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Abstract

Customer satisfaction is an important metric to predict customer behavior and as a result firms' profitability. Expectations of a product's performance serve as a reference point against which customers evaluate their satisfaction with the products' actual performance. However, what is the effect of *uncertainty* in expectations? This paper develops a novel theoretical model of satisfaction, in which expectations reflect distributions of individual beliefs about performance outcomes. Based on this model, uncertainty shifts *subjective* reference points upward. That is, uncertainty increases the performance level at which customers switch from being dissatisfied to being satisfied. Furthermore, uncertainty has an attenuating effect on both positive and negative deviations of actual performance from subjective reference points. Put differently, a bad performance feels less bad and a good performance feels less good when it is expected, compared with unexpected. The authors find support for the model's predictions in an experimental study on product delivery as well as a field study based on online reviews. In addition, the authors develop a model-based tool that predicts the effect of uncertainty on customer satisfaction across different customizable scenarios. The paper's results carry implications for firms' communication, customer valuation and recovery strategies.

Keywords: Customer Satisfaction, Uncertainty, Probabilistic Beliefs, Prospect Theory

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Consumers are oftentimes confronted with uncertain expectations, i.e., beliefs about a product's future performance (Coughlan and Connolly 2001). For example, they may expect product deliveries to arrive early in some cases and late in others. Similarly, customers may expect deviations from a firm's communicated product performance. Expectations are thus subjective and uncertainty in expectations refers to the extent to which customers expect variations in products' future performance. Consumers' expectations about a product's future performance are influenced by past experiences, word of mouth, and firm communications (Kopalle et al. 2017; Kopalle and Lehmann 2001, 2006). In turn, expectations serve as reference points for customers' evaluations and satisfaction: performances above (below) expectations positively (negatively) impact satisfaction (Churchill and Surprenant 1982; Homburg, Koschate, and Hoyer 2006; Szymanski and Henard 2001). However, how can we account for the *uncertain* nature of expectations and how does this uncertainty affect satisfaction judgements? At the moment of evaluation, this uncertainty may trigger comparisons to "could have been" performance outcomes leading to a mix of feelings: positive feeling due to comparisons with worse possible outcomes, as well as negative feelings resulting from comparisons with better possible outcomes (Kahneman 1992; Larsen et al. 2004).

In this paper, we develop a new theoretical model of reference-dependent customer satisfaction with uncertain expectations by allowing reference points to be stochastic. Based on this model, we analytically derive a series of propositions in relation to the impact of uncertainty on customer satisfaction. We then examine the role of uncertainty for satisfaction judgements in an online experiment as well as a field study and find empirical support for our propositions.

Firms' ability to influence levels of uncertainty in expectations as well as the possibility to utilize inferred uncertainty levels underscores the topic's managerial relevance. For example, firms may communicate narrow or broad ranges of expected future performance levels. Furthermore, firms' knowledge about customers' uncertainty in expectations may serve to customize customer retention strategies (e.g., linking recovery amounts after service failures to uncertainty levels). As many studies show, customer satisfaction relates positively to firm profitability (e.g., Bhattacharya, Morgan, and Rego 2021; Malshe, Colicev, and Mittal 2020; Otto, Szymanski, and Varadarajan 2020). Finding new ways to increase customer satisfaction is thus critical, in particular in light of the increasing market dominance of companies built on customer centricity. From a consumer perspective, satisfaction increases well-being, as a desirable end-state of consumption (Oliver 2014), and it reduces the costs of dealing with unfavorable outcomes (e.g., filing complaints).

Satisfaction is defined as a post-consumption judgment of the extent to which a product provides a pleasurable level of usage-related fulfillment, relative to a reference point (Oliver 2014). A common conceptualization of customer satisfaction refers to the disconfirmation paradigm (Churchill and Surprenant 1982; Oliver 1981), according to which expectations provide the reference point. Incorporating uncertainty in expectations directly into the satisfaction response seems important, since it may influence the set of available reference points, by allowing for comparisons to different sets of counterfactuals or outcomes that "might have been" (Epstude and Roese 2008; Gneezy, Gneezy, and Lauga 2014; Inman, Dyer, and Jia 1997; Medvec, Madey, and Gilovich 1995). For example, the worst (best) possible performance probably appears intensified if uncertainty levels are high, unlike the case when consumers face no or little uncertainty.

We highlight two areas depicting the managerial relevance of examining the topic of uncertainty (in expectations) and its impact on customer satisfaction. First, the extent to which and how firms communicate uncertainty may shape expectations (e.g., Outreville and Desrochers 2016; Pracejus, Olsen, and Brown 2003). For example, delivery times communicated in form of ranges (e.g., delivery in 2-12 days) are likely to be perceived with higher uncertainty compared to delivery times communicated as single point estimates (e.g., delivery in 7 days).

Firms' possibilities in communicating uncertainty with respect to future performances are reflected in a wide array of settings beyond the communication of delivery times. For example, call centers have to decide whether and how to communicate waiting times. In the context of ride-sharing platforms (e.g., Uber, Lift, Free Now), information on the estimated time of arrival impacts customers' evaluation of the service as well as their future engagement with the platform (Cohen, Fiszer, and Kim 2022). These estimates are usually provided as point estimates (e.g., arrival in 5 minutes). However, communicating uncertainty (i.e., estimated time of arrival as an interval, for example, in 2 to 8 minutes) may benefit customers and ultimately the ride-sharing platforms in some situations, for example if a delay is likely due to weather or traffic conditions. In the domain of investor relations, earning forecasts are oftentimes communicated as ranges.[1]

Determining the optimal width of these ranges poses a challenge that needs to be informed by the effect of uncertainty on customer satisfaction. Hence, although firms already try to affect customer satisfaction via their communication about future performances, they may not sufficiently account for the communicated *uncertainty*.

Second, firms may account for uncertainty levels in their strategic decisions, for example in the design of strategies to prevent customer churn. There are multiple ways in which firms may infer uncertainty levels, which is facilitated by the increased accessibility of digital

[1] The impact of uncertainty about future earnings on market reactions after earnings announcements has been documented in the accounting literature, see for example Bamber, Hui, and Yeung (2010); Yeung (2009).

customer-firm interaction data. Uncertainty in expectations can be influenced by individuals' past experiences or word of mouth (Rust et al. 1999; Zhao et al. 2013), and may be inferred from customer-level tracking data. In addition, characteristics of available user generated (digital) content may be used to infer uncertainty levels. For example, online product reviews comprise a promising data source to collect information on the likely distribution of expectations, which may in turn inform uncertainty levels.

To help practitioners make more informed decision by accounting for the uncertain nature of expectations, we develop a model-based tool that predicts the effect of uncertainty based on a set of customizable input parameters. The basic tool features allow thus to assess scenarios tailored to specific contexts and requirements.

Our goal is to gain a more accurate understanding of how uncertainty in expectations affects customer satisfaction. We hereby address two research questions. The first one relates to the impact of uncertainty on subjective reference points. Subjective reference points denote switching points from dissatisfaction to satisfaction (Baucells, Weber, and Welfens 2011; Kahneman, Wakker, and Sarin 1997). Knowledge on the interplay of uncertainty and subjective reference points carries theoretical value in relation to the formation of reference points but also meaningful practical value for satisfaction measurement.[2] The second research question relates to the shape of the relationship between uncertainty and satisfaction as a function of actual performance outcomes.

[2] Many established satisfaction scales capture whether customers are (dis)satisfied. YouGov assesses satisfaction with a binary measure. The net promoter score distinguishes "promoters" from "detractors"; on a scale from 0 - 10, 9 - 10 denote "promoters", and 0 - 6 denote "detractors".

Building on behavioral economics studies of (stochastic) reference-point formation (Baucells, Weber, and Welfens 2011; Kőszegi and Rabin 2006, 2007) and theories of mixed feelings (Kahneman 1992; Larsen et al. 2004), we propose a model of customer satisfaction in which we examine the role of uncertainty in an analytically tractable manner. Specifically, uncertainty refers to a larger breadth of possible performance outcomes according to customers' beliefs. Uncertainty thus affects satisfaction by eliciting simultaneous comparisons of the actual performance outcome to outcomes that "could have been". From this model, we derive empirically testable propositions. Notably, we propose that uncertainty shifts customers' subjective reference points upward. Put differently, uncertainty increases the performance level at which customers switch from being dissatisfaction to being satisfied. Furthermore, we propose an attenuating effect of uncertainty on both positive and negative deviations of actual performance levels from subjective reference points. Accounting for uncertainty, good performances feel less good and bad performances feel less bad. To test these predictions, we conduct two empirical studies: an experimental study, pertaining to delivery times, such that we manipulate uncertainty by presenting participants with varying information about expected delivery times, and a field study with real-world review data from Amazon. Here, we analyze the effect of uncertain expectations on satisfaction by leveraging consumer review and objective performance-rating data. In sum, our results support our model-based predictions about the role of uncertainty in customers' evaluations.

Our research makes both theoretical and empirical contributions related to the impact of uncertainty on customer satisfaction. As a main theoretical contribution, we develop a new theoretical, reference-dependent model of customer satisfaction with *stochastic* reference points. We extend prior literature in three important ways. First, we allow expectations to reflect probability distributions and thus broaden past findings relying on single point estimates (Sivakumar, Li, and Dong 2014; Szymanski and Henard 2001). Second, our model offers an explanation on the impact of uncertainty on the evaluation of single experiences which is not reflected in models in which uncertainty informs how reference points are updated across individual's experiences (e.g., according to Bayesian updating, see for example (e.g., Bolton, Lemon, and Bramlett 2006; Rust et al. 1999). Related, our model depicts the possibility that more information might *increase* uncertainty (e.g., think about patient information leaflets in hospitals), which is rarely accounted for in existing models. Third, we build on choice models, in which simultaneous comparisons feed into the underlying utility function (Abeler et al. 2011; Caputo, Lusk, and Nayga 2020; Kőszegi and Rabin 2006) but focus on customer satisfaction as a form of experienced utility (Kahneman, Wakker, and Sarin 1997) where context uncertainty has direct welfare implications.

Second, as empirical contribution, we document two effects concerning the role of uncertainty for satisfaction judgements. First, both empirical studies suggest that uncertainty increases the performance level at which customers switch from being dissatisfied to being satisfied. Past research documents reference point shifts after multiple experiences (e.g., downward shifts of the reference point after equally bad and good experiences, see Bolton, Lemon, and Bramlett 2006; Gijsenberg, van Heerde, and Verhoef 2015). Our findings complement this work by incorporating uncertainty in expectations into single satisfaction responses, while being agnostic as to how exactly expectations are formed (e.g., through past experiences or firm communication). Further, we find an attenuating effect of uncertainty on negative and positive deviations of actual performance outcomes from subjective reference points. Prior empirical studies provide apparently mixed results regarding the impact of uncertainty on product evaluations (see Web Appendix A for a comprehensive summary of this literature). For example, uncertainty due to service variability (negative *and* positive) over time has a positive effect on product retention for contract renewals (Bolton, Lemon, and Bramlett 2006). Other studies find negative effects of uncertainty after quality improvements (Sriram, Chintagunta, and Manchanda 2015). We are able to reconcile and offer a holistic explanation for these results.

Model of Customer Satisfaction with Stochastic Reference Points

Model Development

We begin by outlining our model. As suggested by prior work (e.g., Markle et al. 2018), satisfaction is a form of experienced utility, reflecting the hedonic experience associated with a performance outcome (Kahneman, Wakker, and Sarin 1997). Satisfaction is a function of the performance outcome x and a reference point r, against which the performance level is compared. For simplicity and due to our focus on uncertainty, we assume that both x and r are one-dimensional. We thus seek to model satisfaction based on a single quantifiable attribute.[3]

Building on studies of reference point formation (Abeler et al. 2011; Baucells, Weber, and Welfens 2011; Kőszegi and Rabin 2006), we assume the reference point relative to which consumers assess their satisfaction with an outcome is represented by their beliefs about that outcome. For a consumer i, we therefore allow the reference point to be stochastic, such that it follows a distribution G_i. After consumer i experiences an outcome, the reference-point beliefs may evoke counterfactual comparisons with "might have been" outcomes (Epstude and Roese

[3] As an extension, the model could apply to the role of uncertainty involving multiple attributes, as in Tereyağoğlu, Fader, and Veeraraghavan (2018).

2008; Larsen et al. 2004), and those comparisons induce mixed feelings (Kahneman 1992), because an actual outcome is simultaneously compared to both better and worse reference points.[4]

In our model, an outcome x is evaluated against all possible outcomes, according to consumer i's beliefs, and weighted by the probability of those outcomes. We conceptualize uncertainty as variance in consumers' beliefs about possible outcomes (Olsen, Wilcox, and Olsson 2005). The cognitive process related to these simultaneous upward and downward comparisons likely takes place without explicit consumer awareness (Epstude and Roese 2008). In the expression

$$s_{G_i}(x) = \int \mu_i(x, r)\, dG_i(r), \tag{1}$$

satisfaction is reference-dependent, and the relationship between the outcome x and any random draw r from the distribution is given by $\mu_i(\cdot,\cdot)$. As prior research shows, the relationship between experience-based evaluations and outcomes relative to the reference point is asymmetric and nonlinear. That is, loss aversion exists, such that negatively valenced information is weighted disproportionally more than positively valenced information. In evaluations of experiences, loss aversion applies to a wide range of situations, such as service evaluations (Gijsenberg, van Heerde, and Verhoef 2015; Mittal, Ross Jr, and Baldasare 1998), as well as satisfaction with performance on academic tests (Weingarten, Bhatia, and Mellers 2019), with marathon finishing times (Markle et al. 2018), and with yearly bonus payments (Ockenfels, Sliwka, and Werner 2015). But we also note empirical support for diminishing sensitivity, prompting concavity for

[4] Evidence of the existence of simultaneous comparisons comes from the segregation (cf. adaptation) mechanism, see for example Baucells, Weber, and Welfens (2011); Sprenger (2015). This account has gained support across different domains, for an overview see for example Markle et al. (2018).

gains and convexity for losses (Markle et al. 2018; Mittal, Ross Jr, and Baldasare 1998; Weingarten, Bhatia, and Mellers 2019). Together, loss aversion and diminishing sensitivity create a classic S-shape of prospect-theoretic value functions. We formalize the reference-dependent component μ by introducing such a value function (Tversky and Kahneman 1979) to model reference dependence:

$$\mu_i(x, r) = \begin{cases} -\lambda_i (r - x)^{\alpha_i}, \ x \leq r \\ (x - r)^{\alpha_i}, \ x > r \end{cases}. \tag{2}$$

In this expression, the coefficient $\alpha_i \in [0,1]$ is the exponent in power functions for cases in which the outcome is below or above the reference point. If $\alpha_i < 1$, it represents diminishing sensitivity. Then the coefficient $\lambda_i \in (0, \infty)$ represents asymmetry in the effects of losses and gains. A value of $\lambda_i > 1$ is interpreted as loss aversion, so losses have greater impacts than gains, whereas if $\lambda_i < 1$, losses have smaller impacts than gains, and if $\lambda_i = 1$, losses and gains have impacts of equal magnitude. By considering this functional form for μ, we assume that for a given reference point r, the relationship between the performance outcome x and satisfaction is monotonically increasing. We believe this assumption is realistic in many consumption scenarios, but our model also can be adapted to model alternative relationships, such as settings with ideal reference points, in which deviations in both directions reduce satisfaction (see General Discussion). The well-known S-shaped value function of prospect theory is nested in our model, for the special case in which consumer i has beliefs such that the probability of an outcome under G_i is equal to 1 (i.e., the reference point is deterministic).

Our utility function for satisfaction resonates with existing models of regret in post-choice evaluations (e.g., Inman, Dyer, and Jia 1997; Tsiros 1998), in which the evaluation comprises two reference-dependent components: a comparison of actual outcomes to expected performance and the effect stemming from counterfactual comparisons. Comparing the actual outcome to a better counterfactual (in terms of performance) results in regret; comparing the actual outcome to a worse counterfactual results in rejoicing (Tsiros 1998). Translated to our model, regret and rejoice should result from comparisons with better and worse outcomes, according to individual beliefs. Two important differences with the models by Tsiros (1998) and Inman, Dyer, and Jia (1997) are relevant though. First, the nature of the effect of comparing actual outcomes with counterfactuals varies. In regret literature, a negative effect of comparing the actual outcome with a better counterfactual results because the consumer regrets the decision to *choose* the alternative (Sautua 2017). For our context, choice does not necessarily determine the outcome, which instead is subject to various random factors, such as delivery delays due to bad weather or other external shocks. Second, models of regret examine the effect of single alternatives, though Tsiros (1998) include two and test which of them the individual consumer chooses as a reference point. We model satisfaction as resulting from multiple comparisons and propose a flexible specification of expectations, as a distribution of beliefs about outcomes.

Model Parametrization Based on Uniformly Distributed Beliefs

We examine the model's implications for the theoretical impact of uncertainty on satisfaction and derive a series of propositions, with an assumption of uniformly distributed beliefs. A uniform distribution has several useful properties that are suitable for our study context. First, due to its analytical tractability, we can derive a closed solution to Equation (1) in the presence of both loss aversion and diminishing sensitivity. Second, consumers often form expectations bounded by the "best" and "worse" possible performance (Woodruff, Cadotte, and Jenkins 1983). These upper and lower bounds are likely to stem from firm communications as in the case of communicated ranges of expected performance levels (e.g., delivery time in 2-12 days, see also Dieckmann, Peters, and Gregory 2015).

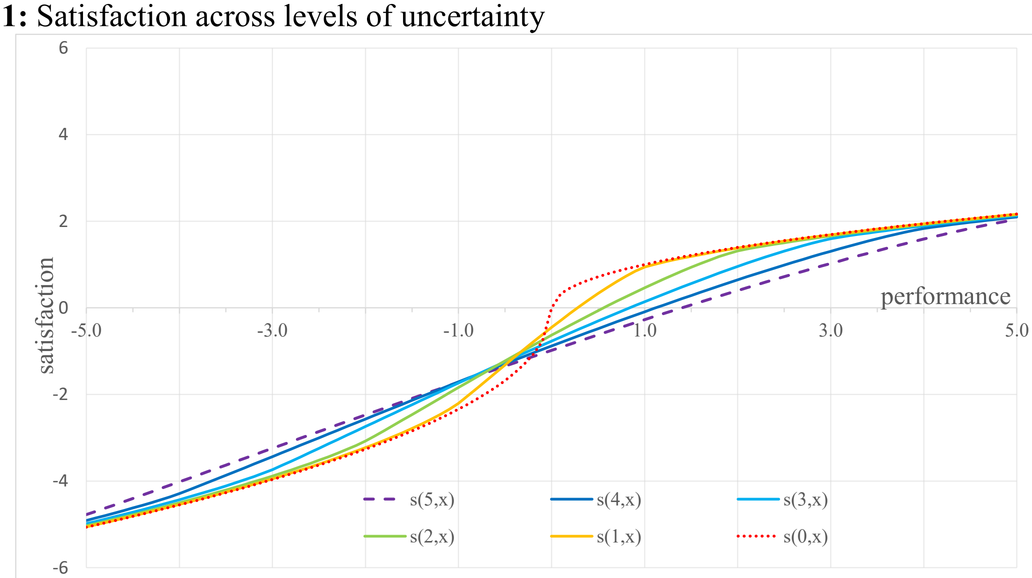
Therefore, let $r \sim U[a, b]$, such that beliefs about future outcomes are uniformly distributed between a and b, with $a \leq b$. We can identify the probability distribution with the two parameters a and b, so we adapt the G_i subscript accordingly. We also drop the i subscript in α and λ for notational convenience. Solving the integral in Equation (1) results in the following expression:

$$s_{a,b}(x) = \begin{cases} \frac{1}{(b-a)(\alpha+1)}[(x-a)^{\alpha+1} - \lambda(b-x)^{\alpha+1}], \text{for } a \leq x \leq b, \\ \frac{-\lambda}{(b-a)(\alpha+1)}[(b-x)^{\alpha+1} - (a-x)^{\alpha+1}], \text{for } x < a, \text{and} \\ \frac{1}{(b-a)(\alpha+1)}[(x-a)^{\alpha+1} - (x-b)^{\alpha+1}], \text{for } b < x. \end{cases} \quad (3)$$

Because we examine *subjective* expectations, consumers also might experience a performance outcome outside the range of believed possible outcomes. Then $x < a$ and $x > b$ represent surprise events, in which the actual performance outcome is worse (better) than the worse (best) expected outcome.

We are interested in the impact of uncertainty, so we can assume $a = -b$ without loss of generality. We set $s(b, x) := s_{-b,b}(x)$. Figure 1 illustrates the effect of uncertainty with the chosen parametrization of the distribution of expectations in cases of loss aversion ($\lambda > 1$) and diminishing sensitivity ($0 < \alpha < 1$). As expected, we find an S-shaped relationship between satisfaction and the performance level. The red (dotted) line represents satisfaction for deterministic beliefs. The purple (dashed) line represents satisfaction with high uncertainty levels, specifically for beliefs uniformly distributed in the plotted interval. The other lines represent satisfaction curves, with uncertainty levels in between. Figure 1 suggests three ways to describe the impact of uncertainty on satisfaction. First, all curves are monotonically increasing in performance. Second, the point where the curves intersect the x-axis increases with uncertainty. That is, a product must offer a higher performance in the case of high uncertainty (cf. low uncertainty) to satisfy consumers. Under the assumption of loss aversion, the subjective reference point (i.e., performance level that results in neither dissatisfaction nor satisfaction) shifts according to the level of uncertainty; models that ignore uncertainty may thus underestimate the reference point. Relatedly, the area below the curves is negative and increasing uncertainty seems to decrease this area below the curve further. Third, increasing uncertainty has a nonlinear effect on satisfaction: At low levels of performance, the impact of uncertainty is positive and takes an inverse U-shape, whereas at high levels of performance, the impact of uncertainty is negative and U-shaped.

Figure 1: Satisfaction across levels of uncertainty

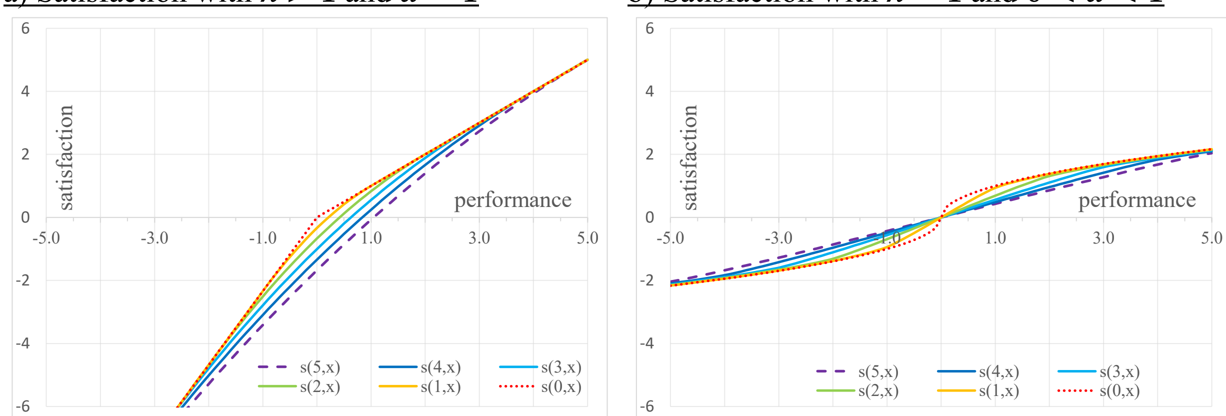


Notes: The values for α and λ are set at 0.48 and 2.34, respectively (Baillon, Bleichrodt, and Spinu 2020).

The important influence of the coefficients λ and α is evident in Figure 2. The graph on the left presents uncertainty in the absence of diminishing sensitivity, i.e. $\alpha = 1$, revealing that the satisfaction curve is concave and its curvature diminishes as uncertainty increases. The graph on the right illustrates the role of uncertainty when there is an equal magnitude of gains and losses, such that $\lambda = 1$. Here, the shape of the effect of uncertainty on satisfaction is similar to the base case of loss aversion (i.e., $\lambda > 1$) and diminishing sensitivity (i.e., $0 < \alpha < 1$). The main difference is that all curves intersect the x-axis at zero satisfaction (curves are symmetric around zero). According to Figure 2, loss aversion is the assumption required to predict an upward shift of the subjective reference point as well as an overall negative effect of uncertainty across all possible outcomes (area below the curves). Conversely, without diminishing sensitivity, uncertainty decreases satisfaction across all performance levels (satisfaction curves for different levels of uncertainty do not intersect). Therefore, diminishing sensitivity represents a necessary assumption to uncover an attenuating effect of uncertainty on satisfaction. The next section tests whether these assumptions are sufficient, with formal propositions derived from the model, and discusses potential managerial implications from this model.

Figure 2: Roles of diminishing sensitivity and loss aversion

a) Satisfaction with $\lambda > 1$ and $\alpha = 1$ b) Satisfaction with $\lambda = 1$ and $0 < \alpha < 1$



Notes: This figure illustrates the roles of the loss aversion coefficient λ and diminishing sensitivity coefficient α. In a case featuring both, the parameters are set $\lambda = 2.34$ and $\alpha = 0.48$.

Propositions

We derive empirically testable propositions from the parametrized model (for proofs of all the propositions, see Web Appendix B); together, they represent the theoretical implications of our model. Throughout, we assume loss aversion ($\lambda > 1$) and diminishing sensitivity ($0 < \alpha < 1$). Proposition 1 holds in the absence of loss aversion and diminishing sensitivity, Proposition 2 holds in the absence of diminishing sensitivity, and Proposition 3 holds in the absence of loss aversion. With a holistic approach, we make general assumptions. The first proposition relates to the general relationship between performance and satisfaction for a given uncertainty level:

Proposition 1: Satisfaction increases with performance, such that $s(b, x)$ is increasing in x for all $b \geq 0$.

The second proposition examines the influence of uncertainty on subjective reference points, which denote performance levels at which customers switch from being dissatisfied to being satisfied. We build on prior literature on subjective reference points (e.g., Kahneman, Wakker, and Sarin 1997) and look at the performance level x at which satisfaction is neither positive nor negative, i.e., for which $s(b, x) = 0$, as a function of b. In a deterministic world (i.e., $b = 0$), this subjective reference point would be indistinguishable from the deterministic reference point in our model, since $s(0,0) = 0$.

Proposition 2 draws on loss aversion. For a deterministic reference point, loss aversion means that the curve below the reference point is steeper than that above the reference point. Uncertainty triggers additional comparisons to worse and better outcomes. Due to loss aversion, comparisons with outcomes that could have been better reduce satisfaction more strongly than comparisons with outcomes that could have been worse. Therefore, under uncertainty, a higher performance level is necessary to turn dissatisfied customers into satisfied customers (compared to a situation without uncertainty). To illustrate with an extreme case, if consumers believe that *all* real outcomes are equally likely, they will never be satisfied, regardless of the outcome level, because they will always compare it with even better possible scenarios that take greater weight than comparisons with worse possible scenarios. Formally, we propose:

Proposition 2: Subjective reference points increase with uncertainty. Specifically, let x_0^b be such, that $s\left(b, x_0^b\right) = 0$. Then, x_0^b is increasing in b.

The third proposition formally describes the shape of the relationship between performance and satisfaction, resulting from different uncertainty levels: How does uncertainty affect satisfaction, contingent on the performance outcome? Therefore, we gauge the difference between satisfaction curves at increasing levels of uncertainty, and we anticipate an attenuating effect of uncertainty on deviations of actual performance from subjective reference points. Uncertainty translates into beliefs that a larger breadth of outcomes is possible. Therefore, good and bad performances (i.e., performances that deviate from subjective reference points) have a stronger effect if they are unexpected compared to expected.

We can derive Proposition 3 mathematically from the property of diminishing sensitivity. After consumers experience a certain performance level x, higher levels of uncertainty trigger more positive and negative comparisons. The former comparisons to worse possible outcomes exert a positive effect on satisfaction, due to “it could have been worse” thoughts. Negative comparisons to better possible outcomes instead evoke a negative effect, due to “it could have been better” thoughts. In the presence of diminishing sensitivity, such that deviations from a reference point have weaker impacts the farther the actual performance level is from the reference point, uncertainty also triggers comparisons with equally weighted, diminished effects that attenuate the effect of good (or bad) performance levels.[5] Thus formally, we propose:

Proposition 3: Uncertainty has a negative, nonlinear effect on satisfaction after good performances (i.e., performances above subjective reference points) and a positive nonlinear effect on satisfaction after bad performances (i.e., performances below subjective reference points). Specifically, if $0 \leq b < b'$, then:

(i) $\lim_{x \to \infty} s(b', x) - s(b, x) = \lim_{x \to -\infty} s(b', x) - s(b, x) = 0$, and

(ii) there exists x_0 such that $s(b', x) - s(b, x)$ is positive for all performance levels $x \leq x_0$, has a maximum in the range $(-\infty, x_0]$, is negative for all performance levels $x \geq x_0$, and has a minimum in the range (x_0, ∞).

Our propositions follow from our theoretical model and carry direct implications for firms looking to increase customer satisfaction levels. Proposition 1 captures the link of performance and satisfaction independent on the uncertainty level and posits that an increase in performance results in increased customer satisfaction. Proposition 1 thus supports the perspective that firms should manage resources spent on performance improvements as satisfaction investments, thereby accounting for the effect of satisfaction on beneficial customer behavior such repurchases (see Mittal and Frennea 2010).

Proposition 2 adds practical value by informing about the potential caveats of communicating uncertainty. Holding everything else constant, customers with high levels of

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[5] Imagine three potential outcomes: -1, 0, 1. Assume the reference point is 0 (deterministic). If performance equals 1, a single comparison to the worse outcome 0 is made, hence satisfaction equals 1. Next, assume the reference point has equal probability of taking values of -1, 0, or 1. If performance equals 1, two comparisons to the worse outcomes, 0 *and* -1 are made. For $\alpha = 0.5$, satisfaction equals 0.80 (< 1).

uncertainty are satisfied only after experiencing a higher performance compared to customers with lower levels of uncertainty. Also, higher uncertainty translates into lower levels of overall satisfaction across all possible outcomes (see Web Appendix B). Firms could leverage these findings by reducing communicated uncertainty. For example, there is high heterogeneity in the presentation format of expected performance levels such as expected delivery times. From an aggregate customer satisfaction perspective, it would make sense to present single point estimates or narrow ranges in contrast to broader ranges. Furthermore, assessing subjective reference points can directly inform uncertainty levels. For individuals, it is likely easier to state their subjective reference point in contrast to provide information on confidence intervals, which is the standard measure to elicit uncertainty (see for example Schlag, Tremewan, and van der Weele 2015 for a discussion and Caputo, Lusk, and Nayga 2020 for an exemplary application).

Proposition 3 offers ways to extract value from inferred uncertainty levels by improving practices with targeting, or customer management purposes. The overall implication is that firms should account for uncertainty levels and that it may be valuable to infer customers' level of uncertainty with respect to the product performance they will receive (e.g., Rust et al. 1999). Specifically, firms might make biased predictions of customer satisfaction levels if they ignore the stochastic nature of expectations: underestimate satisfaction after bad performances (e.g., service failures) and overestimate satisfaction after good performances (e.g., delights). Firms could infer uncertainty levels by assessing the variability of past experiences, or proxy uncertainty levels directly (for example by examining the variance in customers' willingness to pay or deriving uncertainty levels from survey-based measures aimed to assess subjective reference points). Uncertainty levels could then inform customer lifetime values (overall satisfaction and thus potentially the likelihood of repurchasing decreases with increasing uncertainty). Moreover, uncertainty levels could help determine recovery strategies after service failures (recovery amounts should decrease with increasing uncertainty) or strategies aimed at delighting the customer (uncertainty increases performance levels needed in order to delight customers). We next test our model's predictions in an experimental study and a field study.

Empirical Studies

Experimental Study

The aim of the experimental study is to test our predictions in a common customer scenario regarding delivery service for a new refrigerator, reflecting the high relevance of delivery times for online retailers, which in turn affect both consumer choices and service evaluations (Chao 2016; Fisher, Gallino, and Xu 2019). The task consisted of rating satisfaction in order to test the effect of uncertainty (in the range of communicated expected delivery days) on satisfaction across a range of actual performance levels, provided a decision to purchase already had been made.

Experimental design. We used a balanced design and implemented a between-subjects randomization across two levels of uncertainty (low and high) and a within-subjects randomization across seven levels of actual performance outcomes. Each participant first had to imagine that their refrigerator was broken and that they had purchased a new one (same brand) from an online retailer. This information helps keep the scenario simple and mitigates any confounding effects of uncertainty about delivery times on purchase probabilities. We chose a refrigerator due to its suitability for the research context: Consumers tend to care about delayed delivery times, due to the well-being consequences of a broken refrigerator. Late deliveries impair consumers' ability to store fresh produce, while early deliveries benefit consumers by providing these abilities sooner. For utilitarian products such as refrigerators, anticipation prior to consumption also is unlikely to affect satisfaction significantly (Botti and McGill 2011). Next, we manipulated uncertainty by providing information on expected delivery times, in the form of ranges: Participants in the low uncertainty group were shown an expected delivery time of 6-8 days whereas participants in the high uncertainty group were shown an expected delivery time of 2-12 days.

In a second step, after a delay of various seconds, participants were asked to imagine an actual delivery time and rate their satisfaction with the delivery service. This step repeated seven times, with varying outcome levels between 1 and 13 days. The delivery times presented to each participant and the order in which they appeared were determined randomly, to avoid order effects (the Web Appendix C provides the experimental instructions as well as a detailed description of the random assignment procedure). The dependent variable is satisfaction with the service delivery, which we adapted from the American Customer Satisfaction Index (Fornell et al. 1996; Malshe, Colicev, and Mittal 2020), to reflect our study context. The satisfaction scale consisted of three 11-point items and their related response scales: (1) “What is your overall satisfaction with the delivery time?” (1 = very dissatisfied, 11 = very satisfied), (2) “How well has the delivery time met your expectations?” (1 = not at all, 11 = very well), and (3) “How well did the delivery time compare with the ideal service?” (1 = poor, 11 = excellent). Satisfaction scales are typically skewed, so we used 11-point scales with a neutral midpoint to increase dispersion in responses (Burton, Sheather and Roberts 2003).

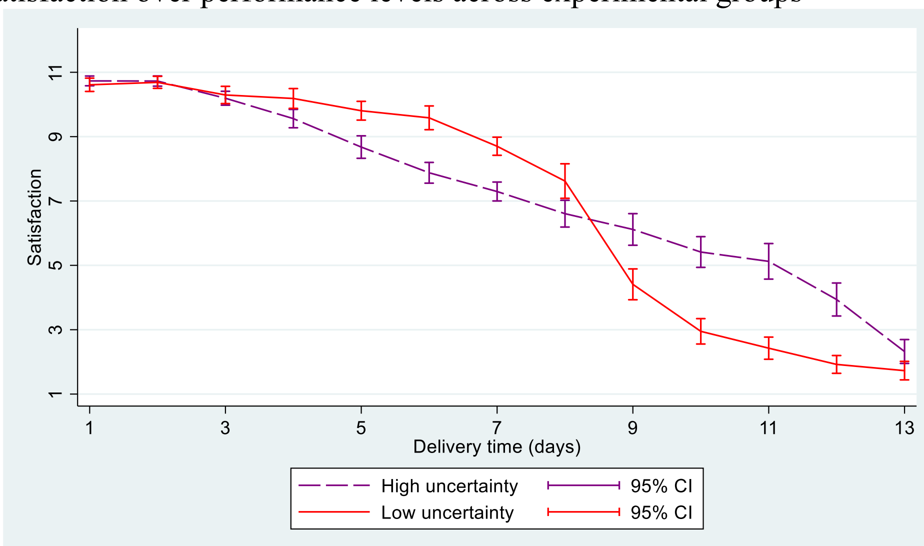
Next, we asked participants about their subjective reference point and their perceptions of uncertainty. To measure subjective reference points, we rely on behavioral economics literature that uses survey-based measures to examine how individuals form and update subjective reference points across time and adapted Baucells' et al (2011) measure to our context. Specifically, we asked participants to state the delivery time (in days) with which they would feel neutral, i.e., neither satisfied nor dissatisfied, about the delivery of the retail store. Participants could provide their answer in form of a numerical value denoting the number of days in an open text field. By manipulating uncertainty, we seek to vary participants' beliefs about service performance. High levels of uncertainty should induce the belief that the product may be delivered quickly in some occasions but after substantial time in others, which creates uncertainty. As a manipulation check, we measured perceived performance uncertainty with three 7-point items: (1) "How certain are you as to how fast the refrigerator will be delivered?" (1 = not at all certain, 7 = very certain), (2) "How well can you judge how fast the refrigerator will be delivered?" (1 = hard for me to judge, 7 = easy for me to judge), and (3) "I feel the delivery service would probably deliver the refrigerator…" (1 = not at all fast, 7 = very fast). Finally, they provided some basic demographic information, such as education, age, and gender. We recruited participants through the online platform Prolific to take part in an experiment in return for GBP 1 as compensation (average hourly wage = GBP 11.15).

Results. A total of 384 U.S.-based respondents (median age = 32, men = 34.4%) successfully completed the experiment. To check the integrity of the between-subjects randomization, we conducted a multinomial logistic regression with the group variable as the dependent variable and age, high education, high income, and gender as independent variables; we find no significant relationships ($p > 0.05$). The only exception is a slightly younger age of participants in the low uncertainty group (median age = 32) compared to the high uncertainty group (median age = 33). We control for demographics in our regression-based analyses. As a manipulation check, we assess the effect of the manipulation on perceived performance uncertainty. The results of a Mann-Whitney U test reveal significant differences among the uncertainty treatment groups, in the expected direction ($Median_{high} = 3.333$, $Median_{low} = 4.667$, z statistic = -8.395, $p < 0.001$).

Next, we test whether the experimental data corresponds with the model's propositions. Proposition 1 predicts a positive relationship between performance and satisfaction, for all uncertainty levels. In support of this proposition, we find a significant negative correlation between the actual delivery time and satisfaction (Spearman's $\rho = -0.819$, $p < 0.001$). Proposition 2 states that uncertainty increases customers' subjective reference point. Translated to our experimental context, we expect participants in the high uncertainty group to have lower subjective reference points (in delivery days) compared to participants in the low uncertainty group. With other words, participants with higher uncertainty in expectations require lower delivery times to switch from being dissatisfied to being satisfied. We also find support for this proposition: participants in the high uncertainty group stated lower subjective reference points, compared to participants in the low uncertainty group (Mann-Whitney U test, $Median_{high} = 7$ days, $Median_{low} = 8$ days, z statistic = -3.267, $p < 0.001$).

Proposition 3 predicts an attenuating effect of uncertainty on the positive (negative) effect of positive (negative) deviations of actual performance from subjective reference points. Figure 3 plots the mean satisfaction levels (y-axis) across actual delivery times (x-axis) for both experimental groups. Here: the curve for the low uncertainty group (represented by the red straight line) follows an S-shape, whereas the curve for the high uncertainty group (represented by the purple dashed line) appears flatter. Specifically, at low levels (fewer delivery days), there is little evidence of an effect of uncertainty. As the number of delivery days increases, this effect increases first, and then decreases again (as evidenced by the difference between the purple dashed line and the red straight line). At about 8 to 9 delivery days, the effect becomes positive and finally decreases toward the end of the range.

Figure 3: Satisfaction over performance levels across experimental groups



Note: Satisfaction is the average response to the three-item satisfaction construct: (1) "What is your overall satisfaction with the delivery time?", (2) "How well has the delivery time met your expectations?", and (3) "How well did the delivery time compare with the ideal service?". Delivery time consists of the actual outcome shown to participants on the basis of which they rated their satisfaction with the delivery service. Outcomes varied from 1 to 13 days.

To test Proposition 3, we estimate the following model:

$$\begin{aligned} satisfaction_{i,d} = \beta_0 + \beta_1 uncertainty\_high_i \\ +\beta_2 loss_{i,d} + \beta_3 gain_{i,d} + \beta_4 loss_{i,d} \times uncertainty\_high_i \\ + \beta_5 gain_{i,d} \times uncertainty\_high_i + \beta_6^T C_i + \varepsilon_{i,d}, \end{aligned} \tag{4}$$

where i represents an individual and d represents an outcome (in delivery days). The variable $uncertainty\_high_i$ is a dummy variables, equal to 1 if participant i is assigned to the high uncertainty group, and 0 otherwise. The variable $loss_{i,d}$ reveals the magnitude of a negative deviation from the subjective reference point, such as a delivery *later* than the subjective reference point, and is given by $max(d - SRP_i, 0)$, where SRP_i denotes the subjective reference point provided by participant i. Then, $gain_{i,d}$ indicates the magnitude of a positive deviation from the subjective reference point, such as a delivery *earlier* than the subjective reference point, given by $max(SRP_i - d, 0)$. Thus, β_4 and β_5 capture the moderating effect of uncertainty on the effect of losses and gains on satisfaction respectively. Finally, C_i is a vector of consumer-related control variables (demographics), and β_6 is a vector of the same length. The Equation (4) results are in Table 1.

Table 1: Regression results

Dependent variable	Satisfaction
loss	-1.204***
	(0.052)
gain	0.517***
	(0.035)
uncertainty_high	-0.048
	(0.186)
uncertainty_high × loss	0.403***
	(0.058)
uncertainty_high × gain	-0.104**
	(0.042)
constant	7.858***
	(0.221)
Observations	2,688
R-squared	0.715

Notes: Standard errors, clustered in 384 unique users, are in parentheses. Regression controls for gender, age, high education, and high income. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We operationalize high education as a dummy variable equal to 1 if the participant has at least a Masters' degree. High income is operationalized as a dummy variable equal to 1 if the participant states a monthly income higher than \$7,000.

As expected, losses have a significant negative effect, and gains have a positive effect on satisfaction. Furthermore and in line with Proposition 3, the coefficients of the interaction terms of both uncertainty and loss as well as uncertainty and gain are positive and in the expected direction: the negative (positive) effect of losses (gains) is mitigated at higher levels of uncertainty.

Discussion. With the experimental study, we test for a (causal) effect of uncertainty on customer satisfaction under controlled conditions. Overall, we find support for our three propositions. First, satisfaction levels increase with performance, i.e., the fewer delivery days, the higher the satisfaction levels. Second, subjective reference points increase with uncertainty. Participants with high uncertainty in expectations need to experience a faster (i.e., lower number of days) delivery to switch from being dissatisfied to being satisfied compared to participants with low uncertainty. Third, uncertainty attenuates both the effects of losses, i.e., deliveries later than the subjective reference point, and gains, i.e., deliveries earlier than the subjective reference point. These results corroborate our theoretical findings and demonstrate the power of firms' communications in shaping the distribution of expectations. As one participant stated in an optional feedback text field at the end of the experiment: "if I am told a delivery would be made in 6–8 days, that's what I would expect". These results are promising, in that they support the main predictions from our theoretical model. To enhance its validity further, we run a field study capturing observations of real-world behavior.

Field Study

We analyze the influence of uncertain expectations on satisfaction by using consumer review data from Amazon. The term “review” refers specifically to product-related reviews, not seller-related assessments. This setting is suitable to address our research questions, considering that most online retailers provide product reviews, which in turn influence consumers’ expectations of product performance (Zhao et al. 2013). The presence of reviews thus can influence expected performance levels and the level of uncertainty associated with these expectations. High variation across reviews indicates that the product may be suitable for some consumers but not for others, which increases the subjective uncertainty in relation to the product’s future performance (e.g., He and Bond 2015). Indeed, prior findings suggest a negative effect of variation in reviews on the probability of product returns (Sahoo, Dellarocas, and Srinivasan 2018). To capture customer satisfaction, we use individual customers’ ratings (Moon, Bergey, and Iacobucci 2010). Therefore, we analyze how the distribution of past star ratings in reviews, relative to the product’s actual performance, affects customer satisfaction (assessed by the focal customer’s star ratings).

We address two challenges in this context associated with testing the impact of uncertainty on satisfaction, conditional on the magnitude of the deviation of actual product performance from the subjective reference point. The first challenge relates to the identification of actual product performances. In line with prior work, we use objective performance ratings to proxy for product performance (e.g., Mitra and Golder 2006), gathered from a neutral, state-supported organization that tests products and services using reliable, scientific methods, namely, *Stiftung Warentest* in Germany, which is similar to *Consumer Reports* in the U.S. market. *Stiftung Warentest* publishes test results on its website, available for a fee (see https://www.test.de/). Its performance measures range from 1 (very bad) to 5 (very good) and are based on fixed evaluation criteria.[6] We include a product (Bluetooth speakers) that can be characterized by transparent, quantifiable performance criteria and gather consumer reviews from Amazon's website in Germany.

The second challenge relates to the identification of the subjective reference point. Here, we use the mean of past ratings for the same product. In our setting, past ratings form the distribution of expectations and mean expectations are likely to correlate with subjective reference points (Kopalle et al. 2017; Oliver and Burke 1999; Yi 1990). Hence, we define losses (gains) as negative (positive) deviations of the actual product performance (as given by the objective performance rating from *Stiftung Warentest*) from the mean expectations.

Empirical Setting & Data. The data comprise all reviews of Bluetooth speakers in a recent *Stiftung Warentest* report (Stiftung Warentest 2021) that also are available on Amazon.de. We collected historic reviews for each product, which produces an initial data set of 47,734 reviews of 49 products. This data set forms the basis for the distribution of expectations: The variable $satisfaction_{t,p}$, our main dependent variable, represents a satisfaction judgment at time t for product p. It is operationalized as the focal customer's star rating in a given review at time t for product p. This consumer's expectations prior to consumption are likely influenced by the available reviews for the same product at the moment of the purchase (Zhao et al. 2013). We operationalize the mean expectations that serve as a baseline for the evaluation $star\_rating_{t,p}$ as

[6] Actually, *Stiftung Warentest* measures performance using the German grading system, which is a scale from 5 (very bad) to 1 (very good). For clarity, we adopt a reverse-coded measure from 1 (very bad) to 5 (very good).

the average over all posted ratings from reviews of product p prior to t. Let T_p represent the set of points in time at which a review for product p is given. Then we define:

$$mean\_expectations_{t,p} = \frac{1}{|\{k \in \mathrm{T}_p, k<t\}|} \sum_{\{k \in \mathrm{T}_p, k<t\}} star\_rating_{k,p}. \tag{5}$$

Next, we turn to the operationalization of uncertainty in expectations about product performance. As in previous work that examines review data, we define uncertainty as the standard deviation over all posted ratings from reviews of product p prior to t (e.g., Moon, Bergey, and Iacobucci 2010; Sun 2012). Accordingly, high levels of uncertainty indicate that a product may perform well in some cases but not in others, which likely translates into higher levels of uncertainty about the product's performance prior to its consumption (Vana and Lambrecht 2021). We thus define:

$$uncertainty_{t,p} = \sqrt{\frac{1}{|\{k \in \mathrm{T}_p, k<t\}|} \sum_{\{k \in \mathrm{T}_p, k<t\}} \left(mean\_expectations_{t,p} - star\_rating_{k,p}\right)^2}. \tag{6}$$

In addition to the star ratings of each review, we collect data about whether it is a verified purchase, in recognition of the possibility of fake reviews (He, Hollenbeck, and Proserpio 2021; Mayzlin, Dover, and Chevalier 2014), which offer limited informational value. Similar to Mayzlin, Dover, and Chevalier (2014), to reduce the risk of potential distortion of our results arising from fake reviews, we control for whether purchases are verified.

The data from *Stiftung Warentest*, which provide performance evaluations of Bluetooth speakers, include the overall test results based on fixed evaluation criteria comprising sound, ease of use, stability, and battery life. We use these data points to proxy for consumers' experienced performance. Although the test results for the selected products are summarized in a single report, heterogeneity exists in the date of publication of the test results. We rule out the potential influence of the published test result on consumers' expectations of product performance by excluding reviews for the same product published after the test result became available. Our final data set consists of 15,463 observations across 45 products (for a list of products, see Web Appendix D). In the data summary in Table 2, the first line refers to satisfaction, our main dependent variable. Then we provide information on the distribution of expectations, in means and uncertainty, calculated in accordance with Equations (5) and (6). Data on the actual performance of the product, operationalized as test results from *Stiftung Warentest* for a given product, are in the fourth line. Finally, we present the values for the control variables. Here, $price_p$ refers to the mean online price (excluding delivery costs) for product p, provided by a leading price comparison website (https://www.idealo.de/). The variable $verified\_purchase_{t,p}$ is a dummy variable equal to 1 if the product review for product p at time t involved a verified purchase and 0 otherwise.

Table 2: Summary of data

Variable	Mean	SD	Min	Max	Observations
$satisfaction_{t,p}$	4.51	0.99	1.00	5.00	15,463
$mean\_expectations_{t,p}$	4.51	0.20	2.00	5.00	15,411
$uncertainty_{t,p}$	0.94	0.19	0.00	2.83	15,363
$test\_result_p$	3.70	0.37	1.40	4.40	15,463
$price_p$	139.48	60.74	25.90	385.00	15,464
$verified\_purchase_{t,p}$	0.86	0.35	0.00	1.00	15,464

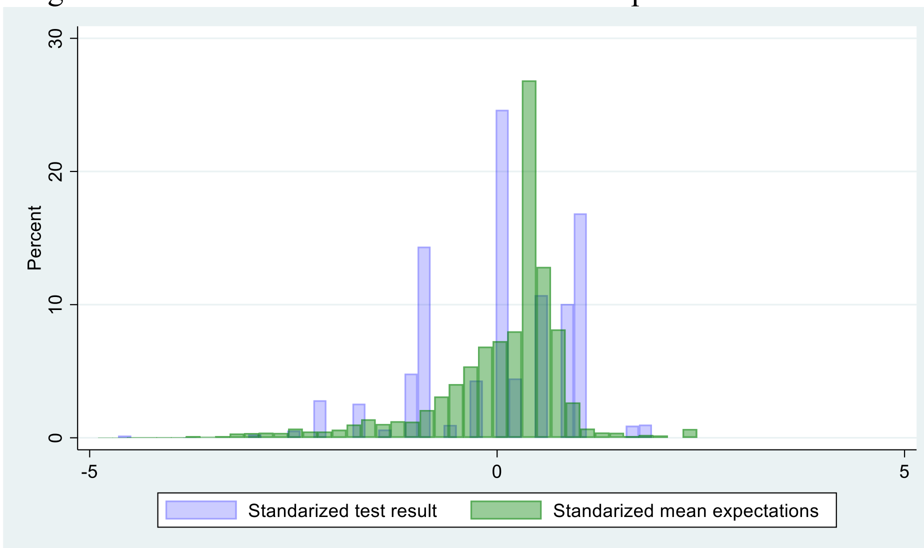
Notes: The difference in observations arises because we exclude observations for which the calculation of $mean\_expectations_{t,p}$ or $uncertainty_{t,p}$ has no solution (e.g., no reviews prior to t).

Results. We begin by testing the model's propositions. First, we examine whether there is a positive link between satisfaction and the test results from *Stiftung Warentest* for a given product. In line with Proposition 1, we find a positive correspondence between these two variables (Spearman's $\rho = 0.016$, $p = 0.003$). This result corroborates prior findings on the role of objective performance ratings for customers' product evaluations (Mitra and Golder 2006).

Proposition 2 predicts that uncertainty increases customers' subjective reference point. We have no direct information on customers' perceived subjective reference points, therefore we look at the correlation between uncertainty and customers' satisfaction response. An increase in subjective reference points translates into a negative correspondence between uncertainty and satisfaction, since performance levels are more often below subjective reference points when uncertainty is high, compared to low (cf. Figure 1). As a result, customers with higher uncertainty are more frequently dissatisfied. Our results are consistent with Proposition 2, indicated by the significant negative correlation between uncertainty and satisfaction (Spearman's $\rho = -0.055$, $p < 0.001$).

Proposition 3 predicts an attenuating effect of uncertainty contingent on whether actual performance levels lie below or above subjective reference points. We operationalize gains and losses as deviations of actual performance outcomes from mean expectations. We ensure the comparability of scales by standardizing the measures for the mean of expectations and the objective performance ratings (see Figure 4 for the distribution of the standardized measures).

Figure 4: Histogram of standardized test results and mean expectations



Notes: The green bars represent the mean of standardized past ratings (mean expectations), the blue bars represent the standardized objective performance ratings (test results).

To test Proposition 3 and given the ordinal nature of the satisfaction variable, we fit an ordinal logistic regression. With the linear function $S_{t,p}$, we estimate the single predicted probabilities of each individual outcome, $\Pr(satisfaction_{t,p}) = k$, for $k = 1,2,3,4,5$:

$$\begin{aligned} S_{t,p} = {} & \beta_1 loss_{t,p} + \beta_2 gain_{t,p} + \beta_3 uncertainty\_standarized_{t,p} \\ & + \beta_4 loss_{t,p} \times uncertainty\_standarized_{t,p} \\ & + \beta_5 gain_{t,p} \times uncertainty\_standarized_{t,p} + \beta_6 expectations\_stdandarized_{t,p} \\ & + \beta_7 price_p + \beta_8 time\_lapsed_{t,p} + \beta_9 verified\_purchase_{t,p} + \delta_t. \end{aligned} \tag{7}$$

The variable $uncertainty\_standarized_{t,p}$ is the coefficient of variation. The variable $loss_{t,p}$ reflects the magnitude of a negative deviation of actual performance from mean expectations, given by $loss_{t,p} = \max(expectations\_standarized_{t,p} - test\_result\_standarized_p, 0)$, where the first argument is the standardized measure of mean expectations, and the second the standardized measure for performance, operationalized as the test score from *Stiftung Warentest*. In contrast, the variable $gain_{t,p}$ is the magnitude of the positive deviation of actual performance from mean expectations, given by $gain_{t,p} = \max(test\_result\_standarized_p - expectations\_stdandarized_{t,p}, 0)$. With the variable $time\_lapsed_{t,p}$ we also control for the duration between when the product became available and t. There could be unobserved time varying or seasonality factors driving customer satisfaction. We control for this by including year-month fixed effects δ_t in our specification. The results are in Table 3.

Table 3: Results from ordinal logistic regression

Dependent Variable	Satisfaction
loss	-0.243***
	(0.075)
gain	0.158*
	(0.085)
uncertainty_standarized	-0.454
	(0.763)
loss × uncertainty_standarized	0.941***
	(0.320)
gain × uncertainty_standarized	0.070
	(0.128)
expectations_standarized	0.332***
	(0.062)
price	-0.002***
	(0.001)
time_lapsed	-0.000
	(0.000)
verified_purchase	0.493***
	(0.043)
Observations	15,363
Log pseudo-likelihood	-13305.802

Notes: Includes year-month fixed effects. Standard errors, clustered in 45 unique products, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3 shows the result of fitting Equation (7); including the interaction effects from losses and uncertainty, as well as gains and uncertainty. Consistent with Proposition 3, uncertainty mitigates the negative effect of losses. However, we do not find evidence for an attenuating effect of uncertainty on gains, which may be attributed to the skewness in the distribution of standardized mean expectations and the fact that there is a natural ceiling of five stars.

Robustness Tests. This section presents the result from a series of robustness analyses aimed to address some challenges in relation to our data. First, to mitigate any potential effect of fake reviews (Mayzlin et al. 2014), we consider only verified reviews and estimate Equation (7) for this subset (about 15% of reviews involve unverified purchases). Second, in an effort to address potential differences between consumers' observed ratings distribution and the distribution resulting from reviews in our data, we exclude the possibility of stand-alone ratings without reviews, which are not captured in our data. At the end of 2019, Amazon started to allow customers to leave a star rating without a review.[7] Thus, as a robustness test, we run Equation (7) for reviews posted up to 2019 (about 36% of reviews appear after 2019). Third, we check whether our results hold after excluding reviews that refer to factors related to the seller (cf. product), which addresses a possible concern regarding systematic differences across sellers' service provision. For example, products sold directly by Amazon might offer enhanced benefits, such as efficient shipping and better customer service, compared with offerings from alternative sellers, a phenomenon referred to as the "Amazon effect" (Daugherty, Bolumole, and Grawe 2019; Vollero, Sardanelli, and Siano 2021). Therefore, we apply a basic text mining technique[8] to detect keywords that refer to seller-related factors. About 35% of reviews mention issues related to the seller and its service provision (e.g., shipping delays, complaint management). This conservative identification strategy excludes reviews that mention both seller-related *and* product-related factors. In Table 4, we present results of the regression estimates of Equation (7)

[7] See https://www.marketplacepulse.com/articles/amazon-replaces-reviews-with-ratings.
[8] Specifically, we iteratively developed a list of 28 keywords (e.g., "service," "seller," "customer care," "delayed," "delivery") and searched for them in the text of the reviews (written in English or German).

for the different subsets. Tests related to Proposition 1 and 2 deliver also consistent results with our main analyses. The results for all three robustness tests in Table 4 are consistent with our main analysis in Table 3. Specifically, we find a mitigating effect of uncertainty on the effect of losses.

Table 4: Robustness test results

Subsample	(1) Verified purchases	(2) Before 2019	(3) No seller-related factors
loss	-0.219**	-0.350***	-0.251***
	(0.090)	(0.075)	(0.071)
gain	0.131	0.126	0.204*
	(0.110)	(0.104)	(0.112)
uncertainty_standarized	0.323	-0.458	0.189
	(1.084)	(0.909)	(0.857)
loss × uncertainty_standarized	0.850**	0.764**	1.051***
	(0.370)	(0.385)	(0.338)
gain × uncertainty_standarized	0.142	0.195*	0.143
	(0.161)	(0.110)	(0.202)
expectations_standarized	0.381***	0.351***	0.402***
	(0.088)	(0.082)	(0.072)
price	-0.002**	-0.004***	-0.002**
	(0.001)	(0.001)	(0.001)
time_lapsed	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
verified_purchase		0.486***	0.504***
		(0.056)	(0.057)
Observations	13,214	9,831	9,996
Log pseudo-likelihood	-11059.012	-8831.982	-8290.565

Notes: Includes year-month fixed effects. Standard errors, clustered in unique products, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Discussion. Our results on the influence of variability in observed star ratings—as a measure of uncertainty in expectations—on the likelihood of giving different star ratings in an online retail setting are largely consistent with our model's predictions: We find support for a positive effect of actual product performance on satisfaction, a positive effect of uncertainty on subjective reference points, and an attenuating effect of uncertainty on the negative effect of losses. That the interaction effect of gains and uncertainty as well as the main effect of gains is insignificant may be explained by the skewness in the distribution of standardized mean expectations (see Figure 4), which may restrict the observations of gains. Overall, the results of our field study are promising, in that they capture observations of real behavior and thus contribute to the external validity of our model.

General Discussion

In most markets (goods or services), consumers exhibit uncertain expectations about product performances, whether due to variations of their own past experiences, or expected performance levels communicated by the sellers themselves or through third-party information (e.g., online reviews). Uncertainty may manifest in a greater breadth of the range of (expected) possible outcomes (Rothschild and Stiglitz 1970). After experiencing the actual performance, satisfaction evaluations incorporate this range of possible (a-priori expected) outcomes as reference points. Our empirical results support our model's predictions and corroborate an account based on simultaneous comparisons to multiple reference points, thereby extrapolating prior findings (Markle et al. 2018; Ordóñez, Connolly, and Coughlan 2000; Wang and Johnson 2012; Weingarten, Bhatia, and Mellers 2019) to a context in which comparisons to counterfactuals as reference points capture mixed feelings of what might have been. The development of a new theoretical model of satisfaction, as resulting from comparisons of the actual outcome to multiple reference points, according to the distribution of expectations prior to the experience of that actual outcome, constitutes our central theoretical contribution.

To our knowledge, only few studies investigate how uncertainty in beliefs influences individuals' post-choice evaluations (cf. purchase decisions). Yet in many situations, consumers may be (willingly or unwillingly) exposed to uncertainty in relation to expected product performances. Our work contributes empirically to this developing literature in two important ways. First, studies that examine the role of beliefs (e.g., expectations of future product performance) in shaping human behavior establish that beliefs held with stronger certainty are more influential (Oliver and Burke 1999; Rucker et al. 2014; Söderlund 2002; Spreng and Page 2001). We extend these findings and provide a new, more exhaustive explanation for the varying influence of beliefs about future performance by examining the role of the distribution of expectations and their level of *uncertainty*. We propose and empirically find that the effect strength of a reference point is contingent on the experienced outcome level. For example, uncertainty helps to mitigate the (negative) effect of late deliveries but also mitigates the (positive) effect of early deliveries. Second, subjective reference points, i.e., performance levels, at which customers feel neither satisfied nor dissatisfied, increase with uncertainty. In our experimental setting, participants with higher uncertainty stated a lower number of delivery days as their subjective reference point compared to participants with lower uncertainty. Uncertainty in expectations thus increases the switching point from dissatisfaction to satisfaction. A simple account that ignores the reference dependence that arises from simultaneous comparisons to counterfactuals fails to explain this phenomenon.

In this paper, we combine the development of a theoretical modeling with empirical tests of this model in order to grasp the role of subjective expectations (which are inherently hard to measure) for satisfaction judgements (Coughlan et al. 2010). Overall, our theoretical model and our empirical findings *together* provide a higher order understanding of the impact of uncertainty on customer satisfaction (Thomadsen et al. 2012).

Managerial Recommendations: Steering Uncertainty in Communication

Based on our results, we propose new avenues for value capturing firm strategies to communicate uncertainty and leverage information about uncertainty benefitting both customers and firms. First, firms (and consumers) would benefit from optimizing the communication in relation to average expectations about a product's performance *and* their underlying uncertainty. This point is highly relevant, considering the many options available to present information about expected performance levels (e.g., ranges vs. single point estimates).

The reduced uncertainty from communicating single point estimates (cf. ranges) can enhance satisfaction. However, in case of a bad performance, customers without uncertain expectations are more dissatisfied. That is, conveying no uncertainty runs the risk of increasing churn, because when uncertainty is low, extreme dissatisfaction is more likely. On the contrary, communicating (higher) uncertainty may translate into more satisfied customers if performances below communicated levels are possible. For example, ride-sharing platforms could benefit from communicating ranges (cf. point estimates) during rush hour or bad weather conditions when delays are likely.

Firms may decide to communicate (i) expected future performance levels, (ii) better than expected future performance levels or *overpromising*, or (iii) than expected future performance levels or *underpromising.* To gain understanding on the mixed role of uncertainty in expectations *and* over/underpromising future performance levels in shaping satisfaction, we develop a model-based tool that predicts the joint consequences of over/underpromising and uncertainty for a wide set of customizable settings. The tool's scope comprises the exemplary use case of waiting times, i.e., the situation in which a firm's call center needs to decide on whether and how to communicate waiting times.[9]

The tool allows to flexibly insert the range of actually observed waiting times as well as the extent of underpromising or overpromising, i.e. communicating longer waiting times than observed on average which may lead to pessimistic expectations, or communicating shorter waiting times than observed on average which may lead to optimistic expectations. The tool provides a visualization of the predicted effects of uncertainty for the given set of parameters. To assess the effects in an integrative and comprehensive way, we develop the Relative Customer Satisfaction Index (RSCI). This metric varies between 0 and 1 and captures overarching satisfaction levels while accounting for the role of uncertainty. Figure 5 depicts a screenshot of the tool's output for a scenario with actual waiting times between 30 and 45 minutes.

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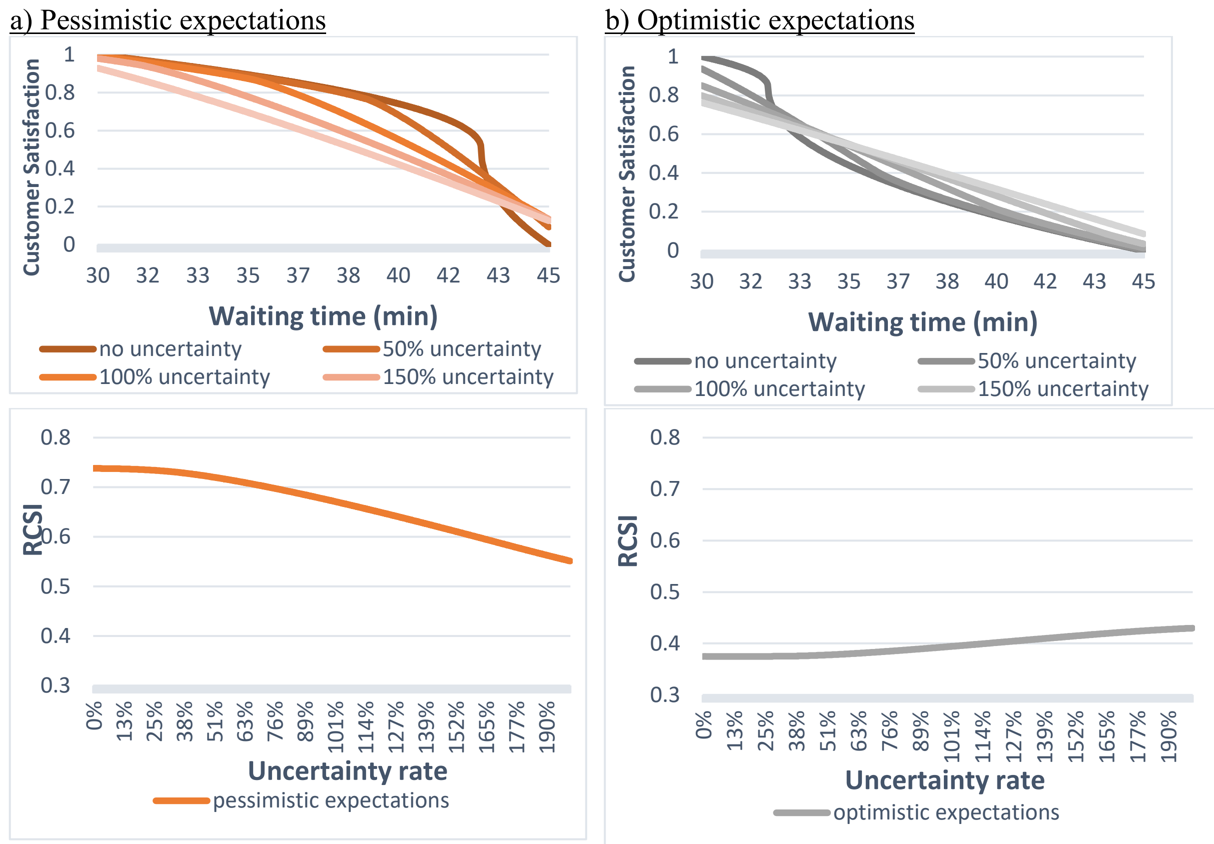
[9] Web Appendix F contains a detailed description of the tool, which is available at https://osf.io/375dt/?view_only=83c4c30542fe4ce3a28932b550dfc179.

Figure 5: Joint effects of over/underpromising and uncertainty on satisfaction



Notes: This figure depicts graphs from the tool for a scenario with actual waiting times between 30 and 45 minutes and the default set of input parameters (loss aversion coefficient = 2.34, diminishing sensitivity coefficient = .48).

The upper left graph in Figure 5 depicts customer satisfaction as a function of actual performance for varying uncertainty levels assuming pessimistic expectations, i.e., underpromising. Specifically, subjective expectations are centered around 43 minutes (instead of 37.5 minutes which represents the middle of the range of actual performances). The lower left graph plots the RCSI metric as a function of uncertainty. RCSI has a downward trend, depicting that uncertainty harms satisfaction. The upper and lower right graphs depict the scenario of optimistic expectations, i.e., overpromising. Specifically, subjective expectations are centered around 32 minutes. Here, RCSI has an upward trend, depicting that uncertainty improves satisfaction. The decision on the magnitude of communicated uncertainty is an important managerial decision and the tool offers guidance in this regard. The tool can be adapted to other use cases such as uncertainty regarding delivery times, investment returns, prices, or other quantifiable product performance attributes such as durability and also implemented as a web-based solution.

Second, low levels of satisfaction result from bad performance and service failures, and recovery strategies often seek to match the discrepancy created between the actual (bad) performance and communicated expected performance levels (Hess, Ganesan, and Klein 2003; Holloway and Beatty 2003; Smith, Bolton, and Wagner 1999). Our findings show that ignoring uncertainty can lead the firm to underestimate satisfaction after poor performances, such that it might overspend on recovery efforts. As data become more accessible, firms might attempt to infer inherent uncertainty levels for each customer (or customer segment), then design recovery strategies that account for these inferred levels. Recovery compensation offered to a customer with uncertain expectations should be lower than those offered to a customer with less uncertain expectations, if the goal is to avoid negative consequences such as churn or complaints. Such a strategy also might improve customer satisfaction levels in digitalized service settings, in which technologies replace human workers (Larivière et al. 2017) and customers expect algorithms to produce less variable outputs, compared with human workers (Dietvorst and Bharti 2020; Kahneman et al. 2016).

Third, our findings shed light on the conditions in which firms have incentives to understate performance variability in their services, which is an important topic for regulators. In general, our results shed light on a potential trade-off between an increase in uncertainty and customer welfare in terms of customer satisfaction. This trade-off is however contingent on uncertainty pertaining to expectations centered around the average of actual performances. In this case, disclosing the full potential range of possible outcomes may eventually impair customer well-being. This finding contrasts with the aim of policies aimed at informing customers about all potential outcome scenarios (or increasing *transparency*). Consumer protection regulation in most domains centers on transparency (e.g., Schwarcz 2013). We thus complement prior findings challenging this approach (e.g., Myatt and Wallace 2014; Tamura 2016). Yet this recommendation does not hold if firms' communication leads to optimistic expectations. In this case, firms should be encouraged to be more transparent about possible alternative scenarios, thus increasing levels of uncertainty in customers' expectations. Regulators may also benefit from using the tool outlined above to assess the impact of transparency on customer welfare.

Future Research on Uncertainty in Expectations and Customer Satisfaction

Several avenues for research also arise from extensions or adaptations of our model. First, we assume a monotone relationship between performance and outcome desirability (i.e., the more, the better), which is not always the case. An interesting extension thus might apply our model to a setting with "ideal" performance levels (e.g., perfect room, food temperature), and deviations in either direction represents a loss (see Web Appendix E). A relevant setting also involves communicating upper bounds, e.g., communicating waiting times of "up to 20 minutes" vs. "10-20 minutes". For a specific set of input parameters, our tool may be used to compare the effect of uncertainty across these scenarios (see Web Appendix F). Second, we derived propositions based on two well-established assumptions: loss aversion and diminishing sensitivity. With the flexible nature of the proposed model, we can investigate the theoretical implications of uncertainty in cases of increasing sensitivity (i.e., $\alpha > 1$) or loss appreciation (i.e., $0 < \lambda < 1$). In turn, $\alpha > 1$ seemingly links our model to the zone of tolerance (Zeithaml, Berry, and Parasuraman 1993;

Zeithaml, Berry, and Parasuraman 1996), in that the effect of an increase (decrease) in performance is smallest if the performance still remains within some adequate range of the desired level. With respect to loss aversion in product choice models, prior research identifies heterogeneous effects of comparing gains and losses across product types, and consumer characteristics (Neumann and Böckenholt 2014). Additional research is warranted to test the boundaries of loss aversion and diminishing sensitivity in customer satisfaction contexts.

Although our mixed methods deliver consistent results, we call for caution before generalizing the empirical results to other settings. It would be interesting to examine our propositions in alternative domains, such as the aforementioned context of customer service by technology (Srinivasan and Sarial-Abi 2021) or when performance assessments are more subjective (Castelo, Bos, and Lehmann 2019). Finally, we clarify the consequences of uncertainty for customer satisfaction, but a comprehensive understanding of uncertainty equally demands insights into its antecedents, in a pre-consumption context. For example, it would be interesting to monitor customers' distribution of expectations dynamically across time. Such an approach could capture the role of past experiences, firm communications, or third party communications in shaping uncertainty. For example, variance in reviews but also the volume in reviews could inform uncertainty. In addition, single point estimates followed by a communication about an update about a (new) expected delivery or waiting time could likewise trigger uncertainty. These examples underscore the overall need to advance our understanding on the customer well-being implications of uncertainty in expectations.

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WEB APPENDIX FOR

„THE IMPACT OF UNCERTAINTY ON CUSTOMER SATISFACTION”

Table of Contents

Web Appendix A: Literature Review

Table W1 depicts literature on the influence of uncertainty on customer product evaluations. We classify the relevant literature into two streams according to how expectations are formed. The first stream encompasses literature on external sources as the basis for expectation formation (e.g., word of mouth). The second stream focuses on expectations formed by internally-driven sources (e.g., past experience).

External sources of uncertainty. Expectations about the performance of a product may be based on external cues such as advertisements, published ratings, reviews or word of mouth (Rust et al. 1999). Within this stream, uncertainty is often operationalized as lack of or mixed information. Most studies analyze the impact of uncertainty on purchase behavior (e.g., He and Bond 2015; Li, Gopinath, and Carson 2021; Sun 2012) and only few studies go beyond consumer choices and examine consumer satisfaction (Moe and Trusov 2011; Moon, Bergey, and Iacobucci 2010). Moe and Trusov (2011) find that uncertainty significantly reduces the likelihood to be extremely satisfied and extremely dissatisfied, i.e., uncertainty discourages extreme satisfaction judgements.

Internal sources of uncertainty. In this stream, many studies report reference effects from comparisons to past experiences and asymmetric effects from positive and negative relative performance evaluations (Bolton, Lemon, and Bramlett 2006). The studies differ in the concrete operationalization of reference points ranging from recent experiences, averaging past experiences with equal weights, averaging past experiences with subjective weights, to assuming a Bayesian updating scheme based on past experiences (Bolton, Lemon, and Bramlett 2006; Rust et al. 1999). This literature also studies the role of service variability (and thus reference point variability) in customers' evaluations. E.g., Voorhees et al. (2021) document a nonlinear effect of variability on consumer confidence, and Sriram, Chintagunta, and Manchanda (2015) show that low levels of variability drive customer retention.

Table W1: Review of empirical research on the impact of uncertainty on product evaluations

Reference	Source of Uncertainty	Context	Key Constructs	Theoretical Background	Main Findings
<u>Studies with external sources of uncertainty</u>					
West and Broniarczyk (1998)	Disagreement across critics' opinions	Movies and restaurants	Product liking / Interest in product	Prospect theory, disconfirmation theory	Consensus among critics is preferred for alternatives above an aspiration level, whereas disagreement is preferred for alternatives below an aspiration level
Spreng and Page (2001)	Product description	Videorecorder	Customer satisfaction, disconfirmation	Disconfirmation theory	The effect of disconfirmation on satisfaction is mitigated for high levels of uncertainty
Moon, Bergey, and Iacobucci (2010)	Variability in user generated content in relation to focal product	Movies	Box office revenues, customer satisfaction	Theory on risk aversion	Uncertainty has a negative effect on customer satisfaction
Moe and Trusov (2011)	Variability in user generated content in relation to focal product	Bath, fragrance, and beauty products	Customer satisfaction	Multiple audience effect	Negative effect of variability on the likelihood of posting extreme opinions (both positive and negative) by new raters
Sun (2012)	Variability in user generated content in relation to focal product	Books	Sales	Informational role of ratings: Signal for both product quality and mismatch cost	If average ratings is high (low), there is a negative (positive) association between uncertainty and sales
Gneezy, Gneezy, and Lauga (2014)	Likelihood of a bad quality induced by price signal	Wine	Subjective quality perceptions	Prospect theory, disconfirmation theory	For low (high) quality wines, subjective quality perceptions decrease (increase) with price
He and Bond (2015)	Variability in user generated content in relation to focal product	• Taste-dissimilar domains: paintings, music • Taste-similar domains: desk lamps, flash drivers	Product choice, purchase intention	Theory of risk aversion	Impact of uncertainty depends on the extent to which the source of uncertainty is attributed to variability in product performance or taste differences

Reference	Source of Uncertainty	Context	Key Constructs	Theoretical Background	Main Findings
Li, Gopinath, and Carson (2021)	Variability in user generated content in relation to focal product	Digital cameras	Sales rank	Theory on risk aversion	Uncertainty in the current (past) generation leads to a higher (lower) carryover effect of ratings from previous generations
<u>Studies with internal sources of uncertainty</u>					
Rust et al. (1999)	Variability in experience with service or product across time	Camera battery life	Product choice	Prospect theory, disconfirmation theory	Uncertainty with regard to the product's quality decreases preference for that option
Bolton, Lemon, and Bramlett (2006)	Variability in experience with service or product across time	Support services for high technology systems (B2B context)	Contract renewal, design quality, experience quality, and price	Prospect theory	Positive effect of variability conditional on the number of positive customer experiences
Sriram, Chintagunta, and Manchanda (2015)	Variability in experience with product across time	Video-on-demand services	Service quality, termination rates	Theory of risk aversion, trade-off between risk aversion and learning deterrence	Uncertainty mitigates the impact of service quality improvements on retention
Voorhees et al. (2021)	Variability in experience with service or product across time	Portrait studio services	Confidence, word-of-mouth intention, sales	Disconfirmation theory	Uncertainty has a diminishing effect on confidence which in turn positively impacts purchase intention and sales

Web Appendix B: Proof of Propositions

Inserting $a = -b$ into Equation (3) results in the following expression for $s(b, x)$:

$$s(b,x) = \begin{cases} \frac{1}{2b(\alpha+1)}[(x+b)^{\alpha+1} - \lambda(b-x)^{\alpha+1}], -b \leq x \leq b \\ \frac{-\lambda}{2b(\alpha+1)}[(b-x)^{\alpha+1} - (-b-x)^{\alpha+1}], x < -b \\ \frac{1}{2b(\alpha+1)}[(b+x)^{\alpha+1} - (-b+x)^{\alpha+1}], b < x. \end{cases} \tag{W1}$$

We now turn to the poofs of Propositions 1-3.

Proposition 1: Satisfaction increases with performance, i.e., $s(b, x)$ is increasing in x for all $b \geq 0$.

Proof: Let $b > 0$. Then $s(b, x)$ is differentiable everywhere in x. We compute the first derivative of $s(b, x)$ with respect to x:

$$\frac{\partial s}{\partial x} = \begin{cases} \frac{1}{2b}[(x+b)^{\alpha} + \lambda(b-x)^{\alpha}], \quad -b \leq x \leq b \\ \frac{\lambda}{2b}[(b-x)^{\alpha} - (-b-x)^{\alpha}], \qquad x < -b \\ \frac{1}{2b}[(b+x)^{\alpha} - (-b+x)^{\alpha}], \qquad b < x. \end{cases} \tag{W2}$$

We can easily see that $\frac{ds}{dx} \geq 0$ for all x. If $b = 0$, $s(0, x)$ is reduced to the prospect theory value function $\mu(x)$ which is strictly increasing in x, completing the proof.

Proposition 2: Subjective reference points increase with uncertainty. Specifically, let x_0^b be such, that $s(b, x_0^b) = 0$. Then, x_0^b is increasing in b.

Proof: For a nonnegative b, it suffices to find $-b \leq x_0^b \leq b$, such that $s(b, x_0^b) = 0$. For $b = 0$, we have $x_0^b = 0$. For $b > 0$, we equate Equation (W1) to zero, which results in the following expression:

$$\frac{1}{2\mathrm{b}(\alpha+1)}[(x_0^b+\mathrm{b})^{\alpha+1}-\lambda(b-x_0^b)^{\alpha+1}]=0$$

$$\Leftrightarrow \left(x_0^b+\mathrm{b}\right)^{\alpha+1}=\lambda\left(b-x_0^b\right)^{\alpha+1}$$

$$\Leftrightarrow \frac{x_0^b+b}{b-x_0^b}=\lambda^{\frac{1}{\alpha+1}}$$

$$\Leftrightarrow x_0^b=\frac{b\left(\lambda^{1/(\alpha+1)}-1\right)}{1+\lambda^{1/(\alpha+1)}}.$$

Moreover, we have $\frac{\partial x_0^b}{\partial b}=\frac{\lambda^{1/(\alpha+1)}-1}{1+\lambda^{1/(\alpha+1)}}>0$, if and only if $\lambda>1$, completing the proof.

As a corollary to this proposition, we seek to grasp the overall effect of uncertainty across all possible outcomes by specifying relationships between the areas below the curves for different uncertainty levels. We formalize this in the following corollary:

Corollary: Uncertainty has an overall negative effect on satisfaction. Specifically, let $x \sim U[-c,c]$ with $c \geq 0$, then for all b, b' with $0 \leq b < b'$, $\int s(b,x)\, dG_c(x) \geq \int s(b',x)\, dG_c(x)$.

Proof: Following the proof of Proposition 2, we know that there exists $x_0<0$ such that (i) $s(b,x)<s(b',x)$ for $x<x_0$, and (ii) $s(b,x)>s(b',x)$ for $x>x_0$. Note that if $\lambda<1$, we have $x_0>0$ for which (i) and (ii) hold. First, we examine the case where $-c \geq x_0$. The proposition follows directly from the inequality in (ii).

Now we let $-c<x_0$. Given loss aversion, i.e. $\lambda>1$, we have $\int s(b,x)\, dG_c(x) <0$ for all $b \geq 0$. We define $S(b,c,\alpha,\lambda) := \int s(b,x)\, dG_c(x)$ It suffices to show that $\frac{\partial S}{\partial b}<0$ for $b>0$. We have

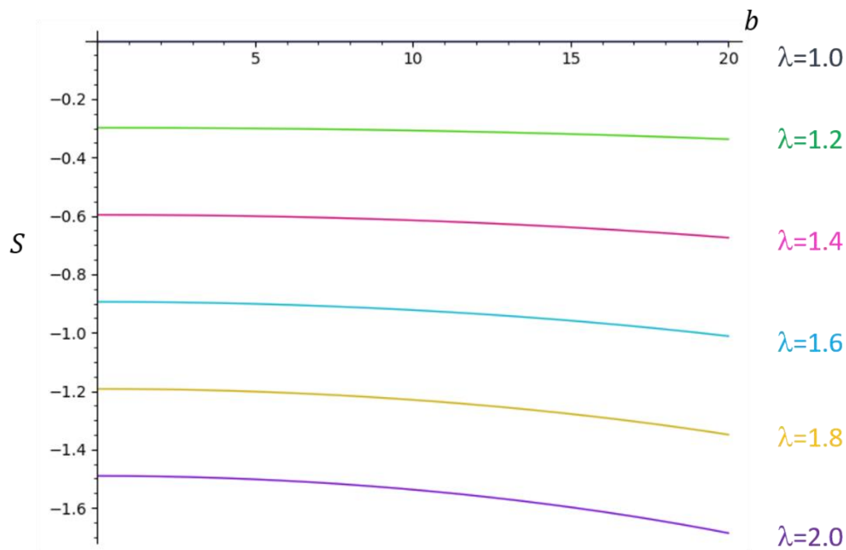
$$S(b,c,\alpha,\lambda)=\int_{-c}^{-b}\frac{-\lambda}{2b(\alpha+1)}[(b-x)^{\alpha+1}-(-b-x)^{\alpha+1}]\frac{1}{2c}dx \qquad \text{(W3)}$$

$$+\int_{-b}^{-b} \frac{1}{2b(\alpha+1)}\left[(b+x)^{\alpha+1}-\lambda(b-x)^{\alpha+1}\right]\frac{1}{2c}\,dx$$

$$+\int_{b}^{c} \frac{1}{2b(\alpha+1)}\left[(b+x)^{\alpha+1}-(-b+x)^{\alpha+1}\right]\frac{1}{2c}\,dx\,.$$

If $\lambda = 1$, $S(b, c, \alpha, \lambda) = \frac{\partial S}{\partial b} = 0$. For $\lambda > 1$, $S(b, c, \alpha, \lambda)$ is monotonically decreasing in $(0, c]$ (see Figure W1 for a graphical illustration). This holds for any values of $0 < \alpha < 1$, $\lambda > 1$, $c > 0$, and $0 < b \leq c$.[1]

Figure W1: Illustration of the trajectory of ***S*** as a function of ***b***



Note: Figure plots $\frac{\partial S}{\partial b}$ as given by Equation (W3). Parameter values are set as $\alpha = 0.5$ and $c = 20$.

Proposition 3: Uncertainty has a negative non-linear effect on satisfaction after good performances and a positive non-linear effect on satisfaction after bad performances. Specifically, let $0 \leq b < b'$, then:

(i) $\lim_{x\to\infty} s(b', x) - s(b, x) = \lim_{x\to-\infty} s(b', x) - s(b, x) = 0$, and

[1] Results verified with SageMath (version 9.2), an open source mathematics software based on Phython. The code and results are available upon request.

(ii) there exists x_0 such that $s(b', x) - s(b, x)$ is positive for all performance levels $x \leq x_0$, has a maximum in the range $(-\infty, x_0]$, is negative for all performance levels $x \geq x_0$, and has a minimum in the range (x_0, ∞).

Proof: We start by proving (i). Given that we want to examine how s behaves for extreme values of x, it suffices to consider the ranges $(x < -b')$ and $(x > b')$. From Proposition 1, we know that $s(b, x)$ is monotonically increasing in x for all $b \geq 0$. Since $s(b', x)$ increases in x at the same rate as $-s(b, x)$ decreases in x, we can conclude that $s(b', x) - s(b, x)$ tends towards zero for $x \to \infty$ as well as for $x \to -\infty$. This becomes clearer if we write out the expression for $s(b', x) - s(b, x)$. For $b > 0$ and large values of x, we have:

$$s(b', x) - s(b, x) = \frac{1}{2b'b(\alpha + 1)}\left[b(b' + x)^{\alpha+1} - b(-b' + x)^{\alpha+1} - b'^{(b+x)^{\alpha+1}} + b'^{(-b+x)^{\alpha+1}}\right]. \tag{W4}$$

Furthermore, for small values of x, we have:

$$s(b', x) - s(b, x) = \frac{-\lambda}{2b'b(\alpha + 1)}\left[b(b' - x)^{\alpha+1} - b(-b' - x)^{\alpha+1} - b'^{(b-x)^{\alpha+1}} + b'^{(-b-x)^{\alpha+1}}\right]. \tag{W5}$$

A closer look at the individual summands in Equations (W4) and (W5) reveals that these offset each other in the limit.[2]

We now turn our attention to the second part of the proposition. First, we want to show that $d(x, b', b) := s(b', x) - s(b, x)$ is non-negative for small values of x, i.e., for values $x \leq x_0$, and negative for large values of x, i.e. for values $x \leq x_0$, for some constant x_0. Then, we will show that $\frac{\partial d}{\partial x}$ has two zeros, which suffices to prove (ii).

Solving the equation $\frac{\partial d}{\partial x} = 0$ is not trivial, given that d is a piecewise function with parametric bounds for each range, which makes the use of a mathematical software system

[2] Results verified with SageMath (version 9.2). The code and results are available upon request.

difficult. We first let $b > 0$. We substitute x in a way that $s(b, x)$ becomes independent of b. We set $y := -\frac{x}{b}$ and define $\tilde{s}(y) := s(-yb, b)b^{-\alpha}$. It follows:

$$\tilde{s}(y) = \begin{cases} \frac{1}{2(\alpha+1)}[(1-y)^{\alpha+1} - \lambda(1+y)^{\alpha+1}], & -1 \leq y \leq 1 \\ \frac{-\lambda}{2(\alpha+1)}[(1+y)^{\alpha+1} - (y-1)^{\alpha+1}], & y > 1 \\ \frac{1}{2(\alpha+1)}[(1-y)^{\alpha+1} - (-y-1)^{\alpha+1}], & y < -1. \end{cases} \tag{W6}$$

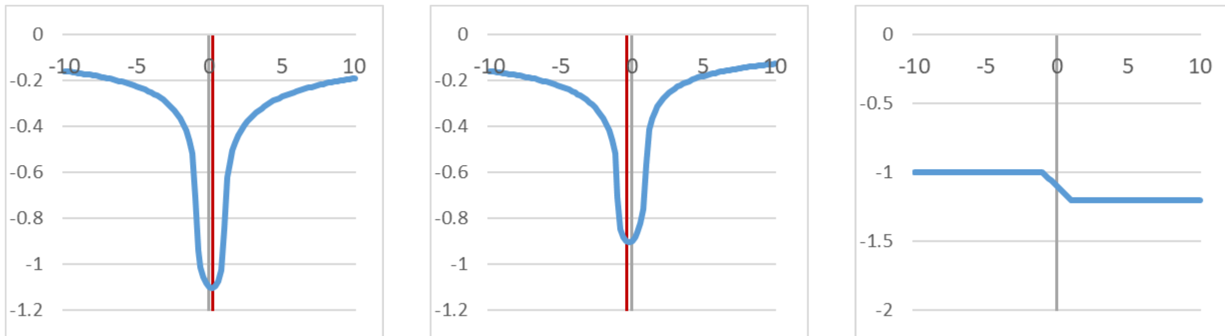
We can see that $\tilde{s}$ is independent of the uncertainty parameter b and by definition we have $s(x\,,\mathrm{b}) = \tilde{s}\left(-\frac{x}{b}\right)b^{\alpha}$. We may now write $\frac{\partial d}{\partial x}$ in terms of $\tilde{s}$ as $\frac{\partial d}{\partial x} = -\frac{1}{b'^{1+\alpha}}\tilde{s}'\left(-\frac{x}{b'}\right) + \frac{1}{b^{\,1+\alpha}}\tilde{s}'\left(-\frac{x}{b}\right)$, where

$$\tilde{s}'(\cdot) = \frac{\partial \tilde{s}}{\partial y} = \begin{cases} \frac{1}{2}[-(1-y)^{\alpha} - \lambda(1+y)^{\alpha}], & -1 \leq y \leq 1 \\ \frac{-\lambda}{2}[(1+y)^{\alpha} - (y-1)^{\alpha}], & y > 1 \\ \frac{1}{2}[-(1-y)^{\alpha} + (-y-1)^{\alpha}], & y < -1. \end{cases} \tag{W7}$$

By taking the second derivative and solving for zero, we see that $\frac{\partial \tilde{s}}{\partial y}$ has one minimum at $y = \frac{1-\lambda^{\frac{1}{\alpha-1}}}{\lambda^{\frac{1}{\alpha-1}}+1}$, and $\lim_{y\to-\infty}\frac{\partial \tilde{s}}{\partial y} = \lim_{y\to\infty}\frac{\partial \tilde{s}}{\partial y} = 0$. Note that $\frac{1-\lambda^{\frac{1}{\alpha-1}}}{\lambda^{\frac{1}{\alpha-1}}+1} \geq 0$ if and only if $\lambda \geq 1$. Moreover, if $\alpha = 1$, $\frac{\partial \tilde{s}}{\partial y}$ becomes a stepwise linear function with $\frac{\partial \tilde{s}}{\partial y} = -1$ for $y < -1$, $\frac{\partial \tilde{s}}{\partial y} = -\lambda$ for $y > 1$ and $\frac{\partial \tilde{s}}{\partial y} = -\frac{1}{2} - \frac{1}{2}(\lambda - 1)y$ for $-1 \leq y \leq 1$ (see Figure W2 for an illustration). Hence, diminishing sensitivity, i.e., $\alpha = 1$, is a necessary condition for $\frac{\partial \tilde{s}}{\partial y}$ having a minimum.

Figure W2: Illustration of functional form of $\frac{\partial \tilde{s}}{\partial y}$

$\lambda = 1.2, \alpha = 0.5$ $\lambda = 0.8, \alpha = 0.5$ $\lambda = 1.2, \alpha = 1$



Notes: Figure plots $\frac{\partial \tilde{s}}{\partial y}$ as given by Equation (W7) for different values of λ and α. The grey line indicates $y = 0$, and the red line indicates the value of y for which $\frac{\partial \tilde{s}}{\partial y}$ assumes its minimum.

We want to prove that $\frac{\partial d}{\partial x}$ has two zeros. It suffices to show that there are only two sets of values $\{w_{1,1}, w_{2,1}\}$ $\{w_{1,2}, w_{2,2}\}$ that satisfy $\frac{b'^{1+\alpha}}{b^{1+\alpha}} \tilde{s}'(w_{1,i}) = \tilde{s}'(w_{2,i})$ for $i = 1,2$. Let $\theta \geq 1$. Then there exist values z_1, z_2 in the domain of $\tilde{s}'$ with $\theta = \frac{z_1}{z_2}$. For z_i in the domain of $\tilde{s}'$, there exist unique values $\widetilde{w}_{i,1}, \widetilde{w}_{i,2}$ with $\tilde{s}'(\widetilde{w}_{i,1}) = \tilde{s}'(\widetilde{w}_{i,2}) = z_i$. We set $w_{i,j} := \widetilde{w}_{i,j}, j, i = 1,2$.

We examine the case $b = 0$. We know that $s(0, x)$ is not differentiable at $x = 0$ and neither is $d(x, b', 0)$. However, $d(x, b', 0)$ is defined at $x = 0$ with $d(0, b', 0) = \frac{1-\lambda}{2(\alpha+1)} b'^{\alpha}$. Moreover, since $d(-\varepsilon, b', 0) > \frac{1-\lambda}{2(\alpha+1)} b'^{\alpha}$ and $d(\varepsilon, b', 0) < \frac{1-\lambda}{2(\alpha+1)} b'^{\alpha}$ for a small ε, we know that $x = 0$ is not a maximum nor a minimum of $d(x, b', 0)$. We may thus consider only $x \neq 0$, where $\frac{\partial d}{\partial x}$ is defined and we can perform all the same steps as in the case where $b > 0$, which completes the proof.

Web Appendix C: Experimental Instructions

In the following, we present the instructions for the experimental study show to participants in the low uncertainty group. Differences in the instructions across treatment groups are in parenthesis “[]”.

<u>Page 1:</u>

Welcome!

Thank you for participating in our study. Below you will find some general information. Please read everything carefully before continuing with the survey.

DESCRIPTION: We are researchers at the BLINDED conducting a research study about consumer judgements. Completing this survey should take you about 8 minutes.

COMPENSATION: In return for completing this study attentively, you will receive £1.

PLEASE NOTE: This study contains a number of checks to make sure that participants are finishing the tasks honestly and completely. As long as you read the instructions and complete the tasks, your submission will be approved. If you fail these checks, we reserve the right to reject your submission.

CONFIDENTIALITY: Your Prolific ID will be used to distribute payment to you but will not be stored with the research data we collect from you. Any reports and presentations about the findings of this study will not include your name or any other information that could identify you.

SUBJECT'S RIGHTS: Your participation is voluntary. You may stop participating at any time by closing the browser window or the program to withdraw from the study.

For additional questions about this research, you may contact: BLINDED

Please indicate, in the box below, that you are at least 18 years old, have read and understand this consent form, and you agree to participate in this online research study.

- **I am at least 18 years old, I have read and understand this consent form, and I agree to participate in this online research study.**
- **I do not agree to participate in this online research study.**

Page 2:

Please transcribe the set of characters (case sensitive) by typing it into the text box below.

Page 3:

Imagine your refrigerator is broken and you want to purchase a new one. After searching for refrigerators online you conclude that you want to buy a newer model of your old refrigerator. You find this model in an online retail store and decide to buy it.

Page 4:

It is the first time you buy something from this online retailer and you don't know how long you are going to have to wait for the delivery of the refrigerator. After the purchase, you receive a notification from the company with the following information:

Expected delivery time: **6 - 8 days**

[Expected delivery time: **2 - 12 days**]

Page 5:

To ensure that you understand the scenario, please answer the following questions.

What product did you buy from an online retail store because yours was broken? (Randomized order)

- A new refrigerator
- A new microwave
- A new vacuum cleaner
- I don't know

Which information was provided on the retail store's website regarding the expected delivery time? (Randomized order)

- A delivery time of 15 days
- A delivery timeframe of 6 to 8 days
- A delivery timeframe of 7 to 13 days
- A delivery timeframe of 2 to 12 days

<u>Page 6:</u>

On the next pages you will be asked to imagine multiple scenarios for the delivery time.

<u>Page(s) 7 (to 13) (exemplary for an outcome of 8 delivery days):</u>

Your refrigerator arrives after **8 days**.

Remember, the expected delivery time was **6 - 8 days.**

[Remember, the expected delivery time was **2 - 12 days.]**

Please answer the following questions:

S1. What is your overall satisfaction with the delivery time?
(1 = very dissatisfied, 11 = very satisfied)

S2. How well has the delivery time met your expectations?
(1 = not at all, 11 = very well)

S3. How well did the delivery time compare with the ideal service?
(1 = poor, 11 = excellent)

S'1. With respect to the delivery time, would you say that you are a satisfied customer?
(no / yes)

S'2. With respect to the delivery time, would you say that you are a dissatisfied customer?
(no / yes)

Page 14:

Please answer the following question based on the information about the expected delivery time:

6 – 8 days [2 - 12 days].

What is the delivery time (in days) with which you would feel neutral, i.e. neither satisfied nor dissatisfied, about the delivery service of the retail store?

Page 15:

1. After receiving the notification about the expected delivery time, how certain were you as to how fast the refrigerator will be delivered?
   (1 = not at all certain, 7 = very certain)

2. After receiving the notification about the expected delivery time, how well could you judge how fast the refrigerator will be delivered?
   (1 = hard for me to judge, 7 = easy for me to judge)

3. After receiving the notification about the expected delivery time, I felt the delivery service would probably deliver the refrigerator…
   (1 = not at all fast, 7 = very fast)

The content of page 7 was shown to participant a total of seven times with different outcome levels. Specifically, participants were randomly assigned to one of four sets (A, B, C, or D) of varying outcomes as shown in Table W2. The order of the presentation of the seven different outcomes was randomized. For example, a participant randomly assigned to the first set viewed performance levels (in a randomized order) consisting of 2, 4, 5, 7, 9, 10 and 12 delivery days.

Table W2: Performance Levels across Randomized Sets

Outcome No. / Set No.	A	B	C	D
1	2	1	2	1
2	4	3	3	3
3	5	6	6	5
4	7	7	7	7
5	9	8	8	9
6	10	11	10	11
7	12	13	12	13

Web Appendix D: List of Products Used in Field Study

Table W3 contains a list with the products that were included in the field study's main analysis.

Table W3: Product name and brand of analyzed Bluetooth speakers in field study

Product	Brand	Product	Brand
Beoplay A1	Bang & Olufsen	Pulse 3	JBL
Beoplay P2	Bang & Olufsen	Pulse 4	JBL
Beoplay P6	Bang & Olufsen	Rockbox Bold S	Fresh 'n Rebel
Beosound A1 (2nd Generation)	Bang & Olufsen	Rockster Go	Teufel
Boom 2	Ultimate Ears UE	S5305	Philips
Boomster Go	Teufel	Soundcore 3	Anker
Charge 3	JBL	SoundLink Revolve	Bose
Charge 4	JBL	SoundLink Revolve II	Bose
Clip 3	JBL	SoundLink Revolve Plus II	Bose
Clip 4	JBL	SoundStone CM51	Huawei
D Cube	Dockin	SRS-XB01	Sony
D Fine+ 2	Dockin	SRS-XB12	Sony
Emberton	Marshall	SRS-XB21	Sony
Envaya DSB-250BT	Denon	SRS-XB32	Sony
Flip 5	JBL	SRS-XB33	Sony
Flip Essential	JBL	Stockwell II	Marshall
GBT Club	Grundig	Too	Libratone
JR Pop	JBL	Wonderboom 2	Ultimate Ears UE
Klang M1	Loewe	XBoom Go PL2	LG
Mini Speaker CM510	Huawei	XBoom Go PL7	LG
Motiv Go	Teufel	Xtreme 3	JBL
Musicbox XS	Canton	Yoyo (S)	Cambridge Audio
PK5	LG		

Web Appendix E: Extension of Model for Ideal Point Reference Points

This section examines an extension of our model to a setting in which there are ideal performance levels. Essentially, deviations in both directions of the actual performance level from the reference point are perceived as a loss. Hence, satisfaction is given by

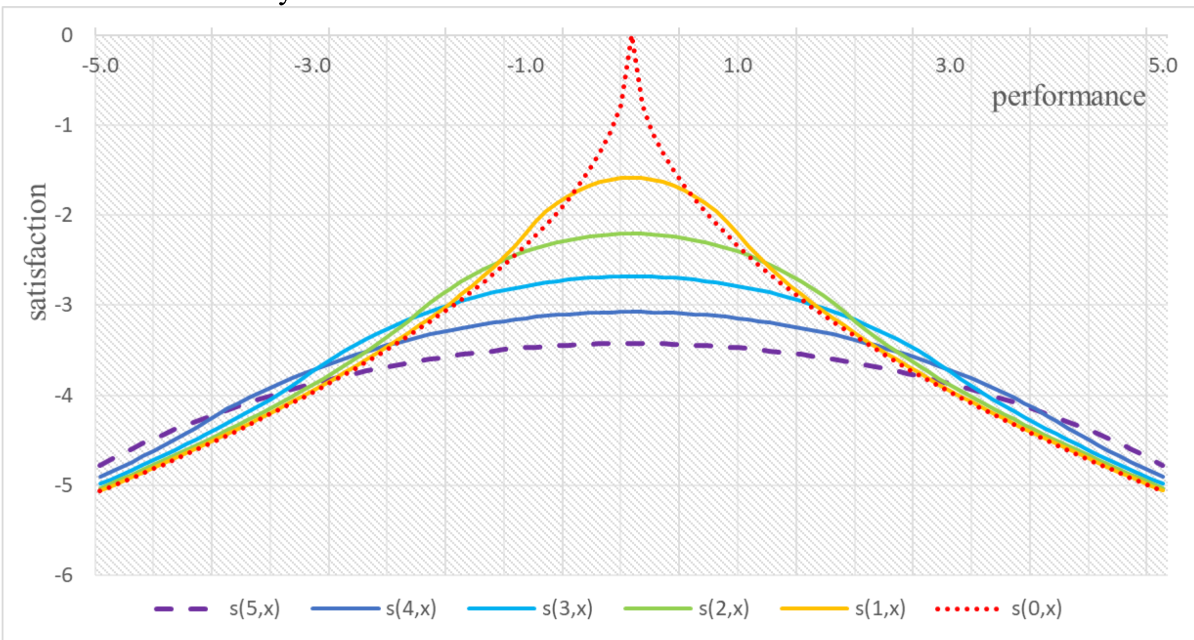
$$s_G(x) = \int -\lambda |r - x|^{\alpha} dG(r), \tag{W8}$$

where *G* represents the distribution of expectations. Solving Equation (W8) for $G \sim U[a, b]$ results in the following expression:

$$s_{a,b}(x) = \begin{cases} \frac{-\lambda}{(b-a)(\alpha+1)}\left[(x-a)^{\alpha+1} + (b-x)^{\alpha+1}\right], & \text{for } a \leq x \leq b, \\ \frac{-\lambda}{(b-a)(\alpha+1)}\left[(b-x)^{\alpha+1} - (a-x)^{\alpha+1}\right], & \text{for } x < a, \text{and} \\ \frac{-\lambda}{(b-a)(\alpha+1)}\left[(x-a)^{\alpha+1} - (x-b)^{\alpha+1}\right], & \text{for } b < x. \end{cases} \tag{W9}$$

Figure W3 illustrates the effect of uncertainty under the chosen parametrization in the presence of loss aversion and diminishing sensitivity. As uncertainty increases, satisfaction depends less on the actual performance outcome (i.e., the curve flattens). The (negative) effect of uncertainty increases the more the actual outcome approaches the expected performance. At larger deviations of the actual performance from the expected level, the effect of uncertainty diminishes and may even become positive.

Figure W3: Satisfaction with (stochastic) ideal point reference points across levels of uncertainty



Notes: Values for α and λ are set at 0.48 and 2.34 respectively (Baillon, Bleichrodt, and Spinu 2020)

Web Appendix F: The RSCI Tool

This section describes the main features of the Relative Customer Satisfaction Index (RSCI) Tool. The aim of the tool is to support decision making targeted at enhancing customer satisfaction by visualizing the predicted effect of uncertainty in expectations on satisfaction across a range of customizable scenarios. The tool's scope currently comprises a setting in which an absolute lower performance metric (e.g., minutes or days) translates into increased satisfaction, as in the case of delivery days or waiting times. Moreover, to make the tool easily usable and understandable, the instructions as well as the provided examples (in this section and in the tool itself) reflect the case of waiting times. However, note that the tool can be further developed and adapted to capture alterative use cases. The tool is available for download at https://osf.io/375dt/?view_only=83c4c30542fe4ce3a28932b550dfc179.

The Microsoft-Excel-based tool consists of three visible tabs: "Instructions", "Input", and "Results" (and a hidden "Calculations" tab). A basic description of the tool, including the input parameters as well as the metrics is provided in the instructions tab. A list with the required input parameters is given in Table W4. The results tab plots a standardized measure of customer satisfaction as a function of the actual performance level (Figure 1a – 3a in the tool). Furthermore, the Relative Customer Satisfaction Index (RCSI) is introduced. This metric captures an aggregate measure of customer satisfaction that accounts for the uncertain nature of expectations. Figure 1b-3b in the tool illustrate the role of increasing uncertainty in shaping RCSI. An increase in uncertainty is depicted as a widening of the range of subjective expectations (e.g., from expecting a waiting time between 30 and 45 minutes to expecting a waiting time between 15 and 60 minutes). Since a scenario involving negative waiting times is unrealistic, we limit the lower bound of the expectations range to 0 minutes. Therefore, the tool's outcomes concerning the role of increasing uncertainty may depict situations in which the upper bound of subjective expectations increases while the lower bound is maintained constant at 0 minutes.

A description of the metrics used in the results section is provided in Table W5 and formal definitions of customer satisfaction (W10), standardized customer satisfaction (W11), as well as RCSI (W12) are provided below. In equations (W10) – (W12), x denotes the actual waiting time, x_1 denotes the lowest observed performance level (e.g., the minimum observed waiting time in minutes), and x_2 denotes the highest observed performance level (e.g., the maximum observed waiting time in minutes). The model parameters a, b, λ, α refer to the lower bound of individuals' subjective expectations, the upper bound of individuals' subjective expectations, the coefficient for loss aversion, and the coefficient for diminishing sensitivity respectively.

$$\tilde{s}_{a,b}(x) = \begin{cases} \frac{1}{(b-a)(\alpha+1)}[-\lambda(x-a)^{\alpha+1} + (b-x)^{\alpha+1}], \text{for } a \leq x \leq b, \\ \frac{1}{(b-a)(\alpha+1)}[(b-x)^{\alpha+1} - (a-x)^{\alpha+1}], \text{for } x < a, \text{and} \\ \frac{-\lambda}{(b-a)(\alpha+1)}[(x-a)^{\alpha+1} - (x-b)^{\alpha+1}], \text{for } b < x. \end{cases} \tag{W10}$$

$$\bar{s}_{a,b}(x) = \frac{\tilde{s}_{a,b}(x) - \tilde{s}_{a,b}(x_2)}{\tilde{s}_{a,b}(x_1) - \tilde{s}_{a,b}(x_2)} \tag{W11}$$

$$RSCI_{a,b} = \frac{\int_{x_1}^{x_2} \bar{s}_{a,b}(x)\,dx}{x_2 - x_1} \tag{W12}$$

Table W4: List of input parameters

Input parameter	Explanation	Example
Earliest performance (min)	The minimum observed waiting time in minutes	30
Latest performance (min)	The maximum observed waiting time in minutes	45
Underpromising index [3]	Depicts the extent of higher communicated average expected waiting times (due to underpromising) relative to the actual observed average, leading to pessimistic expectations. ≥ 0	0.0 ~ indicates communicating an average waiting time equal to the average of actual observed waiting times 1.0 ~ indicates communicating an average waiting time equal to the upper bound of actual observed waiting times (e.g., 45 minutes)
Overpromising index	Depicts the extent of lower communicated average expected waiting times (due to overpromising) relative to the actual observed average, leading to optimistic expectations. ≤ 0	0.0 ~ indicates communicating an average waiting time equal to the average of actual observed waiting times -1.0 ~ indicates communicating an average waiting time equal to the lower bound of actual observed waiting times (e.g., 30 minutes)
Loss aversion coefficient	Degree of loss aversion (> 1 indicates loss aversion)	2.34 (as in the manuscript)
Diminishing sensitivity coefficient	Degree of diminishing sensitivity (> 0 as well as < 1 indicates diminishing sensitivity)	0.48 (as in the manuscript)

[3] Specifically, the tool implements the following relationship between the under/overpromising index (I) and the communicated mean of expected waiting times m: $I\frac{x_2+x_1}{2}+\frac{x_2-x_1}{2}=m$.

Table W5: List of important metrics

Metric	Explanation	Example
Uncertainty rate	Rate of uncertainty in expectations (e.g., due to communicated variability) relative to the actual observed variability	0% ~ no uncertainty (e.g., due to communication of point estimate) 100% ~ uncertainty (e.g., due to communication of entire range of actual observations)
Standardized customer satisfaction	Standardized measure of customer satisfaction (varies between 0 and 1)	1 ~ customer satisfaction for no uncertainty in satisfaction at the earliest observed waiting time 0 ~ customer satisfaction for no uncertainty in satisfaction at the latest observed waiting time
Relative Customer Satisfaction Index (RCSI)	Area below the curve of standardized customer satisfaction as a function of the uncertainty rate divided by the difference between the latest and earliest performance (varies between 0 and 1)	RCSI = 1 indicates the highest possible level of satisfaction for a given performance range RCSI = 0 indicates the lowest possible level of satisfaction for a given performance range

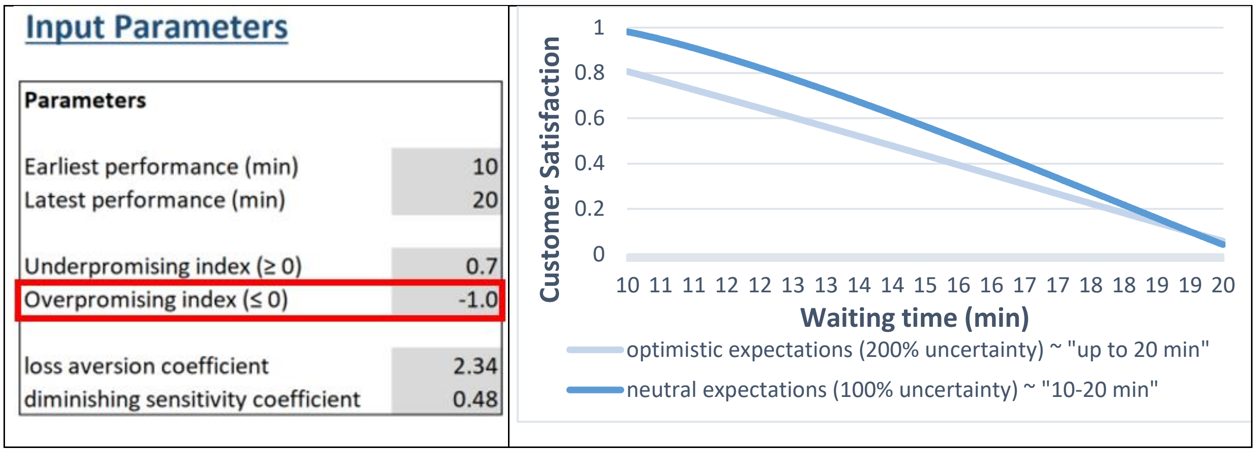
Necessary computations are performed in the calculations tab, which is hidden. The main components comprise three functions and one sub statement, all of which are described in Table W6.

Table W6: Script components

Object	Name	Description
Function statement	sat_inv	User defined function that returns a value of customer satisfaction in accordance to (W10). Required input parameters are the level of actual performance x, a lower bound of expectations *a*, an upper bound of expectations *b*, the coefficient for loss aversion λ, and the coefficient for diminishing sensitivity α.
Function statement	sat_inv_std	User defined function that returns a value of standardized customer satisfaction in accordance to (W11). Required input parameters are the level of actual performance *x*, a minimum actual performance level x_1, a maximum actual performance level x_2, a lower bound of expectations *a*, an upper bound of expectations *b*, the coefficient for loss aversion λ, and the coefficient for diminishing sensitivity α.
Function statement	int_sat_inv	User defined function that returns an aggregated value of standardized customer satisfaction across a range of actual performance levels in accordance to (W12). Required input parameters are a minimum actual performance level x_1, a maximum actual performance level x_2, a lower bound of expectations *a*, an upper bound of expectations *b*, the coefficient for loss aversion λ, and the coefficient for diminishing sensitivity α.
Sub statement	calculate_macro	User defined sub statement that calculates the worksheet.

Furthermore, the tool may be used to reflect the effect of alternative communication strategies. The left hand side of Figure W4 shows input parameters customized to mimic a situation involving communicating upper bounds. For example, managers may be interested in assessing the impact of communicating “up to 20 min” versus “10 to 20 min” on customer satisfaction, assuming actual observed waiting times between 10 and 20 minutes. Specifically, communicating “up to 20 min” translates into subjective expectations ranging from 0 to 20, which translates into an overpromising index of 1.0. In contrast, “10 to 20 min” represent neutral expectations. With this set of parameters, the impact of communicating “up to 20 min” compared to “10-20 min” on customer satisfaction may be assessed, as shown on the right hand side of Figure W4. Here, optimistic expectations refer to subjective expectations centered around 10 minutes following overpromising communication. The labels “200% uncertainty” and “100 uncertainty” refer to the width of the range and is relative to the width of the range of actual observations (i.e., 10 minutes). The models’ predictions hint to the fact the communicating upper bounds harms customer satisfaction and that this effect is more pronounced for short waiting times (cf. long waiting times).

Figure W4: Communication of upper bounds – tool inputs and results



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