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Consumer Uncertainty and Purchase Decision Reversals: Theory and Evidence

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This research examines how prepurchase information that reduces consumer uncertainty about a product or service can affect consumer decisions to reverse an initial product purchase or service enrollment decision. One belief commonly held by retailers is that provision of greater amounts of information before the purchase reduces decision reversals. We provide theory and evidence showing conditions under which uncertainty-reducing information provided before the purchase decision can actually increase the number of decision reversals. Predictions generated from an analytical model of consumer behavior incorporating behavioral theory of reference-dependence are complemented by empirical evidence from both a controlled behavioral experiment and econometric analysis of archival data. Combined, the theory and evidence suggest that managers should be aware that their information provision decisions taken to reduce decision reversals may actually increase them.

Data, as supplemental material, are available at <http://dx.doi.org/10.1287/mksc.2015.0906>.

Keywords: decision reversal; product returns; service cancellations; reference-dependence

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1. Introduction

Consumers will often make a decision under uncertainty only to reverse that decision once the uncertainty is resolved. For instance, a student may choose to enroll in a course without knowing who else will be in the course or the instructor's teaching style, interpersonal communication skills, and lecture materials. After attending the first week of instruction and resolving much of this uncertainty, the student may reverse the enrollment decision by dropping the class. Similarly, consider a consumer who buys an article of clothing online. At the time of the purchase decision, the consumer does not know how well the clothing will fit or match with other elements of an outfit. On receiving the item, this consumer may determine that the clothing is misaligned with her preferences and decide to reverse the purchase decision by returning the product. Consumer actions such as returning a product and cancelling a service are decision reversals stemming from uncertainty that arises at the time of the initial decision. This research focuses on understanding how firm actions that reduce predecision uncertainty affect the likelihood of a consumer decision reversal.

Decision reversals are an important area of study because they carry significant costs to companies. When the decision reversal occurs in reservations of a service, such as enrollment in a course or an online hotel booking service, it can result in an underutilization of service-provider capacity or increased acquisition costs to replace the cancellations. When decision reversals result in product returns, a company has to repack, restock, and attempt to resell the returned units. In the electronics industry alone, product returns were estimated to cost \$16.7 billion in a single year (Douthitt et al. 2011). Across all industries in the United States, the combined value of returned goods and the cost of managing them is over \$100 billion annually (Enright 2003).

To avert these additional costs, companies frequently engage in actions intended to reduce predecision uncertainty. For example, Amazon.com shows sample pictures taken by digital cameras it has for sale. Internet eyeglass retailer Warby Parker allows consumers to upload a picture of themselves and visualize how a pair of eyeglasses would look on their face (Miller 2011). Land's End and Sears used a similar program whereby consumers could input their

physical dimensions and observe how clothing fits on a virtual model (Boone and Kurtz 2007).

In each of these cases, company information provision actions are aimed at resolving a level of uncertainty surrounding the utility a consumer will derive from owning the product (e.g., after receiving the information, the consumer learns that the camera takes good quality indoor pictures or that the frame of the eyeglasses will nicely complement her facial features). However, even with the growing amount of upfront information retailers provide, often consumers only fully ascertain the actual utility of a product after purchase. For example, consumers may not determine the actual fit of the clothes (or eyeglasses), the texture of the materials, or the hue of the color until they receive the item at home even if a website can offer a better approximation of certain features via the use of a computer model. Thus, whereas prepurchase information provided by retailers may reduce consumer uncertainty, actual utility is often not fully revealed until after purchase.

We contribute to the literature on decision reversals by developing an analytical model that uniquely incorporates behavioral theories to predict the effect of a firm providing truthful, uncertainty-reducing information on consumers' decisions to reverse a purchase. By contrast to previous analytical models that predict that decision reversals will be reduced as consumer uncertainty is eliminated (e.g., Anderson et al. 2009, Shulman et al. 2009), we draw on behavioral theory of reference-dependence to show that there may be instances in which there is an *increase* in decision reversals when consumer uncertainty is reduced yet not fully eliminated before the purchase. To our knowledge, this research is the first to incorporate behavioral theory of information processing into an analytical model of decision reversals. In addition to the analytical model, we provide empirical evidence both from experimental and archival data that support the novel prediction that uncertainty-reducing information can increase the likelihood of decision reversals. The model and data suggest that information provided to reduce decision reversals may actually increase them.

The results imply that firms should more carefully evaluate their information provision strategies. Whereas information that can fully resolve uncertainty can reduce decision reversals (e.g., product returns or service cancellations), information that only partially reduces uncertainty can lead to an increase in decision reversals. We identify conditions that will lead to this result.

2. Literature Review

Decision reversals can have important implications for firms' profitability owing to their impact on

underutilization of capacity and salvage costs associated with refund policies. Prior literature has examined the optimal refund policy in addressing the consumer's decision reversal. There is extensive research on the optimal refund policy in dealing with opportunistic consumers who purchase the product with the intent to return it after "free renting" (e.g., Davis et al. 1995, 1998; Chu et al. 1998; Hess et al. 1996). Xie and Gerstner (2007) and Guo (2009) establish equilibrium refund policies for service providers. Che (1996) and Shulman et al. (2009, 2010, 2011) find the profit maximizing partial refund for product returns when consumers are uncertain about the product fit with preferences before purchase.

A body of research looks at the effect of consumer uncertainty about product fit on firm decisions (e.g., Iyer and Kuksov 2012, Gu and Liu 2013). Previous research has examined the effect of full uncertainty resolution, before the consumer decision, on firm profits. Shulman et al. (2009) find that information that eliminates returns can also reduce profit. Xie and Shugan (2001) and Shugan and Xie (2005) show how advanced selling when consumers lack information about fit with preferences can be more profitable than spot selling at a time consumers know the fit with preferences. Kuksov and Lin (2010) and Gu and Xie (2013) find the equilibrium information revelation decisions by competing high- and low-quality firms. Ofek et al. (2011) examine how the online channel affects the level of in-store assistance provided by brick-and-mortar retailers. Whereas information that reduces product returns has been shown to reduce profit via its effect on pricing, we examine whether information can actually increase product returns. This research focuses on the consumer decision rather than the firm decision.

Although a large body of research examines product returns from a theoretical perspective, there is growing interest from empirical researchers to examine this marketing problem. For instance, Anderson et al. (2009) use a structural econometric model to estimate the utility a consumer derives from having the option to reverse the purchase decision. In a behavioral study, Wood (2001) shows that lenient return policies lead to more positive ratings of product quality and an increase in the number of people who order and ultimately keep a purchase. Bechwati and Siegal (2005) find that simultaneous versus sequential presentation of products affects product return likelihood by generating comparative versus noncomparative thoughts.

Our paper contributes to the literature on decision reversals by studying consumers' decision reversal when the initial decision is made with uncertainty about the utility that will be derived from using the product or service. A decision reversal can lead

to service cancellation or product returns. Product returns made for reasons other than uncertainty resolution such as intrachannel returns between channel partners (e.g., Cachon 2003, Gumus et al. 2013), durable good buy-backs (e.g., Desai and Purohit 1998, Desai et al. 2004, Bruce et al. 2006, Shulman and Coughlan 2007, Yin et al. 2010), and product-failure (e.g., Moorthy and Srinivasan 1995, Balachander 2001, Ferguson et al. 2006) are outside the scope of this research.

Our research also adds to the growing body of multimethod research that develops analytical models incorporating behavioral theory and empirically tests the model predictions (e.g., Amaldoss and Jain 2005, 2010; Cui and Mallucci 2013). Specifically, we incorporate the behavioral theory of reference-dependence to the analytical model, a theory that has been shown to be successful in analyzing blocks in a price contract (Lim and Ho 2007), framing a fixed fee (Ho and Zhang 2008), the labor supply (Farber 2008), product line design (Orhun 2009), newsvendor models (Ho et al. 2010), and innovation strategy (Narasimhan and Turut 2013, Chen and Turut 2013). This paper provides further evidence that modeling reference-dependency can have a substantive impact on the effectiveness of the marketing mix elements.

To summarize the contribution of this research relative to the existing literature, our model is the first to incorporate the behavioral theory of reference-dependence in examining the effect on consumer decision reversals of prepurchase information that reduces, but does not fully eliminate, consumer uncertainty. The novel prediction resulting from the analytical model is that such information may lead to an increase in the number of decision reversals. This prediction is empirically supported by a controlled experiment and empirical analysis of archival data of decision reversals.

3. Analytical Model of Decision Reversals

In this section, we build an analytical model of consumer behavior to predict how uncertainty-reducing information affects consumer decision-making as to the purchase and return of a single product (or enrollment and cancellation of a single service). The model is consistent with prior analytical work in product returns and service cancellations in many respects. Specifically, we model a two-stage decision process. In the first stage, consumers decide whether to purchase the offering. In the second stage, consumers decide whether to reverse this purchase decision. As mentioned above, the notable exception is that our model incorporates the behavioral concept of reference-dependence. According to prospect theory

(Kahneman and Tversky 1979), consumer judgments are sensitive to a point of reference. Reference-dependent models of information processing (e.g., Ho et al. 2006, Lattin and Bucklin 1989) have been shown to successfully account for (1) how consumers evaluate discounts in product bundles (Janiszewski and Cunha Jr 2004), (2) why consumers prefer discounts on a product whose actual price deviates most from the point of reference (Saini et al. 2010), (3) how consumers judge changes in brand attributes relative to initial multiattribute reference points (Hardie et al. 1993), and (4) which brands will be preferred in sequential purchases by consumers who are new to a market (Heilman et al. 2000).

3.1. Model Description

Let $U_i = \mu_i + \psi_i + \varepsilon_i$ denote the actual utility of ownership where μ_i is known before purchase, ε_i is unknown at the purchase decision, and ψ_i is the part of utility that becomes known with information provision and is otherwise unknown at the purchase decision. In the absence of information, consumers have rational beliefs that ψ_i follows a distribution with mean a , variance σ_a^2 , and probability density function $f(\psi_i)$. Consumers also have rational beliefs that $\varepsilon_i \sim U[0, 1]$. The uniform distribution of ε_i allows for parsimonious closed-form solutions as to return-probability for a given consumer. The insights of the model are robust to the assumptions about the distribution of ε_i .

We operationalize reference-dependence by allowing perceived utility to be a function of prepurchase expectations. This is consistent with the formulation in Köszegi and Rabin (2006), which is based on empirical evidence in Mellers et al. (1999) and Breiter et al. (2001). Let U_i^E denote the ex post *perceived* utility and $E[U_i]$ denote the ex ante expected utility of ownership (or service use) in the first-stage decision. Ex post perceived utility can be written as

$$U_i^E = \begin{cases} U_i + \alpha_L(U_i - E[U_i]) & \text{if } U_i < E[U_i] \\ U_i + \alpha_G(U_i - E[U_i]) & \text{if } U_i > E[U_i], \end{cases} \quad (1)$$

where α_L is a measure of reference-dependence in losses and α_G is the equivalent measure in gains.¹ We assume that the second stage decision is based on perceived rather than actual utility. The second stage decision rule is described in the following assumption.

¹ Anderson and Sullivan (1993) also start with a model in which gains or losses associated with perceived utility relative to expected utility affect outcomes. However, their model of expectation disconfirmation involves hypothesis testing, which is affected by the variance of expectations. We thank the associate editor for raising this point.

ASSUMPTION. A consumer who has made a purchase will choose to reverse the purchase decision if and only if perceived utility is less than the anticipated refund.

This assumption is consistent with behavioral findings that perceived quality depends on expectations rather than on performance alone (Hoch and Ha 1986). Whereas previous literature treats the return decision as independent of the order in which information is received, our analytical model allows for decisions to depend on the sequence that information is processed.

Next, we analytically show how uncertainty-reducing information can increase returns. We begin the analysis of a special case to demonstrate the mechanism. We subsequently relax an assumption to demonstrate the conditions that will lead to our predicted result.

3.1.1. Basic Model. In this model, we make the following simplifying assumptions. The component of utility that is known by the consumer before the initial decision is sufficiently high such that all consumers will buy (i.e., $\mu_i > P - 1 - \min \psi_i$) in the presence or absence of uncertainty reducing information. We will subsequently relax this assumption. As shown in the literature (Kahneman and Tversky 1979), losses loom larger than gains. Thus, in the interest of parsimony, we standardize $\alpha_G = 0$. We further assume a full refund of the purchase price, P . Though the decision to purchase is never suboptimal with a full refund, we assume an infinitely small purchasing hassle cost such that a consumer will make a purchase initially if and only if the expected utility of purchase is strictly greater than zero.

We analyze the model via backwards induction, first solving for the stage 2 probability of return for consumers who make a purchase and then examining the stage 1 decision to make a purchase. We first examine returns when consumers are uninformed about ψ_i and ε_i . We then examine returns when consumers are informed about ψ_i but not ε_i . We conclude this section by comparing across cases.

By law of total probability, the probability that a consumer who has purchased in stage 1 will reverse the decision and return the purchased item is $\int_{-\infty}^{\infty} \Pr(\text{Return} | \psi_i, \text{purchase}) f(\psi_i) d\psi_i$. Note that we are not assuming that the range of possibilities is infinite. Rather, we flexibly account for general distribution functions $f(\cdot)$. To calculate $\Pr(\text{Return} | \psi_i, \text{purchase})$, recall that a consumer who has purchased in stage 1 will reverse the decision and return the purchased item if $U_i^E < P$ where U_i^E is defined in Equation (1) and $E[U_i] = \mu_i + a + 1/2$. This implies that for any given ψ_i , a consumer will return the item if $\varepsilon_i < P - \mu_i - \psi_i + \alpha_L \max\{0, a + 1/2 - \psi_i - \varepsilon_i\}$. To identify the value of ε_i such that a consumer is

indifferent between keeping and returning the purchased item, we must consider whether this marginal consumer experiences a loss or gain relative to the expected utility of ownership. The former is true if $\mu_i > P - a - 1/2$; otherwise, the latter is true. Collecting terms and integrating over possible values of ε_i , the probability of a return for consumer i for any given ψ_i , is $\Pr_{\text{Lo Info}}^i(\text{Return} | \psi_i, \text{purchase}) = \max\{(2P - 2\mu_i + \alpha_L(1 + 2a))/(2 + 2\alpha_L) - \psi_i, 0\}$ if $\mu_i > P - a - 1/2$ and $\Pr_{\text{Lo Info}}^i(\text{Return} | \psi_i, \text{purchase}) = \max\{P - \mu_i - \psi_i, 0\}$ otherwise. For any consumer i who makes a purchase in stage 1, the return probability is equal to

$$\Pr_{\text{Lo Info}}^i(\text{Return} | \text{purchase}) = \int_{-\infty}^{\infty} \Pr_{\text{Lo Info}}^i(\text{Return} | \psi_i, \text{purchase}) f(\psi_i) d\psi_i. \quad (2)$$

The total number of returns in the low-information case is equal to $\Pr_{\text{Lo Info}}^i(\text{Return} | \text{purchase})$ integrated over the values of μ_i such that the consumer makes a stage 1 purchase.

We now consider the stage 1 purchase decision. A consumer purchases if the expected utility of purchase (accounting for the probability of a return and the probability of keeping) is greater than zero. The expected utility of purchase can be written as

$$\begin{aligned} E_{\text{Lo Info}}^i[\text{purchase}] &= \Pr_{\text{Lo Info}}^i(\text{Return} | \text{purchase}) \cdot 0 \\ &\quad + (1 - \Pr_{\text{Lo Info}}^i(\text{Return} | \text{purchase})) \\ &\quad \cdot E(\mu_i + \psi_i + \varepsilon_i - P | \mu_i + \psi_i + \varepsilon_i > P). \end{aligned} \quad (3)$$

Note that given a full refund, $E_{\text{Lo Info}}^i[\text{purchase}] > 0$ if and only if $\mu_i + \max_{\psi_i, \varepsilon_i} \{\psi_i + \varepsilon_i\} > P$. Thus all consumers for whom $\mu_i > P - \max\{\psi_i\} - \max\{\varepsilon_i\}$ will purchase in stage 1.

Now consider the case wherein ψ_i is known before purchase. For any given ψ_i , a consumer will return the item purchased if $\varepsilon_i < P - \mu_i - \psi_i + \alpha_L \max\{0, 1/2 - \varepsilon_i\}$. Again, the probability of a return depends on whether the indifferent consumer experiences a gain or loss relative to the subjective reference point set at prepurchase. Thus, the probability of a return is $\Pr_{\text{Hi Info}}^i(\text{Return} | \psi_i, \text{purchase}) = \max\{(2P - 2\mu_i + \alpha_L - 2\psi_i)/(2 + 2\alpha_L), 0\}$ if $\mu_i > P - \psi_i - 1/2$ and $\Pr_{\text{Hi Info}}^i(\text{Return} | \psi_i, \text{purchase}) = \max\{P - \mu_i - \psi_i, 0\}$ otherwise. For any consumer i who makes a purchase in stage 1, the return probability is equal to

$$\Pr_{\text{Hi Info}}^i(\text{Return} | \text{purchase}) = \int_{-\infty}^{\infty} \Pr_{\text{Hi Info}}^i(\text{Return} | \psi_i, \text{purchase}) f(\psi_i) d\psi_i. \quad (4)$$

In stage 1, the information about ψ_i changes the expected utility of making an initial purchase relative

to the low-information condition. By logic similar to the low-information condition, it is straightforward to show that $E_{\text{Hi Info}}^i[\text{purchase}] > 0$ if and only if $\mu_i + \psi_i + \max_{\varepsilon_i} \{\varepsilon_i\} > P$. The assumption $\mu_i > P - 1 - \min\{\psi_i\}$ results in all consumers buying initially in both information conditions.

We now compare return probabilities to identify the effect of uncertainty reducing information. First, consider $P - a - 1/2 > \mu_i > P - \max\{\psi_i\} - 1/2$.² Intuitively, the lower bound implies that the known component of utility is high enough such that there is at least one consumer who will keep the purchased item even though its actual utility is less than its expected utility in the high-information condition. The upper bound implies consumers in the low-information condition only keep the purchased item if it represents a gain relative to expected utility. For a given $\psi_i > P - \mu_i - 1/2$, the effect of information on return probability for any μ_i can be written as

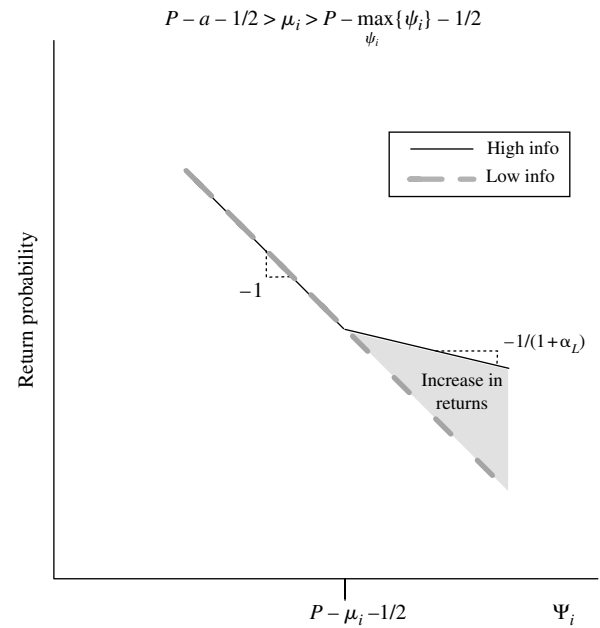
$$\begin{aligned} & \Pr_{\text{Hi Info}}^i(\text{Return} | \psi_i, \text{purchase}) \\ & - \Pr_{\text{Lo Info}}^i(\text{Return} | \psi_i, \text{purchase}) \\ & = (\alpha_L / (1 + \alpha_L))(\mu_i - P + \psi_i + 1/2). \end{aligned}$$

The above is positive by virtue of applying to the case $\psi_i > P - \mu_i - 1/2$. For a given $\psi_i < P - \mu_i - 1/2$, the information has no effect on return probability because all consumers who experience a loss relative to expectations reverse their decision in both information conditions (and thus the marginal consumer who is indifferent between keeping and returning experiences a gain). This is graphically depicted in Figure 1.

Figure 1 shows the return probability in the intermediate range of μ_i . For $\psi_i < P - \mu_i - 1/2$, the return probability as a function of ψ_i has a slope of -1 in either information condition. In this region, the marginal consumer indifferent between maintaining and reversing the purchase decision experiences a gain relative to expectations. The slopes are identical because $\alpha_G = 0$, an assumption we remark on following the analysis. For $\psi_i > P - \mu_i - 1/2$, the marginal consumer in the high-information condition experiences a loss relative to expectations. In this region, the slope in the high-information condition flattens because a higher ψ_i not only increases the utility of keeping the good (or service) but also decreases the perceived utility due to heightening the expected utility of ownership. Note that the shaded region denoting the difference between the high-information condition and the low-information condition is increasing in size as the loss aversion parameter α_L increases.

² Note that this condition is compatible with our assumption on μ_i provided $a - \min\{\psi_i\} < 1/2$. In other words, the average value of ψ_i must be within a range of its minimum.

Figure 1 Return Probability for Intermediate Known Value



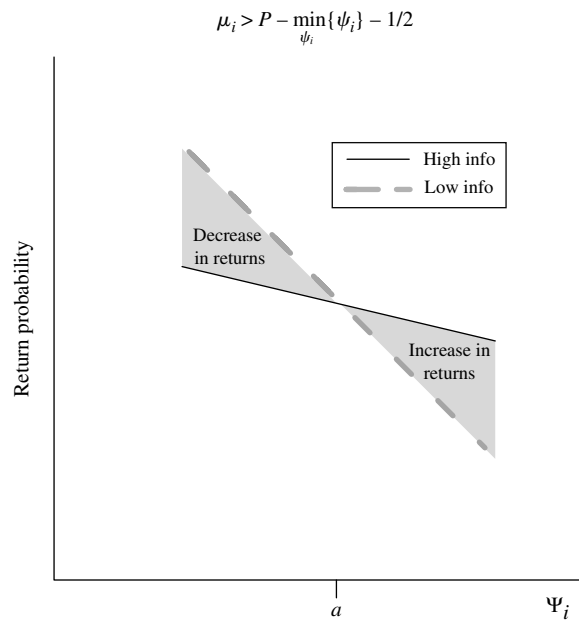
Moreover, this region disappears in the absence of loss aversion (e.g., $\alpha_L = 0$).

Now consider $\mu_i > P - \min\{\psi_i\} - 1/2$. This condition represents when the known component of utility is high enough such that there is at least one consumer, regardless of the amount of information, who will keep the product even though the actual utility is less than the expected utility. In other words, the marginal consumer who is indifferent between keeping and returning experiences a loss relative to expectations. For a given ψ_i , the difference in return probability is $\alpha_L(\psi_i - a)/(1 + \alpha_L)$. Intuitively, the return probability for a given ψ_i is increasing (decreasing) in information if the information reveals that ψ_i is greater than (less than) the mean value of ψ_i . Thus, the effect of information on return probability for any μ_i can be written as

$$\begin{aligned} & \Pr_{\text{Hi Info}}^i(\text{Return} | \text{purchase}) - \Pr_{\text{Lo Info}}^i(\text{Return} | \text{purchase}) \\ & = \int_{-\infty}^{\infty} (\alpha_L(\psi_i - a)/(1 + \alpha_L)) f(\psi_i) d\psi_i = 0. \end{aligned} \quad (5)$$

Figure 2 illustrates what happens to the return probability when the known utility is reasonably high. The slope of return probability as a function of ψ_i is flatter in the high-information condition than the low-information condition for reasons discussed above. Because the known utility is sufficiently high, consumers in both high- and low-information conditions will reverse the decision only if there is a loss relative to expectations. Thus, any increase in return probability for consumers with above average ψ_i is offset by an equal decrease in return probability by

Figure 2 Return Probability for High Known Value

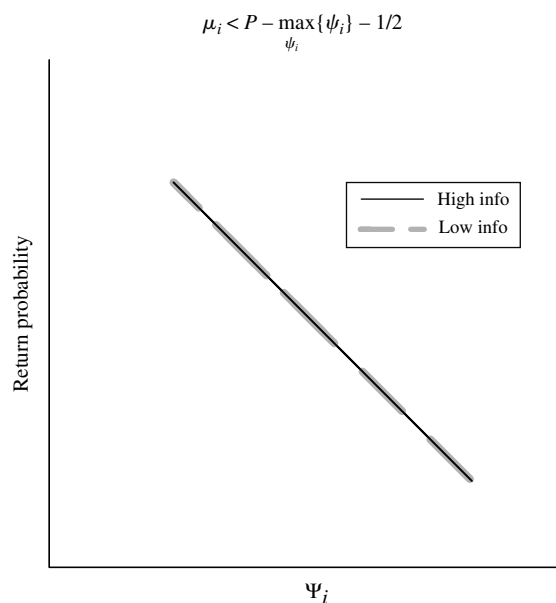


consumers with below average ψ_i , regardless of the loss-aversion parameter.

Next consider $\mu_i < P - \max\{\psi_i\} - 1/2$. This condition represents the case wherein the known component utility is low enough such that the only way a consumer keeps the product, regardless of the information, is if she experiences a gain relative to the expected utility. The return probability is equal across conditions.

Figure 3 demonstrates that when the known utility component is sufficiently low, the return probability as a function of ψ_i is the same for the high- and

Figure 3 Return Probability for Low Known Value



low-information conditions: $P - \mu_i - \psi_i$. By contrast to Figure 2, we see that for high μ_i the increase in return probability for high ψ_i is offset by a decrease in the return probability for low ψ_i , whereas for low μ_i , the return probability is the same in each information condition.

PROPOSITION 1. *In the basic model in which all consumers buy initially regardless of information condition, the effect of the known utility component on the relationship between information and returns is nonmonotonic. Specifically, prepurchase uncertainty-reducing information increases returns if $P - \min_{\psi_i}\{\psi_i\} - 1/2 > \mu_i > P - \max_{\psi_i}\{\psi_i\} - 1/2$ and has no effect on returns if $\mu_i > P - \min_{\psi_i}\{\psi_i\} - 1/2$ or if $\mu_i < P - \max_{\psi_i}\{\psi_i\} - 1/2$. The effect of information on returns is positive only if $\alpha_L > 0$.*

See the appendix for the proof.

Proposition 1, to our knowledge, is the first in the literature to establish that prepurchase information can *increase* returns. The intuition for the result is as follows. Information will reveal that, for some consumers, a utility component is high. This raises the expected utility of ownership and thus increases the probability that these consumers experience a loss relative to ex ante expectations. With loss aversion, ex post utility is diminished and thus returns are increased. Note that the effect of information on returns is positive only if $\alpha_L > 0$. Moreover, the increase in returns is an increasing function of α_L . This effect outweighs the effect on returns from consumers who learn that a utility component is low because losses loom larger than gains.

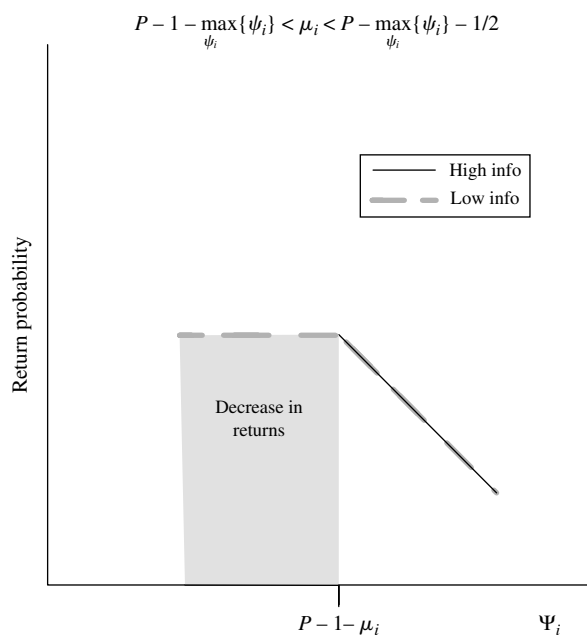
We now briefly consider how the results are affected by a partial return policy. If refund R is less than price P , then $\Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \max\{(2R - 2\mu_i + \alpha_L(1 + 2a))/(2 + 2\alpha_L) - \psi_i, 0\}$ if $\mu_i > R - a - 1/2$ and $\Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \max\{R - \mu_i - \psi_i, 0\}$ otherwise. In the high-information condition $\Pr_{\text{Hi Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \max\{(2R - 2\mu_i + \alpha_L - 2\psi_i)/(2 + 2\alpha_L), 0\}$ if $\mu_i > R - \psi_i - 1/2$ and $\Pr_{\text{Hi Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \max\{R - \mu_i - \psi_i, 0\}$. Note that in each information condition, $\Pr^i(\text{Return}|\psi_i, \text{purchase})$ decreases as R decreases. Thus, given conditions such that all consumers initially buy the product, a partial refund results in fewer returns. A partial refund will result in a utility loss for the consumer when a return occurs. Thus, the value of μ_i such that all consumers buy initially is higher when $R < P$ than when there is a full refund. A decrease in R will shift the cut-offs in μ_i such that uncertainty-reducing information increases returns, but the range (i.e., the difference between the upper and lower cut-offs) is unaffected.

3.1.2. Model of Information-Contingent Purchases. In this model, we relax the assumption that $\mu_i > P - 1 - \min_{\psi_i}\{\psi_i\}$ and allow for consumers not to

make a purchase depending on the realization of ψ_i . Because of the infinitely small hassle cost of purchase, a consumer will make a purchase if and only if the expected utility of purchase is strictly positive. Suppose $P - 1 - \max_{\psi_i} \{\psi_i\} < \mu_i < P - 1 - \min\{\psi_i\}$. As shown above, the lower bound implies that all consumers buy in stage 1 in the low-information condition. However, the upper bound implies that not all consumers will buy in the high-information condition. We first analyze returns in the low-information condition.

For a given ψ_i , realized after purchase, we use the established logic to identify $\Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase})$. If $P - 1 - \max_{\psi_i} \{\psi_i\} < \mu_i < P - \max_{\psi_i} \{\psi_i\} - 1/2$, then the marginal consumer who is indifferent between keeping and returning will experience a gain relative to expectations. In the low-information condition, consumers with $\psi_i < P - 1 - \mu_i$ have $\Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase}) = 1$ and consumers with $\psi_i > P - 1 - \mu_i$ have $\Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase}) = P - \mu_i - \psi_i$. All consumers in the low-information condition buy because ψ_i is unknown at the time of purchase and $P - 1 - \max_{\psi_i} \{\psi_i\} < \mu_i$ ensures a positive probability of experiencing $\mu_i + \psi_i + \varepsilon_i > P$. However, in the high-information condition, consumers are aware of ψ_i before purchase. Consumers with $\psi_i < P - 1 - \mu_i$, find zero probability of $\mu_i + \psi_{i1} + \varepsilon_i > P$ and thus do not buy in stage 1. Consumers with $\psi_i > P - 1 - \mu_i$ have $\Pr_{\text{Hi Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase})$. Thus for a given μ_i , information results in a change in returns equal to $-\int_{-\infty}^{P-1-\mu_i} f(\psi_i) d\psi_i < 0$. Figure 4 shows the effect of information on returns.

Figure 4 Return Probability for Low Known Value When Purchase Depends on Information



Now suppose $P - \max_{\psi_i} \{\psi_i\} - 1/2 < \mu_i < \min\{P - a - 1/2, P - 1 - \min_{\psi_i} \{\psi_i\}\}$. In the low-information condition, the $\Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase}) = 1$ if $\psi_i < P - \mu_i - 1$ and $\Pr_{\text{Lo Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \max\{P - \mu_i - \psi_i, 0\}$ if $\psi_i > P - \mu_i - 1$. In the high-information condition, consumers with $\psi_i < P - \mu_i - 1$ will not purchase in stage 1. Consumers with $P - \mu_i - 1/2 > \psi_i > P - \mu_i - 1$ have $\Pr_{\text{Hi Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \max\{P - \mu_i - \psi_i, 0\}$. Consumers with $\psi_i > P - \mu_i - 1/2$ have $\Pr_{\text{Hi Info}}^i(\text{Return}|\psi_i, \text{purchase}) = \max\{(2P - 2\mu_i + \alpha_L - 2\psi_{i1})/(2 + 2\alpha_L), 0\}$. The effect of information on returns is shown in Figure 5.

Thus for a given μ_i , information results in a change in returns equal to $-\int_{-\infty}^{P-1-\mu_i} f(\psi_i) d\psi_i + 0 + \int_{P-\mu_i-1/2}^{\infty} (\alpha_L/(1 + \alpha_L))(\mu_i - P + \psi_i + 1/2)f(\psi_i) d\psi_i$, where the first term is negative and the final term is positive. Note that this expression is increasing in μ_i . This leads to the following proposition.

PROPOSITION 2. *There exists $\bar{\mu}$ such that information will weakly decrease returns if $\mu_i < \bar{\mu}$.*

Proposition 2 shows the conditions under which the standard result occurs, i.e., that information reduces returns. If the consumer's known utility component is sufficiently low, then some consumers will find that, with additional information, a purchase would result in a return. As such, both purchases and returns are decreased by uncertainty-reducing information. This proposition shows that the results of prior literature can be nested within our modeling framework.

In §3.2, we summarize the conditions that lead to our novel result (Proposition 1) versus the conditions that lead to the standard result (Proposition 2).

Figure 5 Return Probability for Intermediate Known Value When Purchase Depends on Information

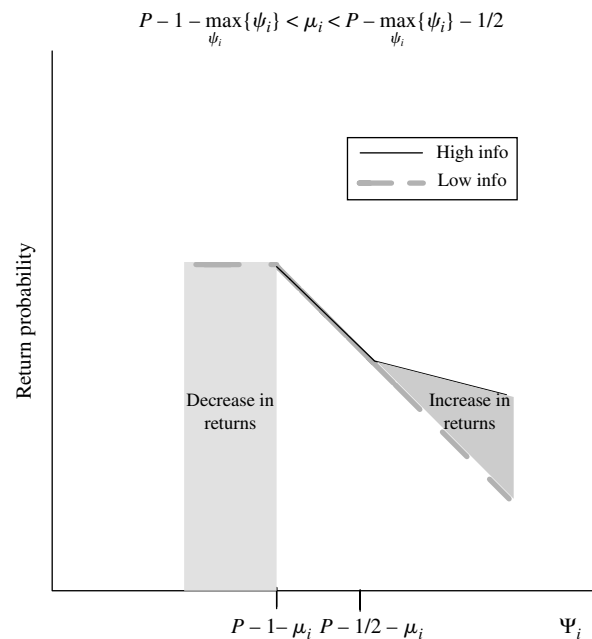


Table 1 Summary of Analytical Results

Range of known values	Purchase prevention effect of information on returns	Subrange of known value	Marginal loss aversion effect of information on returns	Net effect of information on returns
Low μ_i (i.e., $\mu_i < \bar{\mu}$)	—	Lower μ_i $\mu_i < \hat{\mu}$	0	—
		Higher μ_i $\min(\bar{\mu}, \check{\mu}) > \mu_i > \hat{\mu}$	+	±
High μ_i (i.e., $\mu_i > \bar{\mu}$)	0	Lower μ_i $\mu_i < \hat{\mu}$	0	0
		Intermediate μ_i $\bar{\mu} > \mu_i > \hat{\mu}$	+	+
		Higher μ_i $\mu_i > \bar{\mu}$	0	0

Note. $\bar{\mu} = P - 1 - \min_{\psi_i} \{\psi_i\}$, $\check{\mu} = P - a - 1/2$, $\hat{\mu} = P - \max_{\psi_i} \{\psi_i\} - 1/2$, $\tilde{\mu} = P - \min_{\psi_i} \{\psi_i\} - 1/2$.

3.2. Summary of Analytical Findings

The analytical model demonstrates a tension in the effect of information on returns. On one hand, information may reveal a poor fit before purchase and prevent purchases from consumers who would otherwise reverse the purchase decision. This *purchase prevention effect* is present for consumers with sufficiently low μ_i . On the other hand, information may increase the expected utility of purchase and increase returns due to diminished perceived value post-purchase. This *marginal loss aversion effect* is less straightforward.

As can be seen in Figures 1–5, the *marginal loss aversion effect* occurs when the return probability as a function of ψ_i is kinked. In other words, the effect exists if knowing ψ_i changes whether the marginal consumer experiences a gain or loss relative to expectations. If the return probability function is not kinked because μ_i is low, then the return probability for each realization of ψ_i is the same across information conditions. If the return probability function is not kinked due to high μ_i , then any increase in the return probability for high ψ_i is offset by the decrease in return probability for low ψ_i .

This intuition facilitates exploring the robustness to reference dependence in gains (i.e., $\alpha_G > 0$). If $\alpha_G = \alpha_L$, then there will be no kink in the function. As such, the *marginal loss aversion effect* disappears. However, if $0 < \alpha_G < \alpha_L$, as is generally accepted in behavioral research (e.g., Kahneman and Tversky 1979) based on the principle that losses loom larger than gains, the slope of the return probability function in gains is flatter than in the current model, but not as flat as the function in losses. Thus, the marginal loss aversion effect would be dampened because information would decrease returns for low realizations ψ_i . The increasing effect on returns persists, however, because losses loom larger than gains. Thus, the greater $\alpha_L - \alpha_G$ is, the greater the increase in returns associated with information. Table 1 summarizes the cases wherein the purchase prevention effect and the marginal loss aversion effect arise.

Table 1 highlights when each of the established effects are in play. If consumers are homogeneous in μ_i , then Table 1 summarizes the condition on this parameter such that information increases or decreases returns. If consumers are heterogeneous in μ_i , then one can infer from Table 1 that information increases returns on an aggregate level if μ_i is skewed such that there is a greater density of consumers for whom $\mu_i > \bar{\mu}$ than $\mu_i < \bar{\mu}$.

OBSERVATION. Uncertainty-reducing information is more likely to increase returns with a left-skewed distribution of the known-utility component.

We note that, in the interest of parsimony, our model abstracts from another information effect. Under a partial return policy, information can reduce the risk associated with purchase. As can be concluded from Desai et al. (2008) and Roberts and Urban (1988), consumers have a preference for an option that allows them to reduce risk. Thus, prepurchase information may increase purchases by risk-averse consumers. Coupled with the effect of reference-dependent judgments after purchase, this would result in a greater number of returns than in our current model.

4. Overview of the Empirical Testing

To our knowledge, empirical evidence supporting the novel analytical prediction that uncertainty-reducing information may lead to an increased likelihood of decision reversals is, at best, lacking. We used a two-prong approach to provide such empirical evidence. First, we designed a controlled experiment in which we manipulated levels of the amount of information provided at prepurchase and leniency of the return policy in a scenario designed to be consistent with higher levels of μ_i . Second, we analyzed the archival enrollment data of actual decisions from a major university's registration record to allow us to support the external validity of the link between uncertainty-reducing information provisions and purchase-reversal decisions.

4.1. Experiment

We test the impact of uncertainty-reducing information on decision reversals by emulating a situation in which information decreases, but does not eliminate, uncertainty at prepurchase. To test the extent to which the predictions are sensitive to the refund policy, we also manipulated the leniency of the return policy. To truly isolate the effect of the amount of information, we used unfamiliar technical attributes to control for performance expectations based on attribute knowledge.

4.1.1. Method. Participants were 420 Amazon Mechanical Turk workers (42.4% male, average age = 36 years) who participated in the experiment in exchange for monetary compensation. The design of the experiment was a 3 information level (low versus medium versus high) by 2 return policy leniency (high full refund versus low 15% restocking fee) between-subjects design. We manipulated the return policy to observe whether the results are replicated for partial refunds. Participants were randomly assigned to one of six conditions.³

Participants were told they would be making decisions about the purchase of a humidifier. They were given information describing five health benefits of using a humidifier and told to assume that they were interested in these benefits⁴ as a way to induce a higher value of μ_i . They were told that experts generally agree that the key attributes found in high-performing humidifiers are air flow, bucket capacity, coil temperature, evaporation rate, feed rate, mist volume, and temperature operation. These constituted the full set of information that defined the utility of the product. Next, participants were asked to assume that they had found a humidifier from a retailer they trusted at the price they were willing to pay for this type of product (\$199). The amount of uncertainty-reducing information was manipulated by telling participants that they were unable to verify information about all seven attributes given their own time constraints. Participants were then presented with a two-column table with the seven attributes in the left column (order of presentation randomized based on a random sequence generated by random.org) and information about each attribute in the right column (varying according

to the information-amount condition). In the low-, medium-, and high-information conditions, participants received information about two, four, and six of the seven attributes, respectively. Column cells for the undisclosed attribute levels were filled with question marks. To isolate the potential effect of the amount of information on performance (relative to a situation wherein attributes communicate meaningful benefits), attribute information was selected to be technical, and described in unfamiliar terms. This allowed us to decrease the effects of prior knowledge and to more closely examine the effect of the amount of information in setting a reference point. The attribute levels for the seven attribute levels were: 120 CBM/hour, maximum of 18.6 pints, below 13°C, 0.70 gph, 3 gph, 3 Kg/hour, and operates in temperatures below 30°C.

Participants were asked to review the return policy of the store, which was a full refund (i.e., if you buy the humidifier and decide to return it later, you will get the full price \$199 back) or a partial refund 15% restocking fee (i.e., if you buy the humidifier and decide to return it later, you will get \$169 back). These denote the high- and low-lenieny conditions, respectively. Participants were then asked to indicate the likelihood that they would buy the humidifier on a 101-point scale (ranging from 0—very unlikely, to 100—very likely), and to rate how well they expected the humidifier to perform (on a 101-point scale ranging from 0—not well at all, to 100—very well).

After an unrelated five-minute filler task designed to erase participants' short memory, participants were asked to assume that they had purchased the humidifier and that they had the opportunity to take the humidifier home and learn more about the full set of attributes. This was designed to simulate a situation in which the value of μ_i is high such that all consumers buy the humidifier (as in Proposition 1). The picture of the humidifier along with the table featuring the fully disclosed attribute values was then presented and participants were asked to rate the likelihood that they would return the humidifier on a 101-point scale (ranging from 0—very unlikely to 100—very likely). This was the key dependent measure in this experiment. A number of additional measures with respect to manipulation checks, attribute familiarity, retailer intentions, attribute desirability, and attention recall checks were also collected; these measures are described in the appendix.

4.1.2. Results. The manipulation checks showed that the manipulations were successful in affecting participants' perception of the amount of information and the store return policy. The analysis also showed that participants perceived the set of attributes to be

³ Data was collected in two different points in time (approximately five months apart) per request of the review team. Variable controlling for this time lag in data collection is included in all analyses reported hereafter. Given the lack of statistical significance of this variable in the analyses, results are reported collapsed across the two points in time.

⁴ Adapted from <http://www.fitsugar.com/5-Reasons-Why-Important-Own-Humidifier-14569814>.

largely unfamiliar, increasing the odds that any effects observed are likely to stem from the amount of information rather than from attribute knowledge (the full set of results are presented in the appendix).

We performed an analysis of covariance (ANCOVA) on the post-purchase likelihood-to-return measure using the information amount and return policy factors (and the data collection time variable) as independent variables and using the likelihood to buy the humidifier measure as a control variable with likelihood to return as the dependent measure. This analysis revealed a statistically significant effect of the information amount ($F(2,407) = 4.38, p = 0.01$), refund policy ($F(1,407) = 7.21, p = 0.01$), and the likelihood to buy control variable ($F(1,407) = 16.82, p = 0.01$) on the likelihood to return the product. We also analyzed the data using only participants who correctly recalled the refund amount in the scenario. This new analysis ($n = 369$) indicated that these participants were noise in the data as shown by the strengthening of the results despite the 12% drop in sample size. Again, the information amount had a statistically significant effect on the likelihood to return the humidifier ($F(2,356) = 6.38, p < 0.01$). Pairwise comparisons showed that participants in both the high-information ($M = 34.81$) and medium-information ($M = 36.08$) conditions reported a greater likelihood to return the product than their counterparts in the low-information condition ($M = 25.26$, both p -values < 0.01).⁵ There was also a greater tendency to return the product in the full-refund condition ($M = 36.00$) than in the restocking fee condition ($M = 28.11; F(1,356) = 8.90, p < 0.01$).

Supporting our hypothesis that information increases expectations against which actual performance is judged, the expected product performance participants held increased as the number of pieces of information available at prepurchase increased ($M_{\text{low}} = 45.31, M_{\text{medium}} = 52.69, M_{\text{high}} = 58.34; F(2,408) = 6.79, p < 0.01$). The interaction between information amount and return policy ($p > 0.15$) did not reach statistical significance.

Consistent with the analytical model, we find that a greater provision of information at prepurchase indeed leads to a greater likelihood to return the purchased humidifier when the value μ_i is high. This result holds despite participants' low stated familiarity with the product attributes. Combined with the finding that larger amounts of information lead to increased perceived product performance, this result is inconsistent with an alternative expectation-disconfirmation account for our findings. Given that participants were unfamiliar with the product attributes,

and were not provided with posterior attribute performance information that disconfirms prepurchase information, an expectation-disconfirmation explanation is unlikely to account for our results.

Overall, the predictions of the model were confirmed within a controlled experiment test designed to isolate and manipulate the levels of the key amount of information variable of interest. One potential shortcoming stemming from this controlled test of the predictions is the extent to which this intended decision-reversal behavior could also be observed for actual behavior. We address this issue in §4.2.

4.2. Empirical Analysis of Archival Returns Data

To test the prediction that uncertainty-reducing information can lead to an increase in actual decision reversals, we collected archival enrollment data from a major university's registration records. In line with the analytical model, a university course is a bundle of attributes (e.g., lecture materials, reading materials, assignments, peer interaction, instructor teaching style and interpersonal communication skills, etc.) that a student may choose to purchase by enrolling in the course. A student will reverse their decision and drop the course if the utility derived from these attributes is less than the value of the net refund resulting from the decision reversal. Here the net refund captures the value to the student of the time and/or tuition dollars that are returned to the student or their parents. We examine how additional information about the course available at the purchase decision affects the number of decision reversals. Prepurchase information can resolve uncertainty about certain attributes of the course (e.g., assignments, topics covered), but cannot resolve all uncertainty (e.g., lecture materials, instructor's teaching style, and the quality of other students enrolled in the course) before the first day or week of classes. Because the refund value is uncorrelated with information provision, any effect on returns of prepurchase information will be driven by the effect on perceptions of the value of keeping the course.

4.2.1. Data Description. The archival data was obtained from the university time schedule and matched with aggregate purchase (i.e., adding into the course) and decision reversal (i.e., dropping the course) data collected from the university registrar's office. The time schedule, as viewed by students at the time of registration, contains the following information used in our analysis: department, course level, days of instruction, time of instruction, current enrollment, and maximum enrollment. Whereas all courses in the time schedule have titles and links to a brief course description (typically two or three sentences), some courses also provide an external link to a more detailed syllabus. The presence/absence of a link to

⁵ The same pattern of results is found when using the full sample both in terms of means and statistical significance at an alpha level of 0.05.

this additional information for a course offering is the key independent variable of interest as it replicates the situation wherein more (versus less) information is available before purchase. Additional details about the data collection procedure are presented in the appendix.

4.2.2. Empirical Methodology. The unit of analysis is a course (j). The number of drops for a given course during the first week of classes, $DROPS_j$, is the dependent variable of interest. Because the number of drops is an integer greater than or equal to zero, we consider the following relationship between drops and course characteristics:

$$\begin{aligned} DROPS_j = \exp(&\alpha + \gamma_1 INFO_j + \gamma_2 DAY_j \\ &+ \gamma_3 TIME_j + \gamma_4 YEAR_j + \gamma_5 REQ_j \\ &+ \gamma_6 LIMIT_j + \gamma_7 DEPT_j + \gamma_8 LEVEL_j) \\ &+ \varepsilon_j. \end{aligned} \quad (6)$$

The key variable of interest is INFO, which is a binary variable indicating whether there was a more detailed course description available at the time of registration. The model also accounts for other factors that affect a student's decision to drop a course. On the right-hand side of Equation (6), we include dummy variables indicating whether the class met Mondays and Wednesdays or Tuesdays and Thursdays (DAY); whether the class met early morning, i.e., before 10:30 A.M., late morning, i.e., between 10:30 A.M. and 12:20 P.M., early afternoon, i.e., between 1:30 P.M. and 3:20 P.M., late afternoon, i.e., 3:30 P.M. and after (TIME); the academic year in which the course was offered (YEAR); whether the course was required for a business degree (REQ); the department in which the course was offered (DEPT); and whether the course level was 300 or 400 (LEVEL). We also account for the course enrollment limit (LIMIT), which ranges from 19 to 125 in our data. As a benchmark to determine the additional model fit of including INFO, we examine a modified version of Equation (6) in which the INFO variable is not included.

4.2.3. Endogeneity and Estimation. Because the decision to post additional information during registration is made by the instructor, it may be correlated with the error term (ε_j) owing to a simultaneity bias. In other words, the number of drops may depend on the information provided by the instructor, and the instructor's information provision may depend on the (expected) number of students who will drop the course or on an omitted factor that also affects drops (e.g., instructor confidence in material or rigor). In the appendix, we fully describe the procedures used to control for endogeneity and to create instrumental variables (PERCENTDEPT and PERCENTTIME).

Given the characteristics of our data (count dependent and binary endogenous variables) we use the instrumental variable Pseudo Poisson Maximum Likelihood (PPML) estimator technique described in detail in Windmeijer and Santos Silva (1997). Given the vector X_j of exogenous covariates described above and in Equation (6), the model is specified as

$$\begin{aligned} DROPS_j &= \exp(\alpha y_j^* + X_j' \gamma) + \varepsilon_j, \\ y_j^* &= \beta_1 PERCENTDEPT_j + \beta_2 PERCENTTIME_j + \xi_j, \\ \text{Cov}(\varepsilon_j, \xi_j) &= \begin{bmatrix} \sigma_{1j}^2 & \sigma_{12j} \\ \sigma_{12j} & 1 \end{bmatrix}, \end{aligned}$$

where y_j^* is a latent endogenous variable capturing the proclivity to post syllabus information and $E[\varepsilon_j | X_j, PERCENTDEPT_j, PERCENTTIME_j] = 0$. Simultaneity arises through the correlation of ε_j and ξ_j . The PPML estimator is shown to be consistent without requiring assumptions about the distribution of the error terms (Windmeijer and Santos Silva 1997). In fact, the data do not have to be Poisson for the PPML estimator to be consistent (Gourieroux et al. 1984, Santos Silva and Tenreiro 2006). The PPML approach has been shown to appropriately estimate parameters when the dependent variable has a large number of zeroes (Santos Silva and Tenreiro 2010, 2011) and thus is appropriate for our data for which 34 of 202 courses had no drops. The estimation was programmed in STATA.

4.2.4. Empirical Results. We first established a benchmark against which we could observe whether the fit of the model improved once we added the information-level variable (i.e., model presented in Equation (5) excluding the INFO variable). This model was estimated using a one stage PPML estimation (Pseudo R -square = 0.36, adjusted R^2 = 0.30; Table 2).

Instrumental Variable PPML Estimation. The second model estimated included the key variable of interest (INFO) in addition to the variables in the benchmark model (i.e., model presented in Equation (6)). The second stage of the regression (PPML) showed that the effect of the information level variable on the number of students who drop a class is positive and statistically significant ($\beta = 0.29$; $z = 2.01$, $p = 0.02$; Table 2), indicating greater levels of decision reversals (i.e., course drops) when more (versus less) information was available at prepurchase. The model also showed a strong improvement in fit relative to the benchmark model that did not include the INFO variable (Pseudo R -square = 0.64, adjusted R^2 = 0.60; Table 2). The instruments were shown to be strong with large values of adjusted R^2 (0.92) and partial R^2 (0.91) and an F -statistic ($F(2, 184) = 322.43$, $p < 0.0001$) well above the threshold of 10 proposed by Staiger and Stock (1997). This indicates that the estimates of

Table 2 Empirical Model Coefficients

	Baseline PPML model	Instrumental variable PPML model
Coefficients		
(Constant)	−0.501 (0.310)	−0.157 (0.281)
Course information		0.293** (0.146)
Day of classes	0.258** (0.104)	0.270** (0.102)
Course level	0.067 (0.130)	−0.055 (0.127)
Year_2009	0.288* (0.173)	0.287* (0.169)
Year_2010	0.206 (0.194)	0.242 (0.177)
Year_2011	0.297 (0.207)	0.226 (0.203)
Year_2012	0.254 (0.195)	0.400** (0.185)
Finance	0.780*** (0.205)	0.732*** (0.211)
Management	0.979*** (0.212)	0.913*** (0.211)
Marketing	0.317 (0.206)	0.270 (0.209)
ISOM	0.165 (0.285)	−0.218 (0.261)
Late morning	−0.205 (0.155)	−0.232 (0.150)
Early afternoon	−0.014 (0.161)	−0.123 (0.164)
Late afternoon	0.285* (0.169)	0.344** (0.155)
Course required	0.091 (0.211)	0.216 (0.190)
Class enrollment limit	0.014*** (0.004)	0.008** (0.003)

Notes. We used the variance inflation factors (VIFs) from an ordinary least squares (OLS) regression as a measure of multicollinearity. The highest VIF was 2.14 (mean VIF = 1.68), which is well below the recommended threshold of 10. Thus, multicollinearity does not appear to be an issue. Standard errors are in parentheses.

*Significant at $p < 0.10$; **significant at $p < 0.05$; ***significant at $p < 0.01$.

the coefficients are likely unbiased. Overidentification restrictions also do not seem to be an issue in our estimation (Hansen's $J \chi^2(1) = 2.02, p > 0.10$), supporting the assumption of exogeneity of the instruments (Baum 2006).

We further tested the robustness of our results by capturing the likelihood of decision reversal as measured by the proportion of students who dropped each course relative to the total number of students enrolled in each course on the first day of classes. We estimated two models using a fractional response probit model with instrumental variables (ivprobit syntax in STATA). The first model estimated was identical to the full PPML model except that the dependent measure was the proportion of students who dropped the course. In the second fractional response model we removed the control *class_limit* because the number of students enrolled on the first day of classes (the denominator in the proportion) could be strongly influenced by the class-size limit. Both analyses replicated the overall pattern of results with the variable of interest INFO rendering positive and statistically significant estimates in both models ($\beta = 0.234, Z = 2.53, p = 0.01$, and $\beta = 0.227, Z = 2.45, p = 0.01$).⁶

⁶ Given that PPML estimation has been shown to be consistent for any nonnegative distribution, we also estimated both models using this estimation technique. The same pattern of results was found ($\beta = 0.44, Z = 2.67, p < 0.01$, and $\beta = 0.41, Z = 2.42, p = 0.02$).

4.2.5. Empirical Results Discussion. Controlling for a variety of factors that could influence the number of students who drop a course and, accounting for endogeneity, we found that university course descriptions that offer a greater amount of prepurchase information show a greater number of decision reversals (i.e., course drops) relative to courses that offer less prepurchase information. Thus, the data from actual decisions support the prediction that information reducing uncertainty before purchase can increase the number of service cancellations.

5. General Discussion

This research examined how truthful prepurchase information that decreases (but does not fully resolve) uncertainty influences decision reversals. We draw on behavioral theory of reference-dependence to derive a model predicting that the provision of uncertainty-reducing prepurchase information can actually increase the likelihood that consumers will reverse their purchase decision. This research, the first to derive an analytical model of decision reversals from behavioral theory and the first to establish the consequences of reference-dependence in the context of decision reversals, sheds light on the consumer's information processing when deciding whether to reverse a decision as well as on the potential implications for marketers. The proposed model parsimoniously predicts situations wherein greater levels of information reduces or increases decision reversals. To our knowledge, the latter result is novel in the literature and at odds with current marketplace practices.

In both validation studies, information about a dimension of the product was revealed before purchase but full evaluation was not possible until after purchase. Thus, our findings apply to the many market situations wherein a consumer's uncertainty is only partially resolved before purchase. Examples of these situations are the three-dimensional computer models used by online retailers to reduce uncertainty around the physical fit of clothing or accessories, the test driving of cars, and the trial of sound equipment in artificial settings designed to enhance sound performance. In each case, the information about a set of attributes changes the expectations of overall product utility and affects the overall evaluation after purchase when the remaining dimensions are ultimately revealed in full. Thus, compared to a consumer who did not have the prepurchase information, the consumer who learns that a particular size of clothing will fit well may be more likely to return it.

In some instances, consumers choose between multiple products rather than between buying and not buying. In these cases they may have the option to exchange the product (rather than simply return it).

When choosing among multiple products, there are two conflicting effects of uncertainty-reducing information. On one hand, uncertainty-reducing information may help a consumer rule out specific alternative products *ex ante* that would be returned if purchased in a situation where information had not been provided (as shown in Proposition 2). On the other hand, we have found that uncertainty-reducing information can increase expectations and thus diminish the perceived utility of the purchase. This latter effect is present whether the outside option is a refund or an alternate product. Which of the two effects is dominant depends on the importance of the revealed attribute(s) in decision making and the degree of uncertainty about the relative value of each product and the remaining attributes that are unknown at the time of purchase. For example, if the type of fabric is most important in a clothing purchase but is unknown at the time of purchase, a computer model demonstrating the physical fit of each alternative should produce decision reversal effects in line with our predictions.

Future research can also examine decision reversals in both directions. An interesting area of study would be the consequences when uncertainty is fully revealed at a later date regardless of purchase. This would precipitate the possibility for consumers to change from nonpurchase to purchase.

In summary, this paper provides theory and evidence that prepurchase information may increase decision reversals in ways not predicted by the existing literature. The findings suggest that information intended to reduce reversals may actually have the opposite and undesired effect. Therefore, marketers should investigate their own cost structure and carefully consider how their prepurchase information may be viewed when contemplating tactics to reduce consumer uncertainty.

Supplemental Material

Supplemental material to this paper is available at <http://dx.doi.org/10.1287/mksc.2015.0906>.

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Appendix

PROOF OF PROPOSITION 1. From the text, if $P - a - 1/2 > P\mu_i > P - \max_{\psi_i}\{\psi_i\} - 1/2$, then information increases returns by an amount of $\int_{P-\mu_i-1/2}^{P-\mu_i+\alpha_L/2} (\alpha_L(\mu_i - P + \psi_i + 1/2)/$

$(1 + \alpha_L))f(\psi_i) d\psi_i$. This is zero if $\alpha_L = 0$ and is increasing in α_L . If $\mu_i > P - \min_{\psi_i}\{\psi_i\} - 1/2$, then information has no effect on returns because any increase is offset by an equivalent decrease.

Consider now $P - \min_{\psi_i}\{\psi_i\} - 1/2 > \mu_i > P - a - 1/2$.

CLAIM.

$$\Pr_{\text{Hi Info}}^i(\text{Return} | \text{purchase}) > \Pr_{\text{Low Info}}^i(\text{Return} | \text{purchase}).$$

PROOF. If $\psi_i < P - \mu_i - 1/2$, then $P - \mu_i - \psi_i > (2P - 2\mu_i + \alpha_L - 2\psi_i)/(2 + 2\alpha_L)$. Thus,

$$\begin{aligned} \Pr_{\text{Hi Info}}^i(\text{Return} | \text{purchase}) &= \int_{-\infty}^{P-\mu_i-1/2} (P - \mu_i - \psi_i) f(\psi_i) d\psi_i \\ &\quad + \int_{P-\mu_i-1/2}^{\infty} \frac{2P - 2\mu_i + \alpha_L - 2\psi_i}{2 + 2\alpha_L} f(\psi_i) d\psi_i \quad \text{implies} \\ \Pr_{\text{Hi Info}}^i(\text{Return} | \text{purchase}) &> \int_{-\infty}^{\infty} \frac{2P - 2\mu_i + \alpha_L - 2\psi_i}{2 + 2\alpha_L} f(\psi_i) d\psi_i \\ &= \Pr_{\text{Low Info}}^i(\text{Return} | \text{purchase}) \end{aligned}$$

where the equality is shown in Equation (5). Q.E.D.

Experiment—Additional Procedural Details and Results

To account for attribute familiarity, we asked participants to rate the extent of their familiarity with the humidifier attributes presented in the experiment on a 7-point scale (ranging from 1—not at all familiar to 7—very familiar). Participants also rated the extent to which they found the retailer to be misleading (on a scale ranging from 1—not at all misleading to 7—very misleading). For each of the seven attributes, participants also rated the extent to which they agreed that the attribute was desirable on a humidifier (1—strongly disagree to 7—strongly agree). We collected these attribute-desirability measures for use as controls for varying content across information-amount conditions (i.e., when manipulating the presentation of two versus six pieces of information, both the amount and content of information vary). Because refund amounts varied across conditions, participants were also asked to recall expected refund amounts and product prices (from a list of dollar amounts) as attention checks.

Check Measures

To determine the effectiveness of the manipulations, participants were asked to rate on a 7-point scale how much information they perceived to have been provided about the humidifier (ranging from 1—very little to 7—a lot) before the purchase decision and the extent to which they judged the retailer's policy to be lenient (ranging from 1—not at all lenient to 7—very lenient). An ANOVA on the measure of the perceived amount of information at pre-purchase showed a statistically significant effect of the information-amount factor. That is, participants believed they were receiving larger amounts of information as the number of attribute specifications available in the pre-purchase scenario increased ($M_{\text{low}} = 3.08$, $M_{\text{medium}} = 4.30$,

$M_{\text{high}} = 5.26$; $F(2,408) = 78.90$, $p < 0.001$). All pairwise comparisons between the three cells also showed statistical significance (all p -values < 0.001). These ratings did not vary as a function of the return policy manipulation ($F(1,408) = 0.01$, $p > 0.85$) nor as a function of the interaction between these two manipulated factors ($F(2,408) = 1.01$, $p > 0.36$). An ANOVA on the measure of perceived leniency of the return policy showed a strong effect of the return-policy manipulation with participants perceiving a policy offering a full refund as being statistically significantly more lenient than a policy charging a restocking fee ($M_{\text{full_refund}} = 3.06$, $M_{\text{restocking_fee}} = 6.28$; $F(1,408) = 493.11$, $p < 0.001$). These ratings did not vary as a function of the information-amount manipulation ($F(2,408) = 1.42$, $p > 0.20$) nor as a function of the interaction between these two manipulations ($F(2,408) = 0.88$, $p > 0.40$). Overall, these results confirm that the manipulations worked as expected.

An ANOVA on the measure of familiarity with the attributes showed that familiarity did not vary as a function of the information-amount manipulation ($F(2,408) = 1.08$, $p > 0.30$), return-policy manipulation ($F(1,408) = 0.35$, $p > 0.50$), nor as a function of the interaction between these two manipulations ($F(2,408) = 1.15$, $p > 0.30$). A one-sample t -test analysis, however, showed that, as intended by design, participants perceived the attributes to be largely unfamiliar given that the average familiarity rating ($M = 3.25$) was statistically significantly lower than the neutral point (rating of 4) of the familiarity scale ($t(419) = -9.22$, $p < 0.001$). Overall, participants found retailers offering a full refund to be less misleading ($M = 2.49$) than retailers offering a partial refund ($M = 3.11$; $F(1,408) = 7.37$, $p < 0.01$). The main effect of information amount and the interaction between policy and information amount did not statistically significantly affect the misleading ratings (both p -values > 0.05).

Archival Data

Data Collection Procedure. Research assistants, unaware of the research hypotheses, collected the time schedule data and created a dummy variable equal to 1 for courses providing additional course information (high-information level) at the time of registration and 0 otherwise (low-information level). The data consisted of courses offered in the Business School in the Fall term of five consecutive academic years (2008–2012). Fall term was used to temper network effects and information spillovers that are likely when registration occurs shortly before the course begins. Courses for which multiple sections were offered by different instructors were not sampled for two reasons. First, such cases make it difficult for students to determine how much spillover there is from the information provided by one section to the other sections. Second, course drops from one section may be attributable to new openings in other sections that were previously full. A total of 202 courses met all of the criteria and 48 (23.76%) courses provided additional information about the course.

The aggregate data were collected from the university's registrar office. For each of the course identification numbers, the registrar office provided the aggregate number of students enrolled in the course on the first day of class and

the aggregate number of students who reversed their decision and dropped the course during the first week of class (when full tuition refunds are provided and new course registrations are permissible). The average number of drops per course was 3.09 (standard deviation = 3.03) and the number of drops ranged from 0 to 20 across the 202 courses.

Endogeneity and Instrumental Variables Procedures.

To identify appropriate instrumental variables to address the endogeneity issue, we surveyed 34 instructors from the same population as the enrollment data to better understand the decision to post additional information during registration. Participants were asked if they posted additional information, if they were aware that the option to post information was available to them, and to state their agreement (or disagreement) (on a 7-point scale) with the following two statements: "Making the syllabus available online during registration increases course enrollment" and "Making the syllabus available online before the start of the term decreases the number of students who drop the course." We tested the relationship between awareness and agreement with each of the two statements on the decision to post the syllabus by analyzing the correlations between the variables. The decision to provide prepurchase information statistically significantly correlated with awareness of the option to post ($r(34) = 0.47$; $p = 0.005$). Neither the belief that prepurchase information increases enrollment ($r(34) = -0.13$; $p = 0.46$) nor the belief that it decreases drops ($r(34) = 0.20$; $p = 0.25$) statistically significantly correlated with the decision to provide the information. Awareness was not statistically significantly correlated with the degree of agreement with the two statements (both p s > 0.50). The results suggest that awareness of the ability to post has a strong influence on the decision to post.

To control for potential endogeneity issues, we posit that there may be a peer effect in generating awareness about the option to provide prepurchase information. One may learn from other members of their department with whom scholarly interaction is more likely. One may also learn from other instructors who are teaching during the same time window. As such, we created two instrumental variables to capture the peer effects in the decision to post.

For a given course j in the sample, we created the PERCENTDEPT_j (PERCENTTIME_j) variable equal to the number of courses in the department (time of instruction) exclusive of course j that offered the additional information, divided by the total number of courses exclusive of course j in the department (time of instruction). Information made available before registration by an instructor's peers is exogenous to the instructor's course drops in that this information does not affect the value a student receives from the instructor's course and thus $\text{COV}(\text{PERCENTDEPT}_j, \varepsilon_j) = 0$ and $\text{COV}(\text{PERCENTTIME}_j, \varepsilon_j) = 0$.

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