Information Provision under Showrooming and Webrooming

Yuyun Zhong
Department of Computer Information Systems and Business Analytics, College of Business, James Madison University, Harrisonburg, VA 22807
zhongyx@jmu.edu

Wenjing Shen
Department of Decision Sciences and MIS, LeBow College of Business, Drexel University, Philadelphia, PA 19104
ws84@drexel.edu

Oben Ceryan
Bayes Business School, City, University of London, United Kindom
oben.ceryan@city.ac.uk

July 2022, Forthcoming at Omega

Deviations between consumers' information gathering and purchase channels may lead to *showrooming* and *webrooming*, where the former refers to obtaining product information in a brick-and-mortar (BM) store but purchasing online while the latter corresponds to the reverse. In this paper, we endogenize consumers' information gathering and purchase decisions and characterize the optimal information provision decision for an online retailer in the presence of a rival BM store. For instances where showrooming can arise, we find that the optimal information level decreases with the fraction of consumers who consider showrooming. Despite the popular belief that showrooming is always detrimental to the BM store, our results suggest that showrooming may increase the profit of the BM store and decrease the profit of the online store. In instances with webrooming, we again find that the optimal information level decreases with the fraction of consumers who consider webrooming but that the profit of the online retailer always decreases with the fraction of consumers who consider webrooming. In addition, we consider the price matching strategy of the BM store and its interplay with the online retailer's information decisions. Lastly, we briefly extend our work to study settings with return cost, heterogeneity in online shopping cost, all consumers evaluating the product online first, endogenized pricing decisions for retailers, and a retailer owning both online and offline channels.

Key words: Retailing, Product Information, Match Uncertainty, Showrooming, Webrooming

1. Introduction

For many product categories such as food, cosmetics, books, and apparel, consumers' purchase decisions depend significantly on how well a product matches their idiosyncratic needs or preferences. Such preferences are especially relevant in the context of horizontal differentiation. For instance, a consumer may choose a red dress over a green one in spite of the same quality level. Different from quality uncertainty, which can be resolved by applying past experiences or surveying the company's reputation, match uncertainty generally requires more time and effort to resolve because it is less correlated to others' tastes or choices (Jing, 2015).

To ensure a satisfactory purchase, consumers typically gather product information that helps resolve match uncertainty prior to purchase. In this paper, we consider two distinct channels for such information gathering. One way consumers may obtain match information is through visiting a traditional brick-and-mortar (BM) store. In a BM store, consumers can "touch and feel" a product, try the product out, or consult a store assistant. In many cases, consumers' match uncertainty can be fully resolved through such examination of the product in the store. Going to the BM store, however, often requires a consumer to incur some traveling costs, which may preclude some consumers with high traveling costs from visiting the store. The second channel for obtaining match information is online. While the store channel can generally fully resolve match uncertainty, the information provided by the online retailer is often less helpful than that provided by the BM store, especially when resolving match uncertainty requires extensive physical inspection. However, online information can still partially resolve consumers' match uncertainty. How likely the match uncertainty will be resolved depends on the information level provided by the online retailer. In practice, we observe that the level of information online retailers provide vary greatly. While some online retailers provide very limited information such as only a brief product description, many others are increasingly utilizing new technologies to provide various forms of information to help consumers resolve their match uncertainty. For example, some furniture retailers allow consumers to rotate product images (e.g., EQ3) and view the product in augmented reality (e.g., EQ3, Ikea). Amazon also aims to help consumers better understand the fit of furniture by allowing "view 360" and "view in your room." The beauty retailer Charlotte Tilbury provides "try it on me," where consumers can upload a picture of their faces and apply products such as lipsticks. ASOS, a British online fashion and beauty store, provides videos on its website in which models walk on a runway wearing the outfits. In addition, they also offer a size finder that is more sophisticated than the traditional size charts. With the size finder, consumers can receive a size recommendation by entering information such as height, weight, age, body shape, fit preference, and sizing information on other brands they wear. In addition, retailers have been exploring virtual fitting rooms to enhance consumers' online shopping experience. The global virtual fitting room market is predicted to grow from $3 million in 2019 to $6.5 million by 2025 (Dietmar 2021). As these examples indicate, online retailers have the option of investing in the technology and degree of informativeness on their website, and such decisions can have an impact on consumers' choice on the information gathering channel.

After choosing the information gathering channel, a consumer who finds the product a good match then chooses from which channel to complete their purchase based on their traveling/online shopping cost and the prices offered by the two channels. A deviation of the purchase channel from the information gathering channel leads to two common phenomena, *showrooming* and *webrooming*. Specifically, showrooming refers to the practice of examining a product in a BM store and then switching to an online retailer to complete the purchase (as in Zimmerman, 2012). A study conducted by Quint, Rogers, and Ferguson (2013) reports that 70% of mobile shoppers (consumers who use their mobile devices in store) have showroomed at least once in the past year. On the other hand, webrooming refers to the behavior of searching information online and then completing the purchase in a BM store. Similarly, a recent study (Kibo Commerce, 2018) reveals that when asked "*when shopping online for products, what is your preferred method of purchase for the product?*", up to 47% of consumers indicate that one of their preferred channels for purchase is "*in-store, at a major retailer.*" Further, the survey shows that 40% of consumers claim that delivery that takes more than two days would prevent them from purchasing online. Such hassle cost will be incorporated in our model as the online shopping cost, which will be a major driver of consumers' potential webrooming behavior.

For an online retailer, the decision on how much information to provide in the presence of showrooming and webrooming behavior is rather complex. On the one hand, the online retailer might benefit from a higher information level as it helps attract more consumers to its channel in the first place. On the other hand, besides the cost of providing information, there is also a negative effect of providing too much information as it reduces showrooming behavior and/or induces webrooming behavior, both hurting the online retailer. This information decision of the online retailer has been treated as exogenous in the past literature. In this work, we endogenize the online retailer's information decision and aim to provide insights into how the online retailer should select its information level in the presence of consumers' showrooming and webrooming behavior.

Consumers' showrooming behavior is often viewed as a threat to BM stores by news articles (e.g., Gustafson 2014, Numerator 2021) and the general public. These news articles report that online retailers such as Amazon attract consumers with low prices, while those consumers often first visit physical stores owned by retailers such as Walmart, Target, and Best Buy to "touch and feel" the product (i.e., showrooming). Such external switching behavior makes Walmart serve as a showroom without making profits. Note that while retailers such as Walmart also own an online channel, consumers' internal switching from offline to online within a retailer is not necessarily detrimental. Therefore, to capture the main dynamics of interest, we adopt a simplified framework to consider only a BM store and an online retailer as in Mehra, Kumar, and Raju (2018) and Jing (2018). We allow consumers to strategically choose from which channel to collect information and in which to complete their purchases in order to maximize their expected utilities. We first solve the utility maximization problem of consumers for a given information level. We then solve for the online retailer's optimal information decision by using the demand functions derived from the consumers' problem, and characterize the structure of optimal information decision. Further, we extend our work to allow both retailers to determine their prices after the online retailer's information decision.

Our main findings for instances where showrooming can arise, specifically, when the sum of the online price and the online shopping cost is lower than the store price, are as follows. First, we find that only consumers with traveling costs below a certain threshold would consider showrooming and that this threshold decreases with the online information level. Second, while providing more information increases the initial traffic to the online retailer, it does not necessarily guarantee a higher total demand for the online retailer as information increases the demand due to direct online traffic but decreases the demand arising from the showrooming behavior. Third, we find that the online retailer provides a lower information level as the fraction of consumers who consider showrooming increases. Lastly, we also find that the profits of the two retailers are not necessarily monotonic with respect to the fraction of consumers who consider showrooming. Specifically, while increases in the fraction of consumers who consider showrooming beyond a certain threshold benefits the online retailer and impairs the BM store's profitability, when the prevalence of showrooming is low, an increase in the fraction of consumers who consider showrooming may hurt the online retailer and benefit the BM store.

Regarding webrooming, we find that webrooming exists only when the sum of the online price and the online shopping cost is higher than the store price and when the online information is sufficiently high. We show that only consumers with intermediate traveling costs will consider webrooming as consumers with low traveling costs visit the BM store in the first place while those with high traveling costs do not travel to the store to webroom after searching for information online. Further, webrooming behavior increases with the level of online information. Similar to the showrooming case, we again characterize the optimal information level and observe that the optimal information level decreases with the fraction of consumers who consider webrooming. We also observe that a larger fraction of consumers who consider webrooming always hurts the online retailer while it benefits the BM retailer.

We then consider the price matching strategy adopted by many retailers such as Walmart, Home Depot, and Staples in an effort to combat showrooming. Specifically, we study the interplay between the BM store's price matching policy and the online retailer's information decisions. Our analysis suggests that the online retailer always provides more information under price matching. Moreover, we find that the BM store's price matching policy is always detrimental to the profit of the online retailer. However, we also find that the BM store does not necessarily benefit from price matching and that the impact on its own profitability depends on the online price and the fraction of consumers who consider showrooming.

Finally, we consider the following extensions to our main model. As the first extension, we incorporate return cost and obtain the optimal information level. Second, we incorporate the heterogeneity in both traveling and online shopping costs. We characterize consumer behavior in this setting. Next, we look into the case in which all consumers search product information online first. If their uncertainty is not resolved, they then have the option of visiting the BM store to further evaluate the product. In the fourth extension, we endogenize retailers' pricing decisions. Lastly, we briefly discuss the information decision for an online retailer that owns both channels.

To summarize, a key distinction with the literature is that our model considers the online product information as a continuous and endogenous decision of the online store. Our study therefore contributes to the literature by, to the best of our knowledge, being the first to study an online retailer's information provision decision in the presence of consumers' showrooming and webrooming behavior. The results highlight the importance of taking showrooming and webrooming behavior into consideration while making information decisions, and facilitate better understanding of the interaction between retailer's information provision and consumers' strategic purchasing decisions with multiple channels.

The remainder of the paper is organized as follows. In Section 2, we provide a review of the related literature. We present the problem formulation in Section 3 and characterize the retailer's information decisions for instances where showrooming and webrooming can arise in Sections 4 and 5, respectively. We examine settings with price matching in Section 6, present five model extensions in Section 7, and conclude in Section 8.

2. Related Literature

Our study is broadly related to literature on firms mitigating consumers' uncertainty and inducing purchase. Consumers can resolve their valuation uncertainty in different steps along their purchase journey. Consequently, retailers have multiple ways of addressing consumers' valuation uncertainty, including providing product information, which resolves the uncertainty prior to purchase, and offering product returns, through which consumers apprehend their true valuation after purchase. The stream that studies product return considers it a mechanism to signal product quality or to facilitate purchase when consumers are uncertain about product match (e.g., Moorthy & Srinivasan, 1995; Che, 1996; Su, 2009; Shang, Ghosh & Galbreth, 2017; Li, Xie, & Liu, 2020; Altug, Aydinliyim, & Jain, 2021; Yang & Ji, 2022). Abdulla, Ketzenberg, and Abbey (2019) provide a detailed review of the literature. Our paper, on the other hand, focuses on the information provision decision of the retailer, which aims to assist consumers in better understanding the product characteristics prior to purchase. Different types of information have been considered in literature. For instance, information can reveal product quality (Guan & Wang, 2022; Guo & Zhao, 2009), consumers' quality preference (i.e., whether the consumer prefers a high-quality product or a low-quality one) (Lewis & Sappington, 1994; Lewis & Sappington, 1994; Sun et al., 2021), or both (Kuksov & Lin, 2010). Different from the above stream, our work is closely related to studies on firms' information decisions to resolve consumers' match uncertainty rather than quality uncertainty. Many studies consider a monopolistic seller or competing sellers of the same channel (Shulman, Coughlan, & Savaskan, 2009; Hoffmann & Inderst, 2011; Bang & Kim, 2013; Gu & Xie, 2013; Branco, Sun, & Villas-Boas, 2015; Li & Yi, 2017; Wu, Deng, & Jiang, 2018). In contrast, we study the competition between a BM store and an online retailer. Zettelmeyer (2000) studies two retailers competing on multiple channels. In his model, the two retailers select prices and information levels (high or low) on both a physical channel and an online channel. He shows that firms can strategically use information on multiple channels to segment the market and thus soften price competition by differentiating themselves. In Zettelmeyer (2000), information decisions depend largely on the proportion of consumers who have access to the internet. Moreover, he assumes that the effectiveness of information on the two channels is identical and that consumers incur the same search costs across both channels. We model online information as a continuous variable to capture the idea that consumers are more likely to find a match with more information. We also propose an asymmetric structure of information: the BM store can always fully resolve consumer uncertainty while the online store may not. Further, most of the literature focuses on the decision of retailers on the same channel or the store assistance level provided by a BM store. For example, Xia, Xiao, and Zhang (2017) investigate whether the retailer provides store assistance when competing with the manufacturer's direct channel. Some recent work examines the information provision decisions in omni-channel supply chains (Zhang, Li, Cheng, & Shum, 2020). Hao and Tan (2019) study a retailer's and a supplier's incentives to provide information to help consumers resolve their match uncertainty in a supply chain. Kwark, Chen, and Raghunathan (2014) examine the effect of online product reviews that can reveal product quality and fit on retailer and manufacturers. On the consumers side, Shulman, Cunha, and Saint Clair (2015) show the impact of providing information that reduces consumer uncertainty about a product on the number of decision reversals. To the best of our knowledge, the information provision decision of an online retailer when facing a rival BM retailer has not been studied in the literature. Adding to this stream of literature, we study the information decision of an online retailer in the presence of a rival BM retailer assuming that consumers' match uncertainty can be partially resolved by online information. In our model, consumers' match uncertainty can be fully resolved in store, while the uncertainty will be resolved online with a probability that is determined by how much information the online retailer provides.

There is also an extensive literature on information free-riding between two competing retailers of the same channel. Literature generally suggests that free-riding impairs the profit of the retailer that provides the information and thus leads to information underprovision (Telser, 1960; Telser, 1990; Singley & Williams, 1995; Tang & Xing, 2001). In contrast, other studies show that information free-riding can benefit the provider by increasing differentiation or softening price competition. Wu, Ray, Geng, and Whinston (2004) examine the information provision of multiple competing online retailers that sell horizontally differentiated products when free-riding exists. They find that as long as some consumers have positive search costs, the retailer needs to differentiate itself by providing information in order to make positive profits. Shin (2007) studies two competing BM retailers with only one of them providing information. He finds that both retailers may benefit from information free-riding. The information-providing retailer can lock in some consumers who already visit the store due to the existence of a shopping cost. Moreover, such information free-riding softens price competition by allowing the information provider to charge a higher price. Iyer and Kuksov (2012) study a similar free-riding problem in which both retailers can invest in consumers' shopping experience. This stream of literature examines two major questions: whether the retailer should provide more or less information when information free-riding exists and whether free-riding is detrimental to the information provider. Our study also falls into this general information free-riding literature as we study a specific type of free-riding that is between a BM retailer and an online retailer.

Whereas the effect of free-riding on the information provider is inconclusive, many papers on showrooming report a detrimental effect of consumers' showrooming behavior on the BM store. Balakrishnan, Sundaresan, and Zhang (2014) consider the competition between an online retailer and a BM store. Consumers can resolve their valuation uncertainty by visiting the store, while they can also purchase online without knowing for certain whether the product is a good match or not and return the product later. They show that consumers' showrooming behavior intensifies competition and reduces profits for both firms. This result contradicts that of Shin (2007) mainly because a different cost structure is assumed to highlight consumers' relative costs for purchasing online and visiting the store. In the study by Shin (2007), consumers face symmetric costs regardless of purchasing channel. In Balakrishnan et al., (2014), consumers are heterogeneous in the relative cost of visiting the BM store and purchasing online, which captures consumers' preferences in terms of channel selection and thus the difference in the demand of the two retailers. Mehra, Kumar, and Raju (2017) also show that showrooming is detrimental to the profit of the BM retailer. Such literature suggests that showrooming hurts the BM store and thus considers how BM retailers combat showrooming through price matching (Mehra et al., 2017; Wu, Wang & Zhu, 2018) and providing exclusive products (Mehra et al., 2017). Jing (2018) shows that showrooming lowers the profit of both BM store and online retailer.

To the best of our knowledge, only several papers find that showrooming can improve the profit of the BM store, for example, Kuksov and Liao (2018), Jiao and Hu (2020), Li et al. (2021), and Zhang, Yao, & Zhang (2021). Kuksov and Liao (2018) endogenize the manufacturer-retailer contract and find that when the manufacturer's decision is considered, showrooming can increase the retailer's profit. We do not incorporate the manufacturer's decision but our model suggests a similar result - showrooming is not necessarily bad for the BM retailer. Li et al. (2021) and Zhang, Yao, & Zhang (2021) also consider a setting with a manufacturer. Jiao and Hu (2020) consider the case in which BM store and online retailer provide different types of information to resolve consumers' valuation uncertainty. They find that showrooming may be beneficial to both retailers when the uncertainty is high. Our work has two major differences. First, we consider consumers' uncertainty about product match rather than quality. Second, we allow prices offered by the two retailers to be different. There are few papers studying the effect of webrooming. Jing (2018) finds that webrooming can benefit both retailers. Jiao and Hu (2020) show that webrooming can increase the profit of both retailers when the uncertainty is high. Additional works study the incentives for consumers to showroom or webroom (Flavián, Gurrea & Orús, 2016; Wolny & Charoensuksai, 2016).

Our paper also contributes to the literature on price matching. This literature has long focused on price matching in the absence of showrooming. Some studies argue that price matching lessens the competition and leads to price collusion (Salop, 1986; Doyle, 1988; Zhang, 1995; Hviid & Shaffer, 2012). Opposing results suggest that price matching intensifies competition because it facilitates consumer search. Jain and Srivastava (2000) suggest that price matching can lead to lower prices and more intense price competition when some consumers are uninformed of prices and firms are widely differentiated. Chen, Narasimhan, and Zhang (2001) find that price matching can lower profits and thus the retailer should not offer price matching when a major proportion of consumers are price sensitive. Recently, a price matching guarantee provided by a BM store has been studied as a strategy to combat consumers' showrooming behavior. Chen and Chen (2019) find that the BM store should provide price matching when consumers' online shopping cost is moderate. Mehra et al. (2017) examine price matching as a short-term strategy for the BM store to counter showrooming. They find that as more consumers seek price matching, the BM store's profit initially decreases and then increases. The crucial driver behind such non-monotonicity is price coordination: with more consumers seeking price matching, the online retailer raises its price, which will then be matched by the store, resulting in an increase in the profit for the BM store. Meanwhile, more consumers seeking price matching implies that they are buying the product at a lower price than the posted store price, which reduces the store profit. They also find that price matching becomes more effective if the fraction of customers who seek the benefit of price matching increases with the difference between prices of the two stores. We arrive at the same conclusion that price matching need not always benefit the BM store even when prices are fixed. The BM store will choose price matching based on the difference between the store price and the online price. Furthermore, we find that price matching is always detrimental to the profit of the online retailer.

3. The Model

3.1. Retailers

We consider a setting in which a BM store and an online retailer carry the same product (Jing, 2018; Kuksov & Liao, 2018). Each consumer purchases at most one product. Consumers need to determine whether the product is a good fit or not by utilizing information provided by the retailers. We assume that the BM store does not decide on the level of information to provide and that consumers who visit the BM store will fully realize whether the product is a good fit. The online retailer, on the other hand, decides on the informativeness of their website by selecting the information level θ to maximize its total profit. We assume that information provided by the online retailer does not change consumers' idiosyncratic preferences, instead, it reveals the product features so that consumers know whether the product is a good match. For instance, if a consumer prefers an "oversize fit" for a jacket, reading the product's sizing information will help her understand if this jacket can meet her needs for an "oversize fit," but will not lead to a preference for a "normal fit." The online retailer incurs a cost of providing information, which we assume to be $k\theta^2$, a quadratic function of the information level (Kuksov & Liao, 2018). We assume a constant upper bound $\bar{\theta} \leq 1$, which is the highest information level that the online retailer can provide given the current technology. The outcome of information is modeled as a binary variable: with probability θ, the consumer finds out whether she likes the product or not, and with probability $(1-\theta)$, the information she obtains from the website does not resolve her uncertainty. Prices of the online retailer and of the BM store are denoted as p_o and p_s, respectively. As our main focus in this paper is on the information provision decision, we assume that both prices are exogenous and that they are observable to consumers before consumers make their decisions on from which channel to gather information (Telser, 1960; Zettelmeyer, 2000). (We briefly extend the study to incorporate pricing decisions in Section 7.4) We denote the unit product cost for the BM store and the online store as u_s and u_o, respectively. Further, we assume that $p_o > u_o$ and $p_s > u_s$ so that both channels remain viable.

3.2. Consumers

Consumers are initially uncertain regarding whether they like the product. We let $q \in (0,1]$ denote the probability that a particular consumer finds the product a good match. Each consumer derives a value of $V = v$ from the product if it fits his or her preference, and a value of $V = 0$ otherwise. A consumer visiting the store incurs a traveling cost t, which we assume to be uniformly distributed in $[0, \bar{t}]$. On the other hand, visiting the online store incurs an online evaluation cost, c_e, which represents the time and efforts consumers invest in searching product information online. A consumer who purchases online incurs an online shopping cost, c_o, which captures any additional inconveniences such as waiting for delivery. We assume that all consumers face the same online shopping cost. (We relax this assumption in Section 7.2.) To ensure that at least some consumers who like the product are willing to purchase, we assume that $v > p_o + c_o$ and $v > p_s$.

Match uncertainty can be completely resolved by examining the product in store. However, whether the uncertainty is resolved on the online channel is determined by the information provided by the online retailer. With probability θ, the information resolves the uncertainty, while with probability $(1-\theta)$, the consumer does not receive adequate information to resolve her uncertainty. We assume that, if a consumer's uncertainty is not resolved, she will purchase online without knowing the match. She will return the product and receive full refund if it is a poor match. We assume that $c_e \leq q(v - p_o) - c_o$ to ensure that the consumer will obtain a non-negative expected utility if she purchases online without knowing the match.[1] Note that we assume consumers only gather information from one retailer. (This assumption will be relaxed in the extension Section

[1] Note: if the condition $c_e \leq q(v - p_o) - c_o$ is not satisfied, consumers may not purchase when uncertainty is not resolved. We show that our major results remain.

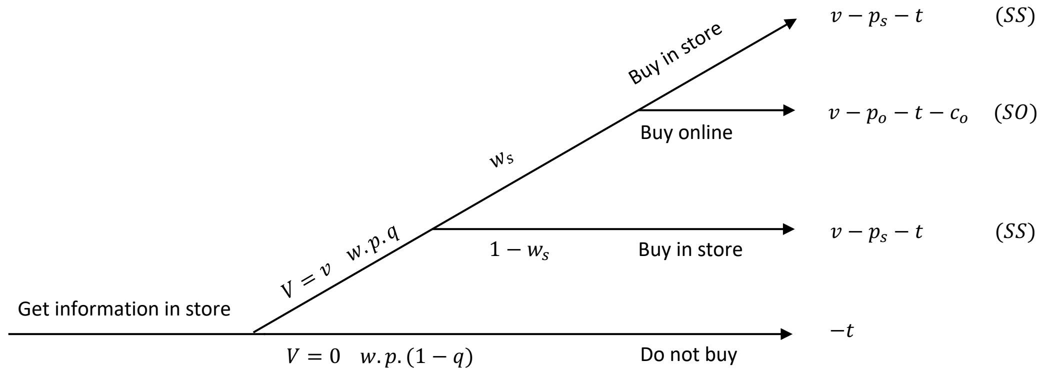


Figure 1 **Decision Tree for Consumers Who Inspect Product in Store**

7.3.) Moreover, the product is available at these two retailers only, so that consumers will gather information from either the BM store or the online retailer. Lastly, the market size is normalized to one.

3.3. Consumer Decision Process

Figures 1 and 2 present how consumers make their decisions. Consumers first decide where to gather product information and then decide if and where to complete purchase. In the first stage, consumers decide where to gather product information. If they visit the BM store, their uncertainty can be fully resolved. They will obtain a valuation of v with probability q, and a valuation of zero otherwise. If they choose to search for the product information online, given that the information level provided by the online retailer is θ, their uncertainty will be resolved with probability θ. In this case, their valuation is the same as in the case in which they obtain the information in the BM store. With probability $(1-\theta)$, the online information is not sufficient and they choose to purchase online and receive full refund in the case of a poor match.

After gathering information, consumers then make a decision on whether and from which channel to purchase the product. A key factor that determines the purchase channel is price. However, there are also non-price factors that affect consumers' channel selection decisions such as consumers' time pressure when shopping (Gensler, Neslin & Verhoef, 2017) and in-store experience (Kibo Commerce, 2018). We incorporate such non-price factors except traveling cost and online shopping cost into the model by allowing a fraction of consumers to compare both channels, with the remaining consumers staying on the information gathering channel to complete purchase. Specifically, let w_s represent the fraction of consumers who consider showrooming, that is, considering switching to the online retailer after examining the product in the BM store. Likewise, let w_o represent the fraction of consumers who will consider webrooming, i.e., considering switching to the BM store

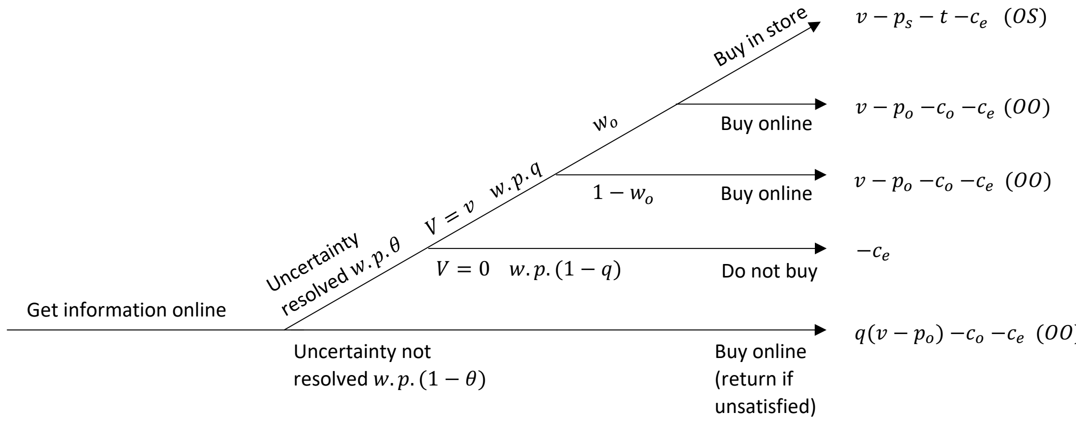


Figure 2 **Decision Tree for Consumers Who Search for Product Information Online**

after examining the product online. Note that the fractions w_s and w_o represent the fractions of consumers who consider comparing both channels prior to purchase, but not the fractions of consumers who eventually adopt showrooming or webrooming. Such consumers will select the channel that maximizes their expected utilities to complete purchase after comparing both. In other words, while the fraction of consumers who *consider* showrooming or webrooming is exogenously given (i.e., w_s or w_o), the actual fraction of consumers who eventually *engage in* showrooming or webrooming is endogenously determined by consumers' comparison of their utilities from each retailer. The purchase channel decision of the showrooming (and webrooming) behavior is affected by a comparison of prices, traveling cost, and costs associated with online shopping. But, by definition, the overall showrooming (and webrooming) behavior must also take into account where consumers first gather information, which depends also on the probability of consumers liking a product and the information level, along with prices, traveling cost, and costs associated with online shopping.

We identify four consumer strategies, each consisting of information gathering and purchase channel selections. Specifically, consumer strategies are as follows:

- Store Direct (SS): Get information in store. Buy in store if $V = v$, and do not buy if $V = 0$.
- Showrooming (SO): Get information in store. Buy online if $V = v$, and do not buy if $V = 0$.
- Webrooming (OS): Get information online. If uncertainty is resolved, buy in store when $V = v$, and do not buy if $V = 0$; if uncertainty is not resolved, purchase online (and return if it is not a good fit).
- Online Direct (OO): Get information online. If uncertainty is resolved, buy online when $V = v$, and do not buy if $V = 0$; if uncertainty is not resolved, purchase online (and return if it is not a good fit).

Retailer and Consumer Decisions

The sequence of events is as follows:

Stage 1: The online retailer decides on how much information to provide.

Stage 2: Consumers determine from which channel to collect information on product attributes.

Stage 3: Consumers decide whether and through which channel to purchase the product based on their realized utilities.

A consumer may choose one of the four strategies as described earlier: Store Direct (SS), Showrooming (SO), Webrooming (OS), and Online Direct (OO). When $p_o + c_o \leq p_s$, only Showrooming takes place and Webrooming is always dominated by Online Direct. The reason is that once the consumer has checked the product online, switching to the BM store derives a lower utility than directly purchasing online as the store price is higher and the consumer will incur the traveling cost. We refer to this situation as the case of showrooming and present the results in Section 4. Similarly, when $p_o + c_o > p_s$, only webrooming may exist. We refer to such a situation as the case of webrooming and present the corresponding results in Section 5.

The objective of the online retailer is to maximize its profit, which is given by $\pi(\theta) = (p_o - u_o)D_o(\theta) - k\theta^2$, where $D_o(\theta)$ is the total online demand determined by consumers' decisions in stages 2 and 3. We implement backward induction to find the optimal information level for the online retailer by first characterizing the channel selection and purchase decisions of consumers for a given information level and then identifying the information level that will maximize the profit of the online retailer.

4. The Case of Showrooming

As a first step to derive the demand functions for the two retailers, we start by characterizing the store and online traffic for a given information level. We consider parameters such that both store traffic and online traffic are viable. Lemma 1 below describes consumers' optimal channel choice for information gathering for a given information level θ.

LEMMA 1. *There exists a traveling cost threshold $t_1(\theta)$ such that a consumer will visit the BM store if her traveling cost is below $t_1(\theta)$ and will search the product information online otherwise. Furthermore, $t_1(\theta)$ decreases with information level θ.*

The expression of $t_1(\theta)$ in Lemma 1 is provided in equation (2) in Online Appendix A. As stated in Lemma 1, a consumer's proximity to the store plays an important role. Consumers who live *close* to the BM store, i.e., $t < t_1(\theta)$, will prefer to first visit the store to examine the product. Similarly, consumers who have higher traveling costs will prefer to search for information online.

Therefore, a fraction of $t_1(\theta)/\bar{t}$ of consumers visit the BM store (henceforth referred to as store traffic) and the remaining fraction goes online (henceforth referred to as online traffic). Store traffic is decreasing with the online information level as a higher information level enhances the probability of uncertainty being resolved online, which, in turn, attracts more consumers to the online retailer. Further, Lemma 2 below provides additional sensitivity results on how store traffic varies with some key parameters. (Online traffic has the opposite monotonicities to those of the store traffic.)

LEMMA 2. *For a given θ, store traffic increases with the fraction of consumers who consider showrooming w_s, online price p_o, online shopping cost c_o, and online evaluation cost c_e; while it decreases with store price p_s.*

Lemma 2 indicates that, for a given online information level, store traffic is increasing in the fraction of consumers who consider showrooming. The reason is as follows: Showrooming provides consumers a second option and hence leads to a potentially higher expected utility from visiting the store. Regarding costs associated with online shopping, our results suggest that, if it is more costly for consumers to search information online or to purchase online, store traffic will increase. We also find that, intuitively, price of a channel negatively affects the traffic of that channel.

Next, we derive the demand functions for a given information level using the findings in Lemma 1. We identify three types of demand based on the strategies that consumers may choose: (*i*) Store Direct demand, denoted by D_{ss}; (*ii*) Showrooming demand (online indirect demand), denoted by D_{so}; and (*iii*) Online Direct demand, denoted by D_{oo}. As previously stated, store traffic is given by $t_1(\theta)/\bar{t}$. These store visitors will find the product a good match with probability q. Among the consumers who find the product a good match, a fraction w_s of them will consider and choose showrooming (as $p_s \geq p_o + c_o$), constituting the Showrooming demand while the remaining $(1-w_s)$ fraction of them will complete the purchase in store and thus constitute the Store Direct demand. Consumers who search for information online (i.e., the online traffic $(1-t_1(\theta)/\bar{t})$) make decisions based on the information level. With probability θ, their uncertainty is resolved, and they will purchase if the product is a good match. Therefore, they purchase with probability θq. With probability $(1-\theta)$, their uncertainty is not resolved, and they will purchase online but return the product and receive full refund in the case of a poor match. Hence, the probability of them purchasing and keeping the product is $(1-\theta)q$. These three types of demand are summarized in Lemma 3.

LEMMA 3. *Store Direct demand is given by $D_{ss}(\theta) = q\,(1-w_s)\,t_1(\theta)/\bar{t}$, which decreases with θ; Showrooming demand is given by $D_{so}(\theta) = q\,w_s\,t_1(\theta)/\bar{t}$, which decreases with θ; Online Direct demand is given by $D_{oo}(\theta) = q\,(1-t_1(\theta)/\bar{t})$, which increases with θ.*

An increase in the information level lowers the store traffic and consequently also leads to a decrease in both the Store Direct demand and the Showrooming demand. Similarly, Online Direct demand increases with information through increase in the online traffic. An interesting implication of Lemma 3 is that providing more information does not necessarily guarantee a higher total demand for the online retailer as information increases Online Direct demand but decreases Showrooming demand. Hence, it is important for the online retailer to decide on the optimal information level, which we characterize next.

PROPOSITION 1. *The optimal information level is given as follows:*

$$\theta_1^* = min\Big\{\frac{(p_o-u_o)q(1-w_s)(1-q)c_o}{2k\bar{t}}, \bar{\theta}\Big\} \tag{1}$$

The optimal information level θ_1^* increases with online price p_o and online shopping cost c_o, while decreases with the fraction of consumers who consider showrooming w_s, information cost k, and traveling cost upper bound $\bar{t}$. When match probability $q < 1/2$, θ_1^* increases with q, otherwise it decreases with q.

Proposition 1 presents the optimal information level and how it changes with key parameters. The online retailer provides less information when the fraction of consumers who consider showrooming rises. If a higher fraction of consumers consider showrooming, then the online retailer will have less incentive to provide information as it can take advantage of the showrooming demand. Regarding the traveling cost upper bound $\bar{t}$ and online shopping cost c_o, the optimal information level changes as the costs incurred change consumers' behavior. Specifically, a higher $\bar{t}$ indicates that some consumers may live too far away to visit the store, and therefore will purchase online. The online retailer can thus take advantage of those consumers and offer less information. The intuition for how online shopping cost c_o affects the optimal information is the exact opposite. The optimal information also depends on the match probability q. When consumers are more unsure about the match (i.e., when q is 1/2), the online retailer tends to provide a higher level of information. In contrast, if consumers are very unlikely to find the product a good match (i.e., when q is very low) or if they are very likely to find the product a good match (i.e., when q is very high), the online retailer tend to provide very limited information.

Next, we study how profits are affected by the fraction of consumers who consider showrooming. The results are presented in Proposition 2.

PROPOSITION 2. *The profit of the online retailer first decreases and then increases with the fraction of consumers who consider showrooming. The profit of the BM store first increases and then decreases with the fraction of consumers who consider showrooming.*

When the fraction of consumers who consider showrooming is low, an increase in the fraction hurts the online retailer while it helps the BM store. When the fraction of consumers who consider showrooming exceeds a threshold, a higher fraction becomes detrimental to the BM store and benefits the online retailer. The reason is as follows: An increase in w_s increases the store traffic (see Lemma 2). Hence, an increase in w_s has dual effects: it negatively affects the Online Direct demand while positively affecting the Showrooming demand. When w_s is low, the attractiveness of visiting the store is lower. Consequently, an increase in w_s will significantly increase the store traffic (and thus lower the online traffic). However, since w_s is still low, the actual proportion of showrooming consumers is low. Hence, the negative effect due to a loss in Online Direct demand dominates any gains from an increased Showrooming demand. When w_s is high, as w_s further increases, the increase in Showrooming demand outweighs the decrease in Online Direct demand, leading to an increase in the online profit. The fraction of consumers who consider showrooming affects the BM store's profit in the exact opposite way.

5. The Case of Webrooming

When the sum of the online price and the online shopping cost is higher than the store price, webrooming may arise instead of showrooming. Specifically, a particular consumer will webroom if the online information reveals that the product is a good match and the price of the BM store is low enough to compensate for any additional traveling cost to the store. In our analysis of the webrooming case, we study price combinations that generate the general case in which, at least for certain information levels, some of the consumers who consider webrooming would choose to webroom while some choose not to. (The corresponding condition is provided in the Online Appendix A, see equation (6).) Similar to our analysis of the showrooming case, we start by characterizing the store and online traffic for a given information level in Lemma 4 below.

LEMMA 4. *There exists a threshold information level, $\bar{\theta}_w$, at and below which consumers will not webroom and above which some consumers will webroom.*

For $\theta > \bar{\theta}_w$, there exists a threshold traveling cost, $t_2(\theta)$, such that a consumer will visit the BM store if her traveling cost is below $t_2(\theta)$ and will search for the product information online otherwise. Similarly, for $\theta \le \bar{\theta}_w$, there exists a traveling cost threshold, $t_3(\theta)$, such that a consumer will visit the BM store if her traveling cost is below $t_3(\theta)$ and will search for the product information online otherwise. Furthermore, both $t_2(\theta)$ and $t_3(\theta)$ are decreasing in θ.

Lemma 4 indicates that the level of information the online retailer provides may not necessarily be sufficient to attract the segment of the consumers who would find webrooming as a viable option.[2] That is, when online information is low, consumers who might have considered it worthwhile to webroom and incur the traveling cost associated with webrooming may instead choose to visit the store in the first place. Hence only information levels above a certain threshold will make webrooming a viable option. Results regarding segmentation based on proximity to the store are consistent with Lemma 1. That is, consumers who live close to the BM store will first visit the store to inspect the product, and consumers who live farther search for product information online. Moreover, store traffic in both cases decreases with the online information level as a higher information level raises the probability of uncertainty being resolved online, attracting more consumers to the online retailer. Below, we provide additional insights on how the store traffic is influenced by various parameters. (The results for the sensitivity of the online traffic are the exact opposite.)

LEMMA 5. *For a given θ, both $t_2(\theta)$ and $t_3(\theta)$ increase with online price p_o, and decrease with store price p_s. Further, $t_2(\theta)$ decreases with w_o while $t_3(\theta)$ is independent of w_o.*

Lemma 5 indicates that store traffic increases with the online price p_o, as an increase in the online price decreases the expected utility a consumer receives from the online channel with no impact on the expected utility of the store channel. Regarding the store price, we find that an increase in p_s always leads to a stronger reduction in the expected utility from visiting the store compared to the reduction in the expected utility from visiting the online channel. Hence, store traffic is decreasing with p_s. Lastly, when webrooming occurs, we find that the store traffic decreases with the probability of webrooming.

Next, we describe the various types of demand based on the online information level. Similar to the showrooming case, we consider parameters that ensure both channels are viable to consumers. Lemma 6 below provides the expressions for the Store Direct, Online Direct, and Webrooming demands, along with their sensitivities with respect to the online information level.

LEMMA 6. *For any information level $\theta \leq \bar{\theta}_w$, Store Direct demand is given by $D_{ss}(\theta) = q\, t_3(\theta)/\bar{t}$, which decreases with θ; Online Direct demand is given by $D_{oo}(\theta) = q\left(1 - t_3(\theta)/\bar{t}\right)$, which increases with θ; and Webrooming demand D_{os} is zero.*

For $\theta > \bar{\theta}_w$, Store Direct demand is given by $D_{ss}(\theta) = q\, t_2(\theta)/\bar{t}$, which decreases with θ; Webrooming demand is given by $D_{os}(\theta) = \theta q w_o \left(p_o + c_o - p_s - t_2(\theta)\right)/\bar{t}$, which increases with θ; Online Direct demand is given by $D_{oo}(\theta) = q\Big(\bar{t} - (p_o + c_o - p_s) + (1 - w_o)\left(p_o + c_o - p_s - t_2(\theta)\right)\Big)/\bar{t} + (1 - \theta)q w_o \left(p_o + c_o - p_s - t_2(\theta)\right)/\bar{t}$, which increases with θ.

[2] The expressions for $t_2(\theta)$, $t_3(\theta)$, and $\bar{\theta}_w$ are available in equations (3), (4), and (5) in Online Appendix A.

If the information level is less than $\bar{\theta}_w$, even though there is online traffic, webrooming does not arise. In this case, store visitors purchase in store with probability q and online visitors purchase online with probability q. In other words, the purchase channels are identical to the information gathering channels. Further, as a higher online information level decreases the store traffic and increases the online traffic (see Lemma 4), the Store Direct demand decreases and the Online Direct demand increases with the information level. The last part of Lemma 6 corresponds to information levels above $\bar{\theta}_w$, which trigger some consumers to webroom. Such consumers constitute the Webrooming demand and contribute to the overall demand of the BM store. Note that more information again reduces Store Direct demand and increases Online Direct demand while it also increases Webrooming demand.

Having described the store and online demand under three possible ranges for the online information level, we now study the corresponding profit functions for each of these cases. While the complicated profit function prevents us from analytically showing unimodality when $\theta > \bar{\theta}_w$, we examine the profit function comprehensively in a numerical study and do not find any case that violates the unimodality of the profit function [3]. When the profit function is unimodal, Proposition 3 states the properties of the optimal information level.

Similar to our characterization of the optimal information level for the showrooming case, we describe the online retailer's optimal information level choice through regions of full and partial information. However, in this case, we find it useful to define further sub-regions of partial information as follows. The partial information level above $\bar{\theta}_w$ is referred to as *partial information with webrooming* and is denoted as $\theta_3^*(w_o, k) \in (\bar{\theta}_w, \bar{\theta})$. The partial information level where $\theta = \bar{\theta}_w$ is referred to as *partial information when indifferent*. Lastly, the partial information level below $\bar{\theta}_w$ is referred to as *partial information without webrooming* and is given by $\theta_4^*(k) \in (0, \bar{\theta}_w)$. Proposition 3 outlines the conditions under which the retailer should provide full or partial information.

PROPOSITION 3. *There exist information cost thresholds $\bar{k}_1(w_o)$, $\bar{k}_2(w_o)$, and $\bar{k}_3$, such that the optimal information level θ^* is given as follows:*

$$\theta^* = \begin{cases} \bar{\theta}, & \text{if } k \leq \bar{k}_1(w_o) \\ \theta_2^*(w_o, k), & \text{if } \bar{k}_1(w_o) < k < \bar{k}_2(w_o) \\ \bar{\theta}_w, & \text{if } \bar{k}_2(w_o) \leq k \leq \bar{k}_3 \\ \theta_3^*(k), & \text{if } k > \bar{k}_3 \end{cases}$$

Further, $\theta_2^*(w_o, k)$ and $\theta_3^*(k)$ are decreasing in k.

[3] Sufficient conditions for unimodality are provided in the Online Appendix A.

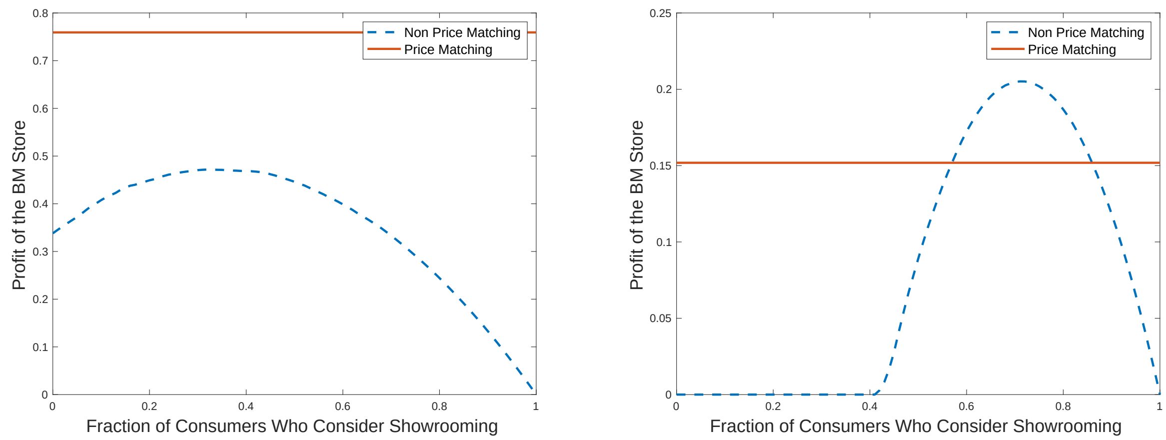
Starting from a high information cost, i.e., $k > \bar{k}_3$, the retailer gradually increases its information level as the information cost decreases. For such high information costs, the information level set by the retailer does not induce webrooming behavior. As the information cost reaches the threshold $\bar{k}_3$, the retailer sets the information level to $\bar{\theta}_w$, which makes consumers indifferent between webrooming and not webrooming. For further decreases in the information cost in the range $(\bar{k}_2(w_o), \bar{k}_3]$, increasing the information level and inducing webrooming do not benefit the retailer as it loses those customers to the store. Hence the retailer chooses to maintain the information level at $\bar{\theta}_w$. If the information cost is lower than $\bar{k}_2(w_o)$, with any further decrease in the information cost, the retailer increases its information level until it reaches the information upper bound $\bar{\theta}$. Even though we are not able to prove the sensitivity of the optimal information level with respect to the fraction of consumers who consider webrooming, our numerical tests suggest that the retailer's optimal information level decreases with the fraction of consumers who consider webrooming.

Proposition 4. *The optimal profit of the online retailer decreases with the fraction of consumers who consider webrooming.*

Similar to the fraction of consumers who consider showrooming w_s, the fraction of consumers who consider webrooming w_o has dual effects. On the one hand, it expands the online traffic. On the other hand, it induces more consumers to switch to the store to complete their purchase. We find that the benefits the retailer gains by the increase in online traffic are always dominated by the losses due to the increase in the number of consumers that webroom. In the webrooming case, consumers with very low traveling costs will always visit the BM store in the first place while those with very high traveling costs will not travel to the BM store to webroom after searching for information online. Consequently, only consumers with intermediate traveling costs will consider webrooming. Hence, the effect of the fraction of consumers who consider webrooming on the online traffic is dampened. It is analytically complex to show how the fraction of consumers who consider webrooming affects the profit of the BM store under optimal information level. Hence, we conduct extensive numerical tests, in which we observe that the profit of the BM store increases with the fraction of consumers who consider webrooming.

6. Price Matching

Many BM stores now offer price matching to combat showrooming. In this section, we study the case in which the BM store matches a lower online price to prevent consumers from showrooming. We examine the interplay between the BM store's price matching policy and the online retailer's information decisions. In practice, the BM store may announce on their own website or display a



(a) Low Price Difference $p_o = 6$ (b) High Price Difference $p_o = 2$

Figure 3 Effect of Price Matching on BM Store's Profit when Price Difference is Low or High ($p_s = 10,\ v = 20,\ q = 0.4,\ \bar{t} = 4,\ c_o = 1,\ c_e = 1,\ k = 5,\ u_s = 1,\ u_o = 0.5,\ \bar{\theta} = 0.8$)

sign in the store to inform consumers of the price matching policy yet some consumers may still not be aware of the price matching policy and thus purchase at a higher price. Nevertheless, here we study the situation in which all consumers are assumed to be aware of the price matching policy. Hence, effectively, the setting is equivalent to identical prices on both channels.

As we have discussed in Section 4, showrooming may arise if the BM store does not implement price matching. On the other hand, if the BM store applies price matching, then showrooming disappears. (We also assume that no consumer conducts webrooming in this case.) Our main goal is to provide insights into how the optimal information level and the corresponding profits for the online retailer and the BM store are impacted by price matching. We characterize the optimal information level and the online profit under price matching in Proposition 5.

PROPOSITION 5. *(a) The online retailer should always provide more information under price matching; (b) The profit of the online retailer when the BM store does not price match is always higher than that when the BM store price matches.*

The first part of Proposition 5 suggests that the online retailer should always provide more information if it faces price matching. We have learned from Proposition 1 that the optimal information level decreases with the fraction of consumers who consider showrooming. Therefore, the online retailer should provide more information as the fraction of consumers who consider showrooming is reduced from w_s to zero. The second part of the proposition suggests that the online retailer is always hurt by price matching, which is straightforward as its competitor lowers price and it loses all the showrooming demand, both reducing profit.

The profit of the BM store depends on the optimal information level determined by the online retailer. In our previous analysis for the showrooming case, we show that in the most general case, the profit of the BM store without price matching first increases and then decreases in the fraction of consumers who consider showrooming (see Proposition 2). Meanwhile, the profit of the BM store under price matching is independent of the fraction of consumers who consider showrooming. Hence, the BM store can be better off or worse off after providing price matching. In Figure 3, we numerically compare the profits of the BM store for the instances with and without price matching taking into account the optimal information level of the online retailer. Specifically, Figure 3 (a) shows that when the price difference between the two retailers is relatively low, the BM store benefits from price matching regardless of the fraction of consumers who consider showrooming. Figure 3 (b) corresponds to an instance in which the price difference is relatively high. In this case, we observe that the BM store may benefit from price matching when the fraction of consumers who consider showrooming is either low or high but may be impaired by price matching for intermediate values of the fraction of consumers who consider showrooming. Providing price matching has two opposite effects on the profitability of the BM store: 1) it increases demand for the BM store; 2) it lowers the profit margin of the BM store. When consumers are very unlikely to showroom (i.e., when w_s is low), they will tend to visit the online retailer, given that they are aware of the large price difference. In this case, the demand increase effect due to price matching dominates the reduction in profit margin. Hence, the BM store prefers to provide price matching to attract consumers to visit the store. When consumers are very likely to showroom (i.e., when w_s is high), price matching helps the store retain a large fraction of consumers from switching channels. In this case, once again, the increase in the store demand due to retained customers overcomes the loss in the store's profit margin and therefore the store again prefers to implement price matching. However, when the fraction of consumers who consider showrooming is intermediate, the demand increasing effect may not be enough to compensate for the loss in profit margin and we find that the BM store may find it more preferable not to price match.

7. Extensions

7.1. Return Cost

In the main model, we assume that consumers incur no cost when returning unsatisfied products. We now relax this assumption to incorporate a return cost c_r. If a consumer examines the product online and purchases when their uncertainty is not resolved, they will incur such a cost when returning the product in case of a poor match. In the main model, consumers receive an expected utility of $(1-\theta)[q(v-p_o)-c_o]$ when their uncertainty is not resolved (see the last branch in

Figure 2). They now receive an expected utility of $(1-\theta)[q(v-p_o)-(1-q)c_r-c_o]$. We find that all qualitative results in the main model still hold for both showrooming and webrooming cases. Moreover, the structure of demand or optimal information does not change compared to the main model. The corresponding results are summarized in Proposition 6.

PROPOSITION 6. *When showrooming exists, the optimal information level is given as follows:*

$$\theta_r^* = min\Big\{\frac{(p_o-u_o)q(1-w_s)(1-q)(c_o+c_r)}{2k\bar{t}}, \bar{\theta}\Big\}$$

The optimal information level θ_r^* increases with return cost c_r.

Our results show that return cost lowers the expected utility of visiting the online retailer. Therefore, thresholds t_1, t_2, and t_3 are all higher than those in the main model, meaning that everything else being equal, with the return cost, more consumers tend to visit the store. As a result, the online retailer provides more information to help consumers resolve their uncertainty and thus increase the attractiveness of visiting its website.

7.2. Heterogeneity in Online Shopping Cost

So far, we have assumed that consumers are heterogenous in traveling cost but homogenous in online shopping cost. It is possible that consumers are heterogeneous in online shopping cost as well. In this section, we examine such a possibility in two different settings. Firstly, we consider a single dimension model, where consumers' traveling cost and online shopping cost are negatively correlated (e.g., Zhang & Choi, 2021). Secondly, we study the case in which traveling cost and online shopping cost follow independent uniform distributions.

7.2.1. Negatively correlated traveling cost and online shopping cost

We assume that consumers are uniformly distributed between 0 and 1. The consumer located at $x\in[0,1]$ will incur a traveling cost of $x\bar{t}$, and an online shopping cost of $(1-x)c_o$. Therefore, the consumer located at $x=0$ has a traveling cost of zero and an online shopping cost of c_o, while the consumer located at $x=1$ has a traveling cost of $\bar{t}$ and an online shopping cost of zero. The expected utility of Store Direct, Showrooming, Online Direct, and Webrooming are thus $E(SS)=-x\bar{t}+q(v-p_s)$, $E(SO)=-x\bar{t}+q[v-p_o-(1-x)c_o]$, $E(OO)=-c_e+\theta q[v-p_o-(1-x)c_o]+(1-\theta)[q(v-p_o)-(1-x)c_o]$, and $E(OS)=-c_e+\theta q(v-p_s-x\bar{t})+(1-\theta)[q(v-p_o)-(1-x)c_o]$, respectively. For the purpose of this extension, we assume the return cost to be zero. Consumers make optimal decisions by comparing the above four expected utilities. We assume that $w_s=1$ and $w_o=1$ for the simplicity of analysis.

Similar to the main model, there exist traveling cost thresholds for different consumer behaviors. For a given information level, consumers with relatively low traveling cost, and thus relatively high online shopping cost, are inclined to purchase in store. In the main model, for any given pair of store price and online price, whether a consumer will adopt showrooming or webrooming does not depend on the information level θ. A major difference now is that for a given pair of store and online price, for different levels of information, showrooming and webrooming can coexist. We identify thresholds on x and θ that determine consumer strategy and thus the market segmentation. In Lemma 7 below, we characterize the demand functions for a given θ. (Details are presented in Online Appendix B.)

LEMMA 7. *Demand is summarized as follows:*

(a) For $\theta < \bar{\theta}_1$, Store Direct demand is given by $D_{ss} = q\,x_1$, which is independent of θ; Showrooming demand is given by $D_{so} = q\,(x_2 - x_1)$, which decreases with θ; Online Direct demand is given by $D_{oo}(\theta) = \theta\,q\,(1 - x_2)$, which increases with θ; Webrooming demand is 0.

(b) For $\bar{\theta}_1 \le \theta < \bar{\theta}_2$, Store Direct demand is given by $D_{ss} = q\,x_3$, which decreases in θ; Online Direct demand is given by $D_{oo}(\theta) = \theta\,q\,(1 - x_3)$, which increases with θ; Showrooming demand and Webrooming demand are 0.

(c) For $\bar{\theta}_2 \le \theta \le \bar{\theta}$, Store Direct demand is given by $D_{ss} = q\,x_4$, which decreases in θ; Webrooming demand is given by $D_{os} = \theta q\,(x_5 - x_4)$, which increases with θ; Online Direct demand is given by $D_{oo}(\theta) = \theta\,q\,(1 - x_5)$, which increases in θ; Showrooming demand is 0.

Part (a) in Lemma 7 corresponds to Lemma 3 in the case of showrooming, and parts (b) and (c) correspond to Lemma 6 in the case of webrooming. How different types of demand change with information level stays the same as in the main model, with the only exception being the Store Direct demand in the region where consumers may choose SS, SO, or OO. In the main model, Store Direct demand in this region decreases with θ, whereas in this extension, Store Direct demand is independent of θ. Finally, our numerical tests suggest that the optimal information level θ^* (weakly) decreases in information cost k, which is consistent with the results in the main model.

7.2.2. Independent traveling cost and online shopping cost

In this subsection, we consider a case in which traveling cost and online shopping cost follow independent uniform distributions, $[0, \bar{t}]$ and $[0, \bar{c}_o]$, respectively. Further, for tractability and to aid the exposition of the main insights, we limit our focus to identical uniform distributions, i.e., $\bar{t} = \bar{c}_o$. The decision trees and expressions of expected utilities are presented in Online Appendix B. Similar to the previous subsection, we again assume that $w_s = 1$ and $w_o = 1$ for the simplicity of analysis.

We find that there exist thresholds on traveling and online shopping costs that determine which strategy a consumer will choose. Since now both costs are uniformly distributed, we can partition the total market into multiple regions, each representing consumers who adopt the same strategy. Market segmentation for cases where $p_s < p_o$ and $p_s \geq p_o$ are presented in Figures 14 and 15 in Online Appendix B, respectively. There exist thresholds $\bar{\theta}_w^{ex}$, $\bar{c}_{o1}$, $\bar{c}_{o2}(t)$, $\bar{c}_{o3}(t)$, $\bar{c}_{o4}(t)$, and $\bar{c}_{o5}(t)$ (expressions provided in Online Appendix B; $\bar{c}_{o2}(t)$, $\bar{c}_{o3}(t)$, $\bar{c}_{o4}(t)$, and $\bar{c}_{o5}(t)$ all increase in t), through which consumer decision rules, i.e., conditions under which consumers choose strategy SS, SO, OS, or OO are summarized in Lemma 8. Based on such decision rules, we fully characterize demand functions, which are also provided in Online Appendix B. Similar to the previous subsection and main model, we again numerically observe that optimal information decreases in information cost k.

LEMMA 8. *Consumer strategies are summarized as follows:*

(a) If $p_s < p_o$,

(i) For $\theta < \bar{\theta}_w^{ex}$, consumers may choose strategy SS if $c_o \geq \bar{c}_{o3}(t)$ and $c_o > \bar{c}_{o4}(t)$; consumers may choose strategy OS if $c_o < \bar{c}_{o3}(t)$ and $c_o > \bar{c}_{o2}(t)$; consumers may choose strategy OO if $c_o \leq \bar{c}_{o2}(t)$ and $c_o \leq \bar{c}_{o4}(t)$.

(ii) For $\theta \geq \bar{\theta}_w^{ex}$, consumers may choose strategy SS if $c_o \geq \bar{c}_{o3}(t)$; consumers may choose strategy OS if $c_o < \bar{c}_{o3}(t)$ and $c_o > \bar{c}_{o2}(t)$; consumers may choose strategy OO if $c_o \leq \bar{c}_{o2}(t)$.

(b) If $p_s \geq p_o$, consumers may choose strategy SS if $c_o > \bar{c}_{o1}$, $c_o \geq \bar{c}_{o3}(t)$, and $c_o > \bar{c}_{o4}(t)$; consumers may choose strategy SO if $c_o \leq \bar{c}_{o1}$ and $c_o > \bar{c}_{o5}(t)$; consumers may choose strategy OS if $c_o < \bar{c}_{o3}(t)$ and $c_o > \bar{c}_{o2}(t)$; consumers may choose strategy OO if $c_o \leq \bar{c}_{o2}(t)$, $c_o \leq \bar{c}_{o4}(t)$, and $c_o \leq \bar{c}_{o5}(t)$.

As shown in Figures 14 and 15, when online price is higher than store price, consumers may adopt strategy SS, OS, or OO. Showrooming does not exist. Consumers with *low* traveling cost and *high* online shopping cost tend to choose strategy SS. Consumers with *high* traveling cost and *low* online shopping cost may adopt strategy OO, as the lower store price does not compensate for the cost of visiting store. Consumers with *high* traveling cost and *high* online shopping cost may choose strategy OS. If information level is *low*, consumers with *intermediate* traveling cost and *low* online shopping cost may choose strategy SS (see Figure 14 (a)). However, if information is sufficiently high, some of those consumers may choose strategy OS instead (see Figure 14 (b)).

When online retailer has a price advantage, consumers may adopt strategy SS, SO, OS, or OO. Corresponding market segmentation is presented in Figure 15. Consumer behavior is now a combination of the separate showrooming and webrooming cases in the main model. The reason is that as c_o increases, we are switching from the previous showrooming case ($p_o + c_o \leq p_s$) to the webrooming case ($p_o + c_o > p_s$). Note that there are two major differences between this scenario (i.e., $p_s \geq p_o$) and the previous one (i.e., $p_s < p_o$). First, consumers with *low* traveling cost and *low* online shopping cost will now adopt strategy SO. Second, consumers with very *high* traveling cost and very *high* online shopping cost will now choose OO instead of OS since store price is higher than online price.

7.3. All Consumers Examine the Product Online First

In the base model, we have assumed that some consumers examine the product in the BM store while the rest gather product information online. In this extension, we consider the scenario where all consumers first examine the product online. The online evaluation cost c_e is assumed to be zero. If their uncertainty is resolved online, they will decide where to purchase based on the expected utilities. If uncertainty is not resolved, consumers then have the opportunity to visit the BM store to evaluate the product. If they choose to do so and find the product a good match, they then decide where to purchase. The decision tree for this extension is provided in Online Appendix B. The structure of the optimal information is similar to the results in the main model. We compare the optimal information level in this case with the one presented in Proposition 1 and summarize the results in Proposition 7.

Proposition 7. *The optimal information level is given as follows:*

$$\theta^* = min\Big\{\frac{(p_o - u_o)q(1-w_s)[-q(1-w_s)p_s + q(1-w_s)p_o + (1-qw_s)c_o]}{2k\bar{t}}, \bar{\theta}\Big\}$$

The optimal information level increases with online price p_o and online shopping cost c_o, while decreases with store price p_s, information cost k and traveling cost upper bound $\bar{t}$. In addition, we find that, under this scenario, the online retailer provides less information than it does in the main model. This is expected as all consumers first examining the product in the online store reduces the pressure for the online retailer to provide information to attract online traffic.

7.4. Endogenous Pricing Decisions

In the main model, we examine the optimal information policy for given prices. In this extension, we briefly investigate a setting in which along with the online retailer's information decision, the two retailers decide on prices. The sequence of events is as follows: the online retailer first decides on information level. The BM store then decides on its price. Lastly, the online retailer decides on its price. For analytical tractability purposes, we study the showrooming case only. Proposition 8 demonstrates how prices change with information level.

Proposition 8. *Store price decreases in θ and online price increases in θ.*

We obtain analytical results for the optimal information level and prices, which are presented in Online Appendix B. We also find that, as suggested by Proposition 8, if information level increases, the BM store needs to lower its price to stay competitive, whereas the online retailer can increase its price since a higher information level makes it more desirable than before. We are not able to obtain comprehensive analytical results for the webrooming case, but we believe this is an important setting for future study.

7.5. Omnichannel Retailer

Finally, we briefly look into the case where both online channel and physical channel are owned by an omnichannel retailer. Consumers might still engage in "showrooming", which is now slightly different, as they switch to the omnichannel retailer's online channel for a lower price. Proposition 9 summarizes our findings in optimal information and how profit of the omnichannel retailer is affected by the fraction of consumers who consider showrooming. In this setting, the decision trees remain the same, but the omnichannel retailer's total demand is now the sum of Store Direct, Showrooming, and Online Direct Demand.

Proposition 9. *In the case of an omnichannel retailer, the optimal information level is lower than the optimal information level in the competitive setting. The profit of the omnichannel retailer first decreases and then increases with the fraction of consumers who consider showrooming.*

Compared to the main model, the retailer can now provide less information online, as it can rely more on the information it provides in the BM store for consumers to resolve their match uncertainty. With the addition of a physical channel, the retailer's profit is also not monotonic with respect to the fraction of consumers who consider showrooming. Particularly, its profit first decreases and then increases with the showrooming fraction.

8. Conclusions

In this study, our focus has been the optimal information provision decisions of an online retailer in the presence of consumers' showrooming and webrooming behavior. Specifically, we consider a setting which consists of a BM store and a competing online retailer and allow consumers to strategically choose from which channel to collect information and in which to complete their purchases in order to maximize their expected utilities. Deviations between consumers' information gathering and purchase channels lead to showrooming or webrooming, e.g., obtaining product information in a BM store but purchasing online and vice versa.

When showrooming is present, we find that providing more information does not necessarily guarantee a higher total demand for the online retailer. We characterize the structure of the optimal information level and find that, the online retailer provides a lower information level if more consumers consider showrooming. Further, while an increase in the fraction of consumers who consider showrooming beyond a certain threshold benefits the online retailer and impairs the BM store's profitability, when showrooming is rare, an increase in the fraction of consumers who consider showrooming may hurt the online retailer and benefit the BM store. For instances where webrooming arises, we find that the optimal information level decreases with the fraction of consumers who consider webrooming and observe that a higher fraction always impairs the online retailer's profits and benefits the BM store. We also consider a setting in which the BM store adopts a price matching strategy to combat showrooming and show that the online retailer always provide more information under price matching. Our analysis indicates that a price matching policy is detrimental to the online retailer and may or may not benefit the implementing BM store depending on the online price and the fraction of consumers who consider showrooming. Lastly, we consider five extensions to our main model, namely, when consumers incur a return cost, when online shopping cost is heterogeneous, when all consumers evaluate the product online first, when retailers also decide on prices, and when a single entity owns both channels.

As the share of online retailing continues to grow and consumers' showrooming and webrooming behavior further intensify the competition between BM stores and online retailers, we believe our study provides important insights into how the information provision decisions impact the market dynamics and the overall profitability of the retailers.

For a long time, the store that provides information has been depicted by media as the victim of consumers' information free-riding behavior, while the competing store as the one that benefits from it. Our model sheds some lights on how showrooming and webrooming affect both. The results suggest managers to recognize that such information free-riding behavior, while diverting demand to competitors, also drives in store traffic in the first place and therefore does not necessarily hurt profit. BM stores, for instance, should not be reluctant to provide product demonstrations to consumers in the fear of potential showrooming behavior.

Although the media discussions as well as most of the literature on showrooming have been centered around BM stores, our paper takes a different angle and focuses on the online retailer's strategies. As it is the insufficiency of product attribute information in the online stores that leads consumers to showroom, the online retailer's information decision will have an impact on the magnitude of the showrooming behavior. Since building a virtual showroom or a Q&A platform requires significant IT investment, our model provides the online retailers a better understanding of when such information investment can increase profit.

Our paper has a few potential extensions. For example, we have briefly introduced an extension to consider a single entity owning both the offline and online channels. We recognize that this entity might be further competing with another online retailer and may make online information decisions. Although this is out of scope of our current work, we believe it would be an interesting future work. Another interesting future extension is to consider how a manufacturer can help providing some product information on its own website that can be shared with both the store and online retailer, and how that would affect the retailer's information decisions.

References

Abdulla, H., Ketzenberg, M., & Abbey, J. D. (2019). Taking stock of consumer returns: A review and classification of the literature. *Journal of Operations Management*, 65(6), 560-605.

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

Balakrishnan, A., Sundaresan, S., & Zhang, B. (2014). Browse-and-switch: Retail-online competition under value uncertainty. *Production and Operations Management*, 23(7), 1129-1145.

Bang, S. H., & Kim, J. (2013). Price discrimination via information provision. *Information Economics and Policy*, 25(4), 215-224.

Branco, F., Sun, M., & Villas-Boas, J. M. (2015). Too much information? Information provision and search costs. *Marketing Science*, 35(4), 605-618.

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

Chen, J., & Chen, B. (2019). When should the offline retailer implement price matching? *European Journal of Operational Research*, 277(3), 996-1009.

Chen, Y., Narasimhan, C., & Zhang, Z. J. (2001). Consumer heterogeneity and competitive price-matching guarantees. *Marketing Science*, 20(3), 300-314.

Dietmar J. (2021). Virtual Dressing Rooms: A Guide For Fashion Retailers. *Forbes Technology Council*, accessed February 2022, available at https://www.forbes.com/sites/forbestechcouncil/2021/09/16/virtual-dressing-rooms-a-guide-for-fashion-retailers/?sh=740eb1ccb87e.

Doyle, C. (1988). Different selling strategies in Bertrand oligopoly. *Economics Letters*, 28(4), 387-390.

Flavián, C., Gurrea, R., & Orús, C. (2016). Choice confidence in the webrooming purchase process: The impact of online positive reviews and the motivation to touch. *Journal of Consumer Behaviour*, 15(5), 459-476.

Gensler, S., Neslin, S. A., & Verhoef, P. C. (2017). The showrooming phenomenon: it's more than just about price. *Journal of Interactive Marketing*, 38, 29-43.

Gu, Z., & Xie, Y. (2013). Facilitating fit revelation in the competitive market. *Management Science*, 59(5), 1196-1212.

Guan, X., & Wang, Y. (2022). Quality disclosure in a competitive environment with consumer's elation and disappointment. *Omega*, 108, 102586.

Guo, L., & Zhao, Y. (2009). Voluntary quality disclosure and market interaction. *Marketing Science*, 28(3), 488-501.

Gustafson, K. (2014). Showrooming left in the dust as shoppers go online. *CNBC* (Jan 13), accessed February 2022, available at https://www.cnbc.com/2014/01/13/showrooming-no-longer-top-threat-to-brick-and-mortar-stores-ibm-survey.html.

Hao, L., & Tan, Y. (2019). Who wants consumers to be informed? Facilitating information disclosure in a distribution channel. *Information Systems Research*, 30(1), 34-49.

Hoffmann, F., & Inderst, R. (2011). Pre-sale information. *Journal of Economic Theory*, 146(6), 2333-2355.

Hviid, M., & Shaffer, G. (2012). Optimal low-price guarantees with anchoring. *Quantitative Marketing and Economics*, 10(4), 393-417.

Iyer, G., & Kuksov, D. (2012). Competition in consumer shopping experience. *Marketing Science*, 31(6), 913-933.

Jain, S., & Srivastava, J. (2000). An experimental and theoretical analysis of price-matching refund policies. *Journal of Marketing Research*, 37(3), 351-362.

Jiao, C., & Hu, B. (2020). Showrooming, Webrooming, and Operational Strategies for Competitiveness. Working paper. Accessed December 15, 2020, available at SSRN: https://ssrn.com/abstract=3701788

Jing, B. (2015). Lowering customer evaluation costs, product differentiation, and price competition. *Marketing Science*, 35(1), 113-127.

Jing, B. (2018). Showrooming and webrooming: Information externalities between online and offline sellers. *Marketing Science*, 37(3), 469-483.

Kibo Commerce. (2018). 2018 Consumer Trends Report, accessed December 2018, available at https://kibocommerce.com/wp-content/uploads/KIBO-Consumer-Trends-Report-2018.pdf.

King, J. (2018). For Online Shoppers, Photos Can Influence a Purchase, accessed February 2022, available at https://www.emarketer.com/content/for-online-shoppers-photos-can-influence-a-purchase.

Kuksov, D., & Liao, C. (2018). When showrooming increases retailer profit. *Journal of Marketing Research*, 55(4), 459-473.

Kuksov, D., & Lin, Y. (2010). Information provision in a vertically differentiated competitive marketplace. *Marketing Science*, 29(1), 122-138.

Kwark, Y., Chen, J., & Raghunathan, S. (2014). Online product reviews: Implications for retailers and competing manufacturers. *Information systems research*, 25(1), 93-110.

Lewis, T. R., & Sappington, D. E. (1994). Supplying information to facilitate price discrimination. *International Economic Review*, 309-327.

Li, F., & Yi, Z. (2017). Trial or no trial: Supplying costly signals to improve profits. *Decision Sciences*, 48(4), 795-827.

Li, T., Xie, J., & Liu, X. (2020). Consumer return policies in presence of a P2P market. *Omega*, 97, 102092.

Li, Y., Li, B., Zheng, W., & Chen, X. (2021). Reveal or hide? Impact of demonstration on pricing decisions considering showrooming behavior. *Omega*, 102, 102329.

Mehra, A., Kumar, S., & Raju, J. S. (2017). Competitive strategies for brick-and-mortar stores to counter "showrooming". *Management Science*, 64(7), 3076-3090.

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

Numerator. (2021). Amazon Captures Over One-third of In-store Shoppers Within a Day, Numerator Reports, accessed February 2022, available at https://www.numerator.com/amazon-captures-over-one-third-store-shoppers-within-day-numerator-reports.

Quint, M., Rogers, D., & Ferguson, R. (2013). Showrooming and the rise of the mobile-assisted shopper. *Columbia Business School. Center on Global Brand Leadership.*

Salop, S. C. (1986). Practices that (credibly) facilitate oligopoly co-ordination. In *New developments in the analysis of market structure* (pp. 265-294). Palgrave Macmillan, London.

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

Shin, J. (2007). How Does Free Riding on Customer Service Affect Competition? *Marketing Science*, 26(4), 488-503.

Shulman, J. D., Coughlan, A. T., & Savaskan, R. C. (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., Cunha Jr, M., & Saint Clair, J. K. (2015). Consumer uncertainty and purchase decision reversals: Theory and evidence. *Marketing Science*, 34(4), 590-605.

Singley, R. B., & Williams, M. R. (1995). Free riding in retail stores: An investigation of its perceived prevalence and costs. *Journal of Marketing Theory and Practice*, 3(2), 64-74.

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

Sun, F., Yang, H., Chen, J., & Wang, F. (2021). Disclosure of quality preference-revealing information in a supply chain with competitive products. *Annals of Operations Research*, 1-27.

Tang, F. F., & Xing, X. (2001). Will the growth of multi-channel retailing diminish the pricing efficiency of the web? *Journal of Retailing*, 77(3), 319-333.

Telser, L. G. (1960). Why should manufacturers want fair trade? *The journal of law and economics*, 3, 86-105.

Telser, L. G. (1990). Why should manufacturers want fair trade II? *The Journal of Law and Economics*, 33(2), 409-417.

Wolny, J., & Charoensuksai, N. (2016). Multichannel customer journeys: Mapping the effects of zmot, showrooming and webrooming. In *Marketing Challenges in a Turbulent Business Environment* (pp. 205-206). Springer, Cham.

Wu, C., Wang, K., & Zhu, T. (2018). Price Match Guarantees in the Age of Showrooming: An Empirical Analysis. Working paper. Accessed December 28, 2018, available at SSRN: https://ssrn.com/abstract=3271305

Wu, D., Ray, G., Geng, X., & Whinston, A. (2004). Implications of reduced search cost and free riding in e-commerce. *Marketing Science*, 23(2), 255-262.

Wu, L., Deng, S., & Jiang, X. (2018). Sampling and pricing strategy under competition. *Omega*, 80, 192-208.

Xia, Y., Xiao, T., & Zhang, G. P. (2017). The impact of product returns and retailer's service investment on manufacturer's channel strategies. *Decision Sciences*, 48(5), 918-955.

Yang, G., & Ji, G. (2022). The impact of cross-selling on managing consumer returns in omnichannel operations. *Omega*, 111, 102665.

Zettelmeyer, F. (2000). Expanding to the Internet: Pricing and communications strategies when firms compete on multiple channels. *Journal of Marketing Research*, 37(3), 292-308.

Zhang, S., Yao, Y., & Zhang, J. (2021). Consumer showrooming with supplier encroachment and omnichannel retailing. *Decision Sciences*.

Zhang, T., & Choi, T. M. (2021). Optimal consumer sales tax policies for online-offline retail operations with consumer returns. *Naval Research Logistics (NRL)*, 68(6), 701-720.

Zhang, T., Li, G., Cheng, T. E., & Shum, S. (2020). Consumer inter-product showrooming and information service provision in an omni-channel supply chain. *Decision Sciences*, 51(5), 1232-1264.

Zhang, Z. J. (1995). Price-matching policy and the principle of minimum differentiation. *The Journal of Industrial Economics*, 287-299.

Zimmerman, A. (2012). Can retailers halt 'showrooming'? *The Wall Street Journal*, 259(1), B1-B8.

Online Appendix A: Proofs

Table 1 Table of Notations

$i = o$ or s ($o = online$, $s = BM$)	$\triangleq$	Index to denote each retailer
θ	$\triangleq$	Information level chosen by online retailer
p_i	$\triangleq$	Price of retailer i
u_i	$\triangleq$	Unit product cost of retailer i
k	$\triangleq$	Information cost
$V = 0$ *or* v	$\triangleq$	Product valuation
q	$\triangleq$	Probability of a good match
w_s	$\triangleq$	Fraction of consumers who consider showrooming
w_o	$\triangleq$	Fraction of consumers who consider webrooming
t	$\triangleq$	Traveling cost
$\bar{t}$	$\triangleq$	Traveling cost upper bound
c_o	$\triangleq$	Online shopping cost
c_e	$\triangleq$	Online evaluation cost
$t_1,\ t_2,\ t_3$	$\triangleq$	Traveling cost thresholds such that consumers whose traveling costs are below the thresholds will visit the BM store
$\bar{\theta}$	$\triangleq$	Highest information level that the online retailer can provide given the current technology
$\bar{\theta}_w$	$\triangleq$	Threshold information level below which consumers will not webroom and above which some consumers will webroom
$\hat{\theta}_s$	$\triangleq$	Threshold information level below which online traffic is zero (in the case of showrooming)
$\hat{\theta}_w$	$\triangleq$	Threshold information level below which online traffic is zero (in the case of webrooming)

Analysis of Consumer Behavior Given Prices

Starting from the consumer decision tree, we first study how an individual consumer makes her decision - she decides which channel to visit and to purchase from by comparing the expected utilities. When $p_o + c_o \le p_s$, webrooming is always dominated, and when $p_o + c_o > p_s$, showrooming is always dominated. Hence, we examine an individual consumer's behavior separately in these two cases.

1) When $p_o + c_o \le p_s$, once the consumer is already in store, showrooming is always a non-dominated strategy (if she is open to showroom) since switching online incurs no cost. Hence, the expected utility of visiting the store has taken into account of both Store Direct and Showrooming. The expected utility of visiting the BM store is thus $E(S) = -t + q[w_s(v - p_o - c_o) + (1 - w_s)(v - p_s)]$, and the expected utility of visiting the online retailer's website is $E(O) = -c_e + \theta q(v - p_o - c_o) + (1 - \theta)[q(v - p_o) - c_o] = -c_e + q(v - p_o) - [1 - \theta(1 - q)]c_o$. We define a threshold traveling cost $t_1(\theta)$, below which $E(S) > E(O)$, where

$$t_1(\theta) = -q(1 - w_s)p_s + q(1 - w_s)p_o + [1 - (1 - q)\theta - qw_s]c_o + c_e \tag{2}$$

We define the number of consumers who adopt Store Direct as the Store Direct traffic T_{ss}, consumers who adopt Showrooming as the Showrooming traffic T_{so}, and consumers who adopt Online Direct as the Online Direct traffic T_{oo}. We segment the market as in Figure 4, and analyze this scenario in Section 4.

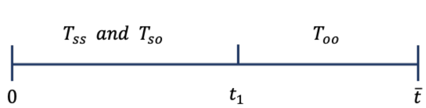
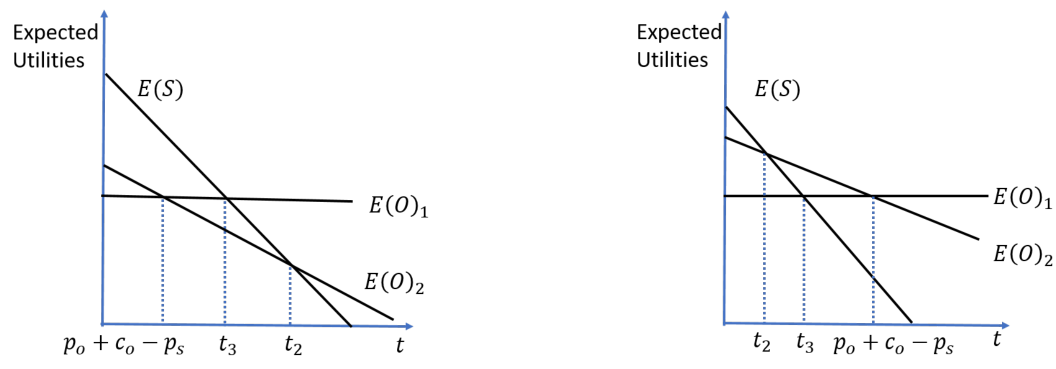


Figure 4 Market Segmentation when $p_o + c_o \le p_s$



(a) When $t_3(\theta) \geq p_o + c_o - p_s$ (b) When $t_3(\theta) < p_o + c_o - p_s$

Figure 5 **Consumer's expected utilities when** $p_o + c_o > p_s$

2) When $0 < p_o + c_o - p_s < \bar{t}$, consumers visiting the online retailer consider webrooming. However, depending on their traveling costs, some will still buy online even though they consider webrooming as an option. We denote the expected utility of visiting BM store, visiting online retailer if buying online after considering webrooming and visiting online retailer if buying in the BM store after considering webrooming as $E(S)$, $E(O)_1$ and $E(O)_2$, respectively. $E(S) = -t + q(v - p_s)$, $E(O)_1 = -c_e + \theta q[w_o(v - p_o - c_o) + (1 - w_o)(v - p_o - c_o)] + (1 - \theta)[q(v - p_o) - c_o] = -c_e + q(v - p_o) - [1 - \theta(1 - q)]c_o$, and $E(O)_2 = -c_e + \theta q[w_o(v - p_s - t) + (1 - w_o)(v - p_o - c_o)] + (1 - \theta)[q(v - p_o) - c_o]$. We define a threshold traveling cost $t_2(\theta)$, below which $E(S) > E(O)_2$, where

$$t_2(\theta) = \frac{-q(1 - \theta w_o)p_s + q(1 - \theta w_o)p_o + (1 - \theta + \theta q - \theta q w_o)c_o + c_e}{1 - \theta q w_o} \tag{3}$$

Similarly, We define a threshold traveling cost $t_3(\theta)$, below which $E(S) > E(O)_1$, where

$$t_3(\theta) = -qp_s + qp_o + [1 - (1 - q)\theta]c_o + c_e \tag{4}$$

$E(O)_2 = E(O)_1$ when $t = p_o + c_o - p_s$. Note that $E(O)_1$ is independent of t. At $t = 0$, $E(O)_2 > E(O)_1$, and $E(S) > E(O)_2$. Moreover, the absolute value of the slope of $E(S)$ is greater than that of $E(O)_2$ w.r.t. t. Figure 5 presents the two possible cases. In Figure 5a, $E(O)_2$ is never the highest, meaning that webrooming is always dominated - the consumer adopts strategy Store Direct if $t < t_3(\theta)$ and strategy Online Direct otherwise. In Figure 5b, the consumer adopts Store Direct if $t \leq t_2(\theta)$, Webrooming if $t_2(\theta) < t < p_o + c_o - p_s$, and Online Direct if $t \geq p_o + c_o - p_s$. Webrooming traffic is denoted as T_{os}.

By comparing $t_2(\theta)$ and $t_3(\theta)$, we find that if $t_3(\theta) > p_o + c_o - p_s$, then $t_2(\theta) > t_3(\theta) > p_o + c_o - p_s$ always holds; if $t_3(\theta) < p_o + c_o - p_s$, then $t_2(\theta) < t_3(\theta) < p_o + c_o - p_s$ always holds. The situation where $t_2(\theta) < p_o + c_o - p_s < t_3(\theta)$ or $t_3(\theta) < p_o + c_o - p_s < t_2(\theta)$ does not exist. Hence, we derive two possible market segmentations as shown in Figure 6. Figure 6b presents the situation where $t_3(\theta) \geq p_o + c_o - p_s$ (i.e., $\theta \leq [(1 - q)(p_s - p_o) + c_e]/[(1 - q)c_o]$); Figure 6a presents the situation where $t_3(\theta) < p_o + c_o - p_s$ (i.e., $\theta > [(1 - q)(p_s - p_o) + c_e]/[(1 - q)c_o]$). We analyze this scenario in Section 5, and thus all results obtained in Section 5 are under the assumptions that $p_o + c_o - p_s < \bar{t}$. Further, let $\bar{\theta}_w$ be the information level at which $t_2(\theta) = t_3(\theta) = p_o + c_o - p_s$, then

$$\bar{\theta}_w = \frac{(1 - q)(p_s - p_o) + c_e}{(1 - q)c_o} \tag{5}$$

If $\theta < \bar{\theta}_w$, $p_o + c_o - p_s < t_3 < t_2$, while if $\theta > \bar{\theta}_w$, $p_o + c_o - p_s > t_3 > t_2$.

In order to focus on cases where webrooming exists at least for some information levels, we assume that

$$\bar{\theta}_w < \bar{\theta} \tag{6}$$

3) If $p_o + c_o - p_s \geq \bar{t}$, for all consumers, traveling cost is lower than the price difference. Consequently, $E(O)_1$ is always lower than $E(O)_2$. All consumers who consider webrooming will actually webroom. This scenario can be viewed as a special case of the webrooming case in Section 5. Therefore, we do not provide detailed analysis for this scenario. The market segmentation is presented in Figure 7.

(a) (b)

Figure 6 **Market Segmentation when** $0 \leq p_o + c_o - p_s < \bar{t}$

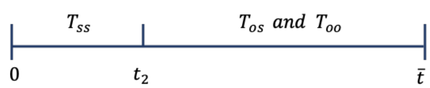


Figure 7 **Market segmentation when** $p_o + c_o - p_s \geq \bar{t}$

Based on the analysis above, we derive the results in the Lemmas and Propositions below.

Proof of Lemma 1

The expression of $t_1(\theta)$ is given by equation (2) on Page EC-1. $\frac{\partial t_1(\theta)}{\partial \theta} = (q-1)c_o < 0$. ■

Proof of Lemma 2

$\frac{\partial t_1(\theta)}{\partial w_s} = q(p_s - p_o - c_o) > 0$. Hence, $t_1(\theta)$ increases with w_s. $\frac{\partial t_1(\theta)}{\partial c_o} = 1-(1-q)\theta - qw_s > 1-(1-q)\theta - q = (1-q)(1-\theta) > 0$. $\frac{\partial t_1(\theta)}{\partial c_e} = 1$. Hence, $t_1(\theta)$ increases in both c_o and c_e. $\frac{\partial t_1(\theta)}{\partial p_s} = -q(1-w_s) < 0$. $\frac{\partial t_1(\theta)}{\partial p_o} = q(1-w_s) > 0$. Hence, $t_1(\theta)$ decreases with p_s and increases with p_o. ■

Proof of Lemma 3

$\hat{\theta}_s$ is the information level at which $t_1(\theta) = \bar{t}$. Let $t_1(\theta) = \bar{t}$ and solve for θ, we have

$$\hat{\theta}_s = \frac{-\bar{t} - q(1-w_s)p_s + q(1-w_s)p_o + (1-qw_s)c_o + c_e}{(1-q)c_o} \tag{7}$$

To focus on the scenarios where both channels are viable (i.e., both store and online traffic are positive), we study the scenario where $\hat{\theta}_s < 0$, which applies to all the proofs for the showrooming case. For store traffic $t_1(\theta)$ to be non-negative at $\theta = \bar{\theta}$, the following condition needs to be satisfied:

$$p_s \leq \frac{q(1-w_s)p_o + [1-(1-q)\bar{\theta} - qw_s]c_o + c_e}{q(1-w_s)} \tag{8}$$

Store Direct traffic is given by $T_{ss} = \frac{1}{\bar{t}}(1-w_s)t_1(\theta)$, Showrooming traffic is given by $T_{so} = \frac{1}{\bar{t}}w_s t_1(\theta)$, and Online Direct traffic is given by $T_{oo} = \frac{1}{\bar{t}}[\bar{t} - t_1(\theta)]$. Demand is given by the corresponding traffic multiplying by the probability of purchasing, q. The sensitivity of demand regarding θ presented in Lemma 3 directly follows the result in Lemma 1.

■

Proof of Proposition 1.

The demand functions shown in Lemma 3 are used directly here. The traffic for different strategies are shown as follows:

$$\begin{aligned}T_{ss}(\theta) &= \frac{1}{\bar t}(1-w_s)t_1(\theta)\\ &= \frac{1}{\bar t}(1-w_s)[-q(1-w_s)p_s + q(1-w_s)p_o + [1-(1-q)\theta - qw_s]c_o + c_e]\\ T_{so}(\theta) &= \frac{1}{\bar t}w_s t_1(\theta)\\ &= \frac{1}{\bar t}w_s[-q(1-w_s)p_s + q(1-w_s)p_o + [1-(1-q)\theta - qw_s]c_o + c_e]\\ T_{oo}(\theta) &= \frac{1}{\bar t}[\bar t - t_1(\theta)]\\ &= \frac{1}{\bar t}[\bar t + q(1-w_s)p_s - q(1-w_s)p_o - [1-(1-q)\theta + qw_s]c_o - c_e]\end{aligned} \tag{9}$$

The corresponding demand for the online retailer is given by:

$$D_{so}(\theta) = qT_{so}(\theta) \tag{10}$$

$$D_{oo}(\theta) = [\theta q + (1-\theta)q]T_{oo}(\theta) = qT_{oo}(\theta) \tag{11}$$

The online retailer maximizes its total profit by solving the following

$$\pi_1^o(\theta) = (p_o - u_o)[D_{so}(\theta) + D_{oo}(\theta)] - k\theta^2 \tag{12}$$

The first and second order conditions are given as follows:

$$\frac{\partial \pi_1^o(\theta)}{\partial \theta} = (p_o - u_o)q\frac{1}{\bar t}(1-w_s)(1-q)c_o - 2k\theta = 0$$

$$\frac{\partial^2 \pi_1^o(\theta)}{\partial \theta^2} = -2k < 0 \tag{13}$$

The second order derivative is negative and thus π_1^o is concave. The interior solution is given as follows

$$\theta_1^* = min\Big\{\frac{(p_o - u_o)q(1-w_s)(1-q)c_o}{2k\bar t}, \bar\theta\Big\} \tag{14}$$

For the sensitivity analysis, we examine the first order derivatives of θ_1^* with respect to the key parameters: $\frac{\partial \theta_1^*}{\partial p_o} = \frac{q(1-w_s)(1-q)c_o}{2k\bar t} > 0$. $\frac{\partial \theta_1^*}{\partial c_o} = \frac{(p_o-u_o)q(1-w_s)(1-q)}{2k\bar t} > 0$. $\frac{\partial \theta_1^*}{\partial w_s} = \frac{-q(p_o-u_o)(1-q)c_o}{2k\bar t} < 0$. $\frac{\partial \theta_1^*}{\partial q} = \frac{(p_o-u_o)(1-w_s)c_o(1-2q)}{2k\bar t}$, which is positive if $q < 1/2$ and negative when $q > 1/2$. Lastly, k and $\bar t$ are in the denominator of θ_1^* so θ_1^* decreases in $\bar t$ and k. ■

Proof of Proposition 2

We first prove that the profit of the online retailer first decreases and then increases as w_s increases.

$$\frac{\partial t_1(\theta)}{\partial w_s} = q(p_s - p_o - c_o)$$

$$\begin{aligned}\frac{\partial \pi_1^o}{\partial w_s} &= (p_o - u_o)\frac{1}{\bar t}q[t_1(\theta) + (w_s - 1)\frac{\partial t_1(\theta)}{\partial w_s}]\\ &= (p_o - u_o)\frac{1}{\bar t}q[t_1(\theta) + (w_s-1)q(p_s - p_o - c_o)]\end{aligned}$$

By Envelope Theorem, we have

$$\frac{\partial \pi_1^o}{\partial w_s}(\theta = \theta_1^*) = (p_o - u_o)\frac{1}{\bar t}q[t_1(\theta_1^*) + (w_s - 1)q(p_s - p_o - c_o)]$$

$$\frac{\partial^2 \pi_1^o}{\partial (w_s)^2}(\theta=\theta_1^*) = (p_o-u_o)\frac{1}{\bar{t}}q[\tfrac{\partial t_1(\theta_1^*)}{\partial w_s}+\tfrac{\partial t_1(\theta_1^*)}{\partial \theta}\tfrac{\partial \theta_1^*}{\partial w_s}+q(p_s-p_o-c_o)]$$
$$= (p_o-u_o)\frac{1}{\bar{t}}q[2q(p_s-p_o-c_o)+\frac{(1-q)^2(p_o-u_o)qc_o^2}{2k\bar{t}}]>0$$

Hence, the first order derivative of $\frac{\partial \pi_1^o}{\partial w_s}(\theta=\theta_1^*)$ is linearly increasing in w_s. Thus, there exists a threshold of w_s that satisfies $\frac{\partial \pi_1^o}{\partial w_s}(\theta=\theta_1^*)=0$. Below this threshold, the profit of the online retailer decreases with w_s, while above this threshold, the profit increases with w_s.

Store profit is given by $\pi_1^s=(p_s-u_s)q\frac{1}{\bar{t}}(1-w_s)t_1(\theta)$.

$$\tfrac{\partial \pi_1^s}{\partial w_s} = (p_s-u_s)[-\frac{1}{\bar{t}}qt_1(\theta)+\frac{1}{\bar{t}}q(1-w_s)\tfrac{\partial t_1}{\partial w_s}]$$

If $\theta=\theta_1^*$,

$$\frac{\partial \pi_1^s}{\partial w_s}(\theta=\theta_1^*) = (p_s-u_s)[-\frac{1}{\bar{t}}qt_1(\theta_1^*)+\frac{1}{\bar{t}}q^2(1-w_s)(p_s-p_o-c_o)+\frac{1}{\bar{t}}q(1-w_s)(q-1)c_o\frac{\partial \theta_1^*}{\partial w_s}]$$
$$\frac{\partial^2 \pi_1^s}{\partial (w_s)^2}(\theta=\theta_1^*) = (p_s-u_s)[-2q^2\frac{1}{\bar{t}}(p_s-p_o-c_o)+2q\frac{1}{\bar{t}}(1-q)c_o\frac{\partial \theta_1^*}{\partial w_s}]<0$$

Hence, the first order derivative of $\frac{\partial \pi_1^s}{\partial w_s}(\theta=\theta_1^*)$ is linearly decreasing in w_s. Thus, there exists a threshold of w_s that satisfies $\frac{\partial \pi_1^s}{\partial w_s}(\theta=\theta_1^*)=0$. Below this threshold, the profit of the BM store increases with w_s, while above this threshold, the profit decreases with w_s. ■

Proof of Lemma 4

The expressions of $t_2(\theta)$, $t_3(\theta)$, and $\bar{\theta}_w$ are provided by equation (3), equation (4), and equation (5), respectively. From the previous analysis and Figure 5, we know that $t_2(\theta)$ is the intersection of $E(S)$ and $E(O)_2$. $E(S)$ is independent of θ, and the line $E(O)_2$ moves up when θ increases. Hence, the intersection, $t_2(\theta)$, decreases. $\frac{\partial t_3(\theta)}{\partial \theta}=(q-1)c_o<0$. ■

Proof of Lemma 5

$\frac{\partial t_2(\theta)}{\partial p_o}=\frac{(1-\theta w_o)q}{1-\theta q w_o}>0$. $\frac{\partial t_3(\theta)}{\partial p_o}=q>0$. $\frac{\partial t_2(\theta)}{\partial p_s}=\frac{-(1-\theta w_o)q}{1-\theta q w_o}<0$. $\frac{\partial t_3(\theta)}{\partial p_s}=-q<0$. $\frac{\partial t_2(\theta)}{\partial w_o}=\frac{\theta q}{(1-\theta q w_o)^2}[(1-q)(p_s-p_o-\theta c_o)+c_e]$. From page EC-2, we know that webrooming exists when $\theta>\bar{\theta}_w$. Therefore, in the webrooming region (i.e., when t_2 is relevant), $\theta>\bar{\theta}_w$ holds. Therefore, $(1-q)\theta c_o>(1-q)(p_s-p_o)+c_e$, which gives $(1-q)(p_s-p_o-\theta c_o)+c_e<0$. Hence, $\frac{\partial t_2(\theta)}{\partial w_o}<0$. ■

Proof of Lemma 6

We define $\hat{\theta}_w$ as the information level at which even the consumer with the highest traveling cost $\bar{t}$ will not visit the online retailer. That is, for this consumer, the highest expected utility of visiting the online retailer $E(O)_1<E(S)$, which gives us

$$\hat{\theta}_w=\frac{-qp_s+qp_o+c_o+c_e-\bar{t}}{(1-q)c_o} \tag{15}$$

By subtracting $\bar{\theta}_w$ from $\hat{\theta}_w$, we have $\hat{\theta}_w-\bar{\theta}_w=\frac{-\bar{t}-p_s+p_o+c_o}{(1-q)c_o}<0$ always holds. To focus on the scenario where online channel is always viable, we assume that $\hat{\theta}_w<0$. We can also prove that the store traffic never drops to zero in the webrooming case. Store traffic dropping to zero means that even for the consumer with the lowest traveling cost $t=0$, her expected utility of visiting the store is lower than her expected utility of searching the information online. Note that $E(O)_1<E(O)_2$ for $t=0$. Hence, she will search the information online only if her $E(S)<E(O)_2$, which gives us $\theta>1$, which never holds. Therefore, the store traffic never drops to zero in the webrooming case. Demand is then given by the corresponding traffic multiplied by the probability of a good match, and thus how demand changes with

θ is based on the results provided in Lemma 4. ■

Proof of Proposition 3.

When $0 < p_o + c_o - p_s \le \bar{t}$, there are two possible market segmentations.

1) When $0 < p_o + c_o - p_s \le \bar{t}$ and $\theta > \bar{\theta}_w$ (see Figure 6 (b)), the traffic for different strategies is shown as follows:

$$\begin{aligned} T_{ss}(\theta) &= \frac{1}{\bar{t}} t_2(\theta) \\ &= \frac{1}{\bar{t}} \frac{-q(1-\theta w_o)p_s + q(1-\theta w_o)p_o + (1-\theta+\theta q - \theta q w_o)c_o + c_e}{1-\theta q w_o} \end{aligned}$$

$$\begin{aligned} T_{os}(\theta) &= \frac{1}{\bar{t}} w_o[p_o + c_o - p_s - t_2(\theta)] \\ &= \frac{w_o}{\bar{t}} \frac{(1-q)(-p_s+p_o+\theta c_o) - c_e}{1-\theta q w_o} \end{aligned}$$

$$\begin{aligned} T_{oo}(\theta) &= \frac{1}{\bar{t}}(1-w_o)[p_o + c_o - p_s - t_2(\theta)] + \frac{1}{\bar{t}}(\bar{t} - p_o - c_o + p_s) \\ &= \frac{1-w_o}{\bar{t}} \frac{(1-q)(-p_s+p_o+\theta c_o) - c_e}{1-\theta q w_o} + \frac{1}{\bar{t}}(\bar{t} - p_o - c_o + p_s) \end{aligned}$$

The corresponding demand for the online retailer is as follows:

$$D_{oo}(\theta) = [\theta q + (1-\theta) q] T_{oo}(\theta) + (1-\theta) q T_{os}(\theta) = q T_{oo}(\theta) + (1-\theta) q T_{os}(\theta)$$

The online retailer maximizes its total profit by solving the following

$$\pi_2^o(\theta) = (p_o - u_o) D_{oo}(\theta) - k\theta^2$$

We are not able to show that $\pi_2^o(\theta)$ is unimodal under general parameters. However, we conduct extensive numerical studies and cannot find a case where it is not unimodal. We provide a sufficient conditions on page EC-7 for the profit function to be unimodal. In the following context, we will assume that $\pi_2^o(\theta)$ is unimodal. We denote the first-order solution as θ_2^*.

2) When $0 < p_o + c_o - p_s \le \bar{t}$ and $\theta \le \bar{\theta}_w$ (see Figure 6 (a)) , the traffic for different strategies are shown as follows:

$$\begin{aligned} T_{ss}(\theta) &= \frac{1}{\bar{t}} t_3(\theta) \\ &= \frac{1}{\bar{t}}[-qp_s + qp_o + (1-\theta+\theta q)c_o + c_e] \end{aligned}$$

$$\begin{aligned} T_{oo}(\theta) &= \frac{1}{\bar{t}}[\bar{t} - t_3(\theta)] \\ &= \frac{1}{\bar{t}}[\bar{t} + qp_s - qp_o - (1-\theta+\theta q)c_o - c_e] \end{aligned}$$

Online demand is

$$D_{oo}(\theta) = q T_{oo}(\theta)$$

The online retailer maximizes its total profit by solving the following

$$\pi_3^o(\theta) = (p_o - u_o) D_{oo}(\theta) - k\theta^2$$

The profit function is concave in θ and the interior solution is given as follows:

$$\theta_3^*(k) = \frac{(p_o - u_o)q(1-q)c_o}{2k\bar{t}}$$

Combining the two situations above, we have the following results:

At $\theta = \bar{\theta}_w$, $t_2(\theta) = t_3(\theta) = p_o + c_o - p_s$. For any $p_o + c_o > p_s$, $\bar{\theta}_w < 1$ holds. $\bar{\theta}_w - \hat{\theta}_w = \frac{p_s - p_o - c_o + \bar{t}}{(1-q)c_o} > 0$. Moreover, at $\theta = \bar{\theta}_w$, $\pi_2^o = \pi_3^o$. When $\theta \le \bar{\theta}_w$, the corresponding profit function is π_3^o; when $\theta > \bar{\theta}_w$, the corresponding profit function is π_2^o. We can identify the shape of the profit functions in the entire region by checking the first order derivatives of the profit functions with respect to θ at $\bar{\theta}_w$.

$$\frac{\partial \pi_2^o}{\partial \theta}(\theta = \bar{\theta}_w) = \frac{(p_o - u_o)q(1-\bar{\theta}_w w_o)}{\bar{t}(1-\bar{\theta}_w q w_o)^2}[q w_o(1-q)(p_o - p_s) + (1-q)c_o - q w_o c_e] - 2k\bar{\theta}_w$$

$$\frac{\partial \pi_3^o}{\partial \theta}(\theta=\bar{\theta}_w)=\frac{1}{\bar{t}}(p_o-u_o)q(1-q)c_o-2k\bar{\theta}_w$$

Let $\bar{k}_1$ be the information cost at which $\theta_2^*=\bar{\theta}$. Let $\bar{k}_2$ be the information cost below which $\frac{\partial \pi_2^o}{\partial \theta}(\theta=\bar{\theta}_w)>0$, where $\bar{k}_2=\frac{(p_o-u_o)q(1-\bar{\theta}_w w_o)}{2\bar{\theta}_w\bar{t}(1-\bar{\theta}_w q w_o)^2}[qw_o(1-q)(p_o-p_s)+(1-q)c_o-qw_oc_e]$. Let $\bar{k}_3$ be the information cost below which $\frac{\partial \pi_3^o}{\partial \theta}(\theta=\bar{\theta}_w)>0$, where $\bar{k}_3=\frac{(p_o-u_o)q(1-q)c_o}{2\bar{t}\bar{\theta}_w}$. It is easy to check that $\bar{k}_2<\bar{k}_3$ always holds since $\bar{\theta}_w<1$ and $\frac{\partial \pi_2^o}{\partial \theta}(\theta=\bar{\theta}_w)<\frac{\partial \pi_3^o}{\partial \theta}(\theta=\bar{\theta}_w)$.

As mentioned earlier, we consider only the case where $\hat{\theta}_w<0$ to focus on the scenario where both channels are viable. Note that $\frac{\partial \pi_3^o}{\partial \theta}(\theta=0)=(p_o-u_o)q\frac{1}{\bar{t}}(1-q)c_o>0$. Figure 8 presents all the possible situations.

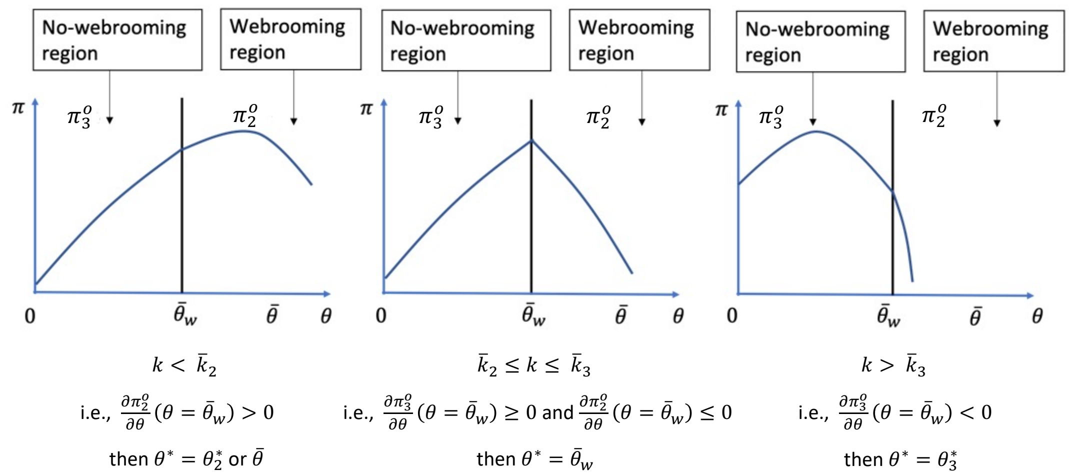


Figure 8 **Possible Scenarios**

To sum up, the optimal information level is as follows:

$$\theta^*=\begin{cases}\bar{\theta}, & \text{when } k\le\bar{k}_1\\ \theta_2^*(k), & \text{when } \bar{k}_1<k<\bar{k}_2\\ \bar{\theta}_w, & \text{when } \bar{k}_2\le k\le\bar{k}_3\\ \theta_3^*(k), & \text{when } k>\bar{k}_3\end{cases}$$

Both θ_2^* and θ_3^* decrease with k. The information level is continuous. Hence, the information (weakly) decreases in k. Note that the above proof corresponds to the case where $\bar{\theta}_w>0$. However, when $\bar{\theta}_w\le 0$, only π_2^o exists, and thus the optimal information level is either $\bar{\theta}$ or $\theta_2^*(k)$, which is a special case of the result above. ■

Sufficient condition for unimodal profit function in the webrooming case.

In the webrooming case, the profit function where webrooming exists is given by

$$\pi_2^o(\theta)=(p_o-u_o)\frac{1}{\bar{t}}q(1-w_o\theta)\frac{(1-q)(p_o-p_s+\theta c_o)-c_e}{1-\theta q w_o}$$
$$+(p_o-u_o)\frac{1}{\bar{t}}q(\bar{t}-p_o-c_o+p_s)-k\theta^2$$

Let $A=-w_o(p_o-u_o)\frac{1}{\bar{t}}q$, $B=(p_o-u_o)q\frac{1}{\bar{t}}$, $C=(1-q)c_o$, $D=(1-q)(p_o-p_s)-c_e$, and $E=qw_o$. Note that A to E are all independent of θ. Then $\pi_2^o=\frac{(A\theta+B)(C\theta+D)}{1-E\theta}-k\theta^2+(p_o-u_o)q\frac{1}{\bar{t}}(\bar{t}-p_o-c_o+p_s)$, and $\frac{\partial \pi_2^o}{\partial \theta}=\frac{-2E^2k\theta^3+E(4k-AC)\theta^2+2(AC-k)\theta+AD+BC+BDE}{(1-E\theta)^2}$. For π_2^o to be unimodal in [0,1], we need $g(\theta)=-2E^2k\theta^3+E(4k-AC)\theta^2+2(AC-k)\theta+AD+BC+BDE=0$ has a unique solution in [0,1]. A sufficient condition for $g(\theta)=0$ having a unique solution in [0,1] is

$$\begin{cases} g(\theta=0)>0, & and \\ \frac{\partial g}{\partial \theta}<0 \quad in \quad [0,1] \end{cases} \tag{16}$$

A sufficient condition for (16) is

$$g(\theta=0)>0, \quad \frac{\partial g}{\partial \theta}(\theta=0)<0, \quad \frac{\partial g}{\partial \theta}(\theta=1)<0, \quad and \quad \frac{\partial^2 g}{\partial \theta^2}>0 \quad in \quad [0,1], \quad or \tag{17}$$

$$g(\theta=0)>0, \quad \frac{\partial g}{\partial \theta}(\theta=0)<0, \quad \frac{\partial g}{\partial \theta}(\theta=1)<0, \quad and \quad \frac{\partial^2 g}{\partial \theta^2}<0 \quad in \quad [0,1]$$

$g(\theta=0)>0$ is equivalent to $AD+BC+BDE>0$. Substitute for A,B,C,D and E in the expression. After some simplification, we get

$$-w_o[(1-q)(p_o-p_s)-c_e]+c_o>0 \tag{18}$$

$\frac{\partial g}{\partial \theta}(\theta=0)<0$ is equivalent to

$$AC-k<0 \tag{19}$$

$\frac{\partial g}{\partial \theta}(\theta=1)<0$ is equivalent to $-3E^2k+E(4k-AC)+(AC-k)<0$, which is equivalent to $(1-3E)(E-1)k<AC(E-1)$ for $q\neq 1$ or $w_o\neq 1$ (i.e., $E=qw_o\neq 1$). Then we have $(1-3E)k>AC$. Substitute for A,C, and E in the expression. After some simplification, we get

$$(1-3qw_o)k>(p_o-u_o)\frac{1}{t}q(q-1)w_oc_o \tag{20}$$

Moreover, since $(1-3E)k>AC$ gives $AC-k<-3Ek$, for any $E\neq 0$ and $k\neq 0$, $-3EK<0$. Condition (19) is satisfied automatically if (20) is satisfied.

$\frac{\partial^2 g}{\partial \theta^2}$ decreases in θ in [0,1]. Hence, $\frac{\partial^2 g}{\partial \theta^2}>0$ is equivalent to $\frac{\partial^2 g}{\partial \theta^2}(\theta=1)>0$. After some simplification, we get

$$-6Ek+(4k-AC)>0 \tag{21}$$

Rearranging this inequality, we have $-6Ek+4k>AC$ for any $E\in(0,1)$. Also, for any $E\in(0,1)$, $-6Ek+4k>(1-3E)k$ holds. Recall that in (20), we have $AC<(1-3E)k$. Hence, (21) is satisfied if (20) is satisfied.
$\frac{\partial^2 g}{\partial \theta^2}<0$ in [0,1] is equivalent to $\frac{\partial^2 g}{\partial \theta^2}(\theta=0)<0$. After some simplification, we have $4k-AC<0$, which cannot be satisfied simultaneously with (19) for any $k\geq 0$. Hence, the only possible sufficient condition is the first case in (17). According to the proofs above, this condition is equivalent to (18) and (20).

Proof of Proposition 4.

Webrooming probability w_o will affect profits only when $\theta>\bar{\theta}_w$. Expression of the corresponding profit function, π_2^o, is given in the proof of Proposition 3, we then have $\frac{\partial \pi_2^o}{\partial w_o}=(p_o-u_o)q\frac{1}{t}\frac{\theta(1-q)}{(1-\theta q w_o)^2}[(1-q)(p_s-p_o-\theta c_o)+c_e]$. We know from the proof of Lemma 5 that, $(1-q)(p_s-p_o-\theta c_o)+c_e<0$. Hence, $\frac{\partial \pi_2^o}{\partial w_o}<0$.

Proof of Proposition 5

When the BM store provides price matching (i.e., when $p_s=p_o$), information free-riding disappears. Consumers stick to the channel where they gather information. Hence, the price matching case is a special case of the showrooming case with $p_s=p_o$ and $w_s=0$. We use the term “no price matching” and “showrooming” interchangeably in this section as they refer to the same situation. Recall that in the showrooming case, the profit of the online retailer, $\pi_1^o(\theta)$, is given by Equation (12), and the corresponding optimal information level θ_1^* is given by Equation (14). Also note that there exists a threshold under price matching that is similar to $\hat{\theta}_s$ in the showrooming case. To make the comparison easy, we denote the counterparts of $\hat{\theta}_s$, $\pi_1^o(\theta)$, and θ_1^* in the price matching case as $\hat{\theta}_s^{pm}$, $\pi_1^{pmo}(\theta)$, and θ_{pm}^*.

Furthermore, the expressions of $\hat{\theta}_s^{pm}$, $\pi_1^{pmo}(\theta)$, and θ_{pm}^* are obtained by setting $p_s = p_o$ and $w_s = 0$ in the expressions of $\hat{\theta}_s$, $\pi_1^o(\theta)$, and θ_1^* (see Equation (22), (23), and (24)). It is easy to check that $\hat{\theta}_s^{pm} > \hat{\theta}_s$ holds for any w_s. We assume that $\hat{\theta}_s^{pm} < \bar{\theta}$. In line with the showrooming case, we consider the scenario where there is always online traffic, i.e., $\hat{\theta}_s^{pm} < 0$.

$$\hat{\theta}_s^{pm} = \frac{c_o - \bar{t} + c_e}{(1-q)c_o} \tag{22}$$

$$\pi_1^{pmo} = (p_o - u_o)q\frac{1}{\bar{t}}[\bar{t} - (1 - \theta + \theta q)c_o - c_e] - k\theta^2 \tag{23}$$

$$\theta_{pm}^* = \frac{(p_o - u_o)q(1-q)c_o}{2k\bar{t}} \tag{24}$$

We first examine how price matching affects the profit of the online retailer by comparing the profit functions. As previously stated, $\hat{\theta}_s^{pm} > \hat{\theta}_s$ holds for any w_s, therefore, we show that the profit of the online retailer is always lower under price matching by proving the following:

$$\pi_1^o(\theta) - \pi_1^{pmo}(\theta) = (p_o - u_o)[D_{so}(\theta) + q\frac{1}{\bar{t}}[qw_s(p_o + c_o - p_s)]] > 0 \tag{25}$$

We then examine how optimal information level is affected by price matching by comparing θ_1^* and θ_{pm}^*: $\theta_{pm}^* - \theta_1^* = \frac{(p_o-u_o)q(1-q)c_o w_s}{2k\bar{t}} \geq 0$.

From the previous analysis, we know that, for a given θ, the store profit under price matching is independent of w_s, and the store profit without price matching is concave in w_s. Hence, the store profit may be higher or lower after price matching depending on how the two lines intersect.

Online Appendix B: Extensions

Table 2 Table of Notations for Extensions

$\bar{c}_o$	$\triangleq$	Online shopping cost upper bound
c_r	$\triangleq$	return cost
x	$\triangleq$	Index for consumer location

Extension 1 Return Cost (Proposition 6)

We follow the previous proof in the main model, with the only difference being the expected utility for the last branch in the decision tree as consumers who find the product a poor match will return the product and incur a return cost if they search information online but their uncertainty is not resolved. In the case of showrooming (i.e., when $p_o + c_o \leq p_s$), the expected utility of visiting BM store is still $E(S) = -t + q[w_s(v - p_o - c_o) + (1 - w_s)(v - p_s)]$, and the expected utility of visiting the online retailer's website is $E(O) = -c_e + \theta q(v - p_o - c_o) + (1 - \theta)[q(v - p_o) - (1 - q)c_r - c_o]$. The threshold traveling cost $t_1(\theta)$ becomes

$$t_1(\theta) = -q(1 - w_s)p_s + q(1 - w_s)p_o + [1 - (1 - q)\theta - qw_s]c_o + c_e + (1 - \theta)(1 - q)c_r$$

Solving the online retailer's profit maximization problem for θ, we get

$$\theta_r^* = min\Big\{\frac{(p_o - u_o)q(1 - w_s)(1 - q)(c_o + c_r)}{2k\bar{t}}, \bar{\theta}\Big\}$$

In the webrooming case, the expected utility of visiting BM store is still $E(S) = -t + q(v - p_s)$. The expected utility of visiting online retailer and buying online after considering webrooming is now $E(O)_1 = -c_e + \theta q[w_o(v - p_o - c_o) + (1 - w_o)(v - p_o - c_o)] + (1 - \theta)[q(v - p_o) - (1 - q)c_r - c_o] = -c_e + q(v - p_o) - [1 - \theta(1 - q)]c_o - (1 - \theta)(1 - q)c_r$. The expected utility of visiting online retailer and buying in the BM store after considering webrooming becomes $E(O)_2 = -c_e + \theta q[w_o(v - p_s - t) + (1 - w_o)(v - p_o - c_o)] + (1 - \theta)[q(v - p_o) - (1 - q)c_r - c_o]$. The new thresholds $t_2(\theta)$ and $t_3(\theta)$ are given as follows:

$$t_2(\theta) = \frac{-q(1 - \theta w_o)p_s + q(1 - \theta w_o)p_o + (1 - \theta + \theta q - \theta q w_o)c_o + c_e + (1 - \theta)(1 - q)c_r}{1 - \theta q w_o}$$

$$t_3(\theta) = -qp_s + qp_o + [1 - (1 - q)\theta]c_o + c_e + (1 - \theta)(1 - q)c_r$$

We repeat the analyses in the main model and find that all qualitative results in the Lemmas and Propositions in the main model still hold. We therefore omit the detailed proof here.

Extension 2.1 Negatively Correlated traveling cost and online shopping cost (Lemma 7)

Consumer decision trees for examining the product in store and online are illustrated in Figure 9 and Figure 10, respectively. Note that for tractability, in this extension, we assume that consumers will return the product if it is not a good fit with no return cost. For a consumer located at x, her expected utility of Store Direct, Showrooming, Online Direct, and Webrooming are $E(SS) = -x\bar{t} + q(v - p_s)$, $E(SO) = -x\bar{t} + q[v - p_o - (1 - x)c_o]$, $E(OO) = -c_e + \theta q[v - p_o - (1 - x)c_o] + (1 - \theta)[q(v - p_o) - (1 - x)c_o]$, and $E(OS) = -c_e + \theta q(v - p_s - x\bar{t}) + (1 - \theta)[q(v - p_o) - (1 - x)c_o]$, respectively. We next identify thresholds on x by comparing the above four utility functions.

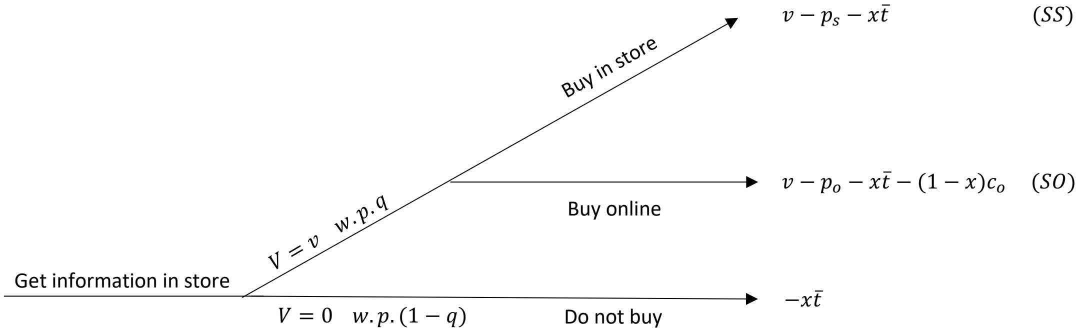


Figure 9 Decision Tree for Consumers Who Inspect Product in Store

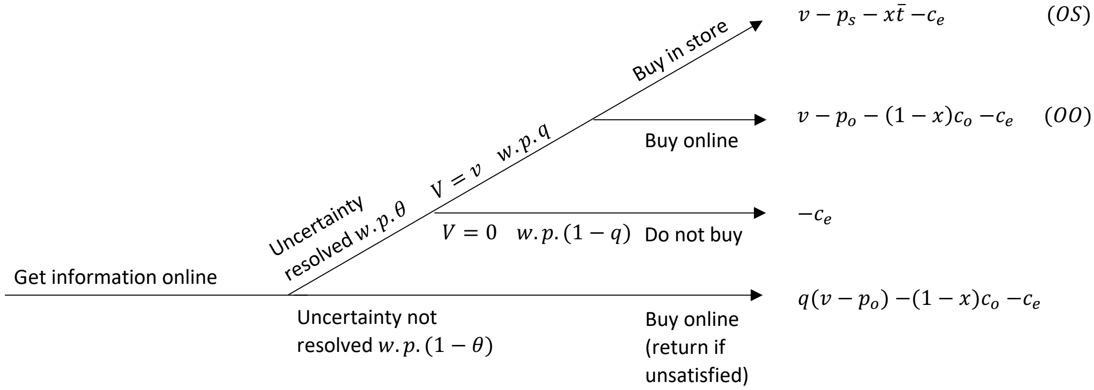


Figure 10 Decision Tree for Consumers Who Search for Product Information Online

- $E(SS) \geq E(SO)$ if and only if $x \leq x_1$, where $x_1 = \frac{p_o - p_s + c_o}{c_o}$.
- $E(SO) \geq E(OO)$ if and only if $x \leq x_2$, where $x_2 = \frac{c_e + (1-\theta)(1-q)c_o}{(1-\theta)(1-q)c_o + \bar{t}}$.
- $E(SS) \geq E(OO)$ if and only if $x \leq x_3$, where $x_3 = \frac{q(p_o - p_s) + c_e + (1+\theta q - \theta)c_o}{(1+\theta q - \theta)c_o + \bar{t}}$.
- $E(SS) \geq E(OS)$ if and only if $x \leq x_4$, where $x_4 = \frac{q(1-\theta)(p_o - p_s) + c_e + (1-\theta)c_o}{(1-\theta)c_o + (1-\theta q)\bar{t}}$.
- If $\theta \leq \frac{\bar{t} + (1-q)c_o}{q\bar{t} + c_o}$, $E(SO) \geq E(OS)$ if and only if $x \leq x_4'$, where $x_4' = \frac{\theta q(p_o - p_s) - c_e + (\theta + q - 1)c_o}{(\theta q - 1)\bar{t} + (\theta + q - 1)c_o}$; If $\theta > \frac{\bar{t} + (1-q)c_o}{q\bar{t} + c_o}$, $E(SO) \geq E(OS)$ if and only if $x \geq x_4'$.
- $E(OO) \geq E(OS)$ if and only if $x \geq x_5$, where $x_5 = \frac{p_o - p_s + c_o}{\bar{t} + c_o}$.

Note that $x_1 > x_5$ always holds, and they are both independent of θ. We first characterize the market segmentation based on x_1 and x_5 and then we further incorporate other thresholds on x mentioned above. If $x < x_5$, then $x < x_1$ always holds. We have $E(OO) < E(OS)$ and $E(SO) < E(SS)$. If $x_5 < x < x_1$, we have $E(OO) > E(OS)$ and $E(SO) < E(SS)$. If $x > x_1$, then $x > x_5$ always holds. We have $E(OO) > E(OS)$ and $E(SO) > E(SS)$. Hence, consumers in the region $[0, x_5]$ will adopt strategy SS or OS. Consumers in the region $[x_5, x_1]$ will adopt strategy SS or OO. Consumers in the region $[x_1, 1]$ will adopt strategy OO or SO. In addition, to ensure $x_5 > 0$ and $x_1 < 1$, condition $p_o < p_s < p_o + c_o$ needs to be satisfied.

Since consumers choose either SS or OS when $x < x_5$, we compare x_4, which is the threshold associated with $E(SS)$ and $E(OS)$, with x_5. Following the same logic, we compare x_5, x_3, and x_1 for the region $x \in [x_5, x_1)$, and compare x_1, x_2, and 1 for the region $x \in [x_1, 1]$. Note that x_2, x_3, and $x_4 > 0$ always holds. Without loss of generality we assume that when indifferent between choosing BM store and online retailer, consumers choose online retailer, regarding both information gathering channel and purchase channel. For example, when indifferent between SS and OS, consumers will choose OS; when indifferent between SS and OO, consumers will choose OO. The results are summarized as follows:

• For $x \in [0, x_5)$:

If $x_4 < x_5$, then consumers in $[0, x_4)$ choose SS, and consumers in $[x_4, x_5)$ choose OS.

If $x_4 \geq x_5$, then consumers in $[0, x_5)$ choose SS.

• For $x \in [x_5, x_1)$:

If $x_5 < x_3 < x_1$, then consumers in $[x_5, x_3)$ choose SS, and consumers in $[x_3, x_1)$ choose OO.

If $x_3 \leq x_5$, then consumers in $[x_5, x_1)$ choose OO.

If $x_3 \geq x_1$, then consumers in $[x_5, x_1)$ choose SS.

• For $x \in [x_1, 1]$:

If $x_2 \leq x_1$, then consumers in $[x_1, 1]$ choose OO.

If $x_1 < x_2 < 1$, then consumers in $[x_1, x_2)$ choose SO, and consumers in $[x_2, 1]$ choose OO.

If $x_2 \geq 1$, then consumers in $[x_1, 1]$ choose SO.

As mentioned above, x_1 and x_5 are independent of θ, but x_2, x_3, and x_4 are dependent of θ. Hence, we now will convert the conditions involving x_2, x_3, and x_4 that we just developed into thresholds on θ. $x_2 < 1$ holds if and only if $c_e < \bar{t}$. This condition captures the reality, where some consumers examine the product online while some visit the BM store. $x_2 < x_1$ holds if and only if $\theta > \bar{\theta}_1$, where $\bar{\theta}_1 = \frac{[(1-q)c_o+\bar{t}](p_s-p_o)-c_o\bar{t}+c_oc_e}{(1-q)c_o(p_s-p_o)}$. $x_3 > x_1$ holds if and only if $\theta < \bar{\theta}_1$. $x_3 < x_5$ holds if and only if $\theta > \bar{\theta}_2$, where $\bar{\theta}_2 = \frac{(1-q)(\bar{t}+c_o)(p_s-p_o)+(\bar{t}+c_o)c_e}{(1-q)c_o(p_s-p_o+\bar{t})}$. $x_4 > x_5$ holds if and only if $\theta < \bar{\theta}_2$. We also find that $\bar{\theta}_1 < \bar{\theta}_2$ holds. We are now ready to characterize the market segmentation by θ.

• If $\theta < \bar{\theta}_1 < \bar{\theta}_2$, we have $x_2 < 1$, $x_3 > x_5$, $x_4 > x_5$, $x_2 > x_1$, and $x_3 > x_1$. Hence, consumers in $[0, x_1)$ will adopt strategy SS, consumers in $[x_1, x_2)$ will adopt strategy SO, and consumers in $[x_2, 1]$ will adopt strategy OO.

• If $\bar{\theta}_1 < \theta < \bar{\theta}_2$, we have $x_2 < 1$, $x_3 > x_5$, $x_4 > x_5$, $x_2 < x_1$, and $x_3 < x_1$. Hence, consumers in $[0, x_3)$ will adopt strategy SS, and consumers in $[x_3, 1]$ will adopt strategy OO.

• If $\theta > \bar{\theta}_2 > \bar{\theta}_1$ holds, we have $x_2 < 1$, $x_3 < x_5$, $x_4 < x_5$, $x_2 < x_1$, and $x_3 < x_1$. Hence, consumers in $[0, x_4)$ will adopt strategy SS, consumers in $[x_4, x_5)$ will adopt strategy OS, and consumers in $[x_5, 1]$ will adopt strategy OO.

Figure 11 illustrates the above results. Based upon the above characterization of consumer strategies, we identify demand functions for a given θ and present the results in Lemma 7.

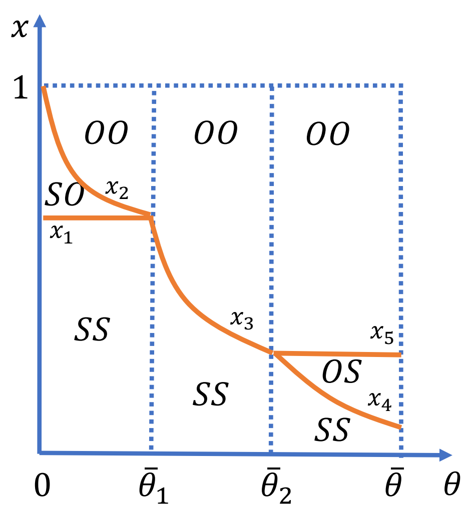


Figure 11 Consumer Strategies

■

Extension 2.2 Independent traveling cost and online shopping cost (Lemma 8)

In this extension, we consider a case in which traveling cost and online shopping cost follow independent uniform distributions, $[0,\bar{t}]$ and $[0,\bar{c}_o]$, respectively. Further, for tractability and to aid the exposition of the main insights, we limit our focus to identical uniform distributions, i.e., $\bar{t}=\bar{c}_o$. The decision trees for this extension are presented in Figures 12 and 13. Consumers again compare the expected utilities of different strategies to make information gathering and purchase decisions. If a consumer chooses to examine the product in store, they could either purchase in store as shown in branch (1), or purchase online as in branch (2). We denote the expected utilities of branch (1) and (2) as Eu_1 and Eu_2, respectively. If a consumer gathers product information online, when their uncertainty is resolved, they could either purchase in store (branch (3)) or online (branch (4)). When their uncertainty is not resolved, they will buy online and return the product with a cost of c_r in the case of a poor match (branch (5)). We denote the expected utility of visiting online retailer and buying in store when uncertainty is resolved while buying online when uncertainty is not resolved (i.e., branch (3) and (5)), as Eu_3. Similarly, we denote the expected utility of visiting online retailer and always buying online (i.e., branch (4) and (5)), as Eu_4. Then, $Eu_1=-t+q(v-p_s)$, $Eu_2=-t+q(v-p_o-c_o)$, $Eu_3=-c_e+\theta q(v-p_s-t)+(1-\theta)[q(v-p_o)-(1-q)c_r-c_o]$, and $Eu_4=-c_e+\theta q(v-p_o-c_o)+(1-\theta)[q(v-p_o)-(1-q)c_r-c_o]$. We next obtain thresholds on c_o by comparing the above four expected utilities: $Eu_1>Eu_2$ if and only if $c_o>\bar{c}_{o1}$, where $\bar{c}_{o1}=p_s-p_o$. $Eu_3>Eu_4$ if and only if $c_o>\bar{c}_{o2}(t)$, where $\bar{c}_{o2}(t)=t+p_s-p_o$. $Eu_1>Eu_3$ if and only if $c_o>\bar{c}_{o3}(t)$, where $\bar{c}_{o3}(t)=\frac{1-\theta q}{1-\theta}t+qp_s-qp_o-\frac{c_e}{1-\theta}-(1-q)c_r$. $Eu_1>Eu_4$ if and only if $c_o>\bar{c}_{o4}(t)$, where $\bar{c}_{o4}(t)=\frac{t}{1-(1-q)\theta}+\frac{qp_s-qp_o-c_e-(1-\theta)(1-q)c_r}{1-(1-q)\theta}$. If $\theta<1-q$, then $Eu_2>Eu_3$ if and only if $c_o>\bar{c}_{o6}(t)$, where $\bar{c}_{o6}(t)=\frac{1-\theta q}{1-\theta-q}t+\frac{\theta q(p_o-p_s)-c_e-(1-\theta)(1-q)c_r}{1-\theta-q}$. If $\theta>1-q$, then $Eu_2>Eu_3$ if and only if $c_o<\bar{c}_{o6}(t)$. $Eu_2>Eu_4$ if and only if $c_o>\bar{c}_{o5}(t)$, where $\bar{c}_{o5}(t)=\frac{t}{(1-\theta)(1-q)}-\frac{c_e}{(1-\theta)(1-q)}-c_r$. Note that $\bar{c}_{o2}(t)$, $\bar{c}_{o3}(t)$, $\bar{c}_{o4}(t)$, $\bar{c}_{o5}(t)$, and $\bar{c}_{o6}(t)$ all increase in t. We can also prove that $\bar{c}_{o1}$, $\bar{c}_{o3}(t)$, and $\bar{c}_{o6}(t)$ intersect at $t=\bar{t}_1$, where $\bar{t}_1=\frac{(1-\theta)(1-q)(p_s-p_o)+c_e+(1-\theta)(1-q)c_r}{1-\theta q}$, while $\bar{c}_{o1}$, $\bar{c}_{o4}(t)$, and $\bar{c}_{o5}(t)$ intersect at $t=\bar{t}_2$, where $\bar{t}_2=(1-\theta)(1-q)(p_s-p_o)+c_e+(1-\theta)(1-q)c_r$. Moreover, $\bar{c}_{o2}(t)$, $\bar{c}_{o3}(t)$, and $\bar{c}_{o4}(t)$ intersect at $t=\bar{t}_3$, where $\bar{t}_3=\frac{(1-\theta)(1-q)(p_s-p_o)+c_e+(1-\theta)(1-q)c_r}{\theta(1-q)}$, while $\bar{c}_{o2}(t)$, $\bar{c}_{o6}(t)$, and $\bar{c}_{o5}(t)$ intersect at $t=\bar{t}_4$, where $\bar{t}_4=\frac{(1-\theta)(1-q)(p_s-p_o)+c_e+(1-\theta)(1-q)c_r}{1-(1-\theta)(1-q)}$. We now can characterize the market segmentation by investigating how the above thresholds intersect and thus which strategy dominates in each region. When $p_s<p_o$, $Eu_1>Eu_2$ always holds. Therefore, only strategies SS, OS, and OO exist. We only need to look into how $\bar{c}_{o3}(t)$, $\bar{c}_{o4}(t)$, and $\bar{c}_{o2}(t)$ intersect. Similar to the $\bar{\theta}_w$ in the main model, we define a threshold on information level, $\bar{\theta}_w^{ex}$, where $\bar{\theta}_w^{ex}=\frac{(1-q)(p_s-p_o)+c_e+(1-q)c_r}{(1-q)c_r}$. When $\theta<\bar{\theta}_w^{ex}$, market segmentation exhibits a pattern as shown in Figure 14 (a), otherwise market segmentation follows the pattern shown in Figure 14 (b). When $p_s\geq p_o$, no strategy dominates. Therefore, we need to examine how $\bar{c}_{o1}$, $\bar{c}_{o2}(t)$, $\bar{c}_{o3}(t)$, $\bar{c}_{o4}(t)$, $\bar{c}_{o5}(t)$, and $\bar{c}_{o6}(t)$ intersect. Figure 15 demonstrates the corresponding market segmentation.

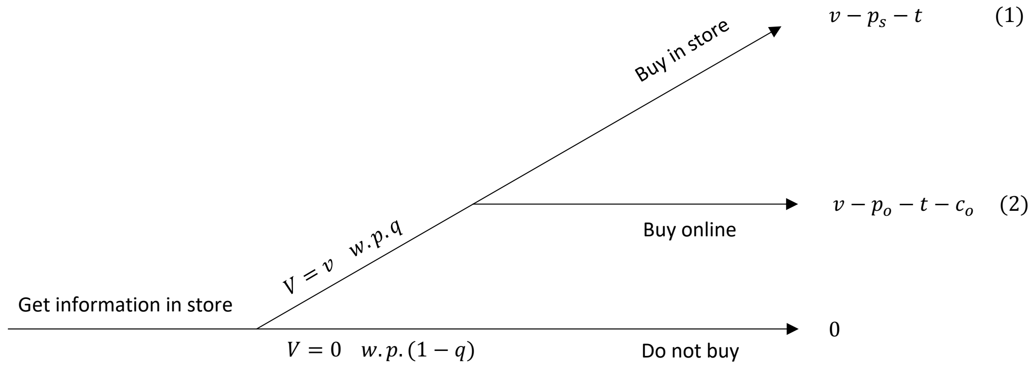


Figure 12 Decision Tree for Consumers Who Inspect Product in Store

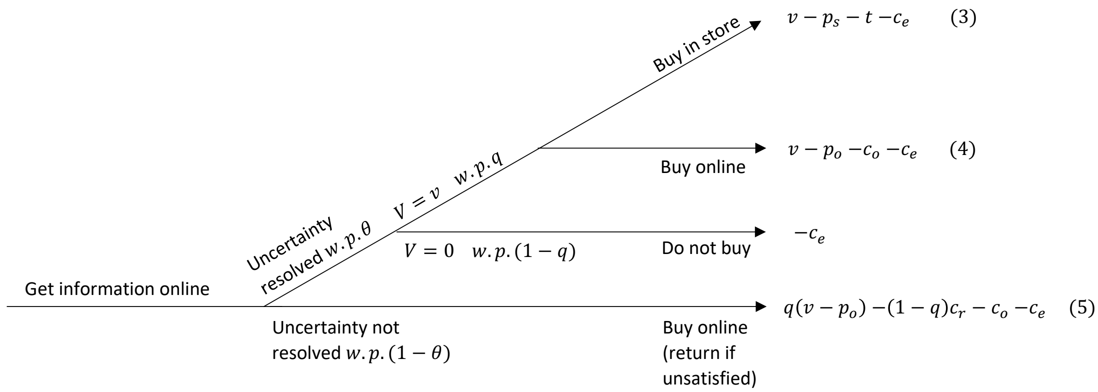


Figure 13 Decision Tree for Consumers Who Search for Product Information Online

Based on Figures 14 and 15, we can now derive the expression for each type of traffic by computing the corresponding area. For Figure 14 (a), we denote the intersection of $\bar{c}_{o2}(t)$ and $\bar{c}_{o3}(t)$ as point A, with coordinates x_A and y_A. Similarly, we denote the intersection of $\bar{c}_{o3}(t)$ and $c_o = \bar{c}_o$ as point B, with coordinates x_B and $\bar{c}_o$; the intersection of $\bar{c}_{o4}(t)$ and $c_o = 0$ as point C, with coordinates x_C and 0; and the intersection of $\bar{c}_{o2}(t)$ and $t = \bar{c}_o$ as point D, with coordinates $\bar{c}_o$ and y_D. Then Store Direct Traffic, T_{ss}, is represented by the area of marked as "SS." Specifically, $T_{ss} = \frac{(x_A + x_B)\bar{c}_o + (x_C - x_B)y_A}{2}$, where $x_A = \frac{(1-\theta)(1-q)(p_s - p_o) + c_e + (1-\theta)(1-q)c_r}{\theta(1-q)}$, $x_B = \frac{(1-\theta)q(p_o - p_s) + c_e + (1-\theta)(1-q)c_r + (1-\theta)\bar{c}_o}{1-\theta q}$, $x_C = q(p_o - p_s) + c_e + (1-\theta)(1-q)c_r$, and $y_A = \frac{(1-q)(p_s - p_o) + c_e + (1-\theta)(1-q)c_r}{(1-q)\theta}$. Online Direct Traffic $T_{oo} = \frac{y_D \bar{c}_o + y_A \bar{c}_o - x_A y_D - x_C y_A}{2}$, where $y_D = \bar{c}_o + p_s - p_o$. Webrooming Traffic $T_{os} = \bar{c}_o^2 - T_{ss} - T_{oo}$. We can find the corresponding demand by multiplying each of the above traffic by q. Following the same logic, we can derive the demand functions for Figures 14 (b) and 15. For Figure 14 (b), we further denote the intersection of $\bar{c}_{o3}(t)$ and $c_o = 0$ as point E, with coordinates x_E and 0; the intersection of $\bar{c}_{o2}(t)$ and $c_o = 0$ as point F, with coordinates x_F and 0. Store Direct Traffic is thus $T_{ss} = \frac{(x_E + x_B)\bar{c}_o}{2}$, where $x_E = \frac{(1-\theta)q(p_o - p_s) + c_e + (1-\theta)(1-q)c_r}{1-\theta q}$. Online Direct Traffic $T_{oo} = \frac{(\bar{c}_o - x_F)y_D}{2}$, where $x_F = p_o - p_s$. Webrooming Traffic $T_{os} = \bar{c}_o^2 - T_{ss} - T_{oo}$. For Figure 15, we denote the intersection of $\bar{c}_{o1}$ and $\bar{c}_{o5}(t)$ as point G, with coordinates x_G and y_G; the intersection of $\bar{c}_{o2}(t)$ and $c_o = \bar{c}_o$ as point H, with coordinates x_H and $\bar{c}_o$; the intersection of $\bar{c}_{o5}(t)$ and $c_o = 0$ as point I, with coordinates x_I and 0. Store Direct Traffic is thus $T_{ss} = \frac{(x_G + x_A)(y_A - y_G) + (x_A + x_B)(\bar{c}_o - y_A)}{2}$, where $x_G = (1-\theta)(1-q)(p_s - p_o) + c_e + (1-\theta)(1-q)c_r$, and $y_G = p_s - p_o$.

Showrooming Traffic $T_{so} = \frac{(x_I + x_G)y_G}{2}$, where $x_I = c_e + (1-\theta)(1-q)c_r$. Webrooming Traffic $T_{os} = \frac{(x_H - x_B)(\bar{c}_o - y_A)}{2}$, where $x_H = \bar{c}_o - p_s + p_o$. Online Direct Traffic $T_{oo} = \bar{c}_o^2 - T_{ss} - T_{so} - T_{os}$.

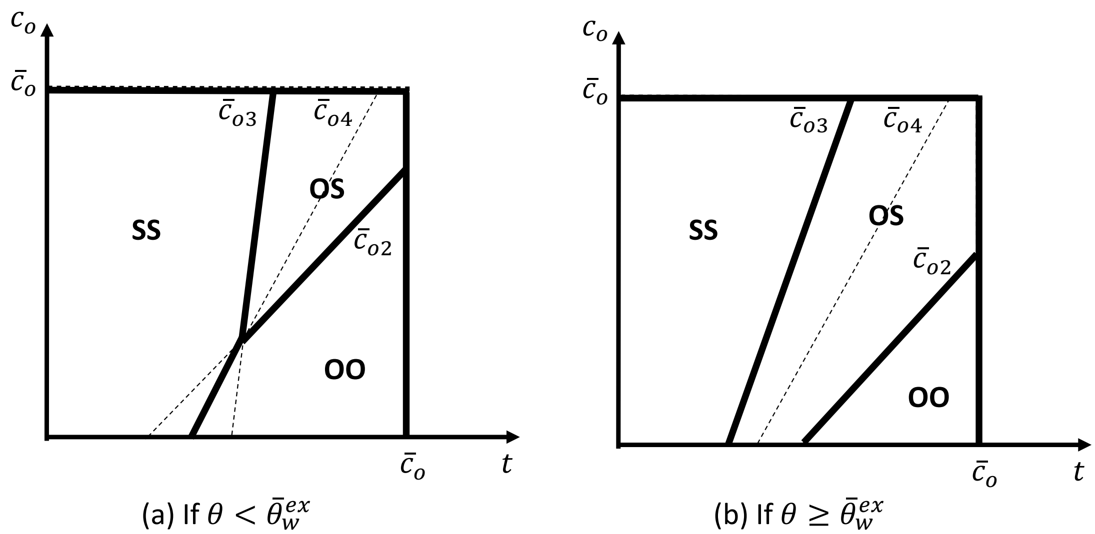


Figure 14 **Consumer Strategies When** $p_s < p_o$

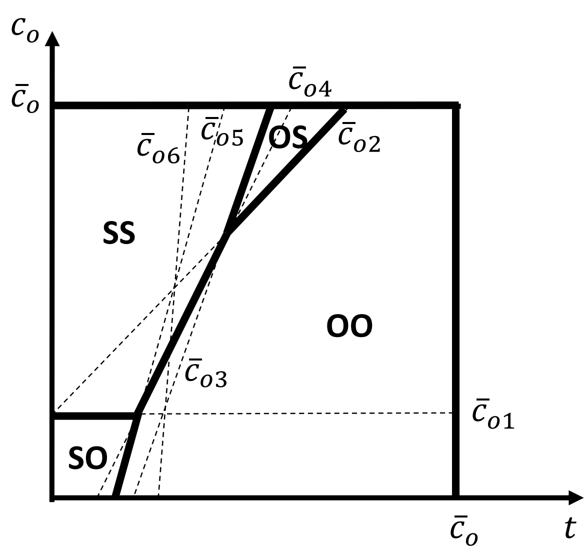


Figure 15 **Consumer Strategies When** $p_s \geq p_o$

Extension 3 All Consumers Examine the Product Online First (Proposition 7)

In this extension, we study the scenario under which all consumers evaluate the product online first. The decision tree is as shown in Figure 16. Note that we study showrooming case only and assume the online evaluation cost c_e to be zero in this extension. The expected utilities of choosing (1), (3) and (5) are $v - p_s - t$, that of choosing (2) is

$v - p_o - c_o$, and that of choosing (4) is $v - p_o - c_o - t$. Therefore, when $p_o + c_o \leq p_s$, (1) is always dominated by (2), and (3) is always dominated by (4). When uncertainty is resolved, consumers will buy online if it is a good match (i.e., choose (2)). When uncertainty is not resolved, consumers who visit the store and are open to showrooming will purchase online (i.e., choose (4)). Specifically, once a consumer realize that their uncertainty is not resolved by online information, they will then decide whether to visit the store buy comparing the following two expected utilities: Expected utility of visiting store $Eu_1 = -t + q[w_s(v - p_o - c_o) + (1 - w_s)(v - p_s)]$ and Expected utility of not visiting store $Eu_2 = q(v - p_o) - c_o$. $Eu_1 > Eu_2$ holds if and only if $t < t_1$, where $t_1 = -q(1 - w_s)p_s + q(1 - w_s)p_o + (1 - qw_s)c_o$. Therefore, online demand is given by the following:

$$\textit{Online demand } D^o = \underbrace{\frac{1}{\bar{t}}\theta q\bar{t}}_{\textit{Uncertainty resolved}} + \underbrace{\frac{1}{\bar{t}}(1-\theta)t_1 q w_s}_{\textit{Uncertainty not resolved, visit store}} + \underbrace{\frac{1}{\bar{t}}(1-\theta)(\bar{t}-t_1)q}_{\textit{Uncertainty not resolved, not visit store}} \tag{26}$$

Solving for θ in the profit function for the online retailer $\pi^o = (p_o - u_o)D^o - k\theta^2$, we have the optimal information $\theta^* = \frac{(p_o-u_o)q(1-w_s)[-q(1-w_s)p_s+q(1-w_s)p_o+(1-qw_s)c_o]}{2k\bar{t}}$. Subtracting θ_1^*, the optimal information level provided in Proposition 1, from θ^*, we can find that the online retailer now provides less information.

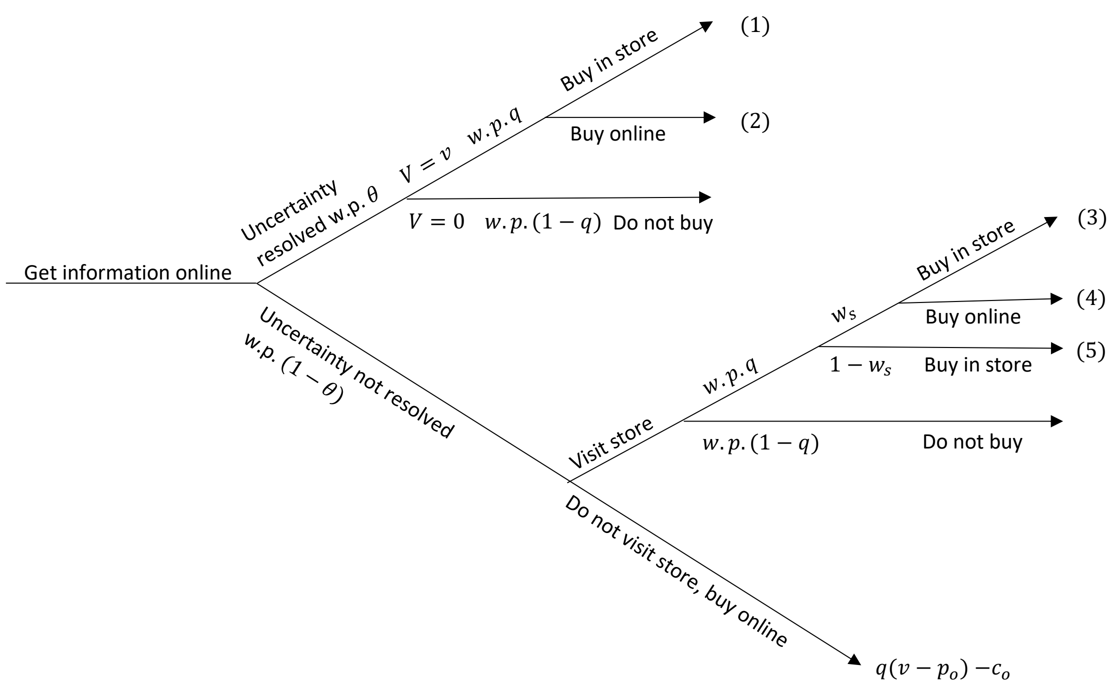


Figure 16 Decision Tree When All Consumers Evaluate Product Online First

■

Extension 4 Endogenous Pricing Decisions (Proposition 8)

In this extension, the online retailer first determines the information level θ, the BM store then decides on the store price p_s, and lastly the online retailer decides on the online price p_o. We follow backward induction to solve for the three decision variables. When $p_o + c_o < p_s$, consumers decision process is the same as the one in the main model. Recall that there exists a threshold t_1 (see Equation (2)), such that consumers whose traveling cost is lower than t_1 will visit the store, while the rest will evaluate the product online. In the last stage, the online retailer determines the optimal p_o to maximize its profit, which is given by $\pi^o = (p_o - u_o)q\frac{1}{\bar{t}}[\bar{t} + (w_s - 1)t_1] - k\theta^2$. Note that the above profit function is the same as the one in the proof of Proposition 1. Solving for p_o, we have the following best response:

$$p_o = \frac{q(1-w_s)^2 p_s - (1-w_s)(1-\theta+\theta q - q w_s)c_o + q(1-w_s)^2 u_o + \bar{t} - (1-w_s)c_e}{2q(1-w_s)^2} \tag{27}$$

Nest, we solve for store's pricing decision. Store profit is given by $\pi^s = (p_s - u_s)q\frac{1}{\bar{t}}(1-w_s)t_1$. Plugging (27) to the above profit function and solve for p_s, we have:

$$p_s = \frac{(1-w_s)(1-\theta+\theta q - q w_s)c_o + q(1-w_s)^2 u_s + q(1-w_s)^2 u_o + \bar{t} - (1-w_s)c_e}{2q(1-w_s)^2} \tag{28}$$

Plugging (28) back to (27), we have:

$$p_o = \frac{-(1-w_s)(1-\theta+\theta q - q w_s)c_o + q(1-w_s)^2 u_s + 3q(1-w_s)^2 u_o + 3\bar{t} - 3(1-w_s)c_e}{4q(1-w_s)^2} \tag{29}$$

We can prove Proposition 8 by taking the first order derivatives of equations (28) and (29) with respect to θ. Lastly, we solve for the online retailer's information decision by plugging (28) and (29) back to the profit function for online retailer and solve for θ. The optimal information level θ^* is given by the following:

$$\theta^* = \frac{(1-q)q(1-w_s)c_o(u_s - u_o) - (1-q)(1-q w_s)c_o^2 + \frac{3(1-q)c_o\bar{t}}{1-w_s} - 3(1-q)c_o c_e}{16k\bar{t} - (1-q)^2 c_o^2} \tag{30}$$

■

Extension 5 Omnichannel Retailer (Proposition 9)

The analysis for this extension is very similar to that for the main model. The difference is that, the profit function for the omnichannel retailer is now the sum of the profit it makes from the BM store and the profit from the online channel. That is, $\pi^{omni} = (p_s - u_s)D_{ss} + (p_o - u_o)(D_{so} + D_{oo}) - k\theta^2$, where $D_{ss} = qT_{ss}$. Please refer to equations (9), (10), and (10) for the expressions of T_{ss},

D_{so}, and D_{oo} respectively. The optimal information level is given by $\theta^* = \frac{(p_o - u_o - p_s + u_s)q(1-w_s)(1-q)c_o}{2k\bar{t}}$, which is lower than the optimal information level in the main model. The proof for how profit changes with w_s follows the same logic as in the main model. ■