Influencing Customers and Product Returns

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Digital platforms expose customers to product fit uncertainty, which may intimidate online purchases. As a result, firms may encourage online order through influence tools such as promotional reviews and influencer posts, which can be skewed in favor of a purchase. However, customers who have ordered due to such influence can ultimately return the product. In this paper, we study how a firm's ability to influence customers may intertwine with its refund policy. We find that if no refund is offered, a firm will adopt an influence tool when the prior belief of a match is moderate and the cost of influence is low. More generous refunds may either cease the influence or invite more aggressive influence actions. We then characterize the optimal joint configuration for refund and influence. When the firm can only choose between a full- and no-refund policy, the use of influence tools can be encroached upon by a full refund even if it is costless. This implies that, depending on the nature of the product, it may be beneficial for firms to let customers learn the true fit through product returns *ex post* rather than influencing customers *ex ante*. Interestingly, the firm will not engage in influencing customers when it can tailor partial refunds. Thus, influencing customers is useful when the firm needs to maintain a naïve or common refund policy across a variety of products. Lastly, we find that allowing product returns may lead to a win-win when the decision space for the refund policy is limited and the prior belief of misfit is high.

Key words: digital platforms, influencer marketing, product returns, refunds, word of mouth
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1. Introduction

From Generation X to Generation Z, consumers are preponderantly driven by social media and influencers in their discovery of new products and in making purchase decisions (Hubspot and Bandwatch 2022). Though the concept of influencers is dynamic, it generally refers to popular social-media users who can influence other consumers' behavior. They can be Internet celebrities with millions of followers; customers who publish reviews, photos, or videos of their purchases and assist other customers in the buying process; salespeople or authorities with specialized knowledge; or even animals or robots, as the concept continues to evolve (Avery and Israeli 2020, McKinsey & Company 2023). According to consumer surveys, 82% of people were highly likely to act upon the recommendation of an influencer, and 91% of respondents said online reviews were "very" or "somewhat important" when it comes to purchasing a general item (Avery and Israeli 2020, Skeldon 2023). As a result, influencer marketing has scaled up rapidly in recent years. In 2022, the shopping platform LTK alone sold $3.6 billion worth of goods through online creators and influencers, with most-loved products ranging from Dyson's Airwrap to Lululemon's Everywhere Belt Bag (Forbes 2023). At the time of this paper's writing, the size of influencer marketing is expected to top $21.1 billion in 2023.[1]

Despite all the marketing heat fuelled by digital platforms and tech-driven experiences, one should not overlook the operational pain that may accompany it. Notwithstanding growing sales in the U.S., the total dollar value of returns in 2022 had more than doubled before the COVID-19 pandemic, to $816 billion, and the average return rate across all merchandise[2] had jumped from 8% to more than 16% (Peinkofer 2023). Figures for the e-commerce and apparel industries are even more dramatic. In 2021, it was estimated that 21% of online orders were ultimately returned and, for clothing and shoes, the numbers were up to 40% (The Economist 2022).

Online orders are returned for various reasons, but the top drivers are acknowledged to be product fit and, more broadly, the gap between customers' perception of the online representation and their assessment of the real item. For instance, a consumer survey across the U.S., U.K., France, Germany, and Australia (Narvar 2019) found that 34–46% of online returns were driven by "The size, fit, or color was wrong", and 12–14% by "The product wasn't as depicted in its description or product photo." Within the U.S., statistics suggest that 33% of online order returns are driven by "fit/size issues" and 23% because "Product was vastly different than what was shown online" (ParcelLab 2022). According to North American apparel retailers, 70% of returns were caused by poor fit or style (McKinsey & Company 2021).

Since easy returns before and early in the pandemic led to hefty business losses, clothing retailers are now starting to sell more nonrefundable items (Wall Street Journal 2023). Even for regular online returns, renowned chain stores like Zara, H&M, and Abercrombie & Fitch are now charging fees so that returning online orders is not entirely free for customers (CNN Business 2023). Although full refunds are still being offered in many scenarios, momentum is building for retailers to be more mindful when crafting return policies based on the nature of the product.

The tide of influencer marketing and the trend in product returns have given rise to interesting questions about how these two elements should integrate with each other. Online orders inspired by influencers need to go through the same customer inspection for fit and match once the products are delivered (as they would if bought in brick-and-mortar stores or online without any influence).

[1] https://www.statista.com/statistics/1092819/global-influencer-market-size/

[2] Based on a survey with 70 retailers by the National Retail Federation.

While viral and influential content may blur consumers' vision of the product match and stimulate more sales at one point, they may also contribute to product returns at a later stage. Thus far, it is not entirely clear, and little discussion has taken place on whether customer influencing activities should take into account future product returns or whether the design of return policies should bear in mind ongoing efforts to influence customers, and further, how these two forces may interact with each other. In light of these ambiguities, we find it imperative to investigate the following questions:

1. How would product returns impact the level of influence a firm may impose on its customers?
2. How should the firm configure influences on customers in conjunction with return policy design?
3. What are the implications of these practices for business profit and consumer welfare?

1.1 Summary of Main Findings

To explore the above questions, we consider a setting in which a firm sells a product to a group of customers who are uncertain about whether the product will fit or match their preferences.[3] Neither the firm nor any of the customer can observe the product fit ahead of purchase, and the customers may rely upon a prior belief, e.g., the chance that the product will fit a population, to make purchase decisions. To encourage orders, the firm may acquire an influence tool at some cost, e.g., influencer reviews, an online review platform and manager, etc., that generates informative but imperfect signals to the customers about the fit. Further, the influence tool may be tuned by the firm, e.g., through favorable influencer review posts, promotional customer reviews, compensation for negative comments, etc., such that there is a higher probability that it will produce a signal in favor of a purchase without compromising the prior belief of fit. Customers will then use the signal to update their beliefs on the odds of a match and decide whether or not to make a purchase. Once the products are delivered, customers will learn the true fit and make product return decisions based on the refund policy announced by the firm prior to purchase.

This stylized framework allows us to explicitly examine the key trade-off between the marketing gain and the operational pain that arise from influencing customers. Tuning the influence tool to encourage a purchase will increase the *true positive rate* or *recall* of its signal, such that more customers who are inherently a good match with the product (but are unsure of this at the time of purchase) will go ahead and order. However, this comes at the cost of lower *precision* for the signal, in the sense that more customers who order will not find the product to be a good fit upon delivery and will return it, where possible.

[3] We will use "match" and "fit" interchangeably in this paper, as well as "prior belief of fit," "odds of a match," and "chance of a match."

Based on this framework, we are able to derive some valuable insights on our research questions. First, we show that, when no refund is offered, the firm should acquire the influence tool when the prior belief of fit is neither too pessimistic to give up nor too optimistic to support an uninfluenced purchase, and the cost of the influence tool is below some threshold. Within this range, the firm should impose a higher level of influence as the prior becomes more optimistic and the baseline informativeness of the influence tool becomes more accurate. These properties are maintained when customers are allowed to return the product in exchange for a refund. However, with a more generous refund policy, the application zone of the influence tool will shift towards more pessimistic priors. As long as the influence tool still applies, there will be a greater tolerance for the cost of the influence tool and a higher level of influence, which may partially explain the hike in online order return rates mentioned earlier in this section.

To answer the second question, we consider two kinds of decision spaces in the firms refund policy. The first, namely, a binary refund, represents a generic return management style where a firm would limit itself to either a full- or no-refund policy. In this scenario, we find that the firm should offer a full refund without using any influence tool when the prior belief of fit is relatively pessimistic; no refund with substantial influencing actions when the prior is moderate; and no refund and no influence tool when the prior belief of fit is optimistic. The thresholds among these offerings reflect a stricter requirement on the cost and the baseline informativeness of the influence tool. Instead of interpreting these results literally, the insight is that refunds and influencing customers are substitutes for each other, with refunds targeting areas where the risk of a mismatch is high (e.g., a niche product), and influence targeting areas where such risk is moderate (e.g., a mass product). In particular, the use of an influence tool may be cannibalized by offering full refunds when the price-value ratio of the product is high. Hence, depending on the nature of the product, it may be beneficial for the firms to let customers learn the true fit through product returns *ex post* rather than influencing customers *ex ante*.

For the second kind of decision space, we examine a scenario where a firm is allowed to offer partial refunds at its own discretion. Interestingly, it turns out that the firm would prefer tailoring partial refunds to adopting an influence tool. This confirms the robustness of partial refunds in dealing with heterogeneous valuation uncertainty, as has been found in the literature. It is also consistent with the observed trend of practices such as costly online returns, restocking fees, non-refundable shipping surcharges, and store credits, concurrent with the regulatory pressure in disclosing customer influencing activities.[4] On the other hand, this finding underscores the value of influencing customers

[4] The Federal Trade Commission (FTC), for example, is responsible for enforcing codes of conduct and compensation disclosure guidelines that aim to limit false advertisement and promote consumer protection. https://www.ftc.gov/business-guidance/advertising-marketing/endorsements-influencers-reviews

when partial refunds are hard to implement or when the firm needs to maintain a common refund policy across a variety of products.

For our final question, we find that under an exogenous refund rate, allowing product returns on top of influencing customers adds non-trivial value to the firm (and to the whole supply chain) when the prior belief of fit is low, with all surplus retained by the firm and none spilled over to the customers. When the prior belief of fit is high, an exogenous refund rate will enhance customer welfare at the cost of the firm's expected profit. However, when the firm can configure the rate itself through a binary refund, both the firm and the customers will be strictly better off when the prior is relatively low, and experience no change in expected profit or welfare when it is high. When the firm can fully engineer the level of refunds, it will further extract all surplus from the customers through partial refunds based on the odds of a match, and the customers will be even worse off compared to a no-refund scenario when the prior belief is relatively low. Overall, the impact on customer welfare depends heavily upon the decision space of the firms refund policy, and a win-win is more likely to appear when the firms decision space is limited and the chance of a product match is low.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature. Section 3 introduces the model with benchmark influence decisions when there is no refund. Section 4 analyzes the optimal level of influence under an exogenous refund rate. Section 5 considers the joint configuration of influence and refund levels. In particular, Section 5.1 considers the case when the firm can only choose between no refund and a full refund, and Section 5.2 allows the firm to set partial refunds at its own discretion. Finally, we discuss managerial insights in Section 6 and conclude with future extensions in Section 7.

2. Literature Review

Our work is broadly related to the streams of literature in 1) electronic word-of-mouth (eWOM), and in particular, the substreams of studies focusing on influencer marketing and 2) product returns and refund policy design.

eWOM refers to the practice in which customers can publicly share their opinions and experiences about a product, a service, or a company through digital platforms, which may impact future sales of the product or service and the business of the company. The effect of eWOM has been extensively studied in the past decades since the beginning of market digitalization (Dellarocas 2003). Interested readers may refer to Rosario et al. (2016) for a summary of the large body of literature on the impact of eWOM on sales. Within this stream of literature, a segment of the studies has investigated the firms role in managing and controlling eWOM contents (Godes et al. 2005). A firm may take a traditional role by making decisions based on eWOM observations (e.g., Chen and Xie 2005, Feng et al. 2019) or by strategically designing and involving eWOM programs (e.g., Chen and Xie 2008, Godes and Mayzlin 2009, Burtch et al. 2018). In addition, the firm may also take an aggressive role by participating in the eWOM and imposing an influence on the customers. For instance, many studies provide empirical evidence that firms may produce eWOM contents or manipulate sentiment to simulate sales, possibly through biased or promotional online reviews (e.g., Mayzlin et al. 2014, Luca and Zervas 2016), free samples (Lin et al. 2019), viral videos (e.g., Tucker 2015, Yang et al. 2021), and tweets (Lee et al. 2018).

Driven by the latter research thread, a number of works have analyzed how firms may strategically participate in eWOM and influence customers. Mayzlin (2006) considers a setting where competing firms may use anonymous and promotional messages to influence consumers posterior beliefs on the quality of their products, and found that firms may spend more resources promoting low-quality products. Dellarocas (2006) examines a generalized class of settings and identified scenarios under which high-quality firms might have more incentive to inflate their ratings. Zhuang et al. (2018) conduct laboratory experiments to compare the effects of different review manipulation approaches, namely, adding positive reviews and deleting negative reviews. Guan et al. (2020) analyze how a firm may strategically disclose its quality information to influence the intertemporal interaction between online reviews and consumers expectation of the product. More recently, Pei and Mayzlin (2022) explicitly model the affiliation between a firm and an influencer posting reviews for the product and analyzed the impact of such an affiliation on consumer welfare. Berman et al. (2022) investigate strategies for competing firms as well as for the platform in providing biased information to customers. Hou et al. (2023) study how firms should integrate influencers with livestream selling.

With rising attention on firms roles and strategies in influencing customers, none of the above modeling work has accounted for the potential of product returns *post-influence*, i.e., after customers receive the product and learn its true fit. Indeed, empirical evidence suggests that “overly positive” or “higher than the true” review ratings (Minnema et al. 2016, Sahoo et al. 2018) and a broad set of marketing instruments that influence sales (El Kihal and Shehu 2022) may also increase product return rates, thus calling for a consideration of returns when modeling the impact of eWOM on profitability. In this regard, recent studies have been more wary of the interaction between online reviews and product returns in the presence of fit or valuation uncertainty. For instance, Gao and Su (2017) consider the effect of product returns on purchases made through virtual showrooms. Sun et al. (2021) investigate the impact of online reviews on competing sellers pricing and return policies. Altug (2023) explores a setting where product returns may stimulate reviews with a negative sentiment and subsequently affect future customers valuations of the product. However, among these works, firms have assumed the traditional role of an eWOM receiver without imposing any influence on the online reviews. As far as we know, our paper represents a first attempt to model firms' proactive participation in eWOM and the design of product return policies.

In this regard, this paper is also relevant to the extensive literature on product returns driven by misfit or valuation uncertainty. In this context, some studies have focused on the choice between a no-refund and a full-refund policy (e.g., Davis et al. 1995, Che 1996). However, once the decision space is opened, partial refunds frequently arise as an optimal solution or equilibrium. Thus far, the literature has identified various reasons supporting partial refunds, including consumer opportunism (e.g., Chu et al. 1998), heterogeneous valuation uncertainty (e.g., Courty and Li 2000, Shulman et al. 2009), capacity scarcity (e.g., Xie and Gerstner 2007), aggregated demand uncertainty (e.g., Su 2009), competition (e.g., Guo 2009, Shulman et al. 2011), return channels (Shulman et al. 2010), coping with product lines (e.g., Huang and Zhang 2020, Zou et al. 2020), and salvage opportunities in omnichannel settings (Nageswaran et al. 2020). Our paper considers both binary (none or full) and continuous (partial) refunds in its return policy design.

In summary, our work contributes to the existing literature in several ways. First, it complements current research in influencer marketing by examining its application and taking into account potential product returns. Further, it explores how influence on customers should be imposed in conjunction with refund policy design. To the best of our knowledge, this is the first paper that analyzes the interaction between eWOM manipulation and product returns. Lastly, the study brings in new elements to the product returns literature by confirming the robustness of partial refunds in the context of influencer marketing and by characterizing the substitution effects between influencing customers *ex ante* and offering a full refund *ex post*.

3. Model

Consider that a firm commits to selling a product at price p to a mass of customers whose size is normalized to 1. The product may or may not be a good match for the customer. The actual fit $F \in \{G, B\}$ is unobservable to the customer until after the purchase. If the product turns out to be a good match ($F = G$), the customer values the product at v where $v \geq p$; otherwise ($F = B$), the customer's valuation is 0. Upon observing the true fit, the customer may return the product and obtain a refund $r \leq p$. It is public knowledge that only a fraction $\rho_0 \in [0, 1]$ of the customers would find the product a good match, i.e., $P(G) = \rho_0$ and $P(B) = 1 - \rho_0 = \bar{\rho}_0$[5]. In the absence of any other information, a customer will rely solely on ρ_0 to form its prior belief of the product's fit and to make

[5] For the rest of the paper, we denote $\bar{y} = 1 - y$ for any $y \in [0, 1]$

a purchasing decision. Consistent with the product returns literature, we assume that the price p, the valuation v, and the prior belief of fit ρ_0 are all exogenously given, whereas the firm is empowered to determine the level of refund $r \in [0, p]$.

Further, suppose that at cost c, the firm can obtain a tool that allows the customers to estimate the product fit in a way that could be influenced by the firm. A variety of intermediaries may serve this purpose, such as online review platforms, virtual fitting rooms, and influencers' posts. For instance, the firm may enable an online review platform that houses ratings and comments of the product. A potential customer may draw a signal from the reviews to infer a match (or mismatch) between herself and the product and then make a purchase decision. The reviews could be under full autonomy of previous users, in which case the signal and its accuracy will be completely exogenous to the firm's decision. Alternatively, the firm may impose some influence on the reviews and skew the user-generated contents in favor of a purchase. In practice, this can be through sponsoring favorable reviews via incentives, eliciting positive reviews from loyal customers, mitigating negative reviews,[6] etc. Therefore, a customer's estimate on product match could be driven by both the reviews from previous users as well as the influence imposed by the firm. Another example of similar mechanism could be influencers' posts, where the base informativeness of such posts is inherent to the influencers' community itself, and a firm may choose to use a particular influencer who is more or less influential.

In this context, we model the signal produced by the influence tool as a binary variable $s \in \{g, b\}$, where $s = g$ indicating a good fit and $s = b$ a bad fit. The signal comes with a baseline quality $P(g|G) = P(b|B) = \gamma \in (0.5, 1)$, which captures the precision of the signal when no influence is imposed. We assume that γ is an intrinsic characteristic of the tool and exogenous to the firm. In particular, $\gamma \to 1$ represents a nearly perfect baseline signal that almost always delivers a correct prediction on the product match, whereas $\gamma \to 0.5$ indicates an unenlightening signal that possesses little information beyond the prior belief of fit. Given the baseline signal quality γ, the firm may set an influence level $a \in [0, 1]$, which will distort the signal distribution to

$$P(g|G, a) = \gamma + a\bar{\gamma} \quad \text{and} \quad P(g|B, a) = a\gamma + \bar{\gamma}. \tag{1}$$

When the firm chooses not to impose any influence on the customers, i.e., $a = 0$, the signal is reduced to its baseline form, i.e., $P(g|G, 0) = P(g|G) = \gamma$ and $P(g|B, 0) = p(g|B) = \bar{\gamma}$. Under full influence, i.e., $a = 1$, the signal is always positive, i.e., $P(g|G, 1) = P(g|B, 1) = 1$. In essence, a high level of influence improves $P(g|G, a)$, the *true positive rate* (TPR, or *recall*) of the influence tool, i.e., the

[6] As witnessed by one of the co-authors, firms may reach out to dissatisfied customers to offer appeasing resolutions at the firm's expense to reverse an undesirable review score.

odds that a matched product will be accompanied by a positive signal, which is statistically traceable and contractible. For this reason and in line with existing literature (e.g., Kamenica and Gentzkow 2011, Pei and Mayzlin 2022), we assume that the signal distribution in (1) (or the quality γ and the influence level a) is common knowledge to all customers. For instance, the customers can infer signal quality out of their own review experiences as uncompensated users. The level of influence could be subject to self-disclosure or third-party forensic, e.g., influencers are often required to make it obvious when they have any "material connection" with a brand;[7] online sellers such as HomeDepot and Amazon label compensated reviews with words like "*This review was collected as part of a promotion*" or "*Vine Customer Review of Free Product;*" browser extensions such as Fakespot and Reviewmeta can help customers detect more hidden influences.

Observing signal s and the influence level a (or merely the signal distribution), a customer can update its posterior belief of the product's fit using Bayes' rule and make a purchasing decision accordingly. In particular, the probabilities of a good fit with signal g and b under influence level a are, respectively,

$$P(G|g,a) = \frac{P(g|G,a).P(G)}{P(g|a)} = \frac{P(g|G,a).P(G)}{P(g|G,a).P(G)+P(g|B,a).P(B)} = \frac{(\gamma+a\bar{\gamma})\rho_0}{(\gamma+a\bar{\gamma})\rho_0+(\bar{\gamma}+a\gamma)\bar{\rho}_0}, \quad (2)$$

$$P(G|b,a) = \frac{P(b|G,a).P(G)}{P(b|a)} = \frac{P(b|G,a).P(G)}{P(b|G,a).P(G)+P(b|B,a).P(B)} = \frac{\bar{\gamma}\rho_0}{\bar{\gamma}\rho_0+\gamma\bar{\rho}_0}; \quad (3)$$

and $P(B|g,a) = 1 - P(G|g,a)$ and $P(B|b,a) = 1 - P(G|b,a)$. In particular, $P(G|g,a)$, namely, the *precision* of the signal, decreases with the level of influence a (see Lemma A2 in the Appendix).

The sequence of the game is modelled as follows:

Stage 1 (Refund Policy): The firm announces its return policy $r \in [0,p]$. Then, nature determines if the product will fit a customer, i.e., $F = \{G,B\}$ with probability $\{\rho_0, \bar{\rho}_0\}$. The outcome F is not visible to the firm or the customer until Stage 4.

Stage 2 (Influence Configuration): The firm decides whether to obtain an influence tool at cost c, and if so, the influence level a. If an influence tool is acquired, a signal $s \in \{g,b\}$ is produced based on the signal distribution in (1).

Stage 3 (Customer Orders): The customer observes signal s, updates their posterior belief on F, and makes a purchase decision; if there is no such signal, the customer will make a purchase decision based on the prior belief ρ_0.

Stage 4 (Product Returns): The customer observes F and decides whether to return the product.

[7] https://www.ftc.gov/system/files/ftc_gov/pdf/1001A_Influencer%20Guide_508.pdf

3.1 Benchmark: No Refund ($r = 0$)

First consider the benchmark case in which the firm does not offer any refund, i.e., $r = 0$. This also represents a reduced instance pursuant to Pei and Mayzlin (2022). Using backward induction, the customer's decision at Stage 4 is moot, and there will be no product return. At Stage 3, in the absence of any signal (i.e., the firm did not acquire an influence tool at Stage 2), the customer will buy if any only if $\rho_0 v - p \geq 0$. Denote the price-to-value ratio $k = \frac{p}{v}$. The purchasing condition can then be represented by $\rho_0 \geq k$. If there is a positive signal, i.e., $s = g$, the customer will make a purchase if and only if $P(G|g,a)v - p \geq 0$, i.e., $\rho_0 \geq \rho_g(a) = \frac{k(1-\gamma\bar{a})}{\bar{k}(\gamma + a\bar{\gamma}) + k(1-\gamma\bar{a})}$. For a negative signal, i.e., $s = b$, the customer will only make a purchase if $P(G|b,a)v - p \geq 0$, or equivalently, $\rho \geq \rho_b = \frac{k\gamma}{\bar{k}\bar{\gamma} + k\gamma}$. Overall, $\rho_g(a)$, k, and ρ_b represent the threshold for purchase when there is a positive signal, no signal, and a negative signal, respectively. Further, it can be shown that

Lemma 1. *The purchase thresholds without refund satisfy $\rho_g(a) \leq k \leq \rho_b$.*

Then, the customer's purchasing decision follows:

- if $\rho_0 < \rho_g(a)$, a customer will never purchase;
- if $\rho_g(a) \leq \rho_0 < k$, a customer will purchase only if a positive signal is observed ($s = g$);
- if $k \leq \rho_0 < \rho_b$, a customer will purchase if there is no signal or a positive signal ($s = g$), but will not purchase if it observes a negative signal ($s = b$);
- if $\rho_0 \geq \rho_b$, the customer will always purchase, with or without the signal, and whether the signal is positive or negative.

Back to Stage 2, the firm needs to decide whether or not to acquire the influence tool, and if so, the level of influence. If the firm chooses not to acquire an influence tool, it will earn a solid p if the prior $\rho_0 \geq k$ and 0 otherwise. The expected profit function can then be written as

$$\Pi_0(N) = \mathbb{1}\{\rho_0 \geq k\}p,$$

where the subscript 0 represents the scenario with no refund, the N represents the choice of no influence tool, and $\mathbb{1}\{\cdot\}$ is an indicator function that yields 1 if a statement is true and 0 otherwise. If the firm acquires an influence tool with an influence level a, the expected profit follows

$$\Pi_0(a) = P(g|a)\mathbb{1}\{\rho_0 \geq \rho_g(a)\}p + P(b|a)\mathbb{1}\{\rho_0 \geq \rho_b\}p - c.$$

The first component of the above captures the chance of a positive signal under influence level a and the respective profit. The second component concerns the scenario of a negative signal. The last term represents the cost for acquiring the influence tool. Let $a_0^* = \arg\max_{0 \leq a \leq 1} \Pi_0(a)$. The following proposition characterizes the optimal solution for the firm at this stage.

Proposition 1. **(Optimal Influence Configuration with No Refund)** *Suppose the firm offers customers no refund. Then,*

(i) when $\rho_0 < \rho_g(0)$, *the firm will not acquire an influence tool and the customers will not make a purchase; the firm's expected profit is* $\Pi_0 = 0$;

(ii) when $\rho_g(0) \le \rho_0 < k$, *there exists* $C > 0$ *such that*

(a) *if* $c \le C$, *the firm will acquire an influence tool and set the influence level*

$$a_0^* = \left(\frac{\gamma}{\bar{\gamma}} - \frac{\bar{\rho}_0 k}{\rho_0 \bar{k}}\right) \Bigg/ \left(\frac{\gamma}{\bar{\gamma}}\frac{\bar{\rho}_0 k}{\rho_0 \bar{k}} - 1\right)$$

and a customer will purchase if a positive signal is observed; the firm's expected profit is $\Pi_0 = \Pi_0(a_0^*) = C - c$;

(b) *otherwise, the firm will not acquire an influence tool and the customers will not make a purchase; the firm's expected profit is* $\Pi_0 = 0$;

(iii) when $\rho_0 \ge k$, *the firm will not acquire an influence tool and the customers will always purchase; the firm's expected profit is* $\Pi_0 = p$.

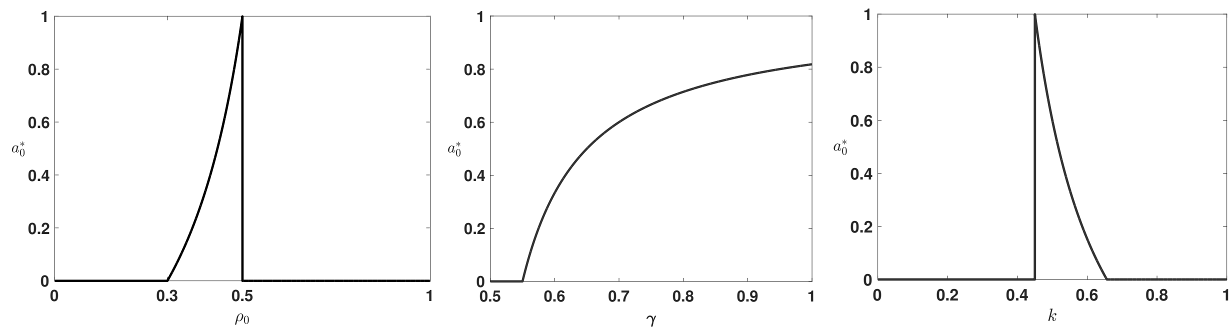
The proposition reveals several important principles for influencing customers. First, customer influencing activities should focus on the zone where the purchase is endangered. For instance, the firm should never intervene and influence the customers when they will purchase based on prior belief, i.e., $\rho_0 \ge k$. Second, within the "endangered purchase" zone, i.e., $\rho_0 < k$, the firm should only invest in the influence tool when the prior belief is not too low and the cost of the tool is not too high, i.e., $\rho_g(0) \le \rho_0 < k$ and $c \le C$. Otherwise, influencing customers is not worthwhile, and the firm should just let that business go. Lastly, the optimal influence level a_0^*, whenever applicable, should generally increase with the prior belief ρ_0, the baseline signal quality of the influence tool γ, and the valuation in case of a match v; but decrease with the price p. These relationships are depicted in Figures 1a, 1b, and 1c, respectively.

Lastly, we underscore that even though customers should only be the influenced when no purchase will happen based on prior belief of fit ($\rho_0 < k$), the influence does not really impact the customer utility. In fact, the expected customer utility remains the same with or without the existence of an influence tool, as summarized in Corollary 1. This suggests that using the influence tool is more for the benefit of the firm, to enhance its own expected profit.

Corollary 1. **(Customer Welfare under No Refund)** *When no refund is allowed, the expected customer utility* $U_0 = 0$ *when* $\rho_0 < k$ *and* $U_0 = \rho_0 v - p \ge 0$ *otherwise.*

Figure 1 Optimal Influence Level (with $p=1$, $v=2$, $c=0$, $\gamma=0.7$, $\rho_0=0.45$, wherever applicable)

(a) varying with the prior belief (b) varying with the signal quality (c) varying with price/valuation



4. Influencing Customers under an Exogenous Refund Rate

We now investigate the scenario where the firm allows some refunds and determines its level of influence on customers based on an exogenous refund rate $r \in (0,p]$. Exogenous refund rates typically apply when firms need to adapt to industry norms or keep its commitment in customer service standard. In general, it is more convenient for a firm to revise its customer influence action than product returns policy.

At Stage 4, the customer must make a product return decision upon observing F. Clearly, if the product matches the customer ($F=G$), the customer will keep the item with a positive net utility $v-p$; otherwise, if the fit is bad ($F=B$), the customer will return it to at least partially recover the price paid and end up with a non-positive net utility $r-p$.

At Stage 3, the customer makes a purchase decision based on the observed signal, if any. In the absence of a signal, the customer will rely on the prior belief ρ_0 to estimate their expected utility at Stage 4. Should the customer go ahead with the purchase, they will end up with an expected utility $U_r = \rho_0(v-p) + \bar{\rho}_0(r-p) = \rho_0 v + \bar{\rho}_0 r - p$. Denote $\tilde{k} = \frac{p-r}{v-r}$. Clearly, the customer will only make the purchase if $U_r \geq 0$ or, equivalently, $\rho_0 \geq \tilde{k}$. Similarly, if a positive signal is observed, the customer will make a purchase if $U_r = P(G|g,a)v + P(B|g,a)r - p \geq 0$. It can be verified that the condition is equivalent to $\rho \geq \tilde{\rho}_g(a)$ where

$$\tilde{\rho}_g(a) = \frac{\tilde{k}(1-\gamma\bar{a})}{\bar{\tilde{k}}(\gamma + a\bar{\gamma}) + \tilde{k}(1-\gamma\bar{a})}. \tag{4}$$

With a negative signal, the customer will purchase if and only if $U_r = P(G|b,a)v + P(B|b,a)r - p \geq 0$, i.e., $\rho \geq \tilde{\rho}_b$ where

$$\tilde{\rho}_b = \frac{\tilde{k}\gamma}{\bar{\tilde{k}}\bar{\gamma} + \tilde{k}\gamma}. \tag{5}$$

The customer's purchasing choice can then be summarized as follows:

Lemma 2. *Suppose the firm will refund $r \in (0,p]$ for any returns. Then, at Stage 3,*

- *if* $\rho_0 < \tilde{\rho}_g(a)$*, a customer will never purchase;*
- *if* $\tilde{\rho}_g(a) \le \rho_0 < \tilde{k}$*, a customer will purchase only if a positive signal is observed;*
- *if* $\tilde{k} \le \rho_0 < \tilde{\rho}_b$*, a customer will purchase if there is no signal or a positive signal, but will not purchase if a negative signal is observed;*
- *if* $\rho_0 \ge \tilde{\rho}_b$*, the customer will always purchase.*

In summary, customer purchase decisions follow the same structure as those without a refund (Lemma 1). However, a refund will generally lower the thresholds for purchase (Corollary 2), and the influence tool will be used when the market possesses a lower prior belief about the fit (ρ_0).

Corollary 2. **(Impact of Refund on Customer Choice)** *The purchasing thresholds* $\tilde{k}$*,* $\tilde{\rho}_g(a)$*, and* $\tilde{\rho}_b$ *decrease in the level of refund* r*. In particular,* $\tilde{k} \le k$*,* $\tilde{\rho}_g(a) \le \rho_g(a)$*, and* $\tilde{\rho}_b \le \rho_b$*.*

Back in Stage 2, the firm compares the expected profit across all scenarios to determine if an influence tool will be acquired, and if so, the level of influence to use. If the firm decides to go without an influence tool, by Lemma 2, a customer will only purchase when $\rho_0 \ge \tilde{k}$, and, with a probability $\bar{\rho}_0$, the customer will come back for a refund r at Stage 4. The firms expected profit without an influence tool is then

$$\Pi_r(N) = \mathbb{1}\{\rho_0 \ge \tilde{k}\}(p - \bar{\rho}_0 r). \tag{6}$$

On the other hand, if an influence tool is acquired, it will produce a positive signal ($s = g$) with probability $P(g|a)$. By Lemma 2 (ii)-(iv), a customer will order as long as $\rho_0 \ge \tilde{\rho}_g(a)$, and the odds they will claim a refund in Stage 4 can be represented by $P(B|g,a)$. This gives rise to the first component in (7). The influence tool may also produce a negative signal ($s = b$) with probability $P(b|a)$, and the fraction of the expected profit in this scenario is provided in the second component of (7). Overall, the firm's expected profit with an influence tool can be written as follows:

$$\Pi_r(a) = P(g|a)\,\mathbb{1}\{\rho_0 \ge \tilde{\rho}_g(a)\}\,[p - P(B|g,a)r] + P(b|a)\,\mathbb{1}\{\rho_0 \ge \tilde{\rho}_b\}\,[p - P(B|b,a)r] - c. \tag{7}$$

Denote $a_r^* = \arg\max_{0 \le a \le 1} \Pi_r(a)$ as the optimal influence level should an influence tool be acquired. The following proposition characterizes the firm's optimal decision in Stage 2:

Proposition 2. **(Optimal Influence Configuration with Refund)** *Suppose the firm will issue a refund* $r \in (0, p]$ *for each product return. Then, at Stage 2,*

(i) when $\rho_0 < \tilde{\rho}_g(0)$*, the firm will not acquire an influence tool and there will be no purchase; the firm's expected profit is* $\Pi_r = 0$*;*

(ii) when $\tilde{\rho}_g(0) \le \rho_0 < \tilde{k}$*, there exists* $\tilde{C} > 0$ *such that*

(a) *if $c \leq \tilde{C}$, the firm will acquire an influence tool and set the influence level as*

$$a_r^* = \left(\frac{\gamma}{\bar{\gamma}} - \frac{\bar{\rho}_0 \tilde{k}}{\rho_0 \bar{\tilde{k}}}\right) \Big/ \left(\frac{\gamma}{\bar{\gamma}} \frac{\bar{\rho}_0 \tilde{k}}{\rho_0 \bar{\tilde{k}}} - 1\right)$$

and the customers will purchase if a positive signal is observed; the firm's expected profit is $\Pi_r = \Pi_r(a_r^*) = \tilde{C} - c$;

(b) *otherwise, the firm will not acquire an influence tool, and there will be no purchase; the firm's expected profit is* $\Pi_r = 0$;

(iii) when $\rho_0 \geq \tilde{k}$, the firm will not acquire an influence tool and, the customers will always purchase; the firm's expected profit is $\Pi_r = p - \bar{\rho}_0 r$;.

Proposition 2 finds that, with a refund, the firm will retain the structure of its influence decision, albeit with more lenient purchasing thresholds (as analyzed in Corollary 2). In particular, given the prior belief of fit, more refunds may compromise the use an influence tool by shifting its application zone towards more pessimistic priors. However, as long as the influence tool remains in application, offering a refund will invite more aggressive customer influencing actions. We explicitly characterize this effect as follows:

Corollary 3. **(Impact of Refund on Influencing Customers)** *As the level of refund r increases, a firm may discontinue the application of an influence tool if the prior belief of fit is relatively high; otherwise, the firm should continue the use of the influence tool and*

(i) the cost threshold $\tilde{C}$ increases in the level of refund r. In particular, $\tilde{C} \geq C$.

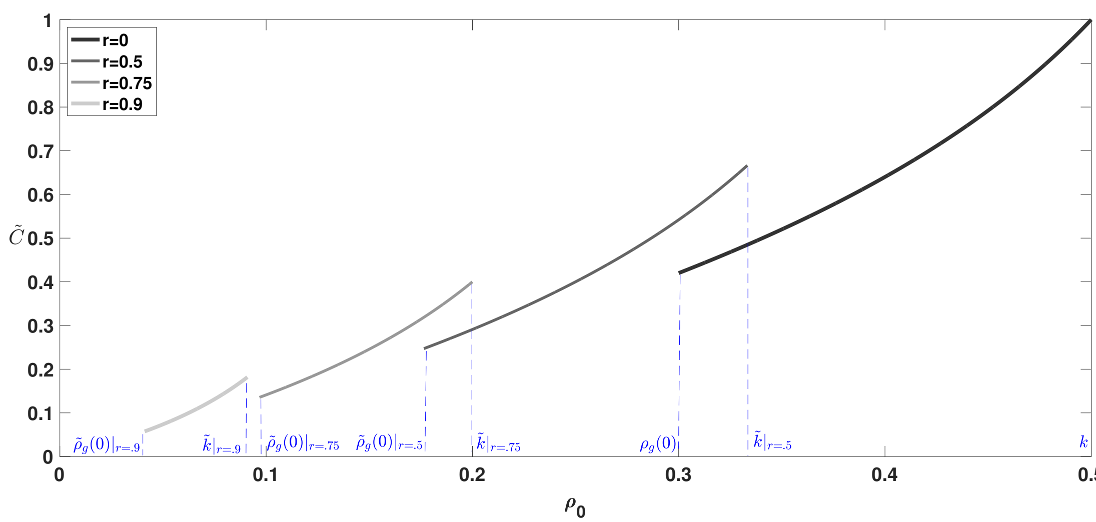
(ii) the optimal level of influence a_r^* increases in the level of refund r. In particular, $a_r^* \geq a_0^*$.

Indeed, with more refunds, the firm should either cease using the influence tool so to reduce the amount of returns, or, keep using the tool but more aggressively in order to benefit from a higher level of *true positive rate*. Corollary 3 finds that it is more beneficial to take the first (cease) approach when the prior is already optimistic, as the influence cost is unlikely to deliver more revenue from the matched customers than the loss in additional refunds to the *falsely* matched ones. If the prior is less optimistic, the firm should instead take the second (continue) approach and impose more influence, hence there will be sufficient *truly* matched customers persuaded to make the purchase. For the latter case, Corollary 3 (i) finds that as the amount of refund increases, the upper bound for $\tilde{C}$ will improve in favor of the acquisition of an influence tool. Corollary 3 (ii) suggests that the firm will also engage in a higher level of influence a_r^*, so to increase the *true positive rate* and mitigate the loss from more refunds. In summary, depending on the joint effect of contrary forces, the level of refund may have a mixed impact on the influence decision.

Figures 2 and 3 illustrate the aggregated impact of refund on the use of the influence tool, the cost threshold $\tilde{C}$ and the optimal level of influence level a_r^*, respectively. Across both figures, the price $p=1$, the valuation with good fit $v=2$, and the baseline signal quality $\gamma=0.7$. We also set $c=0$ to rule out the effect of the cost of acquiring an influence tool. Following Proposition 2 and Corollary 3, the influence tool only plays a role when $\rho_0 < k = \frac{p}{v} = 0.5$. We use darker curves to represent more restrictive refunds and lighter curves for more generous refunds; then, each curve starts on $\tilde{\rho}_g(0)$ and ends on $\tilde{k}$ based on the given level of refund r.

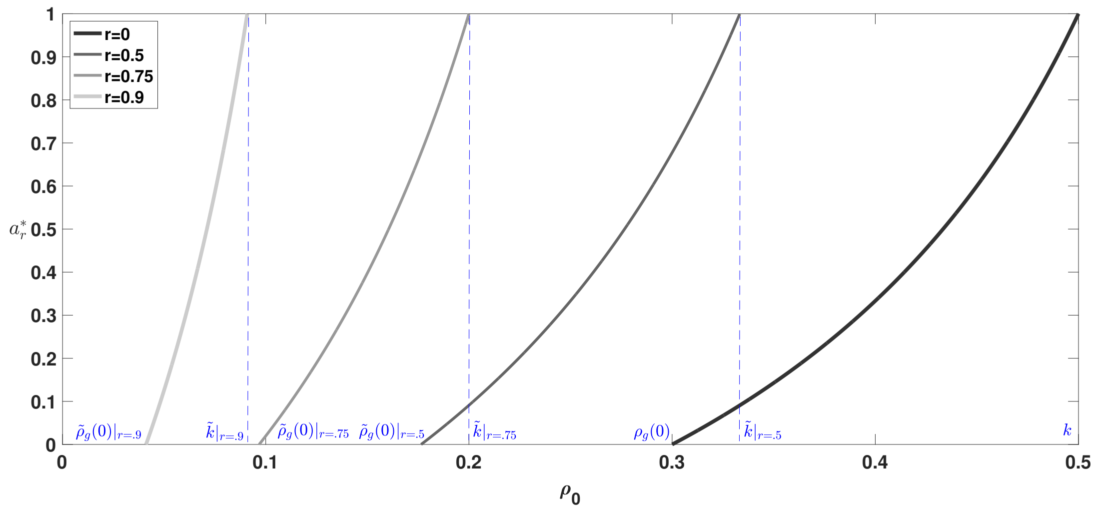
As can be seen from the graphs, with a higher level of refund, the application zone of an influence tool $\rho_0 \in [\tilde{\rho}_g(0), \tilde{k})$ shifts left toward more pessimistic prior beliefs. While the cost threshold $\tilde{C}$ increases in r in general, a higher level of refund may drive the prior belief out of the application zone of the influence tool, making the effective cost threshold generally lower under a high r. For instance, at $\rho_0 = 0.32$, a no-refund policy would employ an influence tool as long as the cost is less than 0.46. For a 50% refund policy, the maximum cost for an influence tool gets more room, up to 0.61. However, for a 75% or 90% refund policy, the influence tool will never be adopted at $\rho_0 = 0.3$. In general, the cost threshold for a no-refund policy across all kinds of prior beliefs ranges from 0.42 to 1, the threshold for a 50% refund policy ranges from 0.25 to 0.67, the threshold for a 75% refund policy ranges from 0.14 to 0.4, and the threshold for a 90% refund policy ranges from 0.06 to 0.18.

Figure 2 Threshold of Influence for the Cost of the Influence Tool $\tilde{C}$ as a Function of Prior Belief ρ_0 ($p=1, v=2, \gamma=0.7$)



The optimal level of influence a_r^* is subject to similar effects as a result of the shift in the application zone of the influence tool: at $\rho_0 = 0.32$, a no-refund policy would set an influence level of 0.05, while a 50% refund policy would raise the influence level to 0.86. This pattern however does not hold for the 75% or 90% refund policy, as no influence tool will be adopted at those levels of refund. Despite these variations, the optimal level of influence consistently ranges from 0 to 1 across all kinds of prior beliefs and for any given refund policy. In particular, the optimal level of influence is more sensitive to changes in prior belief under a more generous refund.

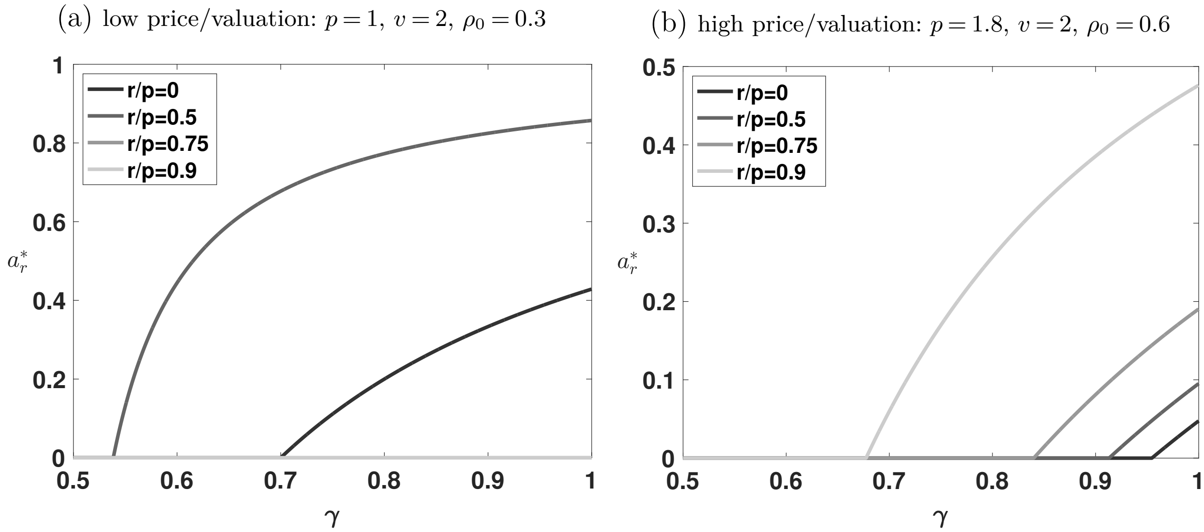
Figure 3 Optimal Level of Influence a_r^* as a Function of Prior Belief ρ_0 $(p=1, v=2, \gamma=0.7)$



The impact of the refund on the optimal level of influence can be more conspicuously illustrated for a given prior belief as in Figure 4. In both graphs, a more generous refund r (lighter curves) generally yields a higher level of influence a_r^* as long as the influence tool is employed. For instance, when the price-to-valuation ratio is high, as depicted in the right panel, the influence tool will be adopted for all refund levels when the baseline informativeness γ is greater than 0.68, and a 90% refund stimulates the most aggressive influence level (the lightest curve) versus no refund the minimum amount of influence (the darkest curve). When the price-to-valuation ratio is low, as in the left panel, the more generous refunds of 75% and 90% will not be accompanied with any influence tool, as the low price and generous refund themselves are sufficient to induce the purchase. As the refund becomes more frugal, the firm is better off expanding the purchase zone by picking up the influence tool and improve the *true positive rate*. At the same time, the influence action will also reduce the signal *precision*. Even though a less precise signal will lead to more returns *ex post*, a lower refund can effectively limit the loss the firm would suffer in this regard. In this scenario, interestingly, the level of influence may increase with the refund rate, as can be seen from the two dark curves in Figure 4a. This suggests that when the influence tool stays in place, a more generous refund may invite more aggressive influence actions.

Corollary 4. **(Impact of Refund on Welfare)**

Figure 4 Optimal Level of Influence a_r^* as a Function of the Baseline Informativeness of the Influence Tool γ



(i) The firm's expected profit Π_r *increases in the level of refund* r *when* $\rho_0 \le \tilde{k}$ *and decreases in the level of refund otherwise.*

(ii) Customer utility $U_r = 0$ *when* $\rho_0 \le \tilde{k}$ *and* $U_r = \rho_0 v + \bar{\rho}_0 r - p \ge 0$ *increasing in the level of refund* r *otherwise.*

Corollary 4 summarizes the impacts of refunds on the parties' welfare. When the prior belief of fit is low ($\rho_0 < \tilde{k}$), customer utility stays at 0 regardless of the refund amount r, but the firm's expected profit increases with r. In particular, the increase in the firm's expected profit is strict when an influence tool is employed, i.e., conditions in Proposition 2 (ii)(a) are satisfied. This implies that allowing product returns on top of influencing the customers has non-trivial value to the firm as well as to the whole supply chain when the chance of a match between the product and the customers is pessimistic.

On the other hand, when the prior belief of fit is high ($\rho_0 \ge \tilde{k}$), allowing product returns will hurt the firm's expected profit but enhance the customer utility. This impact is most significant among customers with moderate prior beliefs, e.g., $\rho_0 \in [\tilde{k}, k]$. Without a refund, these customers will be under configured influence ($a_0^* \ge 0$), resulting in only a fraction of them making the purchase (those observing a positive signal) and possibly enjoying the product. However, with refunds r, all customers in this range will have the chance to learn the true fit through purchase and to return the product if it does not match their preferences.

Thus far, we find that the level of refund will shift the application zone of the influence tool and bring a non-monotone change to the firm's expected profit. The proper refund level for a firm to set from the beginning remains a puzzle. In what follows, we tackle the Stage 1 problem by investigating the firm's optimal choice among various return policies, taking into account the optimal customer influence configuration associated with each.

5. Joint Refund Design and Influence Configuration

In this section, we study the optimal joint design of the return policy and influence tool configuration. In particular, the firm will endogenously decide the refund level r, with the influence tool being employed and configured following Proposition 2.

We first consider a generic case where the decision space of the refund is binary: $r \in \{0, p\}$ in Section 5.1. That is, the firm will only choose between a no-refund and full-refund policy. This covers a broad range of scenarios where a firm would like to adopt a simple rule to ease customer communication and reduce administrative hassles. In Section 5.2, we examine the general case where the decision space of the refund is continuous, i.e., $r \in [0, p]$, representing the benchmark scenario where a firm has the power to offer no refund, or a partial or full one, at its own discretion.

5.1 Binary Refund

When $r \in \{0, p\}$, the problem is reduced to comparing the no-refund scenario as solved in Proposition 1 versus a full refund ($r = p$) as solved in Proposition 2.

PROPOSITION 3. **(Optimal Binary Refund)** *Suppose the firm can choose between no refund and a full refund in Stage 1. Then,*

(i) when $\rho_0 < \rho_g(0)$, the firm will offer a full refund $r^* = p$ without acquiring any influence tool; the customers will always purchase; and the firm's expected profit is $\Pi = \rho_0 p$;

(ii) when $\rho_g(0) \le \rho_0 \le k$, there exist $C_f \in [0, C]$ and $\Gamma_f \in [\frac{1}{2}, 1]$ such that

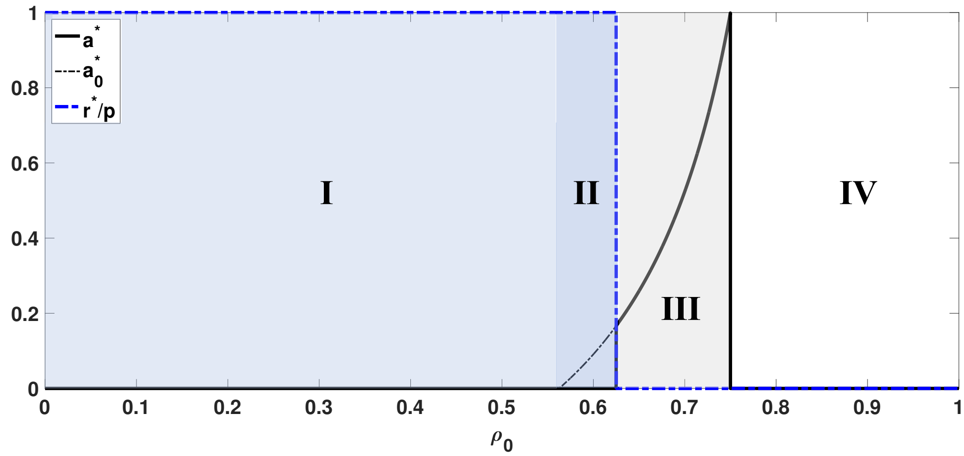
(a) *if $c \le C_f$ and $\gamma \ge \Gamma_f$, the firm will adopt a no-refund policy, $r^* = 0$, acquire an influence tool, and set the level of influence $a^* = a_0^*$; the customers will only purchase if a positive signal is observed; and the firm's expected profit is $\Pi = C - c$.*

(b) *otherwise, the firm will offer a full refund $r^* = p$ without acquiring any influence tool; the customers will always purchase; and the firm's expected profit is $\Pi = \rho_0 p$;*

(iii) when $\rho_0 > k$, the firm will adopt a no-refund policy $r^* = 0$ without any influence tool; the customers will always purchase; and the firm's expected profit is $\Pi = p$.

As an example, Figure 5 illustrates the optimal joint binary refund and influence level when the price-to-value ratio is $k = \frac{p}{v} = 0.75$. In regions I and II where $\rho_0 \le 0.63$, there will be no influence tool but a full refund, and the customers will always purchase. In region III, as ρ_0 increases from 0.63 to 0.75, the firm will acquire an influence tool and configure the influence level from 0.18 to 1

Figure 5 Joint Binary Refund and Influence Configuration ($k = 0.75,\ \gamma = 0.7, c = 0$): **I/II** – Full Refund, No Influence; **III** – No Refund, Moderate to High Influence; **IV** – No Refund, No Influence.



in accordance with the ρ_0; the customer will purchase if the influence tool yields a positive signal, keeping in mind that no refund will be offered if the signal is a false positive. In region IV, the firm will not offer any refunds or acquire any influence tools; the customers will always purchase. As can be observed, endogenizing the refund introduces structural changes to the purchase decision. A joint configuration of binary refund and influence level will allow customers with all kinds of prior beliefs to purchase and learn the true fit of the product. In particular, a refund will encroach on the application zone of the influence tool (marked as region II in Figure 5), where the level of influence is marginal. This implies that, at times, it is more beneficial to let the customers try the product and discover its true fit *ex post* than to impose influence and stimulate nonrefundable sales *ex ante*.

These effects are rooted in Proposition 3, which suggests that a firm will not acquire an influence tool when the customers hold a rather optimistic or pessimistic prior belief about product fit – in cases where the prior is moderate, if the influencing cost is high, or if the baseline informativeness of the influence tool is low. In these scenarios, the firm will offer a full refund if the prior belief is moderate or pessimistic, and no refund if the prior belief is optimistic. In other words, the firm will only adopt an influence tool if the prior belief is moderate, the influencing cost is below some threshold, and the signal is reasonably informative. When adopted, the influence tool will be accompanied by a no-refund policy. Compared to the no-refund scenario, the optimal binary refund restricted the adoption of the influence tool through a tighter cost threshold $C_f \leq C$ and a minimum requirement Γ_f for the degree of informativeness of the influence tool. Figures 6 and 7 demonstrate how these two thresholds vary with the prior belief ρ_0 and the price-to-value ratio k.

In all curves, the price is fixed at $p = 1$ and the baseline level of informativeness of the influence tool is $\gamma = 0.7$. The solid dark curves plot the thresholds with $k = p/v = 0.5$, or equivalently, $v = 2$.

Figure 6 Threshold for the Cost of the Influence Tool under the Optimal Binary Refund ($p=1, \gamma=0.7$)

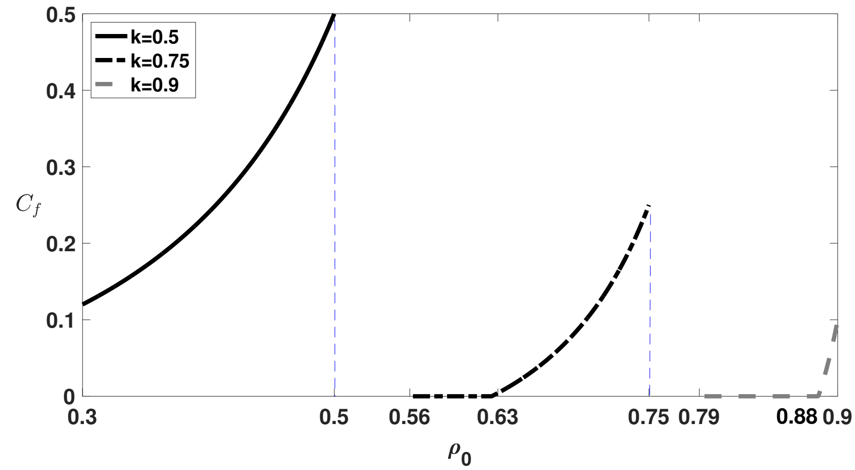
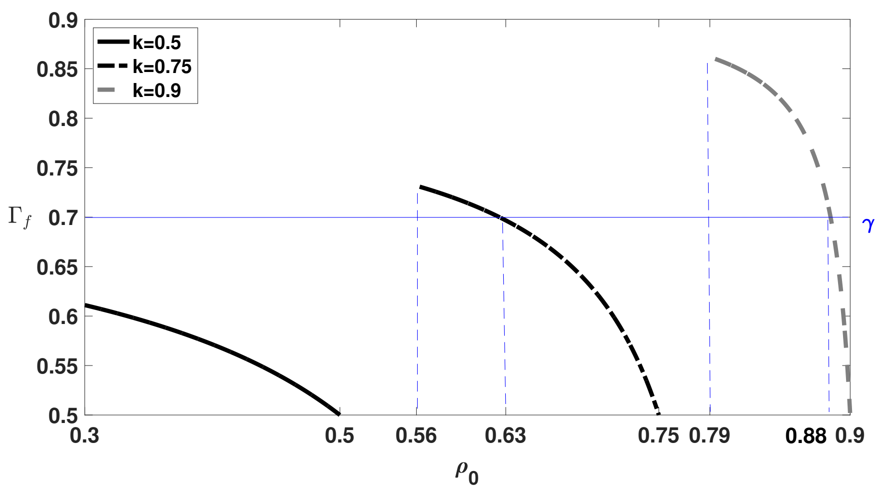


Figure 7 Threshold for the Level of Informativeness of the Influence Tool under the Optimal Binary Refund ($p=1, \gamma=0.7$)



At this price level, a firm offering the optimal binary refund would only employ an influence tool when the prior $\rho_0 \in [0.3, 0.5]$. Within this range, $\gamma = 0.7$ is consistently above Γ_f, thus meeting the minimum requirement of baseline informativeness. In addition, the acquisition of an influence tool is conditioned upon $c \le C_f$, which varies from 0.12 to 0.5 for $\rho_0 \in [0.3, 0.5]$. Compared to Figure 2, where the cost threshold C under a no-refund policy for the same range of ρ_0 varies from 0.42 to 1, it can be observed that a binary refund substantially limits the adoption of the influence tool. As the price-to-value ratio k increases to 0.75, the application zone for an influence tool is shifted to be within $\rho_0 \in [0.56, 0.75]$. In this area, however, $\gamma = 0.7$ only exceeds Γ_f when $\rho_0 \ge 0.63$. That is, the minimum requirement of the baseline informativeness of the influence tool further shrinks its application zone to $\rho_0 \in [0.63, 0.75]$, within which we can observe an even lower but still positive cost threshold C_f. When k goes up to 0.9, the actual application zone of the influence tool $\rho_0 \in [0.88, 0.9]$ is even narrower due to the minimum requirement on informativeness, along with a more stringent cost threshold. This provides numerical illustration for the following result:

COROLLARY 5. **(Full Refund vs. Costless Influence Tool)** *Under the optimal binary refund, the firm may adopt a full refund policy without acquiring the influence tool, even if the latter is costless.*

As can be seen from the above numericals, the effect in Corollary 5 is especially salient when it comes to high price-to-value products. For instance, when $k = 0.9$, the area $\rho_0 \in [0.79, 0.88]$ where the influence tool used to apply is cannibalized by a full refund, whereas the zone of influence stays the same for $k = 0.5$. Therefore, the joint consideration of refund and influence design is particularly relevant for high price-to-value products.

Figure 8 Expected Profit (Π) and Customer Utility (U) under the Optimal Binary Refund ($p = 1, v = 2, \gamma = 0.7, c = 0$)

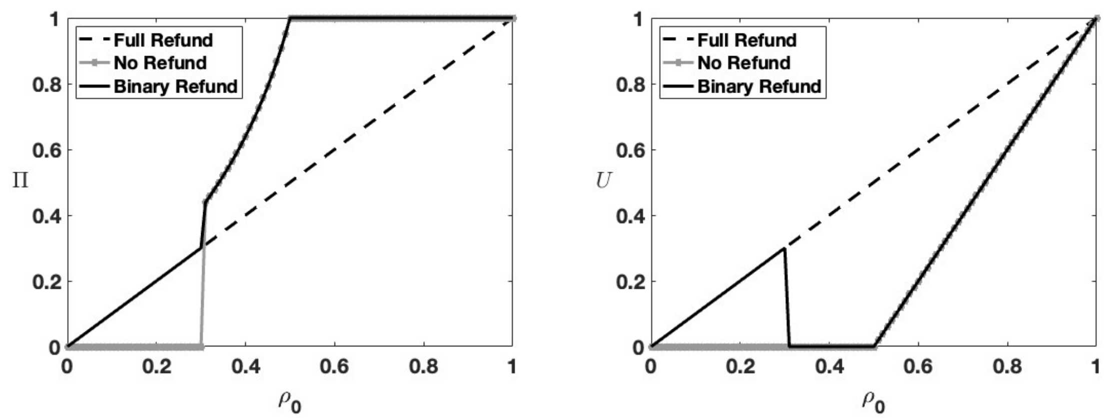
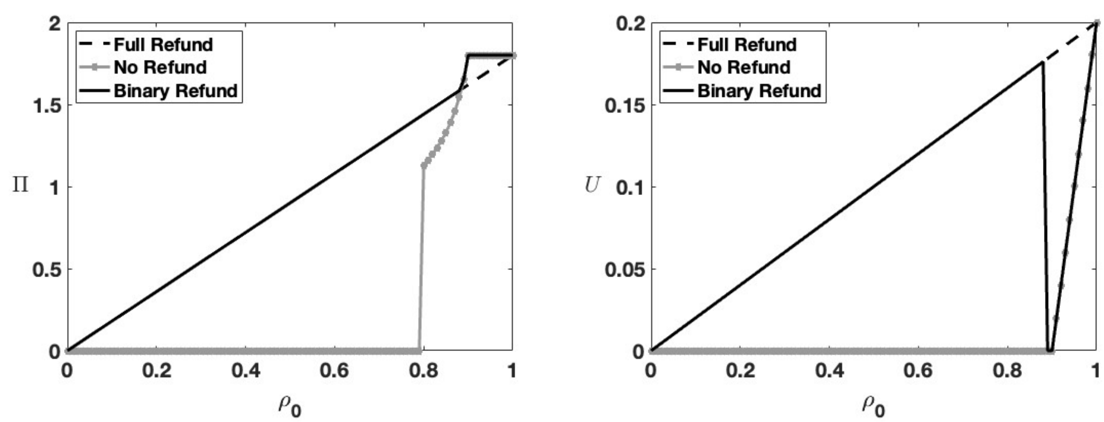


Figure 9 Expected Profit (Π) and Customer Utility (U) under an Optimal Binary Refund ($p = 1.8, v = 2, \gamma = 0.7, c = 0$)



Lastly, we investigate the impact of binary refund on the parties' welfare. Clearly, the optimal binary refund design adds to the firm's expected profit compared to no refund or a full refund alone. This is depicted in the left panel of Figure 8 and Figure 9 for a low price ($p = 1, k = \frac{p}{v} = 0.5$) and high price ($p = 1.8, k = \frac{p}{v} = 0.9$), respectively. Essentially, the optimal binary refund delivers a higher expected profit than no refund when the prior belief is pessimistic, and outperforms a full refund when the prior belief is optimistic. In the same area, the optimal binary refund also strictly improves customer welfare compared to no refund. This is summarized in Corollary 6. Overall, a binary refund enhances the expected profit and customer utility when the prior belief of a match is low. Further, there are scenarios where all parties are better off under a full refund than no refund but influences on customers, e.g., in Figure 9 when $\rho_0 \in [0.79, 0.88]$.

COROLLARY 6. **(Customer Welfare under Optimal Binary Refund)**

(i) Under the optimal binary refund, when $\rho_g(0) \le \rho_0 < k$, $c < C_f$, and $\gamma \ge \Gamma_f$, the customer's expected utility is $U = 0$; otherwise, $U = \rho_0(v - p) \ge 0$ if $\rho_0 < k$ and $U = \rho_0 v - p \ge 0$ if $\rho_0 \ge k$.

(ii) Compared to no refund, endogenizing a binary refund enhances the customer utility. In particular, the enhancement is strict when $\rho_0 < \rho_g(0)$ or when $\rho_g(0) \le \rho_0 < k$, $c \in [C_f, C]$ and $\gamma \in [0, \Gamma_f]$.

5.2 Continuous Refund

Now, consider the case where $r \in [0, p]$. That is, the firm may offer partial refunds for product returns at its own discretion. By Proposition 2, for a given prior ρ_0, the firm may set a refund level such that no purchase will take place, or one that supports the adoption of an influence tool and where the purchase will be conditioned upon a positive signal, or a refund level at which the customer will always purchase. Based on this analysis, we find the optimal continuous refund design, as summarized in the following proposition:

PROPOSITION 4. **(Optimal Continuous Refund)** *If a firm may freely choose its refund level r within $[0, p]$, it will never acquire any influence tools. Instead,*

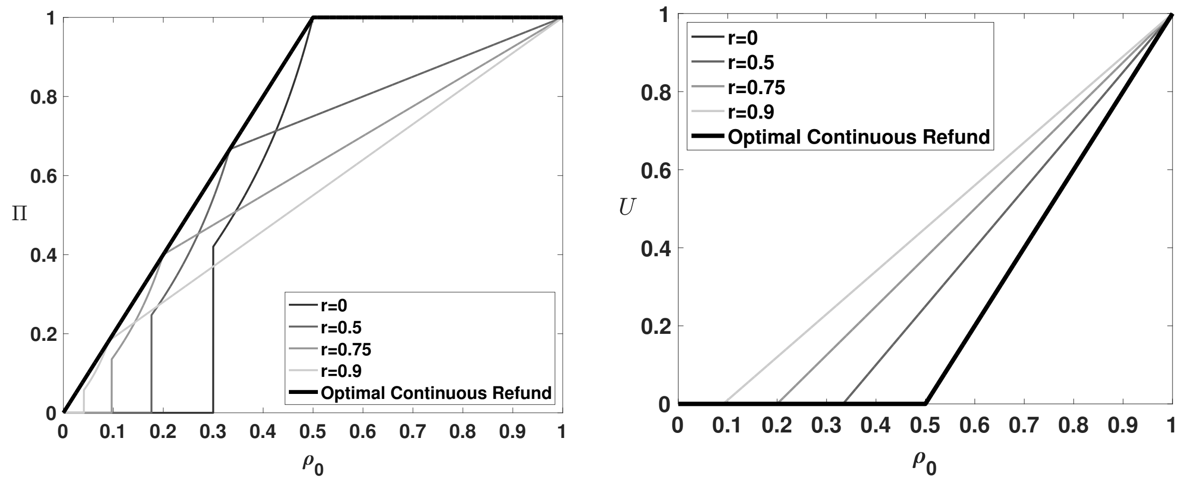
(i) when $\rho_0 < k$, the firm would offer a partial refund $r^* = \frac{p - \rho_0 v}{\rho_0}$, and the expected profit is $\Pi = \rho_0 v$;

(ii) otherwise, the firm would offer no refund $r^* = 0$, and the expected profit is $\Pi = p$.

Interestingly, the result suggests that the firm can solely rely on partial refunds, without using an influence tool to achieve the maximum expected profit. In particular, the refund should be next to full for the most pessimistic prior belief ($r^* \to 1$ when $\rho_0 \to 0$) and gradually reduce as the prior improves, until it hits the point ($\rho_0 = k$) where customers would always make a purchase, after which no refund would apply ($r^* = 0$).

This aligns with the existing literature stating that partial refunds can be used to screen and discriminate against customers with heterogeneous valuation uncertainties (e.g., Courty and Li 2000, Akan et al. 2015, albeit in a more dynamic setting). In a generic setting, as considered in this paper, the result also implies the robustness of partial refunds in the presence of customer influence.

Figure 10 Expected Profit (Π) and Customer Utility (U): Exogenous Refund vs. Optimal Continuous Refund ($p=1, v=2, \gamma=0.7, c=0$)



We plot the expected profit under the optimal continuous refund versus the expected profits under various exogenous refunds (darker curves for low refunds and lighter curves for high refunds) in the left panel of Figure 10. As can be observed, the optimal continuous refund captures the maximum expected profit that can be realized across all plausible refunds, thereby eliminating the need to adopt an influence tool. At the same time, the optimal continuous refund also extracts customer surplus to the maximum extent. As depicted in the right panel of Figure 10 and summarized in Corollary 7, the expected customer utility increases with the level of (exogenous) refund, and the optimal continuous refund delivers the same customer utility with no refund.

COROLLARY 7. **(Customer Welfare under Optimal Continuous Refund)** *Under the optimal continuous refund, the customer's expected utility is* $U=0$ *when* $\rho_0 \le k$ *and* $U=\rho_0 v - p \ge 0$ *otherwise.*

The optimal partial refunds identified in this subsection carry some appealing characteristics and call for tactical implementation in practice. In the next section, we summarize the applicability and benchmark value for these results.

6. Managerial Implications

Thus far, our model and analysis have tackled several interactions between the level of influence and refund policies. The results deliver practical insights on how industries may maneuver these two forces in various contexts.

6.1 Matching Refund Policy with Influence Actions

To begin with, we remark that refund policies can be subject to industry norms or regulations, hence vary significantly across product categories. For instance, major appliance retailers such as Structube often refrain from offering free returns for oversized items. As another example, due to safety and efficacy reasons, drug or healthcare products are advised against accepting returns from consumers (Global News 2022). Conversely, the fashion and clothing sectors traditionally uphold a practice of providing more generous refunds, with clothing exhibiting a higher level (Confente et al. 2018). With respect to our analysis, §4 suggests that customer influence actions should be adjusted according to these refund policies. In particular, under more generous refunds, the influence should focus on items with low probability of a match – in fashion and apparel industry, these would be the niche or new products rather than classical items. Under more restricted refunds, the focus of influence should be among products with high chance of a match – in the case of healthcare products, this implies that influencing efforts should be with more universal products such as blood pressure or blood glucose monitors, rather than over-the-counter drugs whose efficacy might vary largely among individuals.

At times, a company may need to deal with distinct refund policies for products with the same odds of a mismatch. Consider airlines, for example, where trip uncertainties are more or less common among the travellers, but reservations for the business and first class usually boast a comprehensive refund policy versus those for economy class are typically restricted to partial refunds. In this context, our insight is that products subject to a more generous refund may deserve a higher level of influence if it is not off the radar. Indeed, Emirates and Turkish Airlines have strategically focused their influence endeavours on their premium classes, hiring TikTok influencer Cameron Biafore (New York Post 2023) and Fifi, a miniature dachshund with 14.4-thousand Instagram followers,[8] to share their first class flight experiences over social media.

6.2 Shift of Internal Refund Policy

When companies plan to impose a strategic change in their refund policies, it is equally important to recognize the associated moves on influence actions as well as the areas of applicability. To this effect, the endogenous binary refund studied in §5.1 supports a shift from a full to no refund policy with increasing influence for products with a lower chance of mismatch. This implies that companies interested in tightening refund polices should also put elevating their influence levels on the agendas. A compelling example in this scenario can be L.L.Bean, the renowned American retailer of outdoor clothing and gear used to be known for its exceedingly liberal return policy. In recent years, L.L.Bean has modified its policy to limit the terms of returns (Wall Street Journal 2018). Around the same time, in capitalizing this adjustment, L.L.Bean's marketing team has allotted more efforts and promotional campaigns to digital media (Marketing Dive 2017). For instance, the company recently collaborated

[8] https://nypost.com/video/first-class-canine-is-flying-in-style/

with social media influencer Gracie Wiener to blow its classic Boat and Tote (The Boston Globe 2022). The heightened digital marketing efforts, social media campaigns, and collaborations with influencers, are well connected with L.L.Bean's internal shift of refund policy.

6.3 The Value of Partial Refunds

Lastly, we find in §5.2 that a continuous (partial) refund can be more effective in dealing with match uncertainty than any combination of binary refund and influence tools. This suggests that as the scenario allows, a firm may consider using instruments such as restocking fees, non-refundable surcharges (e.g., shipping), non-refundable deposits, store credits, etc., to secure sale revenue at a proper level. Although less pronounced, partial refunds have been commonly practiced in industries. For instance, Air Canada charges various cancellation fees and processing fees for economy-class tickets. Best Buy may impose a 15% restocking fee for open-box items. Many luxury products, such as those from Tiffany & Co. or Chanel, are only allowed to be returned for exchange or store credit. Overall, these implicit return policy terms give firms room to mitigate the persuasion effect of influencer marketing when the latter is not in play.

In some other contexts, however, the optimal partial refunds can be hard to implement. For one thing, it may be hard for customers to accept a perplexing refund policy purely for the benefit of the firm. In addition, the proposed partial refund scheme increases the firm's administrative burden, particularly when prior beliefs vary over time and among different products. When these factors become prominent, it can be more practical for the firm to adopt a standard refund policy and let the variations be handled by an influence tool, which can be configured more conveniently and costlessly. In this scenario, the optimal continuous refund identified in our model may serve as a useful benchmark to measure the efficiency of such a design and configuration.

7. Conclusion and Future Extensions

In this paper, we explore how the marketing momentum from influencing customers can be reconciled with the operations of product returns. Our study focuses on returns caused by product mismatches, which may proliferate if influencing customers induces more orders at the cost of providing less precise signals on individual product fit. Through a stylized model that captures the trade-off between these two factors, we investigate how a firm should adjust its influence level in the presence of product returns and jointly configure the influence level and the refund policy. The managerial implications are manifold. First, generous refunds will shift the focus of influence toward products with higher levels of mismatch risk and may invite more aggressive customer influencing actions. Second, refunds and influence work as substitutes for handling the risk of product mismatch. When the firm can configure both, it may apply refunds to those with the highest risk of a mismatch and influence to those with moderate risk. Further, we find that influencing customers can be replaced by partial refunds based on the odds of a match. Conversely, when such is hard to implement due to large variety of products, product-based influence can be a useful supplement to standard refund policies. Lastly, we note that proper refund policy design brings additional value to the firm on top of influencing customers, which may also benefit customers when the decision space of the firm is limited. As a first attempt to examine these issues, our paper deepens the understanding of how to operationalize influencer marketing in conjunction with product returns.

There are many directions in which this paper can be extended. First, in focusing on the key trade-off, our model does not assume any hassle cost associated with returns, either for the firm or the customers, nor is there any transaction cost, e.g., shipping, that can be allocated among the parties. And further, there could be heterogeneity in the costs associated with product returns. For instance, a tech-savvy engineer may experience a lower hassle cost than someone less proficient with the Internet when filing an online return claim (Hsiao and Chen 2014). It would be meaningful to examine the impact on the current results of these operational factors, as well as the consumer heterogeneity surrounding them.

Second, our model abstracts the influencing cost as a lump sum to the firm, which suits settings like online review platforms, review managers, or influencers charging a flat rate per post featuring a product. However, firms can also nail out commission-based incentives that depend on metrics such as the number of purchases through affiliated links, the number of followers, the number of views, etc. (McKinsey & Company 2023). It would then be valuable to study the explicit contractual relationship between the firm and the influencer as well as the actions of a review manager, taking into account potential product returns.

In addition, future research in influencer marketing should also consider a broader set of operational issues, such as inventory and pricing, in the environment of omnichannel retailing. To this end, a number of recent papers, e.g., Gao and Su (2017), Nageswaran et al. (2020), have studied relevant pricing, inventory, and return policy issues for omnichannel retailers. It would make a promising extension to blend our model with the above frameworks and explore the application of influencer marketing in connection with various operations decisions.

Last but not least, this study opens up the opportunity to revisit a collection of marketing decisions based on passive eWOM observations, as reviewed in §2 and invites a more strategic, proactive design of eWOM programs.

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References

Akan, M., B. Ata, J. D. J. Dana. 2015. Revenue management by sequential screening. *Journal of Economic Theory* **159** 728–774.

Altug, M. S. 2023. The impact of online product reviews on retailer's pricing and return policy decisions. *Working Paper, School of Business, George Mason University* 1–46.

Avery, J., A. Israeli. 2020. Influencer marketing. *Harvard Business School Technical Note 520-075* .

Berman, R., H. Zhao, Y. Zhu. 2022. Strategic recommendation algorithms: Overselling and demarketing information designs. *Working Paper. Available at SSRN: https://ssrn.com/abstract=4301489* 1–56.

Burtch, G., Y. Hong, R. Bapna, G. V. 2018. Stimulating online reviews by combining financial incentives and social norms. *Management Science* **64**(5) 2065–2082.

Che, Y.-K. 1996. Customer return policies for experience goods. *Journal of Industrial Economics* **44**(1) 17–24.

Chen, Y., J. Xie. 2005. Third-party product review and firm marketing strategy. *Marketing Science* **24**(2) 218–240.

Chen, Y., J. Xie. 2008. Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Management Science* **54**(3) 477–491.

Chu, W., E. Gerstner, J. D. Hess. 1998. Managing dissatisfaction: How to decrease customer opportunism by partial refunds. *Journal of Service Research* **1**(2) 140–155.

CNN Business. 2023. Amazon is cracking down on returns. April 12, 2023. https://www.cnn.com/2023/04/12/business/amazon-returns-ups-store-fee/index.html Retrieved on July 5, 2023.

Confente, I., I. Russo, R. Frankel. 2018. Understanding the impact of return policy leniency on consumer purchase, repurchase, and return intentions: A comparison between online and offline contexts. *AMSWMC 2017* 1920.

Courty, P., H. Li. 2000. Sequential screening. *The Review of Economic Studies* **67**(4) 697–717.

Davis, S., E. Gerstner, M. Hagerty. 1995. Money back guarantees in retailing: matching products to consumer tastes. *Journal of Retailing* **71**(1) 7–22.

Dellarocas, C. 2003. The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science* **49**(10) 1407–1424.

Dellarocas, C. 2006. Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management Science* **52**(10) 1577–1593.

El Kihal, S., E. Shehu. 2022. It's not only what they buy, it's also what they keep: Linking marketing instruments to product returns. *Journal of Retailing* **98**(3) 558–571.

Feng, J., X. Li, X. Zhang. 2019. Online product reviews-triggered dynamic pricing: Theory and evidence. *Information Systems Research* **30**(4) 1107–1123.

Forbes. 2023. Influencers sold $3.6 billion of goods in 2022dyson airwrap and lululemon belt bag led the way. January 17, 2023. https://www.forbes.com/sites/marisadellatto/2023/01/17/influencers-s... 2-dyson-airwrap-and-lululemon-belt-bag-led-the-way/?sh=64435eb114bb Retrieved on July 5, 2023.

Gao, F., X. Su. 2017. Online and offline information for omnichannel retailing. *Manufacturing & Service Operations Management* **19**(1) 84–98.

Global News. 2022. Calgary consumer questions pharmacy return policy after buying a faulty medical device. May 31, 2022. https://globalnews.ca/news/8883212/calgary-faulty-medical-device-return-issues/ Retrieved on October 25, 2023.

Godes, D., D. Mayzlin. 2009. Firm-created word-of-mouth communication: Evidence from a field test. *Marketing Science* **28**(4) 721–739.

Godes, D., D. Mayzlin, Y. Chen, S. Das, C. Dellarocas, B. Pfeiffer, B. Libai, S. Sen, M. Shi, P. Verlegh. 2005. The firm's management of social interactions. *Marketing Letters* **16**(3/4) 415–428.

Guan, X., Y. Wang, Z. Yi, Y.-J. Chen. 2020. Inducing consumer online reviews via disclosure. *Production and Operations Management* **29**(8) 1956–1971.

Guo, L. 2009. Service cancellation and competitive refund policy. *Marketing Science* **28**(5) 901–917.

Hou, J., H. Shen, F. Xu. 2023. A model of livestream selling with online influencers. *Working Paper. Available at SSRN: https://ssrn.com/abstract=3896924* 1–50.

Hsiao, L., Y. Chen. 2014. Return policy: Hassle-free or your money-back guarantee? *Naval Research Logistics* **61**(5) 403–417.

Huang, X., D. Zhang. 2020. Service product design and consumer refund policies. *Marketing Science* **39**(2) 366–381.

Hubspot and Bandwatch. 2022. 2022 state of U.S. consumer trends report. https://offers.hubspot.com/2022-consumer-trends-report-download Retrieved on July 5, 2023.

Kamenica, E., M. Gentzkow. 2011. Bayesian persuasion. *American Economic Review* **101**(6) 2590–2615.

Lee, S.-Y., L. Qiu, A. Whinston. 2018. Sentiment manipulation in online platforms: An analysis of movie tweets. *Production and Operations Management* **27**(3) 393–416.

Lin, Z., Y. Zhang, Y. Tan. 2019. An empirical study of free product sampling and rating bias. *Information Systems Research* **30**(1) 260–275.

Luca, M., L. Zervas. 2016. Fake it till you make it: Reputation, competition, and yelp review fraud. *Management Science* **62**(12) 3412–3427.

Marketing Dive. 2017. L.l.bean shifts marketing focus from print to digital, tv. July 20, 2017. https://www.marketingdive.com/news/ll-bean-shifts-marketing-focus-from-print-to-digital-tv/447507 Retrieved on October 25, 2023.

Mayzlin, D. 2006. Promotional chat on the internet. *Marketing Science* **25**(2) 155–163.

Mayzlin, D., Y. Dover, J. Chevalier. 2014. Promotional reviews: An empirical investigation of online review manipulation. *American Economic Review* **104**(8) 2421–55.

McKinsey & Company. 2021. Returning to order: Improving returns management for apparel companies. May 25, 2021. https://www.mckinsey.com/industries/retail/our-insights/returning-to-order-improving-returns-management-for-apparel-companies#/ Retrieved on July 5, 2023.

McKinsey & Company. 2023. What is influencer marketing? April 10, 2023. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-influencer-marketing#/ Retrieved on July 5, 2023.

Minnema, A., T. H. A. Bijmolt, S. Gensler, T. Wiesel. 2016. To keep or not to keep: Effects of online customer reviews on product returns. *Journal of Retailing* **92**(3) 253–267.

Nageswaran, L., S.-H. Cho, A. Scheller-Wolf. 2020. Consumer return policies in omnichannel operations. *Management Science* **66**(12) 5558–5575.

Narvar. 2019. The state of online returns in 2019: A global study. https://see.narvar.com/rs/249-TEC-877/images/narvar-state-of-online-returns-global-consumer-study-2019.pdf Retrieved on July 5, 2023.

New York Post. 2023. What turbulence is like flying first class: turnt drinking free flow dom perignon. October 3, 2023. https://nypost.com/2023/10/03/what-turbulence-is-like-flying-first-class-turnt-drinking-free-flow-dom-perignon/. Retrieved on November 18, 2023.

ParcelLab. 2022. The state of online order returns. https://go.parcellab.com/hubfs/us_returns_study_q4_2022.pdf Retrieved on July 5, 2023.

Pei, A., D. Mayzlin. 2022. Influencing social media influencers through affiliation. *Marketing Science* **41**(3) 593–615.

Peinkofer, S. 2023. Inside the black box of amazon returns. June 14, 2023. https://theconversation.com/inside-the-black-box-of-amazon-returns-206551 Retrieved on July 5, 2023.

Rosario, A. B., F. Sotgiu, K. De Valck, T. H. A. Bijmolt. 2016. The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research* **53**(3) 297–318.

Sahoo, N., C. Dellarocas, S. S. 2018. The impact of online product reviews on product returns. *Information Systems Research* **29**(3) 723–738.

Shulman, J. D., A. T. Coughlan, R. C. Savaskan. 2009. Optimal restocking fees and information provision in an integrated demand-supply model of product returns. *Manufacturing & Service Operations Management* **11**(4) 577–594.

Shulman, J. D., A. T. Coughlan, R. C. Savaskan. 2010. Optimal reverse channel structure for consumer product returns. *Marketing Science* **29**(6) 1071–1085.

Shulman, J. D., A. T. Coughlan, R. C. Savaskan. 2011. Managing consumer returns in a competitive environment. *Management Science* **57**(2) 347–362.

Skeldon, P. 2023. Under the influence: what influences consumer purchases uncovered. June 8, 2023. https://internetretailing.net/under-the-influence-understanding-what-influences-consumer-purchases-uncovered/ Retrieved on July 5, 2023.

Su, X. 2009. Consumer return policies and supply chain performance. *Manufacturing & Service Operations Management* **11**(4) 595–612.

Sun, M., J. M. Chen, Y. Tian, Y. Yan. 2021. The impact of online reviews in the presence of customer returns. *International Journal of Production Economics* **232** 107929.

The Boston Globe. 2022. How social media helped L.L.Bean tote bags become a thing. November 2, 2022. https://www.bostonglobe.com/2022/11/02/lifestyle/how-social-media-helped-ll-bean-tote-bags-become-thing/ Retrieved on November 18, 2023.

The Economist. 2022. A tidal wave of returns hits the e-commerce industry. August 25, 2022. https://www.economist.com/business/2022/08/25/a-tidal-wave-of-returns-hits-the-e-commerce-industry Retrieved on July 5, 2023.

Tucker, C. E. 2015. The reach and persuasiveness of viral video ads. *Marketing Science* **34**(2) 281–296.

Wall Street Journal. 2018. L.l. bean to end unlimited returns, citing customer misuse. February 9, 2018. https://www.wsj.com/articles/l-l-bean-to-end-unlimited-returns-citing-customer-misuse-1518194780 Retrieved on October 25, 2023.

Wall Street Journal. 2023. More online clothing sales come with a catch: No returns; websites offer more final-sale deals, leading shoppers to commit before trying anything on. June 20, 2023. https://www.wsj.com/articles/online-shopping-clothes-returns-16500969 Retrieved on July 5, 2023.

Xie, J., E. Gerstner. 2007. Service escape: Profiting from customer cancellations. *Marketing Science* **26**(1) 18–30.

Yang, J., J. Zhang, Y. Zhang. 2021. First law of motion: Influencer video advertising on tiktok. *Working Paper, MIT Sloan School of Management* 1–55.

Zhuang, M., G. Cui, L. Peng. 2018. Manufactured opinions: The effect of manipulating online product reviews. *Journal of Business Research* **87** 24–35.

Zou, T., B. Zhou, B. Jiang. 2020. Product-line design in the presence of consumers' anticipated regret. *Management Science* **66**(12) 5665–5682.