). The coefficient on SUE decile is positive and significantly different from zero (0.287, $p < 0.01$), consistent

[32] The remaining calibration parameters are: $\gamma = 10$; $\sigma_e = \sigma_\varepsilon = 0.4$ for all firms; the market portfolio $\mathbf{M}$ is a vector whose values are all equal to $1/3000$; the volatility of noise in supply is $\sigma_x = 1/(3000 \times 4)$ for all firms (which ensures that the probability of having negative supplies is negligible); all the betas of the announcing firms are 1; the cost of information is $c = 0.03$. Two additional parameteres would help to further match the data, without having any impact on our results: (i) a positive unconditional value for firms' final payoffs such that the equilibrium price of the every firm remains positive most of the time; (ii) a positive initial wealth for each investor such that the magnitude of the cost of information remains arbitrarily small.

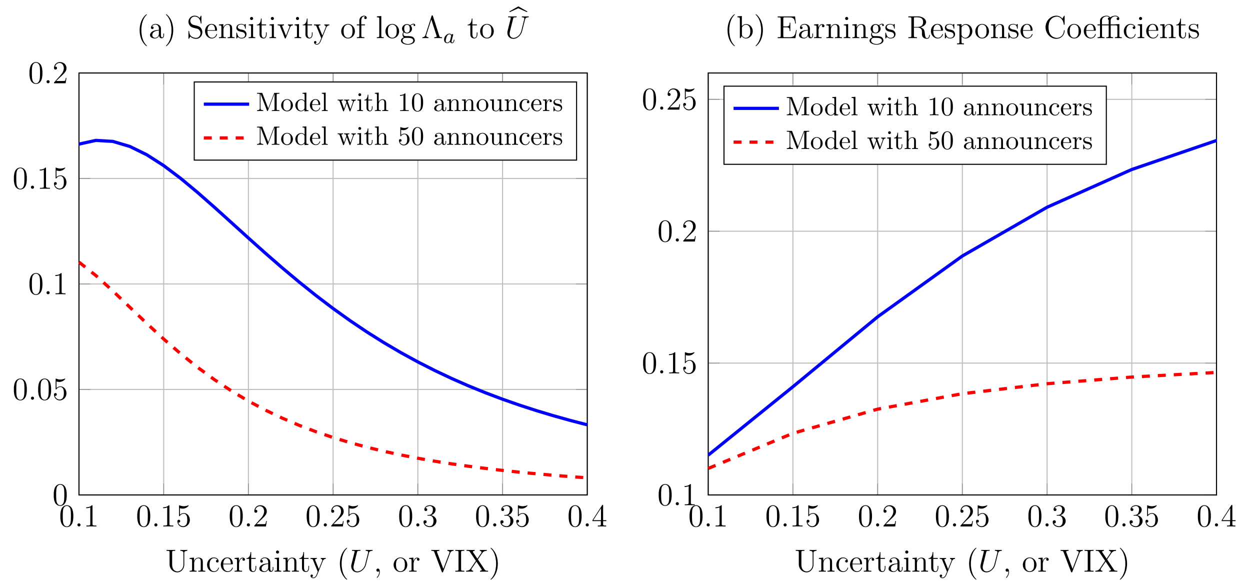

Figure 7: **Response of investor attention to changes in uncertainty, and ERC*s* in a calibration of the theoretical model to an economy with 3000 firms.**
Panel (a) plots the partial derivative of $\log \Lambda_a$ with respect to standardized uncertainty $\widehat{U}$ when $U \in [0.1, 0.4]$, and is thus the theoretical counterpart of the coefficient c_1 in (36) and in Table 3. Panel (b) plots the ERC*s* implied by the theoretical model when $U \in [0.1, 0.4]$ and is thus the theoretical counterpart of the coefficient c_1 in (37) and in Table 4. Both panels consider two alternatives, one with 10 announcers (solid lines), and one with 50 announcers (dashed lines). See footnote 32 for a detailed description of the calibration.

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 $\left(6.1\% = \frac{0.017}{0.287}\right)$.

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, in line with the prediction of our model illustrated in Eq. (27) and Figure 3.

(Insert Table 4 about here)

We also compare the magnitude of the coefficient on SUE Decile in Table 4 (or, equivalently, the coefficient c_1 in (37)) with the numbers that we obtain from our calibrated model. Panel (b) of Figure 7 plots the model-implied ERC*s* as functions of U when 10 firms are announcing earnings (solid line) and when 50 firms are announcing (dashed line). Our model generates plausible magnitudes for the ERC*s*. The plot also shows that (*i*) the ERC*s* increase with U and (*ii*) the ERC*s* are smaller when more firms announce earnings, consistent with the result of panel (a) showing that attention is a substitute for price informativeness. (See also Chen et al., 2020, who document a similar substitution effect between the acquisition of private information and the supply of public information.)

We estimate (37) in several subsamples to provide additional support for the theoretical predictions derived above. As shown in Figures 4 and 5, the effect of macroeconomic uncertainty on earnings response coefficients is not generally monotonic in the splitting variables: the plots show monotonic relations for β_n, $\sigma_{\varepsilon n}$, and σ_{xn}, but not for and σ_{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 4, 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, σ_{xa}, the effects of macro uncertainty on ERC*s* 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 4, panel (d), where the effect of macro uncertainty on ERC*s* 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). It is plausible to assume that retail investors face greater opportunity costs than institutional investors when choosing whether to pay attention to firm-level information. The margin between attending to the stock market versus all other activities is certainly different for retail investors who, in their daily lives, must devote time and effort to a primary job, family matters, or hobbies. Instead, institutional investors' alternative is generally to pay attention to a different financial signal or other job-related tasks (e.g., human resources, calling investors). Indeed, recent empirical evidence (Israeli et al., 2021) supports the view that retail investors are more susceptible to distractions than institutional investors. Consistent with this interpretation and our predictions illustrated in Figure 5, 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, suggesting that higher information acquisition costs reduce the effects of macro uncertainty on ERC*s*.

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 3 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 ERC*s* 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 ($\text{Var}[D_a]$) leading to stronger relations between attention and ERC*s*. 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)

5 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.

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A Appendix

A.1 Proof of Proposition 1

Notation used thorough the Appendix:

- We denote $\mathbf{I}$ as the identity matrix, $\mathbf{1}$ as a vector of ones, and $\mathbf{0}$ 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 set of announcing firms is $\mathcal{A} = \{1, 2, ..., A\}$. Within this set, firms are indexed by a.
- The set of investor types is the power set of $\mathcal{A}$, $\mathscr{P}(\mathcal{A})$, of dimension 2^A. Within this set, investor types are indexed by k.
- $\bar{k}$ denotes the complement of an investor type $k \subseteq \mathcal{A}$, that is, $\bar{k} = \mathcal{A} \setminus k$.
- $|k|$ denotes the cardinality of the set k.
- $\boldsymbol{\iota}_a$ is a standard basis vector of dimension N with all components equal to 0, except the a-th, which is 1. $\boldsymbol{\iota}_k$ ($\boldsymbol{\iota}_{\bar{k}}$) represents the matrix with all the column vectors $\{\boldsymbol{\iota}_a \mid a \in k\}$ ($\{\boldsymbol{\iota}_a \mid a \in \bar{k}\}$). $\boldsymbol{\iota}$ represents the matrix with all the column vectors $\{\boldsymbol{\iota}_a \mid a \in \mathcal{A}\}$.
- $h_a \equiv \frac{\Lambda_a}{\gamma \sigma^2_{\varepsilon a}}$, for $a \in \mathcal{A}$. $\mathbf{h}_k$ and $\mathbf{h}_{\bar{k}}$ denote the column vectors $\{h_a \mid a \in k\}$ and $\{h_a \mid a \in \bar{k}\}$.
- $\text{diag}[y_j \mid j \in z]$ denotes a diagonal matrix whose diagonal is $\{y_j \mid j \in z\}$. $\boldsymbol{\delta}\mathbf{h}_k$ ($\boldsymbol{\delta}\mathbf{h}_{\bar{k}}$) is a diagonal matrix whose diagonal is $\mathbf{h}_k$ ($\mathbf{h}_{\bar{k}}$), e.g., $\boldsymbol{\delta}\mathbf{h}_k = \text{diag}[\{h_a \mid a \in k\}]$.
- $\boldsymbol{\varepsilon}_k$ and $\boldsymbol{\varepsilon}_{\bar{k}}$ denote the column vectors $\{\varepsilon_a \mid a \in k\}$ and $\{\varepsilon_a \mid a \in \bar{k}\}$, and $\boldsymbol{\varepsilon} = \begin{bmatrix} \boldsymbol{\varepsilon}_k \\ \boldsymbol{\varepsilon}_{\bar{k}} \end{bmatrix}$. Similarly for $\mathbf{x}_k$, $\mathbf{x}_{\bar{k}}$, and $\mathbf{x}$.
- $\boldsymbol{\Sigma}_{\varepsilon k}$ denotes the covariance matrix of the vector $\boldsymbol{\varepsilon}_k$ (a diagonal matrix whose elements are $\{\sigma^2_{\varepsilon a} \mid a \in k\}$). $\boldsymbol{\Sigma}_{\varepsilon \bar{k}}$ denotes the covariance matrix of the vector $\boldsymbol{\varepsilon}_{\bar{k}}$. $\boldsymbol{\Sigma}_{x\bar{k}}$ denotes the covariance matrix of the vector $\mathbf{x}_{\bar{k}}$.

Learning for type k investors

Type k investors observe the earnings announcements $\{E_a \mid a \in k\}$, and learn from prices. Conjecture 1 implies that the only prices useful for learning are $\{\widehat{P}_a \mid a \in \bar{k}\}$. (If an investor observes E_a then the price signal $\widehat{P}_a$ is a noisy version of E_a and is not useful for learning.)

Group the information set of type k investors into two vectors, $\mathbf{E}_k$ of dimension $|k|$ and $\widehat{\mathbf{P}}_{\bar{k}}$ of dimension $|\bar{k}|$. Then we can write

$$\begin{bmatrix} \mathbf{D} \\ \mathbf{E}_k \\ \widehat{\mathbf{P}}_{\bar{k}} \end{bmatrix} = \begin{bmatrix} \mathbf{I} \\ \boldsymbol{\iota}'_k \\ \boldsymbol{\delta}\mathbf{h}_{\bar{k}} \boldsymbol{\iota}'_{\bar{k}} \end{bmatrix} \mathbf{D} + \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\delta}\mathbf{h}_{\bar{k}} \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}_k \\ \boldsymbol{\varepsilon}_{\bar{k}} \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \boldsymbol{\iota}'_{\bar{k}} \end{bmatrix} \mathbf{x}, \tag{A.1}$$

and thus

$$\begin{bmatrix} \mathbf{D} \\ \mathbf{E}_k \\ \widehat{\mathbf{P}}_{\bar{k}} \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \text{Var}[\mathbf{D}] & \text{Var}[\mathbf{D}] \begin{bmatrix} \boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}} \boldsymbol{\delta}\mathbf{h}_{\bar{k}} \end{bmatrix} \\ \begin{bmatrix} \boldsymbol{\iota}'_k \\ \boldsymbol{\delta}\mathbf{h}_{\bar{k}} \boldsymbol{\iota}'_{\bar{k}} \end{bmatrix} \text{Var}[\mathbf{D}] & \begin{bmatrix} \boldsymbol{\iota}'_k \\ \boldsymbol{\delta}\mathbf{h}_{\bar{k}} \boldsymbol{\iota}'_{\bar{k}} \end{bmatrix} \text{Var}[\mathbf{D}] \begin{bmatrix} \boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}} \boldsymbol{\delta}\mathbf{h}_{\bar{k}} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\Sigma}_{\varepsilon k} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\delta}\mathbf{h}^2_{\bar{k}} \boldsymbol{\Sigma}_{\varepsilon \bar{k}} + \boldsymbol{\Sigma}_{x\bar{k}} \end{bmatrix} \end{bmatrix} \right). \tag{A.2}$$

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

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

$$\begin{bmatrix}\boldsymbol{\theta}\\ \mathbf{s}\end{bmatrix} \sim \mathcal{N}\left(\left[\begin{array}{c}\boldsymbol{\mu}_{\boldsymbol{\theta}}\\ \boldsymbol{\mu}_{\mathbf{s}}\end{array}\right], \left[\begin{array}{cc}\boldsymbol{\Sigma}_{\boldsymbol{\theta},\boldsymbol{\theta}} & \boldsymbol{\Sigma}_{\boldsymbol{\theta},\mathbf{s}}\\ \boldsymbol{\Sigma}_{\mathbf{s},\boldsymbol{\theta}} & \boldsymbol{\Sigma}_{\mathbf{s},\mathbf{s}}\end{array}\right]\right). \tag{A.3}$$

Provided $\boldsymbol{\Sigma}_{\mathbf{s},\mathbf{s}}$ *is non-singular, the conditional density of* $\boldsymbol{\theta}$ *given* $\mathbf{s}$ *is normal with conditional mean and conditional variance-covariance matrix:*

$$\mathbb{E}[\boldsymbol{\theta}|\mathbf{s}] = \boldsymbol{\mu}_{\boldsymbol{\theta}} + \boldsymbol{\Sigma}_{\boldsymbol{\theta},\mathbf{s}}\boldsymbol{\Sigma}_{\mathbf{s},\mathbf{s}}^{-1}(\mathbf{s}-\boldsymbol{\mu}_{\mathbf{s}}) \tag{A.4}$$

$$\mathrm{Var}[\boldsymbol{\theta}|\mathbf{s}] = \boldsymbol{\Sigma}_{\boldsymbol{\theta},\boldsymbol{\theta}} - \boldsymbol{\Sigma}_{\boldsymbol{\theta},\mathbf{s}}\boldsymbol{\Sigma}_{\mathbf{s},\mathbf{s}}^{-1}\boldsymbol{\Sigma}_{\mathbf{s},\boldsymbol{\theta}}. \tag{A.5}$$

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

$$\mathrm{Var}^k[\mathbf{D}] = \left(\mathrm{Var}[\mathbf{D}]^{-1} + \begin{bmatrix}\boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}}\boldsymbol{\delta}\mathbf{h}_{\bar{k}}\end{bmatrix}\begin{bmatrix}\boldsymbol{\Sigma}_{\varepsilon k}^{-1} & \mathbf{0}\\ \mathbf{0} & (\boldsymbol{\delta}\mathbf{h}_{\bar{k}}^2\boldsymbol{\Sigma}_{\varepsilon\bar{k}} + \boldsymbol{\Sigma}_{x\bar{k}})^{-1}\end{bmatrix}\begin{bmatrix}\boldsymbol{\iota}_k'\\ \boldsymbol{\delta}\mathbf{h}_{\bar{k}}\boldsymbol{\iota}_{\bar{k}}'\end{bmatrix}\right)^{-1} \tag{A.6}$$

$$= \left(\mathrm{Var}[\mathbf{D}]^{-1} + \begin{bmatrix}\boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}}\end{bmatrix}\begin{bmatrix}\boldsymbol{\Sigma}_{\varepsilon k}^{-1} & \mathbf{0}\\ \mathbf{0} & \boldsymbol{\delta}\mathbf{h}_{\bar{k}}^2(\boldsymbol{\delta}\mathbf{h}_{\bar{k}}^2\boldsymbol{\Sigma}_{\varepsilon\bar{k}} + \boldsymbol{\Sigma}_{x\bar{k}})^{-1}\end{bmatrix}\begin{bmatrix}\boldsymbol{\iota}_k'\\ \boldsymbol{\iota}_{\bar{k}}'\end{bmatrix}\right)^{-1} \tag{A.7}$$

$$= \left(\mathrm{Var}[\mathbf{D}]^{-1} + \boldsymbol{\iota}\,\mathrm{diag}\left[\frac{\ell_a^k}{\sigma_{\varepsilon a}^2} \mid a \in \mathcal{A}\right]\boldsymbol{\iota}'\right)^{-1}, \tag{A.8}$$

with ℓ_a^k defined in (13). We have thus obtained $\boldsymbol{\tau}^k \equiv \mathrm{Var}^k[\mathbf{D}]^{-1}$ as in Proposition 1. This simple form for $\boldsymbol{\tau}^k$ allows us to compute its determinant using the Matrix Determinant Lemma:

$$\det(\mathbf{A} + \mathbf{U}\mathbf{W}\mathbf{V}') = \det(\mathbf{W}^{-1} + \mathbf{V}'\mathbf{A}^{-1}\mathbf{U})\det(\mathbf{W})\det(\mathbf{A}), \tag{A.9}$$

where $\mathbf{A} = \mathrm{Var}[\mathbf{D}]^{-1},\ \mathbf{U} = \boldsymbol{\iota},\ \mathbf{W} = \mathrm{diag}\left[\frac{\ell_a^k}{\sigma_{\varepsilon a}^2} \mid a \in \mathcal{A}\right],$ and $\mathbf{V}' = \boldsymbol{\iota}'$.

The Matrix Determinant Lemma implies

$$\det(\boldsymbol{\tau}^k) = \det\left(\mathrm{Var}[\mathbf{D}]^{-1}\right)\left(\prod_{a=1}^{A}\frac{\ell_a^k}{\sigma_{\varepsilon a}^2}\right)\det\left(\mathrm{diag}\left[\frac{\sigma_{\varepsilon a}^2}{\ell_a^k} \mid a \in \mathcal{A}\right] + \boldsymbol{\iota}'\,\mathrm{Var}[\mathbf{D}]\boldsymbol{\iota}\right) \tag{A.10}$$

$$= \det\left(\mathrm{Var}[\mathbf{D}]^{-1}\right)\left(\prod_{a=1}^{A}\frac{\ell_a^k}{\sigma_{\varepsilon a}^2}\right)\det\left(\mathrm{diag}\left[\frac{\sigma_{\varepsilon a}^2}{\ell_a^k} + \sigma_{ea}^2 \mid a \in \mathcal{A}\right] + U^2\boldsymbol{\beta}_{\mathcal{A}}\boldsymbol{\beta}_{\mathcal{A}}'\right), \tag{A.11}$$

where $\boldsymbol{\beta}_{\mathcal{A}}$ is the vector of announcer firms' exposure to the systematic component f.

Further apply the Matrix Determinant Lemma to the last term:

$$\det(\boldsymbol{\tau}^k) = \det\left(\mathrm{Var}[\mathbf{D}]^{-1}\right)\left(\prod_{a=1}^{A}\frac{\ell_a^k}{\sigma_{\varepsilon a}^2}\right)\left(\prod_{a=1}^{A}\left(\frac{\sigma_{\varepsilon a}^2}{\ell_a^k} + \sigma_{ea}^2\right)\right)\left(1 + \boldsymbol{\beta}_{\mathcal{A}}'\,\mathrm{diag}\left[\frac{\ell_a^k}{\ell_a^k\sigma_{ea}^2 + \sigma_{\varepsilon a}^2} \mid a \in \mathcal{A}\right]U^2\boldsymbol{\beta}_{\mathcal{A}}\right) \tag{A.12}$$

$$= \det\left(\mathrm{Var}[\mathbf{D}]^{-1}\right)\left(\prod_{a=1}^{A}\frac{\ell_a^k\sigma_{ea}^2 + \sigma_{\varepsilon a}^2}{\sigma_{\varepsilon a}^2}\right)\left(1 + U^2\sum_{a=1}^{A}\frac{\ell_a^k\beta_a^2}{\ell_a^k\sigma_{ea}^2 + \sigma_{\varepsilon a}^2}\right), \tag{A.13}$$

which completes the proof of Proposition 1. □

A.2 Proof of Proposition 2

The expected utility of a type $\emptyset$ investor (uninformed) at time 1 is:

$$\mathcal{U}_1^{\emptyset} = \max_{\mathbf{q}^k} \mathbb{E}_1^{\emptyset}\left[-e^{-\gamma\left(W^{\emptyset}-c\sum_{a=1}^{A} I_a^{\emptyset}\right)}\right] = \max_{\mathbf{q}^k} \mathbb{E}_1^{\emptyset}\left[-e^{-\gamma(\mathbf{q}^{\emptyset})'\mathbf{R}^e}\right]. \tag{A.14}$$

Further replacing the optimal portfolio choice from Eq. (7) yields

$$\mathcal{U}_1^{\emptyset} = -\mathbb{E}_1^{\emptyset}\left[e^{-\mathbb{E}_1^{\emptyset}[\mathbf{R}^e]' \operatorname{Var}_1^{\emptyset}[\mathbf{R}^e]^{-1}\mathbf{R}^e}\right] \tag{A.15}$$

$$= -e^{-\frac{1}{2}\mathbb{E}_1^{\emptyset}[\mathbf{R}^e]' \operatorname{Var}_1^{\emptyset}[\mathbf{R}^e]^{-1}\mathbb{E}_1^{\emptyset}[\mathbf{R}^e]}. \tag{A.16}$$

Assume that a type $\emptyset$ investor considers acquiring information and becoming of type $k \in \mathscr{P}(\mathcal{A})$, where $|k| > 0$. At time 1, from the perspective of the type $\emptyset$ investor, $\mathbb{E}_1^k[\mathbf{R}^e]$ is a random vector. Denote this random vector by $\mathbf{z}+\mathbf{m}$, with mean $\mathbf{m}$ and variance $\mathbf{\Sigma}$ (i.e., $\mathbf{z}$ has mean $\mathbf{0}$ and variance $\mathbf{\Sigma}$). By the law of iterated expectations,

$$\mathbf{m} \equiv \mathbb{E}_1^{\emptyset}[\mathbb{E}_1^k[\mathbf{R}^e]] = \mathbb{E}_1^{\emptyset}[\mathbf{R}^e], \tag{A.17}$$

and by the law of total variance,

$$\mathbf{\Sigma} \equiv \operatorname{Var}_1^{\emptyset}[\mathbb{E}_1^k[\mathbf{R}^e]] = \operatorname{Var}_1^{\emptyset}[\mathbf{R}^e] - \operatorname{Var}_1^k[\mathbf{R}^e]. \tag{A.18}$$

Therefore, for the type $\emptyset$ investor, $-\frac{1}{2}\mathbb{E}_1^k[\mathbf{R}^e]' \operatorname{Var}_1^k[\mathbf{R}^e]^{-1}\mathbb{E}_1^k[\mathbf{R}^e]$ (that is, the random exponent in (A.16), written for type k) is a random scalar that can be written as (define $\mathbf{\Sigma}^{\emptyset} \equiv \operatorname{Var}_1^{\emptyset}[\mathbf{R}^e]$ to simplify notation):

$$-\frac{1}{2}\mathbb{E}_1^k[\mathbf{R}^e]' \operatorname{Var}_1^k[\mathbf{R}^e]^{-1}\mathbb{E}_1^k[\mathbf{R}^e] = -\frac{1}{2}(\mathbf{z}+\mathbf{m})'(\mathbf{\Sigma}^{\emptyset}-\mathbf{\Sigma})^{-1}(\mathbf{z}+\mathbf{m}) \tag{A.19}$$

$$= \mathbf{z}' \underbrace{\left(-\frac{1}{2}(\mathbf{\Sigma}^{\emptyset}-\mathbf{\Sigma})^{-1}\right)}_{\mathbf{F}} \mathbf{z} + \underbrace{\left(-\mathbf{m}'(\mathbf{\Sigma}^{\emptyset}-\mathbf{\Sigma})^{-1}\right)}_{\mathbf{G}'} \mathbf{z} + \underbrace{\mathbf{m}'\left(-\frac{1}{2}(\mathbf{\Sigma}^{\emptyset}-\mathbf{\Sigma})^{-1}\right)\mathbf{m}}_{\mathbf{H}}. \tag{A.20}$$

Our aim is to compute $\mathbb{E}_1^{\emptyset}[\mathcal{U}_1^k]$, i.e., the type $\emptyset$ agent's expectation of what her expected utility will be if she changes type to k. We will apply the following Lemma (Veldkamp, 2011, p. 102):

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

$$\mathbb{E}\left[e^{\mathbf{z}'\mathbf{F}\mathbf{z}+\mathbf{G}'\mathbf{z}+\mathbf{H}}\right] = \det(\mathbf{I}-2\mathbf{\Sigma}\mathbf{F})^{-\frac{1}{2}} e^{\frac{1}{2}\mathbf{G}'(\mathbf{I}-2\mathbf{\Sigma}\mathbf{F})^{-1}\mathbf{\Sigma}\mathbf{G}+\mathbf{H}}. \tag{A.21}$$

Compute first

$$\mathbf{I}-2\mathbf{\Sigma}\mathbf{F} = \mathbf{I}-2\mathbf{\Sigma}\left(-\frac{1}{2}(\mathbf{\Sigma}^{\emptyset}-\mathbf{\Sigma})^{-1}\right) \tag{A.22}$$

$$= \mathbf{\Sigma}^{\emptyset}(\mathbf{\Sigma}^{\emptyset}-\mathbf{\Sigma})^{-1}, \tag{A.23}$$

which, using (A.18), leads to the determinant in Lemma A2:

$$\det(\mathbf{I}-2\mathbf{\Sigma}\mathbf{F}) = \frac{\det(\mathbf{\Sigma}^{\emptyset})}{\det(\operatorname{Var}_1^k[\mathbf{R}^e])} = \frac{\det(\boldsymbol{\tau}^k)}{\det(\boldsymbol{\tau}^{\emptyset})}. \tag{A.24}$$

The exponent in Lemma A2 is:

$$\frac{1}{2}\mathbf{G}'(\mathbf{I}-2\boldsymbol{\Sigma}\mathbf{F})^{-1}\boldsymbol{\Sigma}\mathbf{G}+\mathbf{H} \tag{A.25}$$
$$=\frac{1}{2}\left(-\mathbf{m}'(\boldsymbol{\Sigma}^{\emptyset}-\boldsymbol{\Sigma})^{-1}\right)(\boldsymbol{\Sigma}^{\emptyset}-\boldsymbol{\Sigma})(\boldsymbol{\Sigma}^{\emptyset})^{-1}\boldsymbol{\Sigma}\left(-\mathbf{m}'(\boldsymbol{\Sigma}^{\emptyset}-\boldsymbol{\Sigma})^{-1}\right)'-\mathbf{m}'\frac{1}{2}(\boldsymbol{\Sigma}^{\emptyset}-\boldsymbol{\Sigma})^{-1}\mathbf{m} \tag{A.26}$$
$$=\frac{1}{2}\mathbf{m}'(\boldsymbol{\Sigma}^{\emptyset})^{-1}\boldsymbol{\Sigma}(\boldsymbol{\Sigma}^{\emptyset}-\boldsymbol{\Sigma})^{-1}\mathbf{m}-\frac{1}{2}\mathbf{m}'(\boldsymbol{\Sigma}^{\emptyset}-\boldsymbol{\Sigma})^{-1}\mathbf{m} \tag{A.27}$$
$$=\frac{1}{2}\mathbf{m}'\left((\boldsymbol{\Sigma}^{\emptyset})^{-1}\boldsymbol{\Sigma}-\mathbf{I}\right)(\boldsymbol{\Sigma}^{\emptyset}-\boldsymbol{\Sigma})^{-1}\mathbf{m} \tag{A.28}$$
$$=-\frac{1}{2}\mathbf{m}'(\boldsymbol{\Sigma}^{\emptyset})^{-1}\mathbf{m}. \tag{A.29}$$

We can then use Lemma A2 to write

$$\mathbb{E}_1^{\emptyset}[\mathcal{U}_1^k]=-e^{\gamma c|k|}\,\mathbb{E}_1^{\emptyset}\left[e^{-\frac{1}{2}\mathbb{E}_1^k[\mathbf{R}^e]'\operatorname{Var}_1^k[\mathbf{D}]^{-1}\mathbb{E}_1^k[\mathbf{R}^e]}\right] \tag{A.30}$$
$$=-e^{\gamma c|k|}\sqrt{\frac{\det(\boldsymbol{\tau}^{\emptyset})}{\det(\boldsymbol{\tau}^{k})}}e^{-\frac{1}{2}\mathbb{E}_1^{\emptyset}[\mathbf{R}^e]'\operatorname{Var}_1^{\emptyset}[\mathbf{R}^e]^{-1}\mathbb{E}_1^{\emptyset}[\mathbf{R}^e]} \tag{A.31}$$
$$=\mathcal{U}_1^{\emptyset}e^{\gamma c|k|}\sqrt{\frac{\det(\boldsymbol{\tau}^{\emptyset})}{\det(\boldsymbol{\tau}^{k})}}. \tag{A.32}$$

At time $t=0$, the type $\emptyset$ investor compares $\mathbb{E}_0[\mathcal{U}_1^{\emptyset}]$ with $\mathbb{E}_0[\mathcal{U}_1^{k}]$ and acquires the additional signals if and only if

$$\mathbb{E}_0[\mathcal{U}_1^{\emptyset}]<\mathbb{E}_0[\mathcal{U}_1^{k}]=\mathbb{E}_0[\mathbb{E}_1^{\emptyset}[\mathcal{U}_1^{k}]], \tag{A.33}$$

which, after replacement of (A.32), yields $e^{\gamma c|k|}\sqrt{\det(\boldsymbol{\tau}^{\emptyset})/\det(\boldsymbol{\tau}^{k})}<1$ (the division by $\mathbb{E}_0[\mathcal{U}_1^{\emptyset}]<0$ flips the inequality sign). Thus, an investor of type $\emptyset$ changes type to k if and only if

$$B_{\emptyset}^{k}\equiv\frac{\det(\boldsymbol{\tau}^{k})}{\det(\boldsymbol{\tau}^{\emptyset})}e^{-2\gamma c|k|}>1. \tag{A.34}$$

Consider now two investor types k and k' as in Proposition 2. The empty set $\emptyset$ is the only common subset of both k and k', for all $k,k'\in\mathscr{P}(\mathcal{A})$. Thus, the uninformed investor si a common reference point for type k and type k' investors, and therefore the investor with the lowest benefit-cost ratio among $\{B_{\emptyset}^{k},B_{\emptyset}^{k'}\}$ will always choose to migrate to the other type. In other words, a type k investor changes type from k to $k'\in\mathscr{P}(\mathcal{A})\setminus k$ if and only if

$$\frac{B_{\emptyset}^{k'}}{B_{\emptyset}^{k}}>1 \quad\iff\quad \frac{1}{2\gamma}\ln\frac{\det(\tau^{k'})}{\det(\tau^{k})}>c(|k'|-|k|). \tag{A.35}$$

This holds regardless of the sign of $|k'|-|k|$. □

A.3 Proof of Theorem 1

An important property of the benefit-cost ratios $B_{\emptyset}^{k}$, for $k\in\mathscr{P}(\mathcal{A})\setminus\emptyset$, is that they can be decomposed into the product of consecutive *one-step* benefit-cost ratios. Formally, let $k(i)$ be the i^{th} element of k and $\kappa(i)$ the subset of k that contains all its elements up to and including $k(i)$. Using the convention $\kappa(0) = \emptyset$ and defining $B_{\kappa(i-1)}^{\kappa(i-1)\cup\{k(i)\}} \equiv \frac{\det(\boldsymbol{\tau}^{\kappa(i-1)\cup\{k(i)\}})}{\det(\boldsymbol{\tau}^{\kappa(i-1)})} e^{-2\gamma c}$, we can write

$$B_{\emptyset}^{k} = \prod_{i=1}^{|k|} B_{\kappa(i-1)}^{\kappa(i-1)\cup\{k(i)\}}. \tag{A.36}$$

We first establish the following Lemma.

Lemma A3. *Consider an announcer $a \in \mathcal{A}$ and any type $k \subseteq \mathcal{A} \setminus \{a\}$. Then*

$$\arg\min_{k} B_{k}^{k\cup\{a\}} = \mathcal{A} \setminus \{a\} \tag{A.37}$$

$$\arg\max_{k} B_{k}^{k\cup\{a\}} = \emptyset \tag{A.38}$$

Lemma A3 states that the type k for which the one-step benefit-cost ratio $B_{k}^{k\cup\{a\}}$ attains its minimum is the highest cardinality type that excludes a, that is, $\mathcal{A} \setminus \{a\}$; and the type k for which $B_{k}^{k\cup\{a\}}$ attains its maximum is the empty set $\emptyset$. In other words, attention has diminishing returns: the lowest benefit from observing E_a belongs to the investor who already observes all the other earnings announcements; and the highest benefit belongs to the uninformed investor. The proof of Lemma A3 follows from writing explicitly $B_{k}^{k\cup\{a\}}$ by means of Proposition 1,

$$\begin{aligned} B_{k}^{k\cup\{a\}} &= \frac{\det(\boldsymbol{\tau}^{k\cup\{a\}})}{\det(\boldsymbol{\tau}^{k})} e^{-2\gamma c} & \text{(A.39)} \\ &= \left(\frac{\sigma_{ea}^2 + \sigma_{\varepsilon a}^2}{\ell_a \sigma_{ea}^2 + \sigma_{\varepsilon a}^2} + \frac{\beta_a^2}{\frac{1}{U^2} + \sum_{\alpha=1}^{A} \frac{\ell_\alpha^k \beta_\alpha^2}{\ell_\alpha^k \sigma_{e\alpha}^2 + \sigma_{\varepsilon\alpha}^2}} \frac{(1-\ell_a)\sigma_{\varepsilon a}^2}{(\ell_a \sigma_{ea}^2 + \sigma_{\varepsilon a}^2)^2} \right) e^{-2\gamma c}, & \text{(A.40)} \end{aligned}$$

which is indeed minimized when $\ell_\alpha^k = 1,\ \forall \alpha \in \mathcal{A} \setminus \{a\}$, and maximized when $\ell_\alpha^k < 1,\ \forall \alpha \in \mathcal{A} \setminus \{a\}$. In the former case, k must be $\mathcal{A} \setminus \{a\}$; in the latter, k must be $\emptyset$. (NB: Lemma A3 is a direct consequence of the fact that the function $\ln(B_{\emptyset}^{k})$ is linearly related to the entropy defined in (14): $\ln(B_{\emptyset}^{k}) = 2(H^{\emptyset}[\mathbf{D}] - H^{k}[\mathbf{D}] - \gamma c|k|)$. By the submodularity propoerty of the entropy, $\ln(B_{\emptyset}^{k})$ is submodular and therefore $B_{k}^{k\cup\{a\}}$ has diminishing returns. See also Appendix A.7.)

Lemma A3, together with the multiplicative property (A.36), will allow us obtain the bounds c_{min} and c_{max}. We will first derive the lower bound c_{min}. When the information cost is below c_{min}, all investors are informed, i.e., $\lambda^{\mathcal{A}} = 1$. In order for this to be a stable equilibrium, the following conditions must hold simultaneously:

$$B_{\mathcal{A}\setminus\{a\}}^{\mathcal{A}} \geq 1 \quad \forall a \in \mathcal{A}, \tag{A.41}$$

meaning that no investor of type $\mathcal{A}$ finds it optimal to renounce being attentive to any signal E_a. If these conditions hold simultaneously, then one can easily show using the multiplicative property (A.36) and Lemma A3 that

$$B_{k}^{\mathcal{A}} \geq 1, \text{ for any type } k \subset \mathcal{A}, \tag{A.42}$$

meaning that no investor of type $\mathcal{A}$ finds it optimal to be of any other possible type. (This can be shown by writing $B_{k}^{\mathcal{A}}$ as a product as in (A.36) and using Lemma A3 for each individual term of the product; it is a direct consequence of the property of diminishing returns to attention.)

Conditions (A.41) further imply $\min_a B^{\mathcal{A}}_{\mathcal{A}\setminus\{a\}} \geq 1$, which will pin down c_{min}. Using the fact that $\lambda^{\mathcal{A}} = 1$, the definition of ℓ_a in Eq. (13) yields upper limits for all the learning coefficients ℓ_a,

$$\bar{\ell}_a = \frac{1}{1+\gamma^2\sigma^2_{xa}\sigma^2_{\varepsilon a}} \quad \forall a \in \mathcal{A}, \tag{A.43}$$

and thus c_{min} solves

$$e^{2\gamma c_{min}} = \min_a \left(\frac{\sigma^2_{ea}+\sigma^2_{\varepsilon a}}{\bar{\ell}_a\sigma^2_{ea}+\sigma^2_{\varepsilon a}} + \frac{\beta^2_a}{\frac{1}{U^2}+\sum_{\alpha=1}^{A}\frac{\bar{\ell}_\alpha\beta^2_\alpha}{\bar{\ell}_\alpha\sigma^2_{e\alpha}+\sigma^2_{\varepsilon\alpha}}} \frac{(1-\bar{\ell}_a)\sigma^2_{\varepsilon a}}{(\bar{\ell}_a\sigma^2_{ea}+\sigma^2_{\varepsilon a})^2} \right). \tag{A.44}$$

Since the right hand side equals $\min_a(\det(\boldsymbol{\tau}^{\mathcal{A}})/\det(\boldsymbol{\tau}^{\mathcal{A}\setminus\{a\}})$ and thus is always larger than one, equation (A.44) has a unique, strictly positive solution c_{min}. Furthermore, it can be easily checked that c_{min} is strictly increasing in U.

Consider now an equilibrium in which no investor is informed, or $\lambda^{\emptyset} = 1$. In order for this to be a stable equilibrium, the following conditions must hold simultaneously:

$$B^a_{\emptyset} \leq 1 \quad \forall a \in \mathcal{A}. \tag{A.45}$$

If these conditions hold, then a consequence of the property of diminishing returns to attention is that $B^k_{\emptyset} \leq 1$ holds for any type $k \subseteq \mathcal{A}$. (This can be shown by writing $B^k_{\emptyset}$ as a product as in (A.36) and using Lemma A3 for each individual term of the product.)

Conditions (A.45) further imply $\max_a B^a_{\emptyset} \leq 1$, and $\lambda^{\emptyset} = 1$ leads to $\ell_a = 0 \ \forall a \in \mathcal{A}$. Thus, c_{max} solves

$$e^{2\gamma c_{max}} = \max_a \left(1 + \frac{\beta^2_a U^2 + \sigma^2_{ea}}{\sigma^2_{\varepsilon a}}\right). \tag{A.46}$$

This equation has a unique, strictly positive solution c_{max}, which is strictly increasing in U. Furthermore, since $B^a_{\emptyset} > B^{\mathcal{A}}_{\mathcal{A}\setminus\{a\}} \ \forall a \in \mathcal{A}$ (by Lemma A3), it is clear that $\max_a B^a_{\emptyset} > \min_a B^{\mathcal{A}}_{\mathcal{A}\setminus\{a\}}$ and therefore $c_{max} > c_{min}$. This completes the proofs of cases (C) and (A) of Theorem 1.

In case (B) of Theorem 1, the information cost is $c \in (c_{min}, c_{max})$. Clearly, when $c \in (c_{min}, c_{max})$ both conditions (A.41) and (A.45) are violated and thus the equilibrium cannot be $\lambda^{\emptyset} = 1$ or $\lambda^{\mathcal{A}} = 1$. Thus, in equilibrium there exists a set $\{\lambda^k \mid k \in \mathscr{P}(\mathcal{A})\}$ such that: $\sum_{k\in\mathscr{P}(\mathcal{A})} \lambda^k = 1$; $\lambda^{\emptyset} < 1$; and $\lambda^{\mathcal{A}} < 1$. Consider now all the pairs of types $\{k, k'\} \in \mathscr{P}(\mathcal{A})$. For each pair, there are four cases:

(i) $\{\lambda^k > 0\} \wedge \{\lambda^{k'} > 0\}$: this can be a stable equilibrium (meaning that no investor has an incentive to migrate from type k to type k' or vice versa) only if $B^{k'}_{\emptyset}/B^k_{\emptyset} = 1$.

(ii) $\{\lambda^k = 0\} \wedge \{\lambda^{k'} > 0\}$: this can be a stable equilibrium (meaning that no investor of type k' has an incentive to migrate to type k) only if $B^{k'}_{\emptyset}/B^k_{\emptyset} \geq 1$.

(iii) $\{\lambda^k > 0\} \wedge \{\lambda^{k'} = 0\}$: this is the reversal of the previous case and requires $B^{k'}_{\emptyset}/B^k_{\emptyset} \leq 1$.

(iv) $\{\lambda^k = 0\} \wedge \{\lambda^{k'} = 0\}$: in this case there is no condition on $B^{k'}_{\emptyset}/B^k_{\emptyset}$ since there are no investors of types k and k'.

Conditions (i)-(iv) are both necessary and sufficient for the stability of the information market equlibrium. See Appendix A.7 for an algorithm that converges to the equilibrium for any set of positive initial values $\{\lambda^k_0 > 0 \mid k \in \mathscr{P}(\mathcal{A})\}$ such that $\sum_k \lambda^k_0 = 1$. □

A.4 Proof of Lemma 1

Lemma 1 results directly after writing $\boldsymbol{\tau}^k$ for each investor type under this form:

$$\boldsymbol{\tau}^k = \mathrm{Var}[\mathbf{D}]^{-1} + \boldsymbol{\iota}\,\mathrm{diag}\left[\frac{\ell_a^k}{\sigma_{\varepsilon a}^2} \mid a \in \mathcal{A}\right]\boldsymbol{\iota}', \tag{A.47}$$

where $\boldsymbol{\iota}$ is a $N \times A$ matrix whose columns are the standard basis vectors $\boldsymbol{\iota}_a$ for all the announcing firms (vectors having all components equal to 0, except the a-th, which is 1).

The weighted average precision is then

$$\boldsymbol{\tau} = \sum_{k\in\mathscr{P}(\mathcal{A})} \lambda^k \boldsymbol{\tau}^k = \mathrm{Var}[\mathbf{D}]^{-1} + \boldsymbol{\iota}\,\mathrm{diag}\left[\sum_{k\in\mathscr{P}(\mathcal{A})} \lambda^k \frac{\ell_a^k}{\sigma_{\varepsilon a}^2} \mid a \in \mathcal{A}\right]\boldsymbol{\iota}', \tag{A.48}$$

with ℓ_a^k defined in (13). Furthermore,

$$\sum_{k\in\mathscr{P}(\mathcal{A})} \lambda^k \frac{\ell_a^k}{\sigma_{\varepsilon a}^2} = \frac{(1-\Lambda_a)\ell_a}{\sigma_{\varepsilon a}^2} + \frac{\Lambda_a}{\sigma_{\varepsilon a}^2} = \frac{\Lambda_a^2 + \Lambda_a\gamma^2\sigma_{xa}^2\sigma_{\varepsilon a}^2}{\Lambda_a^2\sigma_{\varepsilon a}^2 + \gamma^2\sigma_{xa}^2\sigma_{\varepsilon a}^4} = \pi_a(\Lambda_a), \tag{A.49}$$

which yields (21). □

A.5 Proof of Proposition 3

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

$$\sum_{k\in\mathscr{P}(\mathcal{A})} \lambda^k \frac{\mathrm{Var}^k[\mathbf{D}]^{-1}}{\gamma}\,\mathbb{E}^k[\mathbf{D}] - \frac{\boldsymbol{\tau}}{\gamma}\mathbf{P} + \mathbf{x} = \mathbf{M}. \tag{A.50}$$

Using the Projection Theorem and $h_a \equiv \frac{\Lambda_a}{\gamma\sigma_{\varepsilon a}^2}$ we can compute

$$\begin{aligned}\mathrm{Var}^k[\mathbf{D}]^{-1}\,\mathbb{E}^k[\mathbf{D}] = &\left(\mathrm{Var}[\mathbf{D}]^{-1} + \begin{bmatrix}\boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}}\boldsymbol{\delta}\mathbf{h}_{\bar{k}}\end{bmatrix}\begin{bmatrix}\boldsymbol{\Sigma}_{\varepsilon k}^{-1} & \mathbf{0}\\ \mathbf{0} & (\boldsymbol{\delta}\mathbf{h}_{\bar{k}}^2\boldsymbol{\Sigma}_{\varepsilon\bar{k}} + \boldsymbol{\Sigma}_{x\bar{k}})^{-1}\end{bmatrix}\begin{bmatrix}\boldsymbol{\iota}_k' \\ \boldsymbol{\delta}\mathbf{h}_{\bar{k}}\boldsymbol{\iota}_{\bar{k}}'\end{bmatrix}\right)\times \\ &\times \mathrm{Var}[\mathbf{D}]\begin{bmatrix}\boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}}\boldsymbol{\delta}\mathbf{h}_{\bar{k}}\end{bmatrix}\left(\begin{bmatrix}\boldsymbol{\iota}_k' \\ \boldsymbol{\delta}\mathbf{h}_{\bar{k}}\boldsymbol{\iota}_{\bar{k}}'\end{bmatrix}\mathrm{Var}[\mathbf{D}]\begin{bmatrix}\boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}}\boldsymbol{\delta}\mathbf{h}_{\bar{k}}\end{bmatrix} + \begin{bmatrix}\boldsymbol{\Sigma}_{\varepsilon k} & \mathbf{0}\\ \mathbf{0} & \boldsymbol{\delta}\mathbf{h}_{\bar{k}}^2\boldsymbol{\Sigma}_{\varepsilon\bar{k}} + \boldsymbol{\Sigma}_{x\bar{k}}\end{bmatrix}\right)^{-1}\begin{bmatrix}\mathbf{E}_k \\ \widehat{\mathbf{P}}_{\bar{k}}\end{bmatrix},\end{aligned} \tag{A.51}$$

which simplifies to

$$\mathrm{Var}^k[\mathbf{D}]^{-1}\,\mathbb{E}^k[\mathbf{D}] = \begin{bmatrix}\boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}}\boldsymbol{\delta}\mathbf{h}_{\bar{k}}\end{bmatrix}\begin{bmatrix}\boldsymbol{\Sigma}_{\varepsilon k}^{-1} & \mathbf{0}\\ \mathbf{0} & (\boldsymbol{\delta}\mathbf{h}_{\bar{k}}^2\boldsymbol{\Sigma}_{\varepsilon\bar{k}} + \boldsymbol{\Sigma}_{x\bar{k}})^{-1}\end{bmatrix}\begin{bmatrix}\mathbf{E}_k \\ \widehat{\mathbf{P}}_{\bar{k}}\end{bmatrix} \tag{A.52}$$

$$= \begin{bmatrix}\boldsymbol{\iota}_k & \boldsymbol{\iota}_{\bar{k}}\end{bmatrix}\begin{bmatrix}\boldsymbol{\Sigma}_{\varepsilon k}^{-1} & \mathbf{0}\\ \mathbf{0} & \mathrm{diag}\left[\frac{\gamma\Lambda_a}{\Lambda_a^2+\gamma^2\sigma_{\varepsilon a}^2\sigma_{xa}^2} \mid a \in \bar{k}\right]\end{bmatrix}\begin{bmatrix}\mathbf{E}_k \\ \widehat{\mathbf{P}}_{\bar{k}}\end{bmatrix}. \tag{A.53}$$

According to Conjecture 1,

$$\widehat{\mathbf{P}}_{\bar{k}} = \mathrm{diag}\left[\frac{\Lambda_a}{\gamma\sigma_{\varepsilon a}^2} \mid a \in \bar{k}\right]\mathbf{E}_{\bar{k}} + \mathbf{x}_{\bar{k}}, \tag{A.54}$$

which, after replacement into (A.53), yields:

$$\begin{aligned}\mathrm{Var}^k[\mathbf{D}]^{-1}\,\mathbb{E}^k[\mathbf{D}] =&\boldsymbol{\iota}_k \,\mathrm{diag}\left[\frac{1}{\sigma^2_{\varepsilon a}} \mid a\in k\right]\mathbf{E}_k + \boldsymbol{\iota}_{\bar{k}}\,\mathrm{diag}\left[\frac{\Lambda_a^2}{\Lambda_a^2\sigma^2_{\varepsilon a}+\gamma^2\sigma^4_{\varepsilon a}\sigma^2_{xa}} \mid a\in \bar{k}\right]\mathbf{E}_{\bar{k}} \\ &+\boldsymbol{\iota}_{\bar{k}}\,\mathrm{diag}\left[\frac{\gamma\Lambda_a}{\Lambda_a^2+\gamma^2\sigma^2_{\varepsilon a}\sigma^2_{xa}} \mid a\in\bar{k}\right]\mathbf{x}_{\bar{k}}.\end{aligned} \tag{A.55}$$

We now go back to (A.50), which we write as

$$\boldsymbol{\tau}\mathbf{P} = \sum_{k\in\mathscr{P}(\mathcal{A})} \lambda^k\,\mathrm{Var}^k[\mathbf{D}]^{-1}\,\mathbb{E}^k[\mathbf{D}] + \gamma\mathbf{x} - \gamma\mathbf{M}, \tag{A.56}$$

which, after replacement of (A.55) becomes

$$\boldsymbol{\tau}\mathbf{P} = \begin{bmatrix}\mathrm{diag}\left[\pi_a(\Lambda_a) \mid a\in\mathcal{A}\right] \\ \mathbf{0}\end{bmatrix}\mathbf{E} + \gamma\begin{bmatrix}\mathrm{diag}\left[\frac{\pi_a(\Lambda_a)\sigma^2_{\varepsilon a}}{\Lambda_a} \mid a\in\mathcal{A}\right] & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{N-A}\end{bmatrix}\mathbf{x} - \gamma\mathbf{M}, \tag{A.57}$$

where $\mathbf{E}$ is the column vector of earnings announcements and the functions $\pi_a(\Lambda_a)$, $a\in\mathcal{A}$ are defined in Lemma 1. We can now verify Conjecture 1:

$$\begin{aligned}\widehat{\mathbf{P}} &= \frac{1}{\gamma}\begin{bmatrix}\mathrm{diag}\left[\frac{\Lambda_a}{\pi_a(\Lambda_a)\sigma^2_{\varepsilon a}} \mid a\in\mathcal{A}\right] & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{N-A}\end{bmatrix}\begin{bmatrix}\mathrm{diag}\left[\pi_a(\Lambda_a) \mid a\in\mathcal{A}\right] \\ \mathbf{0}\end{bmatrix}\mathbf{E} + \mathbf{x} &(A.58)\\ &= \begin{bmatrix}\mathrm{diag}\left[\frac{\Lambda_a}{\gamma\sigma^2_{\varepsilon a}} \mid a\in\mathcal{A}\right] \\ \mathbf{0}\end{bmatrix}\mathbf{E} + \mathbf{x}, &(A.59)\end{aligned}$$

which completes the proof of Proposition 3. □

A.6 Proof of Corollary 3.1

Define first $\boldsymbol{\Pi} \equiv \mathrm{diag}\left[\pi_a(\Lambda_a) \mid a\in\mathcal{A}\right]$. From (A.57), the matrix of response coefficients to $\mathbf{E}$ for all firms in the economy, $\boldsymbol{\alpha}$, is given by

$$\boldsymbol{\alpha} = \boldsymbol{\tau}^{-1}\boldsymbol{\iota}\boldsymbol{\Pi} = (\mathrm{Var}[\mathbf{D}]^{-1} + \boldsymbol{\iota}\boldsymbol{\Pi}\boldsymbol{\iota}')^{-1}\boldsymbol{\iota}\boldsymbol{\Pi}, \tag{A.60}$$

where $\boldsymbol{\iota}$ represents the matrix with all the column vectors $\{\boldsymbol{\iota}_a \mid a\in\mathcal{A}\}$. Multiplying with $\boldsymbol{\Pi}\boldsymbol{\iota}'$ and applying the Woodbury matrix identity yields:

$$\boldsymbol{\Pi}\boldsymbol{\iota}'\boldsymbol{\alpha} = \boldsymbol{\Pi} - (\boldsymbol{\Pi}^{-1} + \boldsymbol{\iota}'\,\mathrm{Var}[\mathbf{D}]\boldsymbol{\iota})^{-1}. \tag{A.61}$$

We recognize that $\boldsymbol{\iota}'\boldsymbol{\alpha} = \boldsymbol{\alpha}_{\mathcal{A}}$ and $\boldsymbol{\iota}'\,\mathrm{Var}[\mathbf{D}]\boldsymbol{\iota} = \mathrm{Var}[\mathbf{D}_{\mathcal{A}}]$, where $\mathbf{D}_{\mathcal{A}}$ is the $A\times 1$ vector of payoffs for the announcing firms. Thus, after multiplication with $\boldsymbol{\Pi}^{-1}$, we obtain Eq. (24):

$$\boldsymbol{\alpha}_{\mathcal{A}} = \mathbf{I} - (\mathbf{I} + \mathrm{Var}[\mathbf{D}_{\mathcal{A}}]\boldsymbol{\Pi})^{-1}. \tag{A.62}$$

The earnings response coefficients of the announcing firms are given by the diagonal elements of the matrix $\boldsymbol{\alpha}_{\mathcal{A}}$. We also note that Eq. (24) can alternatively be written $\alpha^{-1}_{\mathcal{A}} = \mathbf{I} + \boldsymbol{\Pi}^{-1}\,\mathrm{Var}[\mathbf{D}_{\mathcal{A}}]^{-1}$, by means of the Woodbury matrix identity. □

A.7 Equilibrium solution algorithm

We will first show that the maximization problem (6) is equivalent with the simplified form (25):

$$\max_{k\in\mathscr{P}(\mathcal{A})} \mathbb{E}_0\left[\max_{\mathbf{q}^k}\mathbb{E}_1^k\left[-e^{-\gamma\left(W^k-c|k|\right)}\right]\right] = \max_{k\in\mathscr{P}(\mathcal{A})} e^{\gamma c|k|}\,\mathbb{E}_0\left[\max_{\mathbf{q}^k}\mathbb{E}_1^k\left[-e^{-\gamma\left(q^k\right)'\mathbf{R}^e}\right]\right] \tag{A.63}$$

$$= \max_{k\in\mathscr{P}(\mathcal{A})} e^{\gamma c|k|}\,\mathbb{E}_0\left[-e^{-\frac{1}{2}\mathbb{E}_1^k[\mathbf{R}^e]'\operatorname{Var}_1^k[\mathbf{R}^e]^{-1}\mathbb{E}_1^k[\mathbf{R}^e]}\right], \tag{A.64}$$

which, after using to (A.32) and the law of iterated expectations, yields

$$\max_{k\in\mathscr{P}(\mathcal{A})} e^{\gamma c|k|}\,\mathbb{E}_0\left[\sqrt{\frac{\det(\boldsymbol{\tau}^{\emptyset})}{\det(\boldsymbol{\tau}^k)}}\mathcal{U}_1^0\right] = \max_{k\in\mathscr{P}(\mathcal{A})} e^{\gamma c|k|}\sqrt{\frac{\det(\boldsymbol{\tau}^{\emptyset})}{\det(\boldsymbol{\tau}^k)}}\,\mathbb{E}_0\left[\mathcal{U}_1^{\emptyset}\right]. \tag{A.65}$$

We notice that $\mathbb{E}_0\left[\mathcal{U}_1^{\emptyset}\right]$ is a constant that does not depend on the individual choice of the investor. Dividing by this (negative) constant yields

$$\max_{k\in\mathscr{P}(\mathcal{A})}\frac{1}{2}\ln(\det(\boldsymbol{\tau}^k)) - \frac{1}{2}\ln(\det(\boldsymbol{\tau}^{\emptyset})) - \gamma c|k| = \max_{k\in\mathscr{P}(\mathcal{A})}\frac{1}{2}\ln B_{\emptyset}^k, \tag{A.66}$$

and therefore the optimization problem at time 0 for each investor in this economy is (25).

To prove that the function $\ln B_{\emptyset}^k$ is submodular, consider two types $k, k' \in \mathscr{P}(\mathcal{A})$ with $k \subseteq k'$ and $a \in \mathcal{A}\setminus k'$, then use (A.39)-(A.40) to compute

$$\ln B_{\emptyset}^{k\cup\{a\}} - \ln B_{\emptyset}^{k} = \ln B_{k}^{k\cup\{a\}} \tag{A.67}$$

$$= \ln\left(\frac{\sigma_{ea}^2+\sigma_{\varepsilon a}^2}{\ell_a\sigma_{ea}^2+\sigma_{\varepsilon a}^2} + \frac{\beta_a^2}{\frac{1}{U^2}+\sum_{\alpha=1}^{A}\frac{\ell_\alpha^k\beta_\alpha^2}{\ell_\alpha^k\sigma_{e\alpha}^2+\sigma_{\varepsilon\alpha}^2}}\frac{(1-\ell_a)\sigma_{\varepsilon a}^2}{(\ell_a\sigma_{ea}^2+\sigma_{\varepsilon a}^2)^2}\right) - 2\gamma c. \tag{A.68}$$

The same difference is lower when written for k' instead of k, due to the term $\sum_{\alpha=1}^{A}\frac{\ell_\alpha^k\beta_\alpha^2}{\ell_\alpha^k\sigma_{e\alpha}^2+\sigma_{\varepsilon\alpha}^2}$ in the denominator (this term is larger when written for k' because $k\subseteq k'$). Therefore,

$$\ln B_{\emptyset}^{k\cup\{a\}} - \ln B_{\emptyset}^{k} \geq \ln B_{\emptyset}^{k'\cup\{a\}} - \ln B_{\emptyset}^{k'}, \tag{A.69}$$

and thus the function $\ln B_{\emptyset}^k$ is indeed submodular. We further prove the following Lemma.

Lemma A4. *For any two types $k, k' \in \mathscr{P}(\mathcal{A})$ and $\lambda^k > 0$, a migration of a positive mass of investors $z < \lambda^k$ from k to k'* decreases $B_{\emptyset}^{k'}/B_{\emptyset}^{k}$.

Proof. Consider a type $k \in \mathscr{P}(\mathcal{A})$ and its complement $\bar{k} = \mathcal{A}\setminus k$. Using Proposition 1, write

$$\det(\boldsymbol{\tau}^k) = \det(\operatorname{Var}[\mathbf{D}]^{-1})\left(\prod_{a\in k}\frac{\sigma_{ea}^2+\sigma_{\varepsilon a}^2}{\sigma_{\varepsilon a}^2}\right)\left(\prod_{a\in\bar{k}}\frac{\ell_a\sigma_{ea}^2+\sigma_{\varepsilon a}^2}{\sigma_{\varepsilon a}^2}\right) \times\left(1+U^2\sum_{a\in k}\frac{\beta_a^2}{\sigma_{ea}^2+\sigma_{\varepsilon a}^2}+U^2\sum_{a\in\bar{k}}\frac{\ell_a\beta_a^2}{\ell_a\sigma_{ea}^2+\sigma_{\varepsilon a}^2}\right). \tag{A.70}$$

A migration from $k\to k'$ increases the terms $\prod_{a\in\bar{k}}\frac{\ell_a\sigma_{ea}^2+\sigma_{\varepsilon a}^2}{\sigma_{\varepsilon a}^2}$ and $\sum_{a\in\bar{k}}\frac{\ell_a\beta_a^2}{\ell_a\sigma_{ea}^2+\sigma_{\varepsilon a}^2}$, while all the other terms of the decomposition (A.70) remain constant. Thus, $\det(\boldsymbol{\tau}^k)$ increases. One can show similarly that $\det(\boldsymbol{\tau}^{k'})$ decreases, and therefore $B_\emptyset^{k'}/B_\emptyset^k$ decreases. □

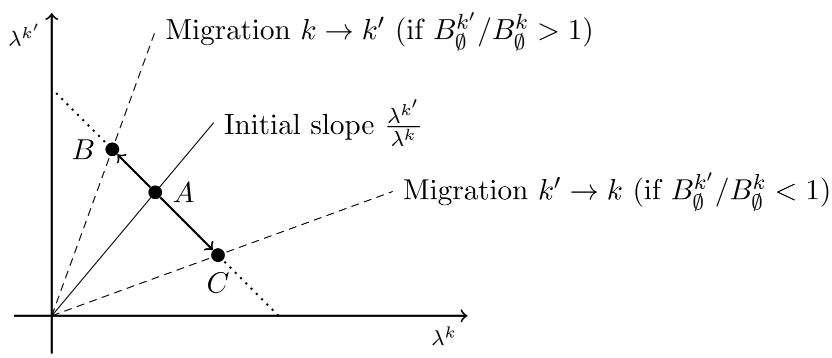
The submodularity property of the function $\ln B_\emptyset^k$, coupled with the monotonicity of $B_\emptyset^{k'}/B_\emptyset^k$ implied by Lemma A4, justify the use of an iterative algorithm that converges towards a stable equilibrium. The algorithm is adapted from Hu and Shi (2019) and Arkolakis et al. (2021) and consists of the following steps:

1. Start from any set of positive initial values $\{\lambda_0^k > 0 \mid k \in \mathscr{P}(\mathcal{A})\}$ such that $\sum_k \lambda_0^k = 1$. Compute the benefit-cost ratios $\{B_\emptyset^k \mid k \in \mathscr{P}(\mathcal{A})\}$.

2. For any two types $k, k' \in \mathscr{P}(\mathcal{A})$, compute $B_\emptyset^{k'}/B_\emptyset^k$:

   (a) if $B_\emptyset^{k'}/B_\emptyset^k = 1$, no further changes in λ^k and $\lambda^{k'}$ are needed at this step.

   (b) if $B_\emptyset^{k'}/B_\emptyset^k > 1$, then allow a small fraction of the population of type k investors to migrate to type k', which will decrease $B_\emptyset^{k'}/B_\emptyset^k$ (Lemma A4). In the illustration below, the dot A depicts the initial values $\{\lambda^k, \lambda^{k'}\}$, located on a line with slope $\lambda^{k'}/\lambda^k$. The algorithm multiplies the slope of the line by $m > 1$ and finds two new values λ_{new}^k and $\lambda_{new}^{k'}$ such that $\lambda_{new}^k + \lambda_{new}^{k'} = \lambda^k + \lambda^{k'}$ and $\lambda_{new}^k < \lambda^k$, thus reaching the dot B:



   After the multiplication, the new values for λ^k and $\lambda^{k'}$ are given by

$$\lambda_{new}^k = \lambda^k \frac{\lambda^k + \lambda^{k'}}{\lambda^k + m\lambda^{k'}} \quad \text{and} \quad \lambda_{new}^{k'} = \lambda^{k'} \frac{\lambda^k + \lambda^{k'}}{\lambda^k/m + \lambda^{k'}}. \tag{A.71}$$

   To ensure stability of the solution, m is set to increase with $(B_\emptyset^{k'}/B_\emptyset^k - 1)$. Finally, compute the benefit-cost ratios $\{B_\emptyset^k \mid k \in \mathscr{P}(\mathcal{A})\}$ using the new values $\{\lambda_{new}^k, \lambda_{new}^{k'}\}$.

   (c) if $B_\emptyset^{k'}/B_\emptyset^k < 1$, apply a similar procedure as in the previous step, moving from A to C.

3. Iterate step 2 until the algorithm has converged to the desired accuracy and the conditions of Theorem 1 are satisfied. Convergence is guaranteed by Lemma A4.

A.8 Dynamic setup

We start by making the following conjecture for equilibrium prices:

$$\widehat{P}_t \equiv \xi^{-1}(P_t + \zeta M) = \frac{\Lambda_t}{\gamma\sigma_\varepsilon^2} Z_t E_t + x_t, \tag{A.72}$$

where Λ_t is the fraction of informed investors and Z_t is to be determined below.

Learning for the informed investor For the informed investor, the only informative signal is E_t. Application of the Projection Theorem yields

$$\mathrm{Var}_t^I[D_{t+1}] = \frac{\mathrm{Var}_t[D_{t+1}]\sigma_\varepsilon^2}{\mathrm{Var}_t[D_{t+1}] + \sigma_\varepsilon^2} = \left(\mathrm{Var}_t[D_{t+1}]^{-1} + \frac{1}{\sigma_\varepsilon^2}\right)^{-1}, \tag{A.73}$$

and

$$\mathbb{E}_t^I[D_{t+1}] = \frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}] + \sigma_\varepsilon^2} E_t = \mathrm{Var}_t^I[D_{t+1}] \frac{1}{\sigma_\varepsilon^2} E_t. \tag{A.74}$$

Learning for the uninformed investor The uninformed investor learns from the price signal $\widehat{P}_t$, and thus the Projection Theorem implies:

$$\mathrm{Var}_t^U[D_{t+1}] = \frac{\mathrm{Var}_t[D_{t+1}]\sigma_\varepsilon^2}{\frac{\Lambda_t^2 Z_t^2}{\Lambda_t^2 Z_t^2 + \gamma^2\sigma_x^2\sigma_\varepsilon^2}\,\mathrm{Var}_t[D_{t+1}] + \sigma_\varepsilon^2} = \left(\mathrm{Var}_t[D_{t+1}]^{-1} + \frac{\Lambda_t^2 Z_t^2}{\Lambda_t^2 Z_t^2 + \gamma^2\sigma_x^2\sigma_\varepsilon^2}\frac{1}{\sigma_\varepsilon^2}\right)^{-1}, \tag{A.75}$$

and

$$\mathbb{E}_t^U[D_{t+1}] = \mathrm{Var}_t^U[D_{t+1}] \frac{\gamma\Lambda_t Z_t}{\Lambda_t^2 Z_t^2 + \gamma^2\sigma_\varepsilon^2\sigma_x^2}\widehat{P}_t \tag{A.76}$$

$$= \mathrm{Var}_t^U[D_{t+1}] \frac{\Lambda_t^2 Z_t^2}{\Lambda_t^2 Z_t^2 + \gamma^2\sigma_x^2\sigma_\varepsilon^2}\frac{1}{\sigma_\varepsilon^2} E_t + \mathrm{Var}_t^U[D_{t+1}] \frac{\gamma\Lambda_t Z_t}{\Lambda_t^2 Z_t^2 + \gamma^2\sigma_\varepsilon^2\sigma_x^2} x_t. \tag{A.77}$$

Defining $R_{t+1}^e \equiv P_{t+1} + D_{t+1} - R_f P_t$, we impose market clearing:

$$\Lambda_t \frac{\mathbb{E}_t^I[D_{t+1} + P_{t+1}] - R_f P_t}{\gamma\,\mathrm{Var}_t^I[R_{t+1}^e]} + (1-\Lambda_t)\frac{\mathbb{E}_t^U[D_{t+1} + P_{t+1}] - R_f P_t}{\gamma\,\mathrm{Var}_t^U[R_{t+1}^e]} = M - x_t. \tag{A.78}$$

The price conjecture (32) implies $\mathbb{E}_t^I[P_{t+1}] = \mathbb{E}_t^U[P_{t+1}] = -\zeta M$ and thus

$$\frac{\Lambda_t\,\mathbb{E}_t^I[D_{t+1}]}{\mathrm{Var}_t^I[R_{t+1}^e]} + \frac{(1-\Lambda_t)\,\mathbb{E}_t^U[D_{t+1}]}{\mathrm{Var}_t^U[R_{t+1}^e]} - \left(\frac{\Lambda_t}{\mathrm{Var}_t^I[R_{t+1}^e]} + \frac{1-\Lambda_t}{\mathrm{Var}_t^U[R_{t+1}^e]}\right)(R_f P_t + \zeta M) = \gamma(M - x_t), \tag{A.79}$$

from which, after replacement of (A.73)-(A.74) and (A.75)-(A.77), we can solve for the undetermined coefficients in the price conjecture $P_t = \alpha E_t + \xi x_t - \zeta M$. Then, Conjecture (A.72) implies $\frac{\alpha}{\xi} = \frac{\Lambda_t}{\gamma\sigma_\varepsilon^2} Z_t$, which yields a cubic equation in Z_t with a unique real solution:

$$Z_t = \frac{\mathrm{Var}_t^I[D_{t+1}]}{\mathrm{Var}_t^I[R_{t+1}^e]}. \tag{A.80}$$

Thus, Conjecture (A.72) is $\widehat{P}_t = \frac{\Lambda_t\,\mathrm{Var}_t^I[D_{t+1}]}{\gamma\sigma_\varepsilon^2\,\mathrm{Var}_t^I[R_{t+1}^e]} E_t + x_t$.

We are now ready to prove Proposition 4. The proof follows similar steps as in the static model, and starts by writing the optimal portfolio of any investor i (informed or not):

$$q_t^i = \frac{1}{\gamma\,\mathrm{Var}_t^i[R_{t+1}^e]}\,\mathbb{E}_t^i[R_{t+1}^e], \tag{A.81}$$

from which we can derive the expected utility of investor i:

$$\mathbb{E}_t^i\left[-\exp\left(-\gamma q_t^i R_{t+1}^e\right)\right] = -\exp\left(-\frac{1}{2}\frac{(\mathbb{E}_t^i[R_{t+1}^e])^2}{\mathrm{Var}_t^i[R_{t+1}^e]}\right). \tag{A.82}$$

The expected utility is different for I or U investors. For the uninformed investor U, $\mathbb{E}_t^I[R_{t+1}^e]$ is a random variable with mean $\mathbb{E}_t^U[R_{t+1}^e]$ and variance:

$$\Sigma \equiv \mathrm{Var}_t^U[\mathbb{E}_t^I[R_{t+1}^e]] = \mathrm{Var}_t^U[R_{t+1}^e] - \mathrm{Var}_t^I[R_{t+1}^e], \tag{A.83}$$

and thus we define z a random variable with mean 0 and variance Σ and write

$$-\frac{1}{2}\frac{(\mathbb{E}_t^I[R_{t+1}^e])^2}{\mathrm{Var}_t^I[R_{t+1}^e]} = -\frac{1}{2}\frac{(z+\mathbb{E}_t^U[R_{t+1}^e])^2}{\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma} \tag{A.84}$$

$$= z^2\frac{-1}{2(\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma)} + z\frac{-\mathbb{E}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma} + \frac{-(\mathbb{E}_t^U[R_{t+1}^e])^2}{2(\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma)} \tag{A.85}$$

$$= z^2F + zG + H. \tag{A.86}$$

Lemma A2 yields:

$$1-2\Sigma F = \frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma} = \frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^I[R_{t+1}^e]} \tag{A.87}$$

$$\frac{1}{2}\frac{G^2\Sigma}{1-2\Sigma F} + H = \frac{1}{2}\frac{\frac{(\mathbb{E}_t^U[R_{t+1}^e])^2\Sigma}{(\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma)^2}}{\frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma}} - \frac{(\mathbb{E}_t^U[R_{t+1}^e])^2}{2(\mathrm{Var}_t^U[R_{t+1}^e]-\Sigma)} = -\frac{1}{2}\frac{(\mathbb{E}_t^U[R_{t+1}^e])^2}{\mathrm{Var}_t^U[R_{t+1}^e]}, \tag{A.88}$$

and thus the uninformed investor computes the following expectation:

$$\mathbb{E}_t^U\left[\mathbb{E}_t^I\left[-\exp\left(-\gamma q_t^I R_{t+1}^e\right)\right]\right] = -\left(\frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^I[R_{t+1}^e]}\right)^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\frac{(\mathbb{E}_t^U[R_{t+1}^e])^2}{\mathrm{Var}_t^U[R_{t+1}^e]}\right) \tag{A.89}$$

$$= \left(\frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^I[R_{t+1}^e]}\right)^{-\frac{1}{2}}\mathbb{E}_t^U\left[-\exp\left(-\gamma q_t^U R_{t+1}^e\right)\right]. \tag{A.90}$$

Then, the uninformed investor is attentive to the earnings announcement if and only if

$$\frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^I[R_{t+1}^e]} > e^{2\gamma c}, \tag{A.91}$$

which proves part (a) of Proposition 4. Using (A.73) and (A.75), the benefit of information is

$$\frac{\mathrm{Var}_t^U[R_{t+1}^e]}{\mathrm{Var}_t^I[R_{t+1}^e]} = \frac{\mathrm{Var}_t[P_{t+1}] + \frac{\mathrm{Var}_t[D_{t+1}]\sigma_\varepsilon^2}{\frac{\Lambda_t^2Z_t^2}{\Lambda_t^2Z_t^2+\gamma^2\sigma_x^2\sigma_\varepsilon^2}\mathrm{Var}_t[D_{t+1}]+\sigma_\varepsilon^2}}{\mathrm{Var}_t[P_{t+1}] + \frac{\mathrm{Var}_t[D_{t+1}]\sigma_\varepsilon^2}{\mathrm{Var}_t[D_{t+1}]+\sigma_\varepsilon^2}} \tag{A.92}$$

which increases in $\mathrm{Var}_t[D_{t+1}]$, proving part (b) of Proposition 4. □

Moving now to Proposition 5, the ERC (i.e., the sensitivity of the price P_t to E_t) follows directly from the market clearing condition (A.79), in which we collect all the terms that multiply E_t. We re-write here the market clearing condition for convenience:

$$\frac{\Lambda_t\,\mathbb{E}_t^I[D_{t+1}]}{\mathrm{Var}_t^I[R_{t+1}^e]}+\frac{(1-\Lambda_t)\,\mathbb{E}_t^U[D_{t+1}]}{\mathrm{Var}_t^U[R_{t+1}^e]}-\left(\frac{\Lambda_t}{\mathrm{Var}_t^I[R_{t+1}^e]}+\frac{1-\Lambda_t}{\mathrm{Var}_t^U[R_{t+1}^e]}\right)(R_fP_t+\zeta M)=\gamma(M-x_t), \tag{A.93}$$

and replace (A.74) and (A.77) to obtain

$$\mathrm{ERC}_t = \tag{A.94}$$

$$=\frac{1}{R_f}\frac{1}{\frac{\Lambda_t}{\mathrm{Var}_t^I[R_{t+1}^e]}+\frac{1-\Lambda_t}{\mathrm{Var}_t^U[R_{t+1}^e]}}\left(\frac{\Lambda_t\,\mathrm{Var}_t^I[D_{t+1}]}{\mathrm{Var}_t^I[R_{t+1}^e]\sigma_\varepsilon^2}+\frac{(1-\Lambda_t)\,\mathrm{Var}_t^U[D_{t+1}]}{\mathrm{Var}_t^U[R_{t+1}^e]\sigma_\varepsilon^2}\frac{\Lambda_t^2Z_t^2}{\Lambda_t^2Z_t^2+\gamma^2\sigma_x^2\sigma_\varepsilon^2}\right) \tag{A.95}$$

$$=\frac{1}{R_f}\left(w_t\frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}]+\sigma_\varepsilon^2}+(1-w_t)\frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}]+\sigma_\varepsilon^2/\ell_t}\right), \tag{A.96}$$

where w_t and ℓ_t are defined as:

$$w_t=\frac{\frac{\Lambda_t}{\mathrm{Var}_t^I[R_{t+1}^e]}}{\frac{\Lambda_t}{\mathrm{Var}_t^I[R_{t+1}^e]}+\frac{1-\Lambda_t}{\mathrm{Var}_t^U[R_{t+1}^e]}} \tag{A.97}$$

$$\ell_t=\frac{\Lambda_t^2Z_t^2}{\Lambda_t^2Z_t^2+\gamma^2\sigma_x^2\sigma_\varepsilon^2}<1. \tag{A.98}$$

Notice that ERC_t is a weighted average. A higher fraction of informed investors Λ_t increases w_t, and thus the weighted average places a higher weight on $\frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}]+\sigma_\varepsilon^2}$. Because $\ell_t<1$, the higher weight on $\frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}]+\sigma_\varepsilon^2}$ increases the weighted average. Moreover, a higher Λ_t increases ℓ_t, which further increases $\frac{\mathrm{Var}_t[D_{t+1}]}{\mathrm{Var}_t[D_{t+1}]+\sigma_\varepsilon^2/\ell_t}$ and thus the weighted average. Overall, these two effects confirm that a higher Λ_t increase the ERC, proving Proposition 5. □

B Variable definitions

Variable	Description
VIX	Closing value of VIX. Source: CRSP.
ESV	Log daily number of EDGAR downloads (search volume) of the company's filings from SEC EDGAR. Source: SEC.
ESVU	Log daily number of EDGAR downloads (search volume) of the company's filings from unique IP addresses. Source: SEC.
EARET	Earnings announcement return. Compound excess return over the size decile portfolio for earnings announcement trading date and one trading day after. Source: CRSP.
SUE Decile	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.
PreRet	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.
Size	Market value of equity on the earnings announcement date in $M. Source: CRSP.
Book-to-Market	Book to market ratio at the end of quarter for which earnings are announced. Source: Compustat.
EPersistence	Earnings persistence based on AR(1) regression with at least 4, up to 16 quarterly earnings. Source: Compustat.
IO	Institutional ownership as a fraction of total shares outstanding. Source: Thomson-Reuters 13F Data, CRSP.
EVOL	Standard deviation of seasonally differenced quarterly earnings over the prior 16 (at least 4) quarters. Source: Compustat.
ERepLag	Days from quarter-end to earnings announcement. Source: Compustat.
#Estimates	Number of analysts making quarterly earnings forecasts. Source: IBES Summary File.
TURN	Average monthly turnover for the 12 months preceding the earnings announcement. Source: CRSP.
Loss	Indicator for negative earnings. Source: Compustat.
#Announcements	Number of concurrent earnings announcements. Source: Compustat, IBES.
CAPM Beta	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

C Tables

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

Variable	**N**	**Mean**	**Std. Dev.**	**25%**	**50%**	**75%**
VIX	236,826	19.625	8.159	13.770	18.020	23.010
ESV	125,570	5.655	1.931	4.277	5.820	7.122
ESVU	125,570	4.048	1.396	3.045	4.205	5.187
EARET	237,416	0.001	0.080	-0.033	0.001	0.037
SUE Decile	237,416	5.535	2.706	3.000	6.000	8.000
PreRet	236,839	0.002	0.081	-0.035	-0.001	0.035
Size	236,862	5930.250	24719.650	281.568	850.259	2963.590
Book-to-Market	237,262	0.534	0.382	0.274	0.458	0.701
EPersistence	236,742	-0.032	26.319	-0.040	0.179	0.500
IO	227,911	0.633	2.276	0.430	0.666	0.842
EVOL	236,768	67.372	7108.010	0.116	0.272	0.654
ERepLag	237,416	30.747	13.644	22.000	28.000	37.000
#Estimates	237,416	7.784	6.567	3.000	6.000	11.000
TURN	237,416	17.439	17.591	6.932	12.824	22.116
Loss	237,416	0.194	0.395	0.000	0.000	0.000
#Announcements	237,416	149.190	92.937	72.000	136.000	221.000

Table 2: **Correlations**

This table presents Spearman (Pearson) correlations above (below) the diagonal for daily measures of news indices, uncertainty proxies, and market activity measures. Detailed definitions of all variables are available in Appendix B. All correlations are significant at the five percent level, except those indicated in bold.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	VIX		-0.129	-0.143	**0.004**	0.005	-0.006	-0.123	0.079	0.029	-0.133	-0.047	-0.066	-0.061	**-0.003**	0.028	0.050
2	ESV	-0.074		0.958	**-0.002**	0.008	0.018	0.318	-0.047	-0.105	0.205	0.158	0.111	0.261	0.149	0.036	-0.097
3	ESVU	-0.074	0.957		**-0.002**	0.010	0.016	0.334	-0.062	-0.103	0.207	0.159	0.105	0.282	0.155	0.042	-0.076
4	EARET	**-0.002**	**-0.001**	**-0.002**		0.316	-0.045	0.022	0.012	**0.001**	0.023	-0.023	-0.023	0.007	-0.015	-0.094	0.004
5	SUE Decile	**0.004**	0.010	0.013	0.299		0.096	0.032	-0.009	**0.004**	0.035	0.030	-0.035	0.019	0.045	-0.146	0.025
6	PreRet	-0.007	**0.005**	**0.004**	-0.043	0.097		0.052	-0.011	0.009	0.004	-0.018	-0.019	0.010	0.025	-0.050	-0.005
7	Size	-0.039	0.178	0.207	**0.001**	**0.001**	0.005		-0.313	**0.004**	0.442	0.133	-0.143	0.746	0.274	-0.179	0.021
8	Book-to-Mkt	0.097	-0.011	-0.022	0.017	-0.018	-0.005	-0.104		-0.087	-0.114	0.198	0.023	-0.254	-0.216	-0.004	-0.020
9	EPersistence	0.004	0.006	0.006	**0.000**	**0.002**	**0.001**	**0.002**	-0.004		**0.002**	-0.359	-0.096	0.049	0.068	-0.052	0.016
10	IO	-0.007	0.016	0.015	**0.000**	**0.002**	**-0.002**	0.004	-0.008	**0.000**		0.192	0.093	0.465	0.508	-0.026	0.005
11	EVOL	0.005	-0.007	-0.007	**-0.001**	**-0.003**	**0.001**	**-0.002**	-0.008	**0.000**	**0.000**		0.163	0.083	0.195	0.196	0.012
12	ERepLag	-0.025	0.078	0.067	-0.022	-0.049	-0.019	-0.095	0.033	-0.009	0.004	0.005		-0.120	0.109	0.199	-0.171
13	#Estimates	-0.047	0.263	0.292	**0.000**	0.014	**-0.004**	0.400	-0.195	**-0.001**	0.043	**-0.003**	-0.139		0.453	-0.067	0.017
14	TURN	0.046	0.103	0.113	-0.022	0.032	0.018	-0.026	-0.085	**-0.003**	0.037	**0.004**	0.041	0.298		0.156	**-0.003**
15	Loss	0.033	0.037	0.042	-0.091	-0.149	-0.040	-0.073	0.050	**0.002**	-0.004	0.016	0.185	-0.070	0.156		**-0.001**
16	#Ann.	0.027	-0.108	-0.082	**0.001**	0.025	**0.003**	-0.026	-0.019	**0.002**	**0.004**	**0.000**	-0.225	-0.016	**0.000**	**0.000**	

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. 36). 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 B. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

Dep. Var.	ESV	ESVU
VIX	0.019***	0.045***
	(0.006)	(0.007)
lag(Dep. Var.)	0.210***	0.499***
	(0.005)	(0.011)
SUE Decile	0.005***	0.007***
	(0.001)	(0.002)
abs(SUE Decile)	0.008***	0.021***
	(0.003)	(0.004)
Size	0.052***	0.077***
	(0.002)	(0.003)
Book-to-Market	-0.009***	-0.016***
	(0.001)	(0.002)
EPersistence	-0.002	-0.003
	(0.002)	(0.002)
IO	0.002	0.001
	(0.001)	(0.002)
EVOL	0.001	0.004
	(0.004)	(0.007)
ERepLag	0.024***	0.024***
	(0.004)	(0.006)
#Estimates	0.065***	0.088***
	(0.003)	(0.003)
TURN	0.027***	0.035***
	(0.002)	(0.002)
Loss	-0.001	0.005***
	(0.001)	(0.002)
#Announcements	-0.034***	-0.012
	(0.008)	(0.010)
Date-clustered SE	Yes	Yes
Year FE	Yes	Yes
Day-of-week FE	Yes	Yes
N	117,461	117,461
R-Square	0.799	0.828

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. 37). 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 B. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

	Dep. Var. = EARET during [0,1] window		
	(a)	(b)	(c)
VIX*SUE Decile	0.017***		0.011*
	(0.005)		(0.006)
ESVU*SUE Decile		0.015***	0.015***
		(0.005)	(0.005)
SUE Decile	0.287***	0.328***	0.341***
	(0.023)	(0.039)	(0.039)
VIX	-0.013***		-0.015**
	(0.005)		(0.006)
ESVU		-0.010**	-0.009*
		(0.005)	(0.005)
lag(ESVU)		-0.004	-0.005
		(0.005)	(0.005)
lag(ESVU)*SUE Decile		-0.017***	-0.016***
		(0.005)	(0.005)
PreRet	-0.075***	-0.076***	-0.077***
	(0.004)	(0.006)	(0.006)
PreRet*SUE Decile	-0.013***	-0.014***	-0.013***
	(0.003)	(0.005)	(0.005)
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

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 B. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

	Dep. Var. = Earnings announcement returns during [0,1] window									
	Subsamples: based on Within-year-of-earnings-announcement Median splits on announcing firm characteristics									
Sample:	Low CAPM Beta	High CAPM Beta	Low Forecast Dispersion	High Forecast Dispersion	Low Idiosync. Volatility	High Idiosync. Volatility	Low TURN	High TURN	Low IO	High IO
VIX*SUE Decile	0.007	0.025***	0.020***	0.020***	0.010**	0.017***	0.005	0.026***	0.008	0.027***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.005)	(0.006)	(0.006)	(0.008)	(0.005)	(0.008)
SUE Decile	0.290***	0.306***	0.328***	0.285***	0.274***	0.328***	0.411***	0.317***	0.277***	0.330***
	(0.027)	(0.043)	(0.038)	(0.038)	(0.025)	(0.034)	(0.030)	(0.039)	(0.033)	(0.036)
VIX	-0.013***	-0.012	-0.010**	-0.019**	-0.005	-0.020**	-0.011**	-0.016*	-0.012**	-0.016***
	(0.005)	(0.009)	(0.005)	(0.008)	(0.005)	(0.008)	(0.006)	(0.008)	(0.006)	(0.006)
PreRet	-0.079***	-0.076***	-0.081***	-0.070***	-0.072***	-0.080***	-0.071***	-0.080***	-0.083***	-0.067***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
PreRet*SUE Decile	-0.015***	-0.011***	-0.016***	-0.012***	-0.010**	-0.015***	-0.018***	-0.011***	-0.010***	-0.015***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)
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	100,365	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 B. Standard errors for the coefficients are clustered by date. ***, **, and * indicate statistical significance at the two-sided 1%, 5%, and 10% levels, respectively.

	Dep. Var. = Earnings announcement returns during [0,1] window									
	Subsamples: based on Within-year-of-earnings-announcement Median splits on announcing firm characteristics									
Sample:	Low CAPM Beta	High CAPM Beta	Low Forecast Dispersion	High Forecast Dispersion	Low Idiosync. Volatility	High Idiosync. Volatility	Low TURN	High TURN	Low IO	High IO
ESVU*SUE Decile	0.007	0.019**	0.003	0.020**	0.007	0.021**	0.007	0.011	0.008	0.022**
	(0.007)	(0.008)	(0.009)	(0.008)	(0.006)	(0.008)	(0.006)	(0.010)	(0.007)	(0.009)
SUE Decile	0.310***	0.437***	0.507***	0.358***	0.312***	0.337***	0.411***	0.641***	0.287***	0.453***
	(0.051)	(0.061)	(0.065)	(0.055)	(0.040)	(0.060)	(0.048)	(0.069)	(0.052)	(0.067)
ESVU	-0.009	-0.009	-0.008	-0.010	-0.012**	-0.005	0.005	-0.021**	-0.010	-0.007
	(0.006)	(0.008)	(0.007)	(0.008)	(0.005)	(0.009)	(0.006)	(0.009)	(0.007)	(0.008)
lag(ESVU)	-0.003	0.000	-0.011*	0.004	-0.003	-0.001	-0.009	0.011	-0.003	0.000
	(0.006)	(0.008)	(0.007)	(0.008)	(0.005)	(0.008)	(0.006)	(0.009)	(0.006)	(0.007)
lag(ESVU)*SUE Decile	-0.014**	-0.027***	-0.028***	-0.025***	-0.020***	-0.013*	-0.009	-0.046***	-0.009	-0.030***
	(0.007)	(0.008)	(0.009)	(0.008)	(0.006)	(0.008)	(0.006)	(0.009)	(0.007)	(0.008)
PreRet	-0.079***	-0.076***	-0.098***	-0.063***	-0.080***	-0.077***	-0.072***	-0.081***	-0.082***	-0.071***
	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)
PreRet*SUE Decile	-0.015**	-0.012*	-0.011	-0.014**	-0.014*	-0.013**	-0.018***	-0.011	-0.012**	-0.016*
	(0.007)	(0.007)	(0.010)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.009)
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	58,136	59,202	53,309	53,244	58,928	58,410	58,391	59,060	57,867	59,584
R-Square	0.142	0.140	0.153	0.134	0.151	0.141	0.168	0.129	0.144	0.138