Influencing Customers, Pricing, and Product Returns

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Digital platforms expose customers to product fit uncertainty, which may inhibit online purchases. As a result, firms may encourage online orders through influence tools such as influencer posts and promotional reviews, which can raise product awareness and be skewed in favor of a purchase. Nevertheless, customers who have ordered under such an influence may eventually return the product if it proves to be a mismatch. In this paper, we study the interplay between a firm's influence decision and its pricing and return policies. We find that a firm is motivated to employ an influence tool if it can effectively promote awareness. Under this scenario, the firm should engage in a meticulous configuration of price, refunds, and level of influence when the net benefit of return is non-negative and the marginal influence cost is low. Otherwise, the firm may rely solely on tailoring influence levels or customizing refunds, but not both, to cope with the price and maximize the expected profit. This highlights the substitution role between influencing customers *ex ante* and providing refunds *ex post*. Overall, the use of an influence tool broadens the situations to allow product returns. It also polarizes pricing strategy in that the firm may apply either premium pricing with a tailored level of influence or reduced pricing without any additional influence. Interestingly, aggressive influence actions may be accompanied by less premium in price and more generous refunds. The results provide an overarching strategy and practical guidance for firms in navigating the use of influence, pricing, and return policy design.

Key words: digital platforms, influencer marketing, pricing, 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 2022, the shopping platform LTK alone sold $3.6 billion worth of goods through online creators and influencers, with the most-loved products ranging from Dyson's Airwrap to Lululemon's Everywhere Belt Bag.[1] At the time of this paper's writing, the size of global influencer marketing is projected to reach $97.55 billion by 2030.[2]

Despite all the marketing heat fuelled by digital platforms and tech-driven experiences, one should not overlook the operational pain that can 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 had jumped from 8% to more than 16%.[3] 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., the UK, France, Germany, and Australia[4] 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 the "Product was vastly different than what was shown online".[5] According to North American apparel retailers, 70% of returns are caused by poor fit or style.[6]

Since easy returns before and early in the pandemic led to hefty business losses, clothing retailers are now starting to sell more nonrefundable items.[7] 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 give rise to interesting questions about how to effectively enhance sales. Online orders inspired by influencers need to go through

[1] https://www.forbes.com/sites/marisadellatto/2023/01/17/influencers-sold-36-billion-of-goods-in-2022-dyson-airwrap-and-lululemon-belt-bag-led-the-way

[2] https://finance.yahoo.com/news/influencer-marketing-statistics-2026-market-150000054.html

[3] https://theconversation.com/inside-the-black-box-of-amazon-returns-206551

[4] https://see.narvar.com/rs/249-TEC-877/images/narvar-state-of-online-returns-global-consumer-study-2019.pdf

[5] https://go.parcellab.com/hubfs/us_returns_study_q4_2022.pdf

[6] https://www.mckinsey.com/industries/retail/our-insights/returning-to-order-improving-returns-management-for-apparel-companies#

[7] https://www.wsj.com/articles/online-shopping-clothes-returns-16500969

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). 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. Similarly, a generous return policy may ease the concerns over profit fit and attract more customers into a purchase, but the firm will ultimately have to assume the burden of product returns. Thus far, it is not entirely clear, and little discussion has taken place on whether customer-influencing decisions should take into account future product returns, or whether operational decisions like pricing and refund policies should consider ongoing efforts to influence customers, and overall, how the firm should maintain a proper balance among these levers to improve profitability. In light of these ambiguities, we investigate the following research questions: (i) How should a firm reconcile the gain from influencer marketing and the pain from product returns? (ii) How does the use of an influence tool affect a firm's pricing and return policies? (iii) What is the optimal joint configuration for price, refunds, and level of influence?

1.1 Summary of Main Findings

To explore these 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.[8] Neither the firm nor any of the customers 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 them, to make purchase decisions. Initially, only a fraction of the customers are aware of the product. To encourage orders, the firm may acquire an influence tool (e.g., influencer posts, managed online review platforms) that can 1) raise awareness of the product among the entire group and 2) generate an informative signal to help the customers estimate the product fit before purchase. In particular, the firm may exert additional influence to distort the distribution of the signal in favor of a purchase. For instance, the influence tool may generate a more optimistic signal via enthusiastic influencer review posts, promotional customer reviews, or compensation for negative comments. Based on the observed signal, the customers update their beliefs regarding the odds of a match and decide whether to make a purchase. Upon receiving the product, customers learn its true fit and make return decisions based on the firm's refund policy and the hassle costs they will incur when executing returns.

This stylized framework allows us to study the key trade-off between the marketing gain and operational pain that arise from influencing customers. Imposing additional influence will increase the *true positive rate* of its signal, stimulating more customers who are inherently a good match with the product (but are unsure of such at the time of purchase) to place an order. However, this comes

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

at the cost of reduced signal *precision*, in the sense that more customers who order will not find the product to be a suitable match upon receipt and will return it if possible. As a result, the firm must consider this trade-off and make a balanced decision among the use of the influence tool, the price, and return policies. Based on this framework, we can derive the optimal influence-price-refund configuration and an overarching strategy that the firm can follow for maneuvering amid the three levers. The results bring valuable insights to our research questions.

First, we find that a pivotal factor for the adoption of an influence tool is its effectiveness in enhancing awareness. Conditional on the employment of an influence tool, the firm can exert additional influence *ex ante*, permit product returns by issuing sufficient refunds *ex post*, or do both. In particular, when the net benefit of returns is salient (i.e., the residual value of a returned item for the firm exceeds the hassle cost of a return for customers) and the marginal influence cost is low, the firm should concurrently engage in exerting additional influence and allowing product returns. Otherwise, if the net benefit of returns is moderately negative but the marginal influence cost is low, the firm should rely solely on a tailored level of influence and exclude returns. Finally, if the net benefit of returns is deeply negative or the marginal influence cost is high, the firm should focus on product returns without exerting additional influence. This portfolio of choice emphasizes the substitutional role of additional influence and allowing product returns — even if the net benefit from allowing returns is negative, product returns may still be a useful lever to replace additional levels of influence when the latter are too costly.

Second, we discover that the use of influence tools polarizes a firm's pricing strategy. When the marginal influence cost or prior probability of fit is low, adopting an influence tool requires the firm to charge a higher price and offer less refunds while exerting a tailored level of influence. However, when the marginal influence cost and the prior probability of fit are both high, the firm should establish a price that is even lower than it would be without any influence tool, provide more generous refunds, and exert no additional influence. In general, the firm should be aggressive in both pricing and influencing decisions when it can implement additional levels of influence efficiently; otherwise, it is more profitable to service the entire group of customers with an undistorted signal and reduced pricing. Interestingly, when the strategy falls into the former (i.e., premium pricing with a tailored level of influence), a higher markup in price or a smaller amount of refund should be accompanied by a lower level of influence. This highlights the trade-off between pricing and additional influence as the marginal influence cost decreases.

Ultimately, we fully characterize the optimal strategy and joint configuration that operationalize the aforementioned insights for the use of the influence tool, the price, and refunds. Notably, the optimal solution is not unique, in the sense that for any influence decision, there is a continuous array of price-refund pairs that consistently achieves the same level of expected profit for the firm. This justifies the myriad of return policies that exist in real world. It also provides ample room for the firm to fine-tune the three levers notwithstanding the presence of other objectives or constraints. We are also able to show that the structure of the optimal strategy sustains whether customers' return decision is independent or driven by the level of refunds.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature. Section 3 introduces the model. Section 4 analyzes the optimal configuration that disables product returns. Section 5 characterizes the optimal joint configuration that allows product returns. Section 6 investigates the rationale for allowing product returns and adopting the influence tool, leading to the joint optimal strategy and managerial insights. Section 7 discusses some model extensions and robustness of the results. Finally, we summarize the insights and future extensions in Section 8. All proofs are relegated to the E-Companion, along with propositions and figures labeled with the prefix EC.

2. Literature Review

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

eWOM refers to customers' public sharing of opinions about products, services, or firms through digital platforms, which can affect future sales and firm performance. The effect of eWOM has been extensively studied since the rise of digital market (Dellarocas 2003). Interested readers may refer to Rosario et al. (2016) for a summary of literature on the impact of eWOM on sales. Within this literature, one stream examines firms' roles in managing eWOM content (Godes et al. 2005). Specifically, firms may simply respond to eWOM observations (e.g., Chen and Xie 2005, Feng et al. 2019), strategically design eWOM programs (e.g., Godes and Mayzlin 2009, Burtch et al. 2018), or more aggressively participate in eWOM to influence customers. In the latter role, firms can generate eWOM content or manipulate sentiment through biased or promotional online reviews (Mayzlin et al. 2014), free samples (Lin et al. 2019), viral videos (Yang et al. 2025), and tweets (Lee et al. 2018).

Following the latter research thread, a number of works have analyzed how firms strategically participate in eWOM and influence customers. Mayzlin (2006) show that competing firms may use anonymous and promotional messages to shape consumers' posterior beliefs and may spend more resources promoting low-quality products, while Dellarocas (2006) identify conditions under which high-quality firms have stronger incentives to inflate ratings. Zhuang et al. (2018) conduct laboratory experiments to compare review manipulation approaches, namely, adding positive reviews and deleting negative reviews. Guan et al. (2020) study strategic quality disclosure in the presence of online reviews and evolving consumer expectations. Pei and Mayzlin (2022) model the firm-influencer affiliation and analyze its impact on consumer welfare. Recent studies concern biased information provision by competing firms and platforms (Berman et al. 2024), and the integration of influencers with livestream selling (Hou et al. 2025).

With rising attention to firms' strategic role in influencing customers, the above modeling work has not considered product returns *post-influence*, i.e., after customers receive the product and learn its true fit. Yet empirical evidence suggests that "overly positive" or "higher than the true" review ratings (Minnema et al. 2016, Sahoo et al. 2018) may increase return rates, highlighting the need to account for returns when modeling the profitability of eWOM. In this regard, some recent studies examine the interaction between online reviews and product returns under 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 (2024) explores a setting where product returns may trigger negative reviews and affect future customers' valuations. However, these works treat firms as eWOM receivers rather than proactive influencers. To our best knowledge, our paper is the first to model firms' proactive participation in eWOM jointly with pricing and return-policy design.

In this respect, 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, Shang et al. 2017, Altug et al. 2021), heterogeneous valuation uncertainty (e.g., Courty and Li 2000, Shulman et al. 2009, Ren et al. 2026), capacity scarcity (e.g., Xie and Gerstner 2007), aggregated demand uncertainty (e.g., Su 2009), competition (e.g., Guo 2009, Shulman et al. 2011), coping with product lines (e.g., Huang and Zhang 2020, Zou et al. 2020), consumer time-inconsistency (e.g., Kuang and Jiang 2023), and salvage opportunities across channels (e.g., Shulman et al. 2010, Nageswaran et al. 2020). Our paper is open to all kinds of return policies and has identified the rationale for no refund, full refunds, as well as partial refunds in the context of influencer marketing.

Further, the product returns literature can be categorized according to whether returns are driven primarily by a binary state of product fit or quality preference (e.g., Davis et al. 1995, Moorthy and Srinivasan 1995, Guo 2009, Hsiao and Chen 2012, Gao and Su 2017, Huang and Zhang 2020, Zou et al. 2020, Kuang and Jiang 2023, Jerath and Ren 2025, Ren et al. 2026), continuous valuation uncertainty (e.g., Che 1996, Courty and Li 2000, Su 2009, Akcay et al. 2013, Shang et al. 2017, Nageswaran et al. 2020, Altug et al. 2021, Ertekin and Agrawal 2021, Nageswaran et al. 2025, Ren et al. 2026), or both sources of uncertainties (e.g., Chu et al. 1998, Shulman et al. 2009, 2010, 2011, McWilliams 2012, Huang et al. 2018, Letizia et al. 2018, Liu and Chen 2022, Zhang et al. 2022, Lin et al. 2024). Our main model aligns with the first stream of literature and with relevant studies in influencer marketing (e.g., Mayzlin 2006, Pei and Mayzlin 2022, Berman et al. 2024, Hou et al. 2025) by focusing on how influence affects belief about product fit. We further extend the model in §7.2 to incorporate both the risk of product misfit and valuation uncertainty, allowing for a more nuanced analysis of how endogenous pricing and refund decisions affect return probabilities and interact with influencer-marketing decisions.

In summary, our work contributes to the existing literature in several ways. First, it extends the current research in influencer marketing to settings with product returns. Further, it examines how firms should exert customer influence in conjunction with pricing and refund design in presence of both misfit risk and valuation uncertainty. Lastly, the study contributes to the product returns literature by rationalizing diverse refund policies in the context of influencer marketing and characterizing the substitution between *ex ante* customer influence and *ex post* refunds.

3. Model

Consider that a firm sells a product to a unit mass of customers at price p. The product may or may not be a good match for the customers. The actual fit $F \in \{G, B\}$ is unobservable to the customers until after the purchase. It is common 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 $P(B) = 1 - \rho_0 = \bar{\rho}_0$[9]. If the product turns out to be a good match ($F = G$), the customer derives a value $v > 0$ out of the purchase; otherwise ($F = B$), the customer's valuation is 0. Upon observing the true fit, a customer may return the product with a hassle cost $h \geq 0$ and obtain a refund $r \leq p$. In the absence of any other information, a customer will rely solely on ρ_0 to form their prior belief of the fit and to make a purchase decision.

Each unit of the sales costs m to the firm, representing the marginal cost of acquiring and delivering the product, and each unit of the returns will result in a residual value d. Essentially, d captures the salvage value of a returned product subtracting any marginal cost in processing the return, e.g., shipping, handling, disposal. Without loss of generality, we assume that $m = 0$ and put no restriction on the sign of d — that is, a positive d implies a diminished gain and a negative d represents a loss from the returned product, respectively.

3.1 Influencing Customers

Initially, only a fraction $\lambda < 1$ of customers are aware of the product. Further, the initial awareness is independent of a customer's inherent fit with the product.

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

Suppose that the firm may acquire an influence tool that can raise product awareness and alter the customers' belief of the product fit (Pei and Mayzlin 2022). A variety of intermediaries may serve this purpose. For example, a firm may hire an online influencer who can broadcast the product to millions of her followers who share similar tastes. The influencer's opinion may also improve the confidence of the followers about the product fit, making them more likely to purchase the product. A similar mechanism is online review platforms. The provision of reviews may boost the presence and popularity of a product. At the same time, the firm may exert additional influence on the reviews by way of incentives, eliciting positive reviews from loyal customers, or mitigating negative reviews,[10] etc., such that user-generated content will be in favor of a purchase.

In this spirit, we assume that the influence tool can facilitate the whole unit mass of customers becoming aware of the product. In some way, the influence tool can increase the market base by $\frac{1}{\lambda}$, which will be an essential indicator for its effectiveness in raising awareness. At the same time, the influence tool will produce a signal that helps the customer gain a better idea of the true fit. We model the signal as a binary variable $s \in \{g, b\}$, where $s = g$ indicates a good fit and $s = b$ a bad fit. When the firm chooses to adopt the tool without exerting additional influence, e.g., a completely neutral influencer post or review platform, the precision of the signal can be represented by a baseline quality $P(g|G) = P(b|B) = \gamma \in (0.5, 1)$. We assume that γ is an intrinsic characteristic of the influence 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.

Conditional upon the adoption of an influence tool, the firm may exert an additional level of influence $a \in [0, 1]$, which will distort the signal distribution to

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

Similar to Pei and Mayzlin (2022), we assume that influence has a linear effect on the probabilistic outcome of the signal — when the firm chooses not to exert any additional influence on customers ($a = 0$), e.g., by maintaining a completely neutral review platform, 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 ($a = 1$), e.g. by heavily investing in compensated reviews and strictly censoring negative opinions, the signal always yields $s = g$, i.e., $P(g|G, 1) = P(g|B, 1) = 1$. The linear formulation allows us to capture the overall effect without loss of tractability. In essence, a high level of influence increases $P(g|G, a)$, the *true positive rate* of the influence tool, i.e., the probability that a matched product will be accompanied by

[10] 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.

a positive signal, which is statistically measurable and contractible. For this reason and in line with existing literature (e.g., Kamenica and Gentzkow 2011, Pei and Mayzlin 2022), we further assume that the signal distribution in (1) (or equivalently, the baseline quality γ and the level of influence a) is common knowledge to all customers. For instance, customers may infer baseline signal quality according to 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 disclose any "material connection" with a brand;[11] online sellers such as Home Depot 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.

Upon observing signal s, customers will form their posterior belief of the product's fit using Bayes' rule. In particular, the probabilities of a good fit under signal $s=g$ or b can be obtained by

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

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

And the posterior probabilities of a bad fit follow $P(B|g,a)=1-P(G|g,a)$ and $P(B|b,a)=1-P(G|b,a)$. In particular, $P(G|g,a)$ decreases with the level of influence a (Lemma EC3), which implies that aggressive influence action can reduce the *precision* of the signal emitted by the influence tool.

We assume that the total cost of adopting an influence tool with a level of influence a is $c(a)=c+ea^2$, where both c and $e\geq 0$. Here, c represents the fixed cost of the tool and ea^2 the level-dependent cost of influence. In general, c can be assessed by the cost for employing an influencer or a review platform that host neutral opinions or customer feedbacks ($a=0$) and e can be measured by the additional cost it may take to keep only the positive opinions or reviews ($a=1$). For the rest of the paper, we refer to e as the *marginal influence cost.*

3.2 Sequence of Events

The sequence of events is modelled as follows:

- Stage 1 (Fit Realization): Nature determines the product fit, i.e., $F=\{G,B\}$ with probability $\{\rho_0,\bar{\rho}_0\}$. Outcome F is invisible to the firm and customers until Stage 5.
- Stage 2 (Price and Refund): The firm decides the price $p\in[0,v]$ and the refund $r\in[0,p]$.
- Stage 3 (Influence Configuration): The firm decides whether to acquire an influence tool, and if so, the level of influence $a\in[0,1]$.

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

- Stage 4 (Customers Order): If an influence tool is in place, a signal $s \in \{g, b\}$ will be produced based on the signal distribution in (1). All customers observe the signal s, update their posterior belief on F following (2), and make purchase decisions accordingly. If no influence tool is adopted, a fraction λ of the customers will make purchase decisions based on the prior belief ρ_0.
- Stage 5 (Product Returns): Fit uncertainty is resolved. The customers observe F and decide whether to return the product.

To tackle the optimal configuration for influence, price, and refunds, we analyze the problem in four scenarios, i.e., $0N$, $0I$, RN, and RI, based on the amount of refund and the adoption of the influence tool. The first letter represents the return policy — "0" for lower refunds ($r < h$) such that there will be no product returns at Stage 5 and "R" for higher refunds ($r \geq h$) that support product returns. The second letter represents the adoption of the influence tool — "N" if no influence tool is acquired at Stage 3 and "I" if an influence tool is in use. These scenarios will be reflected in relevant subscripts.

To avoid trivial cases, we also impose the following technical assumptions throughout the analysis. These reasonably require that the hassle cost h and the residual value d should not exceed the expected valuation of the product under a pessimistic signal outcome.

Assumption 1. *$h \leq \frac{\bar{\gamma}\rho_0}{\bar{\gamma}\rho_0 + \gamma\bar{\rho}_0} v$ and $d \leq \frac{\bar{\gamma}\rho_0}{\bar{\gamma}\rho_0 + \gamma\bar{\rho}_0} v$.*

The difference between the residual value and the hassle cost, $d - h$, then captures how much the system can generate out of a unit of the product by end of the selling season, and will be referred to as the *net benefit of returns*.

4. Optimal Pricing and Influence Configuration Without Returns

First consider the cases in which no product return will take place at Stage 5. This happens when $r < h$, i.e., the refund is not sufficient to cover the hassle cost incurred by the customer in exercising the return. Subsequently, the residual value d is irrelevant to the firm.

Denote the ratio between the price and the maximum value as $k = \frac{p}{v}$. We will refer to k as the *pricing index* without returns and use it to present pricing-related decisions. In what follows, we analyze the optimal pricing and influence configuration, when applicable.

4.1 No Influence Tool ($0N$)

Suppose that the firm does not acquire any influence tool. The market will be limited to the fraction of λ customers who are aware of the product. Then, at Stage 4, a customer will buy the product if and only if $\rho_0 v - p \geq 0$. The expected profit function can then be written as $\Pi_{0N}(p) = \mathbb{1}\{\rho_0 \geq k\} p\lambda = \mathbb{1}\{p \leq \rho_0 v\} p\lambda$, where $\mathbb{1}\{\cdot\}$ is an indicator function that yields 1 if the condition is true and 0 otherwise. Accordingly, at Stage 2, the firm should set:

$$k_{0N} = \rho_0, \quad \Pi_{0N} = \lambda\rho_0 v. \tag{3}$$

4.2 With Influence Tool ($0I$)

Suppose that an influence tool is used. Then, at Stage 4, the whole unit mass of the customers will observe a signal s and decide whether to purchase the product. If the signal $s=g$, the customer will make a purchase if and only if $P(G|g,a)v-p\geq 0$, or equivalently, $\rho_0 \geq \frac{k(1-\gamma\bar{a})}{\bar{k}(\gamma+a\bar{\gamma})+k(1-\gamma\bar{a})}$. If the signal $s=b$, the customer will only make a purchase if $P(G|b,a)v-p\geq 0$, or equivalently, $\rho_0 \geq \frac{k\gamma}{\bar{k}\bar{\gamma}+k\gamma}$. Denote $\rho_g(a)=\frac{k(1-\gamma\bar{a})}{\bar{k}(\gamma+a\bar{\gamma})+k(1-\gamma\bar{a})}$ and $\rho_b=\frac{k\gamma}{\bar{k}\bar{\gamma}+k\gamma}$. Then, $\rho_g(a)$, k, and ρ_b work as the thresholds for purchase when there is a positive signal, no signal, and a negative signal, respectively. It can be verified that $\rho_g(a)\leq k\leq \rho_b$, and the customer's order decision is summarized in the following lemma:

Lemma 1. *Suppose that the firm sets $r<h$. The customer's order decision at Stage 4 follows:*

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

Back to Stage 3, the firm decides the level of influence a that maximizes the expected profit:

$$\Pi_{0I}(a,p)=P(g|a)\mathbb{1}\{\rho_0\geq\rho_g(a)\}p+P(b|a)\mathbb{1}\{\rho_0\geq\rho_b\}p-c-ea^2.$$

The first and second components of the equation capture the fraction of the expected profit generated under signal $s=g$ and $s=b$, respectively. The last componenet represents the cost of acquiring the influence tool with influence level a. Let $a_0(p)=\arg\max_{0\leq a\leq 1}\Pi_{0I}(a,p)$ denote the firm's optimal level of influence conditional on price p. The solution is provided in Proposition EC1.

We then derive the optimal Stage 2 price, $p_{0I}=\arg\max_{0\leq p\leq v}\Pi_{0I}(a_0(p),p)$, and summarize the result using the pricing index $k_{0I}=\frac{p_{0I}}{v}$:

Proposition 1. **(Optimal Price with No Returns)** *Suppose that the firm will set $r<h$ and acquire an influence tool. Then, the optimal pricing index should be as follows:*

(i) if $\rho_0\leq\frac{\gamma^2-\bar{\gamma}}{\gamma(\gamma-\bar{\gamma})}$, there is

$$k_{0I}=\begin{cases}\rho_0, & \text{if } e\leq\frac{\bar{\gamma}\rho_0}{2}v,\\ \dfrac{(\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v}{2e})\rho_0}{(\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v}{2e})\rho_0+(\frac{\gamma}{\bar{\gamma}}\frac{\bar{\gamma}\rho_0 v}{2e}+1)\bar{\rho}_0}, & \text{otherwise;}\end{cases}$$

(ii) if $\rho_0>\frac{\gamma^2-\bar{\gamma}}{\gamma(\gamma-\bar{\gamma})}$, there exists an $\hat{e}>0$ such that

$$k_{0I}=\begin{cases}\rho_0, & \text{if } e\leq\min\{\frac{\bar{\gamma}\rho_0}{2}v,\hat{e}\},\\ \dfrac{(\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v}{2e})\rho_0}{(\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v}{2e})\rho_0+(\frac{\gamma}{\bar{\gamma}}\frac{\bar{\gamma}\rho_0 v}{2e}+1)\bar{\rho}_0}, & \text{if } \min\{\frac{\bar{\gamma}\rho_0}{2}v,\hat{e}\}\leq e\leq\hat{e},\\ \frac{\bar{\gamma}\rho_0}{\bar{\gamma}\rho_0+\gamma\bar{\rho}_0}, & \text{otherwise.}\end{cases}$$

With a slight abuse of notation, Table 1 summarizes the optimal pricing index $k_{0I}=p_{0I}/v$, the optimal influence level $a_0=a_0(p_{0I})$, and the maximum expected profit $\Pi_{0I}=\Pi_{0I}(a_0,p_{0I})$.

Table 1 Optimal Solutions Under Scenario $0I$

When $\rho_0\le\frac{\gamma^2-\bar{\gamma}}{\gamma(\gamma-\bar{\gamma})}$	When $\rho_0>\frac{\gamma^2-\bar{\gamma}}{\gamma(\gamma-\bar{\gamma})}$	Pricing Index k_{0I}	Level of Influence a_0	Expected Profit Π_{0I}
$e\le\frac{\bar{\gamma}\rho_0}{2}v$	$e\le\min\{\frac{\bar{\gamma}\rho_0}{2}v,\hat{e}\}$	ρ_0	1	$\rho_0 v-c-e$
$e>\frac{\bar{\gamma}\rho_0}{2}v$	$\min\{\frac{\bar{\gamma}\rho_0}{2}v,\hat{e}\}\le e\le\hat{e}$	$\frac{(\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v}{2e})\rho_0}{(\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v}{2e})\rho_0+(\frac{\gamma}{\bar{\gamma}}\frac{\bar{\gamma}\rho_0 v}{2e}+1)\bar{\rho}_0}$	$\frac{\bar{\gamma}\rho_0}{2e}v$	$\frac{\bar{\gamma}^2\rho_0^2}{4e}v^2+\gamma\rho_0 v-c$
–	$e\ge\hat{e}$	$\frac{\bar{\gamma}\rho_0}{\bar{\gamma}\rho_0+\gamma\bar{\rho}_0}$	0	$\frac{\bar{\gamma}\rho_0}{\bar{\gamma}\rho_0+\gamma\bar{\rho}_0}v-c$

Overall, when the prior probability of fit ρ_0 is relatively low, the optimal pricing index k_{0I} will be weakly increasing in the marginal cost of influence e, and the firm will exert at least some additional influence (i.e., $a_0>0$) even when the marginal influence cost is rather high. The expected profit Π_{0I} naturally decreases in e. When the prior probability of fit ρ_0 is relatively high, the same impacts hold as long as the marginal influence cost e is below some threshold level $\hat{e}$. Otherwise, it is sensible for the firm to set a low pricing index at which customers will always purchase (as according to the last item in Lemma 1). Subsequently, there is no need to exert any additional influence (i.e., $a_0=0$).

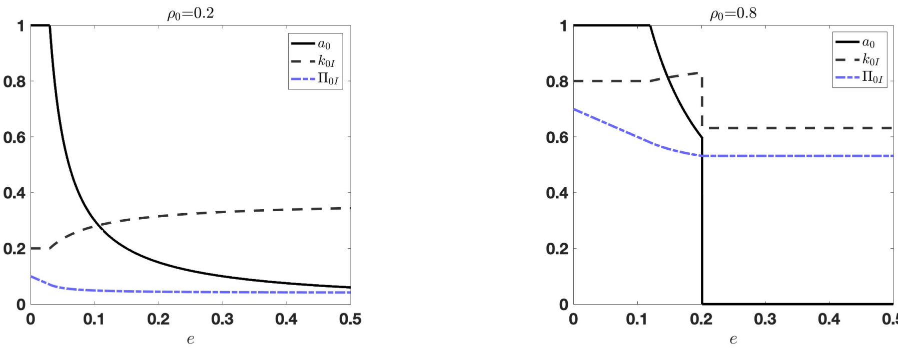
The two types of optimal solutions under Scenario $0I$ are illustrated in Figure 1. By holding the maximum valuation $v=1$, baseline signal quality $\gamma=0.7$, and fixed influence cost $c=0.1$, the left panel presents the case with a low probability of product fit ($\rho_0=0.2$), and the right panel carries a high probability of fit ($\rho_0=0.8$). It can be observed that the impacts of the marginal influence cost e on the optimal solutions are rather similar between the left panel and the right panel where $e\le\hat{e}=0.2$, i.e., the pricing index increases in e, and the level of influence and expected profit decrease in e. As soon as e passes over 0.2, the firm ceases exerting additional influence ($a_0=0$), and the pricing index drops to a lower level than without the influence tool ($k_{0I}=0.63<k_{0N}=0.8$) in attracting the purchase unconditionally.

5. Optimal Pricing and Influence Configuration with Returns

We now investigate the scenarios in which the firm promises sufficient refunds to cover a customer's hassle cost of return, i.e., $r\ge h$. Subsequently, at Stage 5, if the product turns out to be a bad fit, i.e., $F=B$, a customer will simply return the product to improve their personal utility.

Denote the *pricing index* with product returns as $\tilde{k}=\frac{p-r+h}{v-r+h}$. By letting r take the boundary value h, the pricing indexes reconcile with each other with or without returns ($\tilde{k}|_{r=h}=k=\frac{p}{v}$). To simplify the presentation, we omit the $\tilde{}$ on top of the k's when it is self-evident that the situation involves product returns. In general, a higher pricing index is accompanied by a higher price, or a more

Figure 1 Optimal Pricing, Level of Influence, and Expected Profit Under Scenario $0I$ ($v=1,\gamma=0.7,c=0.1$)



restrictive refund, and *vice versa*. In particular, the pricing index $\tilde{k}$ covers an array of price-refund pairs from a full-refund policy $p=r=v-\frac{\bar{\tilde{k}}}{\tilde{k}}h$ to a low-refund policy where $p=\tilde{k}v$ and $r=h$. For the rest of the paper, we use *pricing* to describe the decision of pricing index, which may involve both the price and the amount of refund, if applicable.

5.1 No Influence Tool (RN)

Suppose that the firm chooses not to acquire any influence tool. Then, at Stage 4, if a customer makes the purchase, they will end up with an expected utility $\rho_0 v+\bar{\rho}_0(r-h)-p$. Clearly, the customer will do so if and only if $\rho_0 v+\bar{\rho}_0(r-h)-p\geq 0$ or, equivalently, $\rho_0\geq\tilde{k}$. Conditioned upon a purchase being made, there is a probability $\bar{\rho}_0$ that the customer will return the product, in which case the firm will refund an amount r and receive a residual value d. The firm's expected profit without the influence tool is then $\Pi_{RN}(p,r)=\mathbb{1}\{\rho_0\geq\tilde{k}\}(p-\bar{\rho}_0 r+\bar{\rho}_0 d)\lambda$.

Back to Stage 2, the firm should choose a pair of (p,r) that maximizes Π_{RN}. When $\rho_0\geq\tilde{k}=\frac{p-r+h}{v-r+h}$, there is $p-\bar{\rho}_0 r\leq\rho_0 v-\bar{\rho}_0 h$, and the equality holds when $\rho_0=\tilde{k}$. Therefore, the optimal solutions for (p_{RN},r_N) should satisfy:

$$k_{RN}=\rho_0,\quad \Pi_{RN}=(\rho_0 v-\bar{\rho}_0 h+\bar{\rho}_0 d)\lambda. \tag{4}$$

This includes a full refund policy $p_{RN}=r_N=v-\frac{\bar{\rho}_0}{\rho_0}h$ and a low-refund policy $(p_{RN},r_N)=(\rho_0 v,h)$.

5.2 With Influence Tool (RI)

Now, consider the case that an influence tool has been acquired. At Stage 4, if signal $s=g$ is observed, the customers will make a purchase if $P(G|g,a)v+P(B|g,a)(r-h)-p\geq 0$. It can be verified that the condition is equivalent to $\rho_0\geq\tilde{\rho}_g(a)$, where $\tilde{\rho}_g(a)=\frac{\tilde{k}(1-\gamma\bar{a})}{\bar{\tilde{k}}(\gamma+a\bar{\gamma})+\tilde{k}(1-\gamma\bar{a})}$. Similarly, if signal $s=b$ is observed, the customers will purchase if and only if $P(G|b,a)v+P(B|b,a)(r-h)-p\geq 0$, i.e., $\rho_0\geq\tilde{\rho}_b$, where $\tilde{\rho}_b=\frac{\tilde{k}\gamma}{\bar{\tilde{k}}\bar{\gamma}+\tilde{k}\gamma}$. The customer's purchase decision follows the same structure as Lemma 1, with thresholds k, $\rho_g(a)$, and ρ_b being replaced by $\tilde{k}$, $\tilde{\rho}_g(a)$, and $\tilde{\rho}_b$, respectively. As found in Corollary EC1, allowing product returns will generally lower the thresholds and encourage the purchase.

Back to Stage 3, the firm's expected profit Π_{RI} can be written as in (5). The first component is that upon observing $s=g$, customers will order as long as $\rho_0 \geq \tilde{\rho}_g(a)$, and the odds they will return the product can be represented by $P(B|g,a)$. Similarly, the second component concerns the scenario where $s=b$. The last two components correspond to the cost of acquiring the influence tool and exerting additional levels of influence.

$$\begin{aligned}\Pi_{RI}(a,p,r) = \; & P(g|a)\,\mathbb{1}\{\rho_0 \geq \tilde{\rho}_g(a)\}\,[p - P(B|g,a)r + P(B|g,a)d] \\ & + P(b|a)\,\mathbb{1}\{\rho_0 \geq \tilde{\rho}_b\}\,[p - P(B|b,a)r + P(B|b,a)d] - c - ea^2. \end{aligned} \tag{5}$$

Accordingly, the firm decides the optimal level of influence based on the given pricing and return policy, i.e., $a_R(p,r) = \arg\max_{0\leq a\leq 1} \Pi_{RI}(a,p,r)$. The solution is summarized in Proposition EC2.

In what follows, we present the optimal solutions for the price and the refund at Stage 2 that maximize $\Pi_{RI}(a_R(p,r),p,r)$. We remark that the optimal pair of (p_{RI}, r_I) is not unique but the optimal pricing index $k_{RI} = \frac{p_{RI}-r_I+h}{v-r_I+h}$ is; the results are summarized using the latter in Proposition 2. Essentially, k_{RI} covers a continuum array of (p_{RI}, r_I) from full-refund policy $(v - \frac{\bar{k}_{RI}}{k_{RI}}h, v - \frac{\bar{k}_{RI}}{k_{RI}}h)$ to a low-refund policy $(k_{RI}v, h)$. In particular, a higher pricing index k_{RI} implies a higher price but a smaller amount of refund.

Proposition 2. **(Optimal Pricing with Product Returns)** *Suppose that the firm will set $r \geq h$ and acquire an influence tool. Then, the firm should choose a feasible pair of (p,r) that satisfies $\tilde{k} = k_{RI}$, where k_{RI} is given by the following:*

(i) If $\frac{\bar{\gamma}\rho_0}{\gamma\bar{\rho}_0}v < h-d$, there is $k_{RI} = \frac{\gamma\rho_0}{\gamma\rho_0+\bar{\gamma}\bar{\rho}_0}$. In this case, the level of influence $a_R = 0$ and the expected profit $\Pi_{RI} = \gamma\rho_0 v - \bar{\gamma}\bar{\rho}_0(h-d) - c$.

(ii) If $h-d \leq \frac{\bar{\gamma}\rho_0}{\gamma\bar{\rho}_0}v \leq (1+\frac{1}{\bar{\gamma}}-\frac{1}{\gamma})h-d$, there is

$$k_{RI} = \begin{cases} \rho_0, & \text{if } e \leq \frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2}, \\ \dfrac{[\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2e}]\rho_0}{[\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2e}]\rho_0+[\frac{\bar{\gamma}}{\gamma}\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2e}+1]\bar{\rho}_0}, & \text{otherwise.} \end{cases}$$

(iii) If $\frac{\bar{\gamma}\rho_0}{\gamma\bar{\rho}_0}v > (1+\frac{1}{\bar{\gamma}}-\frac{1}{\gamma})h-d$, there exists an $\hat{e}_R \geq 0$ such that

$$k_{RI} = \begin{cases} \rho_0, & \text{if } e \leq \min\{\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2}, \hat{e}_R\}, \\ \dfrac{[\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2e}]\rho_0}{[\frac{\gamma}{\bar{\gamma}}+\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2e}]\rho_0+[\frac{\bar{\gamma}}{\gamma}\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2e}+1]\bar{\rho}_0}, & \text{if } \min\{\frac{\bar{\gamma}\rho_0 v+\gamma\bar{\rho}_0(d-h)}{2}, \hat{e}\} \leq e \leq \hat{e}_R, \\ \frac{\bar{\gamma}\rho_0}{\bar{\gamma}\rho_0+\gamma\bar{\rho}_0}, & \text{otherwise.} \end{cases}$$

The level of influence a_R and expected profit Π_{RI} in (ii) and (iii) are summarized in Table 2.

Table 2 Optimal Level of Influence and Expected Profit Under Scenario RI

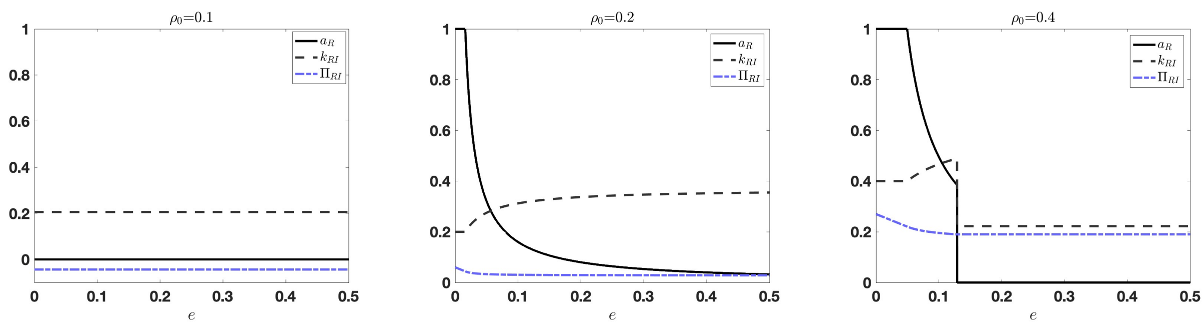
(ii)	(iii)	Influence Level a_R	Expected Profit Π_{RI}
$e \le \frac{\bar{\gamma}\rho_0 v + \gamma\bar{\rho}_0(d-h)}{2}$	$e \le \min\{\frac{\bar{\gamma}\rho_0 v + \gamma\bar{\rho}_0(d-h)}{2}, \hat{e}_R\}$	1	$\rho_0 v + \bar{\rho}_0(d-h) - c - e$
$e > \frac{\bar{\gamma}\rho_0 v + \gamma\bar{\rho}_0(d-h)}{2}$	$\min\{\frac{\bar{\gamma}\rho_0 v + \gamma\bar{\rho}_0(d-h)}{2}, \hat{e}_R\} \le e \le \hat{e}_R$	$\frac{\bar{\gamma}\rho_0 v + \gamma\bar{\rho}_0(d-h)}{2e}$	$\frac{[\bar{\gamma}\rho_0 v + \gamma\bar{\rho}_0(d-h)]^2}{4e} + \gamma\rho_0 v + \bar{\gamma}\bar{\rho}_0(d-h) - c$
–	$e \ge \hat{e}_R$	0	$\rho_0 v - \frac{\gamma}{\bar{\gamma}}\bar{\rho}_0 h + \bar{\rho}_0 d - c$

By allowing product returns, the firm's pricing decision involves both the prior probability of fit (ρ_0) as well as the net benefit of returns ($d-h$). Proposition 2 (i) suggests that when the prior probability of fit is rather low or the net benefit of returns is deeply negative, the firm should not exert any additional influence even if doing so is costless. Instead, the firm should opt for an aggressive pricing policy (note that the k_{RI} is higher in (i) than in the other two cases). This is a new scenario compared to the case without returns (i.e., Proposition 1). Indeed, influencing customers into purchases that will likely end up in costly returns can be detrimental to the firm. In this case, the use of the influence tool should be limited to raising awareness without distorting signal distribution.

Once the condition in (i) ceases to hold, the pricing and influence configuration resemble those without returns. Proposition 2 (iii) characterizes the conditions and a threshold $\hat{e}_R$ above which it would be too costly for the firm to exert additional influences (i.e., $a_R = 0$). In this case, as the hassle cost is lower and the residual value improves, the firm should opt for a low pricing policy. For the rest of Proposition 2 (ii) and (iii), where additional influence is in force (i.e., $a_R > 0$), it can be verified that the firm should generally lift the price, restrict the refunds, and reduce the level of influence, as the marginal cost of influence e becomes more significant.

Figure 2 depicts the shift in optimal solutions as the threshold condition changes. Throughout the three graphs, it constantly holds that the full valuation $v = 1$, the baseline signal quality $\gamma = 0.7$, the fixed cost of the influence tool $c = 0.1$, the hassle cost $h = 0.1$, and the residual value $d = 0.05$. The left graph where $\rho_0 = 0.1$ illustrates a solution in (i). There is no additional influence ($a_R = 0$), but a high pricing index ($k_{RI} = 0.2$) compared to the low odds of fit ($k_{RN} = \rho_0 = 0.1$), and an expected profit below zero. This suggests that it may not be profitable in some cases to allow product returns and acquire an influence tool at the same time. In the middle graph, where $\rho_0 = 0.2$, the solution falls into (ii). The firm will exert a full influence $a_R = 1$ when $e \le 0.014$ and maintain a normal pricing index $k_{RI} = 0.2 = k_{RN} = \rho_0$. As e increases, the level of influence a_R decreases toward 0.029 while the pricing index k_{RI} climbs toward 0.35. Notably in this process, the firm gradually gives up additional influence in exchange for a higher price or less refund. In other words, as long as the firm chooses to impose additional influence, aggressive influence actions should be accompanied by a lower price or more generous refunds. In the graph on the right, where $\rho_0 = 0.4$, the prospect of product fit is more optimistic. As a result, when the marginal influence cost $e \geq 0.13$, the firm will rely entirely upon a low pricing strategy ($k_{RI} < k_{RN} = \rho_0 = 0.4$) to engage customers and exert no additional influence.

Figure 2 Optimal Pricing, Level of Influence, and Expected Profit Under Scenario RI ($v = 1, \gamma = 0.7, c = 0.1, h = 0.1, d = 0.05$)



6. Optimal Joint Configuration

As of now, we can compare the optimal solutions under the four scenarios — $0N$, RN, $0I$, and RI — and investigate the strategy that maximizes the firm's expected profit. To do so, we first analyze in §6.1 the rationale of allowing product returns without any influence tool and with the influence tool. These will be done by comparing Π_{0N} versus Π_{RN}, and Π_{0I} versus Π_{RI}, respectively, Then, in §6.2, we identify the rationale of employing the influence tool by comparing $\Pi_N = \max\{\Pi_{0N}, \Pi_{RN}\}$ and $\Pi_I = \max\{\Pi_{0I}, \Pi_{RI}\}$. Finally, in §6.3, we derive the optimal strategy a firm may follow in using the influence tool and determining its return policy, with a mapping to the optimal joint configuration on the level of influence, price, and refunds as solved back in §4 and §5.

6.1 Rationale of Allowing Returns

6.1.1 No Influence To understand the motivation for a firm to set $r \geq h$ (hence customers would return any misfit product and claim the refund) in the absence of any influence tool, we compare Π_{0N} and Π_{RN} as established in (3) and (4), respectively, and obtain the following result:

LEMMA 2. **(Rational of Allowing Returns Without Influence Tool)** *In the absence of an influence tool, the firm should allow product returns, i.e.,* $\Pi_{RN} \geq \Pi_{0N}$*, if and only if* $d \geq h$*. The optimal expected profit without any influence tool* $\Pi_N = \max\{\Pi_{0N}, \Pi_{RN}\} = \lambda[\rho_0 v + \bar{\rho}_0 (d-h)^+]$.

The lemma indicates that without any influence tool, it is optimal for the firm to set $r \geq h$ and allow product returns provided that the net benefit of returns is non-negative. This perfectly aligns with the social interest in accepting returns. Further, Lemma 2 implies that the spread between the residual value d and the hassle cost h, i.e., $(d-h)^+$, can be entirely kept by the firm. These traits on the preference and benefit of allowing product returns, however, may not hold when an influence tool is in place, as will be discussed in what follows.

6.1.2 With Influence To investigate the rationale of allowing product returns in the presence of an influence tool, we compare Π_{0I} and Π_{RI} characterized in Propositions 1 and 2, respectively. The optimal levels of influence, pricing index, and expected profit are denoted as a_I, k_I, and Π_I, respectively, and the choice of return policy will be indicated separately.

First, it can be proved that, similar to the case without influence, the firm should allow product returns if the net benefit of returns is non-negative, i.e., when $d \geq h$, and block product returns when the net benefit of returns is deeply negative. These are mentioned in Proposition 3 (i) and (iii), respectively. Further, (ii) shows that with an influence tool, the rationale of allowing returns may also exist when the net benefit of returns is negative, i.e., $d < h$. In fact, under a moderately negative net benefit of returns as outlined in (ii), it would be optimal for the firm to exert additional influence, or allowing product returns, but not both. Naturally, as the marginal influence cost grows, it is sensible for the firm to switch from exerting additional influence to allowing product returns. This result reveals the substitution role between influencing customers *ex ante* (via distorting signal distributions) and providing refunds *ex post* (by way of allowing product returns).

PROPOSITION 3. **(Rational of Allowing Returns with an Influence Tool)** *Suppose an influence tool is in place. There exists some $\hat{h}$ such that (i) if $d \geq h$, the firm should allow product returns, i.e., $\Pi_I = \Pi_{RI}$; (ii) if $\hat{h} \leq d < h$, the firm will allow returns if and only if $e \geq e_I$ for some $e_I > 0$. In particular, $a_I = a_0 > 0$ for $e < e_I$ and $a_I = a_R = 0$ for $e \geq e_I$; (iii) if $d < \hat{h}$, the firm should not allow any product returns, i.e., $\Pi_I = \Pi_{0I}$.*

Next, we illustrate the above results through some benchmark cases to provide more concrete insights. First, consider the corner case with zero hassle cost, i.e., $h = 0$, as when customers can easily access return kiosks or the firm covers return shipping. Customers are then highly inclined to exercise the return in case of a product mismatch.

COROLLARY 1. **(Zero Hassle Cost)** *When $h = 0$, there exists some $d_0 < 0$ such that*

(i) if $d \geq 0$, there is always $\Pi_{RI} > \Pi_{0I}$;

(ii) if $d_0 \leq d < 0$, there is $\Pi_{RI} > \Pi_{0I}$ if and only if $e \geq e_d$, for some $e_d \geq 0$;

(iii) if $d < d_0$, $\Pi_{RI} \leq \Pi_{0I}$.

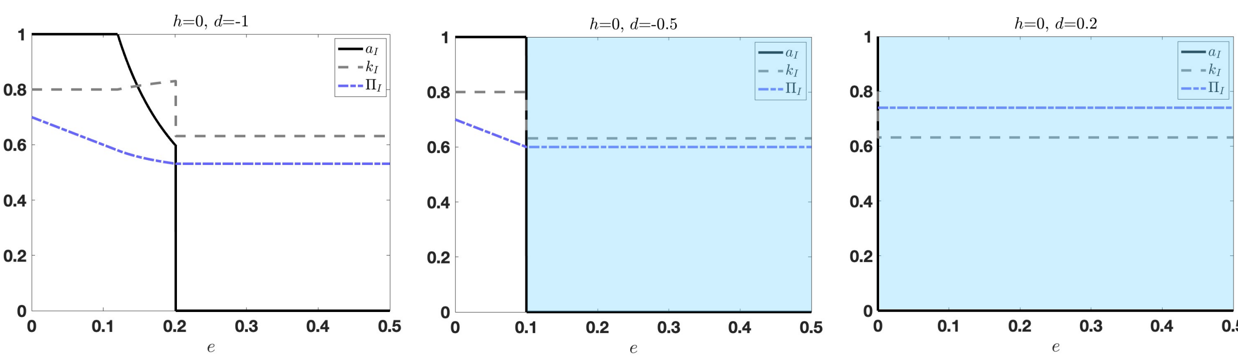
The three cases in Corollary 1 are illustrated in Figure 3, where it holds that the full valuation $v = 1$, the baseline signal quality $\gamma = 0.7$, the prior probability of fit $\rho_0 = 0.8$, the fixed cost of an influence tool $c = 0.1$, the hassle cost $h = 0$, and the residual value d varies among -1, -0.5, and 0.2. The areas where returns should be allowed are highlighted in blue.

According to (i), when $h = 0$ and $d = 0.2$, the firm should always allow product returns and go with the optimal configuration as in scenario RI. As illustrated in the right graph of Figure 3, the firm will constantly permit product returns and set $a_R = 0$.

When $h=0$ and $d=-0.5$, as the middle graph of Figure 3 shows, (ii) applies. The firm should allow product returns with no additional influence ($a_I=a_R=0$) when the marginal influence cost is high, i.e., $e \geq e_d = 0.1$, and no product returns but full influence ($a_I=a_0=1$) when it is low, i.e., $e<e_d=0.1$. When $e \geq 0.1$ where no additional influence will be imposed, the firm may use a high-price-full-refund or low-price-low-refund strategy (e.g., $p=r=1$, or $p \to 0.6$ and $r \to 0$, although other pricing pairs are also feasible) to secure the sales and recover the loss in processing the returns. When $e<0.1$, where full influence applies, the firm should stay with a moderate, non-refundable price ($p=0.8$) so as to avoid the excess cost arising from product returns.

When $h=0$ and $d=-1$, as in the left graph of Figure 3, (iii) finds that product returns should be completely off the table, i.e., the firm should not permit any product returns even if the marginal influence cost is high. Instead, the level of influence may be more tailored and partial (e.g., $0<a_I<1$ when $0.1 \leq e \leq 0.2$). Overall, the rationale of allowing product returns is strengthened by a higher residual value or a higher marginal influence cost. Additional influence and product returns work as substitutes when the residual value is moderately negative.

Figure 3 **Optimal Configuration with Influence Tool Under Low Hassle Cost** ($v=1, \gamma=0.7, \rho_0=0.8, c=0.1$**; area of returns** $\Pi_I=\Pi_{RI}$ **highlighted in blue)**



Another corner case we would like to examine is when the residual value $d=0$. This corresponds to instances where the salvage value is low or the cost of repackaging or disposal is significant, such hat the firm does not gain or lose much from a returned item. Some fashion apparels, personal healthcare products, and home appliances may fall within this category. In this case, the following proposition finds that the firm may not have the incentive to allow product returns when the hassle cost is too high or when the marginal influence cost is too low:

Corollary 2. **(Zero Residual Value)** *When $d=0$, there exists an $h_0>0$ such that*

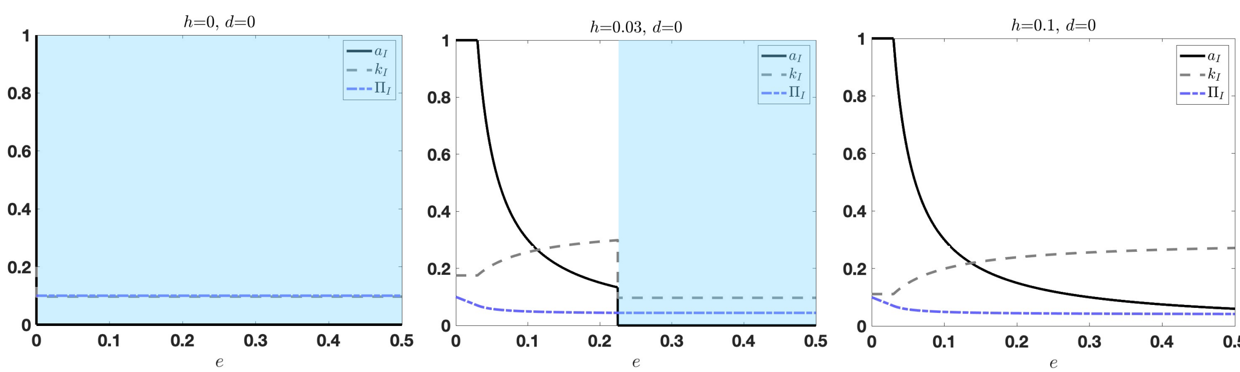
(i) if $h>h_0$, there is $\Pi_{0I} \geq \Pi_{RI}$;

(ii) if $h \leq h_0$, there exists an $e_h \geq 0$ such that $\Pi_{RI} \geq \Pi_{0I}$ when $e \geq e_h$ and $\Pi_{RI} < \Pi_{0I}$ otherwise. In particular, $e_h \to 0$ when $h \to 0$.

Figure 4 demonstrates the findings in Corollary 2 by varying the hassle cost among $h = 0$, 0.03, and 0.1 while keeping the full valuation $v = 1$, the baseline signal quality $\gamma = 0.7$, the prior probability of fit $\rho_0 = 0.2$, the fixed cost of an influence tool $c = 0.1$, and the residual value $d = 0$. As (i) suggests, when the hassle cost is high, e.g., $h = 0.1$ as the right-hand graph in Figure 4 shows, it is wise for the firm to discourage product returns and exert a tailored level of influence ($a_I > 0$) to encourage sales.

According to (ii), when the hassle cost is low, e.g., $h = 0.03$ as in the middle graph, the firm should maintain tailoring the level of influence without allowing returns when the marginal influence cost is relatively low ($e \le e_h = 0.22$). (ii) also implies that as the hassle cost approaches 0, the zone of product returns should gradually increase and cannibalize the area of additional influence, ultimately leading to permitting product returns regardless of the marginal influence cost. The case when $h = 0$ is shown in the left graph of Figure 4. Overall, the rationale of allowing product returns is encouraged by a lower hassle cost and a higher marginal influence cost. Additional influence and product returns may substitute each other when the hassle cost varies at a reasonably low level.

Figure 4 **Optimal Configuration with Influence Tool Under Low Residual Value ($v = 1, \gamma = 0.7, \rho_0 = 0.2, c = 0.1$; area of returns where $\Pi_I = \Pi_{RI}$ highlighted in blue)**

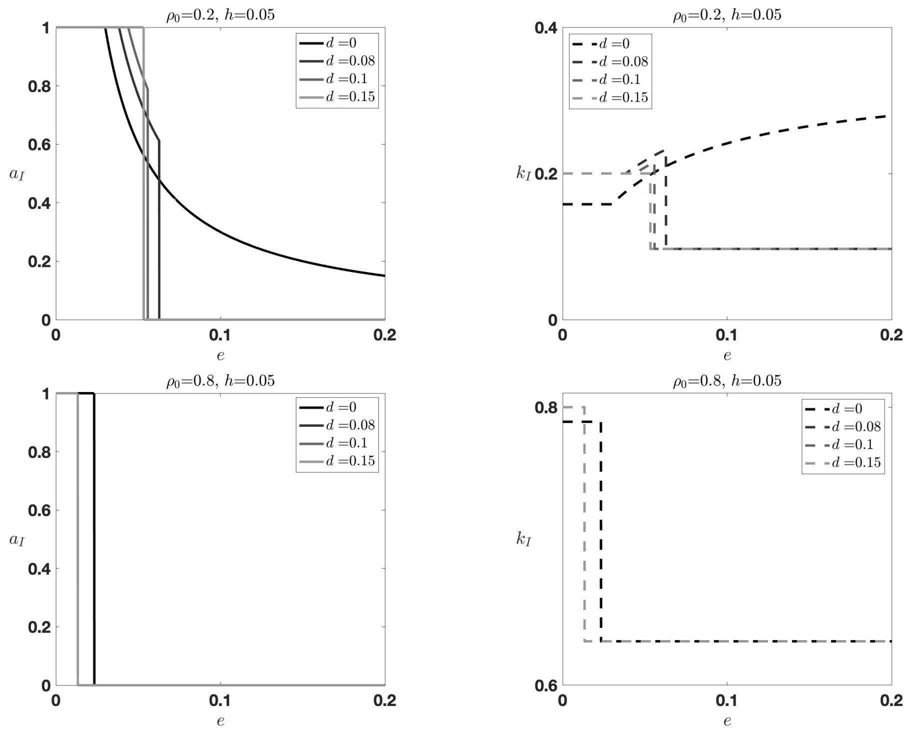


In the above corner cases, product returns and additional influence are strict substitutes under every marginal influence cost e, i.e., the firm would either allow product returns and set $a_I = 0$ or block product returns and set $a_I > 0$. However, it should be noted that this is not universal. In fact, there are many scenarios under which the firm would allow product returns ($\Pi_{RI} > \Pi_{0I}$) and exert additional influence ($a_I > 0$) at the same time.

Corollary 3. *The firm may concurrently allow product returns and exert additional influence.*

The above corollary confirms that the optimal joint configuration may involve a meticulous configuration of the level of influence, price, and refunds at the same time. This is salient as we numerically illustrate the general impact of the residual value d and the hassle cost h in Figures 5 and 6, respectively. In each figure, the top row is tied to a low probability of product fit ($\rho_0 = 0.2$) and the bottom row to a high probability of product fit ($\rho_0 = 0.8$); the left column presents the optimal level of influence a_I, and the right-hand column the optimal pricing index k_I. The optimal decision on whether to allow product returns and other fixed parameters are marked in the title of each figure.

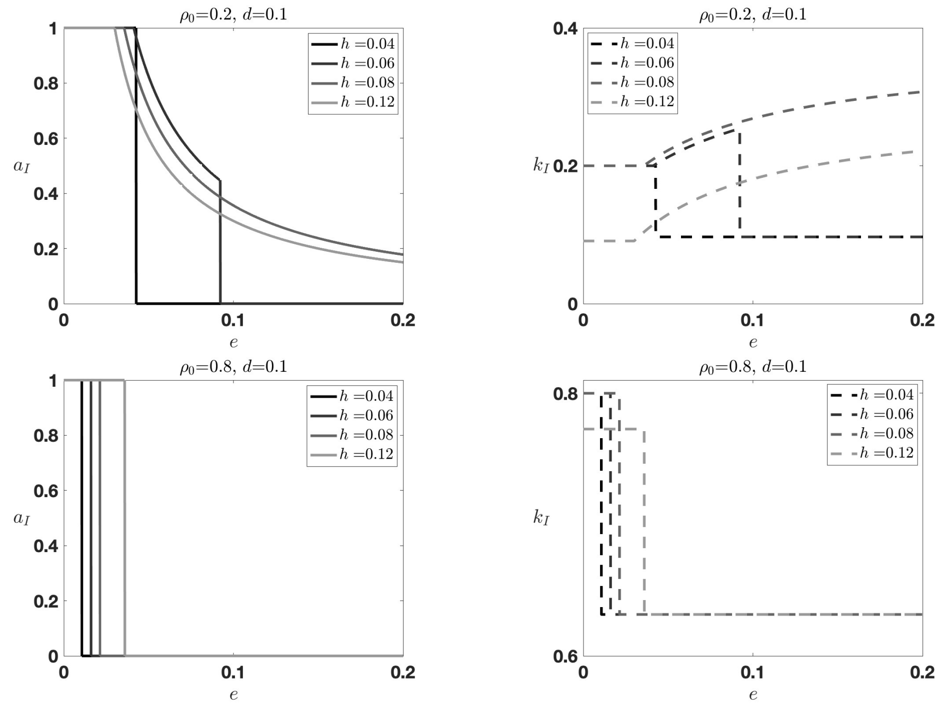
Figure 5 **Impact of d on Optimal Configuration ($v=1, \gamma=0.7, c=0.1$; returns apply to all except for $d=0$ when $\rho_0=0.2$; returns apply to all except for $d=0$ and $e<0.0235$ when $\rho_0=0.8$)**



In Figure 5, the hassle cost is fixed at $h = 0.05$ and the residual value d changes among $\{0, 0.08, 0.1, 0.15\}$, whereas a darker curve represents a smaller d. We remark that for low probability of fit (top row), the firm will allow product returns for any e (i.e., $a_I = a_R$ and $k_I = k_{RI}$) except when $d = 0$. As a result, for $e \in [0.0.54]$ and $d \in \{0.08, 0.1, 0.15\}$, the firm will exert a full or partial level of influence ($a_I > 0$) and allow product returns at the same time. Further, the level of influence a_I is higher but more limited to lower marginal influence costs as the residual value d increases, whereas the pricing index will be lower. Similar insights apply to a high probability of fit (bottom row), except that the optimal solution can be insensitive to the residual value or marginal influence cost when product returns are allowed, i.e., $d \in \{0.08, 0.1, 0.15\}$. Overall, a higher residual value d encourages the firm to allow product returns, set a lower pricing index, and exert a higher level of influence when the marginal influence cost is low.

In Figure 6, the residual value is fixed at $d = 0.1$, and the hassle cost h varies among $\{0.04, 0.06, 0.08, 0.12\}$, whereas a darker curve represents a smaller h. For a low probability of fit

Figure 6 **Impact of h on Optimal Configuration ($v = 1, \gamma = 0.7, c = 0.1$; returns apply to all except for $h = 0.12$ when $\rho_0 = 0.2$; returns apply to all for except for $h = 0.12$ and $e < 0.036$ when $\rho_0 = 0.8$)**



(top row), product returns universally apply when the hassle cost is not too high ($h = 0.04, 0.06$, or 0.08). Within this domain, a higher hassle cost will lower the level but expand the zone of additional influence. It will also lift the pricing index, implying a higher price and a smaller refund. For a high probability of fit (bottom row), a large hassle cost also prohibits the firm from allowing returns unless the marginal influence cost is large enough to make it more preferable than additional influence, i.e., $a_I = 0$ and $\Pi_I = \Pi_{RI}$ when $h = 0.12$ and $e \geq 0.036$. However, when the net benefit of returns is positive (i.e., $h = 0.04, 0.06$, or 0.08), a higher hassle cost will increase the level of influence as well as the pricing index. Therefore, while the hassle cost impacts the pricing index similarly across different probabilities of fit, it may have an opposite impact on the level of influence depending on the odds of product match.

6.2 Rationale of Influence

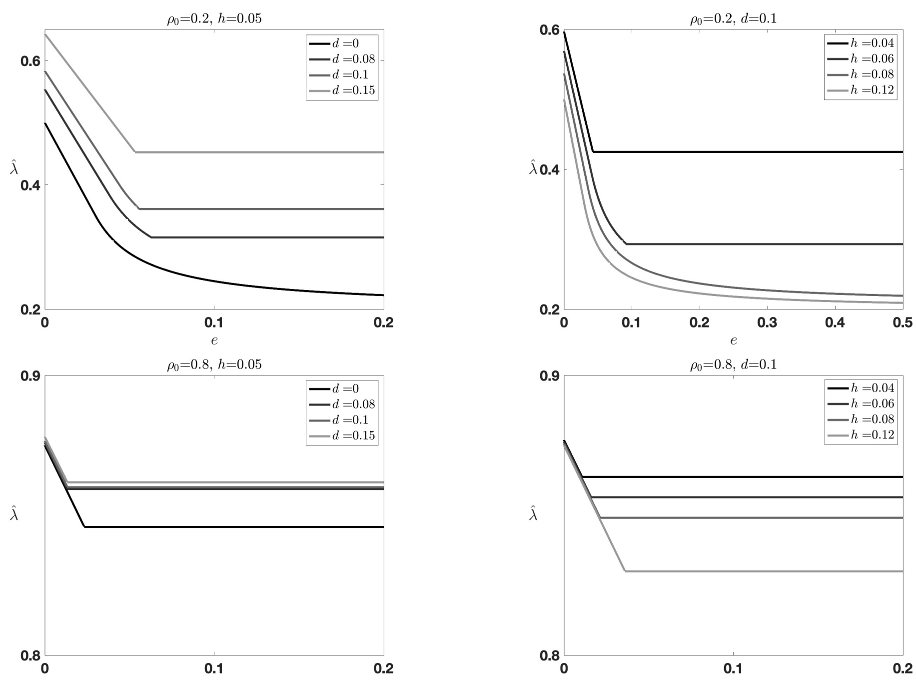
Based on the optimal decision of allowing returns, the firm can compare Π_N versus Π_I and decide whether it should employ the influence tool in the first place. In this regard, the following proposition characterizes how the two key factors of the influence tool, i.e., the effectiveness of raising awareness measured by $1/\lambda$ and the marginal influence cost e, may jointly shape the rationale of influence.

Proposition 4. *There exists a $\hat{\lambda}$ such that the firm should adopt the influence tool if and only if $\lambda \leq \hat{\lambda}$. In particular, $\hat{\lambda}$ weakly decreases in e.*

Essentially, a prime criterion for the firm to adopt the influence tool is its effectiveness in raising awareness, i.e., $1/\lambda \geq 1/\hat{\lambda}$, or equivalently, $\lambda \leq \hat{\lambda}$. Further, as the marginal influence cost e increases, the requirement for this threshold may only be higher, i.e., $1/\hat{\lambda}$ weakly increases in e.

Figure 7 demonstrates how the threshold $\hat{\lambda}$ varies with e and some other model parameters. In the first column, the hassle cost is fixed at $h = 0.05$ and the residual value d varies among $\{0, 0.08, 0.1, 0.15\}$, whereas a darker curve represents a smaller d. In the second column, the residual value $d = 0.1$ and the hassle cost h is among $\{0.04, 0.06, 0.08, 0.12\}$, whereas a darker curve represents a smaller h. Graphs in the top row have a smaller probability of fit ($\rho_0 = 0.2$), and those in the bottom row have a higher probability of fit ($\rho_0 = 0.8$). As can be observed, the threshold $\hat{\lambda}$ weakly decreases in e. The threshold $\hat{\lambda}$ also increases in the residual value d and decreases in the hassle cost h. Comparing the rows, it can also be observed that $\hat{\lambda}$ is higher with a high probability of fit. These imply that an influence tool is more likely to be adopted when the marginal influence cost is low, the residual value is high, the hassle cost is low, and the prior probability of fit is high.

Figure 7 **Threshold λ for the Adoption of An Influence Tool** ($v = 1, \gamma = 0.7, c = 0.1$)



6.3 Optimal Strategy

Integrating the findings from §6.1 and §6.2 provides an overarching guideline for how the firm should navigate the four strategies involving product returns and influencing customers, i.e., $0N$, $0I$, RN, and RI. Denote a^* the optimal level of influence conditional on adopting an influence tool. We distinguish within the strategy RI between an *initial* use of the influence tool ($a^* = 0$), where the tool is adopted only to raise awareness, and *additional* influence ($a^* > 0$), where the tool is also used to distort the signal distribution. The results are summarized in the following proposition:

PROPOSITION 5. **(Optimal Strategy for Influence and Product Returns)** *It is optimal for the firm to adopt strategy*

(i) ***0N****, i.e., disable product returns without using any influence tool, if* $\lambda > \hat{\lambda}$ *and* $d < h$*;*

(ii) ***RN****, i.e., allow product returns without using any influence tool, if* $\lambda > \hat{\lambda}$ *and* $d \geq h$*;*

(iii) ***RI*** *with* $a^* = 0$*, i.e., allow product returns with an initial use of the influence tool, if* $\lambda \leq \hat{\lambda}$ *and either (A)* $d \geq h$ *and* $e > \hat{e}_R$*, or (B)* $\hat{h} \leq d < h$ *and* $e > e_I$*;*

(iv) ***RI*** *with* $a^* > 0$*, i.e., allow product returns with additional influence, if* $\lambda \leq \hat{\lambda}$*,* $d \geq h$*, and* $e \leq \hat{e}_R$*;*

(v) ***0I*** *where* $a^* > 0$*, i.e., disable product returns with additional influence, if* $\lambda \leq \hat{\lambda}$ *and either (A)* $\hat{h} \leq d < h$ *and* $e < e_I$*, or (B)* $d < \hat{h}$*.*

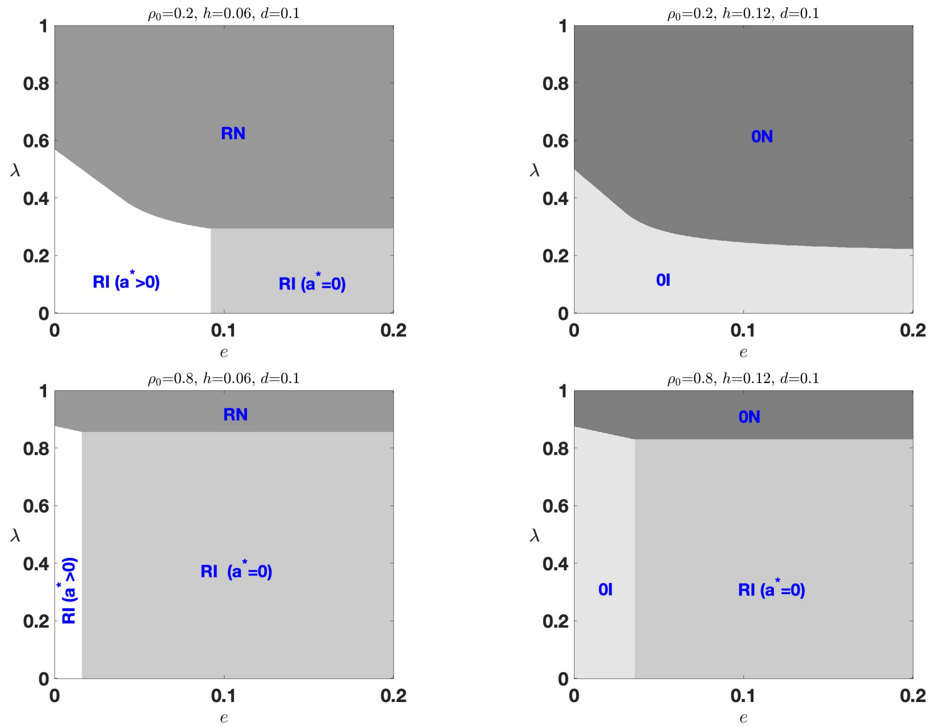
In particular, $\hat{h}$ *decreases in* ρ_0*.*

Figure 8 plots the variation of optimal strategy for the firm across different sets of parameters. For all graphs, it is fixed that the maximum valuation $v = 1$, the baseline signal quality $\gamma = 0.7$, and the fixed cost of an influence tool $c = 0.1$. The top and bottom rows represent instances with a low or high probability of fit, respectively. The left column represents scenarios with a non-negative net benefit of returns ($d \geq h$) and the right column otherwise ($h > d$).

As can be seen across the four graphs, the firm will not use an influence tool nor allow product returns ($0N$) if the effectiveness of the influence tool in raising awareness is limited and the net benefit of returns is negative. These typically apply to the products with inelastic demand or those that customers are already familiar with, such as some healthcare products and end-of-cycle electronic devices, which may imply little resale value or high processing costs if returned. If the effectiveness in raising awareness is low but the net benefit of returns is non-negative, the firm may allow product returns without adopting any influence tools (RN). This has been observed in many commodities or popular models that are already well known to customers, such as iconic toys and classic jeans, and can be easily put back to shelf following a return.

Conditional upon an influence tool being used, and when the net benefit of returns is non-negative, the firm may exert additional influence and allow product returns at the same time if the marginal cost of influence is low (RI with $a^* > 0$ as shown in the two graphs on the left). For instance, small home appliances and tools sold on Amazon or Home Depot are rich in assortment and highly substitutable. Hence customers often rely on reviews to guide their purchasing decisions. Also, the resale values of these products are less affected just because they were returned, and customers typically have easy access to pre-paid return mailing labels or chain store returns. This supports the use of incentivized customer review programs by sellers on these market platforms. As the marginal

Figure 8 **Optimal Strategy for Influence and Product Returns ($0N$: no product returns and no influence tool; $0I$: with influence tool but no product returns; RN: with product returns but no influence tool; RI: with both product returns and influence tool.)**



influence cost becomes high, e.g., when offering free samples in exchange for favourable reviews is too costly for online sellers, or when purchases are primarily driven by technical attributes beyond the realm of further influence, the firm may allow product returns without exerting any additional influence (RI with $a^* = 0$). Relevant examples include neutral or technical reviews on the performance of new electronic devices such as computers or premium sound systems.

When an influence tool shall be used and the net benefit of returns is negative, influencing customers and offering refunds become substitutes to each other. The firm should engage in additional influence or allowing product returns, but not both (as illustrated in the graphs on the right). Specifically, when the probability of fit is high, the firm should exert additional influence without offering any refunds ($0I$) if the marginal influence cost is relatively low. A notable example is the skyrocketed sales of Wove Made's Taylor Swift–inspired friendship bracelet.[12] While jewelry bracelets are more likely to fit, any return would entirely undermine the time and effort that had already been spent personalizing the product. Therefore, the firm's no return policy is consistent with the recommendation of our model. As it becomes more costly to influence a customer's prior belief of fit, the firm should shift to allowing returns rather than additional influence (RI with $a^* = 0$). For instance, Nike applies

[12] https://www.cbsnews.com/philadelphia/news/taylor-swift-travis-kelce-tnt-new-friendship-bracelet-pennsylvania-wove-jewelry/

regular return policy on their Nike By Your Custom Shoes[13], but provides no customer review under each shoes to be customized as opposed to other products. Additionally, for seasonal and customized products, the $0I$ strategy may commonly apply if the prior probability of fit is low (as in the top-right graph). For instance, Kyle × Shahida, a niche designer apparel line co-founded by a mega influencer, has a stringent refund policy that allows minimal flexibility for returning online purchases.[14]

7. Model Extensions

In this section, we verify the robustness of our results and insights by examining two model extensions. The first extension (§7.1) restricts the firm to a full-refund policy and the second extension (§7.2) allows the probability of return to be driven by the level of refunds. We demonstrate that the structure of the solution and managerial insights are sustained under these model variations and discuss the additional insights introduced by these variations.

7.1 Commitment to Full Refunds

Our main model considers a wide spectrum of refund policies, ranging from no refund to partial and full refunds. Specifically with product returns, the optimal solution for pricing index $\tilde{k} = \frac{p-r+h}{v-r+h}$ covers an array of price-refund pairs, and it can be verified that:

Corollary 4. *(i) The optimal pairs of (p, r) in RN and RI include a full-refund policy; (ii) When $d \geq h$, full-refund constitutes an optimal strategy.*

This implies that the firm can simply choose between all-or-none refund policy in its optimal design. In practice, however, firms may be compelled to commit to a full refund policy due to business conventions or a priority for customer satisfaction. In what follows, we conduct a brief examination to verify whether, and to what extent, our results continue to hold when this restriction applies.

By committing to full refunds, the firm is limited between strategies RI and RN. When the net benefit of return is salient ($d \geq h$), this commitment has little impact on the optimal design, as confirmed by Corollary 4 (ii). When the net benefit of return is negative ($d < h$), comparing between Π_{RN} and Π_{RI}, as characterized in §5, immediately yields the following result: the firm should adopt RN if λ is above some threshold and RI otherwise. In the latter case, the firm should impose additional influence ($a^* > 0$) when the marginal influence cost e is sufficiently low, and retreat to an initial use of the influence tool ($a^* = 0$) when the marginal influence cost is high. This resembles a reduced structure of the optimal strategy in Proposition 5.

However, under negative net benefit of returns, a commitment to full refunds can affect the adoption and the use of influence tool in a nuanced way. To illustrate this effect, consider the right panel in

[13] https://www.nike.com/help/a/nike-by-you-return

[14] https://www.kylexshahida.com/en-ca/pages/return-exchange-and-store-credit-policy

Figure 8 where $h = 0.12 > d = 0.1$. We plot the optimal strategy under the same parameters with a commitment to full-refund policy in Figure EC1. As can be observed, the adoption of the influence tool can be marginally inhibited, especially when no returns constitutes the optimum in the main model. For example, when $\rho_0 = 0.2$, or when $\rho_0 = 0.8$ and e is small, the optimal strategy $0I$ may be replaced by RN. On the other hand, the adoption of the influence tool may also be expanded when the benefit of allowing returns emerges. For instance, when $\rho_0 = 0.8$ and e is large, the strategy RI (with $a^* = 0$) dominates some area where $0N$ used to apply. Further, the commitment to full refunds may reduce additional influence. For example, the optimal strategy shifts from $0I$ to RI with $a^* = 0$ when $\rho_0 = 0.8$ and e around 0.35. Often, the firm will need to jointly manage both the product returns and additional influence, as reflected by the wide presence of RI with $a^* > 0$ in Figure EC1. This highlights the importance for firms with negative benefit of returns (e.g., low residual value or high hassle cost) to re-examine their influence configuration before committing to a full refund.

7.2 Endogenous Return Probability

In the main model, we assume that the customer's value of the product under good fit ($F = G$) is a constant $v > 0$. As a result, product returns are only driven by product fit uncertainty, rather than valuation uncertainty. In this subsection, we consider that the customer also faces valuation uncertainty under a good fit. Specifically, we assume that v follows a uniform distribution over $[0, 1]$. The realization of v remains invisible to both the firm and the customer and will only be disclosed after the purchase. Therefore, the firm and the customer have to deal with two folds of uncertainties in their decision makings: product fit uncertainty and valuation uncertainty.

In this extended model, product returns may arise either from a bad fit ($F = B$) or from a low realized value under a good fit ($v \le r - h$). Conditional upon $r > h$, the probability of returns $\bar{\rho}_0 + \rho_0(r - h)$ depends on both the exogenous probability of fit ρ_0 and the endogenous refund amount r. Consequently, generous refunds may increase purchase *ex ante* while introducing more returns *ex post*. The updated sequence of events and detailed analysis are provided in E-Companion.

The optimal price, refunds, and influence levels (p, r, a), can be solved following similar steps as in the main model. We note that the structure of the results is preserved for each region — $0N$, $0I$, RN, and RI — as well as the optimal strategy obtained by comparing across these regions. Figure EC2 illustrates the optimal strategies in comparison with those in the main model (where $v = 0.5$ in aligning with the customer's expected value in the extended model). This yields additional insights into how endogenous return probability affects the optimal strategy.

First, by comparing the left vs. right panels and top vs. bottom panels in Figure EC2, we observe that the optimal strategy is more sensitive to the endogenous return probability when the hassle cost h is low and probability of fit ρ_0 is high. Indeed, as high hassle cost discourages returns, it may also restrain any derivative effect. Similarly, since endogenous return probability roots in valuation uncertainty under a good fit, its impact will naturally be augmented by a high probability of fit.

Second, we note that endogenous return probability may hinder the adoption of influence tools. This is salient with reasonably high marginal influence cost e. In this scenario, valuation uncertainty will motivate the firm to increase the use of RN by dropping off influence tools and adjusting price and refunds. However, as long as the influence tool is employed, endogenous return probability will push for a full use of influence ($a^* > 0$), even if this implies a shift to no-refund policy (as in the bottom-right graph of Figure EC2). This result is summarized in Proposition 6. Overall, endogenous return probability underscores the full use of influence tool while raising the bar for its adoption.

PROPOSITION 6. *Endogenous return probability may (i) discourage the adoption of an influence tool when the marginal influence cost is relatively high; (ii) invite full use of the influence tool when the marginal influence cost is relatively low.*

8. Conclusion and Future Directions

In this paper, we examine how the marketing momentum from influencing customers should be reconciled with the operations of product returns. Our study focuses on returns caused by product mismatches, which may increase when influence activities generate less precise signals about product fit. Through a stylized model that captures the trade-off between these two forces, we characterize how a firm should strategically configure the level of influence, the price, and the amount of refund.

Our analysis yields several managerial insights. First, influencing customers creates more room for the firm to allow product returns. Even if permitting returns is not advantageous *ex post*, the firm may nevertheless commit to substantial refunds alongside influence activities to increase sales *ex ante*. Second, product returns and customer influence can work either concurrently or as substitutes in managing product-mismatch risk. When both levers are costly, the firm may rely on only one of them: allowing returns without additional influence when mismatch risk is low, but using additional influence with a no-return policy when mismatch risk is high. Third, influencing customers can lead to a polarized pricing strategy: the firm may implement premium pricing with a tailored level of influence when the marginal influence cost is low, or adopt reduced pricing with no additional influence otherwise. Notably, the optimal price-refund pair is not unique, reflecting the diversity of refund policies observed in practice and leaving room for context-specific considerations.

Overall, managers should treat influencer marketing, pricing, and product return policy as a holistic system rather than separate functional decisions. Prior to adopting an influence tool, a manager should first examine whether it sufficiently expands product awareness, taking into account the cost of influence, the cost of returns, and the residual value of returned products. Once the influence tool is adopted, managers should recognize that stronger influence can increase the true positive rate of purchases while reducing signal precision, thereby creating more orders that may later become returns. Product returns can therefore serve as an *ex post* substitute for additional influence when influencing customers *ex ante* is costly; conversely, additional influence can substitute for product returns when returns create limited value and influencing customers is inexpensive. However, managers may benefit from using the two levers concurrently when returns generate sufficient value and the marginal cost of influence is low. Managers should also recognize that pricing should be strategically adjusted depending on the functional use of influence tools and the associated refund policy. In practice, firms should avoid evaluating influence tools solely by sales lift and instead align these activities with a broader array of pricing-refund designs to sustain the entire business. As an initial attempt, this paper opens the conversation on how to operationalize influencer marketing in conjunction with pricing and return policy design.

8.1 Future Directions

There are many directions in which this paper can be extended. First, influencers can reshape the distribution of customers' *ex ante* beliefs and perceptions of a product without altering their *ex post* heterogeneity. To focus on this aspect of influencer marketing, our model abstracts away from other sources of *ex ante* heterogeneity. In practice, however, customers may already differ before purchase in many dimensions, such as valuations, information, transaction costs, and responsiveness to influence. For instance, a tech-savvy customer may experience a lower hassle cost of returns than a customer who is less proficient with the Internet when filing an online return claim (Hsiao and Chen 2014). Customers may also hold different prior beliefs about product fit or value distributions conditional on match or mismatch (e.g., Courty and Li 2000, Shulman et al. 2009, Hsiao and Chen 2012, Shang et al. 2017, Nageswaran et al. 2020, Ren et al. 2026). Future research could examine how firms may use influencer marketing more effectively in the presence of such *ex ante* heterogeneity.

Second, our model abstracts the influencing action as a direct cost to the firm, which suits settings like online review platforms, review managers, or pre-agreed rates with influencers. 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, and the number of views (McKinsey & Company 2023). It would then be valuable to study the explicit contractual relationship between the firm and influencers, as well as the incentives behind the actions of review managers, and to examine their implications for both operational and marketing aspects of the matter.

In addition, future research should consider a broader set of operational issues, such as inventory and distribution, in the context of influencer marketing. To this end, a number of papers, e.g., Gao and Su (2017) and 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 relevant operational 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. A number of recent studies on influencer marketing also concern competitive issues among sellers (e.g., Cong and Li 2024) or influencers (e.g., Liu and Liu 2025). As another promising avenue, it would be of strategic importance for firms to understand how to effectively realign their influencer marketing and operations synergy in front of competition.

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References

Akcay, Y., T. Boyaci, D. Zhang. 2013. Selling with money-back guarantees: The impact on prices, quantities, and retail profitability. *Production and Operations Management* **22**(4) 777–791.

Altug, M. S. 2024. The impact of online product reviews on retailer's pricing and return policy decisions. *Working Paper. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3914886* 1–44.

Altug, M. S., T. Aydinliyim, A. Jain. 2021. Managing opportunistic consumer returns in retail operations. *Management Science* **67**(9) 5660–5678.

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

Berman, R., H. Zhao, Y. Zhu. 2024. Strategic design of recommendation algorithms. *Working Paper. Available at: https://ssrn.com/abstract=4301489* 1–56.

Burtch, G., Y. Hong, R. Bapna, V. Griskevicius. 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.

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. https://www.cnn.com/2023/04/12/business/amazon-returns-ups-store-fee/index.html. Retrieved July 5, 2023.

Cong, L. W., S. Li. 2024. Influencer marketing and product competition. *Journal of Economic Theory* **220** 105867.

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.

Ertekin, N., A. Agrawal. 2021. How does a return period policy change affect multichannel retailer profitability? *Manufacturing & Service Operations Management* **13**(1) 210–229.

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

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

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. 2025. Livestream commerce with online influencers. *Working Paper. Available at: https://ssrn.com/abstract=3896924* 1–50.

Hsiao, L., Y.-J. Chen. 2012. Return policy and quality risk in e-business. *Production and Operations Management* **21**(3) 489–503.

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

Huang, T., H. Ren, Y.-J. Chen. 2018. Consumer return policies in competitive markets: An operations perspective. *Naval Research Logistics* **65** 462–476.

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 July 5, 2023.

Jerath, K., Q. Ren. 2025. Customer resaerch and product returns. *Marketing Science* **44**(3) 691–710.

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

Kuang, Y., L. Jiang. 2023. Managing presales with two payments and return policy when consumers are time-inconsistent. *Production and Operations Management* **23**(11) 3594–3613.

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.

Letizia, P., M. Pourakbar, T. Harrison. 2018. The impact of consumer returns on the multichannel sales strategy of manufacturers. *Production and Operations Management* **27**(2) 323–349.

Lin, J., T.-M. Choi, Y.-H. Kuo. 2024. Online retailing operations: Is it wise to offer free sample trial and money-back guarantee together? *Production and Operations Management* **33**(11) 2158–2176.

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

Liu, J., Y. Liu. 2025. Asymmetric impact of matching technology on influencer marketing: Implications for platform revenue. *Marketing Science* **44**(1) 65–83.

Liu, Y., N. Chen. 2022. Dynamic pricing with money-back guarantees. *Production and Operations Management* **31**(3) 941–962.

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) 2421–2455.

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

McWilliams, B. 2012. Money-back guarantees: Helping the low-quality retailer. *Management Science* **58**(8) 1521–1524.

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.

Moorthy, S., K. Srinivasan. 1995. Signaling quality with a money-back guarantee: The role of transaction costs. *Marketing Science* **14**(4) 442–466.

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

Nageswaran, L., E. H. Hwang, S.-H. Cho. 2025. Offline returns for online retailers via partnership. *Management Science* **71**(1) 279–297.

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

Ren, W., C. Ru, W. Xiao, F. Chen. 2026. Why full refunds prevail: A product fit perspective. *Production and Operations Management* Forthcoming.

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. Srinivasan. 2018. The impact of online product reviews on product returns. *Information Systems Research* **29**(3) 723–738.

Shang, G., B. P. Ghosh, M. R. Galbreth. 2017. Optimal retail return policies with wardrobing. *Production and Operations Management* **26**(7) 1315–1332.

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. https://internetretailing.net/under-the-influence-understanding-what-influences-consumer-purchases-uncovered/. Retrieved 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 Economist. 2022. A tidal wave of returns hits the e-commerce industry. https://www.economist.com/business/2022/08/25/a-tidal-wave-of-returns-hits-the-e-commerce-industry. Retrieved 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. 2025. Engagement that sells: Influencer video advertising on TikTok. *Marketing Science* **44**(2) 247–267.

Zhang, C., M. Yu, J. Chen. 2022. Signaling quality with return insurance: Theory and empirical evidence. *Management Science* **68**(8) 5847–5867.

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.