Coarse Categories in a Complex World*

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Preliminary draft – comments welcome!

Abstract

Real-world news environments comprise 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. When processing capacity is limited, these components may compete for attention. We study the hypothesis that more severe processing constraints increase the relative reliance on coarser signals: people still discriminate between categories but distinguish less granularly within them, creating higher sensitivity around category thresholds but lower sensitivity elsewhere. Using stock market reactions to earnings announcements as our empirical setting, we document that hard-to-value stocks are associated with a more pronounced S-shaped response pattern around category thresholds. Naturalistic experiments that exogenously manipulate processing constraints provide supporting causal evidence in individual investor behavior. We then study two determinants of processing constraints in the field. First, more common sizes of surprise may be processed more precisely. Indeed, regions with more historical mass exhibit far higher return sensitivity. Second, a surprise about the category realization may capture attention, leaving less capacity to process the numerical signal. We find that category surprises, e.g., a profit when a loss was expected, are associated with diminished sensitivity to numerical earnings information.

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1 Introduction

News reports characterize events by combining 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 processing information is cognitively costly, numerical information and coarse categorizations can compete for attention. Importantly, coarse categorizations may often be easier to process, or require less mental effort. Intuitively, people may have a sense of or rules of thumb for their reactions to broad categories of news – like whether earnings were above or below expectations – because such categories are stable, familiar, and recurring. These category shortcuts may allow for quick processing without deep analysis. In contrast, interpreting the granular numerical data is often more challenging: what's the market-adjusted return associated with a reported EPS of \$1.90 vs. \$2.03?

In this paper, we study the hypothesis that more severe information processing constraints – either because the decision problem is harder, or because the decision maker's processing resources are more limited – lead people to rely more on categorical information. Intuitively, when information processing is more constrained, people may still discriminate between different categories of situations, but find it harder to granularly distinguish situations within a category based on harder-to-process numerical signals. The behavioral pattern thus associated with higher processing constraints is a more step-shaped response function: higher sensitivity at category boundaries but lower sensitivity elsewhere. We discuss various microfoundations for why coarse information is cognitively cheaper and review the class of models that can predict a more S-shaped response under larger processing constraints.[1] We illustrate the main ideas using a simple framework of constrained Bayesian optimization, where numerical signals are integrated less precisely than categorical information.[2]

We empirically test the predictions about the role of processing constraints 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 naturalistic, individual belief formation experiments with investors. Earnings announcements are a well-suited testing ground for the importance of processing constraints given the high-dimensional nature of news and data that

[1]While step- or S-shaped response functions around thresholds have been widely documented across diverse applications as we review below, the pattern's intensity has not previously been empirically linked to the severity of processing constraints, to the best of our knowledge.

[2]Motivated by our empirical setting, we model categories as exogenous rather than endogenous.

investors have to process in short periods of time.

Field Evidence. Testing our hypothesis in the field requires a characterization of relevant numerical signals and categorizations used in the case of earnings announcements, and variation in the severity of processing constraints. 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.[3] We confirm that a frequent categorization is into beating versus missing the consensus forecast, with other common categorizations being about whether earnings are a profit or a loss, and about the growth or decline of earnings over time.[4] Our main analyses focus on the coarse signal about earnings beating or missing market expectations – the distinction that has received most attention in the previous literature – but we also leverage other categorizations, such as whether a company reports year-over-year earnings growth or decline, in our mechanism analyses to study competition for attention. Second, we adopt a broad definition of processing constraints in the context of stock market valuations as anything that creates subjective uncertainty about the mapping between fundamentals like earnings and predicted stock prices.[5] In practice, we leverage concepts previously explored in the literature on what makes firms "hard to value." In particular, we follow Golubov and Konstantinidi (2023), who propose a measure of *valuation uncertainty* (VU), defined as the dispersion in stock prices implied by valuation models estimated at different points in the distribution for a given industry-year. Valuation uncertainty, hence, captures the uncertainty associated with mapping fundamentals like a company's earnings to stock prices. Importantly, given how VU is calculated, it varies both across firms at a given point in time and within-firm over time.

Equipped with relevant categorizations (next to the numerical earnings signal) and a measure of the severity of processing constraints, 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 perspective on SUE, or earnings *surprises*, 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

[3]Data used: `https://www.kaggle.com/datasets/amogh7joshi/wsj-headline-classification`.

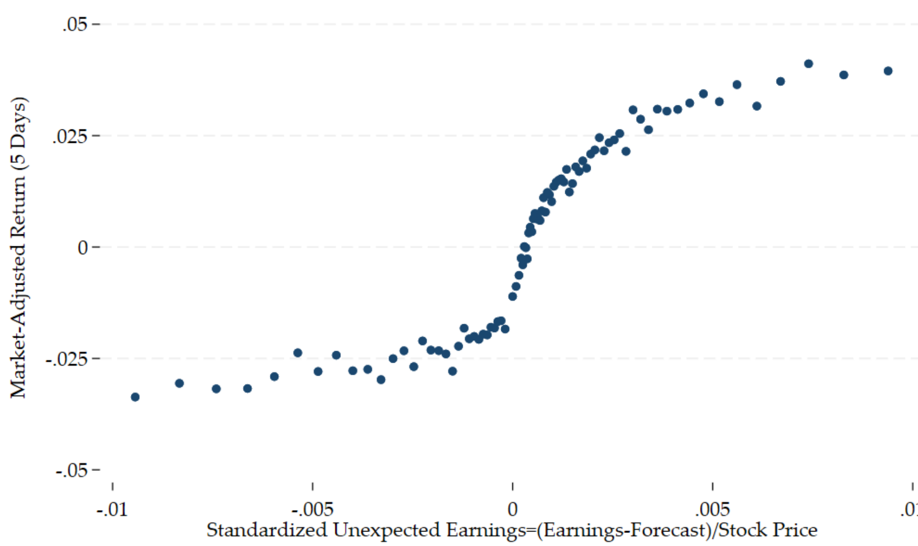
[4]Numerical information about earnings is, in fact, mentioned in fewer than 10% of earnings news headlines.

[5]Sources of such subjective uncertainty thus comprise both features of the "demand side" of information processing, i.e. the difficulty of a task or genuine stochasticity in the mapping, and of the "supply side", i.e. the processing resources supplied by the decision-maker.

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 (non-behavioral) explanations – primarily on the role of earnings persistence – have been put forward in the literature, as we review in detail below. This paper provides a complementary, behavioral hypothesis to help explain this pattern.

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 5 trading days following an earnings announcement.

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 captures 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 hypothesis, 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 the earnings response coefficient (capturing sensitivity to a marginal increase in the size of surprise) and valuation uncertainty is significantly and robustly 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 percent ($p < 0.01$) 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 percent ($p < 0.01$), i.e. valuation uncertainty is associated with *increases* in the sensitivity to surprises by approximately 13 percent ($p < 0.01$).

For a window size of 0.05, a one-unit increase in SUE is associated with a 2.4 percent ($p < 0.01$) 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 percent ($p < 0.01$), i.e. a decrease in the sensitivity to surprises by approximately 13%.

Our finding is robust to varying sets of controls, event study cutoffs 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 earnings quality, differential pre-announcement information acquisition and differential strategic disclosure as factors, among other things. 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.[6] 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

[6]While much previous work in finance estimates a linear earnings response coefficient, some work accommodates nonlinearities by estimating a linear effect of *percentile ranks* of surprises (e.g., Hartzmark and Shue, 2018). Here we directly aim at better understanding the origin of these nonlinearities, see also our discussion in Section 6.

for small and underreaction for larges surprise, yet these estimates are noisily measured.

Uncertainty about earnings announcements could be correlated with time-varying unobservables that drive the S-shaped patterns in our data. To provide evidence against this explanation, we show that – consistent with our behavioral hypothesis – different forms of uncertainty have different effects on the stock market response to earnings announcements. In particular, we exploit variation in uncertainty about the location of category thresholds. We predict that such uncertainty *decreases* investors' sensitivity to surprises *everywhere*, especially around category boundaries.[7] We test this prediction using variation in dispersion of analysts' earnings forecasts. Consistent with our hypothesis, we find that higher dispersion in earnings forecasts – unlike valuation uncertainty – predicts decreases in the sensitivity to surprises, especially close to the category thresholds. We also provide an extensive discussion and analyses of alternative concepts[8] and measurements, documenting further empirical support.

The correlational field evidence motivates our subsequent empirical analyses that shed light on the hypothesized mechanism. We proceed in two steps. First, we complement our correlational baseline findings with causal evidence using individual belief formation experiments. Second, we return to the field application to examine variation in processing constraints across different sizes of surprise, allowing us to test different theories of processing constraints.

Experimental Evidence. To provide causal evidence on the effect of the severity of processing constraints on return expectations at the individual level, we run controlled online experiments with investors. In our *Baseline* condition, respondents make incentivized predictions about same-day stock price movements of five different real companies in a specific earnings news scenario. The use of real companies with scheduled earnings announcements in the days following the experiment allows us to incentivize predictions. 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 role of processing constraints, 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 in two complementary ways. First, we add additional infor-

[7] Intuitively, consider the effect of aggregating horizontally offset S-shaped response functions (reflecting different possible category boundaries), which washes out the high sensitivity around each threshold.

[8] This includes empirical work on the *investor distraction hypothesis* (Hirshleifer et al., 2009b) using measures such as the number of same-day announcements or large sporting events, which we argue leads some investors to not attend to some announcements at all (thus creating insensitivity to it), whereas our prediction explores the implication of attending to information but incorporating it imprecisely, see Section 4.6.

mation to the earnings news piece that is irrelevant for the stock price reaction. This increases the task's inherent demand for information processing, thus creating potential competition for attention. Second, respondents have to submit their estimate within a time limit of 40 seconds to be eligible for a bonus, effectively decreasing the supply of information processing capacity. The results of our pre-registered experiments on individual price forecasts strongly corroborate our main findings from aggregate price data in the field. In both treatment conditions, average and median forecasts as a function of the surprise exhibit a pronounced S-shaped pattern: predicted price reactions are highly sensitive to a switch from the "earnings miss" to the "earnings beat" category but far less sensitive to the magnitude of the surprise within each category. Second, 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. Our findings are robust across a range of different, pre-registered tests and specifications.

Local Variation in Processing Constraints and its Implications. The empirical relationship between excess returns and earnings surprises shown in Figure 1 exhibits various properties that our analyses so far do not address: (i) there is smoothly diminishing sensitivity on either side of zero surprise, rather than a discontinuous jump at the category boundary, and (ii) there is a clear asymmetry in slopes for negative and positive surprises, with much less sensitivity in the negatives. In our theory, the variation in local sensitivities to earnings surprises depends on variation in the local severity of processing constraints. We next examine two theory-guided hypotheses about the local variation of processing constraints in the field, leveraging recent work in the cognitive sciences.

First, a class of theories predicts that the precision of information processing depends on the prior distribution of signals. This includes theories of *decision by sampling* (Stewart et al., 2006) and of *efficient coding* (e.g., Barlow et al., 1961; Laughlin, 1981; Frydman and Jin, 2022; Heng et al., 2020). Intuitively, individuals may face lower cognitive cost (or their cognitive system is better attuned to) processing signals that they are more familiar with or that are more common in the distribution of signals in a given environment. The common prediction is that the local sensitivity to variation in a stimulus is associated with the prior likelihood (or historical density) in that stimulus range.

We test this prediction to our empirical setting, examining how the historical distribution of earnings surprises influences investors' sensitivity to these surprises in the field. To set the stage, we first document two key features of the empirical distribution of earnings surprises: (i) it exhibits a pronounced bell shape centered around zero, rapidly declining as surprises grow in magnitude, and (ii) it is notably asymmetric, with negative surprises being less common than positive ones. Second, we estimate local earnings response coefficients for a fine-grained partition of buckets with earnings surprises of different size. Strikingly, the local sensitivity to the magnitude of earnings surprises is strongly correlated with the local empirical density. Our evidence is compatible with the idea that processing constraints are negatively correlated with their empirical prior mass. 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.[9]

Second, a prominent finding in lower-level cognitive tasks (such as visual perception) is that *more surprising* information draws more attentional capacity (e.g., Friston, 2005; Itti and Baldi, 2009).[10] Applied to our context, surprising category realizations (given expectations) might claim more processing resources, leaving less remaining capacity for the integration of the numerical information. To study this hypothesis, we need variation in whether a category realization is surprising or not, given market expectations. Because beats and misses of the consensus are defined relative to consensus expectations and thus almost equally surprising by construction, we turn to other categories, which allow us to define more versus less surprising realizations. Our prediction is that the locally estimated sensitivity to the magnitude of earnings surprises is lower when the realized category was unexpected rather than expected. Intuitively, the category surprise crowds out attention to the precise size of the surprise. In our field data, we find evidence that surprising category realizations are associated with lower local sensitivity to the magnitude of earnings surprises. For example, the earnings response coefficient (ERC) for year-over-year (YoY) earnings growth is lower when an earnings decline was predicted compared to when growth was expected. Analogously, we find that the ERC for YoY earnings decline is lower when growth was expected compared to when a decline was predicted. Overall, the patterns we document are consistent with a form of competition for attention where surprises driven by unexpected category realizations interfere with attention to numerical information.

[9] Note that these additional findings related to efficient coding are complementary to – rather than an alternative explanation for – our baseline results. Variation in local empirical density cannot explain our baseline results that leverages variation in valuation uncertainty.

[10] Canonical models of rational inattention also predict a link between the (Shannon) cost of information and the degree of surprise implied by information.

Contributions and Related Literature. An expansive literature going back at least to Simon (1955) relates behavioral anomalies to the severity of information processing constraints and bounded rationality (see, e.g., Woodford, 2020).[11] Recent work studies the role of noisy or random behavior, which has been associated with patterns of global insensitivity to variation in choice parameters (Enke and Graeber, 2023; Enke et al., 2025b). Departing from this line of work, we here propose that more severe processing constraints induce relatively stronger reliance on coarse categorical information while leading to insensitivity within category. Applying a variant of Enke and Graeber's (2025) model of bounded rationality and reference points to categories, we show that more constrained decisions thus exhibit locally *more* sensitivity around category boundaries, alongside the previously documented pattern of lower global sensitivity. In this literature, our work most closely connects to recent studies on over- and underreaction to news (Augenblick et al., 2025; Ba et al., 2024). Augenblick et al. (2025) present laboratory and field evidence of overinference from weak signals and underinference from strong ones.[12] In their model, people accurately determine the direction of a belief update given a signal but integrate the signal strength imperfectly. While their model and evidence are not about categorical versus numerical information, we believe that they are close in spirit to ours and discuss the precise relationship in Section 2. We also discuss the relationship to Ba et al. (2024), who propose a two-stage model of belief formation in which individuals first reduce complexity by focusing on a subset of representative states and then incorporate this information subject to cognitive imprecision. Our evidence can be interpreted accordingly: coarse categorization is a form of simplification at the representational stage, and integration of numerical information is imprecise at the computational stage.

A different literature spanning across disciplines studies the precise nature of the cost of information processing (see Oprea, 2024a, for a review). Coarser information structures are associated with lower processing cost according to various information-theoretic concepts, such as Shannon cost (Sims, 2003) and Kolmogorov complexity, which refers to the shortest set of rules to describe a given information structure. In particular, models of rational inattention and resource rationality can generate information discretization (see Maćkowiak et al., 2023, for a

[11]Also related is work on what makes decisions complex and how people respond to such complexity (Enke et al., 2025a; Gabaix and Graeber, 2024; Oprea, 2024b; Enke, 2024). Various simplification strategies and heuristics have been identified, such as people resorting to simpler mental models in the face of complexity (e.g., Oprea, 2020; Graeber, 2022; Banovetz and Oprea, 2023; Kendall and Oprea, 2024; Arrieta and Nielsen, 2024; Salant and Spenkuch, 2022; Musolff and Zimmermann, 2025).

[12]The literature on over- and underreaction to news is extensive, with varying conclusions: some papers document underreaction to news (Benjamin, 2019; Kieren et al., 2023; Goncalves et al., 2024), other papers document overreaction to news (De Bondt and Thaler, 1985; Bordalo et al., 2022).

review). Our results on variation in processing constraints in particular further relate to the line of work on efficient coding (Frydman and Jin, 2022) and decision by sampling (Stewart et al., 2006), both of which are consistent with higher sensitivity of the response function for stimulus ranges with higher empirical density. We are not aware of work that directly tests the role of processing constraints for the relative reliance on coarse versus granular information, and the previous empirical evidence in this space is mostly confined to controlled lab experiments. This paper identifies a high-stakes field context that speaks to several of the concepts put forward in the recent literature.

Our field tests of categorization relate to field studies on reference points (Allen et al., 2017; Pope and Simonsohn, 2011) and left-digit bias (List et al., 2023; Strulov-Shlain, 2023; Lacetera et al., 2012). Meier et al. (2025) shows that financial analysts' individual forecast revisions exhibit a step-shaped pattern that they conclude is consistent with reference-dependent thinking. This individual-level belief formation evidence in the field supports our line of argument that the S-shaped excess return functions are partly a behavioral phenomenon. This line of work finds similar patterns of higher behavioral sensitivity around thresholds but does not study the role of processing constraints, which is our focus here.[13]

Our evidence on the reliance on coarse versus granular information broadly relates to seminal work on "coarse thinking" and "thinking through categories" in economics (Mullainathan et al., 2008; Mullainathan, 2002; Bordalo et al., 2025) and finance (Barberis and Shleifer, 2003). The common thread in this stream of work is that people lump together situations into coarse groups. In Mullainathan (2002), agents coarsely partition the state space and do not continuously update from information unless there is enough evidence to cross a category threshold. Mullainathan et al. (2008) present a model in which the coarse grouping of situations can lead people to accidentally transfer information applicable to one situation to other situations in the same group. 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. Schley et al. (2023) study how categorical thinking may shape the probability weighting function.[14] Yet, this literature on categorization does not directly examine the role

[13]Recent work also models the relationship between the prospect theoretic S-shaped value function and information processing constraints (e.g., Villas-Boas, 2024). Our evidence does not directly speak to this instance of diminishing sensitivity (and loss aversion) observed in risky choice. Future work may determine whether our prediction about the effect of processing constraints on S-shaped response functions holds in this type of decision.

[14]Work in the cognitive sciences shows that adding category boundaries can generate S-shaped response patterns around them, such as in the case of proportion judgments (Hollands and Dyre, 2000). Huttenlocher et al. (2000) suggests that people rely on category priors from which they adjust to make continuous estimates, which aligns well with the model we outline in Section 2.

of processing constraints.[15]

Finally, our paper contributes to the vast finance literature on stock price responses to news (Daniel et al., 1998; Kwon and Tang, 2025; Bordalo et al., 2024a; Tetlock, 2014; Bordalo et al., 2024b; Jin and Peng, 2024; Hong and Stein, 1999; Barberis et al., 1998, 2018; Barberis, 2018; Hong and Stein, 2007) and earnings surprises in particular (Bernard and Thomas, 1989; Kormendi and Lipe, 1987; Bouchaud et al., 2019; Hirshleifer and Teoh, 2003). There are several popular explanations for the S-shaped response to earnings news in the finance and accounting literature: Freeman and Tse (1992) argue that the S-shaped stock price response is driven by the persistence of earnings news. Specifically, small positive and negative surprises are a signal about the persistent component of cashflows, while extreme surprises are not. Relatedly, Skinner and Sloan (2002) show that the S-shape is stronger for growth firms – which have longer duration cashflows on average – than value firms.[16] Adding to these explanations that highlight specific properties of financial markets, we explore an additional, behavioral mechanism. We empirically distinguish our results from the above alternative explanations (and others, such as the role of endogenous disclosure, see Huang et al. (2023)).

Our paper also relates to existing work in behavioral finance: Hirshleifer et al. (2009b) suggest the *investor distraction hypothesis* and find that markets react less to a given piece of news when information load is high. Relatedly, DellaVigna and Pollet (2009) find more underreaction on Fridays, when investor attention is low. Another strand of literature shows that investors may choose to ignore public signals altogether when there is more uncertainty (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 (Giglio et al., 2021; Charles et al., 2024). These mechanisms can explain less sensitivity to the size of surprises when there is more valuation uncertainty, but they fail to account for increased sensitivity to the sign of surprises in the presence of higher valuation uncertainty, which we establish in this paper. We add to this literature by providing evidence that valuation uncertainty affects responses to earnings announcements differentially close to and further away from category

[15]The role of processing constraints, however, has been conjectured to affect reliance on coarse information. For instance, Hsee and Zhang (2010) propose that when an attribute is difficult to assess, people may rely more on qualitative comparisons.

[16]Negative returns for barely meeting the forecast have also been associated with earnings management (Burgstahler and Dichev, 1997; Bhojraj et al., 2009). Specifically, firms have an extreme focus on beating consensus earnings by at least one cent, and engage in earnings management to ensure this happens. Small misses, therefore, are evidence of significant negative news, as even with earnings management, firms were not able to beat by a penny. The earnings management hypothesis, however, does not explain the overall S-shaped pattern.

boundaries.

The paper proceeds as follows: Section 2 discusses the behavioral predictions and outlines a conceptual framework. Section 3 describes the field setting and our empirical strategy. Section 4 reports our results from the field. Section 5 presents our experimental design and results. Section 6 studies different theories of local variation in processing constraints and their implications. Section 7 concludes.

2 Behavioral Predictions

We are interested in the role of the severity of cognitive constraints for how agents form beliefs in environments with both granular and coarse information structures. Two remarks are in order. First, we do not microfound the notion that coarse information structures are "cognitively cheaper" here but refer the reader to the various existing justifications discussed in the previous literature above. 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. The below framework serves to illustrate the logic of the main behavioral predictions (to provide guidance for the empirical tests) using a standard setup of cognitive imprecision. However, we explicitly do not claim that this model is the only or even the most adequate account of the set of behavioral predictions we study. We discuss the relationships to alternative approaches at the end of this section.

Concretely, we model an agent who receives a numerical signal alongside categorical information. The agent fully understands the category memberships, but integrates the numerical signal with noise. We derive predictions in a simple framework of constrained Bayesian optimization. This class of models has been widely applied across disciplines – including in modeling the implications of cognitive noise (e.g., Ilut and Valchev, 2023; Enke et al., 2025b; Enke and Graeber, 2023; Khaw et al., 2021). Enke and Graeber (2025) use this modeling approach to conceptualize the effect of processing constraints on assimilation and contrast effects of reference points, with our framework being a special case. Our model most closely relates to the one of Augenblick et al. (2025), in which a decision maker understands the direction of an update but integrates the signal strength with noise. We discuss the similarities and differences in detail at the end of this section.

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 receive 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, $\{s^1, \ldots, s^K, s\}$. The foundational assumption is that the DM processes the category thresholds without noise, whereas they integrate the numerical signal subject to processing noise.[17] Such noise occurs in the process of integrating information to form a response r. We take a broad view of the potential determinants of such noise, including factors on the "demand side" of information processing, i.e., the difficulty of the optimization problem, and factors on the "supply side" of information processing, i.e., the DM's cognitive processing resources, hard capacity constraints like time constraints, or even perceptual imprecision.

Assumption 1. *Categorical information is incorporated without noise; the numerical signal is processed with noise.*

The DM chooses their response r given the information set, with objective function $U(r, s)$. We assume that the DM's unconstrained optimal response function $r^\star(s)$ in the absence of any noise 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 s, or to an action a as a function of some decision parameter p, with $a^\star(p)$. In different applications, different sources of processing noise likely emerge. 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 (see, e.g., Enke et al., 2025b). We assume 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.

[17] We assume *no* noise 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 processing noise on the numerical component is *higher* than on the qualitative comparisons.

We depart from the notion of a signal-invariant prior by further working with a *category prior* $r^\star \mid s^1, \ldots, s^K \sim \mathcal{N}(r_d, \sigma_d^2)$ 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 central idea of a category prior is that the DM fully parses and understands categorical information and incorporates it in Bayesian fashion. 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 processing of categories is assumed to be "cognitively cheap" and therefore not subject to noise. The distinction between categorical and numerical information (or qualitative and quantitative information more generally) is 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). If there is a single category boundary, $K = 1$, and the optimal response crosses the origin, $r^\star(0) = 0$, our setup is similar to Augenblick et al. (2025), who do not invoke a conditional prior but would obtain similar predictions in that case.[18]

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 are uncertain about whether the conditional default response is actually optimal, captured by the conditional prior uncertainty σ_d^2. The conditional default mean r_d jumps at the category thresholds. The conditional default response is thus a step function.

Processing Noise. Due to processing noise 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 noise as emerging in the mapping between numerical signal and response. Such noise can have various origins: information-processing constraints, uncertainty about preferences, or true stochasticity in the mapping between response and optimal response. Due to noise, the DM can only mentally simulate their best response. This mental simulation creates an unbiased noisy *cognitive signal* about the optimal response:

[18] They model a conditional subjective perception of signal strength.

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

The precision of this cognitive signal is determined by the level of processing noise, $\sigma_r^2(s)$. As shown, for example, in Ilut and Valchev (2023), this form of mapping noise can be modeled as uncertainty about the weight that maps a problem fundamental (here, the signal) into the optimal action (the belief).

Note that we here allow for processing noise to depend on the size of the signal, $\sigma_r^2(s)$. We begin by deriving our main predictions under the assumption of constant noise.

Constrained Optimal Response. The DM is constrained by the (for now, exogenous) presence of processing noise. They optimally combine their imperfect cognitive signal with their conditional prior in Bayesian fashion, which yields:

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

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

Note that under the assumption of constant processing noise that is independent of the signal, σ_r^2, the behavioral response is a piecewise linear function that jumps at the comparison points. In particular, this response function has two key properties in comparison to the optimal response function r^* (again, without assuming any additional characteristics for 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.

Variation in Processing Noise. The conditional prior induces jumps at category thresholds, and the level of processing noise controls response sensitivity everywhere else. If noise is constant, the constrained behavioral response is a piecewise linear step function. In practice, the extent of processing noise 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.[19] Models of decision by sampling (Stewart et al., 2006) and efficient coding (e.g., Barlow et al., 1961; Laughlin, 1981; Frydman and Jin, 2022) predict that processing noise for a given stimulus range is decreasing in its empirical density in the stimulus distribution. The level of noise in processing 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 sources of processing noise in Section 6.

Model Summary and Predictions. Intuitively, the DM understands the central tendency of the responses associated with a collection of category identifiers, but processes the actual numerical information imprecisely. The conditional prior jumps at category thresholds because the conditional expectation of the optimal response jumps when the DM only relies on categorical information. Processing noise only affects the sensitivity to the numerical signal and induces behavioral attenuation. The level of noise might vary in practice, inducing different degrees of sensitivity to the signal in different parameter ranges.

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

Extension: Uncertainty about the Location of the Category Threshold. In practice, there may be a second form of uncertainty directly affecting optimization: prior 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.[20]

[19]Increasing noise in the absolute magnitude of the signal has been documented in a wide variety of experimental tasks by Enke et al. (2025b), 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.

[20]There are two 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 have different comparison levels, but each of them is certain about

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.[21]

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

Discussion. Several remarks are in order. First, the signal s may be multidimensional rather than a scalar. The numerical signal would then be many-dimensional, too. In our model, the agent incorporates all categorical information without noise, and creates one single unbiased mental simulation of the optimal response that is based on all numerical components jointly. This means we model a DM whose global optimization is subject to noise when jointly integrating numerical information, not one who separately perceives or processes individual parameters with noise. Second, we allow but are agnostic about whether 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.[22]

Relationship to Existing Models. This model builds on and is compatible with the main ideas in Augenblick et al. (2025). A central difference is that 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 potentially multiple comparisons to category boundaries. 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.[23] Moreover, we do not model a binary state space but a

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 (3).

[21]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.

[22]Intuitively, it is clear that the conditional response based on categorical information alone must be a step function. We merely require that the unconstrained response based on all information is smoother than this step function.

[23]Augenblick et al. (2025) extend their model to incorporate distortions of the prior in Section II.C. In our framework, as in Enke and Graeber (2023), distortions are formulated directly in action space and can thus accommodate distortions of parameters other than the signal diagnosticity by design.

continuous one, and people process the quantitative signal with noise, rather than the implied signal strength. In our model, the signal does not induce the DM to form an estimate of the signal strength (which the agent in Augenblick et al. (2025) then combines with a prior), 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 many qualitative signals and one or more quantitative ones. All in all, the foundations of our model are consistent with and build 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.

3 Field Setting: Market Responses to Earnings Announcements

In this section, we provide details on the institutional setting of earnings announcements and the data sources we employ.

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, mandated by the Securities and Exchange Commission (SEC) to be disclosed quarterly via Form 10-Q and annually via Form 10-K, 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.

3.1 Data

Data on 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 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).[24]

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".

Stock Price Data. We leverage extensive historical data on stock prices, returns, and trading volumes from CRSP.

Earnings Surprises. To quantify the response of stock prices to earnings news, we start by constructing a variable to capture earnings surprises using analyst expectations from IBES. Following DellaVigna and Pollet (2009) and Hartzmark and Shue (2018), we define standardized unexpected earnings (SUE) as:

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

where $\mathrm{EPS}_{i,t}$ is the earnings per share. $E_{t-1}[\mathrm{EPS}_{i,t}]$ is the mean expected earnings per share

[24]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.

in the last IBES statistical period before earnings were released. $P_{i,t-1}$ is the last closing price before the earnings announcement. To reduce the influence of outliers, we winsorize $\text{SUE}_{i,t}$ at the 1% and 99% level.

Market-Adjusted Returns. We follow Campbell et al. (2001) and 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.[25] 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.

Measures of the Severity of Processing Constraints. To proxy for the severity of processing constraints, we leverage the existing literature on what makes stocks "hard to value" (see, e.g., Laarits and 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.[26] 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 complex" as reviewed in the literature above, cyclical factors (e.g. market or industry environment) that make valuations more difficult or uncertain, the generic difficulty of valuing assets et cetera. We do not claim to distinguish

[25]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.

[26]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.

between these, but rather embrace the multitude of factors contributing to uncertainty about the mapping in line with the broad notion of information processing constraints described in Section 2.

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 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 four days after the earnings announcement are on average zero, but they exhibit large dispersion. The interquartile range spans from -0.047 to 0.045. 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
Dispersion	176,893	0.430	0.449	0.189	0.271	0.450
VU	176,893	0.750	0.232	0.607	0.747	0.894
Mkt. Adj. Ret	176,893	0.000	0.092	-0.048	-0.002	0.046

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.[27] 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, 2021). 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, 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 $t = 4$.[28] 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

[27]Our results are robust to using different time horizons around the event.

[28]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.

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.

4 Field Evidence

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

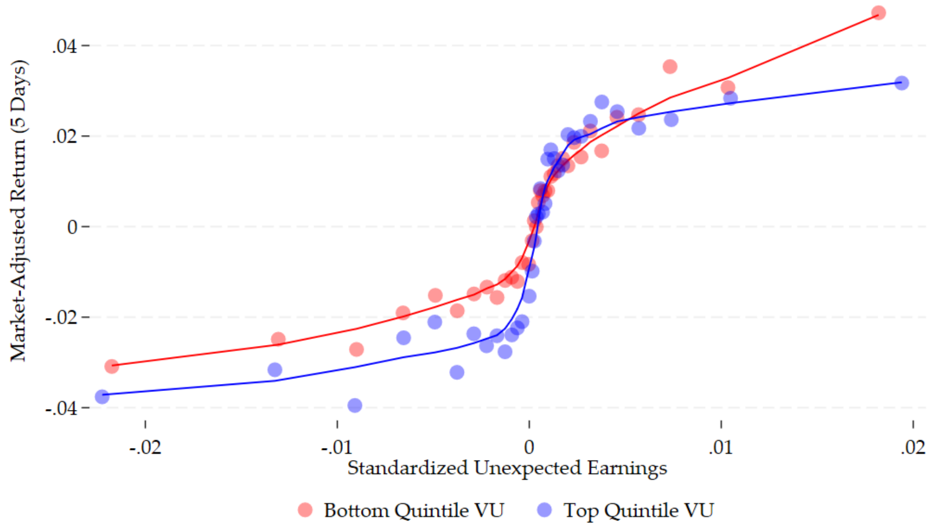
4.1 Raw Data

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. 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 VU quintile 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 now turn to more systematic evidence on the economic and statistical significance of this relationship.

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 which are lower in recessions and higher in booms. So, with time fixed effects, our results should be interpreted as exploiting heterogeneity in post-earnings announcement returns in the cross-section *at each given point in time*.[29]

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.[30] 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., 2021). 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 double clustered at the stock and year-month 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 use 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

[29]In Appendix A.2 we show that our results are qualitatively similar when estimating a pooled specification. In particular, we observe a pronounced amplification of the response to surprises for windows close to zero.

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

sensitivity within the category, so that the overall effect of VU decreases as the window size increases. As the window grows to include the full sample, we know from previous research that measures of harder-to-value stocks operationalized by VU are associated with lower earnings response sensitivity, such that we expect a negative interaction coefficient there. Taken together, the interaction coefficient is predicted to be positive for tight windows around zero, then gradually falls below zero as more and more data are included in the symmetric windows.

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 percentage point 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. This attenuation in coefficients as we widen the support reflects the general S-shaped relationship between market-adjusted returns and earnings surprises shown in Figure 1.

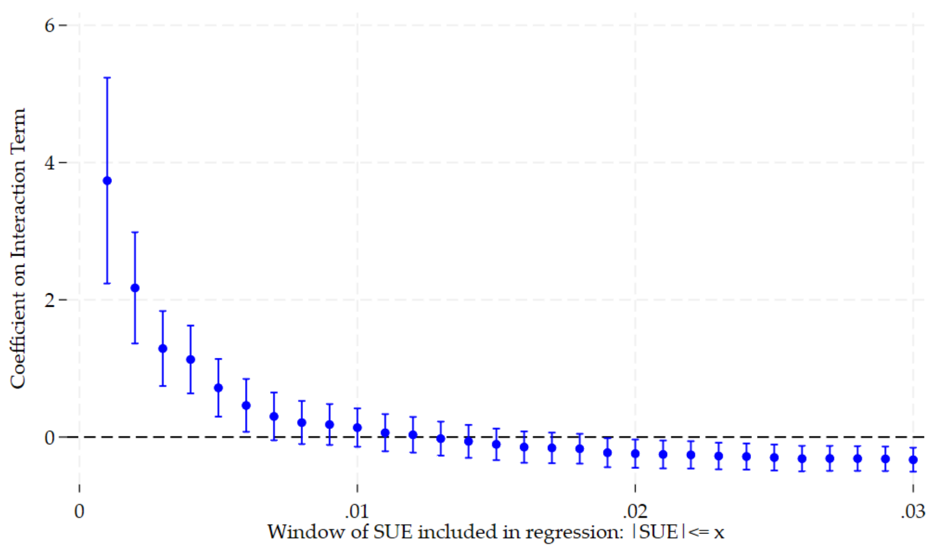
Our main object of interest is the interaction effect between SUE and valuation uncertainty. As predicted by our model, Column 1 reports a positive and significant interaction effect for narrow SUE windows around zero. In other words: valuation uncertainty predicts *increased* sensitivity to the crossing 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 valuation uncertainty predicts *decreased* sensitivity to the magnitude of surprises (conditional on their sign), and this effect dominates in the full sample.

These effects are economically meaningful. For an observation with a one-standard deviation higher valuation uncertainty the market adjusted return is 19.3 percent ($p < 0.01$) compared to 17.12 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 percent ($p < 0.01$) 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 percent ($p < 0.01$), 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 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. Note that this prediction of a more S-shaped relationship and thus a switch in the sign of the effect of valuation uncertainty is quite distinctive and thus hard to rationalize with existing or alternative explanations, which we address in the next subsection.

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.

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-month 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.

4.4 Robustness

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

Robustness to Definition of SUE. 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 ± 10 basis points (about 37% of our sample). Consequently, percentile ranks "spread out" a large number of observations at and around SUE of zero, which interferes with the identification of the sensitivity around the *nominally defined* category threshold. We show corresponding results in the Appendix. What is more, we note that percentile ranks are a good test of the predictions of models that predict a local earnings response sensitivity that is proportional to the local empirical density (such as efficient coding or decision by sampling): taken to the extreme, local sensitivity that is directly proportional to the historical mass in a given bin predicts a linear relationship when looking at earnings response coefficients by percentile rank. We return to this perspective in Section 6.

Robustness to Different Time Periods. 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 larges 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.[31] And second, large surprises for high valuation uncertainty firms would need to be less persistent than large surprises for low valuation uncertainty firms. In Appendix A.4, 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 from zero. To do so, we test 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

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

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. Appendix A.6 provides additional details.

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. Specifically, 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.[32] And, if this channel applies differently to small versus large surprises, one might be concerned that it is driving our results on valuation uncertainty.

To rule out this explanation, we run a series of tests to examine whether high and low valuation uncertainty stocks have different amounts of earnings information incorporated into prices before versus after the announcement itself. As we outline in more detail in Appendix A.8, 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.

4.5 Uncertainty About the Location of Category Thresholds

Valuation uncertainty could be correlated with time-varying unobservables that drive the S-shaped patterns in our data. To provide further evidence getting at this concern, we show that – consistent with our behavioral hypothesis – other forms of uncertainty have very different effects on earnings response sensitivity.

Our basic framework focuses on noise in the integration of the numerical signal but categorization is without noise, i.e. the agent fully understands the implications of the category boundaries. However, uncertainty about the categorizations is highly plausible in practice: it can result from an individual agent being uncertain about the location of the category boundary or from different agents believing in different boundary locations. Prediction 2 shows that uncertainty about the categorization itself should decrease people's sensitivity to surprising news, especially close to category boundaries. Recall that this prediction is thus almost the reverse of our main prediction on the severity of processing constraints, which are associated with *higher* sensitivity around boundaries. In the following, we examine how prior uncertainty about the consensus forecast affects sensitivity 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:

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

[32] 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., 2023).

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.[33] 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. Figure A2 plots the coefficients of the interaction effect between dispersion and SUE for larger SUE windows around zero. The figure clearly demonstrates that for all windows of SUE around zero, the interaction effect is negative.

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.

Relationship Between Dispersion and Valuation Uncertainty. Measures of category uncertainty might be correlated with valuation uncertainty and alternative measures of processing constraints more generally. We discuss and examine these relationships in the following subsection. Appendix Table A13 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 ef-

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

fect 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.

4.6 Related Concepts and Measurements

As illustrated by the preceding analysis and the conceptual framework, different forms of uncertainty capture different concepts that can be measured in a variety of ways.

Different Concepts. Following previous work, we conceptualize the severity of processing constraints as creating uncertainty about the mapping between a signal and one's optimal response.[34] 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 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 cannot generate the pattern that we identify, because it relies on people actually processing (at least) the categorical information content, and is compatible with people attending to numerical information, too. Distraction, by contrast, would lead to global attenuation because (some) people do not process and respond to any of the information components.

This above highlights the specificity of our prediction to measurements that capture uncertainty about the mapping from signal to response. Related concepts, such as distraction and uncertainty about category thresholds, predict global attenuation instead.

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

[34]The previous subsection showed that uncertainty about the location of a category threshold is indeed a distinct concept from this, with different effects.

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, as discussed in Laarits and Sammon (2024), a longer cash-flow duration (Gormsen and Lazarus, 2023) 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 A12 shows that cashflow duration is associated with a more pronounced S-shaped pattern. This result aligns with the early work of Freeman and Tse (1992) who show that growth firms — which tend to have higher cash-flow duration – exhibit more S-shaped return responses to earnings news.

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 A12 shows that amplification of small surprises and the comparative static of a decreasing interaction coefficient for larger surprises qualitatively holds for all three of these other proxies of valuation uncertainty.

Finally, the literature on the investor distraction hypothesis studies measures of expected and unexpected distractions. Measures of expected distraction, such as multiple same-day company announcements (Hirshleifer et al., 2009b), major sports events such as the Olympics, World Series, or March Madness (Drake et al., 2016), the incidence of announcement on Friday (DellaVigna and Pollet, 2009) and releases of key macroeconomic indicators (Kasznik and Kremer, 2014) have been related to pricing inefficiencies in some contexts, although some of these effects appear to be less robust in more recent samples (e.g., Israeli et al., 2021). Israeli et al. (2021) also study measures of unexpected distraction (using a general news pressure instrument) and find that while they do appear to affect retail but not institutional investors, there are no discernible price effects. This class of measures has traditionally been linked to global attenuation effects, and we argue that they are best thought of as capturing the extensive margin of attention, i.e, inattention to the announcement altogether, rather than mapping difficulty.

5 Experimental Evidence

To provide causal evidence on the relationship between the severity of processing constraints and the S-shaped empirical earnings response function, we complement the correlational field evidence with incentivized naturalistic experiments conducted with investors.

5.1 Design

Objectives. First, we aim for a naturalistic setting that emulates the multi-dimensional character of real news stories about earnings announcements, containing both categorical and numerical information. Second, to test the hypothesis that the field evidence – observed in aggregate prices – is partly driven by a pattern that already emerges in individual updating behavior, we require individual-level belief data. Third, we exogenously manipulate the severity of processing constraints in a controlled way.

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 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.[35] This range of SUE captures over 85% of the empirical distribution.

For concreteness, see below the body of the earnings news article for the company *Darden Restaurants* for the scenario of an SUE of -0.0005.

> Darden Restaurants, Inc. is an American multi-brand restaurant operator headquartered in Orlando, Florida. In their earnings announcement for the third quarter

[35] 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.

> 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*,[36] 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. We provide screenshots of the entire experiment in Appendix D, which includes the decision screen for the Baseline condition (Appendix Figure A16). 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.[37] 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.[38] 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, we increase the severity of processing constraints for participants in the *High Constraints* condition in two ways. First, we effectively manipulate the "demand side" of processing

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

[37]The set of companies we used are: Micron Technology, FedEx, Lennar, Darden Restaurants, and Paychex.

[38]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.

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). The combination of time pressure with additional (irrelevant) information load in *High Constraints* aimed at effectively limiting respondents' ability to thoroughly integrate all information. Respondents almost always complied with the time limit: we recorded 6.7% timeouts across all rounds and participants. An example decision screen for this condition is shown in Appendix Figure A16.

The *High Constraints* condition increases the severity of information processing constraints in a way that arguably has ecological validity: 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).

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 formats (both pre-registered, see below). 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.[39] These category defaults are the direct empirical analogue of the conditional default response r_d, see Section 2.

[39]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?"

Equipped with 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. We document the same findings 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 appear practically relevant to us, given our application, but is not meant as a way to precisely identify different potential 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) integrating a piece of information as a result of processing constraints. We think both channels are highly relevant in practice.

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. The prior elicitation of or training on a specific category as experimental manipulations might be a fruitful avenue for future work to identify the role of familiarity for the relative reliance under processing constraints.

5.2 Sample

The data collection took place in December 2024 and was pre-registered on AsPredicted (#205080).[40] 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.

[40] https://aspredicted.org/n3zm-md9t.pdf

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, shown in Appendix Figure A10, 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 state a category prior with a wrong sign. We consider this a low bar for understanding the empirical setting (or paying attention). In particular, we exclude respondents who state a belief indicating that the historical average of same-day price changes in response to positive earnings surprises was non-positive, as well as all respondents who state a belief that the historical average of same-day price changes in response to negative earnings surprises were non-negative. After applying these exclusions, we end up with a final sample size of 897 respondents.[41]

5.3 Results

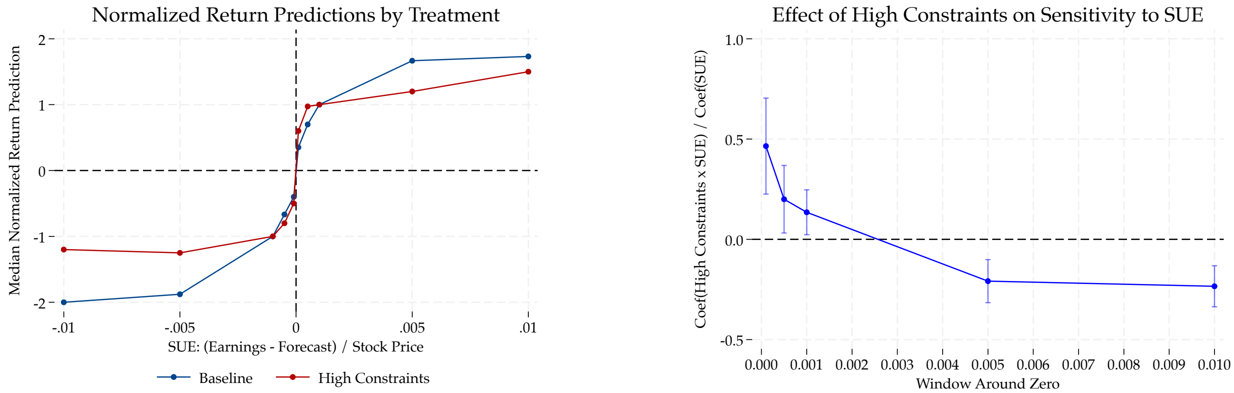
Result 1: Shape of the Empirical Response Function in *Baseline*. The blue markers in Panel (a) of Figure 4 plot the median normalized return prediction for each SUE value in *Baseline*.[42] The blue line illustrates the implied slope. Even in our simple baseline condition without any additional complications, 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

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

[42]We begin with normalized returns, which we pre-registered as our main measure. All results also hold for the raw returns, see Robustness below and all corresponding analyses in Appendix C.

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.

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 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:

$$r_{ij} = \alpha High\ Constraints_i + \beta SUE_{ij} + + \gamma SUE_j \times High\ Constraints_i + \varepsilon_{ij}$$

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_j denotes the size of the surprise for company j. Our key object of interest is the coefficient on the interaction term between SUE and *High Constraints*, γ. Recall from the field evidence we predicted and documented a positive interaction coefficient for small absolute surprises that fell as we iteratively included larger absolute surprises, eventually turning negative for the full sample. Following this approach in the observational data, we here 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 cognitive 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. Table 3 provides these results in regression format.[43] Taken together, these patterns show that respondents in *High Constraints* are significantly more responsive to the category information, yet less sensitive to the numerical magnitude of surprises. We interpret these results as suggesting that the aggregate S-shaped price patterns in the field and our correlational findings on the role of valuation uncertainty may partly be a result of how individuals' beliefs respond to the severity of processing constraints.

Robustness. We conduct a battery of robustness tests and sensitivity analyses, all of which we pre-registered. We summarize these findings, all of which are reported in Appendix C . As jointly illustrated in Figure A8, our results hold when we (a) analyze raw price change predictions instead of normalized predictions; (b) do not normalize the interaction coefficient with the *Baseline* slope; (c) test effects on means instead of medians; (d) drop timeouts in the *High Constraints* condition (6.7% in *High Constraints*); (e) exclude participants who report looking up additional information online (5.24%); and (f) exclude observations where the predicted price change has the opposite sign of the earnings surprise (7.6%), i.e. a negative (positive) price change prediction for a positive (negative) surprise.

[43]The table also shows a level effect: respondents in *High Constraints* predict somewhat higher returns, irrespective of the size of surprise.

Table 3: 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.

6 Variation of Earnings Response Sensitivity and the Determinants of Processing Constraints

Up to this point, our empirical analyses both in the field and the experiment focus on the nonlinear shape of the earnings response function. As noted in Section 2, our framework predicts a piecewise linear step function under the assumption of a constant severity of processing constraints for all possible signal realizations. Yet, the empirical relationship in Figure 1 has several notable features that a piecewise linear fit misses and that our empirical analyses ignore thus far.

First, the return patterns in the field exhibit a smooth pattern of diminishing sensitivity around zero surprise rather than a discontinuous jump. Second, there is a clear asymmetry between consensus beats and misses, with far lower sensitivity in negatives. In this section, we examine whether our hypothesis about the severity of processing constraints also speaks to these patterns.

In the context of the theoretical framework, local variations in the slope of the earnings response function are directly linked to local variation in the severity of processing constraints. Intuitively, locally higher processing noise induces the agent to rely more on the category default and less on local variation in the numerical information. As a result, higher noise makes the agent less sensitive to variation in the magnitude of announced EPS, conditional on a category.

We now relax the working assumption of globally constant processing constraints, examine potential drivers of local variation, and test whether locally more severe processing constraints are indeed associated with locally lower sensitivity to the sizes of surprises.

Rather than proposing a new theory of the determinants of processing constraints, we leverage two prominent hypotheses from recent work in behavioral economics and the cognitive sciences. The first hypothesis suggests that processing constraints are lower for more common stimuli, such that local response sensitivity is linked to the local density in the historical distribution (Section 6.1). The second hypothesis suggests that surprise draws attention, and attention is a scarce resource: a more surprising category realization (given expectations) might require more processing capacity and "distract" from the precise magnitude of EPS, reducing sensitivity to local variation in the numerical signal (Section 6.2).

Both of these (complementary) hypotheses received previous empirical support in laboratory settings and lower-level cognitive tasks such as perception, but have not been tested in an economically relevant field setting. They can be viewed as extensions of our baseline framework that add to and refine our main evidence, and do not stand in conflict with any of the findings reported up to here.

6.1 The Role of Stimulus Frequency for Processing Accuracy

A long-standing hypothesis in the cognitive sciences posits that processing accuracy is higher for stimuli that are encountered more frequently. This idea has been proposed, modeled, and tested experimentally in a variety of ways, prominently including the principle of *efficient coding* (Laughlin, 1981; Barlow et al., 1961). Efficient coding suggests that sensory systems are optimized to represent incoming information in a way that is efficient given biological constraints, typically enhancing stimulus discrimination – and thus higher sensitivity of the response function – in ranges with more empirical mass. Much of the modeling and empirical evidence of efficient coding applies to lower-level cognitive tasks such as perception (e.g. Wei and Stocker, 2015; Girshick et al., 2011). More recently, the efficient coding principle has attracted attention in economics, both in theory (e.g., Woodford, 2012) and empirical studies on subjective value

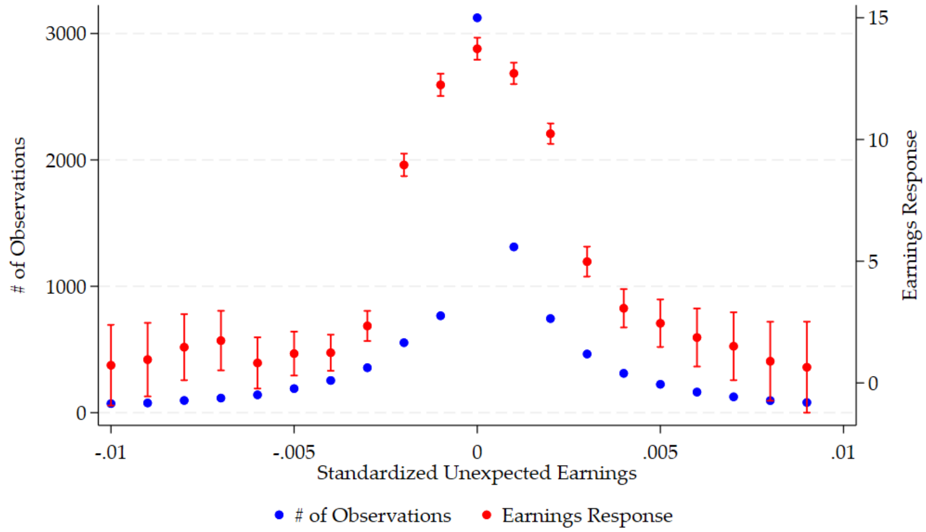
(Polanía et al., 2019), estimation tasks (Heng et al., 2020) and choice under risk (Frydman and Jin, 2022). Efficient coding is not the only theory compatible with higher sensitivity in stimulus ranges with higher density. In particular, *decision by sampling* (Stewart et al., 2006; Stewart and Simpson, 2008) suggests that subjective value is created by comparing a stimulus to samples from memory. The model predicts higher discriminability in denser stimulus regions.

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 is strikingly similar to 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.

Regression Analyses. To formally test and quantify this visual impression of the hypothesized relationship, we conduct additional analyses. Specifically, we first estimate a kernel density on the historical distribution of surprises with 100 points. We restrict our attention to SUEs between -0.05 and $+0.05$, corresponding to 98% of the data. Then, we run the following

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:

$$
\begin{aligned}
r_{i,(t,t+n)} = {} & \beta_1 \text{SUE}_{i,t} + \beta_2 1_{\text{SUE}_{i,t}<0} + \beta_3 1_{\text{SUE}_{i,t}<0} \times \text{SUE}_{i,t} \\
& + \gamma_1 \text{SUE}_{i,t} \times ln(\text{D}_{i,t}) + \gamma_2 1_{\text{SUE}_{i,t}<0} \times ln(\text{D}_{i,t}) \\
& + \gamma_3 1_{\text{SUE}_{i,t}<0} \times \text{SUE}_{i,t} \times ln(\text{D}_{i,t}) + \theta X_{i,t} + \omega ln(\text{D}_{i,t}) + \phi_t + \psi_i + \epsilon_{i,t}
\end{aligned}
\tag{7}
$$

$\text{D}_{i,t}$ 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 7, 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 a 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 4. 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%.[44] 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.[45] 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. Additional evidence presented Appendix A.1 shows that specifications with percentile ranks on the x-axis yield an approximately linear relationship with excess market returns (under some assumptions), providing an additional perspective consistent with this hypothesis. Taken together, we find evidence that is compatible with the idea that processing accuracy is higher 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, Distraction and Competition for Attention

The motivation of our basic 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.[46]

A prominent principle in the cognitive sciences is that more *surprising* information requires more processing resources (e.g., Friston, 2005; Itti and Baldi, 2009). The special role of surprises for shaping attention has also been studied in economics (Bordalo et al., 2021). In ratio-

[44] 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%.

[45] Note that the triple interaction between $1_{SUE_{i,t}<0}$, $SUE_{i,t}$ and $ln(D_{i,t})$ is -0.578.

[46] Our baseline model abstracts from this feature by assuming zero processing noise for categorical information and fixed processing noise for numerical information.

Table 4: 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.

nal 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.

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.[47]

[47]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 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:

$$\begin{aligned} r_{i,(t,t+n)} = {} & \beta_1 \text{SUE}_{i,t} + \beta_2 1_{\text{SUE}_{i,t}<0} + \beta_3 1_{\text{SUE}_{i,t}<0} \times \text{SUE}_{i,t} \\ & + \zeta \text{Running}_{i,t} + \sum_{k=1}^{3} \delta_k 1_{(i,t)\in k} + \sum_{k=1}^{3} \gamma_k 1_{(i,t)\in k} \times \text{SUE}_{i,t} \\ & + \theta X_{i,t} + \phi_t + \psi_i + \epsilon_{i,t} \end{aligned} \tag{8}$$

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 8, 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

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.

the size of the SUE. Importantly, because we include SUE in Equation 8, 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.

Results. Table 5 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.

Specifically, in the first column of Table 5, 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 5 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

Table 5: 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.

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.

7 Conclusion

We study the competition between categorical and numerical information in a high-stakes field setting and using incentivized experiments. A class of models that we illustrate using a framework of constrained Bayesian optimization makes the distinctive prediction that more severe processing constraints lead to *sharpening* across categories and *flattening* within-category: this yields S-shaped behavioral response functions around category thresholds. In the case of stock market responses to earnings surprises, more constrained agents are predicted to overreact to small (positive and negative) surprises yet under-react to large ones. Our empirical setting is motivated by the fact that excess stock returns in practice indeed exhibit a striking S shape.

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 *hard-to-value*. We then confirm our findings with incentivized individual belief formation experiments with investors that leverage causal manipulations of processing constraints.

To go further, we then bring two prominent hypotheses from the cognitive sciences about what causes local variation in processing constraints to the field: that processing accuracy is higher for more frequently encountered stimuli, and that more surprising events capture more processing resources, taking attention away from the numerical magnitude of earnings news. We document evidence in support of both, suggesting that additional properties of the empirical earnings response function – smoothly diminishing sensitivity and an asymmetry between negative and positive surprises – may be described by an account of behavioral responses to limited processing capacity.

We believe that our general hypothesis – that there is competition between easy- and hard-to-integrate information – applies to many other settings. Our approach provides a blueprint for studying the potential cognitive origins of corresponding field phenomena: for the case of coarse versus granular information, our tests required 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 as we did. Second, measures of variation in the severity of processing constraints. 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 accuracy (such as historical stimulus frequency or the degree of surprise).

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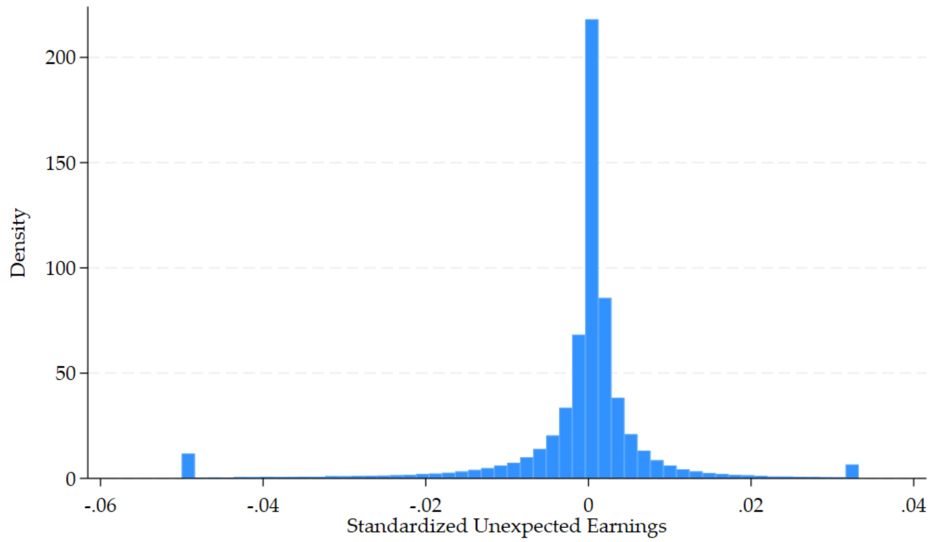
A Additional exhibits for field data on stock returns

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

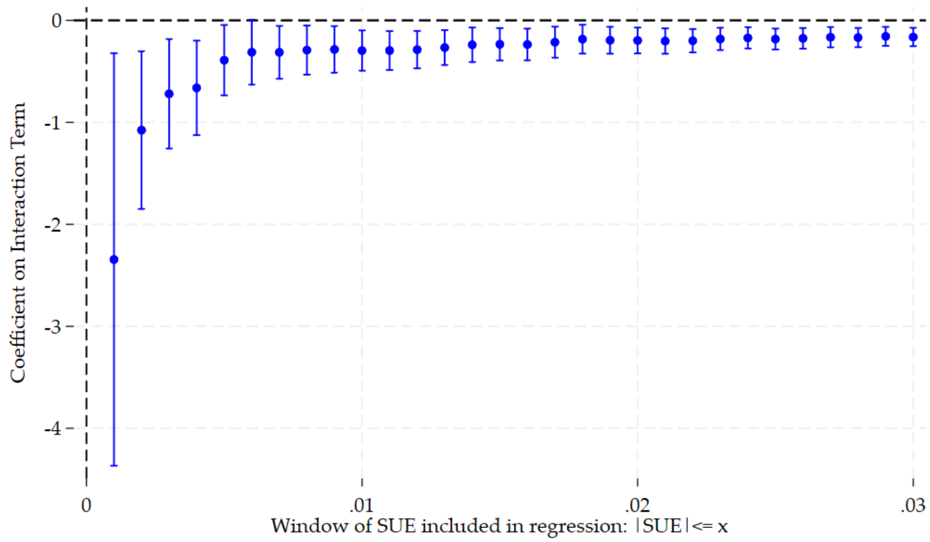
Notes: This table studies how market-adjusted returns respond to standardized unexpected earnings (SUE) and how this varies by Valuation Uncertainty. Panel A includes all observations, while Panel B focuses on the bottom quintile of analyst dispersion. SUE refers to the deviation of a company's reported 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-month 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 Figure A2: Interaction effect of Dispersion and Standardized Unexpected Earnings



Notes: This figure illustrates the interaction effect of Dispersion and Standardized Unexpected Earnings (SUE) on market-adjusted returns. The SUE variable 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 earnings announcement, normalized by the magnitude of the consensus estimate of earnings per share Ben-David et al. (2023). The figure plots the SUE x Dispersion interaction, showing the response of market-adjusted returns within different SUE windows around the earnings announcement. 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.

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	$\leq \lvert 0.002\rvert$	$\leq \lvert 0.005\rvert$	$\leq \lvert 0.01\rvert$	$\leq \lvert 0.025\rvert$	$\leq \lvert 0.05\rvert$
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

SUE Window	(1) ≤ |0.002|	(2) ≤ |0.005|	(3) ≤ |0.01|	(4) ≤ |0.025|	(5) ≤ |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

	(1)	(2)	(3)	(4)	(5)
SUE Window	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |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 i.e. 3 day returns

SUE Window	(1) $\leq \lvert 0.002 \rvert$	(2) $\leq \lvert 0.005 \rvert$	(3) $\leq \lvert 0.01 \rvert$	(4) $\leq \lvert 0.025 \rvert$	(5) $\leq \lvert 0.05 \rvert$
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 latter approach does not allow for testing non-linearity in returns to the size of earnings surprises. Instead, 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.[48] 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.

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

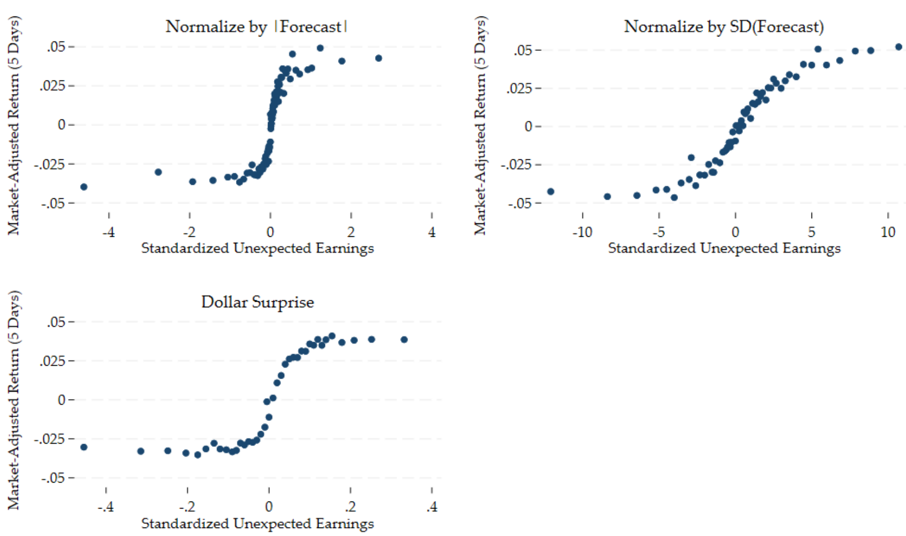
Where $E_{t-1}[EPS_{i,t}]$ is the mean analyst estimate of EPS, and $EPS_{i,t}$ is realized EPS. One down-

[48] 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.

side of working with the dollar surprise, relative to other definitions of SUE is that it is less 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 A3 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 A3: 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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Window Size	50%	75%	90%	95%	All	50%	75%	90%	95%	All	50%	75%	90%	95%	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-month 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 noisy processing 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 precludes a quantitative assessment of potential non-linearities in the relationship between returns and earnings surprises. 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 $SUE > 0$.

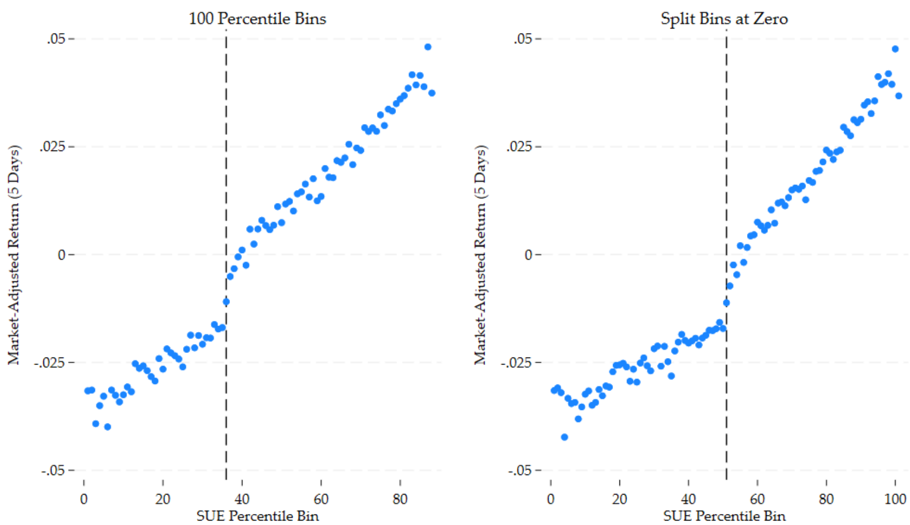
Figure A4 shows the results. In the left panel, we follow Hartzmark and Shue (2018) and form 100 bins based on percentile ranks, where the percentiles are formed each quarter. This panel replicates their result of a linear response of stock prices to percentile ranks of SUE. In the right panel, however, 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).[49] And, the right panel shows that there is indeed a sharp jump in returns at the zero-crossing boundary. Overall, these results imply that our finding of increased sensitivity to SUEs right around zero is not an artifact of how we constructed SUE (or using SUE itself rather than percentile ranks of SUE), but rather a robust empirical pattern.

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

[49]The logic is that forming the percentiles conditional on another variable could cloud the effect of crossing $SUE = 0$, as $SUE = 0$ could fall into a different percentile bin each quarter or for each firm. By forming percentiles unconditionally, we ensure all observations with an SUE of exactly zero are in the same bin.

Appendix Figure A4: 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.

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.

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

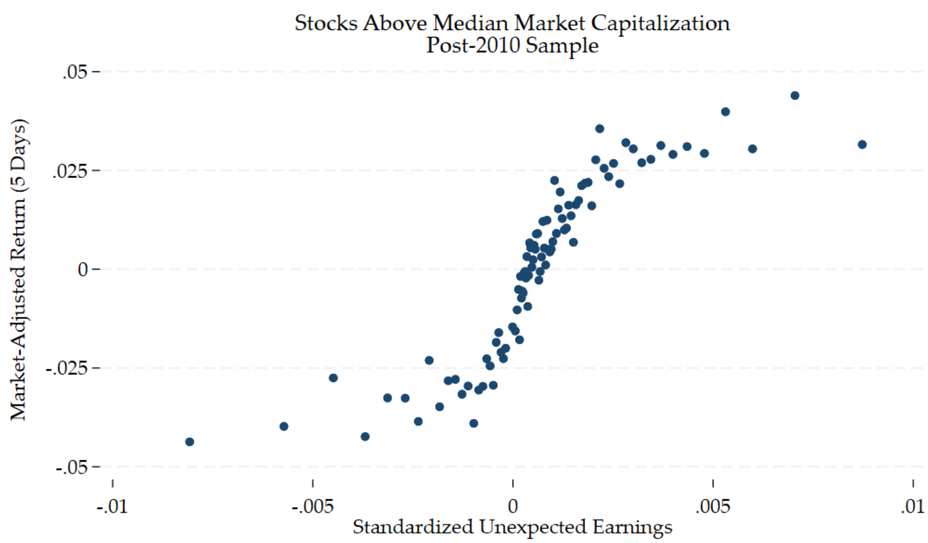
	(1)	(2)	(3)	(4)
SUE x 1_|SUE|<=0.002	15.35***	15.63***	15.90***	15.78***
	(0.638)	(0.636)	(0.633)	(0.647)
SUE x 1_|SUE|>0.002 & |SUE|<=0.005	7.821***	7.909***	8.003***	8.189***
	(0.314)	(0.316)	(0.320)	(0.335)
SUE x 1_|SUE|>0.005 & |SUE|<=0.01	4.609***	4.645***	4.710***	4.908***
	(0.192)	(0.192)	(0.190)	(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-month 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.

A.3 Robustness to different time periods

As discussed in Martineau (2021), the post-earnings-announcement drift (PEAD) is no longer present in recent years, especially among large capitalization stocks. One might be worried, therefore, if the PEAD is driven by under-reaction to extreme news, and the PEAD has disappeared, then the S-shaped response to earnings news has disappeared as well. To test this, first we replicate our baseline plot of market-adjusted returns against SUE, but we restrict to data after 2010 (the last period considered in Martineau (2021)). And, we further restrict to stocks which, within a given quarter, are above the median market capitalization in our sample. Figure A5 shows that the S-shape is still strong among large stocks in more recent years. This suggests that the disappearance of the PEAD does not imply that the general empirical pattern of an S-shaped response of stock prices to earnings news has also gone away.

Appendix Figure A5: S-shaped Response of Market-Adjusted Returns to Earnings Surprises: Post 2010, Large Cap. Stocks



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 4 days after the earnings announcement. Restricts to data after 2010, and stocks which are above median market capitalization in our sample each quarter.

Table A9 replicates our main results on the relationship between valuation uncertainty and earnings response coefficients, again 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. Collectively, the evidence in Figure A5 and Table A9 suggest that the disappearance of the PEAD in recent years does not diminish the strength of our findings.

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	≤ |0.002|	≤ |0.005|	≤ |0.01|	≤ |0.025|	≤ |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-month 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.

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.[50] And second, large surprises for high valuation uncertainty firms would need to be less persistent than large surprises for low valuation uncertainty firms.

[50] 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.

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 from zero. To do so, we test the predictive power of an earnings surprise (i.e. 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 (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 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 A6 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.

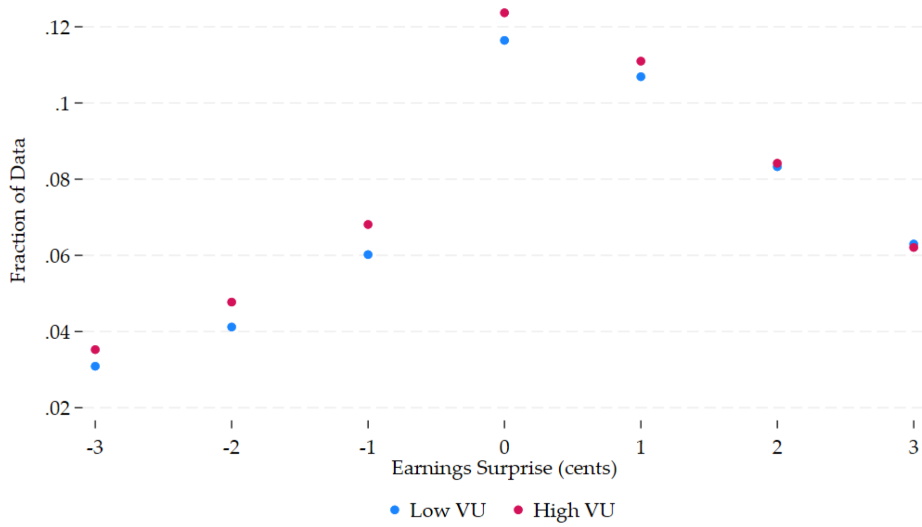
First, we test for differences in bunching just above an $SUE = 0$ for high versus low VU observations. To this end, each quarter, we split the data into two groups depending on whether or not the stock has above or below median VU. Figure A6 plots the fraction of the data in each VU group in 1 cent 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.[51] This is the first piece of evidence suggesting that differences in earnings manipulation do not drive our results.

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 including 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

[51]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.

Appendix Figure A6: 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.

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 A6 and Table A10 are further evidence that differences in earnings manipulation, and earnings persistence are not driving our main findings.

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

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-month 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.

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.

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-month 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.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 A12, 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 A12 shows that for cashflow duration, the patterns are broadly 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 A12 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.[52] 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.

[52]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 A12, we have flipped the indicator to be whether there is no business segment accounting for 80% or more of total revenue

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

A.8 Differences in Pre-Announcement Information Acquisition

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.[53] Overall, the results in Table A14 suggest 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.

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

[53]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 details.

Appendix Table A12: 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-month 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 A13: 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).

Appendix Table A14: Relationship between Valuation Uncertainty and Information Incorporated Into Prices Before Earnings Announcements

	$|RET|/SD$ (1)	PJ (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-month 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.

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.

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

SUE Window	(1) ≤ |0.002|	(2) ≤ |0.005|	(3) ≤ |0.01|	(4) ≤ |0.025|	(5) ≤ |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-month 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 A16 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, $VUxSUEx1_{|SUE|>0.002|SUE|<=0.005}$ 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, $VUxSUEx1_{|SUE|>0.005|SUE|<=0.01}$ is negative and even smaller in magnitude.

The next interaction term, $VUxSUEx1_{|SUE|>0.01|SUE|<=0.025}$ is positive, flipping the sign realtive 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 $VUxSUEx1_{|SUE|>0.025|SUE|<=0.05}$ 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 A16 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 A16 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.

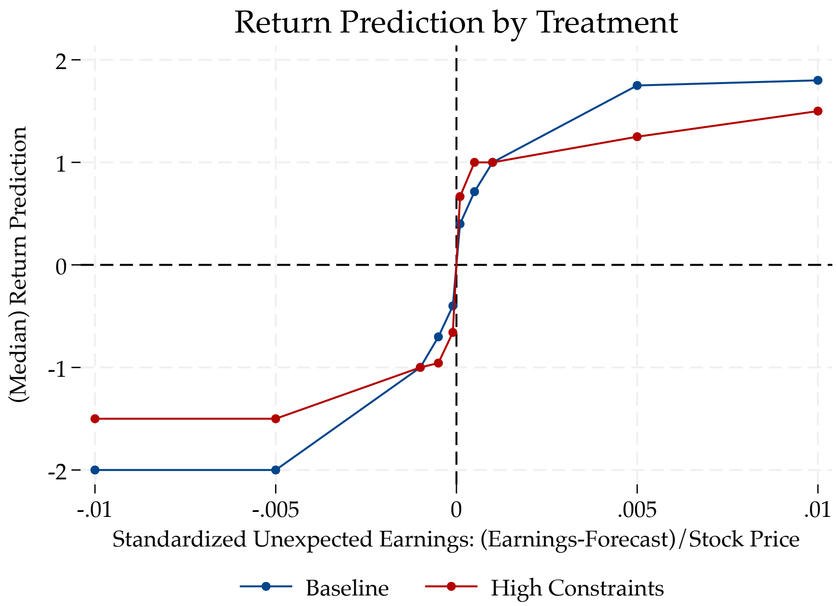
Appendix Table A16: Pooled Regression: Effect of Valuation Uncertainty on PEAD

	[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	

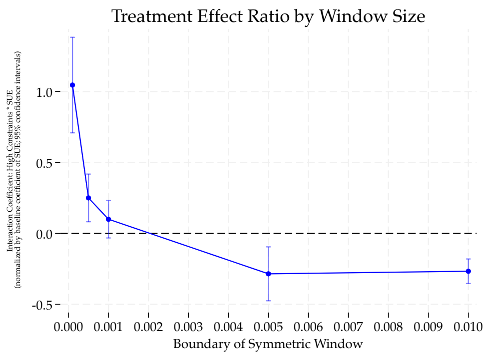
Notes: This table shows data on earnings announcements from 1986-2019. This table studies how the relationship between long-run post-earnings announcement returns and SUE varies by Valuation Uncertainty. The left-hand-side variable in each column is the the market-adjusted return from 5 days after the 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-month 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 intearction 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.

Finally, we would like to highlight that most of our empirical analysis includes firm-level fixed effects. While there are many ways to measure earnings quality (Dechow et al., 2010), we believe that earnings persistence is the most worrying confounder in our setting, as it has already been offered as an explanation for attenuated responses to extreme news. Earnings persistence, however, is a firm-level measure. So differences in the firm level persistence of earnings should already be accounted for by the firm-level fixed effects, and therefore is unlikely to be driving our results.

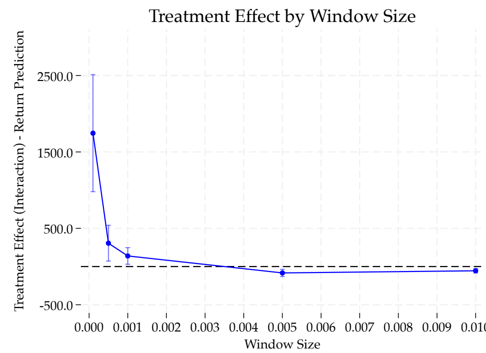
C Additional exhibits for experimental data



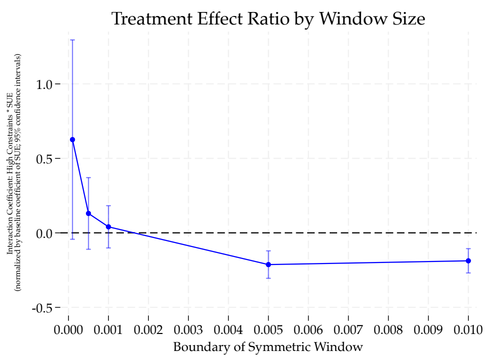
Appendix Figure A7: *Notes:* This figure is constructed in the same way as Figure 4a but excluding observations reflecting predictions with a sign that is opposite to that of the earnings surprise.



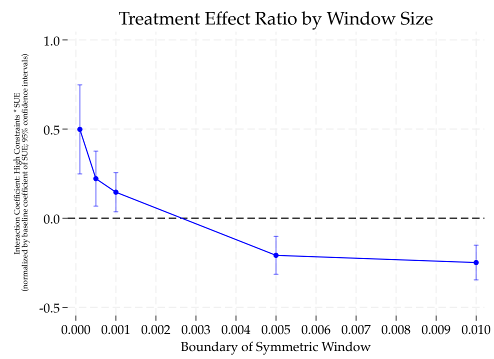
a) Using the raw price change predictions not normalized by priors.



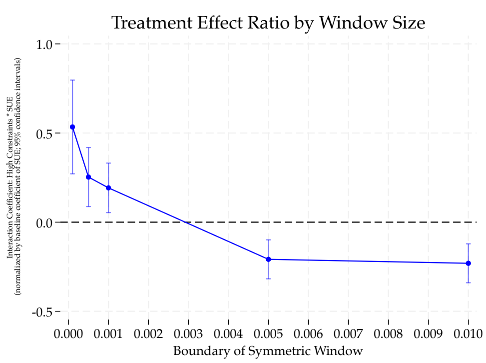
b) Using interaction coefficients not normalized by the SUE slope of Baseline condition.



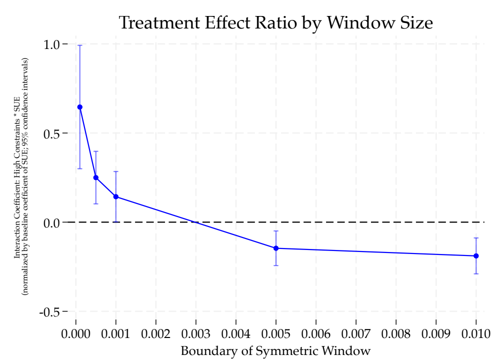
c) Using conditional means instead of medians and winsorized at normalized predictions of +/-3.



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 A8: Robustness checks for Figure 4b.

Appendix Table A17: Dependent variable: Normalized predictions - Robustness Check 1

	(1)	(2)	(3)	(4)	(5)
SUE Window	$\leq \lvert 0.0001 \rvert$	$\leq \lvert 0.0005 \rvert$	$\leq \lvert 0.001 \rvert$	$\leq \lvert 0.005 \rvert$	$\leq \lvert 0.01 \rvert$
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 3 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 Table A18: Dependent variable: Normalized predictions - Robustness Check 2

	(1)	(2)	(3)	(4)	(5)
SUE Window	$\leq \|0.0001\|$	$\leq \|0.0005\|$	$\leq \|0.001\|$	$\leq \|0.005\|$	$\leq \|0.01\|$
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 3 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.

Appendix Table A19: Dependent variable: Normalized predictions - Robustness Check 3

	(1)	(2)	(3)	(4)	(5)
SUE Window	$\leq \|0.0001\|$	$\leq \|0.0005\|$	$\leq \|0.001\|$	$\leq \|0.005\|$	$\leq \|0.01\|$
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 3 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 A20: Dependent variable: Normalized predictions - Robustness Check 4

	(1)	(2)	(3)	(4)	(5)
SUE Window	$\leq \|0.0001\|$	$\leq \|0.0005\|$	$\leq \|0.001\|$	$\leq \|0.005\|$	$\leq \|0.01\|$
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 3 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 A21: Dependent variable: Normalized predictions - Robustness Check 5

	(1)	(2)	(3)	(4)	(5)
SUE Window	$\leq \|0.0001\|$	$\leq \|0.0005\|$	$\leq \|0.001\|$	$\leq \|0.005\|$	$\leq \|0.01\|$
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 3 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 Screenshots of Experiment

Appendix Figure A9: Instruction Screen 1

Instructions

Your Task

In this study, you will be asked to predict the immediate reaction of different companies' stock prices between their quarterly earnings announcements and end of day trading the same day.

- A company's quarterly net income is typically reported in terms of "earnings per share," which is the net income divided by the number of outstanding shares.
- Before every quarterly earnings announcement, analysts predict the company's earnings per share, and the mean of those predictions is referred to as the **consensus analyst forecast**. The forecast is important as it establishes a benchmark for assessing the company's actually reported earnings.
- The consensus forecast reflects the level of earnings that market participants already expect and have accounted for in the stock price prior to the actual announcement.
- This means: on the day of the announcement, the market reacts to **how actual earnings compare to the forecast**, i.e., to the difference between predicted and actual earnings. Put differently, if the announced earnings are **the same** as the forecast earnings, the stock price should not change much after the announcement.
- The stock price is commonly understood to be determined by the expected stream of a company's future earnings. A quarterly earnings announcement provides insights into this future stream of earnings: higher-than-expected earnings in the last quarter can be indicative of higher-than-expected earnings in the future, and lower-than-expected earnings last quarter can be indicative of lower-than-expected earnings in the future.
- Therefore, **even small differences** between the expected and announced earnings in a single quarter **can significantly impact the stock price**, because market participants react to what they believe this implies for all future earnings.
- Historically, quarterly earnings per share averaged to a percentage of the current stock price that **equals about $0.30 per $100 of stock value.**
- In total, you will complete 5 rounds of this task, where each round is about a different company. These rounds are completely independent from one another.

Example

Below you see a screenshot of an example showing the beginning of an earnings announcement.

BioNova Beats Market Expectations

BioNova develops state-of-the-art diagnostic tools and laboratory equipment. In their earnings announcement for the second quarter of

Your Bonus Payment

- One of every ten participants in this survey is eligible to win a **bonus of $50**.
- If you are randomly selected to be eligible for a bonus, one of the rounds will be randomly picked as the round-that-counts.
- In each round, you will predict the stock price change of a real company that will announce their quarterly earnings by the end of this week. For each firm, you will see one scenario showing a potential earnings announcement.
- On one day later this week, the firm will announce their earnings per share, and we will record the difference between the stock price right before the announcement and the closing price at the end of that same day.
- **You win $50 if** (i) the actually announced earnings per share are within 10% of the earnings per share reported in your scenario and (ii) your estimate in the round-that-counts is within 1 percentage point of the real price change recorded on the day of the announcement.

Next

This is the main instructions screen in the experiment. This screen is visible to both the Baseline and High Constraints conditions.

Appendix Figure A10: Instruction Screen 2

Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward.

You can review the instructions here.

1. Which one of the following statements is true?

- ◯ The market primarily responds to the level of announced earnings.
- ◯ The market primarily responds to how the announced earnings compare to the consensus forecast of earnings, because market participants already incorporate the level of expected earnings in their valuations before the announcement.

2. Which one of the following statements is true?

- ◯ The difference between forecast and announced earnings in a given quarter may provide insights on the entire future stream of earnings. Therefore, even small quarterly earnings surprises can have significant effects on the stock price.
- ◯ If the quarterly announced earnings per share look small relative to the stock price, they should not affect the stock price.

3. Which of the following two statements are true?

- ◯ If the announced earnings are **the same** as the forecast earnings, the stock price should not change much after the announcement.
- ◯ If the announced earnings are **the same** as the forecast earnings, the stock price should increase a lot after the announcement.

Next

This is the first comprehension question screen in the experiment. Respondents who do not answer the questions correctly in the first two attempts are disqualified from the survey. This screen is visible to both the Baseline and High Constraints conditions.

Appendix Figure A11: Instruction Screen 3


Before the first round starts, please answer the following estimation questions.

Answer these question as follows: First, select whether you estimate an increase or decrease using the drowdown menu. Second, enter a number to indicate the magnitude of the increase or decrease. For a 1% increase, select "increased" and enter the number 1; for a 5.7% decrease, select "decreased" and enter the number 5.7 etc.

Firm X Falls Short Of Market Expectations

Historically, what do you think was a company's **average stock price change** on a day where **announced earnings** **<u>fell below</u> the consensus forecast?**

It Select by %.

Firm X Beats Market Expectations

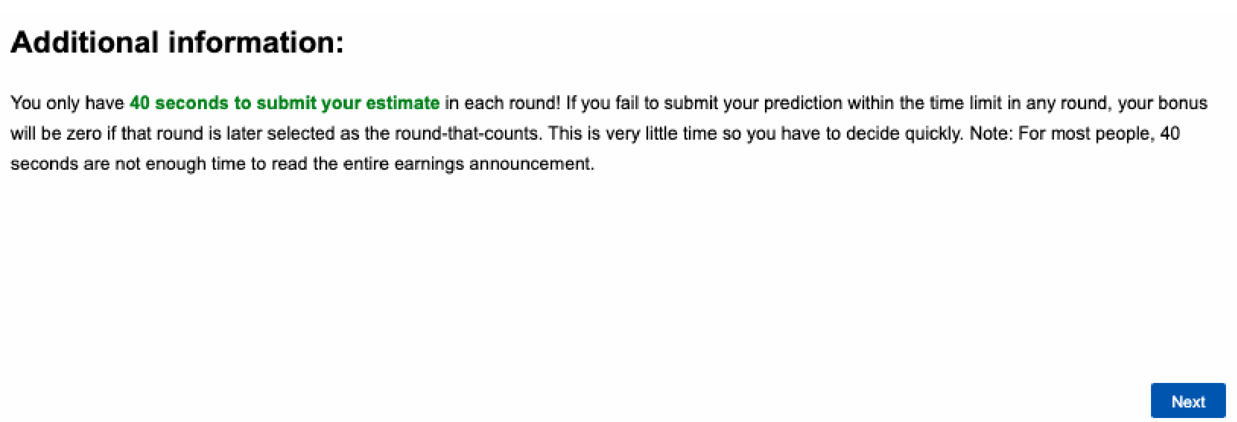
Historically, what do you think was a company's **average stock price change** on a day where **announced earnings** **<u>exceeded</u> the consensus forecast?**

It Select by %.

Next

This screen elicits respondents' priors to a positive or negative earnings surprise. This screen is visible to both the Baseline and High Constraints conditions.

Appendix Figure A12: Instruction Screen 4 (High Constraints)

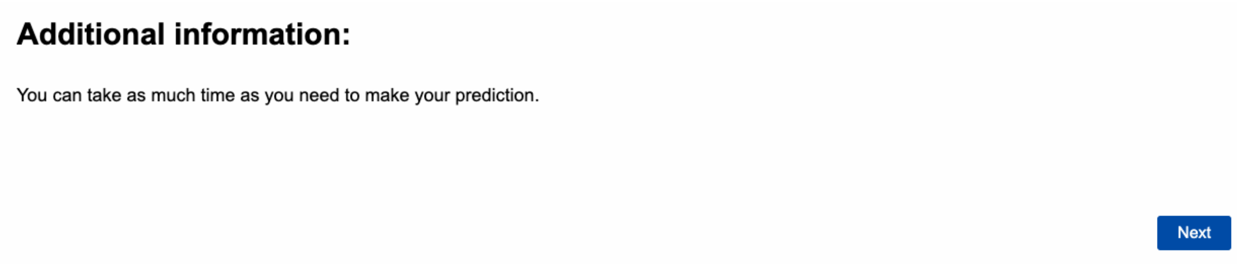

Additional information:

You only have **40 seconds to submit your estimate** in each round! If you fail to submit your prediction within the time limit in any round, your bonus will be zero if that round is later selected as the round-that-counts. This is very little time so you have to decide quickly. Note: For most people, 40 seconds are not enough time to read the entire earnings announcement.

Next

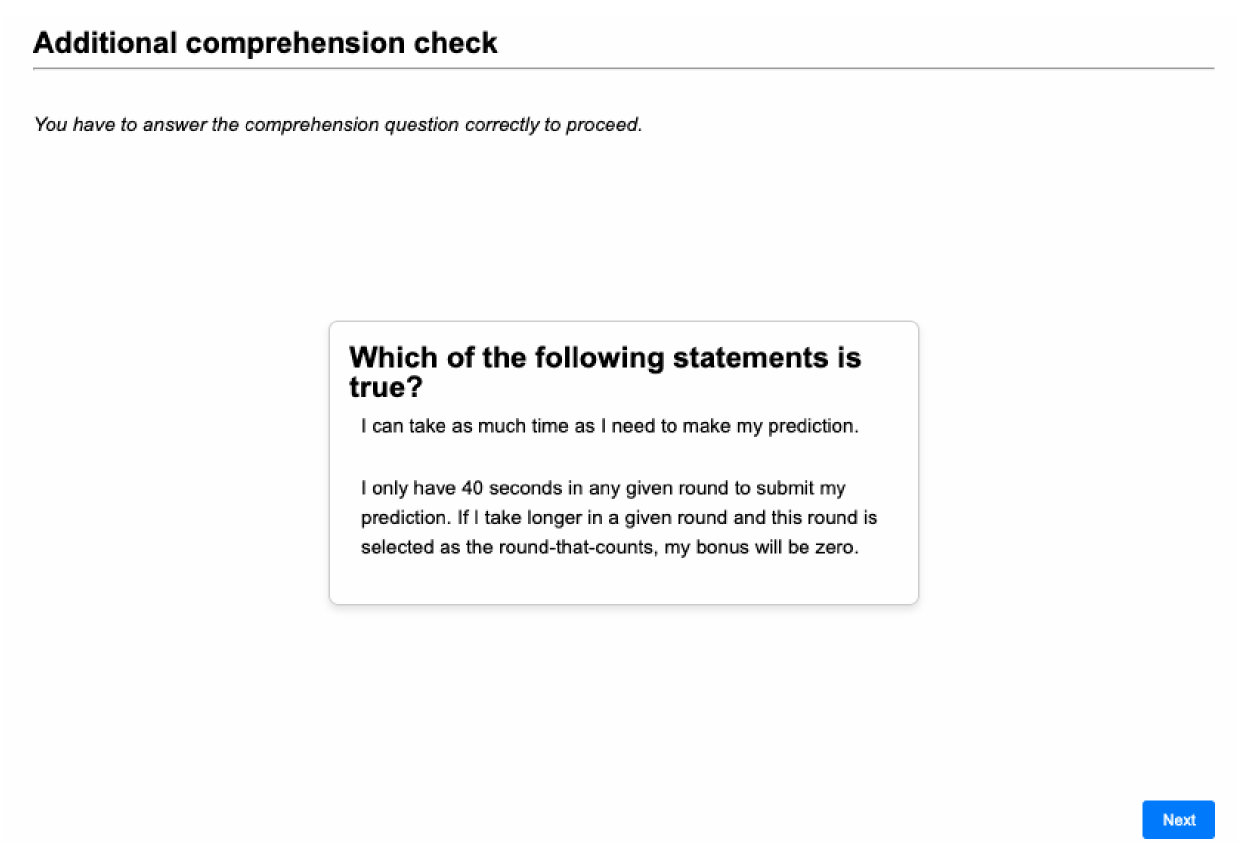
This instruction screen is visible only to the High Constraints condition.

Appendix Figure A13: Instruction Screen 4 (Baseline)



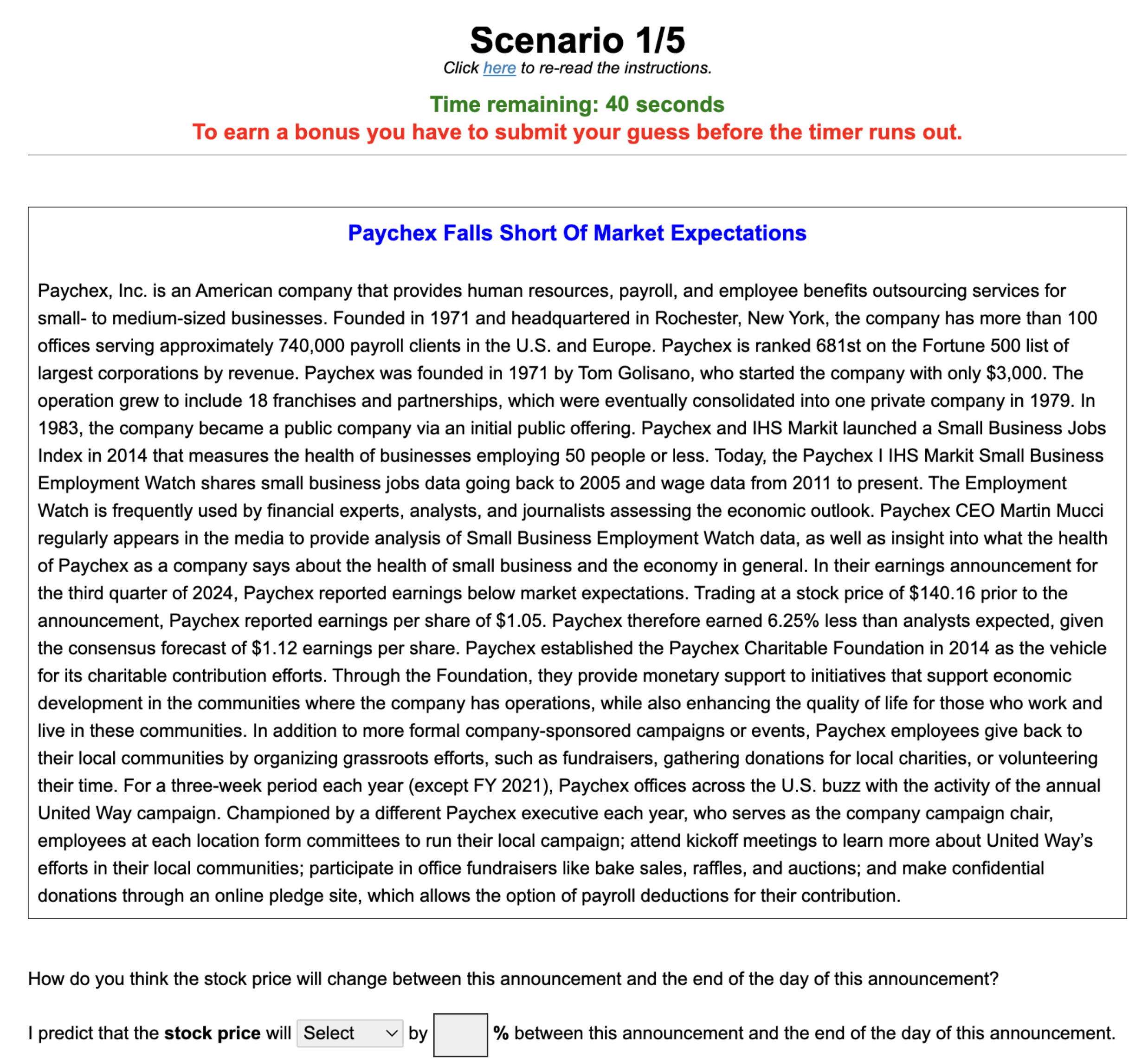
This instructions screen is visible only to the Baseline condition.

Appendix Figure A14: Instruction Screen 5



This is the second comprehension question screen in the experiment. Respondents cannot continue to the next screen until they answer the question correctly. They have unlimited attempts to answer correctly. This screen is visible to both the Baseline and High Constraints conditions.

Appendix Figure A15: Decision Screen (High Constraints)



Scenario 1/5

Click here to re-read the instructions.

Time remaining: 40 seconds

To earn a bonus you have to submit your guess before the timer runs out.

Paychex Falls Short Of Market Expectations

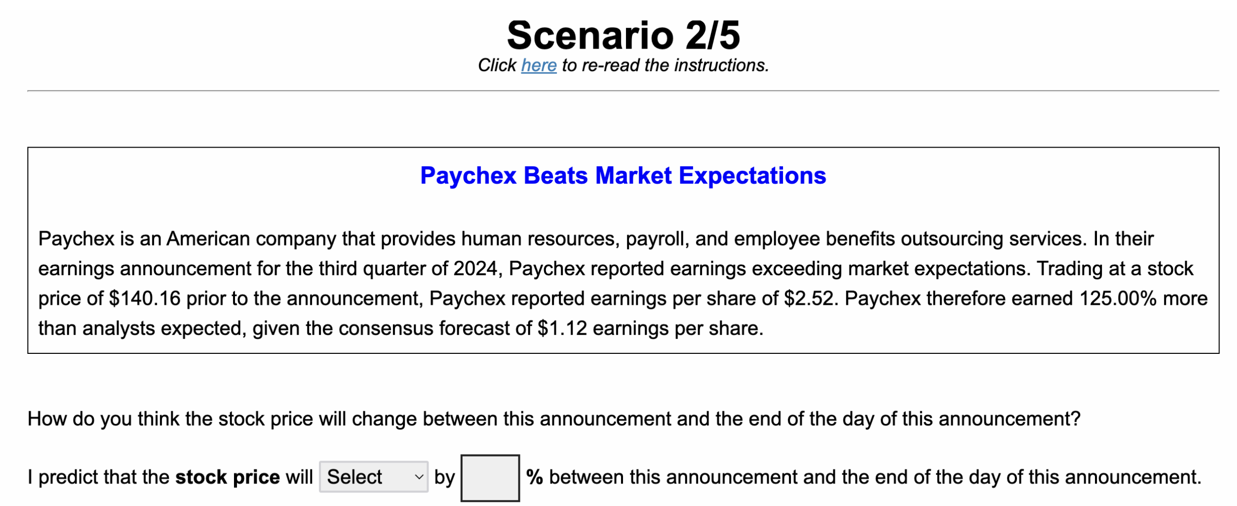
Paychex, Inc. is an American company that provides human resources, payroll, and employee benefits outsourcing services for small- to medium-sized businesses. Founded in 1971 and headquartered in Rochester, New York, the company has more than 100 offices serving approximately 740,000 payroll clients in the U.S. and Europe. Paychex is ranked 681st on the Fortune 500 list of largest corporations by revenue. Paychex was founded in 1971 by Tom Golisano, who started the company with only $3,000. The operation grew to include 18 franchises and partnerships, which were eventually consolidated into one private company in 1979. In 1983, the company became a public company via an initial public offering. Paychex and IHS Markit launched a Small Business Jobs Index in 2014 that measures the health of businesses employing 50 people or less. Today, the Paychex I IHS Markit Small Business Employment Watch shares small business jobs data going back to 2005 and wage data from 2011 to present. The Employment Watch is frequently used by financial experts, analysts, and journalists assessing the economic outlook. Paychex CEO Martin Mucci regularly appears in the media to provide analysis of Small Business Employment Watch data, as well as insight into what the health of Paychex as a company says about the health of small business and the economy in general. In their earnings announcement for the third quarter of 2024, Paychex reported earnings below market expectations. Trading at a stock price of $140.16 prior to the announcement, Paychex reported earnings per share of $1.05. Paychex therefore earned 6.25% less than analysts expected, given the consensus forecast of $1.12 earnings per share. Paychex established the Paychex Charitable Foundation in 2014 as the vehicle for its charitable contribution efforts. Through the Foundation, they provide monetary support to initiatives that support economic development in the communities where the company has operations, while also enhancing the quality of life for those who work and live in these communities. In addition to more formal company-sponsored campaigns or events, Paychex employees give back to their local communities by organizing grassroots efforts, such as fundraisers, gathering donations for local charities, or volunteering their time. For a three-week period each year (except FY 2021), Paychex offices across the U.S. buzz with the activity of the annual United Way campaign. Championed by a different Paychex executive each year, who serves as the company campaign chair, employees at each location form committees to run their local campaign; attend kickoff meetings to learn more about United Way's efforts in their local communities; participate in office fundraisers like bake sales, raffles, and auctions; and make confidential donations through an online pledge site, which allows the option of payroll deductions for their contribution.

How do you think the stock price will change between this announcement and the end of the day of this announcement?

I predict that the **stock price** will Select by **%** between this announcement and the end of the day of this announcement.

This is a screenshot of the decision screen for the High Constraints condition in the experiment.

Appendix Figure A16: Decision Screen (Baseline)



Scenario 2/5

Click here to re-read the instructions.

Paychex Beats Market Expectations

Paychex is an American company that provides human resources, payroll, and employee benefits outsourcing services. In their earnings announcement for the third quarter of 2024, Paychex reported earnings exceeding market expectations. Trading at a stock price of $140.16 prior to the announcement, Paychex reported earnings per share of $2.52. Paychex therefore earned 125.00% more than analysts expected, given the consensus forecast of $1.12 earnings per share.

How do you think the stock price will change between this announcement and the end of the day of this announcement?

I predict that the **stock price** will Select by **%** between this announcement and the end of the day of this announcement.

This is a screenshot of the decision screen for the Baseline condition in the experiment.

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

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

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 $s = 0$. ∎