Coarse Categories in a Complex World*

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Abstract

Most news stories contain both granular quantitative information and coarse categorizations. For instance, company earnings are reported as a dollar figure alongside categorizations, such as whether earnings beat or missed market expectations. We formalize and study the hypothesis that when a decision is harder, people rely more on easier-to-integrate signals: people still discriminate between coarse categories but distinguish less granularly within them, creating higher sensitivity around category thresholds but lower sensitivity elsewhere. Using stock market reactions to earnings announcements, we document that hard-to-value stocks are associated with a more pronounced S-shaped response pattern around category thresholds. Experiments that exogenously manipulate the problem difficulty provide supporting causal evidence in individual investor behavior. We then exploit variation in investor familiarity with earnings surprises of different sizes to show that returns exhibit greater sensitivity in regions with more historical density. Our findings speak to the ongoing debate about why economic agents display insufficient sensitivity in some instances and excessive sensitivity in others, even within the same empirical setting.

Keywords: Categorical Information, Numerical Information, Earnings Surprises, Cognitive Constraints, Behavioral Finance

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1 Introduction

News stories describe events using both granular numerical information and coarse categorizations. Consider a firm's quarterly earnings announcement: Walmart's earnings per share (EPS) for the fourth quarter in 2024 were $1.80. Also, Walmart beat the consensus analyst forecast of $1.65 and reported higher earnings than in the same quarter of the previous year. When integrating all available information into a decision is cognitively demanding, numerical information and coarse categorizations can compete for attention. If the decision-maker finds a problem more challenging, they may rely more on easier-to-integrate information components, such as familiar categories. Intuitively, people may have a sense of what familiar categories of news mean – like whether earnings are above or below expectations – because such categories are stable and recurring. These category shortcuts may allow for quick processing. By contrast, estimating the precise impact of the quantitative signal is much harder. For instance, how does the excess return differ when reported EPS is $1.98 versus $2.03?

In this paper, we study situations in which numerical information is provided alongside category labels, defined through a partition of the numerical scale. We hypothesize that more difficult decisions lead people to rely more on coarse categories. The resulting behavioral pattern is a more step-shaped or S-shaped response function: higher sensitivity at category boundaries but lower sensitivity elsewhere. We discuss various microfoundations for why coarse information can be cognitively "cheaper" and review the class of models that can predict a more non-linear response around category boundaries for harder problems. We illustrate the core ideas using a simple framework of constrained optimization in which decision difficulty creates imprecision: numerical signals are integrated less precisely than categorical information.

We empirically test the predictions about the role of decision difficulty for the relative reliance on coarse versus granular information in the context of stock market returns to earnings surprises, both in aggregate market data and individual belief formation experiments with investors. Earnings announcements have several features that make them a well-suited testing ground for our hypothesis: (i) decision-making is naturally difficult given the high-dimensional nature of data that investors process in short periods of time; (ii) both categorical and quantitative information are explicitly communicated in earnings news; (iii) earnings categories are defined through thresholds on the numerical EPS scale; (iv) there are various categories that investors are highly familiar with.[1]

[1]We do not examine settings where categories are unfamiliar but numerical information is commonly communicated. In such scenarios, numbers might be subjectively easier to integrate than categories, so that our predicted effect reverses – an interesting avenue for future research.

Field Evidence. Testing our hypothesis in the field requires a characterization of relevant numerical signals and categorizations, as well as a measure of and variation in decision difficulty. First, to identify which categories are most commonly communicated in earnings news, we analyze headlines in the Earnings category of the *Wall Street Journal* between 2002 and 2021.[2] We document that a frequent categorization is into beating versus missing the consensus forecast, with other common categorizations being about whether earnings are positive or negative, and about the growth or decline of earnings over time.[3] Our main analyses thus focus on earnings surprises relative to market expectations. To obtain an empirical proxy of decision difficulty, we leverage the literature on what makes a stock "hard to value" (e.g., Laarits and Sammon, 2024), adopting the concept of *valuation uncertainty* (VU) from Golubov and Konstantinidi (2023). This measure captures uncertainty regarding the mapping from firm fundamentals to stock prices, reflecting variation both across firms and within firms over time.

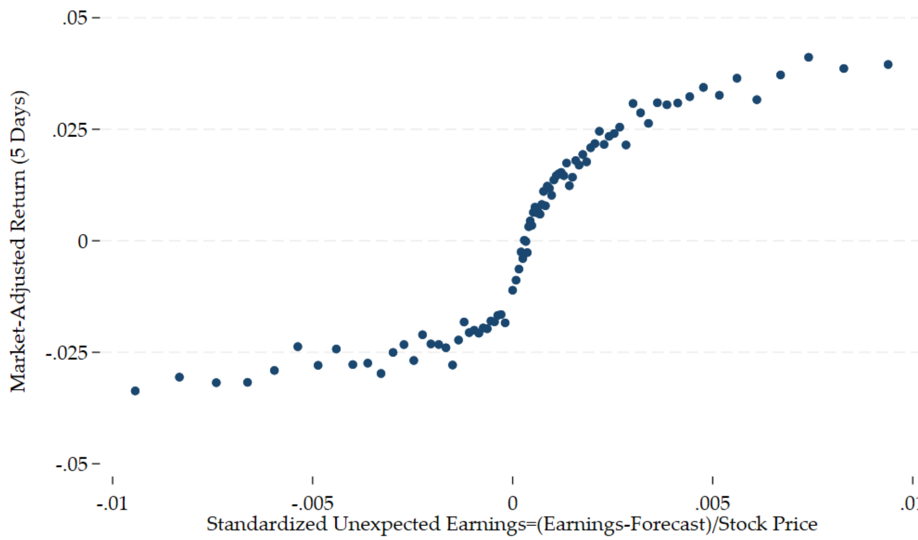
We begin our examination of the field data by studying the relationship between market-adjusted returns in the five days following an earnings announcement and so-called "standardized unexpected earnings" (SUE), calculated as the difference between the actual earnings per share and the consensus forecast, divided by the closing price before the earnings announcement. This allows us to investigate the role of being in the earnings beat versus miss category – the sign of the surprise – alongside the effect of the numerical magnitude of firm earnings – the size of the surprise.

Figure 1 illustrates a striking pattern in our sample of more than 176,000 earnings announcements for over 6,000 unique companies between 1986 and 2019: market-adjusted returns exhibit a pronounced S-shaped relationship with SUE. Returns are, on average, highly sensitive to the sign of earnings surprises but far less sensitive to their size. This non-linear relationship between market-adjusted returns and earnings surprises has, in fact, been well established in finance and accounting over the past three decades (e.g., Freeman and Tse, 1992; Skinner and Sloan, 2002). A variety of explanations – primarily on the role of earnings persistence – have been put forward in the literature, as we review in detail below. This paper examines a complementary, behavioral hypothesis to help explain this pattern.

To study the association between valuation uncertainty and market-adjusted returns, we compare the earnings response curve for observations associated with high VU versus low VU. Our main specification estimates the relationship between market-adjusted returns and SUE for symmetric windows around zero. For small windows around zero surprise, this primarily cap-

[2]Data used: `https://www.kaggle.com/datasets/amogh7joshi/wsj-headline-classification`.
[3]Numerical information about earnings is, in fact, mentioned in fewer than 10% of earnings news headlines.

Figure 1: S-shaped Response of Market-Adjusted Returns to Earnings Surprises



Notes: This figure illustrates the relationship between market-adjusted returns and earnings surprises. The x-axis represents standardized unexpected earnings (SUE), calculated as the difference between actual earnings per share (EPS) and mean expected EPS, normalized by the previous closing price ($P_{i,t-1}$). The y-axis shows the cumulative market-adjusted return over the five trading days following an earnings announcement.

tures the impact of crossing the category threshold (beat versus miss). Within these windows, we predict that observations with greater valuation uncertainty show increased sensitivity to SUE, reflecting a stronger reliance on coarse categorical distinctions. As we gradually expand the width of the symmetric window around zero, the estimated relationship increasingly reflects the sensitivity to the size of surprises. The second part of our hypothesis is that observations with high valuation uncertainty are less sensitive to the magnitude of surprises.

Consistent with our hypotheses, our key finding is that higher valuation uncertainty is associated with *higher sensitivity* of market-adjusted returns to the *sign* of surprises, but *lower sensitivity* to the *size* of surprises. While the estimated interaction between SUE and valuation uncertainty is significantly positive for small symmetric windows around zero (capturing responses to crossing the category threshold), it becomes significantly negative for large symmetric windows around zero (capturing responses to both the sign and size of surprises). The effect sizes are economically meaningful: for a window size of 0.002 SUE around zero surprise, a 0.01 increase (henceforth one unit) in SUE is associated with a 17.12 p.p. ($p < 0.01$) increase in market-adjusted returns for a company with average valuation uncertainty. For a company with a one-standard deviation higher valuation uncertainty, this effect is 19.42 p.p. ($p < 0.01$), i.e., valuation uncertainty is associated with *increases* in the sensitivity to surprises by approximately 13% ($p < 0.01$).

For a window size of 0.05, a one-unit increase in SUE is associated with a 2.4 p.p. ($p < 0.01$) increase in market-adjusted returns for a company with average valuation uncertainty. For a company with a one-standard deviation higher valuation uncertainty this effect is 2.1 p.p. ($p < 0.01$), i.e., a decrease in the sensitivity to surprises by approximately 13%.

Our finding is robust to varying sets of controls, fixed effects, event study horizons and specifications. We conduct an extensive set of tests on how our findings about the role of hard-to-value stocks relate to previous explanations for the S-shaped response to earnings news in the finance and accounting literature. We find that our results are not explained by differences in book-to-market ratios, earnings quality, differential pre-announcement information acquisition and differential strategic disclosure. We argue that the distinctive prediction associated with our hypothesis – a more S-shaped pattern implies *three* crossing points between the earnings response curves of high versus low VU observations – cannot easily be explained by existing explanations. We also explore the relationship between valuation uncertainty and long-run responses to earnings news and, in particular, post-earnings announcement drift (PEAD). In our data, we find patterns consistent with the idea that high VU is associated with overreaction for small and underreaction for larges surprise, yet these effects are more noisily measured.

Our framework makes distinct predictions about different forms of uncertainty. In particular, the model predicts that uncertainty about the location of category thresholds *decreases* investors' sensitivity to surprises *everywhere*, especially around category boundaries. Intuitively, such uncertainty can also be conceptualized as the difficulty or imprecision involved in integrating categorical information. Consequently, our model predicts opposite effects of imprecision for categorical versus numerical information. We test this prediction using variation in dispersion of analysts' earnings forecasts. Consistent with our framework, we find that higher dispersion in earnings forecasts – unlike valuation uncertainty – predicts decreases in the sensitivity to surprises, especially close to the category thresholds. This evidence also mitigates concerns that our results are driven by unobservable characteristics that are correlated with different forms of uncertainty.

Experimental Evidence. To provide causal evidence on the effect of decision difficulty on return expectations, we run controlled online experiments with investors. In our experiments, investors make incentivized predictions about same-day stock price movements of five different real companies for a specific scenario of an impending, actual earnings announcement. In each scenario, respondents receive a news story about a company's earnings that contains both numerical information about EPS and categorical information on whether the firm beat or missed the consensus forecast. Our design varies the realized earnings surprises across participants. To provide causal evidence on the difficulty of the decision problem, we randomly assign half of the participants to a *Baseline* condition and the other half to a *High Constraints* condition. In *High Constraints*, we increase the severity of processing constraints by adding some irrelevant (but naturalistic) information to the earnings news piece and by imposing a 40 second time limit for bonus eligibility. The results of our pre-registered experiments on individual price forecasts strongly corroborate our main findings from aggregate price data in the field. We find a large treatment difference in line with the distinctive pattern implied by our behavioral prediction. Incentivized forecasts in *High Constraints* are more S-shaped: Expected price adjustments are relatively larger for small earnings surprises – more positive for small beats and more negative for small misses – but diminish in magnitude for larger surprises. The experiment allows us to test a more specific notion of decision difficulty than our field proxy: here, the more pronounced S shape is unambiguously driven by more severe processing constraints rather than, e.g., preference uncertainty or stochasticity in the real world.

Local Variation in Decision Difficulty. Under constant decision difficulty for earnings surprises of different sizes, the model predicts a symmetric and step-shaped (rather than S-shaped) response function. The actual relationship between excess returns and earnings surprises, however, exhibits (i) smoothly diminishing sensitivity around zero rather than a sharp jump at category boundaries, and (ii) pronounced asymmetry, with weaker sensitivity for negative surprises. In the model, these patterns can result from differences in the difficulty of integrating large versus small and positive versus negative earnings surprises, respectively. To understand the potential role of such variation, we leverage a well-documented idea from the cognitive sciences, suggesting that more familiar stimuli are easier to process and thus integrated more precisely, implying higher sensitivity in stimulus ranges with higher historical density.[4]

We test this prediction by examining how the historical density of earnings surprises influences investors' sensitivity to these surprises. To set the stage, we first document that the empirical distribution of earnings surprises (i) exhibits a pronounced bell shape centered around zero, rapidly declining as surprises grow in magnitude, and (ii) is notably asymmetric, with negative surprises being less common than positive ones. In a next step, we estimate local earnings response coefficients for a fine-grained partition of buckets with earnings surprises of different sizes. Strikingly, the local sensitivity to the magnitude of earnings surprises is strongly

[4]Recent contributions have applied this principle of *efficient coding* (Laughlin, 1981; Barlow et al., 1961) to economic choices in controlled experiments (e.g., Frydman and Jin, 2022, 2024).

positively correlated with the local historical density, consistent with a negative relationship between problem difficulty and historical density. In fact, the empirical density explains away 58% of the difference in sensitivities between positive and negative earnings surprises, as well as 50% of the "jump" at the category threshold between beating and missing market expectations. These findings complement rather than substitute our baseline results, as variation in local density alone cannot fully explain the jump at zero, nor for the effects of valuation uncertainty on return sensitivity. We test additional theories about variation in decision difficulty in Section 6.

Contributions and Related Literature. An extensive literature, dating back to at least Simon (1955), links behavioral anomalies to information processing constraints and bounded rationality (e.g., Woodford, 2020). Recent studies emphasize how complexity shapes decision-making and often induces simplification strategies (e.g., see the review of Oprea, 2024), such as the reliance on simplified mental models. Relatedly, a recent literature emphasizes behavioral inattention and attenuation as sources of global insensitivity to variations in choice parameters (e.g., Gabaix, 2019; Enke and Graeber, 2023; Enke et al., 2025).

Complementing this literature, we propose that decision difficulty amplifies the reliance on easier-to-integrate information, such as familiar categories, increasing sensitivity around category thresholds while reducing responsiveness away from these thresholds. Our framework relates to recent analyses of over- and underreaction to news (Ba et al., 2024; Bastianello and Imas, 2025). Augenblick et al. (2025) empirically demonstrate decision-makers' tendency to overinfer from weak signals and underinfer from strong signals. Similarly, Ba et al. (2024) propose a two-stage belief formation model: complexity is initially reduced via a coarse state representation, followed by cognitively imprecise integration of detailed information. Our findings are compatible with this interpretation, highlighting simplification through categorization at the representational stage and numerical imprecision at the computational stage.

A cross-disciplinary literature argues that coarser information structures entail lower cognitive processing costs, drawing on information-theoretic principles such as Shannon cost (Sims, 2003) and Kolmogorov complexity (see Oprea, 2024, for a review). This idea aligns with rational inattention models, which predict discretization of information (see Maćkowiak et al., 2023, for a review). Our results on variation in historical density of surprises in particular relate to work on efficient coding (Frydman and Jin, 2022, 2024) and decision by sampling (Stewart et al., 2006). Our paper contributes evidence from a high-stakes field context that speaks to these theories, moving beyond the existing evidence which is confined to lab experiments.

Our field evidence relates to studies on reference dependence and left-digit bias (Allen et al., 2017; Pope and Simonsohn, 2011; List et al., 2023; Strulov-Shlain, 2023; Lacetera et al., 2012). Meier et al. (2025) finds step-shaped forecast revisions by financial analysts consistent with reference-dependent thinking, supporting our interpretation that the observed S-shaped excess returns partly reflect behavioral phenomena. Unlike prior studies, we explicitly analyze the role of decision difficulty.[5]

Our findings relate to foundational work on coarse thinking in economics (Mullainathan et al., 2008; Mullainathan, 2002; Bordalo et al., 2020) and finance (Barberis and Shleifer, 2003). In Mullainathan (2002), agents discretely partition the state space, updating beliefs only upon crossing categorical thresholds. Similarly, Mullainathan et al. (2008) propose that coarse categorization may inadvertently cause individuals to generalize information from one scenario to others within the same coarse category. These tendencies for coarsening may have a similar psychological origin as the patterns of competition between coarse and granular information structures that we study in this paper.[6]

Our findings contribute to the literature on stock market reactions to earnings news (e.g., Daniel et al., 1998; Bordalo et al., 2025; Hong and Stein, 1999; Barberis et al., 1998; Kwon and Tang, 2025) and specifically to the understanding of S-shaped responses to earnings surprises (Bernard and Thomas, 1989; Bouchaud et al., 2019; Hirshleifer and Teoh, 2003). Prior explanations emphasize earnings persistence (Freeman and Tse, 1992), characteristics of growth versus value firms (Skinner and Sloan, 2002), and earnings management practices (Burgstahler and Dichev, 1997; Bhojraj et al., 2009). We propose an additional behavioral mechanism and empirically distinguish it from these established financial-market explanations and endogenous disclosure effects (Huang et al., 2025).

Our paper relates to behavioral finance literature documenting reduced investor sensitivity to news under high information load or low attention (Hirshleifer et al., 2009b; DellaVigna and Pollet, 2009), and evidence that uncertainty can lead investors to neglect public signals (Banerjee et al., 2024; Hirshleifer et al., 2009a; Engelberg, 2008; Cohen et al., 2020). Laarits and Sammon (2024) show that hard-to-value stocks are globally insensitive to earnings surprises, aligning with broader evidence on insensitivity of behavioral responses to beliefs in finance

[5]Recent models link the prospect-theoretic value function to processing constraints (e.g., Villas-Boas, 2024), but our findings do not directly address this form of diminishing sensitivity.

[6]Schley et al. (2023) examine how categorical thinking influences probability weighting, linking it to cognitive science evidence that categories induce S-shaped response patterns around boundaries, consistent with evidence from the cognitive sciences (Hollands and Dyre, 2000; Huttenlocher et al., 2000; Hsee et al., 1999); however, these papers do not explicitly study decision difficulty.

(Giglio et al., 2021; Charles et al., 2024). We demonstrate that valuation uncertainty does not merely reduce sensitivity globally, but increases sensitivity near categorical thresholds.

2 Behavioral Predictions

We study the role of decision difficulty (modeled as imprecision affecting optimization) for how agents form beliefs in environments where granular numerical information is presented alongside coarse categorical information. Categories are defined by threshold-based partitions of the numerical scale. The agent understands the category memberships, but integrates the numerical signal imprecisely.

Setup. A decision maker (DM) receives a quantitative signal $s \in \mathbb{R}$, such as a company's earnings per share, and chooses their response $r \in \mathbb{R}$. They further see a collection of K category thresholds $c^k \in \mathbb{R}; k = 1, \ldots, K$. These category thresholds may include, for example, the consensus forecast, the EPS in the same quarter last year or simply the origin of the EPS scale. Given s, each category threshold c^k implies a qualitative signal $s^k = \mathbb{1}\{s > c^k\}$. The DM's full information set thus comprises a collection of binary categorizations alongside the numerical signal itself, $\{s^1, \ldots, s^K, s\}$. We assume that the DM processes the category thresholds precisely, whereas they integrate the numerical signal imprecisely.[7] Such imprecision emerges in the process of integrating information to form a response r. We take a broad view of the potential determinants of decision difficulty and the associated imprecision, including factors on the "demand side" of information processing, e.g., the complexity of the optimization problem, and factors on the "supply side", e.g., the DM's cognitive processing resources, subjective uncertainty about preferences, hard capacity constraints like time constraints, or even perceptual imprecision.

Assumption 1. *Categorical information is incorporated precisely; the numerical signal is integrated imprecisely.*

The DM chooses their response r given the information set by maximizing an objective function $U(r, s)$. We assume that the DM's unconstrained optimal response function $r^\star(s)$ in the absence of any imprecision is differentiable and monotonic. Without loss, we further assume that it is increasing. We do not require that this unconstrained response function is linear or takes any particular shape. The model is general: it applies to a belief r as a function of a signal

[7] We assume *no* imprecision in processing the category thresholds for simplicity here. This assumption can be relaxed in ways Augenblick et al. (2025) show. The more general version of Assumption 1 is that cognitive imprecision on the numerical component is *higher* than on categorical information.

s, or to an action a as a function of some decision parameter p, with $a^\star(p)$. There are likely different sources of imprecision in different situations. Given our application to earnings news, in what follows we focus on the interpretation of how a belief responds to information.

Category Prior and Default Response. In recent applications of cognitive imprecision, the DM's prior captures what they would do if they were completely incapable of simulating the optimum. In this vein, we start with a normal unconditional prior $\mathcal{N}(r_{ud}, \sigma^2_{ud})$. The objective function and this prior pin down an unconditional "default response," which is the action the DM would take before receiving information, e.g., the prior mean given a quadratic loss function. In this class of models, the prior is thus *signal-invariant*; it induces an unconditional default response r_{ud} that does not depend on the signal itself.

We then depart from and complement the notion of a signal-invariant prior with a *category prior* $r^\star \mid s^1, \ldots, s^K \sim \mathcal{N}(r_d, \sigma^2_d)$ that induces a conditional default response r_d, which already incorporates the set of qualitative signals $\{s^1, \ldots, s^K\}$. In particular, before integrating the numerical signal, the agent identifies their mean optimal action conditional on the categorical information:

$$r_d = \mathbb{E}[\ r^\star \mid s^1, \ldots, s^K\ ]. \tag{1}$$

The idea behind the category prior is that the DM parses and understands categorical information. Intuitively, the agent forms a costless "first impression" by processing categorical information such as, e.g., "earnings beating expectations" and forms a corresponding conditional belief, e.g., the average excess return for companies with positive surprises.

The DM's understanding of threshold information allows them to *categorize* their default response. Because the DM is aware that playing this conditional mean action only leads to optimal behavior on average, they remain uncertain about whether the conditional default response is actually optimal, captured by the conditional prior uncertainty σ^2_d. The conditional default mean r_d jumps at the category thresholds. The conditional default response is, thus, a step function.

Imprecision in Optimization. Due to imprecision that only affects the integration of the numerical signal s, the DM does not have direct access to their optimal response $r^\star(s)$. We model this imprecision as emerging in the mapping between numerical signal and response.[8] Given

[8]Again, we embrace the different potential origins: information-processing constraints, uncertainty about preferences, or true stochasticity in the mapping between response and optimal response.

imprecision, the DM can only mentally simulate their best response. This mental simulation creates an unbiased but noisy *cognitive signal* about the optimal response:

$$r^c(s) \sim \mathcal{N}\left(r^\star(s), \sigma_r^2(s)\right) \tag{2}$$

The noisiness of this cognitive signal is determined by the imprecision parameter $\sigma_r^2(s)$. Note that we generally allow for this level of imprecision to depend on the signal itself. We derive our main predictions under the assumption of constant imprecision before turning to the role of variation in imprecision. Proofs are provided in Appendix E.

Constrained Optimal Response. The DM integrates their imprecise cognitive signal with their conditional prior, yielding:

$$r(s) = \lambda\, r^c(s) + (1-\lambda) r_d(s), \tag{3}$$

where the weight on the cognitive signal, $\lambda = \frac{\sigma_d^2}{\sigma_r^2(s)+\sigma_d^2}$ decreases in imprecision, $\sigma_r^2(s)$, and increases in the degree of prior noise. Crucially, the behavioral response is a weighted average of optimal and default (step function) response.

Under the assumption of constant imprecision that is independent of the signal, σ_r^2, the behavioral response is a piecewise linear function that jumps at the threshold points. We do not have to assume additional characteristics for r^*.[9] In particular, the behavioral response function has two key properties in comparison to the unconstrained response function r^*:

- The behavioral response r is *more sensitive* than the unconstrained optimal response r^* at the boundaries induced by the category thresholds. Intuitively, this originates from the jump in the piecewise linear behavioral response caused by the jump in the default response function, which is absent from the smooth unconstrained response.

- The behavioral response r is *less sensitive* than the unconstrained optimal response r^* everywhere except at the comparison thresholds. Intuitively, this originates from mixing the unconstrained optimal response with a default response function that is completely inelastic (flat) everywhere but at the category thresholds.

[9]We allow for, but remain agnostic about, the possibility that the unconstrained optimal response, $r^\star$, itself responds more strongly at category boundaries. For example, it might be that making a profit instead of a loss indeed affects the optimal response. Our prediction is merely that processing constraints would make the behavioral response *even more sensitive* around category boundaries.

Prediction 1. *An increase in imprecision increases sensitivity of the expected behavioral response at category boundaries (amplification) and decreases it everywhere else (attenuation).*

Variation in Imprecision. In practice, the extent of processing imprecision might vary across the range of stimuli. For example, assuming that noise increases in the absolute magnitude of the unexpected earnings surprise would induce a smoother, sigmoid shaped response as a function of SUE. In that case, the region of excess sensitivity is not constrained to the category boundary, but excess sensitivity is predicted in a window around zero.[10] Models of decision by sampling (Stewart et al., 2006) and efficient coding (e.g., Barlow et al., 1961; Laughlin, 1981; Frydman and Jin, 2024, 2022) predict that processing noise for a given stimulus range is decreasing in its empirical density in the stimulus distribution. The degree of imprecision in integrating the numerical signal might also directly depend on the set of categorizations: in the cognitive sciences, a common finding is that more surprising information draws higher attentional capacity (e.g., Itti and Baldi, 2009; Friston, 2005), potentially leaving a lower stock of processing resources to the numerical signal. We empirically explore different determinants of variation in imprecision in Section 6.

Extension: Imprecision in Categories. In practice, a second, distinct form of uncertainty directly affects optimization: uncertainty about the location of the category thresholds, such as the analyst forecast of EPS. Uncertainty about what constitutes the expected level of the announced variable introduces uncertainty about categorizing the surprise.[11] We introduce normal noise about the category threshold that pins down what gets coded as zero surprise, so $\tilde{s} \sim \mathcal{N}(s, \sigma_s^2)$. The noise parameter σ_s^2 captures the degree of dispersion.[12] Technically, this noise parameter can also be thought of as reflecting the difficulty or imprecision in integrating categories, akin to what $\sigma_r^2(s)$ captures for integrating the numerical signal. Notably, Prediction 2 highlights that this empirically distinguishable form of uncertainty yields contrasting and testable implications.

[10]Increasing noise in the absolute magnitude of the signal has been documented in a wide variety of experimental tasks by Enke et al. (2025), who argue that noise is driven by the distance to "simple points" where the DM understands the mapping between parameter and action, akin to category thresholds.

[11]There are three different ways of thinking about analyst forecast dispersion. First, it may capture a given individual's uncertainty about the category threshold, for example because they saw several contradicting analyst forecasts. Second, different individuals may use different benchmarks, but every one of them is certain about their expectations. In the latter case, the resulting behavioral response of the model captures the (equal-weighted) aggregation of individuals with different reference points, each of them behaving constrained optimal according to equation (3).

[12]Note that uncertainty about a reference level is examined in the literature on stochastic reference points (e.g., Sprenger, 2015), but has not been explored with respect to its effect on the shape of the response function.

Prediction 2. *An increase in uncertainty about the location of the category threshold decreases sensitivity for all levels of surprise, but most strongly around the category threshold of zero surprise.*

Discussion. First, we do not microfound the notion that integrating coarse partitions of numerical information is "cognitively cheaper" here but refer the reader to the various existing justifications discussed in the prior literature in Section 1. Second, under this assumption, there are various modeling approaches that can, in principle, generate the key behavioral prediction we derive here. The objective of our empirical approach is to test this shared prediction but not to sharply distinguish between modeling approaches. This class of models has been widely applied across disciplines – including in modeling the implications of cognitive imprecision (e.g., Ilut and Valchev, 2023; Woodford, 2020, 2012; Khaw et al., 2021). Our model aligns well with key ideas in Augenblick et al. (2025). While Augenblick et al. (2025) model an agent who knows the direction of an update but not the strength, in our model people form a conditional prior that depends on comparisons to (potentially multiple) category boundaries.[13] One implication is that our model, applied to belief formation, supports updating in the wrong direction (as often documented in standard belief updating experiments when priors are extreme, e.g., in the data of Enke and Graeber (2023)). This partly results from the fact that we formulate our model in action space, i.e., the signal provides a noisy signal of the optimal action rather than of the signal strength.[14] Moreover, we do not model a binary state space but a continuous one, and people process the quantitative signal with noise, rather than the implied signal strength. In our model (and unlike in Augenblick et al. (2025)), the DM does not form an estimate of the signal strength, but of the optimal response directly. In their model, the conditional expectation of signal strength $\widehat{\mathbb{S}}(s_d)$ "jumps" as the direction of the Bayesian update switches; in our model, the conditional prior jumps at category boundaries. While Augenblick et al. (2025) develop a highly instructive general updating setup that does not require Bayesian updating or any specific functional form, we restrict our attention to a setup with normal estimates, which are similar in spirit to their log-normal setup in updating space. Augenblick et al. (2025) focus on a setup with one qualitative signal (the direction of the update) and one or more quantitative signals; our setup is about (potentially multiple) qualitative signals and one or more quantitative ones. All in all, the foundations of our model are consistent with and build

[13]If there is a single category boundary, $K = 1$, and the optimal response crosses the origin, $r^*(0) = 0$, our setup delivers some similar predictions.

[14]Augenblick et al. (2025) extend their model to incorporate distortions of the prior in Section II.C. In our framework, distortions are formulated directly in action space and can thus accommodate distortions of parameters other than the signal diagnosticity by design.

on Augenblick et al. (2025); but people in our framework know the central tendency of their response to a stimulus category (rather than the direction of an update) and mentally simulate their response (rather than responding to the signal strength). Above and beyond Augenblick et al. (2025), we acknowledge that alternative formulations, such as the feature-specific noise in Bastianello and Imas (2025), may be consistent with our main predictions under specific assumptions. The distinction between categorical and numerical information (or qualitative and quantitative information more generally) is also reminiscent of the distinction between the initial *representation* of a problem, driven by attentional phenomena, based on which the DM then (imprecisely) processes the different components of the problem, the *computational* stage (e.g., Ba et al., 2024).

3 Field Setting: Market Responses to Earnings Announcements

3.1 Data

Setting. Earnings announcements are important events in the financial reporting calendar of U.S. publicly traded companies, heavily scrutinized by investors and analysts alike. These announcements provide a comprehensive overview of a company's financial performance. The key metric often highlighted is earnings per share (EPS), which serves as a critical indicator of a company's profitability. Companies typically release earnings through press releases and conduct earnings calls, during which senior executives discuss the results and provide forward guidance. Analysts and investors closely monitor these earnings surprises, making EPS a focal point of financial analysis and investment decisions.

Earnings Announcements. Our paper focuses on market-adjusted returns around earnings announcements. To study these, we need to determine when investors can first trade on earnings information. Using the Institutional Brokers' Estimate System (IBES) earnings release date and time, we identify the first trading day with available earnings information. If earnings are released before 4:00 PM ET on a weekday, we label that day as the effective earnings date. If released on or after 4:00 PM ET, on a weekend, or on a trading holiday, the next trading day is the effective earnings date. We link IBES data to stock price data from the Center for Research in Security Prices (CRSP) using the mapping file provided by Wharton Research Data Services (WRDS) and restrict the sample to firms with non-missing earnings and consensus (mean) earnings expectations. We use IBES' measure of earnings-per-share in the unadjusted detail file, that is, "street" earnings. This measure is designed to take out the effect of one-time items (Hillenbrand and McCarthy, 2024).[15]

Analyst Expectations. The IBES also provides comprehensive information on analyst expectations and forecasts for EPS for publicly traded companies at various horizons. To quantify uncertainty about a company's earnings, we use the measure of analyst dispersion from Ben-David et al. (2023), defined as "the standard deviation of EPS forecasts divided by the absolute value of the average EPS forecast".

Earnings Surprises. To quantify earnings surprises, we use analyst expectations from IBES. Following DellaVigna and Pollet (2009), we define standardized unexpected earnings (SUE) as:

$$\text{SUE}_{i,t} = \frac{\text{EPS}_{i,t} - E_{t-1}[\text{EPS}_{i,t}]}{P_{i,t-1}} \tag{4}$$

where $\text{EPS}_{i,t}$ is the earnings per share. $E_{t-1}[\text{EPS}_{i,t}]$ is the mean expected earnings per share in the last IBES statistical period before earnings were released. $P_{i,t-1}$ is the last closing price before the earnings announcement. To mitigate the influence of extreme outliers, we winsorize $\text{SUE}_{i,t}$ at the 1% and 99% level.

Market-Adjusted Returns. We use historical data on stock prices, returns, and trading volumes from CRSP. Following Campbell et al. (2001), we define market-adjusted returns as the difference between the stock's return and the return on the value-weighted market portfolio. Specifically, the stock's return (R_i) is calculated as the cumulative total return on the stock (inclusive of capital gains and dividends) over a given period, while the market return (R_m) represents the weighted average cumulative total return of all ordinary common shares traded on major exchanges in the United States stock market.[16] The market-adjusted return (R_{MA}) is then given by $R_{MA} = R_i - R_m$, effectively isolating the stock's performance from broader market movements.

Proxies for Stock Valuation Difficulty. To proxy for the severity of processing imprecision, we leverage the existing literature on what makes stocks "hard to value" (see, e.g., Laarits and

[15]The term "unadjusted" means that earnings were not adjusted by IBES for stock splits. We use data from the unadjusted file because in constructing the adjusted file, IBES rounds estimates and actual earnings to the nearest penny, which can reduce the precision of any earnings surprise measure.

[16]We use market-adjusted returns instead of factor-adjusted returns to avoid noise inherent in estimating factor betas. Further, given that we are focusing on such a narrow window around earnings announcements, the earnings news (rather than e.g., factor news) is likely the main driver of returns.

Sammon, 2024). From this body of work, the measure of "valuation uncertainty" (VU) in Golubov and Konstantinidi (2023) is most closely related to our object of interest, as it captures uncertainty regarding the mapping between fundamentals and stock prices. Concretely, valuation uncertainty, $\text{VU}_{i,t-1}$, of company i at time $t-1$ is defined as the interquartile range of expected firm value given by a multiples-based valuation model at different points in the distribution of a given firm's industry at a given point in time. The measure varies both within companies over time and across companies at a given point in time.[17] We will therefore refer to "observations with high/low valuation uncertainty" rather than "firms with high/low valuation uncertainty", because a given firm might be associated with high or low VU at different times.

Intuitively, high valuation uncertainty means that translating information about, say, earnings, into prices or returns is associated with higher uncertainty. This may be due to a variety of reasons, including attributes that make a firm "more complicated" (e.g., having multiple business segments Cohen and Lou (2012)), cyclical factors (e.g., market or industry environment) that make valuations more difficult or uncertain and the generic difficulty of valuing certain types of assets (e.g., intangible capital (Lev and Gu, 2016)). We do not claim to distinguish between these sources of valuation uncertainty, but rather embrace the multitude of factors contributing to uncertainty about the mapping in line with the broad notion of processing imprecision described in Section 2. That said, the within-stock across-time variation in valuation uncertainty we explore is unlikely to be due to corresponding variation in preference uncertainty.[18]

Data Filtering. To construct our final sample, we start with the set of all CRSP ordinary common shares (share codes 10-11) that are traded on major exchanges (exchange codes 1-3). We then further restrict to stocks which can be matched to IBES, and to stock-quarters with non-missing earnings-per-share and consensus earnings-per-share estimates. Next, we require that each stock-quarter has non-missing data for our measure of analyst dispersion (Ben-David et al., 2023), which requires that at least 3 analysts cover the stock, and a non-zero value for consensus expected earnings. We also require that the stock has a non-missing value for valuation uncertainty. Finally, we require that the stock has non-missing returns on the earnings announcement day itself, and the following four trading days, as well as a non-missing closing

[17] To avoid look-ahead bias, we identify month-end values of VU based solely on information that was public as of that month's end. For each earnings announcement, we use the value from the last month-end before the announcement date.

[18] In our experiments, we are able to manipulate the decision difficulty due to the severity processing constraints more directly, see Section 5.

price on the last trading day before the earnings announcement. After applying these filters, given our standard error clustering strategy, we then remove all singletons both in terms of year-quarters and stocks. This filtering procedure yields a final sample of more than 176,000 earnings announcements for more than 6,000 unique companies between 1986 and 2019.

Summary Statistics. We present summary statistics in Table 1. SUE has a median of zero and a standard deviation of 0.079. EPS are on average \$0.33 with a standard deviation of \$0.72. Market-adjusted returns over the first five trading days on and after the earnings announcement are on average zero, but they exhibit large dispersion. The interquartile range spans from -0.048 to 0.046. The total number of observations in our main regression tables is slightly smaller than the number of observations in Table 1, as they restrict to subsets of the SUE distribution.

Table 1: Summary Statistics

	Obs.	Mean	SD	P25	P50	P75
SUE	176,893	-0.003	0.079	-0.001	0.000	0.002
EPS	176,893	0.327	0.719	0.050	0.250	0.510
Mkt. Adj. Ret	176,893	0.000	0.092	-0.048	-0.002	0.046
Valuation Uncertainty	176,893	0.750	0.232	0.607	0.747	0.894
Dispersion	176,893	0.430	0.449	0.189	0.271	0.450

Notes: This table presents equal-weighted summary statistics for all earnings announcements in our sample. Market-adjusted returns are computed as the difference between the cumulative return on the stock over the first five trading days in which earnings information could be traded on, and the cumulative return on the value-weighted market portfolio over the same period. Valuation Uncertainty and Dispersion are measured as of the last month-end prior to each earnings announcement.

3.2 Event Study Approach

Our main analyses focus on the cumulative market-adjusted returns from the first day the information could have been traded on to four trading days after.[19] Our analyses focus on a relatively short time horizon around the event for several reasons: First, most of the price adjustment to new information should occur on the announcement day or within a few days after, as investors rapidly process and act on the new information (Martineau, 2022). Second, by focusing on a short window around the earnings announcement, the study minimizes the influence of other unrelated news or events that could affect stock prices. Over a longer window, it becomes increasingly likely that other factors (e.g., macroeconomic news, industry developments, or non-earnings-related firm-specific events) will confound the analysis. In other words,

[19]Our results are robust to using different time horizons around the event (Appendix Table A5).

a shorter event window ensures that the observed abnormal returns can be more confidently attributed to the earnings announcement rather than other extraneous variables.

3.3 Market-Adjusted Returns and Earnings Surprises

Descriptive Evidence. We first start by plotting the average stock market response to earnings surprises. Figure 1 (Section 1) displays the raw data on the relationship between SUE (on the x-axis) and market-adjusted returns from the earnings announcement day itself ($t = 0$), to four trading days after the earnings announcement ($t = 4$) (on the y-axis).

The figure shows a pronounced S-shaped response to earnings news on average: the stock market response to earnings news is highly sensitive around zero surprise but fairly insensitive further away from zero surprise. Moving from a SUE of -0.01 to 0.01 is associated with an average difference of 8.56% in cumulative market-adjusted returns from $t = 0$ to $t = 4$.[20] Moving from a SUE of 0.01 to 0.02 is associated with a change of 30 basis points in cumulative market-adjusted returns. Similarly, moving from a SUE of -0.02 to -0.01 is associated with a change of 58 basis points in market-adjusted returns.

The slope of the empirical response function is steepest where the sign of the surprise switches. In terms of the magnitudes of the slope, the steepest part of the curve is observed around the point where SUE is zero and flattens out for larger absolute surprises, where only the magnitude of the surprise varies. Notably, rather than a discrete jump around zero surprise, the pattern exhibits rather smooth diminishing sensitivity. Moreover, there is a clear asymmetry: conditional on the sign of the surprise, returns are far less sensitive to the magnitude of negative surprises than to the magnitude of positive surprises.

This non-linear relationship between market-adjusted returns and earnings surprises is well-established (Freeman and Tse, 1992; Skinner and Sloan, 2002). Several explanations exist: Freeman and Tse (1992) link the S-shape to earnings persistence, where small surprises signal lasting cash-flow changes. Alternatively, earnings management, where firms strive to slightly exceed analyst forecasts, explains the sharp response to small negative surprises but not positive ones (Burgstahler and Dichev, 1997; Bhojraj et al., 2009; Stein, 1989). Recent work highlights

[20]A salient feature of Figure 1 is that for small positive SUEs – which one would think is good news – average market-adjusted returns are negative. This is because many of the surprises in this range are less than 1 penny. Recall that our measure of SUE is the earnings surprise relative to the pre-earnings announcement price, so there will be a range with sub-penny earnings beats e.g., a 5 dollar stock or 100 dollar stock could both have a 1/2 of a cent surprise, and have different SUEs. These sub-penny earnings beats are viewed less favorably by the market than a beat of at least one cent per share. If we re-make this figure with dollar earning surprises, and form bins in one cent increments, the first positive bin (i.e., the bin with surprises of at least 1 cent) has positive average returns, i.e., we restore the expected result.

strategic disclosure by firms withholding modestly positive news to enhance price reactions (Huang et al., 2025). Our subsequent analysis tests predictions of our behavioral framework and shows that the patterns in our data are inconsistent with these alternative explanations.

4 Field Evidence on Valuation Uncertainty and the S-Shape

In this section, we provide basic tests of our first hypothesis: that the difficulty of the decision problem – as proxied by valuation uncertainty – predicts increased sensitivity to the crossing of category boundaries, but is associated with decreased sensitivity within categories.

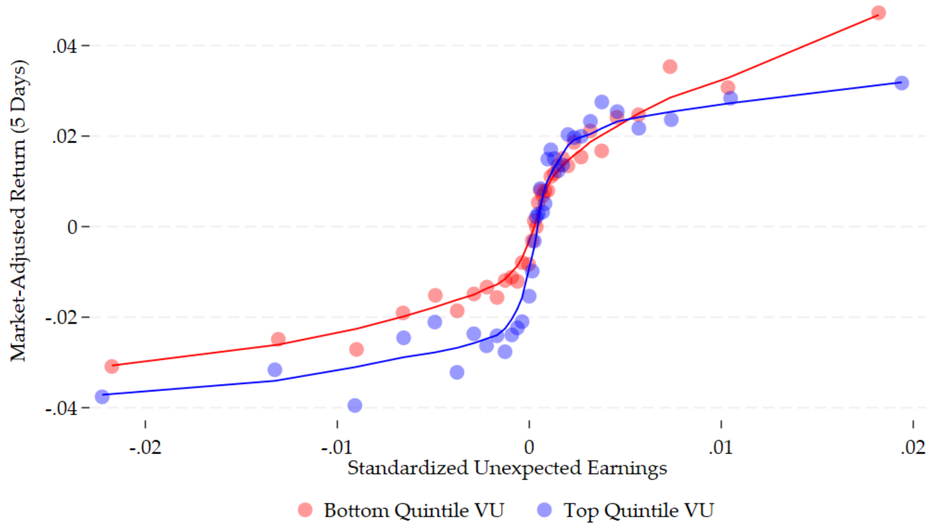
4.1 Raw Data

We begin with a look at the raw data before turning to empirical tests. For illustration, Figure 2 displays the raw data on the relationship between standardized unexpected earnings (on the x-axis) and the cumulative market-adjusted return from $t = 0$ to $t = 4$ on the y-axis, separately for observations with high versus low valuation uncertainty. The red dots show observations with valuation uncertainty in the top quintile, while the blue dots show observations with bottom quintile valuation uncertainty.[21] The figure illustrates that the sensitivity to the sign of the earnings surprise is higher for observations in the top quintile of valuation uncertainty than for those in the bottom quintile of valuation uncertainty. Top quintile VU observations exhibit more negative excess returns for small negative surprises and more positive excess returns for small positive surprises.

These patterns flip once we consider earnings surprises further away from zero. Return responses appear to be less sensitive to the magnitude of surprises for observations with top quintile valuation uncertainty than for those with bottom quintile valuation uncertainty, especially for positive surprises. This plot provides suggestive evidence of a relationship between valuation uncertainty and market-adjusted returns that follows the distinctive predictions of our framework. We next provide more systematic evidence on this relationship.

[21]We choose a window of four days, rather than e.g., one day, as one might be concerned that stocks with more valuation uncertainty might respond slower to news than stocks with less valuation uncertainty. Therefore, focusing on a shorter window of just the earnings day itself might mechanically generate differences between how high and low valuation uncertainty stocks appear to respond to news. In Appendix A, Tables A5 and A6 show that our results are not sensitive to the post-earnings return window we consider

Figure 2: Earnings Responses: Top versus bottom quintile of Valuation Uncertainty



Notes: This figure illustrates the earnings responses under different levels of valuation uncertainty. The x-axis represents standardized unexpected earnings (SUE), calculated as the difference between actual earnings per share (EPS) and mean expected EPS, normalized by the previous closing price ($P_{i,t-1}$). The y-axis shows the cumulative market-adjusted return, reflecting the total return on the stock from the announcement day itself to four trading days after the announcement, minus the value-weighted market return over the same period. The red dots represent data from stock quarters with top-quintile valuation uncertainty, and the blue dots represent data from stock quarters with bottom-quintile valuation uncertainty. Valuation uncertainty is defined as the dispersion in expected market capitalization given by a multiples based valuation method at different points in the industry-year distribution (Golubov and Konstantinidi, 2023).

4.2 Empirical Specification

Baseline Specification. To quantify the stock market response to earnings announcements, we follow Kothari and Sloan (1992) and estimate canonical earnings response regressions of the following form:

$$r_{i,(t,t+n)} = \alpha \mathrm{VU}_{i,t-1} + \beta \mathrm{SUE}_{i,t} + \gamma \mathrm{SUE}_{i,t} \times \mathrm{VU}_{i,t-1} + \delta X_{i,t} + \phi_t + \psi_i + \epsilon_{i,t}, \tag{5}$$

where $r_{i,(t,t+n)}$ is the cumulative market-adjusted return from the first day investors could trade on earnings information to n days later. Our main specification focuses on the cumulative market-adjusted returns from $n = 0$ (the first day investors could have traded on the earnings information) to $n = 4$ (four trading days later). Our key object of interest in this equation is γ, which illustrates how the response to earnings surprises depend on the valuation uncertainty associated with a company i before the earnings announcement at t. To ease interpretation of magnitudes, we normalize VU to have mean zero and a standard deviation of one.

We control for both security (Permno) fixed effects, ψ_i and year-month fixed effects, ϕ_t. With security fixed effects, our regression captures differences in post-earnings announcement returns when for a given stock there is more or less valuation uncertainty. The time fixed effects account for time-variation in average returns around earnings announcements. Our results should therefore be interpreted as exploiting heterogeneity in post-earnings announcement returns in the cross-section *at each given point in time*.

In addition, we control for several time-varying firm-level characteristics in $X_{i,t-1}$: time since listing (age), market capitalization, returns from t-12 to t-2 (the returns typically used to form momentum portfolios), book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months.[22] The logic of including these controls is that being hard to value may be correlated with other characteristics known to predict how stocks respond to earnings news, e.g., growth firms respond differently than value firms (Skinner and Sloan, 2002) and institutions tend to lower their inventory of volatile firms ahead of earnings announcements (Di Maggio et al., 2023). By including these controls, we aim to understand the role of variation in valuation uncertainty *above and beyond* its correlation with these other time-varying firm characteristics. All control variables are computed as of month end for the last month before the earnings announcement. Standard errors are clustered at the stock and year-quarter level.

Estimating Stock-Price Sensitivity Within and Across Categories. Our main prediction concerns the correlation between valuation uncertainty and the sensitivity of stock market returns across a category threshold – for a switch in the sign of the surprise – as well as the sensitivity within-category – as the magnitude of surprises varies. We begin with an “expanding windows” approach: we estimate our main specification for many symmetric windows around zero SUE with varying width. For tiny windows around zero surprise, the slope coefficient picks up the sensitivity of stock market responses to crossing the category threshold. Here, our prediction is that VU is associated with higher sensitivity, corresponding to a positive interaction effect between VU and the earnings response coefficient. As we gradually expand the window size, the earnings response coefficient increasingly *also* captures the sensitivity to the magnitude of surprises on either side. Our prediction is that VU is associated with lower earnings response sensitivity within the category, so that the overall effect of VU decreases as the window size

[22]Table A1 demonstrates the robustness of our results to excluding these control variables and fixed effects.

increases.[23]

Table 2: Effect of Valuation Uncertainty on Earnings Response Coefficients by Earnings Size

	(1)	(2)	(3)	(4)	(5)
SUE Window	$\leq \|0.002\|$	$\leq \|0.005\|$	$\leq \|0.01\|$	$\leq \|0.025\|$	$\leq \|0.05\|$
SUE	17.12***	9.938***	6.473***	3.691***	2.393***
	(0.662)	(0.384)	(0.257)	(0.169)	(0.123)
VU	0.000693	0.000707	0.000814	0.00118**	0.00130**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SUE x VU	2.302***	0.859***	0.254*	-0.261***	-0.331***
	(0.427)	(0.226)	(0.150)	(0.099)	(0.072)
Observations	95,081	133,062	153,221	167,506	173,587
R-squared	0.116	0.112	0.111	0.103	0.095

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

4.3 Valuation Uncertainty and Sensitivity to Surprises

Table 2 shows that SUE is positively and significantly associated with market-adjusted returns across all specifications, i.e., the earnings response coefficient is positive, as expected. Specifically, in column (1), when focusing only on surprises close to zero, a one-unit increase in SUE (defined as a SUE of 0.01 i.e., a 1% surprise in *earnings yield* given our definition of SUE) is associated with a 17.12 p.p. increase in market-adjusted returns ($p < 0.01$). This positive relationship persists under larger surprise windows, though attenuated, across columns (2) through (5), with coefficients ranging from 9.94 to 2.39, all significant at the 1% level.

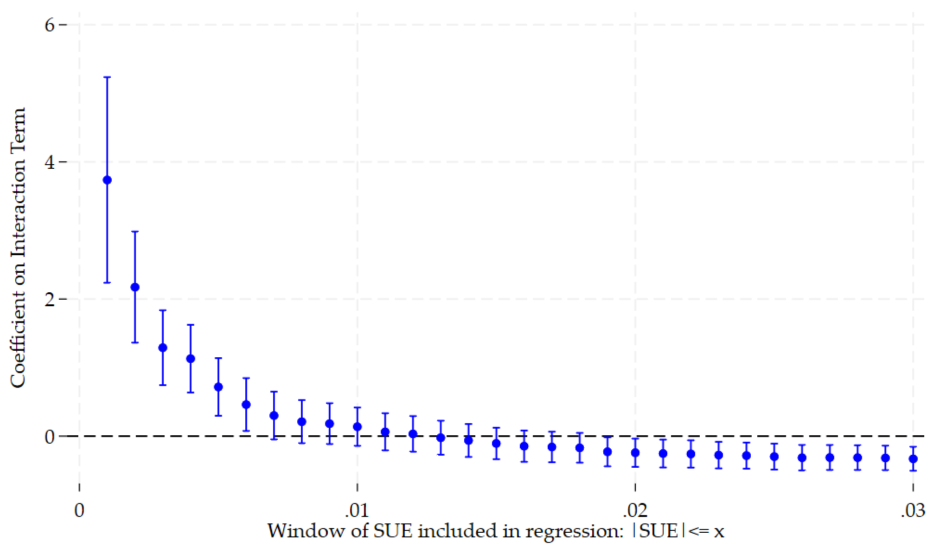
Our main object of interest is the interaction effect between SUE and valuation uncertainty. As predicted by our model, Column 1 reports a positive and significant interaction coefficient for narrow SUE windows around zero. In other words: valuation uncertainty predicts *increased*

[23] In Appendix A.2 we show that our results are qualitatively similar when estimating a pooled specification. Specifically, rather than estimating Equation 5 in expanding windows, we estimate a single regression on the entire sample, and include dummy variables to partition the space of earnings surprises. In the pooled specification, we observe a pronounced amplification of the response to surprises for windows close to zero.

sensitivity to the crossing of a category boundary. Yet, this interaction coefficient falls as we gradually expand the window of support, and finally turns negative and significant for windows larger than 0.01 (see Columns (3), (4) and (5)). This means that valuation uncertainty predicts *decreased* sensitivity to the magnitude of surprises conditional on their sign.

These effects are economically meaningful. For an observation with a one-standard deviation higher valuation uncertainty the market adjusted return is 19.3 p.p. ($p < 0.01$) compared to 17.12 p.p. for an observation with an average valuation uncertainty. This means that a one-standard deviation higher valuation uncertainty predicts increases in the sensitivity to surprises by 13 percent. For a window size of 0.05, a one unit increase in SUE is associated with a 2.4 p.p. ($p < 0.01$) increase in market-adjusted returns for a company with average valuation uncertainty. For a company with a one-standard deviation higher valuation uncertainty this effect is 2.1 p.p. ($p < 0.01$), i.e., it predicts decreases in sensitivity to surprises by 13 percent. For comparison, DellaVigna and Pollet (2009) show that the immediate stock response is 15% lower for Friday announcements than for non-Friday announcements.

Figure 3: Effect of Valuation Uncertainty on Earnings Response Coefficients



Notes: This figure shows the coefficients of the interaction effect between the Standardized Unexpected Earnings (SUE) and valuation uncertainty (VU) for varying sizes of the window of SUE around zero. The smallest window size (i.e., the leftmost coefficient) is +/- 0.002 around zero, and each dot represents adding 0.001 to each side of the window. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. The x-axis represents the window size around zero for standardized unexpected earnings, and the y-axis shows the interaction coefficient. Error bars indicate the 95% confidence intervals for each coefficient.

Figure 3 zooms in on the analysis of the interaction between the earnings surprise and valuation uncertainty for a larger number of window sizes around zero. The figure shows that the interaction coefficient is highly significant and positive for relatively small windows around zero. Consistent with the evidence from the table, the interaction coefficient becomes negative and significant for windows larger than 0.01 of SUE. Taken together, these correlational findings are consistent with the central behavioral prediction of our model. The prediction of a more S-shaped relationship is quite distinctive and thus hard to rationalize with alternative explanations, which we address in the next subsection.

4.4 Robustness

In this subsection, we discuss our findings regarding a series of alternative mechanisms and considerations brought forward in the existing literature.

Definition of Surprise. Is the S-shaped response of stock prices to earnings news a function of how we define SUE? In Appendix A.1, we show that our main findings are robust to a variety of alternative definitions of SUE. In addition, we consider the relationship between post-earnings returns and percentile *ranks* of SUE, as discussed in Hartzmark and Shue (2018). We argue that percentile ranks of SUE would not be well suited to test our hypotheses about the effects of within- versus across-category earnings response sensitivity. There is a substantial mass of observations exactly at $SUE = 0$ (over 10% of our sample) and an even larger mass within a SUE of $\pm$ 0.001 (about 37% of our sample). Consequently, percentile ranks "spread out" a large number of observations at and around $SUE = 0$, which interferes with the identification of the sensitivity around the *nominally defined* category threshold (see results in Appendix A.1).

Firm Size, Time Period, and Return Horizon. As we show in Appendix A.3, our results are robust to restricting to large market capitalization stocks (stocks above the median market capitalization each quarter) and to data after 2010. Our results are thus not entirely driven by small stocks, or data from earlier time periods. Moreover, a significant body of work in finance has studied the long-run response to earnings news, i.e., excess returns up to 90 days after an announcement. Historically, this literature documented a tendency for stocks with good news to continue to outperform, and stocks with bad news to continue to underperform, the so-called post-earnings announcement drift (PEAD). In Appendix B, we explore the relationship between long-run responses to earnings news and valuation uncertainty. In our data, we find patterns consistent with the idea that high VU is associated with overreaction for small and underreaction for large surprise. Yet, these estimates are noisily measured given the increased noise present for the longer time horizon where additional news event shape stock prices.

Earnings Persistence. One possible alternative explanation for the differences in how valuation uncertainty affects the response to earnings news for SUEs close to zero versus away from zero is differences in the persistence of earnings news. For this to explain our results, however, two things would need to be true. First, small surprises for high valuation uncertainty firms would need to be more persistent than small surprises for low valuation uncertainty firms. And second, large surprises for high valuation uncertainty firms would need to be less persistent than large surprises for low valuation uncertainty firms. To test for such differential persistence, we examine the predictive power of an earnings surprise for earnings *growth* over the subsequent year. As we explain in more detail in Appendix A.4, differences in earnings persistence cannot account for our findings.

Earnings Manipulation. A potential concern with our main results is that managers engage in earnings manipulation to ensure a small positive SUE in order to avoid the negative returns associated with missing earnings expectations. Specifically, the concern is that a small earnings miss is a signal of a larger problem at the firm – as management was unable to engineer a positive surprise. And, this signal – rather than SUE itself – explains the significant jump in returns at the category boundary of $SUE > 0$. Further, if companies with more valuation uncertainty have a stronger incentive to engage in earnings manipulation (i.e., the signal for a small earnings miss is perceived by the market to be stronger), this might explain our results on heterogeneity in the S-shaped response to earnings news. If this was the case, we would expect to see more bunching of earnings news just above zero for high VU stocks. As we explain in Appendix A.5, we do not see pronounced differences in bunching across high and low VU observations. Moreover, our results on earnings persistence (described in the previous paragraph) are also inconsistent with systematic differences in earnings manipulation by valuation uncertainty.

Accounting for Accruals. One potential concern is that firms with high valuation uncertainty may be more likely to use accruals to engineer small earnings beats. We address this concern by re-estimating our main specification controlling for abnormal accruals, and interactions of accruals with SUE. Appendix Table A11 shows that positive accruals per se predict more negative market responses, especially for values of SUE close to zero. Yet, controlling for accruals leaves the estimated interaction coefficient between SUE and VU virtually unchanged.

Differences in Pre-Announcement Information Acquisition. One concern with the results in Table 2 is that they might be driven by differences in the amount of information incorporated into stock prices *before* the earnings announcement itself between high and low valuation uncertainty stocks and depending on the size of the surprise. As we outline in more detail in Appendix A.8, we conduct a series of tests which show that, if anything, *more* information is incorporated into prices ahead of time for high VU stocks – which would work against our main finding. We conclude, therefore, that differences in the incorporation of information pre-announcement are unlikely to be driving our baseline results.

Effect of Contemporaneous News Releases. One potential concern with the results in Table 2 is that they may not reflect a nonlinear reaction to earnings news itself, but instead arise mechanically from the presence of other contemporaneous disclosures that are also nonlinearly related to SUE. For example, if managerial EPS guidance is issued at the same time as earnings announcements – and if that guidance exhibits an S-shaped relationship with SUE – then the observed return pattern may be driven by market reactions to the guidance rather than to the earnings surprise alone. To address this possibility, Appendix A.10 restricts the sample to observations with no contemporaneous management EPS guidance. Table A16 confirms that our baseline results from Table 2 are nearly identical on the no guidance subsample. Together, these findings suggest that our results are not driven by the correlation between SUE and contemporaneous disclosures or by market reactions to such disclosures.

4.5 Uncertainty About the Location of Category Thresholds

Our framework makes distinct predictions about different forms of uncertainty. While uncertainty about the mapping of earnings to stock valuations increases sensitivity around category thresholds (Prediction 1), uncertainty about the location of category thresholds decreases sensitivity (Prediction 2). In this subsection, we examine how prior uncertainty about the category threshold in our setting – the consensus forecast – affects the sensitivity of stock prices to news. We proxy this uncertainty with dispersion of analysts' earnings forecasts.

Specification. To estimate heterogeneous earnings response sensitivity by degree of forecast dispersion, we estimate the following specification:

$$r_{i,(t,t+n)} = \alpha \text{SUE}_{i,t} \times \text{Dispersion}_{i,t-1} + \beta \text{SUE}_{i,t} + \gamma \text{Dispersion}_{i,t-1} + \delta X_{i,t-1} + \phi_t + \psi_i + \epsilon_{i,t}, \quad (6)$$

where $\text{Dispersion}_{i,t-1}$ is the standard deviation of analyst forecasts for the earnings of company

i in the last IBES statistical period before the earnings announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). We include the same set of controls and fixed effects as in the previous section.[24] This measure thus captures the extent of analyst uncertainty about a company's earnings before the earnings announcement. Again, to ease interpretation, we normalize Dispersion to have mean zero and standard deviation one.

Results. Table A2 displays our results on analyst dispersion. The first column again confirms the expected baseline positive earnings response coefficient, i.e., a strong positive relationship between SUE and market-adjusted returns, with a coefficient of 16.49 ($p < 0.01$). The interaction term between SUE and dispersion is *negative* (-1.40, $p < 0.01$), suggesting that the effect of SUE on returns is significantly diminished when analyst dispersion is high, consistent with our predictions and inconsistent with the idea that uncertainty per se leads to a more pronounced S shape.

The interaction coefficient remains negative and significant at the 1% level for larger windows of SUE of 0.005, 0.01, 0.025 and 0.05. The magnitude of the effects of analyst dispersion on earnings responses is sizable. For a window of 0.002 a one-standard deviation increase in analyst forecast dispersion decreases the earnings response by almost 10 percent. For a window of 0.005 the magnitude of the response is reduced by 5 percent.

Taken together, the evidence clearly highlights that uncertainty about the location of a category threshold is associated with earnings response insensitivity across the board, and especially so close to the category threshold. This evidence mitigates concerns that our findings on valuation uncertainty can be explained by unobservables that are correlated with our uncertainty measure.

Relationship Between Dispersion and Valuation Uncertainty. Measures of category uncertainty might be correlated with valuation uncertainty and alternative measures of processing constraints more generally. Appendix Table A12 shows a pairwise correlation matrix with a set of related measures. We estimate a correlation of 0.3 between VU and Dispersion. Given this positive correlation and the opposing effects of these different measures on returns, our main estimates of the effect of VU on the S shape might be downward-biased. Table A4 shows that, if anything, our results on the amplifying effect of valuation uncertainty for small surprises become stronger after controlling for dispersion.

[24]Table A3 examines robustness to the exclusion of controls.

4.6 Related Concepts and Measurements

As illustrated by the preceding analysis and the conceptual framework, different forms of uncertainty capture different concepts with distinct behavioral predictions.

Different Concepts. We conceptualize decision difficulty as creating uncertainty about the mapping between a signal and one's optimal response. This is often characterized as people attending to a specific information while struggling to precisely incorporate it into their response. This form of uncertainty, hence, at least partly operates on the *intensive* margin of attention: people process signals but imprecisely. A related yet different concept is the idea that distraction might induce (some) people to not attend to a signal at all. This channel operates on the *extensive* margin of attention: variation in information content cannot affect behavior if it is not processed to begin with. The existing literature on measures of distraction highlights this latter channel: multiple same-day earnings announcements, extreme macro news, Friday earnings announcements and the occurrence of major sports events plausibly affect which fraction of investors attend to a given firm announcement versus not, but do not necessarily shift uncertainty about how to map the announcement into a best response (conditional on attending). We deem this distinction important: inattention is unlikely to generate the pattern that we identify, because our proposed channel relies on people actually processing (at a minimum) the categorical information content, and is compatible with people attending to numerical information as well. Distraction, by contrast, would lead to global attenuation because (some) people do not process and respond to any of the information components.

Alternative Measurements. Among the many proxies for "hard-to-value," valuation uncertainty appears to be the closest measure to our characterization of processing constraints. This is because, by definition, it suggests that for a given firm at a given point in time, there is a wider possible range of valuations. This translates directly to the idea in the model of the mapping between numerical signals and best response.

The literature on what makes stocks hard to value, however, discusses many other possible measures. First, a longer cash-flow duration may make a stock harder to value because investors need to forecast fundamentals further in the future to accurately estimate the stock's true value today. Cash-flow duration might partly affect the mapping uncertainty we are interested in, while it seems unrelated to the concepts of uncertainty about category thresholds as well as distraction. It clearly also captures features unrelated to the severity of processing constraints, as e.g., some companies have different payout ratios at different points in their life cycles. Appendix Table A13 shows that cashflow duration is associated with a more pronounced S-shaped pattern. Second, the literature has also used measures of whether a company spans many business functions/geographical regions (Cohen and Lou, 2012), idiosyncratic volatility and trading volume (Ben-David et al., 2023) as proxies for valuation uncertainty. Appendix Table A13 shows that amplification of small surprises and the comparative static of a decreasing interaction coefficient for larger surprises holds for all three of these other proxies of valuation uncertainty.

5 Experimental Evidence

To provide causal evidence on the relationship between decision difficulty and the S-shaped empirical earnings response function, we complement the correlational field evidence with incentivized experiments conducted with investors. Screenshots of the core experimental instructions are available on the following link: `https://raw.githubusercontent.com/cproth/papers/master/CoarseCategories_instructions.pdf`.

5.1 Design

Baseline Setting. Participants receive a hypothetical earnings news article about a real company, which has their actual quarterly earnings announcement scheduled within five days of the study. While the earnings news piece is created by us for the purpose of this experiment, it closely follows the structure and information of real earnings news coverage and includes real-time information about the company. The news article mentions (i) the company's consensus forecast of EPS (actual value at the time of experiment), (ii) the current stock price (actual value), (iii) a realization of the EPS, which is the earnings scenario that we vary across participants, (iv) categorical information about whether realized EPS beat or miss the consensus forecast, which is also mentioned in the headline, and (v) very basic firm background for context.

The earnings scenario – characterized by a realized EPS – is determined by randomly drawing a value for the implied standardized unexpected earnings (as defined above) from +/- [0.0001, 0.0005, 0.001, 0.005, 0.01] and by then calculating the implied EPS value.[25] This range of SUE captures over 85% of the empirical distribution. See below the body of the earnings news article for the company *Darden Restaurants* for the scenario of an SUE of -0.0005.

[25]The firm's realized earnings are calculated based on the firm's actual consensus forecast of earnings, its actual stock price at the time of the experiment, and this SUE.

> Darden Restaurants, Inc. is an American multi-brand restaurant operator headquartered in Orlando, Florida. In their earnings announcement for the third quarter of 2024, Darden reported earnings below market expectations. Trading at a stock price of $164.73 prior to the announcement, Darden reported earnings per share of $1.94. Darden therefore earned 3.96% less than analysts expected, given the consensus forecast of $2.02 earnings per share.

Participants are asked to consider the scenario that the upcoming, actual earnings announcement of the company was actually occurring *right now*,[26] and the actually announced EPS equals the displayed realized earnings. The main task is to then predict the change between the current stock price (which in the scenario is the stock price right before the earnings announcement) and the same-day closing price. Our baseline task thus provides the standard set of numerical information provided in earnings news coverage alongside the most common categorization as beating or missing the forecast (also mentioned in the header), emulating the type of simultaneous provision of coarse and granular information structures that motivates this paper.

We present five independent scenarios to participants, each about a different real U.S. company with a quarterly earnings announcement occurring within the five days following the data collection. For each participant, we randomly draw the order of the companies as well as the SUE realization.

Incentives. In addition to a $1.70 base payment, one out of 10 participants is randomly drawn to be eligible for a $50 bonus, with one round randomly selected as the round-that-counts. An eligible participant wins $50 if two conditions are met: First, the standardized unexpected earnings implied by the company's actual earnings announcement (in the days following the study) falls within 10% of the scenario provided.[27] Second, the participant's stock price prediction must fall within 1 percentage point of the actual change observed on the announcement day.

Treatments. Participants are randomly assigned (with equal probability) to one of the following two between-subject conditions: *Baseline* and *High Constraints*. Relative to the *Baseline* condition, the *High Constraints* condition attempts to increase decision difficulty in the specific

[26]The full data collection was conducted between late morning and early afternoon EST, in the time window earnings announcements are most common.

[27]In a follow-up question at the end of the study, participants estimated the likelihood to be 56.54% on average, suggesting that they viewed the task as relevant for their payoff.

sense of increasing the severity of information processing constraints. We do so in two complementary ways. First, we effectively manipulate the "demand side" of processing constraints by increasing the information load of the task without adding any information that should affect estimates. In particular, in addition to the exact same earnings news presented in *Baseline*, *High Constraints* displays further background information on the company's history that is neutral in character and irrelevant for the price movement on the announcement day. To provide an example, below is an excerpt of the irrelevant information provided for one company:

> Darden is an American multi-brand restaurant operator headquartered in Orlando, Florida. Darden has more than 1,800 restaurant locations and more than 175,000 employees, making it the world's largest full-service restaurant company. The company began as an extension of Red Lobster, founded by William Darden and initially backed by General Mills. Red Lobster was later sold in July 2014.

Second, we manipulate the "supply side" of processing constraints by limiting the processing capacity available to respondents in this condition. Specifically, to remain eligible for a bonus payment, respondents need to submit their estimate in a given round within a time limit of 40 seconds, effectively inducing time pressure. In *Baseline*, median response time was 25 seconds (25th percentile: 15 seconds; mean: 47 seconds, 75th percentile: 45 seconds). Respondents almost always complied with the time limit: we recorded 6.7% timeouts across all rounds and participants.

Notably, the *High Constraints* condition manipulates a specific determinant of decision difficulty: how the demand for cognitive processing resources relates to available capacity. In general, as discussed in Section 2, decision difficulty can also capture other sources, such as uncertainty about preferences. While our field data does not allow to disentangle these conclusively, our experiments do.

Predictions and Category Defaults. In each round, we elicit the same-day price change prediction in percent and restrict the entry range to a window ranging from -15% to +15% of the current stock price. We analyze the prediction data in two pre-registered formats. First, we analyze the raw predictions. Second, we also elicit *category defaults*, which is a respondent's best estimate of the historical average of same-day percent price change for companies who beat the forecast, and for those who missed the forecast.[28] These category defaults are the direct empirical analogue of the conditional default response r_d, see Section 2. Equipped with

[28]The specific question we ask is: "Historically, what do you think was a company's average stock price change on a day where announced earnings [exceeded / fell below] the consensus forecast?"

each respondent's individual category defaults, we can express their predictions in a specific firm scenario in relation to the corresponding category default, which we refer to as our *normalized predictions*. Specifically, predictions of price changes for positive (negative) surprises are divided by the respondent's category default for positive (negative) earnings surprises. The normalized predictions have the intuitive interpretation that a stated prediction that equals the individual's category prior equals a value of one. Our findings are similar for both measures.

Discussion. Two remarks about the experimental design are in order. First, our *High Constraints* manipulation intends to manipulate the severity of processing constraints in ways that have some ecological validity and appear practically relevant: on financial markets, investors routinely face large amounts of information, some of which is technically irrelevant to a given valuation, and are time-constrained in their decisions (Hirshleifer and Teoh, 2003). That said, the intervention is not meant as a tool to precisely identify different cognitive channels. For example, one might draw a distinction between individuals not processing some component of information altogether (a form of selective attention) versus individuals attending to but not fully (or imprecisely) integrating a piece of information. We believe that both channels are important in practice, and additional experiments could be used to disentangle them.

Second, how strongly people respond to different components of information – especially under constraints – is likely a function of the extent to which they have encountered and deliberated about a given signal in the past. This applies to both numerical and categorical information. It is plausible that a relatively stronger reliance on categorical information is a function of how familiar people are with the corresponding categories. In our context, earnings beats and misses is the most common set of categories for investors, so we might expect them to have a good sense of their category defaults.

5.2 Sample

The data collection took place in December 2024 and was pre-registered on AsPredicted (#205080; `https://aspredicted.org/n3zm-md9t.pdf`). The pre-registration includes the experimental design, hypotheses, outcomes, sample size, and exclusion criteria. We recruited participants on Prolific, a widely used online platform. Our final sample comprises data from a total of 1,000 U.S. investors who successfully completed the experiment. All of our participants have an account on a trading platform and are at least 18 years of age.

Comprehension Questions and Exclusion Criteria. We pre-specified that respondents who fail to pass a set of three comprehension questions on the instructions within the first two attempts are not allowed to proceed with the study. We do not screen on prior knowledge; rather, the correct answers are mentioned in the instructions. The three comprehension questions test whether people have understood the general instructions about earnings announcements and stock responses. 9% of the respondents who started the experiment failed the comprehension check and were thus not allowed to participate. To ensure our data only include investors who have at least some basic understanding of the setting, we further pre-specified the exclusion of respondents who believe the historical average same-day price reaction was non-positive for positive earnings surprises or non-negative for negative earnings surprises. After applying these exclusions, we end up with a final sample size of 897 respondents.[29]

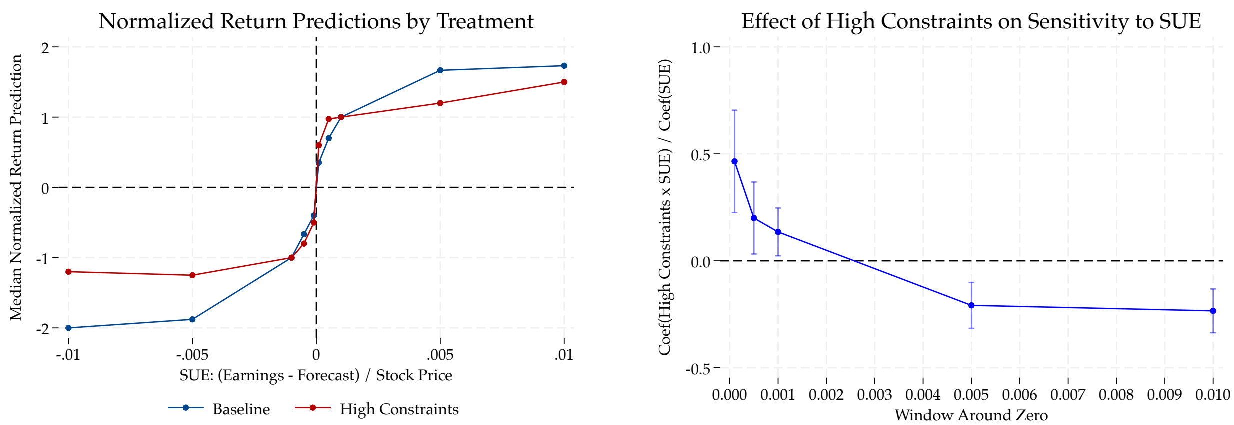
5.3 Results

Result 1: Shape of the Empirical Response Function in *Baseline*. The blue markers in Panel (a) of Figure 4 plot the median normalized return prediction for each SUE value in *Baseline*. The blue line illustrates the implied slope. Even in our simple baseline condition without any additional complications, we find that the data from our individual prediction experiment exhibit a pattern that is qualitatively highly similar to the price patterns observed in the field data: the response function exhibits a pronounced S shape. Median return predictions are very sensitive to crossing the category threshold – from missing to beating expectations – but are far less sensitive to the magnitude of a surprise (conditional on its sign).

Result 2: Processing Constraints and Price Predictions. Next, we test for the effect of the treatment manipulation on the sensitivity of the price change predictions to variation in surprises. The red markers in Panel (a) of Figure 4, showing predictions in *High Constraints*, follow a noticeably more S-shaped pattern than the empirical response function of condition *Baseline*. We document the distinctive prediction of our framework that implies three different crossing points of the implied response functions: first, the implied slope around zero surprise is steeper in *High Constraints* than in *Baseline*, meaning that more severe processing constraints cause more extreme predictions for small surprises, i.e., more positive (negative) predictions for small positive (negative) surprises. Focusing on either only positive or only negative surprises, however, the implied slope of the response function is *lower* in *High Constraints*. As a result, the directional effect of more severe processing constraints *reverses* for sufficiently large absolute

[29] Our findings also hold for a sample that does not apply these pre-specified exclusion criteria.

Figure 4: Experimental Results



a) Raw Data

b) Main Treatment Effect Coefficient Plot

Notes: This figure presents the main evidence from the experiment with 897 respondents. Panel (a) presents the median return predictions across all treatment cells. The blue line depicts data from respondents in the baseline condition, while the red line displays data from the high constraints condition. Panel (b) presents the coefficients on the interaction term between SUE and the high constraints dummy for varying window sizes of SUE.

surprises: *High Constraints* causes more extreme predictions for small positive and negative surprises yet less extreme predictions for large positive and negative surprises. In our data, these two crossing points happen to be symmetrically located at SUE values of -0.001 and $+0.001$. At those values, median normalized predictions in both conditions equal one, meaning that respondents state predictions equal to their two category defaults at the median.

To test the statistical significance and size of these effects, we pre-specified an approach that mirrors our analyses for the field data. We estimate a simple regression equation of the following form:

$$r_{ij} = \alpha High\ Constraints_i + \beta SUE_{ij} + +\gamma SUE_{ij} \times High\ Constraints_i + \varepsilon_{ij} \qquad (7)$$

where r_{ij} is the response (a price change prediction) of individual i for company j. $High\ Constraints_i$ is an indicator taking value one for respondents in *High Constraints* and value zero for respondents in *Baseline*. SUE_{ij} denotes the size of the surprise for company j encountered by individual i. Our key object of interest is the coefficient on the interaction term between SUE and *High Constraints*, γ. Following the approach used in the observational data, we run this regression repeatedly for expanding symmetrical windows around zero SUE. To account for the effect that the local sensitivity to SUE also changes in *Baseline*, we normalize the interaction coefficient by dividing by the coefficient on SUE, β.

Panel (b) of Figure 4 presents the resulting estimates ($\hat{\gamma}/\hat{\alpha}$) for expanding symmetric ranges of surprises. The coefficient of about 0.5 for the smallest window around zero SUE means that more severe processing constraints increase the sensitivity to SUE by 50% ($p < 0.01$), relative to *Baseline*. As we gradually increase the window size, the interaction coefficient falls, eventually turning negative once we include data with SUE > 0.001. For the full dataset, the interaction coefficient equals -0.2 ($p < 0.01$), indicating a 20% lower sensitivity to SUE compared to Baseline. Appendix Table A18 provides these results in regression format. Taken together, these patterns show that respondents in *High Constraints* are significantly more responsive to the crossing of category thresholds, yet less sensitive to the numerical magnitude of surprises. We interpret these results as indicative that the correlation between valuation uncertainty and the S shape in excess returns may partly be a result of how individuals' beliefs respond to the severity of processing constraints.

Robustness. We conduct a battery of pre-registered robustness tests and sensitivity analyses, summarized in Appendix C. As illustrated in Figure A6, results remain robust when we (a) use raw rather than normalized price change predictions; (b) do not normalize the interaction coefficient by the *Baseline* slope; (c) analyze means instead of medians; (d) exclude timeouts in the *High Constraints* condition (6.7%); (e) exclude participants reporting online information searches (5.24%); and (f) drop observations where predicted price changes contradict the sign of earnings surprises (7.6%).

6 Local Variation in Processing Constraints

Our empirical analyses so far have focused on the main qualitative pattern of the earnings response function: high sensitivity at category thresholds and insensitivity elsewhere. Under constant imprecision for all earnings announcements, our model predicts a symmetric and step-shaped (rather than S-shaped) response function. We thus left two key features of the actual empirical relationship unexplored. First, rather than exhibiting a discontinuous step-function, returns display a smoothly diminishing sensitivity around zero surprises. Second, the response function exhibits a pronounced asymmetry: reactions to negative surprises are substantially muted compared to those for positive surprises. In the model, these patterns can only result from differences in the precision of integrating large versus small and positive versus negative earnings surprises, respectively. This section investigates two hypotheses from behavioral economics and cognitive science regarding variation in local processing constraints.

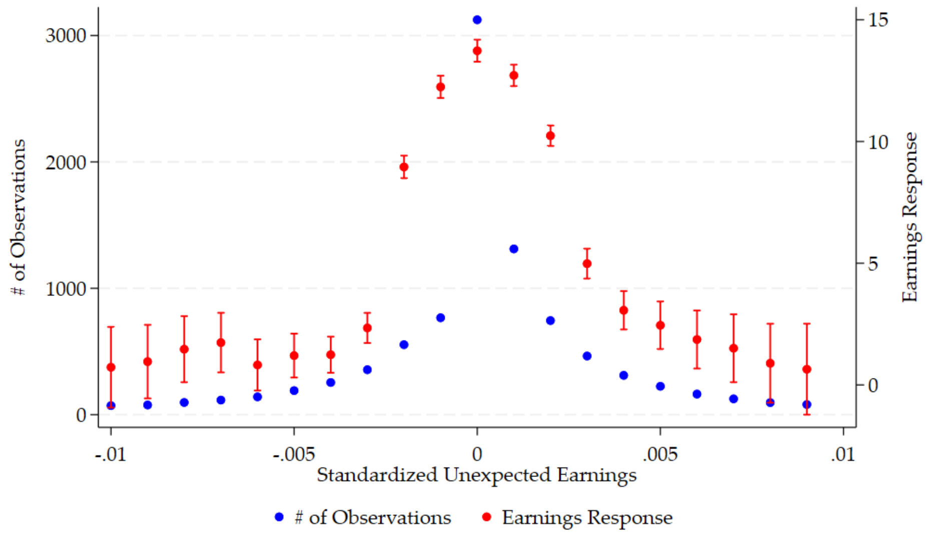
6.1 The Role of Stimulus Frequency for Processing Accuracy

A central hypothesis in cognitive science asserts that stimuli encountered more frequently are processed more accurately, as prominently articulated by the principle of *efficient coding* (Barlow et al., 1961; Laughlin, 1981). This principle posits that sensory systems optimize stimulus representation within biological constraints, leading to greater sensitivity in stimulus ranges with higher empirical density. Originally applied to lower-level cognitive processes such as perception (e.g., Girshick et al., 2011; Wei and Stocker, 2015), efficient coding has recently influenced economic models (e.g., Woodford, 2012) and empirical analyses of subjective value (Polanía et al., 2019), estimation accuracy (Heng et al., 2020), and risk-related choices (Frydman and Jin, 2022, 2024). A complementary perspective, *decision by sampling*, similarly predicts higher discriminability in denser stimulus regions, proposing that subjective valuations arise from comparisons to memory-based samples (Stewart et al., 2006; Stewart and Simpson, 2008).

Stimulus Frequency and Local Earnings Response Sensitivity: Illustration. To empirically approach this hypothesis, we first correlate the local sensitivity to variation in earnings magnitudes, i.e., the local earnings response coefficient (ERC) in a given window of surprises, with the relative frequency of that stimulus window. Specifically, we partition earnings surprises into SUE bins of width 0.001. The blue markers in Figure 5 plot the total number of observations in each bin. We make two main observations: First, the historical distribution is strongly bell-shaped with mass concentrated around zero surprise (11.8% of the data is clustered at exactly zero surprise). This is unsurprising: larger surprises should happen less often. Second, there is a pronounced asymmetry: positive surprises are more common (52.9%) than negative surprises (35.3%).

To illustrate the relationship with local earnings response sensitivity, we next run standard earnings response regressions in 5-bin rolling windows, i.e., for each SUE bin, we run a regression that includes observations in that bin as well as the two adjacent bins on either side. The red markers in Figure 5 indicate the locally estimated earnings response coefficients with 95% confidence intervals. The shape of the distribution of local earnings response coefficients tracks the distribution of data mass. ERCs are generally higher for less extreme surprises and higher for positive bins than the corresponding negative ones. Note that this evidence directly speaks to the two features of the overall shape of the empirical response function that our previous analyses did not speak to: diminishing sensitivity away from zero surprise and a pronounced positive-negative asymmetry.

Figure 5: Historical Stimulus Frequency and Earnings Response Coefficients



Notes: First, we assign stocks into bins of SUE in increments of 0.001. Dots are centered at the minimum SUE within each bin, so e.g., the dot at exactly zero contains SUEs in the interval [0, 0.001). Each blue dot represents the number of observations in that bin. Then, in 5-bin rolling windows, we run an earnings response regression of cumulative market-adjusted returns from the day of the earnings announcement ($t = 0$) to the close 4 days after the earnings announcement ($t = 4$) on SUE. The red dots represent the earnings response coefficient, and the red lines represent a 95% confidence interval.

Regression Analyses. To formally test the hypothesized relationship, we first estimate a kernel density on the historical distribution of surprises with 100 points. In line with the analysis in Table 2, we restrict our attention to SUEs between −0.05 and +0.05, corresponding to 98% of the data. Then, we run the following regression:

$$\begin{aligned} r_{i,(t,t+n)} = {} & \beta_1 \text{SUE}_{i,t} + \beta_2 1_{\text{SUE}_{i,t}<0} + \beta_3 1_{\text{SUE}_{i,t}<0} \times \text{SUE}_{i,t} \\ & + \gamma_1 \text{SUE}_{i,t} \times ln(\text{D}_{i,t}) + \gamma_2 1_{\text{SUE}_{i,t}<0} \times ln(\text{D}_{i,t}) \\ & + \gamma_3 1_{\text{SUE}_{i,t}<0} \times \text{SUE}_{i,t} \times ln(\text{D}_{i,t}) + \theta X_{i,t} + \omega ln(\text{D}_{i,t}) + \phi_t + \psi_i + \epsilon_{i,t} \end{aligned} \tag{8}$$

$\text{D}_{i,t}$ is the kernel density estimate for the point closest to a given observation's SUE and $X_{i,t}$ are the same controls as in Section 4. In Equation 8, we use the natural logarithm of density rather than the density itself, as the distribution of $\text{D}_{i,t}$ is heavily skewed, with over 10% of the data mass concentrated exactly at an SUE of zero. Finally, to ease the interpretation of the regression coefficients, we normalize $ln(\text{D}_{i,t})$ so that it takes a value of 1 when SUE is exactly equal to zero.

The results are shown in Table 3. Column 1 replicates the baseline earnings response regression (restricting to SUE $\in [-0.05, 0.05]$) with both a linear term for SUE (capturing sensitivity to numerical magnitude) and a category indicator for negative SUE. Column 2 adds the log density and its interaction terms. We first examine the effect of conditioning on density (including its interactions) on the effect of switching the category from an earnings beat to an earnings miss. We find that this reduces the effect by approximately 50%.[30] This result is consistent with the idea that about half of the jump that a piecewise linear model attributes to the category switch might be explained by local variation in the frequency of data.

Next, we turn to the role of the historical distribution for the observed slope asymmetry between positive versus negative SUE. The baseline difference in estimated slopes for positive versus negative SUE is large: the estimated sensitivity to the magnitude of positive surprises is 2.7, and it is 2.5 lower for negative surprises. Upon including the log data density and its interactions, the estimated difference in slopes is dramatically reduced from −2.5 to −1.04, a 58% reduction. This suggests that a substantial portion of the empirical asymmetry between positive and negative surprises in Figure 1 can be explained away when accounting for the fact that negative surprises are far less common. Consistent with this, Appendix A.1 shows that percentile ranks (constructed so each bin contains equal historical density) exhibit an approximately linear relationship with excess market returns.

Taken together, we find evidence that is compatible with the idea that decision difficulty – and thus, processing imprecision – is lower for more frequently encountered stimuli, allowing us to demonstrate the potential relevance of these principles for higher-level cognitive tasks in a relevant economic field context.

6.2 Surprise and Competition for Attention

Our principal hypothesis is that decision difficulty increases reliance on easier-to-process problem components. This means more binding cognitive constraints can create competition between processing coarse categorical and granular numerical information. We have so far assumed differential processing cost, but not modeled such competition directly. A prominent principle in the cognitive sciences is that more *surprising* information requires more processing resources (e.g., Friston, 2005; Itti and Baldi, 2009).[31] Surprising news therefore, may reduce

[30] Specifically, the effect in Column 1 was −3.09%. After including the baseline effect and the interaction term with density—evaluated at SUE = 0, where we have normalized $\ln(D_{i,t}) = 1$ we obtain a total effect of $-3.4\% + 1.87\% = -1.53\%$, which is roughly half of −3.09%.

[31] The special role of surprises for shaping attention has previously been studied in other economic contexts (e.g., Bordalo et al., 2020). In rational inattention models (Sims, 2003), Shannon information cost implies that agents' cognitive processing effort scales with the informativeness of signals. As a result, more surprising events are more cognitively costly to process.

Table 3: Historical Density and Earnings Response Sensitivity

	(1)	(2)
SUE	2.714***	1.739***
	(0.124)	(0.180)
$1_{SUE<0}$	-0.0309***	-0.0340***
	(0.001)	(0.002)
$1_{SUE<0}$ x SUE	-2.494***	-1.044
	(0.141)	(0.756)
ln(Density)		-0.0181***
		(0.001)
ln(Density) x SUE		0.718***
		(0.054)
$1_{SUE<0}$ x ln(Density)		0.0187***
		(0.002)
$1_{SUE<0}$ x SUE x ln(Density)		-0.578***
		(0.130)
Observations	173,587	173,587
R-squared	0.115	0.128
Fixed Effects	YQ + Permno	YQ + Permno
Controls	ALL	ALL

Notes: This table studies how the density of the data in a given range of SUEs affects earnings responses. For this exercise, we restrict to SUEs between -0.05 and 0.05, and estimate a kernel density with 100 points. Column 1 is an earnings response regression restricted to the subset of data with SUEs between -0.05 and 0.05, allowing for a differential level and slope effect for SUEs less than zero. Column 2 includes the kernel density estimate from the point in the kernel density function closest to a given observation's SUE (the variable "Density"), as well as interactions between Density and SUE, the indicator variable for negative SUE, and the interaction term between the indicator variable for negative SUE and SUE itself. Clustered standard errors are reported in parentheses. Significance levels are denoted as follows: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

the capacity to process remaining information. Applied to our setting, a natural question is whether a more surprising category realization – a profit when a loss was expected, compared to a profit when a profit was expected – consumes greater cognitive resources, reducing the capacity to process granular numerical information. This question explores direct competition between categorical and numerical information, leveraging the link between surprise and processing load.

In a set of additional empirical analyses, we find that returns exhibit significantly lower sensitivity to numerical earnings information when categorical outcomes deviate unexpectedly from market expectations. For example, firms experiencing earnings growth when a decline was expected by the market display diminished responsiveness to the numerical magnitude of earnings surprises, consistent with the notion that surprising categorical outcomes redirect limited cognitive resources away from detailed numerical processing. We report similar findings for other categorizations, e.g., profits versus losses. Appendix D provides additional details on the empirical strategy and all results. Taken together, these analyses use the degree of surprise in an easier-to-process piece of (categorical) information to predict the responsiveness to harder-to-process (numerical) information, directly speaking to a well-established cognitive principle in an economic field setting.

7 Conclusion

We hypothesize that decision difficulty increases the reliance on easier-to-process problem components. We apply this idea to the competition between categorical and numerical information in a high-stakes field setting and using incentivized experiments. A class of models makes the distinctive prediction that higher decision difficulty, by creating processing imprecision, leads to *sharpening* across categories of news and *flattening* within-category: this yields step-shaped or S-shaped behavioral response functions around category thresholds.

Using a dataset of over 176,000 earnings announcements from the field, we provide evidence of more pronounced S-shaped response functions for stocks that are harder to value. We confirm our findings with incentivized individual belief formation experiments with investors that leverage causal manipulations of processing constraints. We then exploit local variation in decision difficulty in the field. We document evidence in support of the idea that processing accuracy is higher for more frequently encountered stimuli, suggesting that additional properties of the empirical earnings response function – smoothly diminishing sensitivity and an asymmetry between negative and positive surprises – may be partly explained by an account of behavioral responses to limited processing capacity.

Our approach provides a blueprint for studying concepts like decision difficulty in the field: for the case of coarse versus granular information, our tests require two main ingredients. First, a selection of relevant categorizations that decision makers face in practice. These can be readily identified in practical applications, e.g., using news reporting. Second, empirical proxies that capture variation in decision difficulty. Here, too, one can leverage existing measures (such as proxies of what makes a stock hard to value) and resort to characteristics of the decision environment that previous work argues should be related to processing difficulty (such as historical stimulus frequency or the degree of surprise).

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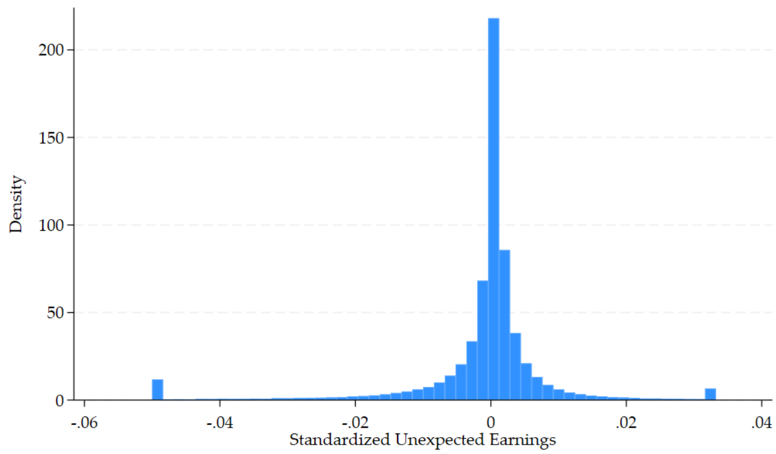
Coarse Categories in a Complex World

Thomas Graeber Christopher Roth Marco Sammon

A Additional exhibits for field data on earnings responses

Appendix Figure A1: Histogram of SUE



This figure presents a histogram of Standardized Unexpected Earnings (SUE) in our sample. SUE is calculated as the difference between the actual earnings per share and the consensus forecast, divided by the closing price before the earnings announcement (DellaVigna and Pollet, 2009; Hartzmark and Shue, 2018). Our measure of earnings-per-share takes out the effect of one-time items.

Appendix Table A1: Effect of Valuation Uncertainty on Earnings Response Coefficients by Earnings Size: no controls and no fixed effects

	(1)	(2)	(3)	(4)	(5)
SUE Window	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |0.05|
SUE	15.35***	9.121***	6.034***	3.490***	2.271***
	(0.638)	(0.350)	(0.241)	(0.160)	(0.117)
VU	-0.00233***	-0.00157***	-0.00121**	-0.00092	-0.00088
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SUE x VU	1.980***	0.672***	0.134	-0.297***	-0.332***
	(0.416)	(0.213)	(0.142)	(0.096)	(0.069)
Observations	95,723	133,490	153,511	167,678	173,668
R-squared	0.028	0.043	0.048	0.044	0.037

Notes: This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. Panel A includes all observations, while Panel B focuses on the bottom quintile of analyst dispersion. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table A2: Effect of Analyst Dispersion on Earnings Response Coefficients by Earnings Size

	(1)	(2)	(3)	(4)	(5)
SUE Window	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |0.05|
SUE	16.49***	9.903***	6.562***	3.681***	2.276***
	(0.673)	(0.397)	(0.266)	(0.155)	(0.102)
Dispersion	-0.00092	-0.00114**	-0.00100**	-0.000899**	-0.000647*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
SUE x Dispersion	-1.396***	-0.454**	-0.314***	-0.197***	-0.111***
	(0.410)	(0.182)	(0.103)	(0.054)	(0.033)
Observations	95,081	133,062	153,221	167,506	173,587
R-squared	0.116	0.112	0.112	0.103	0.095

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Dispersion is the z-scored standard deviation of analyst forecasts about earnings in the last IBES statistical period before the announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table A3: Effect of Analyst Dispersion on Earnings Response Coefficients by Earnings Size: no controls and no fixed effects

	(1)	(2)	(3)	(4)	(5)
SUE Window	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |0.05|
SUE	14.87***	9.166***	6.144***	3.466***	2.152***
	(0.643)	(0.361)	(0.246)	(0.142)	(0.096)
Dispersion	-0.00504***	-0.00446***	-0.00386***	-0.00339***	-0.00308***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
SUE x Dispersion	-1.167***	-0.380**	-0.284***	-0.174***	-0.107***
	(0.392)	(0.176)	(0.102)	(0.053)	(0.033)
Observations	95,723	133,490	153,511	167,678	173,668
R-squared	0.03	0.045	0.05	0.045	0.038

Notes: This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Dispersion captures the z-scored standard deviation of analyst forecasts about earnings in the last IBES statistical period before the earnings announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table A4: Robustness: Simultaneous heterogeneous effects by Valuation Uncertainty and Dispersion

	(1)	(2)	(3)	(4)	(5)
SUE Window	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |0.05|
SUE	16.91***	9.980***	6.542***	3.737***	2.416***
	(0.669)	(0.391)	(0.264)	(0.173)	(0.126)
VU	0.000701	0.000793	0.000947*	0.00135**	0.00144***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dispersion	(0.001)	-0.00109**	-0.00105**	-0.00106***	-0.000820**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
SUE x VU	2.815***	1.065***	0.384**	-0.212**	-0.313***
	(0.427)	(0.231)	(0.152)	(0.101)	(0.072)
SUE x Dispersion	-2.222***	-0.746***	-0.411***	-0.151***	-0.0560*
	(0.406)	(0.184)	(0.102)	(0.054)	(0.033)
Observations	95,081	133,062	153,221	167,506	173,587
R-squared	0.117	0.112	0.112	0.103	0.095

Notes: This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty and Analyst Dispersion. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Analyst Dispersion captures the z-scored standard deviation of analyst forecasts about earnings in the last IBES statistical period before the earnings announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). We use the same controls and fixed effects as Table 2. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table A5: Returns on only earnings day

SUE Window	(1) ≤ |0.002|	(2) ≤ |0.005|	(3) ≤ |0.01|	(4) ≤ |0.025|	(5) ≤ |0.05|
SUE	14.24***	8.174***	5.262***	2.951***	1.916***
	(0.664)	(0.378)	(0.239)	(0.149)	(0.105)
VU	0.00039	0.000414	0.000554*	0.000826***	0.000910***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUE x VU	2.014***	0.677***	0.241**	-0.178**	-0.235***
	(0.346)	(0.183)	(0.117)	(0.081)	(0.056)
Observations	95,081	133,062	153,221	167,506	173,587
R-squared	0.115	0.114	0.114	0.104	0.096

Notes: This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by valuation uncertainty. Panel A includes all observations, while Panel B focuses on the bottom quintile of analyst dispersion. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. We use the same controls and fixed effects as Table 2. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table A6: Returns from earnings day to t+2

SUE Window	(1) ≤ |0.002|	(2) ≤ |0.005|	(3) ≤ |0.01|	(4) ≤ |0.025|	(5) ≤ |0.05|
SUE	16.58***	9.677***	6.244***	3.554***	2.287***
	(0.643)	(0.376)	(0.245)	(0.160)	(0.116)
VU	0.000498	0.000481	0.000597	0.00101**	0.00106**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
SUE x VU	2.321***	0.804***	0.226	-0.250***	-0.290***
	(0.384)	(0.208)	(0.137)	(0.095)	(0.068)
Observations	95,081	133,062	153,221	167,506	173,587
R-squared	0.116	0.114	0.113	0.105	0.096

Notes: This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. Panel A includes all observations, while Panel B focuses on the bottom quintile of analyst dispersion. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. We use the same controls and fixed effects as Table 2. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

A.1 Sensitivity to Definition of SUE

One might be concerned that our baseline S-Shaped response of stock prices to earnings news is a function of the way we have defined SUE. In this subsection, we show that our baseline S-shape is present under a variety of alternative definitions of SUE. Further, we show that high valuation uncertainty companies' increased sensitivity to small surprises also holds under these alternative definitions of SUE. Finally, we consider the relationship between post-earnings returns and percentile *ranks* of SUE, as discussed in Hartzmark and Shue (2018). This approach could be considered a way to test predictions of models of efficient coding that would predict a linear relationship if the mass is equally distributed on the x-axis.

The first alternative definition of SUE we consider is the percentage earnings surprise relative to the magnitude of the consensus earnings estimate. This is how earnings surprises are defined e.g., on the Nasdaq website.

$$SUE^{A1}_{i,t} = \frac{EPS_{i,t} - E_{t-1}[EPS_{i,t}]}{|E_{i,t-1}[EPS_{i,t}]|} \tag{9}$$

Where $E_{t-1}[EPS_{i,t}]$ is the mean analyst estimate of EPS, and $EPS_{i,t}$ is realized EPS.

The second alternative definition of SUE we consider is the earnings surprise relative to the standard deviation of analyst estimates. This is the definition of earnings surprise used in e.g., Mendenhall (2004).

$$SUE^{A2}_{i,t} = \frac{EPS_{i,t} - E_{t-1}[EPS_{i,t}]}{SD(E_{i,t-1}[EPS_{i,t})} \tag{10}$$

Where $E_{t-1}[EPS_{i,t}]$ is the *median* analyst estimate of EPS, $SD(E_{i,t-1}[EPS_{i,t})$ is standard deviation of analysts' estimates of EPS and $EPS_{i,t}$ is realized EPS.[32] When computing $SUE^{A2}_{i,t}$, we restrict to earnings announcements covered by at least 3 analysts to ensure we can compute $SD(E_{i,t-1}[EPS_{i,t})$.

The final alternative definition of earnings surprise we consider is a dollar surprise. This is how earnings surprises are quoted on e.g., Yahoo finance and many large financial news media websites.

$$SUE^{A3}_{i,t} = EPS_{i,t} - E_{t-1}[EPS_{i,t}] \tag{11}$$

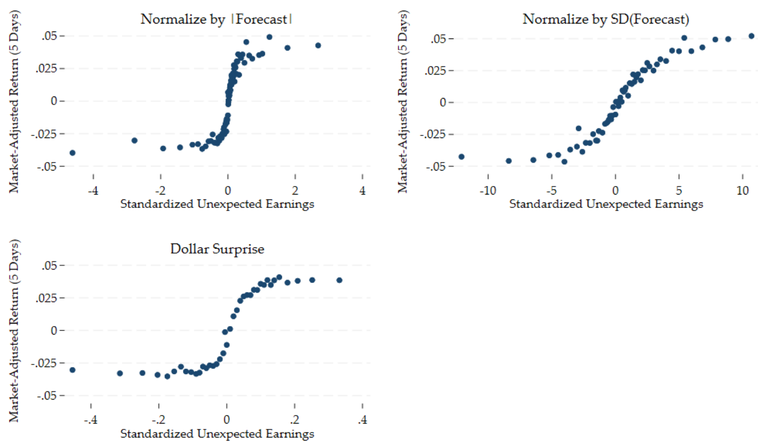
Where $E_{t-1}[EPS_{i,t}]$ is the mean analyst estimate of EPS, and $EPS_{i,t}$ is realized EPS. One downside of working with the dollar surprise, relative to other definitions of SUE is that it is less

[32]We use the median analyst estimate instead of the mean (which we use in all other definitions of SUE) in $SUE^{A2}_{i,t}$ for consistency with Mendenhall (2004). Results are similar using the mean estimate of EPS instead.

directly comparable across stocks e.g., the effect of a 1 cent earnings surprise on a stock with an EPS of \$1 might be very different than the effect of a 1 cent earnings surprise on a stock with an EPS of \$0.

Figure A2 shows the relationship between post-earnings market-adjusted returns and SUE for each of these alternative definitions. While the strength of the S-shape's curvature varies across these alternative definitions, the broad empirical pattern of increased sensitivity around zero, and decreased sensitivity away from zero is still present.

Appendix Figure A2: S-Shapes for Alternative Definitions of SUE



This figure presents the relationship between the alternative definitions of SUE and market-adjusted post-earnings announcement returns. In each panel, we truncate the data at the 1st percentile and 99th percentile of SUE.

Table A7 replicates our main results studying how VU affects the earnings response coefficients with each alternative definition of SUE in expanding windows of $|SUE|$ around zero. In our main results, our expanding windows start at absolute values of SUE less than 0.002, then expand to 0.005, 0.01, 0.025 and 0.05. This roughly corresponds to the 50^{th} percentile, 75^{th} percentile, the 90^{th} and 95^{th} percentile of SUE. So, to make the results with our alternative definitions of SUE comparable to our baseline findings, for each definition of SUE, we also examine expanding windows which contain roughly these fractions of the data. Note that the number of observations is not exactly the same within each set of columns (i.e., keeping SUEs less than the median in column 1 versus column 5), because there are exact ties in SUE, especially in dollar terms. Further, the security fixed effects drop singleton observations, and the set of singletons is different across columns. Across all the definitions of SUE, the pattern of high VU being correlated with increased sensitivity to earnings news for small surprises holds. And, across all the definitions of SUE, the coefficient on the interaction term shrinks as we expand the window. Different from the baseline results, however, we do not observe a flipping for the second and third alternative definitions of SUE, where high VU implies an attenuated response for extreme SUEs.

Appendix Table A7: Effect of Valuation Uncertainty on Earnings Response Coefficients by Earnings Size

Window Size	(1) 50%	(2) 75%	(3) 90%	(4) 95%	(5) All	(6) 50%	(7) 75%	(8) 90%	(9) 95%	(10) All	(11) 50%	(12) 75%	(13) 90%	(14) 95%	(15) All
$SUE^{A1}_{i,t}$	0.415***	0.168***	0.109***	0.0800***	0.0271***										
	(0.155)	(0.020)	(0.012)	(0.008)	(0.002)										
$SUE^{A1}_{i,t}$ x VU	0.0238	0.0782***	0.0247*	0.00661	-0.00693***										
	(0.256)	(0.025)	(0.013)	(0.008)	(0.002)										
$SUE^{A2}_{i,t}$						0.00822	0.00551***	0.00579***	0.00519***	0.00442***					
						(0.005)	(0.001)	(0.001)	(0.001)	(0.000)					
$SUE^{A2}_{i,t}$ x VU						0.0146*	0.0133***	0.00946***	0.00897***	0.00473***					
						(0.008)	(0.001)	(0.001)	(0.001)	(0.001)					
$SUE^{A3}_{i,t}$											0.668***	0.336***	0.192***	0.155***	0.107***
											(0.182)	(0.070)	(0.035)	(0.028)	(0.015)
$SUE^{A3}_{i,t}$ x VU											0.610**	0.711***	0.469***	0.383***	0.120***
											(0.252)	(0.084)	(0.040)	(0.033)	(0.016)
Observations	27,261	93,312	134,354	151,318	171,269	34,303	93,870	119,568	126,467	137,620	50,771	91,087	139,193	151,849	173,345
R-squared	0.197	0.125	0.116	0.112	0.088	0.171	0.121	0.125	0.129	0.126	0.143	0.119	0.116	0.116	0.102
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how market-adjusted returns respond to alternative definitions of standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership, total daily stock volatility over the past 12 months and the level of valuation uncertainty. Clustered standard errors are reported in parentheses. The window size indicates the percentile of the SUE measure used to filter the data. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

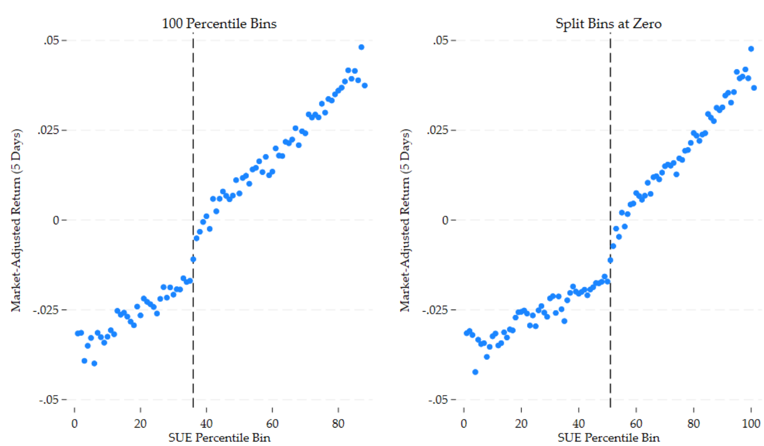
Percentile ranks Another alternative way of measuring SUE is to calculate percentile ranks of our baseline measure of SUE, as discussed in Hartzmark and Shue (2018). Our comparative framework predicts behavioral responses to both the sign and magnitude of surprises. However, the use of percentile ranks complicates interpreting the data within the framework of our model. Specifically, this approach may obscure potential nonlinearities in the relationship between returns and earnings surprises due to the substantial mass of observations with a SUE of exactly zero. Instead, percentile ranks are better suited for testing models of efficient coding, which predict a linear relationship under the assumption of evenly distributed mass along the x-axis – a condition met when percentile ranks are used. In fact, when using percentile ranks of SUE, rather than SUE itself, Hartzmark and Shue (2018) find that earnings responses appear to be linear, rather than S-shaped, consistent with models of efficient coding.

Further, we believe that examining the response to percentile ranks can miss the importance of crossing the boundary of $SUE > 0$ versus $SUE < 0$, which is crucial in our theoretical framework. Specifically, over 10% of the announcements in our data have an SUE of exactly zero, and almost half the data has an absolute SUE of less than 10 basis points. A graph constructed based on percentile ranks will spread this half of the data out, and thus even if there is a sharp jump in returns right at zero, using percentile ranks will make the response appear flatter. Similarly, less than 15% of the data has an SUE of more than 100 basis points. Using percentile ranks would tend to pull these data points together (i.e., reduce their spread), making our observed pattern of attenuated responses in the tails of SUE seem weaker.

Given our theoretical framework, we are especially interested in understanding differences across the $SUE = 0$ boundary. To better understand the effect of using percentile ranks of SUE, but make the effect of crossing zero more clear, we consider the following alternative percentile rank construction: First, we form 50 buckets based on percentile ranks of SUE but only for $SUE < 0$. Then, we have 1 bucket for observations with an SUE of exactly zero. Finally, we form 50 buckets based on percentile ranks of SUE, but only for $SUE > 0$.

Figure A3 shows the results. In the left panel, we follow Hartzmark and Shue (2018) and form 100 bins based on percentile ranks, where the percentiles are formed each quarter. This panel replicates their result of a linear response of stock prices to percentile ranks of SUE. In the right panel, however, we use our alternative structure which breaks out the observations with an SUE of exactly zero into their own bin, and does not form the percentile ranks conditional on another variable (e.g., each quarter, or at the firm level). And, the right panel shows that there is indeed a sharp jump in returns at the zero-crossing boundary.

Appendix Figure A3: S-Shapes for Percentile Ranks of SUE



This figure presents the relationship between SUE grouped by percentile ranks and market-adjusted post-earnings announcement returns. Vertical line denotes the bin with an SUE of exactly zero.

A.2 Robustness to pooled specification

In Table 2, we estimate our main regression specification in expanding windows. This approach is useful for quantifying how sensitivity to SUE changes over different magnitudes of earnings news. However, that method has two key limitations: first, the controls and fixed effects are re-estimated in each window. Second, it implicitly imposes a linear structure on a relationship that becomes increasingly nonlinear as we move into the tails of the distribution.

To allay these concerns, in Table A8, we pool the full sample and estimate a piecewise linear specification that allows the response to earnings news to vary flexibly with the magnitude of the standardized earnings surprise (SUE). The pooled regression resolves issues described above by incorporating all observations simultaneously and modeling the earnings response as a series of SUE-magnitude-specific linear segments. In the pooled specification, we find results broadly similar to those in Table 2, with VU leading to increased sensitivity to small earnings surprises, and decreased sensitivity to larger earnings surprises, although the latter result is not statistically significant.

A.3 Robustness to Firm Size and Time Period

Table A9 replicates our main results on the relationship between valuation uncertainty and earnings response coefficients for the large-cap post-2010 sample. Reassuringly, our results of amplification for surprises around zero, and attenuation for large surprises also holds on this subsample.

A.4 Earnings persistence

One possible alternative explanation for the differences in how valuation uncertainty affects the response to earnings news for SUEs close to zero versus away from zero is differences in the persistence of earnings news. For this to explain our results, however, two things would need to be true. First, small surprises for high valuation uncertainty firms would need to be more persistent than small surprises for low valuation uncertainty firms.[33] And second, large surprises for high valuation uncertainty firms would need to be less persistent than large surprises for low valuation uncertainty firms.

[33] More specifically, when we discuss persistence near an SUE of zero, we mean that small positive surprises are followed by subsequent small positive surprises, and vice versa for small negative surprises.

Appendix Table A8: Pooled Regression: Effect of Valuation Uncertainty on Earnings Responses

	(1)	(2)	(3)	(4)
SUE x 1_|SUE|<=0.002	15.35***	15.63***	15.90***	15.78***
	(0.638)	(0.636)	(0.633)	(0.647)
SUE x 1_|SUE|>0.002 & |SUE|<=0.005	7.821***	7.909***	8.003***	8.189***
	(0.314)	(0.316)	(0.320)	(0.335)
SUE x 1_|SUE|>0.005 & |SUE|<=0.01	4.609***	4.645***	4.710***	4.908***
	(0.192)	(0.192)	(0.190)	(0.197)
SUE x 1_|SUE|>0.01 & |SUE|<=0.025	2.352***	2.377***	2.423***	2.577***
	(0.125)	(0.125)	(0.125)	(0.132)
SUE x 1_|SUE|>0.025 & |SUE|<=0.05	1.178***	1.190***	1.221***	1.310***
	(0.079)	(0.079)	(0.079)	(0.086)
VU x SUE x 1_|SUE|<=0.002	1.980***	2.096***	1.905***	1.950***
	(0.416)	(0.414)	(0.413)	(0.419)
VU x SUE x 1_|SUE|>0.002 & |SUE|<=0.005	0.594***	0.612***	0.544**	0.642***
	(0.207)	(0.208)	(0.212)	(0.213)
VU x SUE x 1_|SUE|>0.005 & |SUE|<=0.01	0.19	0.183	0.165	0.232*
	(0.124)	(0.124)	(0.123)	(0.126)
VU x SUE x 1_|SUE|>0.01 & |SUE|<=0.025	-0.101	-0.0991	-0.0923	-0.0658
	(0.075)	(0.075)	(0.075)	(0.081)
VU x SUE x 1_|SUE|>0.025 & |SUE|<=0.05	-0.0353	-0.0414	-0.0405	-0.0329
	(0.057)	(0.056)	(0.055)	(0.059)
Observations	173,668	173,668	173,668	173,587
R-squared	0.066	0.068	0.077	0.127
Controls	No	Yes	Yes	Yes
FE	None	None	YQ	Permno + YQ
Ratio 0.002	0.129	0.134	0.120	0.124
Ratio 0.005	0.076	0.077	0.068	0.078
Ratio 0.01	0.041	0.039	0.035	0.047
Ratio 0.025	-0.043	-0.042	-0.038	-0.026
Ratio 0.05	-0.030	-0.035	-0.033	-0.025

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Some columns control for security (Permno) fixed effects and year-quarter fixed effects. Some columns also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01. The final rows of the table report the ratios of the coefficients on SUE with the VU interaction terms.

We test whether there is differential persistence in earnings surprises for high- versus low-valuation uncertainty firms and whether this differs for surprises close to zero and far away

Appendix Table A9: Effect of Valuation Uncertainty on Earnings Response Coefficients by Earnings Size: Post 2010, Large Cap. Stocks

	(1)	(2)	(3)	(4)	(5)
SUE Window	$\leq \|0.002\|$	$\leq \|0.005\|$	$\leq \|0.01\|$	$\leq \|0.025\|$	$\leq \|0.05\|$
SUE	22.18***	13.37***	9.212***	5.980***	4.611***
	(1.168)	(0.586)	(0.384)	(0.345)	(0.337)
VU	0.000898	0.0013	0.00145*	0.00197**	0.00275***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SUE x VU	4.449***	1.995***	0.808***	0.117	-0.489*
	(0.923)	(0.456)	(0.285)	(0.238)	(0.263)
Observations	17,745	22,604	24,075	24,591	24,689
R-squared	0.164	0.157	0.152	0.137	0.13

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Restricts to data after 2010, and stocks which are above median market capitalization in our sample each quarter. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

from zero. To do so, we test the predictive power of an earnings surprise (SUE) at a given point in time for earnings *growth* over the next year. To further make things comparable across firms and time, we control for lagged earnings growth, and interact that quantity with all the coefficients of interest.

Table A10 contains the results. Similar to our baseline regression specification, we run these earnings persistence regressions in expanding windows around zero. The first column uses all data, while the second column restricts to a small window around zero. Columns 3 to 6 progressively expand the window considered. In the smallest window (column 2), we find that for high VU firms, earnings growth is negatively related to SUE today. This would work against finding a stronger S-shape for high VU firms, as if small surprises are less persistent, we would expect stock prices to react less, rather than more.

Further, in columns 7-12, we add in interaction terms for lagged earnings growth. There, we find the same pattern: in tight windows around a SUE of zero, there is a negative coefficient on the interaction term between SUE today and VU when trying to predict future earnings growth, while for wider windows, the coefficient on the triple interaction term turns positive and significant. Again, this would exactly work against the stronger S-shaped response for high VU firms we find in the data. Collectively, the evidence in Figure A4 and Table A10 are further evidence that differences in earnings manipulation, and earnings persistence are not driving our main findings.

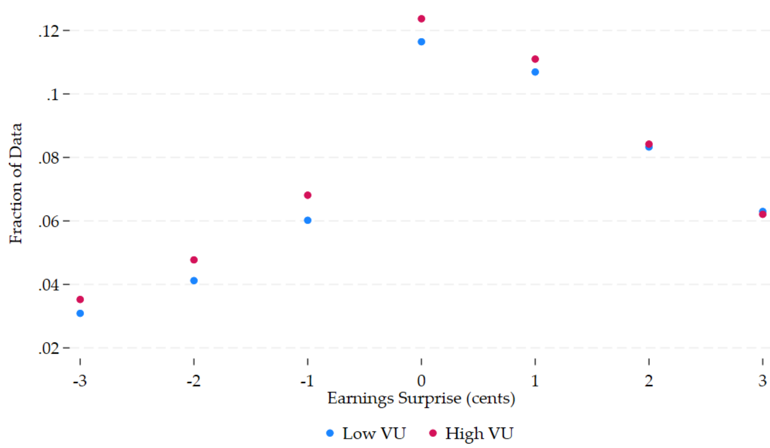
A.5 Earnings Manipulation

One concern with our main results is that crossing the boundary from $SUE < 0$ to $SUE > 0$ affects how investors' adjust their expectations of a stock's value for a reason outside of our model. For example, one might be worried that managers engage in earnings manipulation to ensure a small positive SUE. And therefore, when investors observe a small negative surprise, crossing zero is not actually about moving across a category boundary. Instead, it signals that managers were unable to manipulate earnings to ensure a positive SUE, which conveys to investors that either (1) the company's fundamentals are much worse than previously thought or (2) management is incompetent. And further, perhaps companies with more valuation uncertainty have a stronger incentive or scope to engage in earnings manipulation, which drives our results on cross-sectional heterogeneity in the S-shaped response to earnings news.

If this were the case, however, one would expect two things. First, one would expect differences in bunching right around the cutoff at $SUE = 0$ for high and low VU observations. The logic is that if high VU stocks manipulated earnings more, we would see a greater mass of earnings just above the consensus estimate. Second, if managers of high VU firms engaged in more earnings manipulation, we would expect differential persistence in their earnings news – as management cannot manipulate earnings in the same direction forever. Therefore, one might expect that positive SUEs for high VU firms predict relatively lower earnings growth going forward than for low VU observations. In this section, we show that neither of these patterns hold in the data, suggesting that differential earnings manipulation by valuation uncertainty is not driving our main results.

First, we test for differences in bunching just above an $SUE = 0$ for high versus low VU observations. To this end, each quarter, we split the data into two groups depending on whether or not the stock has above or below median VU. Figure A4 plots the fraction of the data in each VU group in 1 cent bins of dollar earnings surprise, defined as the difference between realized earnings and the mean estimate of earnings. While there is a large mass of data at a surprise of almost exactly zero, there is no difference in bunching for high versus low VU observations.[34] This is the first piece of evidence suggesting that differences in earnings manipulation do not drive our results.

Appendix Figure A4: Share of the Data Around $SUE = 0$: High versus Low VU Split



Each quarter, we split the data into two groups depending on whether or not the stock has above or below median VU. This figure plots the fraction of the data in each VU group in 1 cent bins of dollar earnings surprise, defined as the difference between realized earnings and the mean estimate of earnings. Each bin takes the floor of the earnings surprise so e.g., the bin at zero includes all surprises greater than or equal to zero, and less than a full penny per share. For clarity, we only plot data with earnings surprises between -3 cents, and 3 cents.

Next, we test whether SUE is differentially persistent for high and low VU observations. Table A10 contains the results. Similar to our baseline regression specification, we run these earnings persistence regressions in expanding windows around zero. The first column uses all data, while the second column restricts to a small window around zero. Columns 3 to 6 progressively expand the window considered. In the smallest window (i.e., column 2), we find that for high VU firms, earnings growth is negatively related to SUE today. This would work against finding a stronger S-shape for high VU firms, as if small surprises are less persistent, we would expect stock prices to react less, rather than more.

Further, in columns 7-12, we add in controls and interaction terms for lagged earnings growth. Including lagged earnings growth is important, as earnings growth is mechanically correlated with SUE, and earnings growth is persistent (Novy-Marx, 2015). Therefore, not in-

[34]We say *almost* because the bin at exactly zero includes all surprises greater than or equal to zero, and less than a full penny per share, i.e., the bins take the floor of the earnings surprise in one cent increments. So there are some observations in that bin with slightly positive surprises. Results are similar replicating this plot using the ceiling within each 1-cent increment, as opposed to the floor.

cluding lagged earnings growth could lead to omitted bias. There, we find the same pattern: in tight windows around a SUE of zero, there is a negative coefficient on the interaction term between SUE today and VU when trying to predict future earnings growth, while for wider windows, the coefficient on the triple interaction term turns positive and significant. Again, this would exactly work against the stronger S-shaped response for high VU firms we find in the data. Collectively, the evidence in Figure A4 and Table A10 are further evidence that differences in earnings manipulation, and earnings persistence are not driving our main findings.

Appendix Table A10: Predictive Power of SUE for Future Earnings Growth

	4 Quarters Ahead Earnings Growth											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SUE Window	All	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |0.05|	All	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |0.05|
SUE	-1.218***	-0.115*	-0.330***	-0.366***	-0.463***	-0.634***	-0.802***	-0.0256	-0.254***	-0.304***	-0.431***	-0.608***
	(0.190)	(0.062)	(0.039)	(0.035)	(0.029)	(0.039)	(0.212)	(0.069)	(0.045)	(0.037)	(0.029)	(0.037)
VU	0.00153***	0.000614***	0.000708***	0.00104***	0.00120***	0.00136***	0.00124***	0.000677***	0.000742***	0.00111***	0.00119***	0.00130***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUE x VU	-0.298*	-0.101	-0.0907**	-0.0314	0.0282	0.0148	0.00427	-0.0815	-0.118***	-0.0535	0.00464	-0.00694
	(0.153)	(0.066)	(0.040)	(0.027)	(0.027)	(0.036)	(0.131)	(0.086)	(0.045)	(0.034)	(0.027)	(0.036)
Lagged Earnings Growth	-0.0465	-0.000908	-0.0028	-0.00485	-0.00214	-0.00248	0.019	-0.0621**	-0.0621***	-0.0565***	-0.0370***	-0.0449***
	(0.048)	(0.001)	(0.002)	(0.004)	(0.002)	(0.003)	(0.049)	(0.028)	(0.022)	(0.020)	(0.009)	(0.014)
Lagged Growth x SUE							5.539***	3.759	-1.443	-2.737	-0.573	-1.848***
							(2.114)	(13.510)	(4.782)	(3.144)	(0.851)	(0.587)
Lagged Growth x VU							-0.0832***	0.021	0.0363**	0.0320**	0.0223***	0.0306***
							(0.031)	(0.028)	(0.016)	(0.015)	(0.007)	(0.009)
Lagged Growth x SUE x VU							0.519	-33.43**	-6.374	-5.243	0.673	1.166***
							(0.907)	(15.680)	(5.498)	(4.695)	(0.566)	(0.418)
Observations	143,703	82,184	113,150	128,550	138,489	142,207	143,703	82,184	113,150	128,550	138,489	142,207
R-squared	0.171	0.218	0.176	0.149	0.144	0.135	0.557	0.22	0.178	0.152	0.147	0.139

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how SUE can predict future fundamentals, as measured by next year's earnings growth, and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Lagged earnings growth is the earnings growth over the past year (i.e., relative to the same quarter the previous year), divided by the pre-earnings announcement price. 4-quarters ahead earnings growth is defined as year-over-year earnings growth over the next 12 months (i.e., relative to the same quarter the next year), divided by the pre-earnings announcement price. Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

A.6 Accruals

One potential concern is that firms with high valuation uncertainty may be more likely to use accruals to engineer small earnings beats. Accruals on their own, however, are mechanically correlated with SUE. Specifically, accruals are a component of net income, and net income underlies EPS and thus SUE. Including raw accruals alongside SUE in a regression creates a multicollinearity problem, obscuring the true interaction effect. To address this, we construct a version of accruals that is uncorrelated with SUE and captures abnormal behavior relative to the firm's typical accruals pattern. First we construct two measures of accruals: (1) cash flow accruals defined as net income minus operating cash flows and (2) balance sheet accruals calculated as the change in non-cash current assets minus the change in non-debt, non-tax current liabilities, minus depreciation expense Sloan (1996). Both measures are normalized by total assets to make them comparable across firms and across time. We then residualize each accruals measure by regressing it on SUE and including firm and year-quarter fixed effects. The "Residualized" accruals used in Table A11 reflect these orthogonalized, abnormal components of accruals.

At a high level, the results in Table A11 suggest that the empirical evidence is inconsistent with this story. In particular, the interaction between accruals and earnings surprises is negative, consistent high accruals signaling lower earnings quality and thus dampening the market's reaction to news. Further, our results on the interaction between SUE and VU are unchanged by including accruals.

A.7 Other measures of Hard to Value

While our main analysis uses valuation uncertainty as a proxy for processing constraints, it is just one of many possible measures that might capture how difficult it is for investors to interpret earnings news. In Table A13, we explore a range of alternative proxies drawn from the literature. These include measures related to cash flow duration (Gormsen and Lazarus, 2023), business complexity, measured as an indicator variable for whether a single business segment generates more than 80% of the firm's total revenue (Cohen and Lou, 2012), idiosyncratic volatility, and stock turnover, defined as the monthly trading volume scaled by the total shares outstanding (Ben-David et al., 2023). Broadly, all of which have been linked to uncertainty in how investors value firms.

For each proxy, we estimate the effect of earnings surprises (SUE) on announcement returns, and interact SUE with the alternative measure to test whether they also exhibit the same "flipping" pattern that we observe in Table 2. Further, we include analyst dispersion, as we have shown in Table A2 that this generally attenuates the response to earnings news. Finally, for each measure, we fully saturate the regression by including every possible interaction term between SUE, dispersion and the measure itself (although we only report the interaction terms with SUE).

The first panel of Table A13 shows that for cashflow duration, the patterns are broadly

Appendix Table A11: Accruals, Dispersion, Valuation Uncertainty and Earnings Responses

	Cash Flow Accruals/Total Assets					Balance Sheet Accruals/Total Assets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUE	17.74***	10.68***	7.117***	4.180***	2.729***	17.38***	10.31***	6.786***	3.913***	2.539***
	(0.664)	(0.377)	(0.253)	(0.161)	(0.120)	(0.672)	(0.395)	(0.266)	(0.173)	(0.129)
SUE x VU	1.879***	0.214	(0.243)	-0.599***	-0.558***	2.655***	0.927***	0.279*	-0.311***	-0.392***
	(0.481)	(0.240)	(0.150)	(0.091)	(0.066)	(0.440)	(0.239)	(0.156)	(0.101)	(0.073)
SUE x Accruals (Residualized)	-15.98	2.92	0.694	-1.094	0.101	-21.48**	-4.999	-0.365	-0.605	0.359
	(10.360)	(4.357)	(2.342)	(1.069)	(0.715)	(9.447)	(3.724)	(2.014)	(1.145)	(0.715)
SUE x Dispersion	-2.297***	-0.833***	-0.429***	-0.166***	-0.0546	-2.269***	-0.790***	-0.450***	-0.160***	-0.0565
	(0.417)	(0.190)	(0.104)	(0.057)	(0.035)	(0.426)	(0.191)	(0.106)	(0.057)	(0.034)
Observations	89,284	123,987	142,317	155,390	161,014	90,751	126,469	145,235	158,584	164,273
R-squared	0.121	0.118	0.118	0.11	0.101	0.12	0.116	0.116	0.108	0.099
Window Size	0.002	0.005	0.01	0.025	0.05	0.002	0.005	0.01	0.025	0.05

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty, Accruals and Analyst Dispersion. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement.
Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Dispersion is defined as the z-scored standard deviation of analyst forecasts for the earnings of company i in the last IBES statistical period before the earnings announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). Cash Flow Accruals are defined as net income minus operating cash flows. Balance Sheet Accruals are calculated as the change in non-cash current assets minus the change in non-debt, non-tax current liabilities, minus depreciation expense Sloan (1996). Both measures of accruals are normalized by total assets. To identify the piece of accruals uncorrelated with SUE itself, and abnormal relative to a firm's historical average, we run a first stage regression of accruals on SUE and firm and year-quarter fixed effects. In each regression in this table, we include these "Residualized" measures of accruals.
Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

similar to VU, with the interaction term being positive for small earnings surprises and negative for large earnings surprises. Note that inputs to the Gormsen and Lazarus (2023) measure are "value" (book-to-market), "profit" (operating profitability/book equity), "investment" (annual growth in total assets), "beta" (market beta) and "payout" (payout ratio). In their calibration, value, profit and payout tend to decrease duration, while investment and beta tend to increase duration. Therefore, the result in the first panel of Table A13 that high duration firms have a more S-shaped response to earnings news is likely related to the results in Skinner and Sloan (2002) that low book-to-market firms i.e., growth firms have a more S-Shaped response to earnings news. However, in our sample (which extends well beyond the original sample in Skinner and Sloan (2002)), we find that growth firms generally have an amplified response to earnings news at *all points in the SUE distribution*, but that effect is strongest for earnings surprises near zero.

The second panel shows a similar pattern of a decreasing interaction term for complicated firms, although the interaction term in each case retains the same sign.[35] Results are similar when replicating the second panel using geographic segments, instead of business segments. The third panel shows that having more volatile stock returns also generates the flipping pattern observed in Table 2. Finally, the fourth panel shows that increased trading volume leads to a decreased interaction term as the windows expand, but the interaction term in each window is positive.

In Table A12, we report the correlations between valuation uncertainty, dispersion in analyst estimates and the proxies of hard to value in Table A13.

Appendix Table A12: Correlation Between Proxies for Hard to Value

Variables	Valuation Uncertainty	Dispersion	Cashflow Duration	Indicator: 1 Biz. Seg.>80% Revenue	Indicator: 1 Geo. Seg>80% Revenue	Idiosyncratic Volatility	Turnover
Valuation Uncertainty	1						
Dispersion	0.3	1					
Cashflow Duration	0.326	0.304	1				
Indicator: 1 Biz. Seg.>80% Revenue	0.034	0.064	-0.024	1			
Indicator: 1 Geo. Seg>80% Revenue	0.084	0.078	0.039	0.481	1		
Idiosyncratic Volatility	0.462	0.351	0.441	0.058	0.063	1	
Turnover	0.15	0.108	0.28	0.16	0.234	0.342	1

Notes: Valuation uncertainty is defined as the interquartile range of market capitalization implied by a multiples-based valuation method at different points in a given industry-year distribution (Golubov and Konstantinidi, 2023). Dispersion is the standard deviation of analyst forecasts for the earnings of company i in the last IBES statistical period before the earnings announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). Duration is defined as cashflow duration from Gormsen and Lazarus (2023). The indicator for the largest business segment accounting for more than 80% of sales is from Cohen and Lou (2012). The measures of idiosyncratic volatility and turnover are from Ben-David et al. (2023).

[35] Recall that the measure in Cohen and Lou (2012) is whether a single business segment accounts for 80% or more of total revenue. And, firms with a single business segment are arguably *simpler* to value. So, in Table A13, we have flipped the indicator to be whether there is no business segment accounting for 80% or more of total revenue

Appendix Table A13: Alternative Measures of "hard-to-value"

	Duration				
	(1)	(2)	(3)	(4)	(5)
SUE	16.58***	9.900***	6.541***	3.683***	2.305***
	(0.674)	(0.395)	(0.265)	(0.158)	(0.108)
SUE x Measure	1.306***	0.533***	0.321***	-0.0109	-0.111**
	(0.376)	(0.182)	(0.117)	(0.066)	(0.045)
SUE x Dispersion	-1.819***	-0.631***	-0.402***	-0.197***	-0.0934***
	(0.415)	(0.173)	(0.098)	(0.053)	(0.033)
Observations	95,059	133,019	153,175	167,457	173,538
R-squared	0.116	0.112	0.112	0.103	0.095
SUE x Measure / SUE	0.079	0.054	0.049	-0.003	-0.048
	Indicator: Largest Biz. Segment < 80%				
	(6)	(7)	(8)	(9)	(10)
SUE	16.45***	9.932***	6.614***	3.721***	2.307***
	(0.573)	(0.332)	(0.217)	(0.128)	(0.089)
SUE x Measure	3.298***	2.070***	1.469***	0.871***	0.534***
	(0.399)	(0.199)	(0.122)	(0.068)	(0.053)
SUE x Dispersion	-1.748***	-0.664***	-0.459***	-0.281***	-0.155***
	(0.386)	(0.172)	(0.099)	(0.052)	(0.033)
Observations	94,783	132,557	152,575	166,722	172,720
R-squared	0.117	0.114	0.114	0.105	0.097
SUE x Measure / SUE	0.200	0.208	0.222	0.234	0.231
	Idiosyncratic Volatility				
	(16)	(17)	(18)	(19)	(20)
SUE	16.82***	9.915***	6.525***	3.721***	2.311***
	(0.661)	(0.389)	(0.267)	(0.172)	(0.116)
SUE x Measure	2.650***	0.971***	0.366**	-0.146	-0.0919
	(0.525)	(0.250)	(0.145)	(0.095)	(0.059)
SUE x Dispersion	-2.358***	-0.767***	-0.414***	-0.166***	-0.0938***
	(0.408)	(0.162)	(0.091)	(0.051)	(0.033)
Observations	95,059	133,017	153,172	167,454	173,534
R-squared	0.117	0.112	0.112	0.103	0.095
SUE x Measure / SUE	0.158	0.098	0.056	-0.039	-0.040
	Turnover				
	(21)	(22)	(23)	(24)	(25)
SUE	16.55***	9.982***	6.611***	3.688***	2.271***
	(0.613)	(0.353)	(0.237)	(0.143)	(0.097)
SUE x Measure	3.863***	1.887***	1.048***	0.434***	0.246***
	(0.524)	(0.224)	(0.130)	(0.072)	(0.053)
SUE x Dispersion	-2.091***	-0.709***	-0.436***	-0.223***	-0.120***
	(0.388)	(0.171)	(0.100)	(0.052)	(0.033)
Observations	95,055	133,011	153,164	167,443	173,522
R-squared	0.117	0.113	0.113	0.104	0.095
SUE x Measure / SUE	0.233	0.189	0.158	0.118	0.108
Window Size	0.002	0.005	0.01	0.025	0.05
Firm-Level Controls	YES	YES	YES	YES	YES
Fixed Effects	Permno + YQ	Permno + YQ	Permno + YQ	Permno + YQ	Permno + YQ

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by different measures of processing constraints. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Duration is defined as cashflow duration from Gormsen and Lazarus (2023). The indicator for the largest business segment accounting for more than 80% of sales is from Cohen and Lou (2012). The measures of idiosyncratic volatility and turnover are from Ben-David et al. (2023). Turnover is defined as the monthly trading volume scaled by the total shares outstanding. Dispersion is the standard deviation of analyst forecasts for the earnings of company i in the last IBES statistical period before the earnings announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

A.8 Differences in Pre-Announcement Information Acquisition

Motivation Suppose that, owing to the increased ex-ante uncertainty, investors learn relatively less about high valuation uncertainty stocks pre-announcement – and thus less of the earnings information is incorporated into prices before it is formally released. This might specifically apply to small earnings surprises, because as shown in Figure 1, prices are very responsive to earnings surprises just around zero – and thus being wrong in this region could be extremely costly to investors.[36] And, if this channel applies differently to small versus large surprises, one might be concerned that it is driving our results on valuation uncertainty.

Approach To test for differences in pre-announcement information acquisition, we run regressions of the form:

$$\text{Outcome}_{i,t} = \beta \text{VU}_{i,t-1} + \delta X_{i,t} + \phi_t + \psi_i + \epsilon_{i,t}, \tag{12}$$

where $\text{Outcome}_{i,t}$ is a measure of how much information was incorporated into prices after the earnings information was made public i.e., larger values denote that less information was incorporated ahead of time. We include the same controls and fixed effects as in Equation 5.

In column 1, we examine the absolute earnings day return normalized by the standard deviation of pre-announcement returns. The logic is that large earnings-day returns are evidence that less information was incorporated into prices before the announcement (Frazzini, 2006). There are, however, unconditional differences in volatility between high and low valuation uncertainty stocks. To account for this, we normalize the earnings-day return by the standard deviation of returns over the month before the announcement itself (Sammon, 2024). Here, we find a negative coefficient, suggesting that relatively more information is incorporated into prices pre-announcement for high valuation uncertainty stocks.

In column 2, we examine the price jump measure of Weller (2018), which is designed to capture the *fraction* of earnings information incorporated into prices after the announcement information was made public. Here, we see no relationship between valuation uncertainty and the price jump measure, evidence that high and low valuation uncertainty stocks are similar on this dimension.[37] Overall, the results in Table A14 suggest that, if anything, more information

[36] This is just one reason for why high valuation uncertainty stocks might have a different amount of information incorporated into prices pre-announcement e.g., it could also be that stocks with high valuation uncertainty have different disclosure strategies (Dye, 1985; Huang et al., 2025).

[37] Column 2 has significantly fewer observations than column 1 because of the "non-event filter," which removes observations where the total return around the earnings announcement is close to zero, see Weller (2018) for

is incorporated into prices ahead of time for high VU stocks – which would work against our main finding. We conclude, therefore, that differences in the incorporation of information pre-announcement are unlikely to be driving our baseline results.

Appendix Table A14: Valuation Uncertainty and Pre-announcement Information Incorporation

	$\lvert RET \rvert / SD$	PJ
	(1)	(2)
VU	-0.0413***	-0.00261
	(0.013)	(0.003)
Observations	168,061	63,752
R-squared	0.22	0.17
Firm Level Controls	YES	YES
FE	Permno + YQ	

Notes: This table contains the results from a regression of measures of the amount of information incorporated into prices before the earnings announcement itself on valuation uncertainty. Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

A.9 Trading Volume

One possible mechanism through which valuation uncertainty may affect the response to earnings surprises relates to attention. In particular, it is conceivable that there are differences in attention between high and low VU observations. Specifically, high VU stocks may receive relatively more attention for less extreme earnings surprises, and therefore respond more to earnings news that are close to zero surprise.

In this section, we aim to test for differences in attention between high and low VU observations – depending on the size of the earnings surprise – around earnings announcements. We follow Hou et al. (2009) and use turnover around earnings announcements, defined as trading volume divided by shares outstanding, as a proxy for investor attention. Specifically, to match our baseline specification in Table 2, we calculate cumulative turnover from $t = 0$ to $t = 4$ around the earnings announcement i.e., we match the horizon we use to compute returns.

details.

The results are in Table A15. Column 1 shows that there is no level effect of valuation uncertainty. In other words, valuation uncertainty is not related to the trading volume. The table shows that, in general and across all specifications, earnings surprises are negatively associated with trading volume. For small surprises this means that there is a lot less trading volume for positive than for negative surprises, consistent with higher attention paid to earnings misses. For small earnings surprises, there is no interaction effect between valuation uncertainty and SUE. As we widen the distribution of SUEs we consider, we find a positive coefficient on the interaction term between VU and SUE. This suggests that, if anything, high VU stocks may receive *more* attention around earnings announcements when the surprises are bigger. This runs contrary to the alternative story that differences in attention are driving our main results.

Appendix Table A15: Effect of Valuation Uncertainty on Turnover Around Earnings Announcements

	(1)	(2)	(3)	(4)	(5)
SUE Window	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |0.05|
SUE	-1.861***	-0.495***	-0.194***	-0.0754**	-0.0378
	(0.255)	(0.104)	(0.058)	(0.038)	(0.028)
VU	0.000429	0.000677	0.000543	0.00053	0.000447
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUE x VU	0.109	0.158**	0.156***	0.127***	0.0781***
	(0.203)	(0.078)	(0.047)	(0.029)	(0.021)
Observations	95,081	133,062	153,221	167,506	173,587
R-squared	0.546	0.529	0.516	0.505	0.498

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how cumulative turnover responds to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

A.10 Contemporaneous Guidance

One potential concern with our finding of an S-shaped return response to SUE is that it may not reflect a nonlinear reaction to earnings news per se, but rather could arise mechanically due to the presence of other contemporaneous disclosures that are themselves nonlinearly related to SUE. As a specific example, if managerial EPS guidance is issued contemporaneously with earnings announcements and if the guidance itself has a S-shaped relationship with SUE, then the observed S-shaped return response may be due to market reactions to guidance rather than to the SUE news alone.

To investigate this possibility, we restrict our sample to earnings announcements that have no contemporaneous management EPS guidance, identified using guidance data from IBES. Table A16 shows that our main results on the interaction between VU and SUE and the baseline effects of SUE remains nearly unchanged on the no-guidance subsample. The patterns suggest that the S-shaped return pattern is not an artifact of contemporaneous managerial guidance but rather reflects a genuine nonlinear reaction to earnings surprises. And further, that our results on the sharper S-shaped response for high VU firms is also not explained by management guidance.

Appendix Table A16: Effect of Valuation Uncertainty on Earnings Response Coefficients by Earnings Size: Excluding Announcements with Contemporaneous Management Guidance

	(1)	(2)	(3)	(4)	(5)
SUE	15.86***	9.113***	5.982***	3.447***	2.252***
	(0.638)	(0.354)	(0.236)	(0.157)	(0.114)
VU	0.000796	0.000692	0.000754	0.00109*	0.00124**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SUE x VU	2.252***	0.857***	0.274*	-0.196**	-0.272***
	(0.434)	(0.225)	(0.145)	(0.096)	(0.068)
Observations	78,740	112,122	130,863	144,630	150,634
R-squared	0.122	0.115	0.115	0.107	0.101
Window Size	0.002	0.005	0.01	0.025	0.05
Firm-Level Controls	YES	YES	YES	YES	YES
Fixed Effects	Permno + YQ	Permno + YQ	Permno + YQ	Permno + YQ	Permno + YQ

Notes: This table shows data on earnings announcements from 1986-2019. We exclude all announcements with contemporaneous management guidance on earnings per share, identified using the IBES Guidance data. This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. Our specifications control for both security (Permno) fixed effects and year-quarter fixed effects. We also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

B Post-Earnings Announcement Drift (PEAD)

Our main results in Table 2 show that when valuation uncertainty (VU) is high, investors appear to react relatively more to small earnings surprises, and relatively less to large earnings surprises compared to when VU is low. This could be consistent with – in the face of valuation uncertainty – investors systematically over-reacting to small earnings beats/misses and under-reacting to large earnings beats/misses. If this were true, however, when VU is elevated we would expect to observe return reversion after the small earnings surprises, and return continuation after the large earnings surprises. In this section, we test for this type of systematic over and under reaction, and how this depends on valuation uncertainty.

To quantify post-earnings announcement return reversion and continuation, we build on the pooled specification in Appendix A.2. Specifically, we re-run the pooled regression in Table A8, but use the cumulative market-adjusted returns from 5 days after the earnings announcement to 29 or 59 days after the earnings announcement as the left-hand-side variable. We start these windows 5 days after the earnings announcement, as this is when our baseline earnings response regression windows in Table 2 end. To reduce the influence of outliers, we Winsorize these returns at the 1% and 99% levels. Given that the right-hand-side variables are interaction terms with SUE, positive coefficients are evidence of return continuation, and thus under-reaction to the initial news. On the other hand, negative coefficients are evidence of return reversal, and over-reaction to the earnings release.

Table A17 contains the results. The first thing that stands out about the table is that all of the interaction terms between SUE and the indicator variables for particular SUE ranges (i.e., the first 5 coefficients in each column) are positive and statistically significant. This is broad evidence of continuation, and is consistent with the existence of the post-earnings announcement drift (PEAD).

The first column presents results for market-adjusted returns from 5 days to 29 days after the earnings announcement. The interaction term for the smallest window, $VUxSUEx1_{|SUE|<=0.002}$ is negative, evidence of over-reaction to small earnings beats when valuation uncertainty is elevated. The magnitude is also large, at over 40% of the baseline responsiveness to news, as reported in the "Interaction/ Baseline" column. The interaction term is not statistically significant, although this may be because the dispersion in returns at such long horizons is high, lowering the power of this test.

The interaction term between the next largest window and VU, $VU \times SUE \times 1_{|SUE|>0.002 \& |SUE|<=0.005}$ is also negative, but the magnitude is significantly smaller, at only 8% of the baseline effect. This is consistent with less over-reaction in the presence of high VU in this range, relative to the observations with SUE closest to zero. The next interaction term, $VU \times SUE \times 1_{|SUE|>0.005\&|SUE|<=0.01}$ is negative and even smaller in magnitude.

The next interaction term, $VU \times SUE \times 1_{|SUE|>0.01\&|SUE|<=0.025}$ is positive, flipping the sign relative to the first three interaction terms. Further, the magnitude is large at over 15% of the baseline effect. This is consistent with under-reaction to news in the presence of high VU for these relatively large earnings surprises. The last interaction term $VU \times SUE \times 1_{|SUE|>0.025\&|SUE|<=0.05}$ is large and negative, however, there are only $\approx$ 5,000 observations with a SUE in that range, so we do not wish to draw too many conclusions from the point estimate, which we believe is likely noisy.

The next column of Table A17 presents the results for returns from 5 days to 59 days after the earnings announcement. Broadly, the results are consistent with the first column: It appears that there are reversals for SUE close to zero, and increasingly large (in magnitude) continuation in the windows further from zero. Collectively, the evidence in Table A17 is consistent with the story outlined above: when VU is high, investors appear to over-react to small earnings beats/misses, leading to reversion, and appear to under-react to large earnings beats/misses, leading to continuation.

Appendix Table A17: Pooled Regression: Effect of Valuation Uncertainty on PEAD

	[5,29]		[5,59]	
	(1)	Interaction/ Baseline	(2)	Interaction/ Baseline
SUE x 1_|SUE|<=0.002	1.392**		4.379***	
	(0.537)		(0.923)	
SUE x 1_|SUE|>0.002 & |SUE|<=0.005	1.115***		1.816***	
	(0.268)		(0.444)	
SUE x 1_|SUE|>0.005 & |SUE|<=0.01	0.788***		1.452***	
	(0.148)		(0.255)	
SUE x 1_|SUE|>0.01 & |SUE|<=0.025	0.425***		0.641***	
	(0.090)		(0.147)	
SUE x 1_|SUE|>0.025 & |SUE|<=0.05	0.404***		0.701***	
	(0.092)		(0.126)	
VU x SUE x 1_|SUE|<=0.002	-0.608	-0.437	-0.519	-0.119
	(0.560)		(0.857)	
VU x SUE x 1_|SUE|>0.002 & |SUE|<=0.005	-0.0931	-0.083	0.0171	0.009
	(0.205)		(0.321)	
VU x SUE x 1_|SUE|>0.005 & |SUE|<=0.01	-0.0127	-0.016	0.0757	0.052
	(0.139)		(0.229)	
VU x SUE x 1_|SUE|>0.01 & |SUE|<=0.025	0.0677	0.159	0.236*	0.368
	(0.083)		(0.131)	
VU x SUE x 1_|SUE|>0.025 & |SUE|<=0.05	-0.102	-0.252	-0.113	-0.161
	(0.071)		(0.129)	
Observations	172,526		172,526	
R-squared	0.098		0.118	
Controls	Yes		Yes	
Fully Saturated with Interaction Terms	Yes		Yes	
FE	Permno + YQ		Permno + YQ	

Notes: This table shows data on earnings announcements from 1986-2019. This table studies how the relationship between long-run post-earnings announcement returns and SUE varies by Valuation Uncertainty. The left-hand-side variable in each column is the market-adjusted return from 5 days after the earnings announcement, to 29 or 59 days after the earnings announcement. SUE refers to the deviation of a company's reported earnings per share from the consensus earnings forecast by analysts, normalized by the last closing price before the earnings announcement. Valuation uncertainty is defined as the z-scored dispersion in expected market capitalization given by a multiples-based valuation method at different points in the industry-year distribution. All columns control for security (Permno) fixed effects and year-quarter fixed effects. All columns also control for time since listing (age), market capitalization, returns from t-12 to t-2, book-to-market, CAPM beta, institutional ownership and total daily stock volatility over the past 12 months. Clustered standard errors are reported in parentheses. The column "Interaction/ Baseline" reports the ratio of the interaction term, divided by the baseline responsiveness to SUE in the same SUE range. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

C Additional exhibits for experimental data

Appendix Table A18: Dependent variable: Normalized predictions

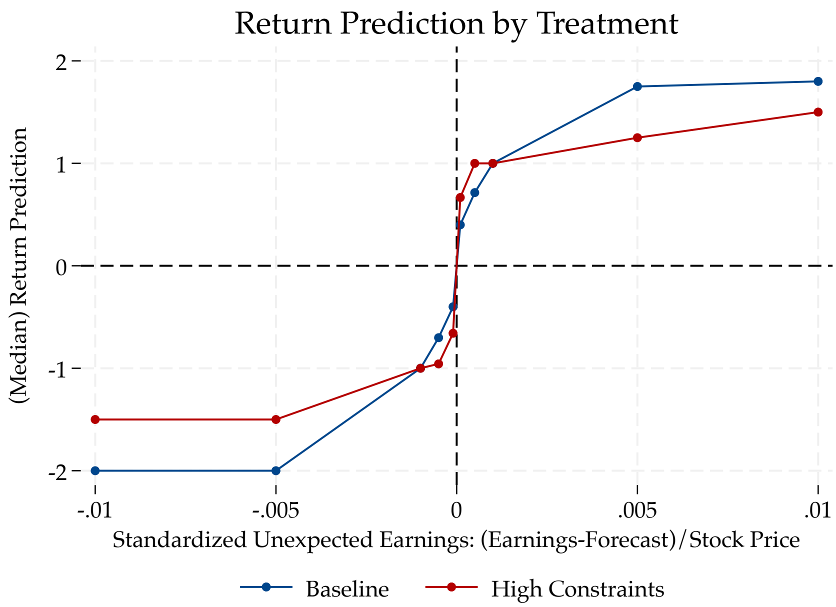
SUE Window	(1) ≤ |0.0001|	(2) ≤ |0.0005|	(3) ≤ |0.001|	(4) ≤ |0.005|	(5) ≤ |0.01|
SUE	3754.4***	1527.8***	1027.9***	400.0***	236.7***
	(224.1)	(82.47)	(34.58)	(15.82)	(11.29)
SUE x HC	1745.6***	305.6**	138.8**	-83.33***	-55.38***
	(390.4)	(119.2)	(55.61)	(23.94)	(14.33)
HC	0.0746**	0.0694*	0.0971***	0.0833	0.113**
	(0.0350)	(0.0374)	(0.0335)	(0.0508)	(0.0508)
Constant	-0.0246	0.0139	-0.0138	4.97e-09	0.0333
	(0.0211)	(0.0219)	(0.0171)	(0.0218)	(0.0275)
Observations	900	1813	2677	3557	4483
R-squared	0.0641	0.103	0.157	0.183	0.208

Notes: This table shows the results of regressing normalized predictions on SUE, an indicator for the High Constraints treatment (HC), and the interaction of both (SUE x HC) in the experimental data using median regressions. The results are shown for expanding windows around zero SUE. Regression (1) contains rounds for SUE in the window [-0.0001, 0.0001], Regression (2) for SUE in [-0.0005, 0.0005], Regression (3) for SUE in [-0.001, 0.001], Regression (4) for SUE in [-0.005, 0.005] and Regression (5) for SUE in [-0.01, 0.01], where the latter window corresponds to the full sample. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table A19: Dependent variable: Normalized predictions - Robustness Check 1

SUE Window	(1) ≤ |0.0001|	(2) ≤ |0.0005|	(3) ≤ |0.001|	(4) ≤ |0.005|	(5) ≤ |0.01|
SUE	4000.0***	1600.0***	1166.7***	426.0***	246.7***
	(240.9)	(78.65)	(61.56)	(16.78)	(11.94)
SUE x HC	2666.7***	400.0***	166.7**	-62.34***	-46.67***
	(557.0)	(104.8)	(76.90)	(22.85)	(14.47)
HC	-7.26e-17	1.09e-16	0.0500	0.00519	-0.0333
	(0.0527)	(0.0325)	(0.0308)	(0.0441)	(0.0491)
Constant	2.43e-17	-3.82e-17	-0.0167	0.0130	0.0333
	(0.0231)	(0.0211)	(0.0195)	(0.0225)	(0.0286)
Observations	805	1660	2466	3284	4143
R-squared	0.154	0.212	0.286	0.281	0.283

Notes: This table shows the results of the same regressions as in Table A18 but excluding observations reflecting predictions with a sign that is opposite to that of the earnings surprise, i.e., a negative predicted price change for positive SUE and vice versa. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

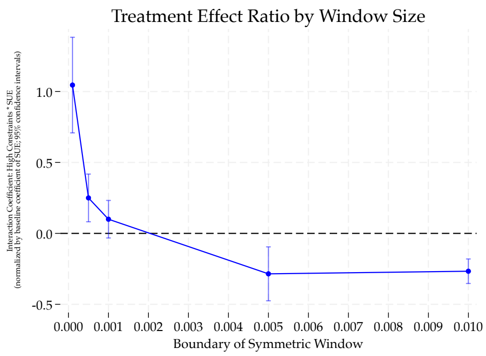


Appendix Figure A5: *Notes:* This figure is constructed in the same way as Figure 4a but excluding observations reflecting predictions with a sign that is opposite to that of the earnings surprise.

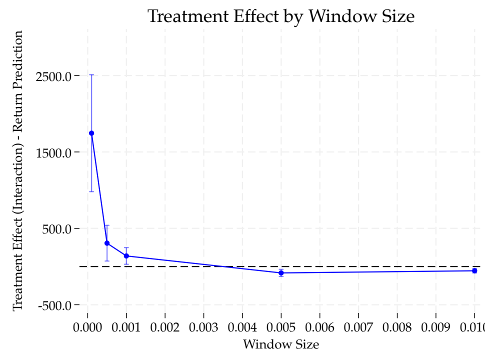
Appendix Table A20: Dependent variable: Normalized predictions - Robustness Check 2

SUE Window	(1) $\leq \|0.0001\|$	(2) $\leq \|0.0005\|$	(3) $\leq \|0.001\|$	(4) $\leq \|0.005\|$	(5) $\leq \|0.01\|$
SUE	3754.4***	1527.8***	1027.9***	400.0***	236.7***
	(226.8)	(84.51)	(34.95)	(15.67)	(11.46)
SUE x HC	1870.6***	338.9***	149.9***	-83.33***	-58.89***
	(406.2)	(104.6)	(54.16)	(23.71)	(13.96)
HC	0.0871**	0.0528	0.0916***	0.0833	0.0778
	(0.0364)	(0.0330)	(0.0323)	(0.0521)	(0.0483)
Constant	-0.0246	0.0139	-0.0138	4.97e-09	0.0333
	(0.0214)	(0.0222)	(0.0173)	(0.0216)	(0.0277)
Observations	869	1759	2591	3440	4330
R-squared	0.0644	0.101	0.156	0.185	0.208

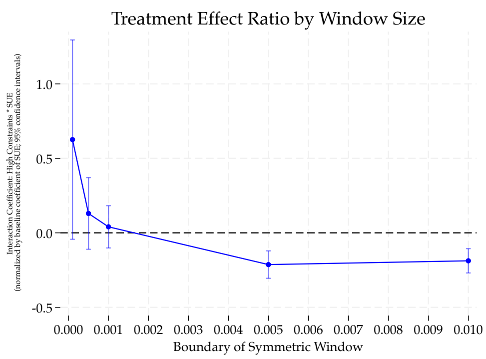
Notes: This table shows the results of the same regressions as in Table A18 but excluding observations in the "High Constraints" group that timed out. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.



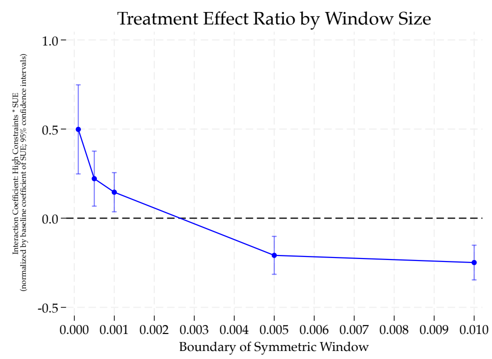
a) Using the raw price change predictions not normalized by priors.



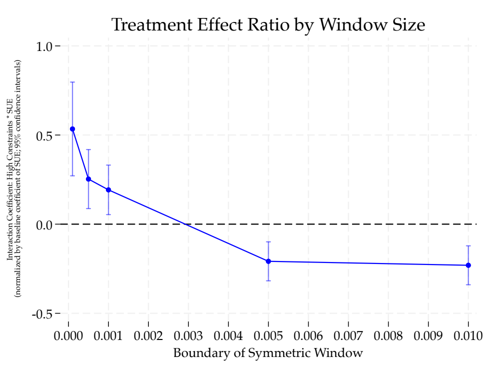
b) Using interaction coefficients not normalized by the SUE slope of Baseline condition.



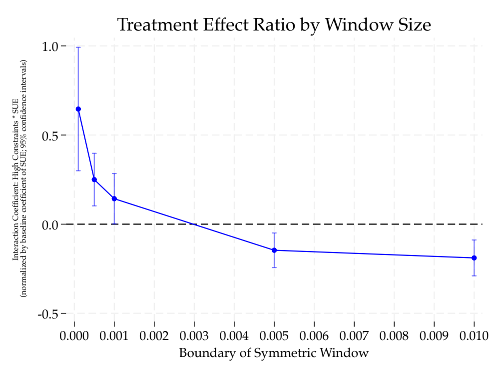
c) Using conditional means instead of medians and winsorized at normalized predictions of +/-3.



d) Excluding observations in the High Constraints group that timed out.



e) Excluding observations from subjects who indicated that they looked up additional information on any company online.



f) Excluding observations reflecting predictions with a sign that is opposite to that of the earnings surprise.

Appendix Figure A6: Robustness checks for Figure 4b.

Appendix Table A21: Dependent variable: Normalized predictions - Robustness Check 3

SUE Window	(1) $\leq \|0.0001\|$	(2) $\leq \|0.0005\|$	(3) $\leq \|0.001\|$	(4) $\leq \|0.005\|$	(5) $\leq \|0.01\|$
SUE	3666.7***	1527.8***	1047.8***	400.0***	243.2***
	(239.6)	(88.32)	(34.36)	(16.32)	(12.46)
SUE x HC	1958.3***	386.5***	201.7***	-83.33***	-56.09***
	(404.9)	(110.4)	(70.78)	(24.43)	(15.71)
HC	0.0958***	0.0290	0.0553	0.0833	0.0847*
	(0.0367)	(0.0348)	(0.0349)	(0.0520)	(0.0492)
Constant	-0.0333	0.0139	-0.00478	-2.50e-16	0.0322
	(0.0225)	(0.0223)	(0.0163)	(0.0216)	(0.0281)
Observations	854	1715	2535	3367	4248
R-squared	0.126	0.162	0.237	0.239	0.241

Notes: This table shows the results of the same regressions as in Table A18 but excluding observations from subjects who indicate that they looked up additional information on any company online. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Appendix Table A22: Dependent variable: Normalized predictions - Robustness Check 4

SUE Window	(1) $\leq \|0.0001\|$	(2) $\leq \|0.0005\|$	(3) $\leq \|0.001\|$	(4) $\leq \|0.005\|$	(5) $\leq \|0.01\|$
SUE	11000.0***	6000.0***	4818.2***	1818.2***	1000.0***
	(707.4)	(302.7)	(181.1)	(98.28)	(30.54)
SUE x HC	11500.0***	1500.0***	481.8	-518.2***	-266.7***
	(1407.5)	(461.6)	(314.2)	(189.1)	(48.76)
HC	0.150	0.250**	0.532***	0.409**	0.667***
	(0.127)	(0.119)	(0.131)	(0.205)	(0.214)
Constant	0.100	5.55e-17	-0.182**	0.0909	-1.01e-14
	(0.0689)	(0.0666)	(0.0711)	(0.104)	(0.138)
Observations	900	1813	2678	3559	4485
R-squared	0.321	0.375	0.436	0.384	0.430

Notes: This table shows the results of the same regressions as in Table A18 but using the raw price change predictions (i.e., predictions not normalized by priors) for completeness. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Appendix Table A23: Dependent variable: Normalized predictions - Robustness Check 5

SUE Window	(1) $\leq \lvert 0.0001 \rvert$	(2) $\leq \lvert 0.0005 \rvert$	(3) $\leq \lvert 0.001 \rvert$	(4) $\leq \lvert 0.005 \rvert$	(5) $\leq \lvert 0.01 \rvert$
SUE	5039.7***	1766.4***	1339.3***	475.4***	292.3***
	(1413.6)	(151.9)	(107.7)	(30.69)	(20.10)
SUE x HC	1345.9	231.2	125.3	-92.30**	-63.14**
	(1576.5)	(198.7)	(142.4)	(41.77)	(27.22)
HC	0.255*	0.144	0.180	0.0939	0.172*
	(0.153)	(0.127)	(0.116)	(0.106)	(0.0986)
Constant	-0.0727	0.0240	-0.0200	0.00403	-0.0193
	(0.142)	(0.119)	(0.107)	(0.0926)	(0.0857)
Observations	900	1813	2677	3557	4483
R-squared	0.0656	0.103	0.157	0.183	0.208

Notes: This table shows the results of the same regressions as in Table A18 but using OLS regressions instead of median regressions. To account for the potential skew in the normalized prediction measure, we winsorize at normalized predictions of +/-3. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

D Competition for Attention

The motivation of our framework is that integrating information requires cognitive processing, which is a scarce resource. Instead of modeling the competition between categorical and numerical information for the limited stock of processing capacity, we assume that numerical information has a higher, constant processing cost. If, however, integrating categorical information requires more processing in a given situation, fewer resources remain to parse the numerical information.

A prominent principle in the cognitive sciences is that more *surprising* information requires more processing resources (e.g., Friston, 2005; Itti and Baldi, 2009). Applied to our empirical application, surprising category realizations – e.g., a profit when a loss was expected – might draw more processing resources, leaving less capacity to integrate the precise numerical magnitude of EPS and thus reducing the observed earnings response sensitivity. This hypothesis thus introduces direct competition between categorical and numerical information, leveraging the notion that surprise drives processing load.[38]

[38]Note the difference between a surprising realization *given the forecast for a specific company* and the notion of globally more or less frequent (and thus more or less globally surprising) events as studied in Section 6.1: the empirical density argument from before refers to how a realization compares to the historical distribution, while a surprise characterizes how a realization compares to a firm-specific expectation.

Empirical Strategy. We test whether a *more surprising* category realization given a firm's consensus forecast is associated with *lower sensitivity* to variation in the magnitude of surprises. In particular, we estimate the local sensitivities for a given range of SUE and given category realizations, and compare whether these sensitivity estimates systematically depend on whether the realized category was expected or not. Put differently, we fix realized values (SUE and categories) and explore variation whether the corresponding category expectations were fulfilled or not.

This test requires variation in whether a category realization is surprising or not relative to consensus market expectations. Note that the categorization as a consensus beat or miss – the focus of our analyses so far – is defined relative to the consensus forecast itself and thus equally surprising by construction. This exercise thus requires commonly used categorizations which vary in whether they are surprising. As reviewed in Section 1, our analysis of *Wall Street Journal* headlines revealed that there are two other highly common categorizations: EPS growth versus shrinkage year-over-year, and EPS being positive (profits) versus negative (losses).

We estimate the following type of specification:

$$\begin{aligned} r_{i,(t,t+n)} = {} & \beta_1 \text{SUE}_{i,t} + \beta_2 1_{\text{SUE}_{i,t}<0} + \beta_3 1_{\text{SUE}_{i,t}<0} \times \text{SUE}_{i,t} \\ & + \zeta \text{Running}_{i,t} + \sum_{k=1}^{3} \delta_k 1_{(i,t)\in k} + \sum_{k=1}^{3} \gamma_k 1_{(i,t)\in k} \times \text{SUE}_{i,t} \\ & + \theta X_{i,t} + \phi_t + \psi_i + \epsilon_{i,t} \end{aligned} \tag{13}$$

where $1_{(i,t)\in k}$ is an indicator variable for firm i's earnings announcement at time t belonging to group k. First, we consider four mutually exclusive categories of year-over-year earnings growth, defined by the sign of actual and expected growth. Specifically, we distinguish between: (1) cases where both actual and expected earnings growth are negative (*Shrink & E[Shrink]*), (2) cases where actual growth is negative but expected to be positive (*Shrink & E[Grow]*), (3) cases where actual growth is positive but expected to be negative (*Grow & E[Shrink]*), and (4) cases where both actual and expected growth are positive (*Grow & E[Grow]*). This last category serves as the omitted reference category. The running variable, $\text{Running}_{i,t}$, is year-over-year earnings growth, divided by the pre-earnings announcement price. Therefore, in equation 13, the coefficients δ_i capture the level effect of belonging to a given category compared to the omitted category. The coefficients γ_i capture how different category realizations affect sensitivity to the size of the SUE. Importantly, because we include SUE in Equation 13, we are effectively comparing how events with similar SUE respond differently depending on an expected versus unexpected category realization.

We also consider an alternative set of categorical realizations based on whether profits are positive or negative, defining four categories by the expected and actual sign of profits. Here, the running variable, $\text{Running}_{i,t}$, is earnings per share divided by the pre-announcement stock price.

Table A24 reports the regression results. We find that, first, surprising category realizations have substantial level effects on returns: these additional categorizations do seem to affect returns, which is a pre-condition for this exercise. Second, and in line with the hypothesis, more surprising category realizations are associated with lower sensitivity to the magnitude of the earnings surprise.

Appendix Table A24: Surprising Categorical Realizations and Earnings Responses

	(1)		(2)
SUE	2.978***	SUE	3.360***
	(0.140)		(0.166)
$1\_SUE < 0$	-0.0290***	$1\_SUE < 0$	-0.0294***
	(0.001)		(0.001)
$1\_SUE < 0$ x SUE	-2.883***	$1\_SUE < 0$ x SUE	-2.729***
	(0.154)		(0.145)
EPS Growth/Price	0.000	EPS/Price	0.000
	(0.000)		(0.006)
Shrink & E[Shrink]	-0.00511***	Loss & E[Loss]	-0.00729***
	(0.001)		(0.001)
Grow & E[Shrink]	0.0142***	Gain & E[Loss]	0.0251***
	(0.001)		(0.004)
Shrink & E[Grow]	-0.0145***	Loss & E[Gain]	-0.0143***
	(0.001)		(0.003)
(Shrink & E[Shrink]) x SUE	-0.101	(Loss & E[Loss]) x SUE	-0.805***
	(0.077)		(0.125)
(Grow & E[Shrink]) x SUE	-1.135***	(Gain & E[Loss]) x SUE	-2.089***
	(0.188)		(0.229)
(Shrink & E[Grow]) x SUE	-0.265***	(Loss & E[Gain]) x SUE	-0.741***
	(0.086)		(0.139)
Observations	165,018	Observations	165,018
R-squared	0.12	R-squared	0.121
Fixed Effects	YQ + Permno	Fixed Effects	YQ + Permno
Controls	ALL	Controls	ALL

Notes: This table studies how surprising category realizations affect how stock prices respond to standardized unexpected earnings. The left-hand-side variable is the cumulative market-adjusted returns from the day of the earnings announcement ($t = 0$) to the close 4 days after the earnings announcement ($t = 4$). Both columns include time-varying firm-level controls, as well as year-quarter fixed effects and firm fixed effects. Clustered standard errors are reported in parentheses. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

Specifically, in the first column of Table A24, we study categorical realizations with respect to year-over-year (YOY) earnings growth. We find that companies who report YOY earnings growth experience a 1.4 p.p. higher market-adjusted return ($p < 0.01$) when a decline was expected, relative to when growth was expected (recall that Grow & E[Grow] is the omitted category). Among observations reporting EPS shrinkage, returns are approximately 1 p.p. ($p < 0.01$) more negative when EPS growth (rather than shrinkage) was expected. These effects of category thresholds are striking as they control for the precise numerical information on SUE and EPS.

We now turn to the interaction terms between these indicator variables and SUE itself, which capture the sensitivity to variation in the numerical information about EPS. Consistent with our hypothesis, the ERC for YOY growth observations is 1.13 p.p. ($p < 0.01$) lower when a decline was expected than when growth was expected. This is a sizable drop in sensitivity by 39%. Conversely, the ERC for observations with YOY earnings shrinkage is significantly lower when growth was predicted than when a decline was expected ($p < 0.05$).

Column 2 of Table A24 replicates the analysis from Column 1, instead focusing on expected versus surprising profits and losses i.e., EPS greater than and/or less than zero. Broadly, we find analogous patterns to column 1. First examining level effects, we find that average excess returns are significantly higher after reported gains when a loss was expected, rather than a gain ($p < 0.01$). Average excess returns after reported losses are lower when a gain (rather than a loss) was expected ($p < 0.01$). Next, there are also substantial differences in the corresponding interaction terms between these indicator variables and SUE itself. Consistent with our hypothesis about the effect of surprises on categorical versus continuous signals, the marginal response to SUE for positive profits is significantly lower when a loss was expected than when a gain was expected ($p < 0.01$). Indeed, sensitivity to quantitative earnings information drops by almost 65 percent. Our analysis reveals no statistically significant difference in the response to marginal SUE news between surprising and expected losses. This might be explained by the very low baseline response to SUE for companies reporting losses to begin with.

Taken together, this additional set of results is compatible with the idea that more surprising category realizations draw more attention away – and thus distract from – the size of surprises.

E Proofs

E.1 Prediction 1

Proof. Let $r^*(s)$ denote the unconstrained best response, strictly increasing and differentiable in the quantitative signal s. Let $r_d(s)$ be the *conditional default* induced by qualitative categories, a step function with jumps at the thresholds c_k.

Constrained response. A decision maker (DM) observes an unbiased but noisy cognitive signal

$$r_c(s) \sim \mathcal{N}\big(r^*(s), \sigma_r^2(s)\big),$$

and forms the constrained response

$$r(s) = \lambda\, r_c(s) + \big(1-\lambda\big)\, r_d(s), \quad \text{with} \quad \lambda = \tfrac{\sigma_d^2}{\sigma_r^2(s)+\sigma_d^2} \in (0,1).$$

Here σ_d^2 is the variance of the (Gaussian) conditional prior; λ is *strictly decreasing* in the processing (mapping) noise $\sigma_r^2(s)$.

Sensitivity inside a category ($s \neq c_k$)**.** Because $r_d(s)$ is locally flat away from thresholds,

$$S(s) := \frac{\partial\, \mathbb{E}[r(s)]}{\partial s} = \lambda\, r^{*\prime}(s).$$

If processing noise rises from σ_r^2 to $\widetilde{\sigma}_r^2 > \sigma_r^2$, then $\widetilde{\lambda} < \lambda$ and hence $\widetilde{S}(s) < S(s)$ for all $s \neq c_k$. Thus sensitivity is *attenuated* between category boundaries.

Sensitivity at a boundary c_k**.** Let

$$\Delta_k = \lim_{\varepsilon \downarrow 0}\Big[\mathbb{E}\big[r(c_k+\varepsilon)\big] - \mathbb{E}\big[r(c_k-\varepsilon)\big]\Big].$$

Continuity of $r^*(s)$ implies

$$\Delta_k = \big(1-\lambda\big)\big[\, r_d(c_k^+) - r_d(c_k^-)\,\big].$$

A higher processing noise lowers λ, which *increases* the jump Δ_k. Hence sensitivity is *amplified* exactly at category boundaries. ■

E.2 Prediction 2

Proof. Introduce *surprise–coding* noise by assuming the DM perceives the zero–surprise threshold with error:

$$\tilde{c} \;=\; 0 + \varepsilon_s, \qquad \varepsilon_s \sim \mathcal{N}(0, \sigma_s^2).$$

The binary qualitative signal therefore equals

$$\tilde{s}_1(s) = \mathbf{1}\big\{\, s > \tilde{c} \,\big\} = \mathbf{1}\big\{\, s + \varepsilon_s > 0 \,\big\},$$

so that the probability of being classified "above forecast" is $p(s) = \Phi\big(s/\sigma_s\big)$, where Φ is the standard normal CDF.

Smoothed default. Let μ_+ and μ_- denote the average optimal responses when the firm is perceived to beat or miss the forecast, respectively. Then

$$r_d(s) = \mu_+ \, p(s) + \mu_- \, [1 - p(s)], \qquad r_d'(s) = \big(\mu_+ - \mu_-\big) \, \frac{\varphi(s/\sigma_s)}{\sigma_s},$$

with φ the standard normal pdf.

Effect of more surprise-coding noise. For any s and for $\tilde{\sigma}_s > \sigma_s$,

$$\frac{\varphi\big(s/\tilde{\sigma}_s\big)}{\tilde{\sigma}_s} \;<\; \frac{\varphi\big(s/\sigma_s\big)}{\sigma_s},$$

and the proportional decline is maximized at $s = 0$ (the former jump-point).

Overall sensitivity. Expected local sensitivity now equals

$$S_{\text{coding}}(s) = \lambda \, r^{*\prime}(s) + \big(1 - \lambda\big) \, r_d'(s).$$

Because $r^{*\prime}(s)$ and λ are unaffected by σ_s, the entire impact runs through $r_d'(s)$ and is therefore *negative for all* s, with the greatest absolute reduction at $s = 0$.

Precise comparative-statics statement. For every surprise satisfying $|s| < \sigma_s$ an increase in surprise-coding noise σ_s *always* lowers expected local sensitivity $S_{\text{coding}}(s)$, with the largest reduction occurring at the threshold $s = 0$. For $|s| > \sigma_s$ the derivative formally becomes positive, yet the effect is immaterial because (i) the pdf factor $\varphi(s/\sigma_s)$ is already exponentially small (e.g. $\varphi(3) < 4 \times 10^{-3}$), so the upward bump is quantitatively negligible; and (ii) such extreme surprises represent only a vanishing fraction of the data. ■