Why Providing Return Policies for Probabilistic Selling

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Abstract. Probabilistic selling, whereby the exact identity of a product remains unknown until after purchase. The existing literature on probabilistic selling primarily focus on its attractiveness under the non-refundable condition. In this paper, we aim to study whether probabilistic selling integrated with return policies is still a lucrative marketing tool. This is an important new inquiry because of the prevalence of return policies in E-commerce platforms as well as heterogeneity in consumer preferences occurring in almost all markets. We develop a game-theoretic model to capture the fit uncertainty stemmed from online purchasing and the assignment uncertainty rooted in the stochastic assignment of probabilistic products. We characterize the seller's optimal pricing and integrated strategies of probabilistic selling and return policies. We find the attractiveness of the probabilistic selling strategy and its return policies depends on the degree of the fit uncertainty and the assignment uncertainty. Counterintuitively, we find that sellers should decrease rather than increase the customer hassle cost of returns. The higher prices of component products are used as an additional lever to suppress customers' return of the probabilistic products. We demonstrate the integrated strategies of probabilistic selling with return policies, as a general marketing tool, can be more valuable than a separate one. The integrated strategies can create a win-win situation, improving both profit and consumer welfare.

Keywords: Probabilistic selling; return policy; fit uncertainty; assignment uncertainty.

1. Introduction

Probabilistic selling, whereby the identity of a product remains unknown until a consumer makes a payment [1], was first adopted in the travel industry by Priceline.com and Hotwire.com in business concerning airline tickets, rental cars, and hotel rooms. Recently, many online retailers, including Amazon.com, eBay.com, Etsy.com, ToyWiz.com, Tmall.com, and so forth, started using this strategy or its variations. Retailers put traditional products (such as apparel, shoes, toys, etc.) into a “Grab Bag”, “Lucky Bag”, or “Mystery Box”, a method by which a customer can figure out the product's identity only after purchasing and opening the “Black Box”. The retailing industry saw increasing popularity in probabilistic selling. According to the data provided to The Goods by Etsy.com, there have been over 495,000 search queries for “mystery boxes” on the site between January 2019 and July 2019 [2]. When we searched “grab bag, mystery box, lucky bag” in Amazon.com and Tmall.com, more than 49,000 and 85,000 results were respectively shown on their site as of September 2020. Thus, our research question is as follows:

1. In the context of the return policy being widely used in online retailing, should a seller still introduce a probabilistic product?

2. Under what circumstances should a seller venture the acquired profits on a partial refund or even a full refund for returning the probabilistic products, and under what circumstances lock-in those customers with a no-refund policy?

3. If the seller provides a returnable probabilistic product, should the seller further arise the prices? If yes, what are the interactions between the pricing and the returns?

To answer our research questions, we build a model wherein an online seller sells two horizontally differentiated products, which can compose a probabilistic product with a certain proportion. The seller does the assortment planning (i.e., whether and when to add the probabilistic product in the assortment) and decides the return policies (i.e., whether and when to provide a full refund policy for the probabilistic product).

The remainder of this study is organized as follows. In section 2, we briefly summarize the related literature. In section 3, we describe our model. In section 4, we derive the optimal integrated strategy from analyzing the advantage of probabilistic selling and return policies. In section 5, we summarize the insights drawn from the analysis, offer concluding remarks, and suggest areas for future research.

2. Literature Review

Our work studies the return policies in probabilistic selling, pertaining to two fields of research: probabilistic selling and return policies.

The existing literature on probabilistic selling extensively study why, when, and how probabilistic selling is used in a non-refundable setting. [1] First demonstrate that probabilistic selling can be a general marketing tool that potentially benefits sellers in many different industries. Probabilistic selling can separate heterogeneous consumers, thus encouraging customers to reveal their heterogeneity via self-selecting whether or not to purchase the uncertain product, which is used by a seller [1, 3, 4, and 5] as well as an opaque intermediary [6]. Although the existing literature richly illustrate the advantage of probabilistic selling within a non-refundable framework, whether it still profitable in a refund-available setting remains an uncharted domain. To the best of our knowledge, this study is the first to shed light on return policies in probabilistic selling. In contrast to the conventional wisdom that a no-refund policy should be strictly enforced in probabilistic selling, we find that profits are accessible from the approach of providing partial return policies or even full return policies.

The other related literature stream investigates return policies, which are oriented to two broad and interrelated domains of research: consumer behavior and planning and execution [7]. In contrast with the finding in [8], we find that a generous return policy of probabilistic products, which have no supplementary fixed costs and lead time incurred from design and physical production, may lead to a larger assortment.

3. Model

The seller offers two horizontally differentiated component products, which have symmetric production costs through the online channel. To rule out trivial cases where the demand drops to zero because of exorbitant production cost, we assume$0 \leq c < 1$. We assume that the seller is aware of the demand. The seller has three alternative integrated strategies: traditional selling with refunds ($K = TC$), probabilistic selling in which refunds are only accessible for component products ($K = PC$), and Probabilistic selling in which refunds are available for all products ($K = PA$).

Returns from customers are salvaged at the value$s$. A low value of s represents a situation where the reverse logistics cost for the seller to remarket the returned product is high. The returned products may need an inspection, and in some cases reconditioned before being put back to inventory.

For online consumers, physically inspecting ("touch and feel") products before purchasing is not available, from which fit uncertainty emerges. To capture this fit uncertainty (also referred to in the returns literature as valuation uncertainty), we assume that the homogeneous ex-ante probability of a product fit isα, and the mismatch with probability$1 - \alpha$, in which the consumer receives zero utility [9]. In addition, when consumers purchase a probabilistic product, which can turn out to be any of the component products, they will also face uncertainty about the product assignment. After receiving the probabilistic product, this assignment uncertainty will be resolved [3]. Additionally, under the PA strategy, consumers can decide whether to keep the probabilistic product based on their heterogeneous ex-post valuation net of the purchase price and the "return hassle cost"h.

We assume that consumers are distributed uniformly over $[0, 1]$ as in the Hotelling model, and we scale the market size to 1. For a consumer located at x on the Hotelling line, the valuation from purchasing product is given by $v_J\ (x)$ where:

$$v_J = \begin{cases} 1 - tx, & J = 1 \\ 1 - t(1-x), & J = 2 \\ 1 - \frac{t}{2}, & J = o \end{cases} \tag{1}$$

Each rational consumer is assumed to purchase no more than one unit of one product, i.e., there is no value from consuming a second product. Each consumer makes three decisions sequentially. Initially, they decide whether to purchase a product and which product to purchase based on their ex-ante expected surplusES_J^K, which is given by:

$$ES_J^K = \begin{cases} \alpha(1-tx) + (1-\alpha)(p-h) - p, & J = 1 \\ \alpha(1-t+tx) + (1-\alpha)(p-h) - p, & J = 2 \\ \alpha\left(1-\frac{t}{2}\right) - p, & J = o, K = PC \\ \alpha\left(1-\frac{t}{2}\right) + (1-\alpha)(p-h) - p, & J = o, K = PA \end{cases} \tag{2}$$

After receiving the purchased product, both fit uncertainty and assignment uncertainty will be resolved. Customers then decide whether to keep or return it for a refund based on their ex-post surplus$S_J^K(x)$, which is given by:

$$S_J^K = \begin{cases} v - p, & fit\ and\ keep \\ -h, & fit\ but\ reture \\ -p, & unfit \end{cases} \tag{3}$$

Sequence of events. (1) The seller decides the integrated strategy$K$. (2) The seller determines the product pricep_J^K. (3) Consumers make their purchase decisions. (4) Customers make their return decision. We solve the game backward to ensure subgame perfection.

4. Analysis—Optimal Integrated Strategy

We derive the seller's optimal integrated strategy from the three alternative strategies--TC, PC, andPA. Proposition 1 shows when each of the three integrated strategies could be optimal.

PROPOSITION 1 (OPTIMAL INTEGRATED STRATEGY). Probabilistic selling which creates the assignment uncertainty and return policies which clear away both fit uncertainty and assignment uncertainty can help the seller depending on (a) the fit probability between component products and the consumer's taste and (b) the horizontal differentiation of component products. The conditions under which one strategy dominates the others are given in the table below.

Table 1. Optimal Integrated Strategy.

Optimal strategy	Conditions required		Implication
	Fit probability	Horizontal differentiation	
Traditional selling with refunds	Low	Does not matter	$\Rightarrow$ *Strong fit uncertainty*
Probabilistic selling in which refunds are accessible only for component products	High	High	$\Rightarrow \begin{cases} Weak\ fit\ uncertainty \\ Strong\ assignment\ uncertainty \end{cases}$
Probabilistic selling in which refunds are available for all products	Mid-range	High	$\Rightarrow \begin{cases} Moderate\ fit\ uncertainty \\ Polarized\ assignment\ uncertainty \end{cases}$
	Mid-range	Low	

Formally, TC is optimal if $t < \bar{t}^{PA_N}$ *and* $\alpha < \alpha_3$ *or* $\bar{t}^{PA_N} < t < \underline{t}^{PA_P}$ *and* $\alpha < \alpha_4$ *or* $t > \underline{t}^{PA_P}$ *and* $\alpha < \alpha_5$; PC is optimal if $\bar{t}^{PA_N} < t < \underline{t}^{PA_P}$ and $\alpha > \alpha_4$ or $t > \underline{t}^{PA_P}$ and $\alpha > \alpha_2$; otherwise, PA is optimal.

Proposition 1 illustrates that the optimal strategy mainly depends on two variables: (a) the fit probability between the component products and the consumer's taste α and (b) the horizontal differentiation of the component products$t$. We present a visual illustration of Proposition 1 in Figure 1.

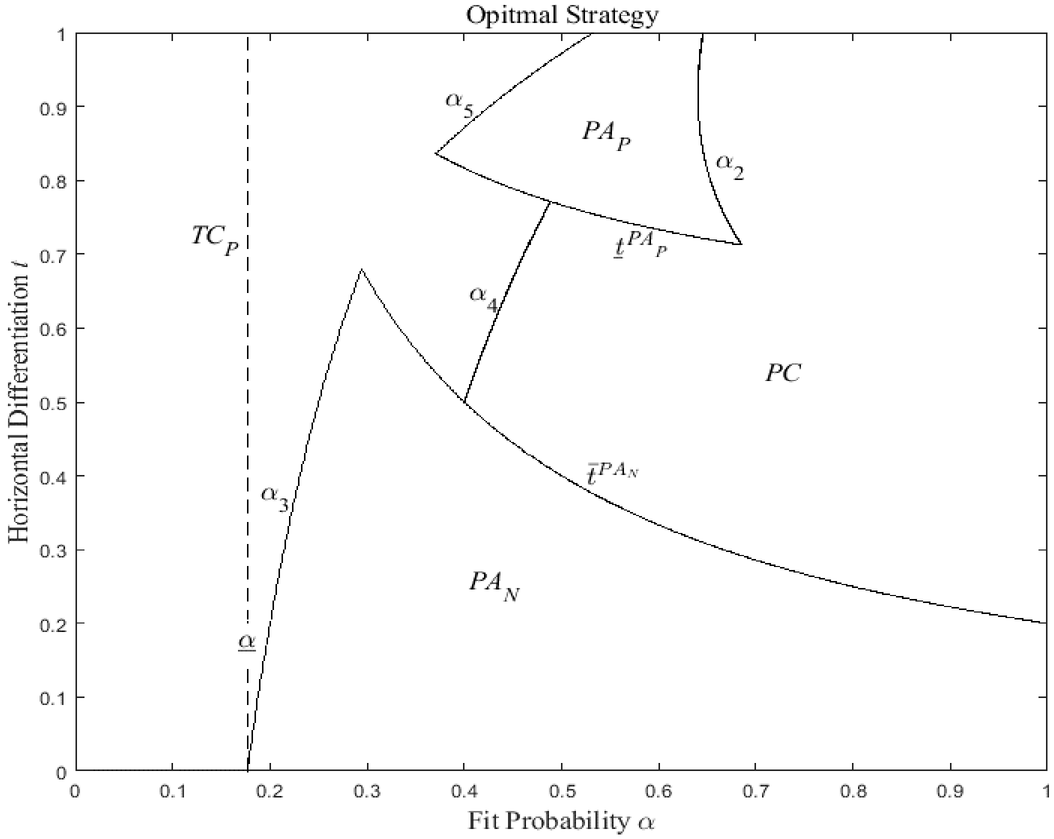

Figure 1. Optimal Strategy.

Notes. The following parameter values are used:$c = 0.3,\ s = 0.2$, and $h = 0.05$. The notations TC_P, PA_P and PA_N represent partial market target under TC strategy, partial return target under PA strategy, and no return target under PA strategy, respectively. Qualitatively, the results do not change for other values of the parameters.

5. Conclusion

Given that probabilistic selling has penetrated into many industries and well-studied by scholars. Conventional wisdom posits that sales of the probabilistic products need to be non-refundable so that a customer will face some risk (assignment uncertainty) after purchasing a probabilistic product, else the probabilistic products would cannibalize all component products. However, several practical examples contradict this conventional wisdom, such as those in Amazon.com, 101Apparel.com, ToyWiz.com, and so on. Inspired by these interesting phenomena, we theoretically explore why, when, and how a seller can benefit from introducing a returnable probabilistic product.

We have come to several interesting results. First, we find that when refunds are accessible for component products, sellers should still introduce probabilistic products if the fit probability between component products and the consumer's taste is sufficiently high. The sufficiently low fit uncertainty opens up the opportunity for creating assignment uncertainty. Probabilistic selling which creates the assignment uncertainty and return policies which clear away both fit uncertainty and assignment uncertainty benefit the seller depending on (a) the fit probability between component products and the consumer's taste and (b) the horizontal differentiation of component products.

Second, sellers should offer non-refundable probabilistic products when the fit probability and the horizontal differentiation are sufficiently high, while offer refundable probabilistic products when the fit probability is at mid-range and the horizontal differentiation is sufficiently low or high. The profit improvement by non-refundable probabilistic products comes from the price discrimination effect and effective demand increase. The profit improvement derived from refundable probabilistic products comes from the price discrimination effect and price of the probabilistic product increase effect.

Third, under PA strategy, sellers may deploy the return suppression pricing tactic that further increase the price of component products to induce a lower return rate. Although permitting customers to return the probabilistic product, it is still attractive to keep the product in exchange for a discounted price.

Fourth, PA strategy can create a win-win situation, enhancing both sellers' profit and market efficiency, which is attributed to that (a) sellers achieve higher profit margin, and (b) customers have the right to remedy against assignment uncertainty.

Finally, sellers' profit is not affected by the amount of refunds. The refund effect is offset by the price. To inspire customers' long-term loyalty and boost future demand, sellers should always offer full refund policies for probabilistic selling.

In this study, we demonstrate probabilistic selling can be more beneficial than previously shown. The integrated strategy of probabilistic selling and return policies is still a lucrative marketing tool. It would be interesting to study the role of the integrated strategy in a supply-chain context. Specifically, considering the probabilistic selling strategy used by an opaque intermediary (such as Hotwire.com), upward return policies between firms and the intermediary, and downward return policies between the intermediary and consumers may derive more insights.

Acknowledgements

The authors thank Yunchuan Liu and Rachel R. Chen for their valuable and constructive suggestions. This work is supported by the National Natural Science Foundation of China under grant number 71571102.

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