# Responding to Surprises in an Uncertain World*

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*Preliminary and incomplete. Please do not circulate.*

August 29, 2024

**Abstract**

In real news environments, information about economic quantities is not just expressed in numbers but also communicated in qualitative terms. This paper studies how people respond to surprises when they are uncertain about their optimal response. A domain-general simplification strategy for handling such uncertainty is to focus on parts communicating the qualitative aspect of a surprise—its *sign*—while disregarding its *size*, resulting in a two-step response function. Higher uncertainty about the best response induces an optimizing agent in our model to rely on this simplification strategy more strongly, creating an S-shaped pattern around zero surprise. We empirically test this prediction in the context of stock market returns to earnings surprises. Higher valuation uncertainty strongly predicts an S shape in short-term excess returns: higher sensitivity to the sign but lower sensitivity to the size of earnings surprises. Controlled experiments with investors provide causal evidence for the behavioral mechanism and the role of selective attention to the qualitative vs. quantitative components of news. Using field data we test and confirm the model's prediction about another, different type of uncertainty: higher prior uncertainty about expected earnings is associated with less response sensitivity everywhere.

*Keywords:* Uncertainty, Learning, Earnings Surprises, Qualitative Information, Quantitative Information, Behavioral Finance

*We thank Dustin Fichmann, Julian König, Max Müller and Nicolas Röver for outstanding research assistance. We thank Jesse Shapiro, Chloe Xie and seminar audiences in Berlin and Harvard Business School for helpful comments and suggestions. We thank Andrey Golubov and Sonia Konstantinidi for sharing their valuation uncertainty measure and Byungwook Kim for sharing his measure of analyst dispersion. The research described in this article was approved by the Institutional Review Board at Harvard Business School. Graeber: Harvard Business School, tgraeber@hbs.edu. Roth: University of Cologne, IZA, ECONtribute, CEPR, NHH, and Max-Planck Institute for Research on Collective Goods, roth@wiso.uni-koeln.de, Sammon: Harvard Business School, mcsammon@gmail.com.

# 1 Introduction

Much of economics and finance studies how behavior and market outcomes respond to news: understanding responses to shocks is the basis for prediction and policy design. Each piece of news is characterized by a *surprise* – the difference between realization and expectations. For example, the information contained in macroeconomic data releases, central bank communication, political events, regulatory changes and firm announcements is interpreted relative to market expectations. While the quantitative surprise about a given economic quantity can usually be expressed as a single number, news in practice are communicated in natural language, conveying additional content. In particular, news stories contain not only quantitative parts but also qualitative statements, for example, about whether a surprise is positive or negative. In fact, real news articles almost always contain *separate* statements communicating the quantitative part—the *size* of a surprise—and statements mentioning a qualitative interpretation of it—its *sign*. As a result, the qualitative and quantitative elements of information may compete for attention in high-dimensional real news environments.

In this paper, we study how uncertainty about the optimal response affects how people respond to the quantitative vs. the qualitative information content about surprises, both in tightly controlled individual decision-making experiments and aggregate market data. Our basic hypothesis is that when people have more uncertainty about how to optimally respond to the size of a surprise, they resort to a simplification strategy under which attention gravitates more towards relying on qualitative statements about its sign. Intuitively, the direction of the response to the sign of a surprise is often straightforward because it only requires qualitative knowledge about the best response: for example, a higher-than-expected interest rate should temper inflation, GDP growth exceeding forecasts should bolster investor confidence and lift stock markets, earnings announced above analyst expectations should benefit stock returns, and an unexpected increase in unemployment rates should dampen consumer spending and economic growth.

We propose that relying more strongly on information about the sign of a surprise is a domain-general simplification strategy in the presence of uncertainty about the optimal response, and we study its implications in the context of stock market reactions to company earnings announcements. Quarterly earnings announcements are key events in the financial reporting calendar of publicly listed companies. Based on analyst forecasts, a "consensus forecast" of a company's earnings per share (EPS) in the preceding quarter is formed and serves as the reference level for actual earnings. Market responses to the "surprise" in earnings – the difference between actual earnings and the consensus estimate – has been a central topic in financial economics in recent decades (e.g., Kothari and Sloan, 1992; Skinner and Sloan, 2002; Freeman and Tse, 1992).

To conceptualize the effects of uncertainty on responses we leverage a simple model of Bayesian optimization.[1] To illustrate the central prediction, assume that the best response as a function of the

[1]This class of models has found widespread applications, including recently in modeling the economic impli-

surprise is, without loss of generality, continuous and monotonically increasing, and that the individual is certain their optimal response is zero when the surprise is zero (e.g. announced earnings equal the consensus forecast).[2] Now consider a person who only processes the sign of the surprise but ignores its size: their response is a two-step function around zero surprise, because they lack the basis to distinguish between responses of different size. Specifically, they play the same action for all negative surprises before the response function jumps around the zero point to a different action that they play for every possible positive surprise. Intuitively, the individual who only responds to the sign is infinitely sensitive to the sign but has zero sensitivity to the size. This two-step response function constitutes an extreme benchmark: even under maximal uncertainty in approximating the best response, they can still respond step-wise to the sign of the surprise; it is a simplification strategy in that sense. An individual who, instead, responds to the sign of the surprise but exhibits some uncertainty about their optimal response is located between the step function and the continuous optimal response curve: higher mapping uncertainty pushes their behavioral response closer to the step function. This captures the key prediction of the framework: as uncertainty about the optimal response increases, behavioral sensitivity to the sign increases while sensitivity to the size decreases. Uncertainty about best responses generically predicts an "S-shaped" (sigmoid) response function around zero surprise.

Two central features characterize our hypothesis in relation to two innovative recent contributions showing, i.a., that information-processing constraints can lead to overreaction to weak surprises and underreaction to strong ones (Augenblick et al., 2024; Ba et al., 2024). First, we focus on naturalistic information environments with the critical feature that surprises are not communicated stand-alone as a single quantitative number, but are also described separately in qualitative terms and natural language. We predict and experimentally confirm that presenting the surprise in isolation as a single, continuous number *does not* lead to the S-shape around zero surprise. This differs from the probabilistic balls-and-urns updating environments primarily studied in those papers. Yet, our results do not contradict their findings either, as these papers rely on probabilistic beliefs and signals about binary events rather than continuous signal realizations.[3] Second, our approach is focused on surprises in the field and does not take a strong cognitive perspective on the mechanism. Instead, uncertainty about what the best response is can have many possible origins in our model, including non-cognitive ones: it may be external to the decision-maker, e.g., because the optimal response to a given surprise is highly stochastic, or internal,

cations of cognitive noise (e.g. Ilut and Valchev, 2023; Enke et al., 2024; Enke and Graeber, 2023). Here, we apply it to how people respond to surprises given different types of noise.

[2]Intuitively, this means that the individual (subjectively) best-responds to their current information set. If they wanted to change their action or forecast at a surprise of zero, they could do so prior to the announcement.

[3]For example, Augenblick et al. (2024) propose a compression of the signal diagnosticity, which is related to but different from the explicit surprise implied by the actual signal realization as studied here. Despite the differences, we see our paper more closely related in spirit to Ba et al. (2024), who suggest that selective attention plays a critical role, as we do here. While they propose selective attention to subsets of the state space induced by their representativeness with the single signal, we suggest that people selectively attend to different components of news pieces.

e.g., due to uncertainty about one's tastes or noise originating from information processing constraints.

**Field data.** We test our predictions in two empirical applications. We begin with a high-stakes field setting: we conduct event studies on the stock market response to earnings surprises using data from more than 190,000 earnings announcements for more than 6,000 unique companies between 1986 and 2019. To motivate this setting, we examine the relationship between market-adjusted returns the four days after an earnings announcement (inclusive of the announcement day itself) and so-called "standardized earnings surprises" (SUE), 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). As illustrated in Figure 1, market-adjusted returns exhibit a pronounced S-shaped relationship with SUE. In particular, returns are, on average, highly sensitive to the sign of earnings surprises but far less sensitive to their size. This non-linear relationship between excess returns and earnings surprises has been documented in the finance and accounting literature for decades (Freeman and Tse, 1992; Skinner and Sloan, 2002). A variety of explanations have been put forward in the literature, but no consensus on the origins of this pattern has been reached so far. We use this setting as a testing ground for the predictions of our framework of information-processing constraints and study whether empirical proxies for mapping uncertainty systematically shape returns.

We analyze how uncertainty about the optimal response affects sensitivity to the sign and size of surprises. To operationalize the concept of mapping uncertainty in this setting we rely on *valuation uncertainty* – uncertainty in the mapping between fundamentals and stock prices. In practice, we follow Golubov and Konstantinidi (2023), defining valuation uncertainty as the dispersion in expected stock prices given by different accounting-based valuation methods.

To study sensitivity to the sign of surprises, we analyze the relationship between market-adjusted returns and SUE for windows of earnings surprises that are small and symmetric around zero. As we gradually expand the width of the symmetric window around zero, the estimated relationship increasingly reflects the sensitivity to the size of surprises, given their sign. Our key hypothesis is that valuation uncertainty increases the sensitivity to the sign of surprises but decreases sensitivity to the size of surprises. In our empirical specifications, valuation uncertainty should amplify the stock market response for small symmetric surprises around zero. For large surprises, on the other hand, valuation uncertainty should attenuate the stock price response to earnings surprises.

Consistent with these theoretical predictions, our key finding is that — when there is more uncertainty about the mapping of fundamentals to stock valuations – stock prices are *m*ore sensitive to the *s*ign of surprises, but *l*ess sensitive to the *s*ize of surprises. While the interaction term of valuation uncertainty and standardized earnings surprises is significantly positive for small symmetric windows around zero (capturing responses to the sign of surprises) it becomes significantly negative for large symmetric windows around zero (capturing responses to both the sign and size of surprises). These effects are also

economically meaningful. For a window size of 0.002 a 0.01 increase (henceforth one unit) in SUE is associated with a 14 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 22 percent ($p < 0.01$), i.e. valuation uncertainty *increases* the sensitivity to surprises by more than one third.

For a window size of 0.025, a one unit increase in SUE is associated with a 8 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 4 percent ($p < 0.01$), i.e. it almost halves the sensitivity to surprises.

**Experimental data.** To study the hypothesized behavioral mechanism, we run controlled online experiments with investors. These investors all have some holdings on an online trading platform and were recruited on Prolific.

Respondents in our baseline design make predictions about four different hypothetical earnings news scenarios. Our design closely mimics the real world news environment in which learning takes place by embracing the high-dimensional signals that investors receive. In each scenario, respondents receive a news story about a company's earnings which contains both qualitative information about the sign of the surprise and quantitative information about how the EPS differ from the consensus forecast. The design of these news stories closely follows real news reporting about earnings announcements. Our design varies the size of surprise across participants. To shut down beliefs about the reasons behind the earnings surprises as a mechanism, we provide all respondents with tailored narratives – one for positive surprises and a different one for negative surprises. In our experiment, half of the respondents are assigned to this baseline condition, while 50% of respondents are assigned to a "high uncertainty" condition. This later condition is identical to the baseline condition, except that respondents additionally receive explicit information communicating a comparably high valuation uncertainty for this company. The additional information in this treatment describes internal recalibrations in the companies that introduce significant valuation uncertainty. These recalibrations highlight the complex interplay between internal data adjustments and external market factors, leading to varying degrees of volatility in stock prices.

The experiment replicates the core results from the field data. First, across both treatment conditions, there is more sensitivity to the sign of surprises than to the size of surprises. Second, the experimental manipulation of valuation uncertainty increases perceived uncertainty among respondents—our manipulation check—and strongly increases sensitivity to the sign of surprises, while decreasing sensitivity to their size.

**Uncertainty about the reference level.** Our framework makes a secondary prediction about a different type of uncertainty. In practice, there is prior uncertainty about the expected level of a given state, e.g., the analyst forecast of EPS. This uncertainty about the reference level propagates into uncertainty about coding the surprise itself: is it positive or negative, and how large? Intuitively, a decision-maker may not be sure about the zero point that determines what is a positive versus a negative surprise, which we will refer to as surprise-coding uncertainty. This implies more than one possible "surprise coding" for a given realization, and the decision-maker optimally weighs those. We examine how prior uncertainty about the earnings announcements affects sensitivity to news. In the context of our model, uncertainty about surprises can be thought of either as a given agent being uncertain what EPS to expect, and thus, how to code the surprise implied by the actual announcement, or as different market participants holding different expectations about the announcement, which entail different interpretations of the surprise implied by the announced figure. Our application provides a direct measure of variation in EPS expectations: dispersion of analysts' earnings forecasts. The more dispersion there is in earnings forecasts, the more likely it is that different market participants form different EPS expectations, leading to different surprise codings, or that individual market participants are uncertain about the implied surprise. With the intuition of aggregating horizontally stacked S-shaped response functions, the prediction of our model is that more dispersion in earnings forecasts decreases the sensitivity to earnings announcements.

In our field data, we find that higher dispersion in earnings forecasts decreases the sensitivity to surprises – irrespective of the size of the surprise. For a window size of 0.01, a one unit increase in SUE is associated with an 8 percent increase in market adjusted return ($p < 0.01$). For a one-standard deviation higher analyst dispersion this effect is muted by about 2 percent ($p < 0.01$), i.e. sensitivity to surprises is reduced by approximately one quarter. This underscores a both statistically and economically meaningful impact of uncertainty about the size of surprises on market-adjusted returns.

**Literature.** Our paper contributes to the growing literature on the effects of complexity on information processing and decision-making (Enke et al., 2023; Oprea, 2020, 2022; Banovetz and Oprea, 2023; Kendall and Oprea, 2024; Graeber, 2022; Gabaix and Graeber, 2023; Arrieta and Nielsen, 2024; Fehr and Wu, 2023; Kieren et al., 2023; Goncalves et al., 2024).[4] Enke and Graeber (2023) present a model of cognitive uncertainty where individuals perceive new information noisily, leading them to shade their answers toward their prior beliefs. This results in insensitivity to variation in different features of new information, such as the base rate, diagnosticity and sample size. Yang (2023) provides evidence that individuals often struggle to incorporate beliefs about a quantity into their decision-making processes, rendering their actions insensitive to their beliefs. Charles et al. (2023) experimentally demonstrate that participants' valuations are significantly less sensitive to their expectations than predicted by a fric-

[4]Enke (2024) provides an overview of this broader literature and Benjamin (2019) reviews the literature on errors in statistical reasoning.

tionless model. Bordalo et al. (2023) find evidence for insensitivity to signal strength and document multimodality in belief updating patterns.

Augenblick et al. (2024) present both laboratory and field evidence showing that individuals overinfer from weak signals and underinfer from strong signals. This aligns with a model of noisy cognition where people accurately determine the signal's direction but perceive its strength imperfectly. Their field evidence, based on basketball matches and stock options, shows overreaction at long forecast horizons and underreaction at short horizons.[5] Additionally, Ba et al. (2024) propose a two-stage model of belief formation where individuals first reduce complexity by focusing on a subset of representative states and then incorporate this information subject to cognitive imprecision, confirming their findings through laboratory experiments.

Our first key contribution lies in gathering new systematic evidence on the role of uncertainty, whether internal or external, in shaping the response to the sign and size of surprises. Our findings highlight that increased mapping uncertainty increases people's reliance on a simplification strategy, focusing solely on the qualitative aspects of the surprise. Second, we provide a blueprint to test the noisy information-processing hypothesis *in the field*, enabling us to analyze the impact of different types of uncertainty on high-stakes market outcomes. This stands in contrast to much of the prior literature which has mostly been confined to to controlled lab and online evidence. Third, as opposed to prior work, our experiments with investors rely on naturalistic stimuli in the form of news stories and thus embrace the importance of qualitative information in shaping the interpretation of surprises.

We also contribute to the finance literature that examines how stock prices respond to news more broadly (Kwon and Tang, 2024; 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) and earnings surprises in particular (DellaVigna and Pollet, 2009; Bernard and Thomas, 1989; Kormendi and Lipe, 1987; Bouchaud et al., 2019; De Bondt and Thaler, 1985; Hirshleifer and Teoh, 2003). Laarits and Sammon (2023) show that hard-to-value stocks – e.g. as the first principal component of turnover, analyst forecast dispersion, and idiosyncratic volatility – are globally insensitive to earnings surprises, aligning with broader evidence on insensitivity of behavioral responses to beliefs in finance (Giglio et al., 2021; Drerup et al., 2017). Prior work has focused on different behavioral mechanisms that could affect responses to stock market news. For example, valuation uncertainty could lead different investors to focus on different pieces of the news, resulting in more disagreement Hong and Stein (2007). Alternatively, investors may choose to ignore public signals altogether when there is more valuation uncertainty (Banerjee et al., 2021; Hirshleifer et al., 2009; Engelberg, 2008; Cohen et al., 2020).

These mechanisms can explain more insensitivity 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

[5]This evidence builds on pathbreaking papers in psychology which study how updating depends on signal strength (Griffin and Tversky, 1992; Phillips and Edwards, 1966).

of higher valuation uncertainty, which we establish in this paper. We add to this literature by providing evidence that uncertainty about the mapping between fundamentals and stock prices affects responses to earnings announcements differentially for small versus large surprises.

This paper proceeds as follows. Section 2 presents the theoretical framework. Section 3 describes the data and setting for the field evidence. Section 4 studies how mapping uncertainty affects sensitivity to surprises both using field data and an experiment. Section 5 examines the effects of uncertainty about the size of surprises on the sensitivity to surprises. Section 6 concludes.

# 2 Theoretical Framework

The essence of our model is that due to different forms of noise, a decision maker (DM) may be uncertain about how to optimally respond to surprises. Such uncertainty may induce a behavioral response function with two key features: the DM will be (i) insufficiently sensitive to different magnitudes of surprises, and (ii) rely more strongly on the direction of the response. Intuitively, because figuring out the quantitative response in response to the size of a surprise is hard in the presence of noise, the DM relies more on the sign of the response which is typically far easier to determine from qualitative information.

To formalize how a DM may optimally respond to noise entering at different stages of figuring out their response, we rely on a simple model of constrained Bayesian optimization. Such Bayesian models have been widely applied across many fields – including recently in modeling the implications of cognitive noise (e.g. Ilut and Valchev, 2023; Enke et al., 2024; Enke and Graeber, 2023) – and our contribution is to apply this adapt this framework to responses to surprises and specific types of noise.

The DM chooses their response $r$ to a surprise $s$, 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, monotonic and goes through origin, $r^\star(0) = 0$. Without loss, we further assume that it is increasing. We do not need to assume that this response function is linear or takes any particular shape.

Two remarks are in order. First, the model does not require assumptions on the nature of the response. It can be an action or a belief. For different types of responses, different sources of noise are likely to emerge. Second, this model assumes that the DM codes a given piece of news about a variable *in surprise space*, i.e., relative to expectation. This diverges from previous applications of this framework which are formulated in levels and creates distinctive predictions we explore below.

**Surprise-Response Mapping Noise.** However, due to noise, the DM does not have direct access to their optimal response $r^\star(s)$. We model this noise as emerging in the mapping between surprise 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:

$$r^c(s) \sim \mathcal{N}\left(r^\star(s), \sigma_r^2(s)\right) \tag{1}$$

The precision of this cognitive signal is determined by the level of surprise-response mapping noise, $\sigma_r^2(s)$. As shown, for example, in Enke (2024), this form of mapping noise can be modeled as uncertainty about the weight that maps a problem fundamental (here, the surprise) into the optimal action (the response).

Note that we here allow for surprise mapping noise to depend on the size of the surprise, $\sigma_r^2(s)$. We will derive our main predictions under the assumption of constant noise and discuss the implications of plausible assumptions on the relationship between noise and surprise in the end.

**Default Response.** Equipped with a noisy cognitive signal, the Bayesian agent needs a prior to form a posterior. We refer to this prior as the DM's default response function, which intuitively captures what they would do if they were completely incapable of simulating the optimum. If surprise-response mapping noise is infinite, the DM lacks a basis for treating one surprise differently from another, meaning that the default response should be surprise-invariant.

However, we make the novel assumption that the DM always understands the direction of their response. This assumption captures several possible intuitions. First, the agent may know the sign of their comparative static and parse the sign of the surprise "for free", i.e. without any noise, because this only requires a simple binary understanding.[6] Knowing the magnitude of the comparative static and parsing the size of the surprise, by contrast, is hard. Second, the agent may receive additional *qualitative* information next to the quantitative surprise $s$ that communicates the sign of the surprise and response. For example, headlines about earnings announcements typically mention whether the surprise is negative or positive. This allows the agent to calibrate before even observing and processing the actual size of the surprise. This interpretation captures that some qualitative information and the response to it may often be "cognitively cheap" and therefore not subject to noise. The qualitative-quantitative split directly relates to the distinction between the initial *representation* of a problem, driven by attentional phenomena, based on which the DM then processes the different components of the problem, the *computational* stage (e.g. Ba et al., 2024).

The DM's understanding of the sign allows them to *categorize* their default response. So before observing the size of the surprise, the agent identifies their mean optimal action conditional on the sign of surprise: $r_d = \mathbb{E}[\ r^\star \mid \text{sgn}(s)\ ]$. Because the DM is aware that playing this conditional mean action only leads to optimal behavior on average (knowing the sign of their response), they are adequately uncertain about whether the default response is actually optimal, inducing a normal prior of distributed as $\mathcal{N}(r_d, \sigma_d^2)$. Here, the default mean $r_d$ jumps at zero surprise. The mean default response is thus a

[6] This is trivial for many important applications: for example, people know how to respond to news about the stock market when good news are released.

step function.

Note that $\sigma_d^2$ controls the precision of the prior. In some circumstance, knowing the sign might be all there is to know to identify the unconstrained optimal action, e.g. when the $r^*$ resembles a step function itself. In other situations, optimal responses might vary drastically even conditional on the sign, inducing large prior uncertainty. This directly translates to empirical settings where people might be more or less certain about what to do if they just know in which direction to respond.

**Optimal Behavioral Response.** The DM combines their imperfect cognitive signal with their prior in Bayesian fashion:

$$r(s) = \lambda\ r^c(s) + (1-\lambda) r_d(s), \tag{2}$$

where the weight on the cognitive signal, $\lambda = \frac{\sigma_d^2}{\sigma_a^2(s)+\sigma_d^2}$ decreases in the level of mapping noise, $\sigma_a^2(s)$ 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 coding noise in the size of the surprise, $\sigma_a^2(s)$, the behavioral response is a piecewise linear function that jumps at zero surprise. 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 zero surprise. 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 zero surprise. Intuitively, this originates from mixing the unconstrained optimal response with a default response function that is completely inelastic (flat) everywhere but at zero.

Assuming increasing noise in the size of the surprise $\frac{\partial \sigma_a^2(s)}{\partial s} > 0$ induces a smoother, sigmoid shaped response function. In that case, the region of excess sensitivity is not constrained to the zero point, but excess sensitivity is predicted in a window around zero (See Appendix XX).

**Surprise Coding Noise.** In practice, there may be a second form of noise affecting the process of optimizing: prior uncertainty about the expected level, e.g., the analyst forecast of EPS. Uncertainty about what constitutes the expected level of the announced variable introduces uncertainty about coding the surprise. So far the model assumes a given surprise as the primitive, which primarily captures the intuition that people "code news in surprise space". Uncertainty about the reference level has two main intuitions. First, it may capture a given individual's uncertainty about the reference level, for example because they saw several contradicting analyst forecasts. Second, different individuals may have different

reference levels, but each of them is certain about their expectation. 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 (2).

We introduce normal surprise coding noise about the expected level that pins down what gets coded as zero surprise, so $\tilde{s} \sim \mathcal{N}(s, \sigma_s^2)$. The noise parameter $\sigma_s^2$ captures the degree of dispersion. 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.

**Predictions.** We are now equipped to spell out the comparative static predictions for the effect of the two sources of noise on

**Prediction 1.** *An increase in surprise-response mapping noise increases sensitivity of the behavioral response at zero response (amplification) and decreases it everywhere else (attenuation).*

**Prediction 2.** *An increase in surprise coding noise decreases sensitivity for all levels of surprise, but most strongly around zero surprise. [Note: for far away, the prediction may reverse.]*

**Amplification and Attenuation vs. Over- and Underreaction.** Note that we formulate our main predictions in terms of *sensitivities* to changes in the surprise. Related recent work studies belief updating and tests predictions about *over- and underreaction*, i.e. the size of belief movements in relation to a rational Bayesian benchmark (Augenblick et al., 2024; Ba et al., 2024). The following remarks are in order. First, the response we model need not be a belief, but may be an action that also depends on tastes and sources of noise that are external, rather than internal (i.e., cognitive noise). Correspondingly, we do not rely on strong assumptions about – and cannot generally identify – the level of the unconstrained response. This means we cannot generally identify "over"- or "under"-reaction relative to what's unconstrained optimal. Second, and despite our non-reliance on the level of the unconstrained optimal response, our model generates predictions about the effect of the different sources of noise on the *level* (not just the sensitivity) of responses. Specifically, our model predicts overreaction whenever the absolute optimal response is below the default response, $|r^*(s) < r_d|$, and underreaction otherwise. For testing these complementary predictions empirically, the defaults need to be assumed or estimated. While these defaults are pinned down by the model as conditional expectations, they need not be well-calibrated in practice. Our model is then compatible with, for example, overreaction "everywhere" if the empirical defaults are close to zero, and underreaction "everywhere" if the defaults are far away from zero. Our baseline sensitivity predictions for mapping noise, which posits mapping noise predicting excess sensitivity *only at zero*, is particularly conservative and directly implies overreaction just around zero, and is compatible with both "higher" and "lower" level reactions (but not necessarily "over"- and

"under"-reaction as those relate to the unconstrained response) away from zero depending on the location of defaults. By relaxing our simplifying assumption of constant mapping noise in the size of the surprise and instead assuming increasing noise (as would be expected, in spirit, from the results of Enke et al., 2024), the amplification effect extends further around zero. This highlights the complementarity of the two perspectives focusing on amplification/underreaction versus higher or lower level reactions. Following the recent literature on behavioral attenuation effects (Enke and Graeber, 2023; Enke, 2024), we opted for predictions and empirical tests focused on the sensitivity of actions.

# 3 Field Evidence on the Sensitivity to Earnings Surprises

## 3.1 Data

In this section, we provide some 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.

**Data on earnings announcements.** Our paper focuses on market-adjusted returns around earnings announcements. To test these, we need to determine when investors could first trade on earnings information. Using the 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 CRSP using the WRDS mapping file 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). 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.

**Analyst expectations.** The Institutional Brokers' Estimate System (IBES) is a database that provides comprehensive information on analyst expectations and forecasts for publicly traded companies. IBES contains earnings per share (EPS) estimates from financial analysts at various horizons. These estimates are updated regularly and include both short-term and long-term forecasts. 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 earnings per share (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 (Center for Research in Security Prices).

**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:

$$\text{SUE}_{i,t} = \frac{\text{EPS}_{i,t} - E_{t-1}[\text{EPS}_{i,t}]}{P_{i,t-1}} \tag{3}$$

where $\text{EPS}_{i,t}$ is the earnings per share. $E_{t-1}[\text{EPS}_{i,t}]$ is the mean expected earnings per share in the last IBES statistical period before earnings were released. $P_{i,t-1}$ is the last closing price before the earnings announcement. To 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.[7] 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.

**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

[7]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.

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, constructed using the method in Golubov and Konstantinidi (2023). 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 all 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 190,000 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 0.028. EPS are on average $0.178 with a standard deviation of $0.379. 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.

**Table 1:** Summary Statistics

| Variable | Obs. | Mean | SD | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| SUE | 191,458 | -0.003 | 0.028 | -0.002 | 0.000 | 0.002 |
| EPS | 191,458 | 0.178 | 0.379 | 0.026 | 0.136 | 0.282 |
| Dispersion | 191,458 | 0.430 | 0.448 | 0.189 | 0.273 | 0.453 |
| VU | 191,458 | 0.749 | 0.233 | 0.605 | 0.747 | 0.895 |
| Mkt. Adj. Ret | 191,458 | 0.000 | 0.092 | -0.047 | -0.002 | 0.045 |

## 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.[8] 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. 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,

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

a shorter event window ensures that the observed abnormal returns can be more confidently attributed to the earnings announcement rather than other extraneous variables. We choose a window of four days, rather than one day, as one might be concerned that stocks with more valuation uncertainty might respond slower to news than stocks with less valuation uncertainty. Therefore, focusing on a shorter window of e.g., just the earnings day itself might mechanically generate differences between how high and low valuation uncertainty stocks respond to news.

## 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 displays the raw data on the relationship between standardized earnings surprises (on the x-axis) and cumulative market-adjusted stock returns from the earnings announcement day itself ($t = 0$), to four trading days after the earnings announcement ($t = 4$) (on the y-axis).

Figure 1 displays a striking S-shaped response to earnings news on average. In other words, the stock market response to earnings news is highly sensitive to the sign of surprises but fairly insensitive to the size of surprises. Moving from a standardized earnings surprise of -0.01 to 0.01 is associated with an average difference of 8.56% in cumulative market adjusted returns from $t = 0$ to $t = 4$.[9] Moving from a standardized earnings surprise of 0.01 to 0.02 is associated with a change of 30 basis points in cumulative market adjusted returns. Similarly, moving from a standardized earnings surprise of -0.02 to -0.01 is associated with a change of 58 basis points in cumulative market-adjusted returns.

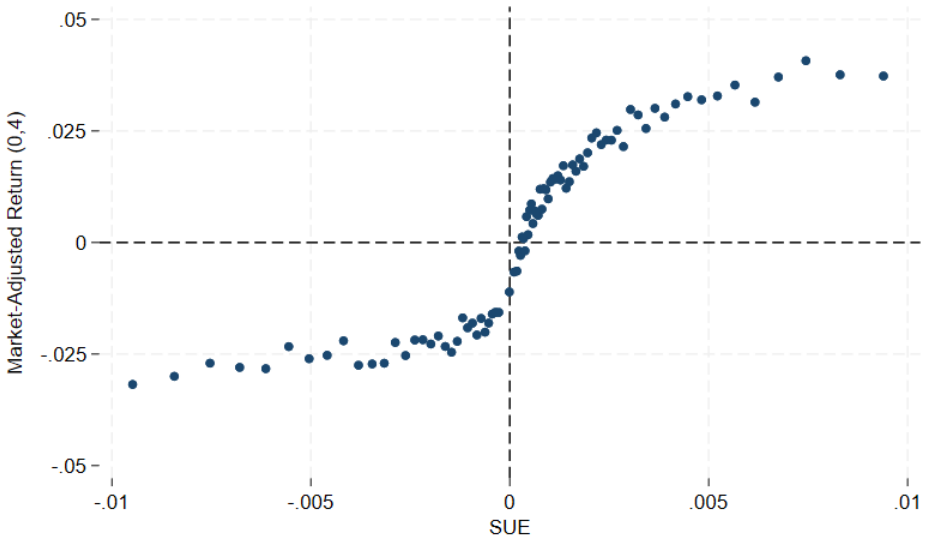
In terms of the magnitudes of the slope, the steepest part of the curve is observed around the point where SUE is zero. Here, even small changes in SUE result in significant changes in market-adjusted returns. This suggests that the market is highly sensitive to earnings surprises close to expectations. As SUE moves further away from zero, either positively or negatively, the slope of the curve flattens, indicating a diminishing marginal effect on market-adjusted returns. This flattening suggests that large deviations from expected earnings (either positive or negative) have a relatively smaller incremental impact on market-adjusted returns compared to smaller deviations near the zero point.

This non-linear relationship between excess returns and earnings surprises has been documented in the finance and accounting literature for decades (Freeman and Tse, 1992; Skinner and Sloan, 2002). While these patterns are consistent with our model of noisy cognition, a variety of other explanations

[9] A salient feature of Figure 1 is that for small positive SUEs – which one would think are 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.

have been put forward. Freeman and Tse (1992) document the S-shape, and argue that it is a function of 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. And from a valuation perspective, the persistent component of news should matter more for valuations – and thus small earnings surprises have a relatively larger effect on prices. Further, and consistent with this explanation, Skinner and Sloan (2002) show that the S-shape is stronger for growth firms than value firms. This directly builds on the results in Freeman and Tse (1992), as growth firms have longer duration cashflows on average (Gormsen and Lazarus, 2023). Another popular explanation for this empirical pattern is 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, only explains the functional form to the left of zero, and not to the right – as if the market anticipates firms' earnings management behavior, it should have no effect on prices in equilibrium (Stein, 1989). More recently, others have argued that the sigmoid shape is a function of endogenous disclosure (Huang et al., 2023). The proposed mechanism is that, in an effort to avoid disappointing investors, firms which themselves expect to have small positive earnings news may withhold that information – and thus when the information is eventually disclosed prices react strongly. In the subsequent sections, we test some of the predictions of our noisy cognition framework, which might provide another potential mechanism underlying the S-shaped response function.

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




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.

# 4 Valuation Uncertainty and Sensitivity to Surprises

In this section, we provide basic tests of our first hypothesis: that uncertainty about the mapping of fundamentals to optimal actions increases sensitivity to the sign of surprises, but decreases sensitivity to the size of surprises.

## 4.1 Descriptive evidence

**Defining valuation uncertainty.** To operationalize mapping uncertainty in this setting we rely on *valuation uncertainty* – uncertainty in the relationship between fundamentals and stock prices. We define valuation uncertainty, $\text{VU}_{i,t-1}$, of company $i$ at time $t-1$, i.e. before an earnings announcement at time $t$, as the dispersion in expected stock prices given by different accounting-based valuation methods (Golubov and Konstantinidi, 2023). The measure of valuation uncertainty varies both within companies over time and across companies and plays an important role in fundamental analyses of stock valuations.[10]

[10]The measure in Golubov and Konstantinidi (2023) is based on year-end accounting information. To avoid a look-ahead bias, we require that the information became public before the end of month before the earnings announcement.

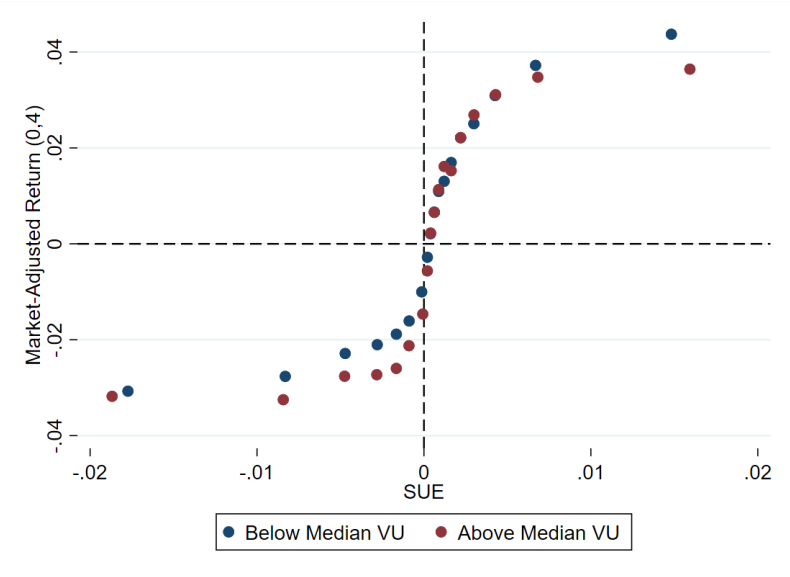
**Raw data.** Figure 2 displays the raw data on the relationship between standardized earnings surprises (on the x-axis) and the cumulative market-adjusted return from $t = 0$ to $t = 4$ on the y-axis, separately for companies with high versus low valuation uncertainty. The red dots show data for companies with above median valuation uncertainty, while the blue dots show responses for companies with below median valuation uncertainty.

Figure 2 shows that the sensitivity to the sign of the earnings surprise is seemingly higher for companies with above median valuation uncertainty compared to those with below median valuation uncertainty. This is illustrated by the slope of dots close to zero. In particular, the red dots just below zero are below the blue dots just below zero.

These patterns flip once we include the full support of earnings surprises. Earnings surprises appear to be less sensitive to the size of surprises for companies with above median valuation uncertainty compared to those with below median valuation uncertainty – at least for positive surprises.

This plot provides suggestive evidence of a systematic relationship between valuation uncertainty and market-adjusted returns. Indeed, the relationship is more S-shaped for companies with high valuation uncertainty. In the following section, we provide much more systematic evidence on the economic and statistical significance of this relationship.

**Figure 2:** Earnings Responses: High vs. Low 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 above-median valuation uncertainty, and the blue dots represent data from stock quarters with below-median valuation uncertainty. Valuation uncertainty is defined as the dispersion in expected stock prices given by different accounting-based valuation methods (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 earnings response regressions of the following form:

$$r_{i,(t,t+n)} = \alpha \text{SUE}_{i,t} \times \text{VU}_{i,t-1} + \beta \text{SUE}_{i,t} + \text{VU}_{i,t-1}\gamma + \delta X_{i,t} + \phi_t + \psi_i + \epsilon_{i,t}, \tag{4}$$

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 $\alpha$, 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 standard deviation one.

We control for both security (Permno) fixed effects, $\psi_i$ and year-month fixed effects, $\phi_t$. With se-

curity fixed effects, our regression captures differences in post-earnings announcement returns when a stock is *relatively* harder or easier to value. 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*.

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.[11] 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.

**Sensitivity to the sign and size of surprises.** The key distinction in our analysis concerns sensitivity to the sign versus size of surprises. To analyze the effect of sensitivity to the sign of surprises we estimate our main specification for small and symmetric windows close to an SUE of zero. By focusing on small and symmetric windows close to zero, we aim to isolate the impact of positive versus negative news on market-adjusted returns. This allows for a clear analysis of directional sensitivity.

To study the sensitivity to the size of surprises we gradually expand this window. As the analysis includes larger deviations from expectations, it captures how the magnitude of surprises influences stock prices.

## 4.3 Valuation Uncertainty and Sensitivity to Surprises

Table 2 shows that standardized unexpected earnings (SUE) are positively and significantly associated with market-adjusted returns across all specifications. Specifically, in column (1), when focusing only on surprises close to zero, a one-unit increase in SUE leads to a 16.82 percentage point increase in market-adjusted returns ($p < 0.01$). This positive relationship persists, though attenuated, across columns (2) through (5), with coefficients ranging from 9.65 to 2.20, all significant at the 1% level. This attenuation in coefficients as we widen the support reflects the S-shaped relationship between market-adjusted returns and the size of surprises depicted in the previous subsection.

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

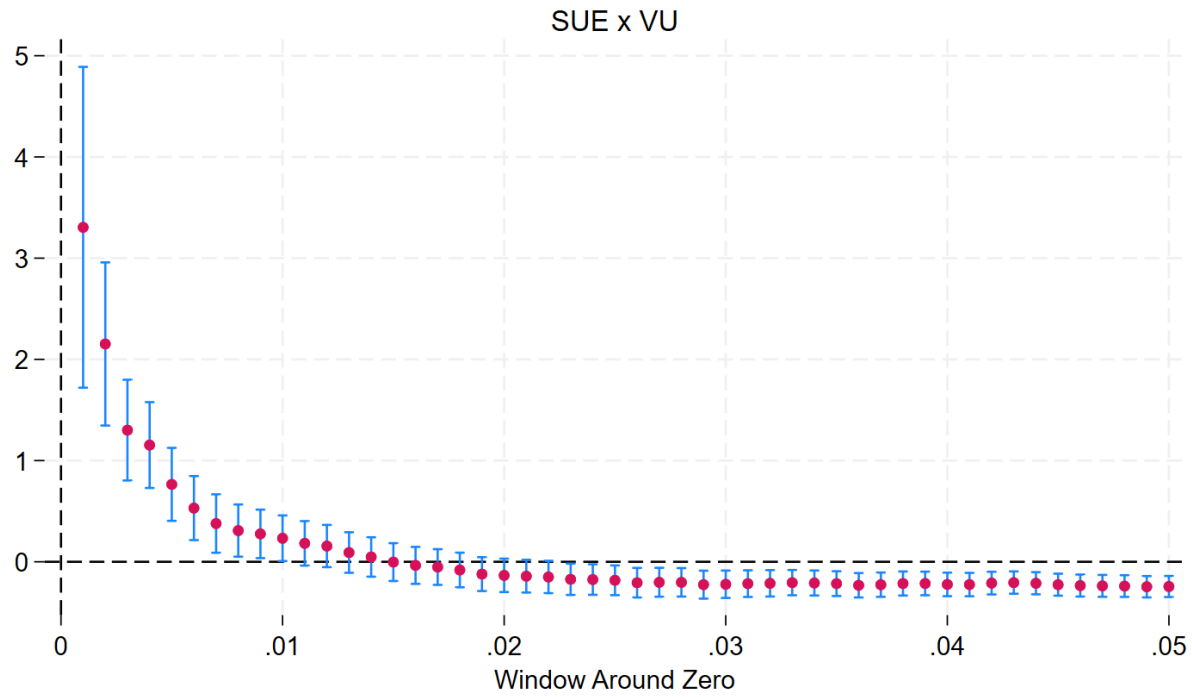
Our core object of interest concerns the interaction effect between SUE and valuation uncertainty. As predicted by our model, Column 1 shows a positive and significant interaction effect for SUE windows close to zero. In other words: mapping uncertainty increases sensitivity to the sign of surprises. Yet, this interaction coefficient turns negative and significant for windows larger than 0.01, as illustrated by Columns (3), (4) and (5).

These effects are also economically meaningful. For a window size of 0.002, a unit increase in SUE is associated with a 16.8 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 19.3 percent ($p < 0.01$), i.e. a one-standard deviation higher valuation uncertainty increases the sensitivity to surprises by approximately fifteen percent. For a window size of 0.025, a one unit increase in SUE is associated with a 2.2 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 percent ($p < 0.01$), i.e. it decreases sensitivity to surprises by approximately ten 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 standardized 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 a standardized earnings surprise.

Taken together, these patterns are consistent with our theoretical framework according to which people know how to qualitatively respond to the sign of surprises, but they are uncertain how to quantitatively incorporate the size of surprises.

**Figure 3:** Effect of Valuation Uncertainty on Earnings Response Coefficients




*Notes:* This figure shows the coefficients of the interaction effect between the standardized earnings surprise (SUE) and valuation uncertainty (VU) for varying sizes of the window of standardized earnings surprises 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 stock prices given by different accounting-based valuation methods. Panel A displays the results for the full sample, while Panel B shows the results for the bottom quintile of analyst dispersion. The x-axis represents the window size around zero for standardized earnings surprises, and the y-axis shows the interaction coefficient. Error bars indicate the 95% confidence intervals for each coefficient.

## 4.4 Robustness

One concern with the results in Table 2 is that they are 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.[12] And, if

[12]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

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

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SUE | 16.82*** | 9.654*** | 6.199*** | 3.442*** | 2.196*** |
| | (0.532) | (0.283) | (0.190) | (0.125) | (0.092) |
| VU | 0.000996* | 0.00102** | 0.00113** | 0.00144*** | 0.00150*** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| SUE x VU | 2.524*** | 0.973*** | 0.356*** | -0.157** | -0.259*** |
| | (0.400) | (0.188) | (0.119) | (0.078) | (0.056) |
| Observations | 99,720 | 140,700 | 162,803 | 178,998 | 185,250 |
| R-squared | 0.121 | 0.115 | 0.113 | 0.105 | 0.097 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*Notes:* This table shows data on earnings announcement 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 stock prices given by different accounting-based valuation methods. 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.

this channel applies differently to small versus large surprises, one might be concerned that it is driving our baseline results.

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. Specifically, we run regressions of the form

$$\text{Outcome}_{i,t} = \beta \text{VU}_{i,t-1} + \delta X_{i,t} + \phi_t + \psi_i + \epsilon_{i,t}, \tag{5}$$

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 4.

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 infor-

different disclosure strategies (Dye, 1985; Huang et al., 2023).

mation 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, 2022). 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.[13] Overall, the results in Table 3 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 is unlikely to be driving our baseline results.

**Table 3:** Relationship between Valuation Uncertainty and information incorporated into prices before earnings announcements

| | \|Ret\|/SD | PJ |
|---|---|---|
| | (1) | (2) |
| VU | -0.165*** | -0.007 |
| | (0.053) | (0.013) |
| Observations | 176,324 | 66,333 |
| R-squared | 0.221 | 0.169 |
| 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.

## 4.5 Discussion: Rational Benchmark

Our theory and empirical evidence describe behavioral responses and market outcomes in response to surprising news. They are, however, silent about the rational response to these news. In this subsection,

[13]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.

we argue why it is empirically challenging to identify the rational response to a particular piece of earnings news.

One possible approach to quantify the rational response would be to study the longer-run effects of earnings surprises on stock returns, say over a time-horizon of 45 trading days i.e., the expected number of trading days until the next earnings announcement. The logic is that with a sufficiently long post-earnings announcement window, all the information from the announcement should be rationally incorporated into prices. Using these longer post-earnings announcement windows, however, could be confounded by a variety of factors. First, it could be that ahead of the next earnings announcement, investors gather information, and the information from the next announcement is incorporated into prices before it is formally released (Ball and Brown, 1968; Fama et al., 1969). In addition, earnings news are positively autocorrelated (Novy-Marx, 2015). This means that e.g., companies that released negative earnings news are more likely to issue further bad news – or guidance that future earnings will be worse than expected – after the announcement. And, a fraction of the expected news in the next announcement will be incorporated into prices before the announcement itself. For these reasons, by examining longer-run returns, we risk mixing news from multiple earnings announcements, rather than capturing the causal effect of a particular announcement.

Second, by examining longer horizons, it increases the probability of other non-earnings related news being released e.g., changes in expected taxes (or other government policies), which have significant implications for firm value. By focusing on a narrow window around earnings announcements, we can avoid including the response to these other non-earnings news in our regression.

Third, the rational response to any piece of new information is difficult to determine. For example, it's not clear how persistent any piece of earnings news could be – and therefore how much we should adjust expected future cashflows. Further, the "true" discount rate, and expected long-run growth rate of future cashflows are not directly observable. For example, sell-side analysts often disagree on the exact value of these inputs for the same company at the same point in time when performing a discounted cashflow (DCF) valuation (Décaire and Graham, 2024). In addition, in a DCF model, firms are assumed to survive in perpetuity and typically, a large share of the total valuation is in the terminal value, which again is subject to significant uncertainty and is extremely sensitive to expected discount rates. And so, even with perfect knowledge of the earnings news, the rational response is not obvious.

Given the challenges inherent in measuring the rational response to news, we instead focus on short-run observed response to earnings surprises in Table 2. By focusing on returns in a narrow post-earnings announcement window, we only rely on the assumption that markets reflect all available public information in a timely manner (Fama, 1970).

## 4.6 Experimental Evidence

To provide clean evidence on the behavioral mechanism from our model, we complement the field evidence with experimental evidence from a more controlled setting. This experimental evidence additionally helps us to rule out the role of confounding variables and to shed light on the thought processes of investors.

**Sample.** We conducted our experiments on Prolific, a widely used online platform to conduct experiments. The baseline experiment was run with 400 US respondents in August 2024.

**Baseline design.** Our baseline setting is guided by the following objectives: First, our baseline design tries to mimic the high-dimensional nature of real news stories about economic quantities. Next to quantitative information, they also convey a rich set of qualitative information. Second, our design collects precise data on the expected stock response to earnings surprises of different sign and size. Third, our design allows us to exogenously manipulate perceived valuation uncertainty.

Respondents in the baseline condition make predictions about four different hypothetical companies. They receive a news story about a company's earnings news which contains information about each company's stock value as well as the expected earnings per share. Respondents additionally learn about the actual realization of earnings per share and how they differ from the market expectations. We vary the size of surprise across participants. In particular, respondents receive an either positive or negative SUE of the following magnitude: 0.0001, 0.0002, 0.0003, 0.0005, 0.001, 0.003 or 0.005.

Finally, to shut down beliefs about the reasons behind the earnings surprises as a mechanism, we provide all respondents with tailored narratives – one for positive surprises and a different one for negative surprises.[14] For Moeagle Industries, a negative earnings surprise is presented to respondents as follows:

> Calhoun, GA, August 21, 2024 – Moeagle Industries, Inc., a global leader in flooring solutions, reported disappointing earnings for the second quarter of 2024, falling short of expectations. The company posted earnings per share of $2.80, missing the forecasted $2.95. The company's profit was 25 million lower than expected. Moeagle Industries, Inc offers a wide range of products including carpet, hardwood, laminate, and tile. The company cited increased raw material costs and supply chain disruptions as key factors behind the earnings miss. Additionally, the company faced challenges in achieving the anticipated efficiencies in its operations, which impacted overall profitability despite stable revenues. The company's stock was trading at $120.45 on the day before the announcement.

[14]The controlled experimental setting allows us to shut down this mechanism, which could plausibly be at work in our field data.

Respondents are then asked to predict stock returns until the end of the trading day on which the earnings news are announced. After making the return prediction, respondents are asked to state how certain they are about their prediction given the earnings surprise. We incentivize the responses of 50% of our respondents by telling them that they will receive a payout if their estimate of the stock return is with 1 percentage point of the average estimate of all other respondents. To understand how people arrived at their prediction, we ask an open-ended question where they can explain, in their own words, the reasoning behind it.

**Valuation uncertainty treatment.** In our experiment, half of the respondents are assigned to the baseline condition, while 50% of respondents are in the high mapping uncertainty condition. This later condition is identical to the baseline condition, except that respondents additionally receive information about the high valuation uncertainty for this company. The additional information in this treatment describes internal recalibrations in the companies that introduce significant valuation uncertainty. These recalibrations highlight the complex interplay between internal data adjustments and external market factors, leading to varying degrees of volatility in stock prices. The uncertainty in each company's valuation is driven by factors such as regulatory changes, market conditions, technological advancements, and economic trends. For Moeagle Industries, Inc., a global leader in flooring solutions, respondents in the high valuation uncertainty treatment receive the following additional information:

> Notably, the company also engaged in a detailed reassessment of its actuarial assumptions related to the discount rate applied to its long-term pension obligations, resulting in a potential variance of $\pm 0.25\%$ in the applied discount rate. This reassessment involved a comprehensive analysis of over 2,000 data points related to current and projected interest rate trends, as well as demographic shifts that could impact future liabilities. While this adjustment has a negligible impact on quarterly earnings—estimated to influence net income by approximately $2 million—it underscores the complexity of managing future financial liabilities in an environment where interest rates are increasingly volatile, with potential fluctuations of $\pm 50$ basis points anticipated over the next two years. Despite these uncertainties, there is significant upside potential; should interest rates stabilize or decrease, Moeagle could see a reduction in the present value of its pension obligations by up to 10%, freeing up capital for other strategic initiatives. Additionally, the valuation of Moeagle's long-term pension obligations, currently estimated at $350 million with a potential variance of $\pm 5\%$, introduces a level of uncertainty to the company's overall financial health. However, favorable demographic trends, such as a slower-than-expected increase in life expectancy or adjustments in retirement age, could lead to a positive variance of up to 5% in the present value of these commitments, enhancing the company's financial flexibility and potentially boosting its intrinsic value beyond the current $8.5 billion estimate. Moeagle's

stock has a 12-month beta of 1.10, reflecting a 10% higher volatility than the market, with typical daily price swings of ±2%, driven by fluctuations in interest rate expectations and broader economic conditions.

**Results.** Figure 4 illustrates the findings from the experiment. The experiment replicates the core results from the field data. Across both treatment conditions there is more sensitivity to the sign of surprises than to the size of surprises. One key strength of this experimental data is that it holds constant the narrative behind large and small earnings surprises. As such, it allows us to isolate cognitive mechanisms.

Figure 4 and Table 4 further reveal that increasing perceived valuation uncertainty about the company strongly increases sensitivity to the sign of surprises. In particular, the figure clearly shows that for small surprises close to zero respondents in the high mapping uncertainty condition predict significantly higher stock prices than do respondents in the baseline condition. For large surprises further away from zero these patterns flip: i.e. there is a more muted predicted stock market response for respondents in the high mapping uncertainty treatment.

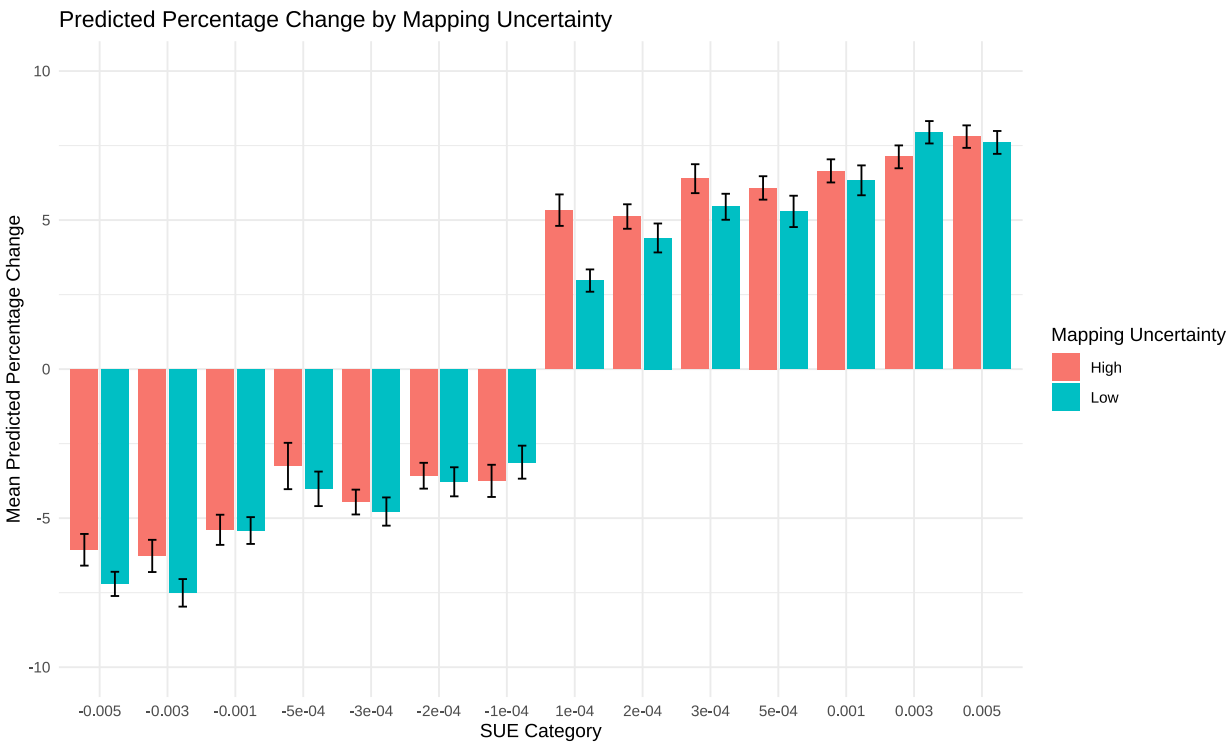
As a final step, we verify that respondents in the high mapping uncertainty condition exhibit more subjective uncertainty in their predictions than respondents in the baseline condition. Indeed, respondents in the high mapping uncertainty condition are 6 percentage points less certain than respondents in the baseline condition ($p < 0.01$).

**Additional pilot evidence.** We have conducted pilot experiments that dissect the cognitive origins of these patterns. These pilots demonstrate that only providing the quantitative EPS numbers to respondents without embedding them in the context of a qualitative news story does not lead to an S-shaped response pattern around zero surprise.[15] Only when the exact same quantitative information is embedded in a news story with a qualitative interpretation does an S-shaped response pattern emerge. This highlights the crucial role of selective attention in driving people's response to surprising news.

In ongoing work, we aim to disentangle different possible behavioral mechanisms that increase people's reliance on simplification strategies in complex information environments. In particular, we are conducting experiments that manipulate (i) time pressure, (ii) cognitive load, (iii) the presence of irrelevant and distracting information and (iv) the salience of the qualitative information.

[15]In this sense, the patterns stand in contrast to Augenblick et al. (2024) who document overreaction to low quality information and under-reaction to high quality information. This difference in findings can be reconciled by the different nature of signal structures they employ: they rely on probabilistic signals about binary events, while we leverage continuous quantitative signals. Probabilistic signals are potentially harder to interpret than quantitative information on continuous scales.

**Figure 4:** Predicted Percentage Change by Mapping Uncertainty




*Notes: The vertical axis measures the mean of respondents predictions of the percentage change in stock price by the end of day of the earnings announcement by SUE and treatment group. The error bars are given by the standard error of the mean.*

**Table 4:** High vs. Low Treatment

| | Dependent variable: Predicted Percent Change | | | | | | |
|---|---|---|---|---|---|---|---|
| | PredPer | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| SUE | 45,410.260*** (3,547.334) | 21,737.620*** (1,563.506) | 18,080.580*** (1,106.109) | 9,328.431*** (787.186) | 6,020.122*** (319.920) | 2,231.313*** (107.509) | 1,386.061*** (61.943) |
| Low-dummy | −0.868* (0.512) | −0.462 (0.460) | −0.630 (0.457) | −0.776 (0.575) | −0.171 (0.464) | −0.207 (0.448) | −0.670 (0.425) |
| SUE:Low-dummy | −14,952.050*** (5,124.255) | −1,287.619 (2,297.567) | −1,039.603 (1,522.688) | −20.856 (1,149.454) | −146.138 (464.422) | 343.912** (149.382) | 94.979 (84.988) |
| Constant | 0.792** (0.355) | 0.772** (0.313) | 0.965*** (0.332) | 1.414*** (0.394) | 0.630* (0.320) | 0.427 (0.323) | 0.870*** (0.310) |
| Observations | 150 | 172 | 156 | 171 | 155 | 143 | 145 |
| $R^2$ | 0.618 | 0.670 | 0.778 | 0.621 | 0.814 | 0.883 | 0.891 |
| Adjusted $R^2$ | 0.610 | 0.665 | 0.774 | 0.614 | 0.810 | 0.880 | 0.889 |

*Notes:* Each regression in the table only includes positive and negative surprises with the same magnitude SUE. The magnitude of SUE increases with respect to the regression number with (1) having the smallest SUE magnitude and (7) having the largest. The SUE window sizes we used in this experiment are 0.0001, 0.0002, 0.0003, 0.0005, 0.001, 0.003 and 0.005. The outcome variable Predicted Percentage Change measures respondents predictions of the percentage change in stock price by the end of day of the earnings announcement. Low-dummy is a dummy variable for the low mapping uncertainty group. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

# 5 Uncertainty about the Size of Surprises

This section examines the second prediction of our theoretical framework: that uncertainty regarding the magnitude of surprises decreases the sensitivity of market-adjusted returns to earnings surprises everywhere. To proxy uncertainty regarding the magnitude of surprises, we use variation in dispersion of analyst forecasts about a company's earnings.

**Specification.** To estimate heterogeneous responses to earnings surprises by analyst forecast dispersion, we estimate the following equation:

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

where $\text{Dispersion}_{i,t-1}$ is the standard deviation in analyst forecasts for the earnings of company $i$ in the last IBES statistical period before the earnings announcement. We include the same set of controls and fixed effects as in the previous section.[16] 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 5 displays our results on dispersion. The first column indicates a strong positive relationship between SUE and market-adjusted returns, with a coefficient of 16.11 ($p < 0.01$). The interaction term between SUE and dispersion is also negative (-1.3, $p < 0.01$), suggesting that the effect of SUE on returns is significantly diminished when analyst dispersion is high.

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 5 plots the coefficients of the interaction effect between dispersion and SUE for a larger number of SUE windows around zero. Figure clearly demonstrates that for all windows of SUE around zero that previously occurred in the data, the interaction effect is negative.

Taken together, the evidence clearly highlights that uncertainty about the consensus forecast attenuates the stock market response to earnings surprises substantially.

[16] Table A2 examines robustness to the exclusion of controls.

**Table 5:** Effect of Analyst Dispersion on Earnings Response Coefficients by Earnings Size

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SUE | 16.11*** | 9.595*** | 6.283*** | 3.451*** | 2.111*** |
| | (0.541) | (0.296) | (0.197) | (0.116) | (0.078) |
| Dispersion | -0.000898* | -0.000960** | -0.000884** | -0.000802** | -0.000690* |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| SUE x Dispersion | -1.294*** | -0.443*** | -0.296*** | -0.152*** | -0.0870*** |
| | (0.421) | (0.166) | (0.091) | (0.049) | (0.030) |
| Observations | 99,720 | 140,700 | 162,803 | 178,998 | 185,250 |
| R-squared | 0.12 | 0.114 | 0.113 | 0.105 | 0.096 |
| Window Size | 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. 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 at a given data. 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.

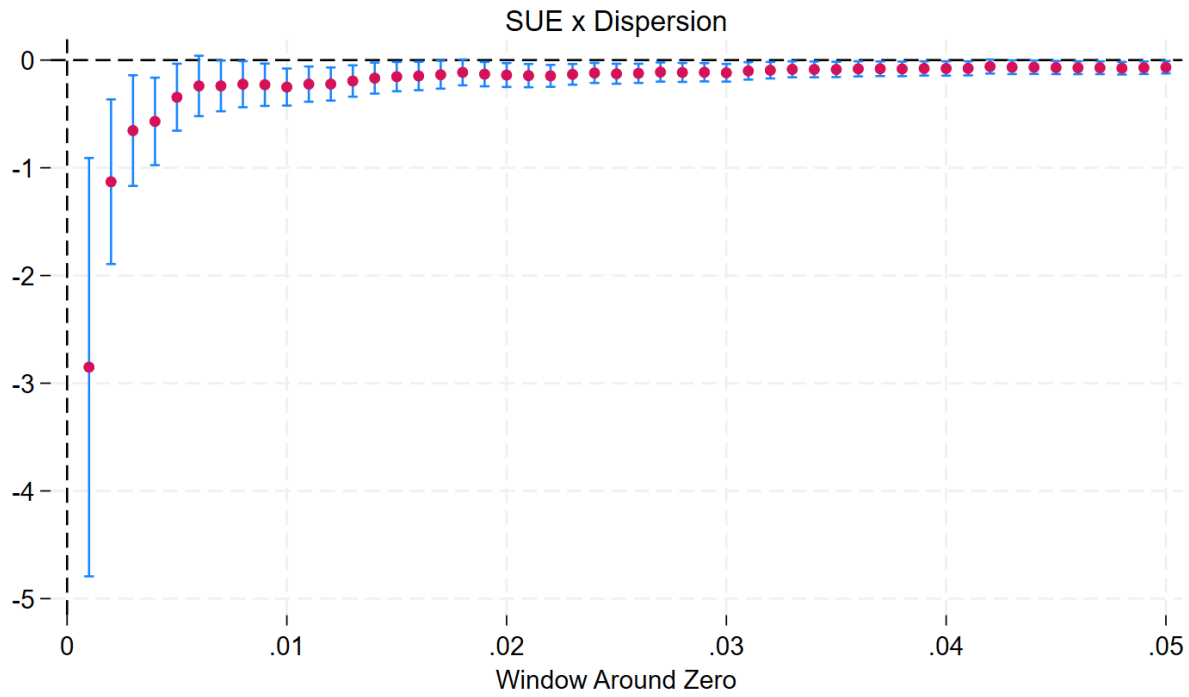
One concern with the results in Table 5 and Figure 5 is that one might expect valuation uncertainty to be positively correlated with dispersion in analysts' estimates. Naturally, companies with lots of growth potential where there is more uncertainty about their valuations might also be subject to greater analyst disagreement.

Empirically, we find a correlation of 0.3 between VU and Dispersion. Given this positive correlation and the opposing effects of these different measures on returns, one might worry that our main estimates might be downward- biased. Table A3 shows that, indeed, the estimates of interaction terms of SUE with VU and Dispersion both become larger when these terms are simultaneously included in the regressions.

# 6 Conclusion

We study how people respond to surprising news when they are uncertain about their optimal response in a high-stakes economic context. Our framework predicts that more mapping uncertainty increases response sensitivity to the sign of a surprise but decreases sensitivity to its size. This induces an S-shaped response pattern around zero surprise. More prior uncertainty about the news, by contrast, creates uncertainty about coding the implied surprise, leading to less sensitivity everywhere.

**Figure 5:** Interaction effect of Dispersion and Standardized Earnings Surprises




*Notes*. This figure illustrates the interaction effect of Dispersion and Standardized Earnings Surprises (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 at a given data. 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 earnings surprises, and the y-axis shows the interaction coefficient. Error bars indicate the 95% confidence intervals for each coefficient.

We test these predictions using data from more than 190,000 earnings announcements for more than 6,000 unique companies between 1986 and 2019. Consistent with our framework, increased uncertainty about the mapping of fundamentals to stock valuations heightens stock prices' sensitivity to the sign of surprises, yet diminishes their sensitivity to the size of surprises. This implies that when the relationship between fundamentals and valuations is unclear, investors react more strongly to whether the earnings surprise is positive or negative rather than to the magnitude of the surprise. We then confirm these predictions in a tightly controlled online experiment with investors where we can rule out several confounds and where we identify subjective mapping uncertainty as a causal pathway.

Our second main finding is that uncertainty regarding the size of earnings surprises significantly reduces stock price sensitivity. We study this mechanism by exploiting variation in analyst dispersion about analyst forecasts. Our results are consistent with a model where uncertainty about the size of

surprises attenuates responses. Our findings illuminate the nuanced ways in which different types of uncertainty systematically shape high-stakes market outcomes.

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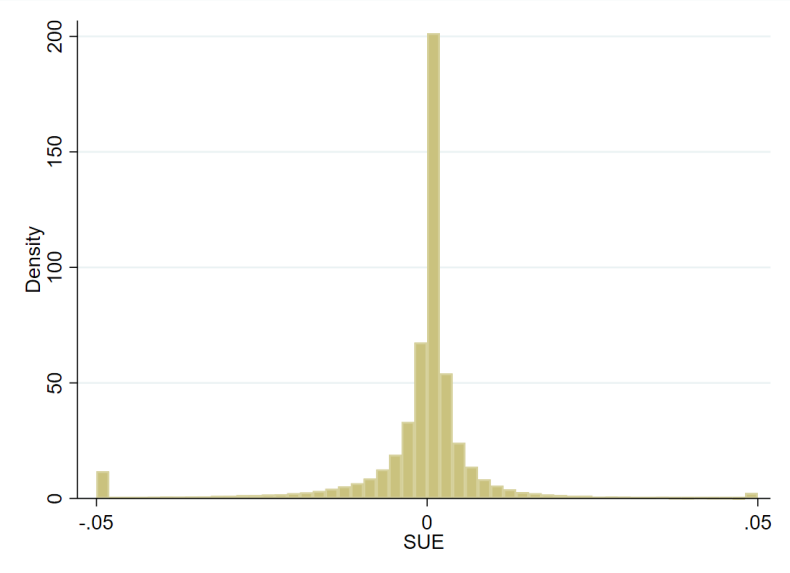
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# A Additional exhibits

**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 | 14.84*** | 8.770*** | 5.724*** | 3.212*** | 2.055*** |
| | (0.516) | (0.259) | (0.177) | (0.116) | (0.086) |
| VU | -0.00246*** | -0.00167*** | -0.00127** | -0.000925* | -8.01E-04 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| SUE x VU | 2.152*** | 0.765*** | 0.232** | -0.183** | -0.244*** |
| | (0.411) | (0.184) | (0.115) | (0.075) | (0.053) |
| Observations | 100,785 | 141,818 | 164,012 | 180,322 | 186,596 |
| R-squared | 0.027 | 0.041 | 0.046 | 0.041 | 0.034 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*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 stock prices given by different accounting-based valuation methods. 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: no controls and no fixed effects

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SUE | 14.29*** | 8.793*** | 5.829*** | 3.212*** | 1.965*** |
| | (0.517) | (0.269) | (0.182) | (0.106) | (0.072) |
| Dispersion | -0.00514*** | -0.00440*** | -0.00379*** | -0.00332*** | -0.00295*** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| SUE x Dispersion | -1.129*** | -0.345** | -0.250*** | -0.127*** | -0.0664** |
| | (0.390) | (0.159) | (0.088) | (0.047) | (0.030) |
| Observations | 100,785 | 141,818 | 164,012 | 180,322 | 186,596 |
| R-squared | 0.029 | 0.042 | 0.047 | 0.042 | 0.034 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*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 at a given data. Clustered standard errors are reported in parentheses. The window size indicates the range of SUE around zero considered in each regression. Significance levels are denoted as follows: * p<0.1, ** p<0.05, *** p<0.01.

**Appendix Table A3:** Robustness: Simultaneous heterogeneous effects by Valuation Uncertainty and Dispersion

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SUE | 16.61*** | 9.693*** | 6.266*** | 3.478*** | 2.212*** |
| | (0.534) | (0.287) | (0.194) | (0.127) | (0.093) |
| VU | 0.00101 | 0.00109** | 0.00126*** | 0.00160*** | 0.00165*** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| Dispersion | -0.000842 | -0.000925** | -0.000952** | -0.000971*** | -0.000867** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| SUE x VU | 3.031*** | 1.187*** | 0.489*** | -0.116 | -0.246*** |
| | (0.402) | (0.192) | (0.122) | (0.080) | (0.056) |
| SUE x Disp. | -2.184*** | -0.774*** | -0.423*** | -0.126** | -0.0415 |
| | (0.423) | (0.168) | (0.093) | (0.050) | (0.030) |
| Observations | 99,720 | 140,700 | 162,803 | 178,998 | 185,250 |
| R-squared | 0.121 | 0.115 | 0.113 | 0.105 | 0.097 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*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 stock prices given by different accounting-based valuation methods. Analyst Dispersion captures the z-scored standard deviation of analyst forecasts about earnings at a given date. 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 A4:** Returns on only earnings day

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SUE | 13.87*** | 7.836*** | 4.979*** | 2.726*** | 1.748*** |
| | (0.498) | (0.270) | (0.172) | (0.107) | (0.075) |
| VU | 0.000573 | 0.000576* | 0.000721** | 0.00100*** | 0.00104*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| SUE x VU | 2.170*** | 0.768*** | 0.309*** | -0.0992 | -0.185*** |
| | (0.316) | (0.150) | (0.095) | (0.061) | (0.044) |
| Observations | 99,720 | 140,700 | 162,803 | 178,998 | 185,250 |
| R-squared | 0.116 | 0.113 | 0.112 | 0.101 | 0.093 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*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 stock prices given by different accounting-based valuation methods. 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 from earnings day to t+2 i.e., 3 day returns

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SUE | 16.23*** | 9.356*** | 5.961*** | 3.297*** | 2.103*** |
| | (0.508) | (0.276) | (0.181) | (0.119) | (0.086) |
| VU | 0.000803 | 0.000792** | 0.000932** | 0.00130*** | 0.00124*** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| SUE x VU | 2.550*** | 0.931*** | 0.319*** | -0.158** | -0.234*** |
| | (0.366) | (0.177) | (0.111) | (0.074) | (0.053) |
| Observations | 99,720 | 140,700 | 162,803 | 178,998 | 185,250 |
| R-squared | 0.118 | 0.114 | 0.113 | 0.104 | 0.095 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*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 stock prices given by different accounting-based valuation methods. 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.

# B Trading Volume

One possible mechanism through which valuation uncertainty may affect the response to earnings surprises relates to attention. In particular, it is conceivable that there are differences in attention between high and low VU stocks. 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 stocks – 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 A6. 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 A6:** Effect of Valuation Uncertainty on Turnover Around Earnings Announcements

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| SUE | -1.878*** | -0.478*** | -0.185*** | -0.0599* | -0.0367* |
| | (0.222) | (0.086) | (0.049) | (0.031) | (0.022) |
| VU | 0.000273 | 0.000518 | 0.000473 | 0.000483 | 5.73E-04 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| SUE x VU | 0.0353 | 0.151** | 0.138*** | 0.114*** | 0.0760*** |
| | (0.190) | (0.073) | (0.043) | (0.026) | (0.017) |
| Observations | 99,720 | 140,700 | 162,803 | 178,998 | 185,250 |
| R-squared | 0.549 | 0.534 | 0.522 | 0.51 | 0.506 |

*Notes:* This table shows data on earnings announcement 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 stock prices given by different accounting-based valuation methods. 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.

# C Long-Run Response

One concern with the results in Table 2 is that there may be differences in the post-earnings announcement drift (PEAD) between high and low valuation uncertainty stocks (Bernard and Thomas, 1989). And, if these differences are concentrated in the tails of earnings news – as the PEAD is empirically – it may partly drive our main results. Already alleviating this concern is that the PEAD has become weaker in recent years (Martineau, 2021). In this subsection, we propose an additional test to rule out differences in PEAD driving our main results.

Specifically, we re-run a version of Equation 4, except we put cumulative market-adjusted returns from $t = 0$ to $t = 29$ (i.e., 30 trading days after the announcement itself) on the left-hand-side. The logic of including a longer post-earnings announcement window is that differences in PEAD should be less relevant over a longer horizon, because by 30 trading days after the announcement, all the information from the earnings announcement should be already impounded into prices. As outlined in the main body of the paper, however, we would like to highlight that by including such a long post-earnings announcement window, our estimates of

the response to earnings news may now be contaminated by non-earnings news released after $t = 4$ but before $t = 29$.

Also, relative to the results in Table 2, we apply two additional filters: (1) we require non-missing returns in CRSP for all trading days between $t = 0$ and $t = 29$ and (2) to avoid contamination with other *earnings* news releases, we require that there is no earnings announcement within the next 29 trading days. This second filter removes e.g., stock quarters where a firm released late the previous quarter, or released early in the quarter of interest.

Table A7 contains the results. Panel A replicates the results in Table 2, but restricting the sample to observations that pass the two filters described above to ensure comparability. Our main pattern, of VU amplifying responses to small SUEs, but eventually attenuating responses to large SUEs holds in this subsample. Panel B considers the longer-horizon returns from the first day earnings information could be traded on ($t = 0$) to the close 29 days later ($t = 29$). Panel B confirms that our results are qualitatively unchanged even when using a this longer-post earnings announcement window.

Comparing the coefficients across Panel A and B of A7 shows that the interaction coefficient between SUE and VU is 40% larger for the short-run response with the smallest window around zero. This is consistent with some differential overreaction to the sign of earnings surprises if we believe that long-run responses over the 30-day horizon can be considered a credible benchmark for the rational response. For larger windows around zero, the short-run and medium response become more similar, suggesting neither over-reaction nor undereaction to information. Over course, these results should be cautiously interpreted given that the rational benchmark is likely biased given the positive autocorrelation of news.

# D One-sided regressions

In our main specifications, we examine sensitivity to the sign and size of earnings surprises using symmetrically expanding windows around a SUE of zero. Intuitively, in our model the effects on amplification are strongest at zero when there is a jump in the default response to a surprise. Yet, such an analysis does not enable us to identify differences in the patterns of amplification and attenuation when only analyzing positive surprises or when only studying negative surprises.

In Table A8, we re-run our main regression, but split the sample based on whether the SUE was strictly positive or strictly negative. In Panel A, we focus on the subset of earnings announcements with strictly positive surprises. In this subsample, we observe the same flipping

**Appendix Table A7:** Effect of Valuation Uncertainty on Long-Run Post-Earnings Returns

| | Panel A: Matched Sample (0,5) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| SUE | 17.34*** | 10.12*** | 6.466*** | 3.652*** | 2.389*** |
| | (0.574) | (0.309) | (0.212) | (0.141) | (0.105) |
| VU | 0.00138** | 0.00135*** | 0.00150*** | 0.00183*** | 0.00196*** |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) |
| SUE x VU | 2.799*** | 1.205*** | 0.473*** | -0.141 | -0.290*** |
| | (0.440) | (0.207) | (0.131) | (0.087) | (0.063) |
| Observations | 83,534 | 117,425 | 135,354 | 148,115 | 152,871 |
| R-squared | 0.133 | 0.126 | 0.124 | 0.115 | 0.108 |
| | Panel B: Matched Sample (0,29) | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| SUE | 19.06*** | 11.94*** | 7.872*** | 4.619*** | 3.087*** |
| | (0.801) | (0.384) | (0.239) | (0.163) | (0.131) |
| VU | 0.00394** | 0.00396** | 0.00407*** | 0.00401*** | 0.00402*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| SUE x VU | 1.987*** | 1.334*** | 0.501** | -0.142 | -0.290*** |
| | (0.749) | (0.340) | (0.202) | (0.130) | (0.101) |
| Observations | 83,534 | 117,425 | 135,354 | 148,115 | 152,871 |
| R-squared | 0.135 | 0.126 | 0.125 | 0.124 | 0.121 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*Notes:* This table shows data on earnings announcement from 1986-2019. This table studies how cumulative post-earnings 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. Panel A considers returns from the first day earnings information could be traded on ($t = 0$) to the close 4 days later ($t = 4$). Panel B considers returns from the first day earnings information could be traded on ($t = 0$) to the close 29 days later ($t = 29$). Both panels only contain earnings announcements where (1) there are non-missing returns in CRSP for all days between $t = 0$ and $t = 29$ and (2) there is no earnings announcement within the next 29 trading days.
Valuation uncertainty is defined as the z-scored dispersion in expected stock prices given by different accounting-based valuation methods. 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.

pattern as in our main specification. For small positive surprises, we see amplification of the response of stock prices to earnings surprises. And, in larger windows, the negative coefficient

suggests there is an attenuation of responses to news. These effect are sizable in magnitude – on par with our baseline estimates in Table 2.

In Panel B, we focus on the subset of earnings announcements with strictly negative surprises. For negative surprises, we see more muted patterns of heterogeneity by valuation uncertainty. For the smallest window of negative surprises we see evidence consistent with amplification (albeit not statistically significant). For larger windows, however, the point estimates are near zero and not statistically significant, suggesting neither amplification nor attenuation.

These patterns can be explained by the fact that positive surprises that are very close to zero are often actually interpreted as negative news. Specifically, the market reacts on average negatively to earning surprises which are positive, but less than a penny per share. As such, the analysis using only positive surprises contains richer variation in the extent to which surprises are interpreted as negative or positive. Negative earnings surprises are always interpreted as bad news, limiting variation in default responses that we expect is driving our results on amplification and eventual attenuation.

**Appendix Table A8:** Effect of Valuation Uncertainty on Responses to Positive and Negative SUEs

| | Panel A: Positive SUEs | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| SUE | 24.30*** | 13.50*** | 8.166*** | 4.303*** | 2.739*** |
| | (1.049) | (0.426) | (0.265) | (0.175) | (0.134) |
| VU | -0.00381*** | -0.00230*** | -9.42E-04 | 0.00107 | 0.00209*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| SUE x HTV | 5.382*** | 1.930*** | 0.619*** | -0.192 | -0.360*** |
| | (0.966) | (0.339) | (0.185) | (0.121) | (0.089) |
| Observations | 52,485 | 77,113 | 88,564 | 95,366 | 97,465 |
| R-squared | 0.142 | 0.134 | 0.134 | 0.128 | 0.124 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |
| | Panel B: Negative SUEs | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| SUE | -5.924*** | -3.211*** | -2.092*** | -1.085*** | -0.567*** |
| | (1.314) | (0.408) | (0.203) | (0.101) | (0.068) |
| VU | 0.00262* | 0.00213** | 0.00214** | 0.00171** | 1.28E-03 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| SUE x HTV | 0.539 | 0.162 | -0.000997 | 0.108 | 0.0926* |
| | (1.067) | (0.344) | (0.165) | (0.083) | (0.050) |
| Observations | 24,299 | 40,572 | 51,258 | 60,743 | 64,897 |
| R-squared | 0.232 | 0.198 | 0.181 | 0.169 | 0.165 |
| Window Size | 0.002 | 0.005 | 0.01 | 0.025 | 0.05 |

*Notes:* This table shows data on earnings announcement from 1986-2019. This table studies how cumulative post-earnings 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. Panel A considers observations where $SUE$ is strictly greater than zero, while Panel B considers observations where $SUE$ is strictly less than zero. In both panels, the left hand side variable is returns from the first day earnings information could be traded on ($t = 0$) to the close 4 days later ($t = 4$).
Valuation uncertainty is defined as the z-scored dispersion in expected stock prices given by different accounting-based valuation methods. 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.