Flagging Frequently Returned Products under Consumer Information Processing

Sergey Turlo
Goethe University Frankfurt

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Abstract

Online retail has grappled with high product return rates, a problem exacerbated by industry leaders like Amazon due to their lenient return policies, setting a norm in consumer expectations. Despite a wide range of interventions aiming to provide consumers with comprehensive product information, the challenge persists, imposing significant burdens on retailers and the environment. This article questions Amazon's recent proposal to label "frequently returned items" as a strategy to encourage deeper consumer engagement with product information. With an analytical model focusing on costly pre-purchase consumer information processing, this article demonstrates how flagging frequently returned products might reduce information processing by consumers, leading to increased return rates. It also proposes alternative interventions to increase consumer information processing and identifies avenues for future empirical investigations.

Keywords: *product returns, labeling, consumer information processing*
Track: *Retailing & Omni-Channel Management*

1 Introduction

The landscape of online retail is witnessing continued growth, led by industry giants such as Amazon or Zalando, both renowned for their liberal return policies that set a standard in consumer expectations. However, the surge in product return rates has become a central concern. These returns pose substantial logistical and financial challenges for retailers as well as significant environmental implications due to high shipping and refurbishment costs associated with reselling returned items. Moreover, this trend introduces competitive disparities, burdening smaller entities in online retail with disproportionate costs, often exceeding their operational capacities.[1]

A spectrum of tools has emerged aimed at equipping consumers with information to reduce product returns. Strategies encompass detailed product descriptions, augmented reality experiences, or online reviews, all designed to bridge the gap between consumer expectations and delivered products. However, the simple provision of information may fall short in itself since consumer may simply choose not to process such information as doing so takes time and effort.

Amazon's latest proposal involves the introduction of a labeling system aimed at highlighting "frequently returned items".[2] This initiative aligns with their overarching goal to incentivize consumers to engage more deeply with product information before making a purchase. By flagging these items, Amazon intends to prompt customers to take greater notice of product details and consider them more thoroughly, ultimately aiming to reduce returns by fostering more informed purchasing decisions.

This article proposes an analytical model that allows to study the effects of such an intervention. Its contributions are threefold. First, it proposes a simple model of product returns with costly pre-purchase consumer information processing. Second, it shows that flagging frequently returned products may backfire. In the present model, backfiring may occur sometimes in the short-run, when the label is new to consumers, and it will always occur in the long-run, when consumers get accustomed to such a label. Finally, the article identifies alternative interventions that may increase consumer information processing, and it identifies opportunities for future empirical research.

In the proposed model, the consumer can learn about the product and its characteristics ("information processing") both before and after the purchase. A key premise is that returning a product comes with some hassle costs, e.g., the consumer needs to package the product and bring it to the post office. By processing information before the purchase, he can potentially avoid spending hassle costs in case the product does not fit his taste. After the purchase, he learns

[1] See El Kihal and Shehu (2022) for further current background information. Abdulla et al. (2019) provides a recent literature review on consumer product returns.

[2] The Verge, 2023, "Amazon starts flagging 'frequently returned' products that you maybe shouldn't buy," https://www.theverge.com/2023/3/28/23659868/amazon-returns-warning-product-reviews-tag-feature, retrieved 30th November 2023.

perfectly the value of the product, which is a typical assumption for experience goods such as fashion items (Che, 1996).

Since information processing is costly, the consumer's prior beliefs over possible outcomes (i.e., will the product fit or not) will determine how much he will learn about the product. If it is rather likely that the product is a match or not, the consumer will engage less in information processing. If it is rather uncertain whether it is a match or not, he will learn rather more. A core assumption of the article is that the firm can shift the consumer's prior belief about the match by flagging a frequently returned item. This in turn will affect the consumer's information processing effort and ultimately product return rates.

The rest of the article is organized as follows. In the next section, we discuss the relevant literature. Section 3 develops the model including consumer information processing. Then, in Section 4, we study the effect of flagging frequently returned items on product returns. Section 5 concludes the article by discussing managerial implications and future research.

2 Literature

There is an ongoing interest in the effects of marketing instruments and the design of product return rights on product returns and sales in both marketing and economics. For instance, El Kihal and Shehu (2022) show in a recent observational study that a variety of marketing instruments such as catalogs or free-shipping increase product returns. Another recent example is Minnema et al. (2016) who investigate product returns in the presence of online reviews.

The present article contributes specifically to a long standing literature studying product returns with analytical models in marketing and economics such as Che (1996) or Davis et al. (1995). Closely related is the contribution by Shulman et al. (2015). In that model, however, only the firm determines information set that is used by consumers, and the authors rely on loss aversion to generate an increase in product returns as a consequence of information provision. In the present article, in contrast, consumers optimally determine the degree of information processing and a change in consumers' incentives to process information motivates an increase in product return rates following the firm's provision of information.

Related are also consumer search models such as Petrikaite (2017) where consumers are ex ante uncertain about some part of the product value prior to buying and incur a fixed hassle cost of returning the product (e.g., going to the post office) if they choose to return it. However, these are typically models of *post-purchase* information processing whereas in this article (partial) learning of the product value may occur *before* the purchase. Economically, it allows the consumer to avoid spending the hassle costs in case the product does not match preferences. To the best of my knowledge, there is no other work in marketing yet that studies costly consumer information processing before a purchase with consumer rights to return products.

3 The Model

3.1 Setup and timing

Suppose there is a monopolistic firm and a single consumer. The firm offers a product that is either a match to the consumer's preferences or not. Specifically, it provides payoffs $u_H > u_L$ with $\Pr(u = u_H) = \mu_f$.[3] Alternatively, the consumer can choose an outside option that yields a safe payoff of R.

The consumer is uncertain about the match between his preferences and the offered product. However, he can process information about the offered good, e.g., by reading and thinking about product descriptions. We will present the specifics of this process further below. A key assumption is that the consumer holds a *subjective* prior belief μ_c that is different from μ_f and $\mu_f < \mu_c$ without loss of generality. This prior belief then affects how the consumer processes information. The firm knows the true prior distribution μ_f and it can reveal the true prior distribution thereby affecting the consumer's information processing and the product return rate.

After purchasing the product, the consumer learns perfectly the value of the product. He then has the option to either keep the product or to return it. In the latter case, he has to incur hassle costs $h > 0$ so that the total value of returning the product is given by $R - h$. The firm obtains the price p (paid by the consumer) if the consumer purchases and keeps the product and zero otherwise. We impose that $u_H - p > R$ and $R - h > u_L - p$. Marginal costs of production are given by $c \geq 0$.

The timing of the model is as follows. First, the firm decides whether to use a label and thereby revealing the true prior distribution. The consumer observes the provided information and forms a prior belief which may be either μ_c or μ_f. Given his prior belief, he then decides how to learn. Learning allows the consumer to update beliefs which then determine whether the consumer purchases the product or not. After purchasing the product, the true value of the product is revealed to the consumer who then decides whether to return the product. Lastly, all payoffs are realized.

3.2 Information processing

For tractability, we impose that the consumer learns according to an all-or-nothing (AON) protocol (also known as a "truth-or-noise" learning technology, see, e.g., Johnson and Myatt, 2006). The consumer observes a binary signal $S \in \{u_L, u_H\}$. Denote with s_i the event that $S = u_i$, $i = L, H$. With probability q the signal reveals the true value of the product ("all") and with probability $1 - q$ the signal is a random draw from the prior distribution ("nothing"). We interpret q as the quality of the signal. Further below, we refer to q also as the information processing effort of the consumer, and the consumer will determine the optimal level of information processing

[3] With some abuse of notation, we refer to μ_f both as a probability and as a full distribution.

effort.[4] A core building block of the present article is the assumption that the consumer has a subjective belief μ_c that the payoff is high $u = u_H$ which may be different from the objective (or empirical) prior distribution μ_f.

The ex ante probability that the consumer observes a specific signal realization reads

$$\Pr(S = u_H) = q\mu_f + (1-q)\mu_f = \mu_f \tag{1}$$
$$\Pr(S = u_L) = 1 - \mu_f. \tag{2}$$

However, because the consumer has subjective prior beliefs, he expects to observe s_h with probability $\Pr(S = u_H) = \mu_c$ and s_L with probability $\Pr(S = u_L) = 1 - \mu_c$. The consumer is a Bayesian updater. After receiving the signal his posterior beliefs are given by

$$\Pr(u = u_H | s_H) = q + (1-q)\mu_c \tag{3}$$
$$\Pr(u = u_L | s_H) = (1-q)(1-\mu_c) \tag{4}$$

and

$$\Pr(u = u_H | s_L) = \mu_c(1-q) \tag{5}$$
$$\Pr(u = u_L | s_L) = 1 - \mu_c(1-q). \tag{6}$$

Denote with $\mu_s(s_H, q) \equiv \Pr(u = u_H | s_H)$ and $\mu_s(s_L, q) \equiv \Pr(u = u_H | s_L)$. Note that the posterior beliefs of the consumer depend only on his subjective prior as well the quality of the signal q which we endogenize next.

The consumer can process information in order to improve the quality of the signal. For instance, he can read product descriptions in catalogs or online consumer reviews and think about that information in order to predict whether the product will match his taste. Because finding such information and integrating this into a purchase decision is cognitively taxing and time-consuming, this process is costly. Specifically, costs of information processing are given by

$$C(q) = \frac{1}{2}\lambda q^2. \tag{7}$$

This formulation ensures that solutions are in closed-form. In the present context, $\lambda > 0$ is interpreted as the costs of a higher quality signal and may capture concepts such as the opportunity costs of time or may vary with cognitive ability or prior experiences.

[4] In this article, the terms "signal quality" and "information processing effort" are used interchangeably to clarify that the consumer ultimately determines the quality of the signal.

3.3 Consumer Behavior under Subjective Prior Beliefs

In this subsection, we characterize the consumer's behavior by solving his problem via backward induction. In what follows, I impose that the consumer behaves as if μ_c is the true distribution of uncertainty. After the consumer has purchased the product, he will keep it if the price is sufficiently low and the hassle costs are sufficiently high

$$u_i - p \geq R - h. \tag{8}$$

In order to reduce the number of case distinctions, we impose $u_H - p \geq R - h \geq u_L - p$. Otherwise, the consumer would not have any incentives to process any information. Consequently, the consumer returns the product when $u = u_L$ and keeps it otherwise. After receiving an informative signal $S = s_i$, the consumer's expected value of purchasing the product is

$$\mu_s(s_i, q)(u_H - p) + (1 - \mu_s(s_i, q))(R - h). \tag{9}$$

In an equilibrium where the consumer chooses to process information, so that $q^* > 0$, the consumer purchases when $S = s_H$ and turns to the outside option otherwise (when $S = s_L$).[5] Thus, the consumer's objective function is given by

$$V(q) = \mu_c \left[\mu_s(s_H, q)(u_H - p) + (1 - \mu_s(s_H, q))(R - h)\right] + (1 - \mu_c)R - \frac{1}{2}\lambda q^2 \tag{10}$$

and the consumer's problem is $\max_q V(q)$. We can solve the resulting first-order condition for q^* to determine the optimal signal quality which is summarized in the following Lemma.

Lemma 1 *The consumer's information processing effort q^* is given by*

$$q^* = \frac{\mu_c(1 - \mu_c)}{\lambda}\left(u_h - p - R + h\right). \tag{11}$$

Intuitively, the signal's quality q^* decreases in the costs of processing information λ and it is increasing the hassle costs h that capture the consumer's effort of returning the product.

Interestingly, the relation between prior beliefs μ_c, held by the consumer, and the subjectively optimal signal quality q^* is inverse U-shaped. The reason is that with sufficiently extreme prior beliefs the probability of a choice error (when choosing based on prior beliefs only) is rather low—so that incentives for information processing are also rather low. In contrast, the signal quality is high when the consumer is a priori (without learning) rather uncertain, so that μ_c is close to $1/2$, whether the product matches his preferences. Note that q^* is only optimal from the consumer's perspective as his prior beliefs are not necessarily equal to the true distribution

[5] If, in an equilibrium with $q^* > 0$, the consumer would always choose the same action, then the resulting information would generate no value and he would be strictly better off not processing any information, thus violating optimality of behavior in an equilibrium.

of payoffs. The following Corollary formally describes how q^* changes as a function of the consumer's prior beliefs μ_c. This is a core building block for the main result of this article.

Corollary 1 *The consumer's information processing effort q^* is strictly concave in μ_c. Specifically, it increases in μ_c for $\mu_c < 1/2$ and it decreases in μ_c for $\mu_c > 0.5$.*

We close this Section by providing a sufficient condition for consumer information processing so that $q^* > 0$. Recall that the consumer can choose without processing information either the outside option (which provides a payoff R) or the offered product.

Lemma 2 *When costs of information processing λ are sufficiently low, the consumer prefers learning about the product before purchasing it, so that $q^* > 0$, both to i) choosing the outside option and to ii) purchasing without processing information.*

The claim follows from the fact that q^* approaches 1 once the costs of information processing λ are sufficiently low, so that the signal is fully revealing, as well as from the parameter restriction that $u_H - p > R$. In what follows, we restrict attention to cases where the consumer strictly prefers to process some information and to purchase only if the signal is high.

4 Product Returns and Firm Profits

In this section we characterize the consumer's behavior from the perspective of a firm or an external analyst who knows the true value of the prior distribution. This may be due to a large sample of consumers' past purchasing and return decisions. We denote the true empirically verifiable prior distribution with μ_f and the perceived subjective prior with μ_c. Consumers are naive in the sense that they do not consider it possible that the firm could withhold information. This is a rather innocuous assumption for a real world market that has not been subject to the instrument of product labels flagging frequently returned products.

The firm obtains a payoff only if the consumer purchases and keeps the product:

$$\pi = (p-c)\Pr(u = u_H)\Pr(S = u_h | u = u_h) \tag{12}$$

where $c \geq 0$ are the costs of producing the product. In order to streamline the exposition, costs are sufficiently low so that even without processing information a purchase would be welfare enhancing. The following proposition expresses the probability to purchase as well as the relative rate of product returns.

Proposition 1 *Suppose the true probability that the product matches the consumer's preferences is μ_f while the consumer beliefs that this is the case with a probability of μ_c. Then, the consumer purchases the product with probability $\Pr(S = u_h) = \mu_f$ and he returns the product with*

$$\Pr(u = u_L | S = u_h)|_{q^*,\mu_f} = (1-q^*)(1-\mu_f) \tag{13}$$

so that the product return rate is given by $(1-q^*)(1-\mu_f)/\mu_f$. *The firm's profits are*

$$\pi = (p-c)\mu_f(q^* + (1-q^*)\mu_f). \tag{14}$$

Note that firm profits are strictly increasing in the consumer's learning effort q^* which in turn depends on the consumers prior belief μ_c and not on the true distribution μ_f. Moreover, we note that firm benefits if the consumer returns the product less frequently. Next, we turn to the question how a product return label affects the likelihood to return the product. Lastly, note that Proposition 1 and Corollary 1 together imply that the realized return rate and the firm's profits are both inverse U-shaped in the consumer's subjective belief μ_c.

4.1 Impact of Labeling on Product Returns

In order to study the impact of a label that indicates frequently returned products, we distinguish two cases. In the first case, the firm introduces the label for the first time for a product where it already knows (though prior sales and product returns) the true distribution μ_f. If the consumer observes the label, he updates his prior belief from μ_c to μ_f, and there is no updating if there is no label. This represents, for instance, a case where the retailer wants to learn through A/B testing about the effect of such an intervention on product returns.

In the second case, we study the long-run effects of committing to a policy of labeling products that have been returned sufficiently often so that the firm does *not* know the true distribution μ_f but has some beliefs γ over possible payoff distributions.[6] This is, for instance, the case when new products are introduced and the firms is uncertain about the aggregate match probability. From a consumer's perspective, the absence of such a label is then a positive signal and an indicator for a rather high probability for a product match.

4.2 Short-Run Effects

In this part, we impose that the firm knows the true prior value which will be revealed to the consumer and without loss of generality that $\mu_f < \mu_c$. If the firm uses a label, then the consumer applies μ_f instead of μ_c as his prior when choosing his information processing effort q^*. The following proposition characterizes the effects of such a label on q^* and other outcomes.

Proposition 2 *An informative label that reveals the true likelihood of a match μ_f decreases q^* when $\mu_c \leq 1/2$. When $\mu_c > 1/2$, there is a cutoff $\widehat{\mu} = 1-\mu_c$ so that q^* increases when $\widehat{\mu} < \mu_f < \mu_c$. Otherwise, when $\mu_f < \widehat{\mu}$, the optimal learning effort decreases.*

The intuition for this result is that by revealing the information (through a return label) the firm shifts the prior belief of the consumer. This, in turn, affects his incentives to process information as characterized in the discussion leading to Corollary 1.

[6]For example, due to prior experience with similar products the firm may believe that with $\gamma = 0.5$ the distribution is given by $\mu_f = 0.25$ and with $1-\gamma$ it may expect that $\mu_f = 0.75$.

4.3 Long-Run Effects

Now, the firm commits ex ante to labeling products that have been returned frequently by consumers. Over time consumers will interpret the absence of such a label as a positive signal about a product's quality. For simplicity, assume that with equal ex ante probability it is possible that a specific product has many or only few product returns. Specifically, with equal probability (so that $\gamma = 0.5$) the label reveals that μ_f^l or μ_f^h with $\mu_f^l < \mu_f^h$ and $(\mu_f^l + \mu_f^h)/2 = \mu_c$. The firm does not know a priori whether the product is rather good or bad.

Proposition 3 *A cancellation label decreases the expected learning effort and increases the expected product return rate.*

The above proposition follows immediately from the strict concavity of the optimal signal quality q^*. While the focus of this article lies on product return labels, other pieces of information that may either increase or decrease the (expected) product value (either due to the revelation of consumer specific or product specific utility components) will have similar implications for behavior.

5 Discussion

5.1 Managerial Implications

From a managerial perspective, this research suggests that in the long run the provision of information through labeling products which are frequently returned will not have the desired effect of reducing product returns since such information provision reduces in expectation the incentives to process information—which is the opposite of the intention behind the proposed instrument.

Managers must be careful when interpreting results in the short-run from A/B tests of such an intervention. This article shows that there may be cases where in the short-run such a product label may indeed reduce product return rates. However, inferring implications for long-run outcomes from a short-run success of such an intervention without clearly understanding the underlying incentives may lead to detrimental conclusions.

This analysis suggests alternative instruments that indeed increase the information processing efforts. Two examples are the following. First, the firm can influence the expected hassle costs of a consumer by providing informative labels that make explicit the costs (e.g., time) associated with a product return or that spell out the environmental damages created through product returns. Second, the firm can affect the value of the consumer's outside option through the design of its assortment. A formal treatment of this proposal is, however, beyond the current scope of this article.

5.2 Future Research

This article points towards exciting future avenues both for analytical modeling and empirical research. From a theoretical perspective, it is important to study the robustness of this article's predictions with respect to more general models of consumer information processing such as rational inattention (see, e.g., Jerath and Ren, 2021). Further, it is of interest to study such predictions once we allow firms to set other components of the marketing mix such as the price simultaneously with their labeling policy.

From an empirical perspective, this article provides novel hypotheses regarding information provision in the context of online retail and product returns. For instance, it makes testable predictions on the effect of labels targeting different economic fundamentals (such as prior beliefs or expected hassle costs) on consumer information processing and product returns.

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