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Evidence from a field experiment

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## **Abstract**

Many online stores are designed such that shoppers can easily access any available discounted products. We propose that deliberately increasing search frictions by placing small obstacles to locating discounted items can improve online retailers' margins and even increase conversion. We demonstrate using a simple theoretical framework that inducing consumers to inspect higher-priced items first may simultaneously increase the average price of items sold and the overall expected purchase probability by inducing consumers to search more products. We test and confirm these predictions in a series of field experiments conducted with a dominant online fashion and apparel retailer. Furthermore, using information in historical transaction data about each consumer, we demonstrate that price-sensitive shoppers are more likely to incur search costs to locate discounted items. Our results show that increasing search frictions can be used as a self-selecting price discrimination tool to match high discounts with price-sensitive consumers and full-priced offerings with price-insensitive consumers.

*Keywords:* e-commerce, online retailing, friction, effort, search costs, price discrimination

Online retail accounts for a rapidly growing proportion of revenues in many product categories. As of the fourth quarter of 2018, e-commerce accounted for 9.8% of total U.S. retail sales, compared to less than 4% in 2008 (U.S. Census Bureau 2018). While online retail broadens firms' access to consumers through an additional channel, operating margins are often lower in online stores than in physical stores. Amazon, the largest online retailer in the U.S., averaged 1.3% in operating margins from 2011 to 2013 while its brick-and-mortar counterparts typically experienced 6% to 10% (Rigby 2014). Reasons for this difference are well recognized: prices are easy to compare online, discount coupons and codes have high uptake, and sellers often bear the cost of shipping products to buyers.

These factors are in part a consequence of many online sellers' efforts to make online shopping as convenient as possible. Pure online sellers such as Bonobos, Wayfair, and Overstock are known for minimizing the search, transaction, and delivery costs for shoppers in an attempt to lure them from offline channels. In industries ranging from consumer electronics to flight and hotel booking, third-party sites reduce search costs even further by enabling cross-website comparisons. Dominant online sellers, such as Amazon and Alibaba, are also known for their efforts to minimize frictions for consumers. The focus of this paper is on such firms, which have no competitors of the same size.

This trend is in stark contrast with the practice of brick-and-mortar retailers, who have long embraced the deliberate use of search frictions to improve in-store margin performance. In making lower-priced and lower-margin items harder to locate, by placing the sale section in the back of the store, using bargain bins and discount racks, or having a separate outlet store miles away, physical stores induce a self-selection among consumers who are heterogeneous in their willingness to pay (e.g., Coughlan & Soberman 2005; Ngwe 2017).

In this paper, we seek to challenge the prevailing assumption that minimizing search frictions, i.e., facilitating consumer search across a retailer's entire assortment, is always the optimal strategy for dominant online retailers (Bakos 1997; Brynjolfsson & Smith 2000). We contend that just as in physical selling contexts, careful incorporation of search frictions can facilitate price discrimination in online retail. While the price obfuscation literature (e.g., Ellison & Ellison 2009; Brown, Hossain & Morgan 2010) has identified ways in which firms mask prices and thus increase search frictions through product line design and price partitioning, in our setting we hold both constant and only vary website navigation elements.

The existing literature has typically conceived of search costs as the time, mental or physical effort, and money required to physically identify and consider additional options prior to making a purchase decision (Bell, Ho & Tang 1998). In offline retail contexts, these often take the form of travel costs or time spent shopping in measurable intervals. In an interesting example of this, Hui et al. (2013) find that increasing in-store travel as a result of changing the location of particular products increases purchases by seven percent for a grocery store. Given the ease and immediacy of online shopping, it is perhaps unsurprising that equivalent search costs have not been widely manipulated in online settings.

We attempt to bridge this gap by exploring the potency of search frictions—deliberately built-in search costs—in online settings. Examples of search frictions that we employ include: the effort in clicking an additional link, viewing an additional page, scrolling through a catalogue of items, mentally calculating the percentage discount on a sale item, as well as the psychological costs associated with extending the search process, all of which increase the time and effort required to locate discounted products.

Our hypothesis is that under certain conditions, an online seller can improve its average

selling price and overall expected purchase probability rate by increasing search frictions associated with accessing discounted items on its website. The first condition is that increasing search frictions changes the order in which consumers consider items, forcing consumers to view full-priced items prior to discounted items. The second condition is that upon encountering these added search frictions, price-insensitive consumers would not always incur the search cost to view the discounted items, and instead would substitute from discounted items to full-priced items. The third condition is that price-sensitive consumers would exert the extra effort required to find discounted items on the website, similar to what has been observed in physical settings (e.g., Seiler & Pinna 2017). We offer a simple model of search that generates these predictions under a basic set of assumptions and when search costs are moderate.

In order to test our hypothesis, we run a series of field experiments with an online fashion and apparel retailer. This category is particularly appropriate for our purposes because it features moderate frequency and value of purchase. Consumers are broadly aware of price points for apparel but are not completely certain of product assortment on any given purchase occasion. Item prices are material but not the sole consideration for most shoppers. Lastly, it is common practice for apparel retailers to frequently offer sizeable discounts in order to acquire and retain customers. The firm we work with is dominant in its market and there are no equivalent discounts from other online sellers available. While this places some limitations on the generalizability of our results, it also allows us to abstract from strategic considerations in our investigation.

In our first experiment, we randomly assign new visitors to the online store over the course of nine days to either a control group or one of three treatment groups. Product availability and prices are held constant across all conditions. Each treatment involves increasing

search frictions in some way: (i) removing the direct link to the outlet section, which is a catalog for highly discounted products; (ii) removing the option to sort product listings by discount percentage; and (iii) removing item-specific visual markers that indicate discount percentage. We find that the average discount of purchased items is significantly lower in the treatment groups than in the control group while conversion—the fraction of customers who purchase at least one product—is higher. These results demonstrate that our experimental manipulations have significant effects on purchase behavior and provide preliminary evidence for our hypothesis.

In the succeeding analyses, we aim to establish the relationship between consumers' price sensitivity and their responses to added search frictions. We use historical transaction data for existing customers to pre-classify them according to their price sensitivity. We do so by regressing the average discount of their most recent transaction on demographic and past purchase variables, then using the predicted values as a proxy for price sensitivity. We validate this classification by showing that consumers identified as price-sensitive are more likely to click on randomly assigned discount-oriented versus full price-oriented email newsletters.

In our second experiment, we randomly assign nearly 350,000 visitors—new and existing customers—to the online store over the course of two weeks to either a control group or one of four treatment groups. Again, product availability and prices are held constant across all conditions. We carry over the treatments from our first experiment and include the replacement of discount banners with non-discount banners as an additional condition. We identify the presence of self-selection among the firm's entire customer base, utilizing past purchase behavior to measure heterogeneous treatment effects. We find that, as in the first experiment, the addition of search costs lowers the average discount of purchased items and increases conversion. Moreover, gains from increased selling prices are mostly attributed to price-



insensitive consumers buying disproportionately more full-priced items in the treatment groups. These results imply that placing obstacles to locating discounted items causes price-insensitive consumers to switch to full-priced items. They also show that the main effects we capture are stable across varying demand conditions, as our second experiment included new as well as existing customers and was run more than a year after our first experiment during the sale season.

### *RELATED LITERATURE*

Our work relates to the literature on search costs in online settings, much of which explores the effect of diminishing information frictions on consumer choice, welfare, and market structure. Early papers associate decreases in search costs with an increase in price competition (e.g. Bakos 1997). Subsequent work finds that online search may be costlier than originally understood, possibly due to online shoppers having higher search costs than offline shoppers, and that there may be substantial heterogeneity in search costs among online shoppers (Brynjolfsson & Smith 2000; Wilson 2010).

Lynch and Ariely (2000) find conditions under which increased quality transparency online can mitigate price competition, providing support for their claim that “in a competitive environment, the strategy of keeping some search costs high is arguably doomed to fail.” Yet others show that some firms have found it profitable to artificially increase search costs in an attempt to make price comparison between sellers more effortful. Ellison and Ellison (2009) show that firms participating in a marketplace have an incentive to obfuscate the actual price and quality information of goods sold online so as to reduce search-sensitive consumers’ inclination

to exhaustively compare prices across firms.

As examples of obfuscation, Ellison and Ellison (2005) show how online retailers profitably offer complicated menus of prices, products that seem to be bundled but are not, hidden prices, complex product descriptions, and other tactics designed “to make the process of examining an offer sufficiently time-consuming.” They claim that many advances in search engine technology that presumably were intended to facilitate consumer information gathering have been subsequently accompanied by firms’ investments in hampering search.

Consumer preferences for transparency have been established in the literature. Seim, Vitorino, and Muir (2017) use data on driving schools in Portugal to show that consumers are willing to pay 11 percent of the service price for price transparency in an industry that is notorious for hidden fees. Unlike this and related work on obfuscation, the frictions we study do not primarily operate on the consumer’s information set, but rather on the costliness of navigating a website even when consumers have full information.

In our approach, we introduce search frictions in order to manipulate the order in which consumers consider items in an online store. Our findings thus relate to research on how position, with respect to search order, influences consumer choice (e.g., Weitzman 1979; de los Santos & Koulayev 2014; Narayanan & Kalyanam 2015; Armstrong 2017). Some recent papers use field experiments to cleanly identify the impact of search order and rankings on purchase outcomes in single-category settings (e.g., Choi & Mela 2016; Ursu 2017). We build on this stream of literature by demonstrating the relevance of website navigation links on search, particularly where a multi-category seller offers a large number of choices that cannot be presented to the consumers in a single comprehensive list.

Our work relates to research that links search and price discrimination. Varian (1980)

formulates a model of price discrimination that allows a firm to extract surplus from uninformed consumers via high prices and, concurrently, sell to the informed consumers via low prices using a mixed-strategy pricing equilibrium. More recent models featuring heterogeneous search also find equilibria in which sellers adopt a mixed strategy (Ratchford 2009). For example, Stahl (1996) finds a mixed strategy equilibrium that, when implemented by two retailers, creates a separation in the market such that fully informed consumers always buy from the lower-priced firm while uninformed consumers stop short of comprehensive search and pay higher prices. Our findings show that in addition to strategic incentives, there are benefits to increasing search frictions that accrue to dominant firms.

We focus specifically on cases where a monopolistic seller designs an optimal menu of products such that consumers self-select according to their willingness to pay (Mussa & Rosen 1978). Previous empirical research has demonstrated the occurrence of this practice in such settings as Broadway theater (Leslie 2004) and coffee shops (McManus 2007). We build on this research by demonstrating through online field experiments how second-degree price discrimination can be exercised in e-commerce settings.

Related research has explored the use of effort to allocate discounts to price-sensitive consumers, particularly in the context of discount coupons (e.g. Narasimhan 1984) and waiting in line (e.g. Nichols et al 1971). Crucially, our implementation of increasing search frictions differs from earlier work in that part of the added effort induced on consumers involves inspecting additional items sold by a multiproduct firm, which we show has positive effects on average selling price and conversion.

## *OVERVIEW OF EMPIRICAL ANALYSIS*

In this section, we present an overview of our empirical analysis, which consists of both field experiments and analyses of historical purchase data in partnership with an online fashion and apparel retailer in the Philippines. We also offer a simple theoretical framework that is conceptually aligned with our field experiments, which we detail in the next section.

Our partner online retailer sells branded merchandise as well as items under its private label. The firm offers the widest online selection of men's and women's fashion items in the country. While statistics on industry concentration are not available, according to its managers the firm accounts for about 40% of overall online fashion retail in the country, with the next largest competitor having less than 5% market share. The market structure is therefore one in which there is a dominant firm, with smaller firms comprising a competitive fringe.

Items are listed on the website under three catalogs: main, sale, and outlet. The main catalog contains all full-priced offerings as well as some lightly discounted items. The sale catalog contains moderately discounted items, while the outlet catalog contains heavily discounted items, where the precise cutoffs between light, moderate, and heavy discounting vary over time. The three catalogs are mutually exclusive. All products offered by the firm are first listed in the main catalog, then gradually discounted and listed in the other catalogs as newer products are introduced, a common industry practice.

We run two field experiments through the online store. The first is an exploratory study in which new visitors to the website are exposed to added search frictions in one of three ways: (i) removing the direct link to the outlet section; (ii) removing the option to sort product listings by discount percentage; and (iii) removing item-specific visual markers that indicate the discount

percentage. A key objective in running this pilot experiment is to assess which, if any, of the treatments represent search costs that induce changes in purchase activity, while not increasing search costs to such an extent as to deter purchasing altogether.

In our second field experiment, we expose both new and returning customers to increased search frictions and measure how the treatment effects differentially impact conversion, discounts, and margins, depending on a shopper's estimated price sensitivity. This experiment complements our initial field experiment to achieve multiple objectives:

- It increases the sample size to include the firm's existing customers
- Because it is run during a sale season, the second experiment more closely aligns with the assumption of price being common knowledge in our theoretical framework
- It allows us to disentangle and explore additional means of implementing search frictions in an online store
- It allows us a replication of results on conversion and average selling price
- It allows us to assess whether varying levels of consumer information, particularly on prices, has impacts on the findings

The available data from the firm consists chiefly of transaction records containing product and customer attributes. Limited and high-level browsing data such as average session length and average number of sessions in each condition are available from a third-party web analytics provider; however, we do not have access to granular clickstream data and server logs. In order to measure heterogeneous treatment effects from our second field experiment, we use a regression model to classify existing consumers according to their price sensitivity using historical transaction data. We validate our classification by means of measuring response rates to randomly assigned email newsletters. Details for these classification steps are found in

## Appendix A.

*THEORETICAL FRAMEWORK*

We present a simple theoretical framework that is conceptually aligned to our field experiment design, which will help guide and interpret our empirical results and highlight differences between our operationalization of increasing search frictions versus other means outlined in our literature review.

*Model*

Consider a retailer who offers two horizontally-differentiated products—denoted by  $j = \{L, H\}$ —at two different prices,  $p_L$  and  $p_H$ , with  $p_L < p_H$  and  $p_L, p_H \in [0,1]$ . When a consumer lands on the retailer’s home page<sup>1</sup>, she decides which product to view first; this is analogous to either clicking a category tab (e.g. dresses, where displayed products are typically full-price) or clicking the sale/outlet button (where displayed products are typically discounted). After viewing a product and realizing her utility, the customer chooses whether to incur a search cost,  $s$ , to view the other product. Finally, she makes a purchase decision to buy at most one of the products she viewed. Since we consider only customers who search at least one product, we assume there is no search cost for the first product without loss of generality.

In our theoretical framework, we model the addition of search frictions—the treatment conditions in our field experiments—as the removal of the consumer’s option to view the low-priced product first, e.g. the removal of the outlet link on the home page. This forces the

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<sup>1</sup> As is the case with our partner retailer and many others, such a home page has banners directing the customer to other parts of the site and does not display products for sale.

customer to incur a search cost to view the low-priced product. Figure 1 provides an illustration of possible search paths in our theoretical framework and how they are related to the customers in the treatment and control groups in our field experiments. For ease of exposition and analogous to our empirical analysis, we will refer to customers offered search paths in Figure 1a as being in the control group and customers offered search paths in Figure 1b as being in the treatment group.

[Insert Figure 1 about here.]

Our customer utility and search model within this framework follows recent work in the search literature that examines obfuscation in settings with monopolistic competition (e.g. Petrikaitė 2018; Gamp 2016; Armstrong 2016). Specifically, we suppose there is a mass of consumers that is normalized to one, and each consumer has unit demand and wants to buy at most one of the two products. The net utility of consumer  $i$  who buys product  $j$  is denoted by  $u_{ij}$ , which equals the difference between her match value  $\epsilon_{ij}$  and the price  $p_j$  of the product, given the consumer's price sensitivity<sup>2</sup>  $\alpha \in [0,1]$ :  $u_{ij} = \epsilon_{ij} - \alpha p_j$ .

The match value indicates the valuation of product  $j$  by consumer  $i$ ; it is consumer- and product-specific. Match values are distributed independently and identically among consumers and independently among products, and we denote the pdf of  $\epsilon_{ij}$  as  $f_j(\cdot)$ . Product prices are common knowledge, but match values are only realized when products are inspected (e.g., Gu & Liu 2013).<sup>3</sup> The customer purchases the product that gives her greater utility, as long as it is

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<sup>2</sup> For ease of exposition, we do not index each consumer's price sensitivity,  $\alpha$ , and search cost,  $s$ ; instead, we provide results for varying  $\alpha$  and  $s$ .

<sup>3</sup> We follow the established convention in the search literature by modeling match values as random and prices as common knowledge. This is appropriate in our context because the scenario of interest is one in which the relative price comparisons are known (i.e., the average price in the sale section is lower than that in the main section), whereas such a comparison does not necessarily hold for realized match values. We also note that, strictly speaking, we require that consumers merely have correct expectations of prices rather than full information. We present empirical evidence in the *Caveats and Limitations* section that suggests this modeling assumption is appropriate.

positive. Since we consider a single, representative consumer in our following exposition, we will remove the subscript  $i$  for brevity.

Note that if the consumer views product  $j$  first, she is indifferent between continuing to search product  $j' \neq j$  if the expected gain from search equals the search cost, i.e.

$$\int_{\epsilon_{j'} = \epsilon_j - \alpha p_j + \alpha p_{j'}}^{\infty} (\epsilon_{j'} - \alpha p_{j'} - \epsilon_j + \alpha p_j) f_{j'}(\epsilon_{j'}) d\epsilon_{j'} = s$$

Define  $x_{j'} = \epsilon_j - \alpha p_j + \alpha p_{j'}$ , such that the above is satisfied. If  $\epsilon_j - \alpha p_j > x_{j'} - \alpha p_{j'}$ , then the expected gain from search is lower than the search cost and the consumer will not search product  $j'$ . However, if  $\epsilon_j - \alpha p_j < x_{j'} - \alpha p_{j'}$ , then it is worthwhile for the consumer to continue searching. Note that product  $j'$  has a positive probability of being inspected only if  $s \leq$

$$\int_{\epsilon_{j'} = \alpha p_{j'}}^{\infty} (\epsilon_{j'} - \alpha p_{j'}) f_{j'}(\epsilon_{j'}) d\epsilon_{j'}.$$

Let  $U^j$  be a random variable representing the customer's utility if she views product  $j$  first. The expected utility for a customer in the treatment group is  $E[U^H]$ , and the expected utility for a customer in the control group is  $\max\{E[U^L], E[U^H]\}$ . Finally, let  $d_k^j$  represent the demand (purchase probability) of product  $k$  if product  $j$  is viewed first, and let  $d^j = d_L^j + d_H^j$ . We omit the dependence of these terms on model parameters for brevity.

### *Impact of Increasing Search Frictions*

In this section, we analyze the model to better understand the impact that increasing search frictions has on two important retail metrics: conversion and revenue. Here, we define conversion as the probability that the customer purchases one of the two products rather than choosing the outside option, i.e.  $d^j$ . First, we will prove analytical results and build our intuition



for the special case where  $\epsilon_j \sim_{iid} Unif[0,1]$  and then extend our analysis and intuition for other common and non-identical match value distributions in Web Appendix D. Proofs of all results can be found in Web Appendix F.

As illustrated in Figure 1a, customers in the control group must choose which product to view first after landing on the home page, whereas customers in the treatment group are forced to view the high-priced product first.

**Lemma 1:** *When  $\epsilon_j \sim_{iid} Unif[0,1]$ ,  $E[U^L] \geq E[U^H]$ .*

Lemma 1 specifies that all customers in the control group choose to view the low-priced product first; thus, we will equate the search path starting with product  $L$  to customers in the control group and the search path starting with product  $H$  to customers in the treatment group. We note that this is not necessarily the case when the match values are not independent and identically distributed  $Unif[0,1]$ , and we address this further in Web Appendix D.

One may naturally hypothesize that conversion in the control group would always be greater than conversion in the treatment group, i.e. that increasing search frictions for low-priced products would make them costlier to find and therefore decrease overall conversion. Although this is sometimes true, the following theorem shows a somewhat surprising result that increasing search frictions may increase conversion.

**Theorem 1 (Conversion Comparison):** *When  $\epsilon_j \sim_{iid} Unif[0,1]$ ...*

- (i) *If  $s \leq \frac{1}{2}(1 - \alpha p_H)^2$ ,  $d^L = d^H$  and conversion would be the same regardless of if the customer was in the control or treatment group.*

- (ii) If  $\frac{1}{2}(1 - \alpha p_H)^2 < s \leq \frac{1}{2}(1 - \alpha p_L)^2$ ,  $d^L < d^H$  and conversion would be greater if the customer was in the treatment group.
- (iii) If  $s > \frac{1}{2}(1 - \alpha p_L)^2$ ,  $d^L > d^H$  and conversion would be greater if the customer was in the control group.

Theorem 1(ii) highlights the condition where conversion increases with search frictions. When  $\frac{1}{2}(1 - \alpha p_H)^2 < s \leq \frac{1}{2}(1 - \alpha p_L)^2$ , customers in the control group find it too costly to ever search the high-priced product and thus only consider the low-priced product, whereas customers in the treatment group may choose to search the low-priced product. Put differently, the search cost is high enough to force customers in the control group to only consider the low-priced product for purchase, but not too high to prevent customers in the treatment group from considering both products for purchase. With more products to choose from, customers in the treatment group are more likely to make a purchase, resulting in higher conversion. Upon inspection, we can see that as the consumer's price sensitivity  $\alpha$  increases, the range of search costs for which expected conversion is larger in the treatment group increases and shifts towards smaller values of  $s$ . Finally, note that the average selling price will be greater for customers in the treatment group since they are the only ones who purchase the high-priced product with positive probability.

In contrast, when  $s \leq \frac{1}{2}(1 - \alpha p_H)^2$ , Theorem 1(i) shows us that the search cost is low enough such that customers in either group will search and consider both products for purchase before choosing the outside option, and thus there is no difference in conversion. In this case, since customers in the treatment group view the high-priced product first, they are more likely to purchase this product than customers in the control group; given conversion is the same for both

groups, we conclude that the average selling price is also greater for customers in the treatment group. When  $s > \frac{1}{2}(1 - \alpha p_L)^2$ , Theorem 1(iii) shows us that the search cost is high enough such that customers in either group only view and consider the first product for purchase; since the low-priced product has greater demand when each are considered alone, conversion is greater in the control group. Trivially, average selling price is greater for customers in the treatment group.

Another important metric for retailers is revenue, and the following theorem reports on the impact of increasing search frictions on revenue. Although average selling price is greater for customers in the treatment group, we find that decreased demand may outweigh the benefit for high search costs.

**Theorem 2 (Revenue Comparison):** When  $\epsilon_j \sim_{iid} Unif[0,1]$ ...

- (i) If  $s \leq \frac{1}{2}(1 - \alpha p_L)^2$ ,  $p_L d_L^L + p_H d_H^L \leq p_L d_L^H + p_H d_H^H$  and the expected revenue would be (weakly) greater if the customer was in the treatment group.
- (ii) If  $s > \frac{1}{2}(1 - \alpha p_L)^2$  and  $\left| (1 - \alpha p_L)p_L - \frac{1}{2\alpha} \right| \geq \left| (1 - \alpha p_H)p_H - \frac{1}{2\alpha} \right|$ ,  $p_L d_L^L + p_H d_H^L \leq p_L d_L^H + p_H d_H^H$  and the expected revenue would be (weakly) greater if the customer was in the treatment group.
- (iii) If  $s > \frac{1}{2}(1 - \alpha p_L)^2$  and  $\left| (1 - \alpha p_L)p_L - \frac{1}{2\alpha} \right| \leq \left| (1 - \alpha p_H)p_H - \frac{1}{2\alpha} \right|$ ,  $p_L d_L^L + p_H d_H^L \geq p_L d_L^H + p_H d_H^H$  and the expected revenue would be (weakly) greater if the customer was in the control group.

The condition in Theorem 2(i) corresponds to the conditions in Theorem 1(i)-(ii).

Intuitively, since conversion and average selling price are weakly greater for customers in the treatment group, revenue is also weakly greater for customers in the treatment group.

Alternatively, when  $s > \frac{1}{2}(1 - \alpha p_L)^2$ , conversion is greater for the control group, yet average selling price is greater for the treatment group, and Theorem 2(ii)-(iii) highlights the conditions under which the additional revenue gain from showing the high-priced product first outweighs the decrease in conversion and when it does not. Figures 2 and 3 illustrate the magnitude of conversion and revenue for customers in the treatment and control groups for varying model parameters.

To summarize our analysis, we find that increasing search frictions may lead to higher or lower conversion and revenue, depending on the magnitude of the search cost. For low search costs, we find that conversion is identical and revenue is greater due to increased search frictions. For moderate search costs, we find that conversion and revenue are both greater due to increased search frictions. For high search costs, we find that conversion declines but revenue may or may not decline due to increased search frictions. The relative ranges of search costs (low, moderate, and high) shift as a function of the consumer's price sensitivity  $\alpha$ , and in particular, these ranges shift towards smaller search costs as consumers become more price sensitive; Figure 2 helps illustrate this observation. Our extended analysis in Web Appendix D suggests that our results are robust even under other, non-identical match value distributions. Given that the ranges of low, moderate, and high search costs—and even the search cost itself—are difficult for a retailer to estimate in practice, the remainder of the paper reports on field experiments we conducted to estimate the impact of increasing search frictions on conversion and revenue in practice. With this theoretical framework in mind, we can better understand and interpret the results of our experiment.

## *FIELD EXPERIMENT I*

In our first experiment, we seek preliminary evidence that specific changes to website design can have significant effects on shopper behavior and purchase outcomes. We vary the presence of website features that potentially facilitate shopper inspection of discounted items. We include only new visitors to the desktop version of the online store in order to mitigate potentially negative effects on the firm's performance and to control for prior information among consumers. In evaluating the outcomes, we are particularly interested in the treatment effects on the discount levels of completed transactions and conversion.

We run the experiment on the retailer's website over a period of nine days.<sup>4</sup> During this period, all new visitors to the website were randomly assigned to the control group or one of three treatment groups with equal probability. New visitors are defined as customers who do not have the website's cookies on their computers and sign up for a new account before making any purchase. Only visitors who were using a desktop, laptop, or tablet computer were included in the study. In total, 104,605 shoppers were included in the experiment. Posterior randomization checks confirm that the firm correctly implemented the randomization of new visitors to treatment and control groups. (See Table W3 in Web Appendix E for randomization checks.)

Additionally, only consumers who arrived at the site via the main landing page are included; we exclude consumers who visit the site via an email coupon, newsletter, or link from a third-party website. During the experiment no other changes were made to the website. Descriptions of the control and treatment conditions follow. In each of the treatment conditions, neither the available product assortment nor any product prices were different from the control

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<sup>4</sup> Field Experiment I ran on June 17-June 25, 2015.

condition.

*Control*

The control condition is simply the website as is at the time of the study. The website features elements designed to facilitate consumer search for discounted items. Customers have three ways to find discounted items: clicking on a prominent link from the landing page to the outlet catalog, sorting products according to discount level in each catalog through a drop-down option, and viewing markers that highlight discounts above 40% (see Figure W19 in Web Appendix E). In each of the treatment conditions, we eliminate each of these elements with the objective of reordering consumers' search paths and increasing the required effort to locate discounted items.

*Treatment 1: No link to outlet catalog from main landing page*

In this condition, we eliminate the most direct path to discounted items: the outlet link from the landing page. The remaining links to the outlet catalog are within the website's sale section, requiring at least one additional click from a shopper to arrive at the outlet catalog relative to those in the control group. In line with our theoretical framework, this would require consumers to view higher-priced items before viewing items with the largest discounts.

*Treatment 2: No discount filter and no discount markers*

Here we remove the ability of consumers to order product listings according to discount percentages. We also remove the accompanying discount markers, which provide visual cues for identifying high discounts. These elements are widely used together by online retailers to facilitate shopper search and navigation. Similarly to Treatment 1, this would cause consumers to load pages with higher-priced items first.

*Treatment 3: No outlet link, no discount filter, and no discount markers*

In our third treatment we simultaneously remove all website elements taken out piecemeal in the first two treatments. Our objective is to induce variation across our treatments in the magnitude of the search cost associated with inspecting discounted items. As with the first two treatments, visitors can still find discounted items with the requisite effort in typical locations throughout the site. Eliminating links, filters, and markers merely adds to the number of clicks, browsing time, and page views required to locate discounted items.

### *Evaluation*

In evaluating the effects of each treatment we consider several outcome variables<sup>5</sup>:

1. Average discount: the average ratio of selling prices to original prices<sup>6</sup> over items bought in each treatment group. Given that each treatment makes locating discounts more difficult, we expect percent discounts to be lower in treatment conditions relative to the control on average. We use this variable in place of selling prices as a means of enabling a consolidated presentation of results given the multi-category setting.
2. Percent full-priced purchases: the proportion of purchased items sold without discounting. Historically, about 50% of purchases on the website are made at full price. Similarly to the average discount, an increase in this variable in our treatment groups would be supportive of our hypothesis.
3. Average selling price: the average selling price of all items sold. Similarly to average discount and percent full-priced purchases, an increase in this variable in our treatment groups would be supportive of our hypothesis and results from our theoretical analysis.

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<sup>5</sup> We note that two of our outcome variables (average discount and percent full-priced purchases) are defined conditional on purchase; hence, they are computed using selected samples by construction. While not ideal for evaluating experimental results, this is a direct consequence of the behavior being studied and is in line with our theoretical framework (e.g. Sahni, Wheeler & Chintagunta 2018).

<sup>6</sup> The firm does not inflate original prices.

4. Conversion: the percent of consumers who opt to make a purchase on the website within the testing period. Our theoretical framework suggests that by inducing consumers to inspect more products, our manipulations may result in higher conversion, depending on relative search costs and price sensitivities. We track conversion to assess if this is true given consumer preferences in our empirical setting.

[Insert Table 1 about here.]

Table 1 contains results of the experiment. Customers in all three treatment groups purchased items at significantly lower discounts on average (11.5 to 12.3% off versus 15.7% off), and purchased more full-priced items (64.2% to 67.5% versus 59.8%).<sup>7</sup> The average selling prices of items purchased in the three treatments were significantly higher than in the control condition, indicating that a majority of consumers do not substitute to lower-priced items and possibly lower-margin items in response to the treatments.

We show in our theoretical framework that overall conversion may either increase or decrease depending on the sensitivity of consumers to price and search costs. A natural concern is that if search frictions for finding discounted items are increased too much, then the expected result of reducing discounted purchases could also be accompanied by lower conversion. This is of particular concern for first time shoppers, who may be unaware of the availability of lower-priced items on the website. Yet, we found no significant decrease in conversion, as measured by the number of transactions completed in any of the treatment conditions versus the control group. As shown in Table 2, conversion was slightly higher in treatments 1 and 2. Combining these results with our theoretical analysis suggests that for some customers, their search costs and price sensitivities were such that they would choose to incur a search cost to view the discounted

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<sup>7</sup> The average discount across the three treatment groups was 11.8%, which is significantly different from the control at  $p=0.000$ .



products if assigned to a treatment group, but would not incur a search cost to view the full-priced products if assigned to the control group (analogous to condition (ii) in Theorem 1).

As a robustness check, we performed a comparison across treatments and control groups at the basket level (versus item level) to compare differences in shopping behavior with respect to total purchase value and composition decisions. Confirming the main item-level results, Table 2 shows that the average discount of purchase baskets in two out of the three treatments is significantly lower than for the control group (11.6 to 12.2% versus 14.5%). For treatment 3, it is marginally significantly lower. Average basket sizes in any of the treatment groups are not significantly smaller than the control group, although in treatment 3 there were fewer items in each basket on average.

[Insert Table 2 about here]

These results provide supporting evidence for our hypothesis and demonstrate that our manipulations have a measurable impact on consumer choice. Given that discounts in fashion and apparel retail are directly tied to gross margins, our results additionally show that online retailers can increase their margins without sacrificing conversion by slightly increasing search frictions associated with their discounted offers. (See Table W4 in Web Appendix E for measurements of the impact on profitability of the treatment conditions.)

In a setting without search frictions, we contend that consumers inspect discounted options “for free.” By increasing search frictions, online retailers can direct consumers toward full-priced options while still making discounted options available for price-sensitive shoppers willing to incur the extra search cost to find them. In the following sections, we verify that such heterogeneous treatment effects underlie our main results.

## *FIELD EXPERIMENT II*

In our second experiment we investigate the pattern in which shopper responses to added search frictions vary according to price sensitivity and their familiarity with the retailer. Analogous to Field Experiment I, we expose consumers to different versions of the online store, each with a manipulation designed to increase search frictions. We compare the impact of the treatments versus control on retailer performance measures and use consumer purchase histories to characterize the heterogeneity in shopper responses. In addition, this experiment also serves as a replication of our first experiment, run during a sale season approximately one year afterward with a wider set of treatments and a broader set of subjects.

### *Experimental Design*

We ran this experiment for two weeks on the desktop and tablet versions of the online store. All consumers were randomly assigned to either the control group or to one of four treatment groups with equal probability. Whereas in Field Experiment I we included only new visitors entering through the main landing pages, here we include new as well as returning consumers regardless of which page they view first. This is a strong test of our model-based predictions as it seeks to find the conjectured shopper behavior in a population with presumably high variation in information. A total of 348,110 visitors are included in this experiment (see Table W6 in Web Appendix E for randomization checks.) The treatment conditions are as follows:

*Treatment 1:* Removal of links from main pages to outlet and sale sections of the website

*Treatment 2:* Removal of discount markers

*Treatment 3:* Removal of discount sorting option

*Treatment 4:* Replacement of discount-oriented banners with non-discount oriented banners

In contrast to Field Experiment I, we assign the removal of discount markers and sorting options into two different treatments to separately measure the effects of each intervention. We also add a fourth treatment, the use of non-discount-oriented banners throughout the site (see Figure W22 in Web Appendix E for examples of discount banners). In practice, discount-oriented banners serve a dual purpose: to communicate the existence of marked down items as well as a navigation tool to access the relevant product listings.

The design of specific discount and replacement banners can introduce additional factors that may impact our results. Similar, if less pronounced, contamination is present in each of our other manipulations, particularly since correlation between discounts and non-price attributes are likely to be nonzero. Given the nature of our proposed mechanism and natural constraints in the field experiment setting, we cannot completely eliminate these confounds; however, we seek to mitigate them by including multiple variations between treatments.

[Insert Table 3 about here.]

## *Results*

Before assessing the impact of price sensitivity on shoppers' propensities to find and buy discounted items, we conduct the same analysis as in Table 1, which pools all types of consumers and present the results in Table 3. Further validating the main findings in Field Experiment I, this time including existing and new customers, we find that removing discount markers, sorting by discount and discount-oriented banners (Treatments 2 to 4) decreases both the average discount of items purchased as well as the incidence of purchasing items on

discount.<sup>8</sup> As before, this is achieved without a decrease in conversion. An exception to this, and counter to the findings in Field Experiment I, is the null effect of the removal of outlet and sales links from the home page (Treatment 1). A possible explanation is that current customers were not as deterred as new shoppers from finding the high discounts, in the sense of differences in perceived search costs.<sup>9</sup> With the exception of this treatment, the addition of search costs impacts new and current customers in a qualitatively very similar manner.

[Insert Table 4 about here.]

Next, we measure the interaction between shoppers' price sensitivity and their willingness to incur search costs to find discounted items. We classify existing customers according to their price sensitivity using historical transaction data. (Details are in Appendix A.) While using observational data as we do to infer price sensitivity has limitations, we note that any deficiency in predictive accuracy would bias our results toward a false negative in detecting heterogeneous treatment effects.

In Table 4, we group consumers into three quantiles according to their price sensitivity as indicated by predicted values from the full model (column 4 of Table A3 in the appendix). In an additional validation of our classification model, we find that low price sensitivity consumers are directionally more likely to purchase full-priced items in all treatment groups (first row). In three of four treatment groups, we observe statistically significant increases in the proportion of full-priced items bought by customers with low price sensitivity. Equally notable, this is not the case for medium or high price sensitivity consumers, who willingly incur search costs to avail of

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<sup>8</sup> The average discount across the three treatment groups was 17.0%, which is significantly different from the average discount in the control condition of 18.2% at  $p=0.0042$ .

<sup>9</sup> See Web Appendix C for a description of the difference in outcomes for new versus existing customers.

discounts. This result provides additional evidence, by including current users and adding other forms of search costs to the website, that online retailers can improve their margins and, thus, profitability, by deliberately adding small frictions to the shopping process. We present actual profitability measures in Table W7 in Web Appendix E using item-level marginal cost data provided by the firm.

Our theoretical framework posits that higher conversion is a consequence of more products inspected in regions of moderate search costs. Unfortunately, we lack the granular data required to precisely measure the number of products inspected by consumers. We do, however, have access to aggregate data on browsing behavior available through the firm's web analytics provider. Table 5 presents key measures of browsing behavior across each treatment group. On average, visitors falling within each treatment group visited the website more times during the testing period, spent more time during each visit, and viewed more pages. These are consistent with our proposed mechanism for employing search frictions. Specifically, locating discounted items would necessarily involve more time spent on the website in the treatment conditions. As suggested by our theoretical analysis, we conjecture that these changes in browsing behavior may have concurrently resulted in shoppers considering a broader set of products, thus leading to higher conversion.

[Insert Table 5 about here.]

### *Caveats and Limitations*

Our two field experiments provide convergent evidence that increasing search frictions may be profitable for a monopolistic online seller in the short run. While we replicate our results under different demand conditions and consumer profiles, natural questions remain pertaining to

alternative explanations for our empirical findings, the generalizability of our results to other online retail contexts, and the long-term viability of increasing search frictions. In this subsection we provide suggestive evidence that points to probable answers to some of these questions, and to potential directions for future research.

While the results of our experiments conform to the main predictions of our theoretical framework, the nature of our empirical setting allows for alternative explanations to potentially be at play. A few such mechanisms arise when our assumption that consumers have rational expectations is violated. If, contrary to our assumptions, consumers have mistaken beliefs about product quality or prices, then inducing them to take alternative search paths may cause them to change their purchase behavior by updating their beliefs. Alternatively, consumers may update their priors about outside options differently depending on their realized search patterns.

Another potential factor that we do not account for are store-level preferences that may be influenced by our treatments. For instance, customers who do not see links to sale or outlet sections may perceive the firm as being of higher quality than those in the control condition. The elimination of links in our treatment conditions may also simply present a more pleasing interface, thus resulting in better sales results.

We are constrained in our ability to determine how important these alternative accounts are relative to that laid out in our model. Some of these constraints are natural, such as our inability to measure consumer beliefs; others pertain to data limitations, such as our lack of clickstream data. One source of variation in the data we can inspect is that between new and existing customers. There is a reasonable expectation that, relative to existing customers, new customers have less information about firm and product attributes.

We explore the differences in results between new and existing customers and find no systematic differences (see Figure W2, Table W9, and Table W10 in Web Appendix C and E). Our treatments appear to increase both conversion and the proportion of full-priced purchases among both groups at comparable margins. This suggests that information updating likely has a limited role in generating our experimental results. Furthermore, it suggests that both new and existing consumers have reasonable expectations on prices offered by the retailer, in line with our theoretical model. Nonetheless, we recognize that the mechanism we emphasize in this paper is unlikely to fully account for our experimental results.

We consider the conjecture that increasing search frictions may cause consumers to switch to alternatives in the presence of competing firms. While our data provider has no similar-sized competitors online, they offer items under a private label in addition to items from national and global brands. The firm faces less competition for its private label products, which are available only on their online store, than for the rest of its products, which are available from offline sellers. We examine the outcomes within each of these categories in an effort to find evidence of heterogeneous treatment effects, which would be indicative of the role of competition. If consumers are prone to switching to competitors upon facing added search frictions, then they should be more likely to buy store brand products in the treatment conditions. Table 6 presents the portion of items sold in each treatment group that are store brand products.

[Insert Table 6 about here.]

We find that in none of the treatment conditions is the ratio of store brand to national/global brand items sold significantly higher than in the control, which suggests that the

presence of competitors for branded products does not play a significant role in mitigating our results within this setting.

We turn our attention to the potential long run effects of increasing search frictions in an online store. Transaction and web browsing data are available for several periods beyond the end of our experimentation, and may point to specific long run effects. We consider cohorts of consumers falling into each of the randomly assigned groups from Field Experiment II and track their revisit rates and conversion over time. Table W8 in Web Appendix E shows the number of consumers who visited the website during our sample period of two weeks in 2016. For each half-month period thereafter, until the end of the year, we list the number of users from the original sample who visit the website and corresponding conversion.

We find no evidence that consumers in the treatment conditions had lower revisit rates than that in the control. In fact, for every month and treatment group, the revisit rate is higher among the treatment cohorts than in the control cohorts at  $p < 0.01$ . Qualitatively similar measurements are obtained from groups in Field Experiment I. This is perhaps unsurprising given that the conversion was higher in the treatment groups compared to the control group, implying that customers were able to more successfully find products they like and are therefore more likely to be return shoppers. Interestingly, this suggests the possibility that increasing search frictions leads to improvements in customer satisfaction and retention.



## *CONCLUSION*

Online retail represents a rapidly growing proportion of overall retail sales. However, margins in online retail can often be smaller than in offline retail. One conjecture for this discrepancy is that online sellers are less able to price discriminate compared to their offline counterparts. In this paper, we explore how deliberately imposing additional search costs on online shoppers can improve gross margins by increasing the number of items inspected and serving as a sorting mechanism among customers.

We find encouraging evidence that minor changes to the design of an online store can substantially improve its margins and profitability. By increasing search frictions in simple ways—removing selected links, narrowing down product sorting options, and limiting visual markers—online sellers can achieve more full-priced sales from price-insensitive shoppers who face higher search costs. As a result, the average selling price increases due to a higher proportion of full-priced items sold.

Our theoretical model shows how increasing search frictions may either increase or decrease conversion depending on consumer preferences. Through our field experiments, we find that conversion increases upon the addition of search frictions in a typical online retail setting. Inspecting browsing behavior in the treatment groups suggests that as visitors spend more time on the website given higher search frictions, they may also be considering a larger set of products.

Our results have direct implications for online sellers. Without changes to product prices or assortment, online sellers can improve their margin performance by implementing subtle changes to website design. We note with particular excitement that this is a low-cost

manipulation with low data requirements, and one that can deliver large gains in margin. Our findings imply that by indiscriminately prioritizing ease of search and purchase, online sellers may be giving up gross margins by unwittingly giving away discounts to price-insensitive consumers and curtailing consumer exploration of the product assortment.

Our research also suggests that some online browsing behavior can be effortful or time-consuming enough for shoppers to prefer paying higher prices. We consider it a fruitful area for future research to determine which specific properties of online interaction consumers find most effortful. This can provide helpful guidance for a wide array of applications, from online store design to digital advertising.

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## TABLES

Table 1: Results of Field Experiment I

Group	Number of Visitors	Average discount of purchased items	Percent full-priced purchases	Average selling price (Philippine Pesos)
Control	26,014	15.74% (0.81)	59.77%	751.75 (27.20)
Treatment 1	26,199	11.54%*** (0.71)	67.48%***	907.05*** (42.08)
Treatment 2	26,343	12.32%*** (0.69)	64.19%*	1,137.07*** (64.44)
Treatment 3	26,049	11.49%*** (0.75)	66.04%**	1,035.87*** (61.45)

H<sub>0</sub>: value is equal to that in the control condition. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Standard errors are in parentheses.

**Table 2: Basket level results from Field Experiment I**

<b>Group</b>	<b>Average discount</b>	<b>Average basket size</b>	<b>Transactions completed</b>	<b>Number of items</b>
<b>Control</b>	14.53% (1.01)	1,609.87 (74.15)	318	2.14 (0.14)
<b>Treatment 1</b>	11.56% ** (0.88)	1,775.78 (115.74)	355*	1.96 (0.08)
<b>Treatment 2</b>	12.23% ** (0.86)	2,280.55*** (203.33)	355*	2.01 (0.08)
<b>Treatment 3</b>	11.96% * (0.88)	1,826.73 (158.13)	334	1.76*** (0.06)

H<sub>0</sub>: value is equal to that in the control condition. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Standard errors are in parentheses.



**Table 3: Results of Field Experiment II**

<b>Group</b>	<b>Number of visitors</b>	<b>Average discount of purchased items</b>	<b>Percent full-priced purchases</b>	<b>Number of transactions (Conversion)</b>
<b>Control</b>	68,343	18.25% (0.42)	48.83%	1,351 (1.98%)
<b>Treatment 1 No outlet and sales links</b>	70,058	17.32%* (0.37)	50.15%	1,599 (2.28%)***
<b>Treatment 2 No discount markers</b>	70,025	16.69%*** (0.36)	51.78%**	1,605 (2.29%)***
<b>Treatment 3 No discount sorting</b>	69,859	17.09%** (0.37)	51.47%**	1,605 (2.30%)***
<b>Treatment 4 No discount banners</b>	69,825	16.80%*** (0.35)	52.58%***	1,713 (2.45%)***

H<sub>0</sub>: value is equal to that in the control condition. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Standard errors are in parentheses.

**Table 4: Proportion of items bought at full price**

<b>Price sensitivity</b>	<b>Control</b>	<b>Treatment 1 No outlet and sale links</b>	<b>Treatment 2 No discount markers</b>	<b>Treatment 3 No discount sorting</b>	<b>Treatment 4 No discount banners</b>
<b>Low</b>	58.73% (2.59)	67.90%** (2.49)	66.82%** (2.29)	63.91% (2.16)	67.38%*** (2.17)
<b>Medium</b>	54.02% (1.85)	52.17% (1.69)	56.95% (1.67)	53.12% (1.73)	57.08% (1.52)
<b>High</b>	36.30% (2.01)	40.64%* (1.87)	38.52% (2.04)	32.62% (2.07)	33.22% (1.93)

$H_0$ : value is equal to that in the control condition. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Standard errors in parentheses. We test whether the differences between price sensitivity bins within treatment and control groups are statistically significant and find that pairwise comparisons all have p-values less than 0.05. We report p-values for each pairwise comparison in Table W11 in Web Appendix E.

**Table 5: Browsing behavior**

<b>Treatment group</b>	<b>Avg. sessions per user</b>	<b>Avg. session duration (seconds)</b>	<b>Avg. pages viewed per session</b>
<b>Control</b>	2.13	438.99	7.37
<b>Treatment 1: No outlet and sale links</b>	2.21	457.44	7.59
<b>Treatment 2: No discount markers</b>	2.27	456.65	7.59
<b>Treatment 3: No discount sorting</b>	2.26	458.63	7.65
<b>Treatment 4: No discount banners</b>	2.27	459.25	7.63

Disaggregated data and standard deviations are unfortunately not available, precluding hypothesis testing. A session is defined as a set of interactions, no two of which occur more than 30 minutes apart.

**Table 6: Store branded products as percent of items sold**

	<b>No. of store brand items sold as percent of total number of items sold</b>	<b>p-value</b>
Control	18.97	
Treatment 1: No outlet and sale links	18.88	0.9242
Treatment 2: No discount markers	16.71	0.0224
Treatment 3: No discount sorting	17.22	0.0809
Treatment 4: No discount banners	19.14	0.8639

$H_0$ : value is equal to that in the control condition.

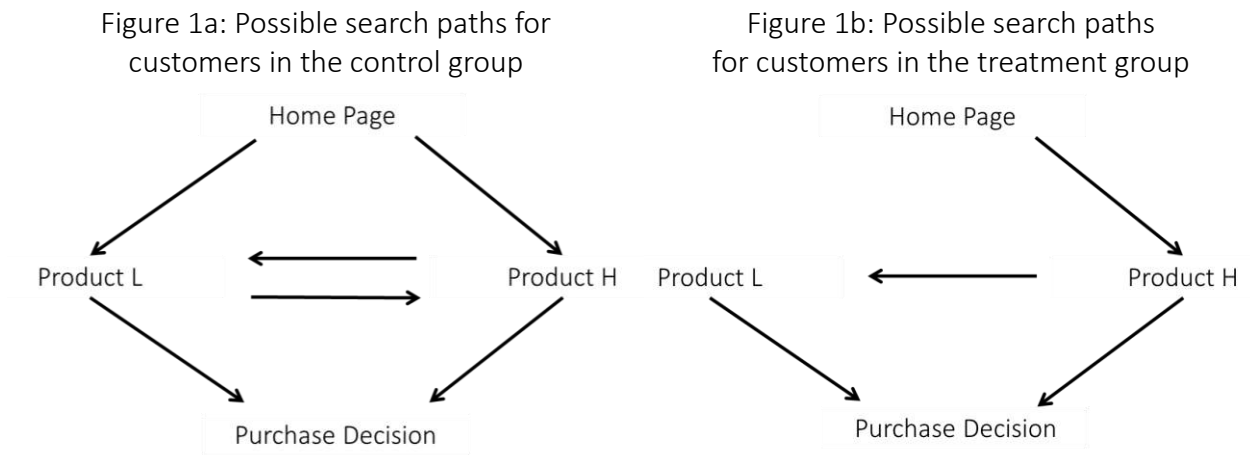
**FIGURES****Figure 1: Possible Search Paths**

Figure 2: Conversion Comparison for  $\epsilon_j \sim \text{Unif}[0, 1]$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$

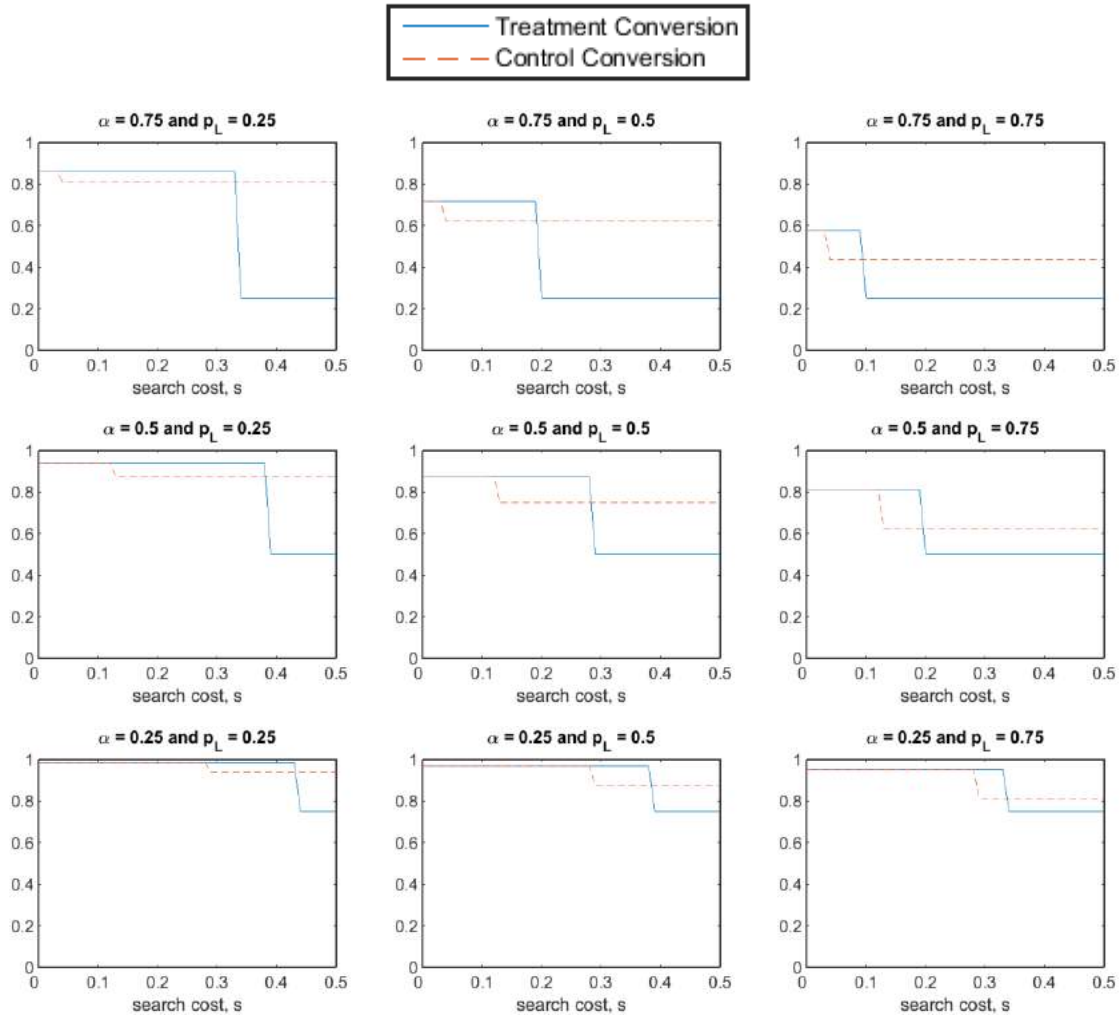
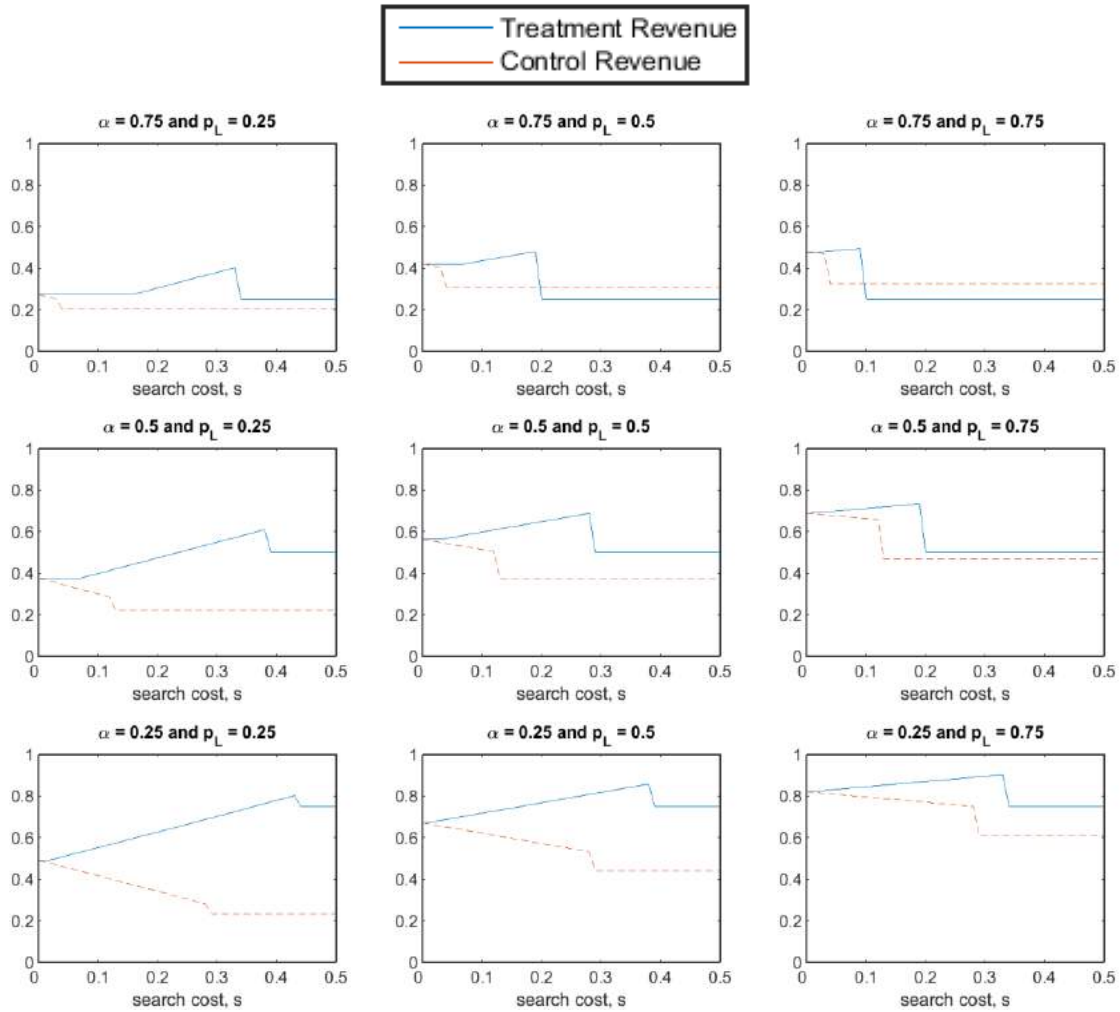


Figure 3: Revenue Comparison for  $\epsilon_j \sim iid \text{Unif}[0, 1]$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$



## **APPENDIX A: Approximating Price Sensitivity**

Our theoretical framework predicts differential effects of search frictions on price-insensitive versus price-sensitive shoppers. The predicted impact on purchase behavior should disproportionately affect the former. We develop a parsimonious empirical model of price sensitivity for shoppers in our setting. Its purpose is to provide us with a means of classifying consumers according to their baseline appetite for discounts. We use the predicted values of this model as a proxy for price sensitivity. After estimating the model, we assess its predictive accuracy by comparing the behavior of pre-classified groups of shoppers in a validation field experiment.

### *Data*

The data for this analysis consists of the retailer's historical transaction-level sales records from its inception in September 2012 until September 2015. Over 2.5 million individual items were sold whereby 418,039 consumers made over one million transactions during that period. Each record (an item sold) contains shopper attributes, product attributes, and transaction attributes. Tables A1 and A2 provide a description of the available data and basic transaction-level summary statistics.



**Table A1: Classification data set summary statistics**

<b>Start date</b>	3 September 2012
<b>End date</b>	30 September 2015
<b>Records (items sold)</b>	2,609,421
<b>Transactions</b>	1,099,683
<b>Unique customers</b>	418,039
<b>Unique items</b>	547,574
<b>Unique brands</b>	2,380

**Table A2: Transaction summary statistics**

	<b>Mean</b>	<b>S.D.</b>
Item selling price (in Ph. Pesos)	651.69	700.70
Item original price (in Ph. Pesos)	903.23	1,017.00
Discount percentage	15.94	22.44
Items per transaction	2.37	2.50
Basket size (in Ph. Pesos)	1,546.38	1,940.27

*Model*

We estimate a simple model of price sensitivity in order to determine through a succeeding field experiment whether price sensitive shoppers are more willing to bear search costs to locate discounted items online. Since the primary objective of estimation is not to identify primitives of consumer utility, but merely to discriminate between price-insensitive and price-sensitive shoppers, we adopt a parsimonious model that aims to explain the basket-level discount of completed transactions. The underlying assumption is, all else equal, that highly price-sensitive shoppers are more likely to purchase discounted items than price-insensitive

shoppers. Categories of explanatory variables for price sensitivity include demographic characteristics, prior transaction behavior, and shopping conditions known to be associated with discount-seeking behavior.

These variables were chosen based on availability and management's expectation of their relationship to discount purchasing. We run a series of Tobit regressions of most recent average basket discount on these covariates and present estimates in Table A3. As per prior literature, we use a Tobit model given that discounts are a left-censored (at zero) proxy for price-sensitivity, our conceptual variable of interest (Lambrecht & Skiera 2006; Van Heerde, Gijsbrechts & Pauwels 2008). In order to evaluate the relative importance of demographics, prior transaction behavior, and current shopping conditions, we estimate separate regressions for each subcategory of explanatory variables in addition to the full model.

### *Results*

In general we find that relationships between consumer attributes, prior shopping behavior, current shopping conditions, and current shopping behavior are strong and robust to the usage of different choices of covariates. Each category of explanatory variables (corresponding to columns in Table A3) improves the ability of the model to predict preference for discounts. Observed discounts are lower for men and older customers. They are higher for customers who have previously bought at higher discounts, used coupons, and bought more store branded items. Meanwhile, discounts are lower for consumers who redeem coupons in the current purchase instance, use store credit, and have more previously completed transactions.

We use the empirical model estimated in this section to pre-classify shoppers according to their levels of price sensitivity in order to articulate the mechanism behind our main result in

Field Experiment 1. In effect we use all of the available information on consumers to achieve this classification, assigning weights to each variable according to its estimated coefficient. We consider this to be an improvement over an ad hoc classification, say, by grouping shoppers according to the average discount in their purchase histories. However, we also recognize the shortcomings of this approach owing to the aggregation of information, the lack of information on visits that result in no purchase, and the changing assortment over time. In order to increase our confidence in the resulting classification, we seek to establish its external validity. In the next section, we describe how we validate our classification model by measuring responses to email newsletters in a field experiment.

**Table A3: Tobit regression for price sensitivity**

Variables		1	2	3	4	
<b>Model</b>	Male	-0.254*** (0.009)			-0.197*** (0.011)	
	Age	-0.126*** (0.011)			-0.111*** (0.013)	
	Prev average discount		0.396*** (0.002)		0.392*** (0.002)	
	Prev coupon usage <sup>10</sup>		0.325*** (0.009)		0.458*** (0.009)	
	No. of previous transactions		-0.645*** (0.049)		-0.500*** (0.049)	
	Prev store brand ratio		0.170*** (0.013)		0.125*** (0.012)	
	Time since first purchase		0.174*** (0.021)		0.149*** (0.020)	
	Store credit dummy			0.150*** (0.014)	-0.323** (0.147)	
	Coupon dummy			-0.336*** (0.008)	-0.544*** (0.010)	
	Constant	0.141*** (0.007)	-0.166*** (0.008)	0.704*** (0.013)	0.278*** (0.100)	
	<b>Sigma</b>	Constant	0.331*** (0.000)	0.310*** (0.000)	0.329*** (0.000)	0.307*** (0.000)
		Billing region FE	yes	no	no	yes
Month FE		no	no	yes	yes	
Observations		1,112,297	698,456	1,112,298	698,456	
Pseudo R2	0.00324	0.0576	0.0105	0.0729		

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Standard errors are in parentheses.

<sup>10</sup> The dependent variable is the discount before any coupons; hence, this coefficient implies substitution by consumers between product-specific discounts and coupon-based discounts.

## APPENDIX B: Validation Experiment

We test the external validity of our empirical model of price sensitivity. We send discount and non-discount oriented email newsletters to randomly assigned consumers and test whether the classification determined by the Tobit model of the previous section is indeed associated with a higher response rate for discount (versus non-discount) emails for price-sensitive (versus price-insensitive) shoppers.

### *Experimental Design*

We include the firm's entire mailing list of 246,688 consumers in this experiment. A consumer gets on the mailing list by providing his or her email address to the firm through registering an account, signing up for updates, or requesting a coupon. Consumers were randomly assigned to two groups, henceforth Group 1 and Group 2. Each group received a schedule of both discount- and non-discount-oriented newsletters as presented in Table B1 in order to counteract day-of-week effects.

**Table B1: Schedule of newsletter treatments**

	<b>Group 1 (50%)</b>	<b>Group 2 (50%)</b>
<b>Sunday</b>	Control	Control
<b>Monday</b>	Discount	Full price
<b>Tuesday</b>	Discount	Full price
<b>Wednesday</b>	Discount	Full price
<b>Thursday</b>	Full price	Discount
<b>Friday</b>	Full price	Discount

The control newsletters sent out on Sunday were non-discount oriented and identical

between groups whereas, within each day, only the discount versus non-discount messaging was different between groups. For each newsletter sent, we observe whether the email was opened and which link within the email, if any, was clicked by the recipient. We also observe all transactions on the website, which we can link to consumers in the experiment via their email addresses.

Product categories featured on the email newsletters varied between days, but were kept constant between control and treatment groups within days. Care was also taken to keep all creative elements on the newsletters constant, such that only discount messaging (e.g. “up to 40% off”) and any price information varied in the execution. This variation in messaging was also reflected in the subject line. For an example of a discount and full-price email used, see Figure W21 in Web Appendix E.

Customers on the mailing list vary in the frequency with which they opt to receive newsletters. The breakdown is that 62.34% of subscribers receive them every day, 3.32% receive them three times a week, and 34.35% receive them once a week. Figure W20 in Web Appendix E shows the daily schedule for each pattern. The newsletter schedule shown in Table B1 was designed to gain maximum variation among consumers regardless of their frequency as well as minimize any day-of-week effects.<sup>11</sup>

In order to establish the validity of the classification of the Tobit model, we generate predicted values from the model given each consumer’s purchase history prior to the newsletter experiment in this paper.<sup>12</sup> We argue that our model is indicative of price sensitivity if consumers

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<sup>11</sup> The original plan included a pair of newsletters for Saturday that followed Friday’s pattern; however due to a server failure the emails were never sent out.

<sup>12</sup> Only consumer-specific and purchase history variables (male dummy, customer age, previous discount, previous coupon dummy, number of previous transactions, store brand purchase ratio, time since first purchase) will be included in the prediction. The predicted values themselves will have no direct interpretation, but will be treated as sufficient statistics for price sensitivity.

we predict to be more price-sensitive have a higher propensity to open and click on discount-oriented versus non-discount-oriented emails. Since the final experiment will compare average shopping behavior across groups of consumers, price-sensitive and insensitive, the classification model only needs to be accurate at the group level rather than at an individual level, thus the choice of a parsimonious model specification.

### *Results*

We regress newsletter outcome variables on our variables of interest. Each record in the following regressions is an email-customer pair. The dependent variables are binary, where success is either an opened or a clicked email. The independent variables are: a discount email dummy, predicted price sensitivity from the empirical model, the interaction between discount email and price sensitivity, and day of the week.<sup>13</sup>

**Table B2: Regressions on newsletter response variables**

<b>VARIABLES</b>	<b>(1) open</b>	<b>(2) click</b>	<b>(3) click   open</b>
Constant	0.207*** (0.00630)	0.0328*** (0.00324)	0.152*** (0.0141)
Discount dummy*Price_sensitivity	0.125*** (0.0420)	0.0505** (0.0216)	0.0728 (0.0933)
Discount dummy	-0.0149* (0.00811)	-0.00103 (0.00417)	0.0188 (0.0181)
Price_sensitivity	0.0402 (0.0297)	0.0248 (0.0153)	0.0868 (0.0671)
Day dummies	yes	yes	yes
Observations	106,534	106,534	22,043
R-squared	0.002	0.001	0.003

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

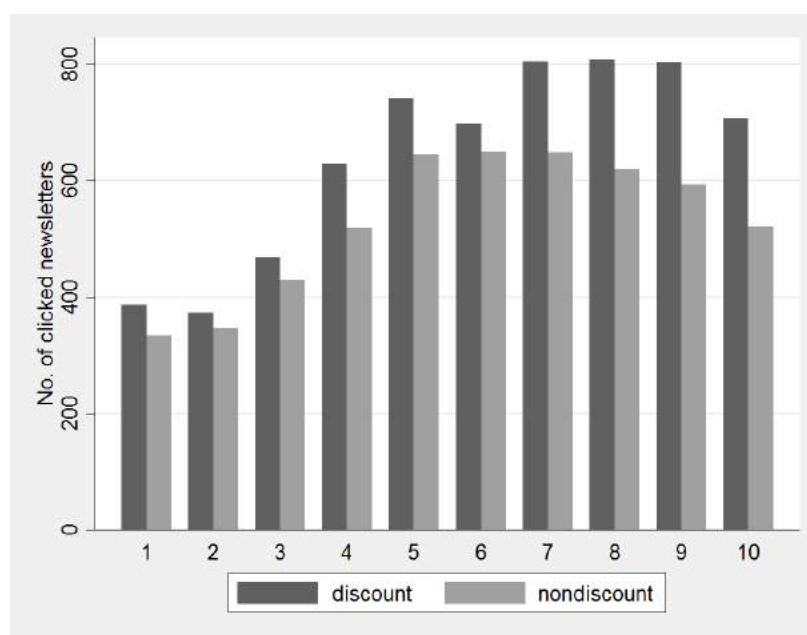
We find that our measure of price sensitivity is significantly positively correlated with the

<sup>13</sup> We include only consumers with at least one past purchase in this analysis. Hence, consumers in this regression are a subset of consumers in the classification analysis in Appendix A—namely those that have not opted out of receiving email newsletters.

probability of responding (e.g., click or open) to a discount-oriented email relative to a non-discount oriented email. Table B2 considers the relationship between price sensitivity and three response variables: (1) whether the email was opened, (2) whether a link in the email was clicked, and (3) whether a link was clicked conditional on the email being opened. We find that price sensitivity is positively associated with the first two measures.<sup>14</sup>

Figure B1 provides evidence of the relationship between our constructed price sensitivity measure and the likelihood of responding to each type of newsletter. There is a clear positive relationship between price sensitivity, as measured in decile membership, and the likelihood of clicking a discount newsletter relative to the probability of clicking a non-discount newsletter.

**Figure B1: Newsletter click counts by price sensitivity decile**



Note: Higher deciles correspond to higher price sensitivity.

<sup>14</sup> We include the third measure, click conditional on open, for completeness; however because random assignment is not preserved for this measure the associated parameters are not relevant for our purposes.



**Web Appendix of**  
**“The Impact of Increasing Search Frictions on Online Shopping Behavior:**  
**Evidence from a Field Experiment”**

**WEB APPENDIX A: Variation in non-price attributes**

Our theoretical framework assumes the same distribution of non-price attributes for different price and discount levels. While not crucial to our main results, variation in non-price attributes may influence the results from our field experiments. For instance, if by re-ordering search paths we expose consumers to products that are of higher quality in addition to being higher priced, this may cause a further increase in purchase probabilities overall and of full-priced products in particular. Our empirical setting of fashion and apparel retail limits our ability to generate non-price variables that can reliably be thought of as corresponding to product quality. However, the data include brand variables as well as indicators for whether an item was returned. We consider these variables as proxies for product quality.

We begin exploring this possibility by measuring the correlation between discounts and non-price attributes in the data. For this analysis, we use the entire data set of transactions available to us, excluding periods covered by our field experiments. To avoid conflating category-specific factors we focus our analysis on shoes, the most commonly purchased category.

**Table W1: Average discount percentage (top entries) and transaction counts (bottom entries) by brand and return status**

	<b>Store brand</b>	<b>Not store brand</b>	<b>Total</b>
<b>Returned</b>	24% 16,603	22% 59,048	22% 75,651
<b>Not returned</b>	26% 199,534	20% 852,845	21% 1,052,379
<b>Total</b>	25% 216,137	20% 911,893	21% 1,128,030

Inspecting average discounts shows that store brand shoes have higher discounts on average (statistically significant with  $p < 0.01$ ), by about a five percentage point spread. Return status seems to have a less straightforward relationship with discounts on average. Store brands are widely considered to be less desirable than branded items, and such is the case for our partner firm. Therefore, there does seem to be a relationship between quality and discounts in at least one dimension.

In order to gauge the impact of this variation on our findings, we split our purchase outcome measures by store-brand and non-store brand purchases and present counts in Table W2. Most relevantly for our research objectives, we find that there are more items sold for both store brand and non-store brand items in each of our treatment conditions relative to the control. This implies that the dominant impact is the increase in purchase likelihood as a result of more items being inspected by the average consumer, rather than a substitution from store brand to non-store brand items.

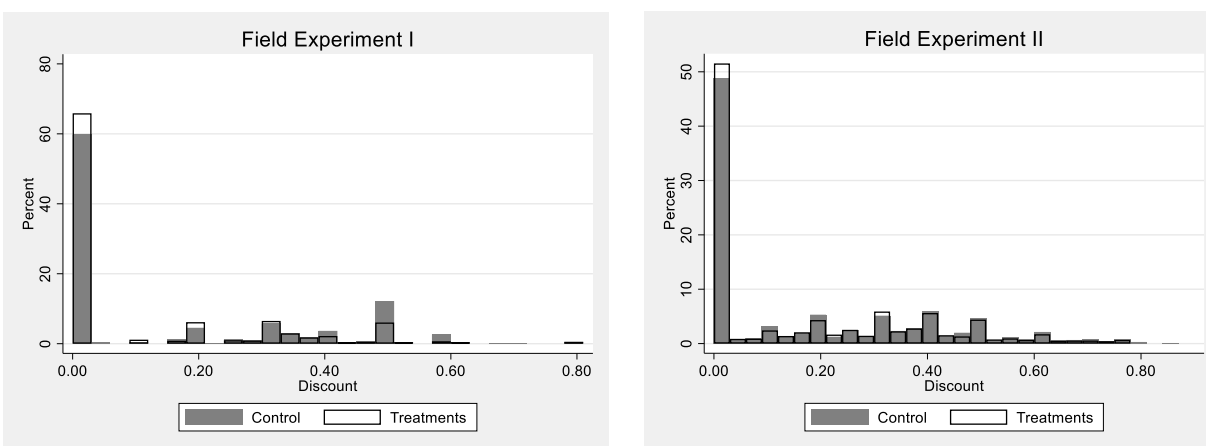
**Table W2: Store brand and non-store brand products sold in Field Experiment II**

<b>Treatment Group</b>	<b>Number of items sold</b>	
	<b>Store brand</b>	<b>Non-store brand</b>
<b>Control</b>	514	2,195
<b>Treatment 1 No outlet and sales links</b>	546	2,722
<b>Treatment 2 No discount markers</b>	622	2,673
<b>Treatment 3 No discount sorting</b>	546	2,625
<b>Treatment 4 No discount banners</b>	694	2,931

## WEB APPENDIX B: Distribution of product discounts

We present histograms that show the distribution of product discounts from both of our field experiments. In each subplot of Figure W1, we pool observations from the treatment conditions and overlay the histogram with that of the control condition. In both field experiments, substitution between control and treatment occurs primarily between full-priced purchases and discounted purchases more generally, with little substitution from higher discounts to lower discounts otherwise.

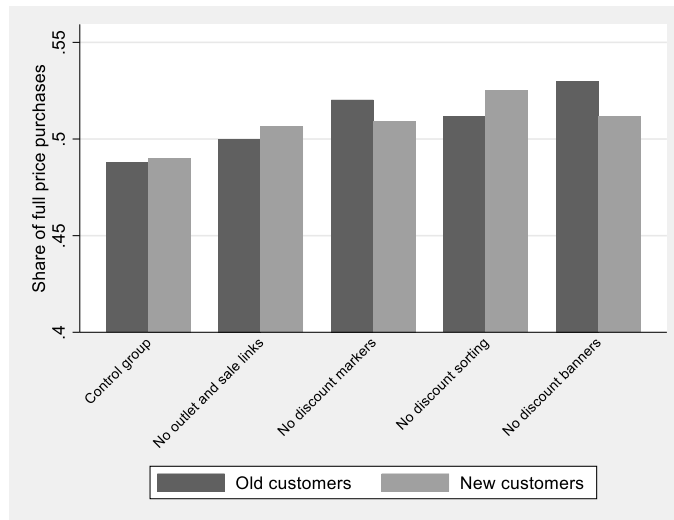
**Figure W1: Histograms of product discounts**



## **WEB APPENDIX C: New and Existing Customers in Field Experiment II**

Including both new and existing customers in Field Experiment II allows us to explore possible heterogeneous treatment effects. While our theoretical framework does not provide sharp predictions in this regard, there is a reasonable argument that our assumptions on consumers' information sets—that consumers are aware of the distribution of match values and product prices—are more appropriate for existing than for new customers. One may also conjecture that search costs are intrinsically lower for existing customers, who are more familiar with the website and are selected based on having made a prior purchase.

Figure W2 graphs the share of full-priced purchases by old and new customers in each treatment group. We observe that both old and new customers buy more full-priced items in the treatment groups than in the control group, which is directionally consistent with our model's predictions. We also observe that there exists no consistent pattern in the relative effects between groups within each treatment condition. The differences we observe are potentially artifacts of the specific experimental manipulations in each condition; however, given that we lack the browsing data required to fully explore these differences and that this is not central to our research objectives, we leave an investigation of these differences for future research.

**Figure W2: Full-priced purchases by old and new customers**

**WEB APPENDIX D: Model Analysis for Match Value Distributions beyond**  
 $\epsilon_j \sim iid \text{ Unif}[0,1]$

In this appendix, we explore the impact of increasing search frictions on conversion and revenue for other common match value distributions and for the case where the low-priced product has a stochastically smaller match value than the high-priced product (i.e., is of stochastically lower quality). We first present extensions of Theorems 1 and 2 for general match value distributions, followed by extensive numerical simulations.

**Theorem 3 (Conversion Comparison):** For general match value distributions...

- (i) If  $s \leq \min \left\{ \int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L, \int_{\epsilon_H = \alpha p_H}^{\infty} (\epsilon_H - \alpha p_H) f_H(\epsilon_H) d\epsilon_H \right\}$ ,  $d^L = d^H$ .
- (ii) If  $\int_{\epsilon_H = \alpha p_H}^{\infty} (\epsilon_H - \alpha p_H) f_H(\epsilon_H) d\epsilon_H < s \leq \int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L$ ,  $d^L < d^H$ .
- (iii) If  $\int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L < s \leq \int_{\epsilon_H = \alpha p_H}^{\infty} (\epsilon_H - \alpha p_H) f_H(\epsilon_H) d\epsilon_H$ ,  $d^L > d^H$ .
- (iv) If  $s > \max \left\{ \int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L, \int_{\epsilon_H = \alpha p_H}^{\infty} (\epsilon_H - \alpha p_H) f_H(\epsilon_H) d\epsilon_H \right\}$ ,  $d^j \geq d^{j'}$   
 iff  $j = \operatorname{argmax}_{j=\{L,H\}} \int_{\epsilon=\alpha p_j}^{\infty} f_j(\epsilon) d\epsilon$ .

Similar to Theorem 1, Theorem 3 highlights ranges for which expected conversion of a customer who views the high-priced product first is the same, less than, or greater than expected conversion of a customer who views the low-priced product first. As before, when the search cost is sufficiently small, customers may search and consider both products for purchase, regardless of if they view the high or low-priced product first. If the expected gain from searching the low-priced product is greater than the expected gain from searching the high-priced product – as we had when  $\epsilon_j \sim iid \text{ Unif}[0,1]$  – Theorem 3(ii) shows us that for moderate search costs, expected conversion is higher when customers view the high-priced product first, analogous to Theorem 1(ii). In this case, the search cost is high enough to force customers who

view the low-priced product first to never search the high-priced product, but not too high to prevent customers who view the high-priced product first from searching the low-priced product; with more products to choose from, customers who view the high-priced products first are more likely to make a purchase. If the expected gain from searching the low-priced product is less than the expected gain from searching the high-priced product, Theorem 3(iii) shows us that for moderate search costs, expected conversion is higher when customers view the low-priced product first, for similar reasons as above. Finally, similar to Theorem 1(iii), Theorem 3(iv) shows us that when the search cost is sufficiently large, the customer will never search the second product, and conversion is greatest for whichever product is more likely to be purchased.

**Theorem 4 (Revenue Comparison):** For general match value distributions, if

$$s \leq \int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L, \text{ we have } p_L d_L^L + p_H d_H^L \leq p_L d_L^H + p_H d_H^H.$$

Similar to Theorem 2(i), Theorem 4 shows us that when the search cost is sufficiently low (corresponding to cases (i) and (ii) in Theorem 3), expected revenue is greater when customers view the high-priced product first; intuitively, this is because expected conversion is weakly greater for these customers.

To better understand the impact of increasing search frictions on conversion and revenue for various match value distributions, we next present a series of simulations. For each simulation, we randomly drew match values for the low and high-priced products for 100,000 customers. Customers in the treatment group were forced to view/consider the high-priced product first. Unlike for the case where  $\epsilon_j \sim_{iid} Unif[0,1]$ , it may be optimal for customers in the control group to view either the low or high-priced product first. Thus in our simulations, we specify that customers in the control group choose to view product  $\operatorname{argmax}_{j \in \{L,H\}} U^j$  first. If



viewing the high-priced product first is utility maximizing, then expected conversion and revenue are identical for customers in the treatment and control groups and increasing search frictions would have no impact on these metrics; any differences in expected conversion and revenue are thus attributed to the case where it is optimal for customers in the control group to view the low-priced product first.

Figures W3-W18 show our simulation results for uniform, normal, and exponential match value distributions, including the case where the high-priced product has a stochastically larger match value than the low-priced product (i.e. higher price is due to expected higher quality). Parameters of the normal and exponential match value distributions were chosen to match the mean and variance of the standard uniform distribution used in the main body of the paper, when possible. We can see that as the high-priced product becomes stochastically more appealing, it is optimal for customers in the control group to view the high-priced product first and the impact of increasing search frictions vanishes. Otherwise, we find that our results presented in the main body of the paper are robust to common and stochastically ordered match value distributions.

**Figure W3: Conversion Comparison for  $\epsilon_L \sim Unif[0, 1]$ ,  $\epsilon_H \sim Unif[0.1, 1.1]$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**

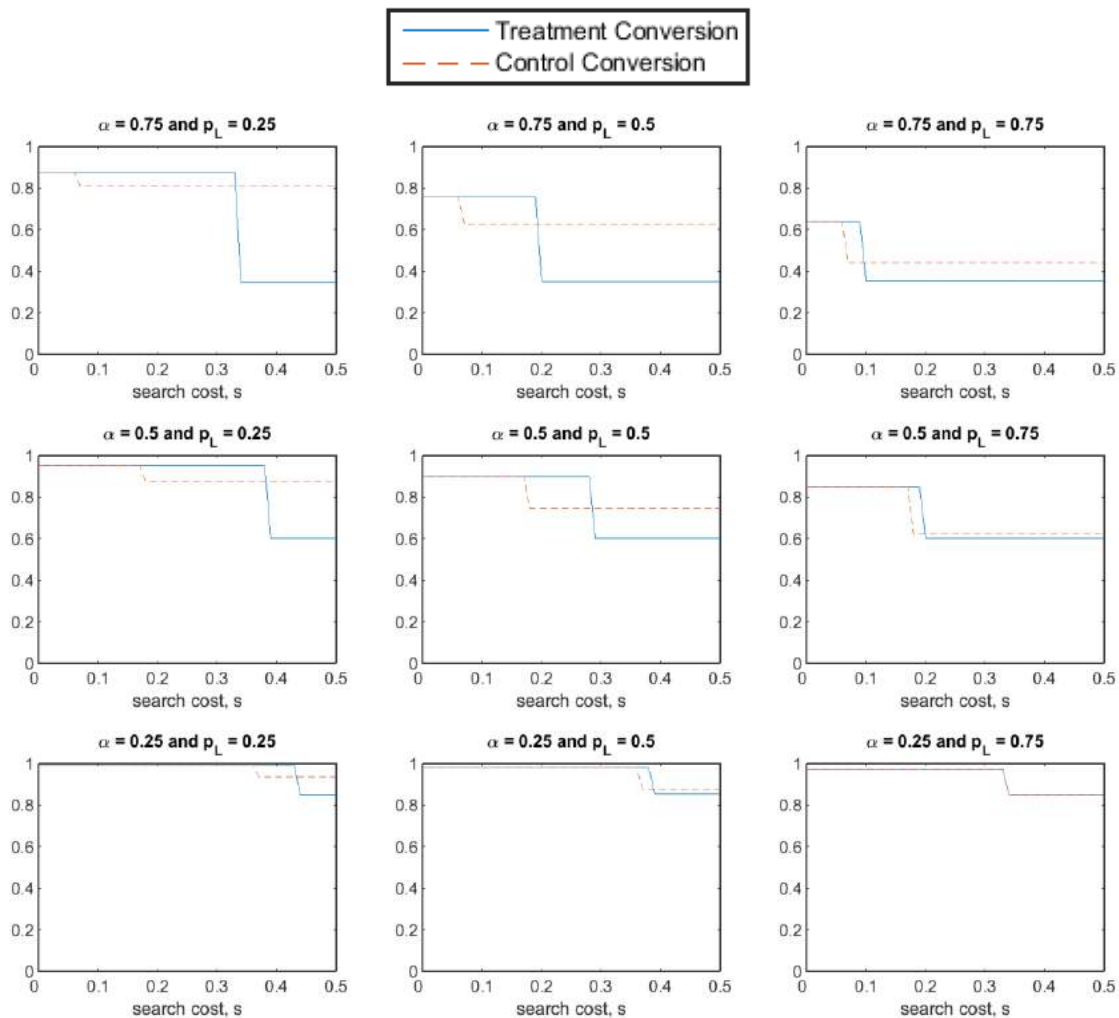
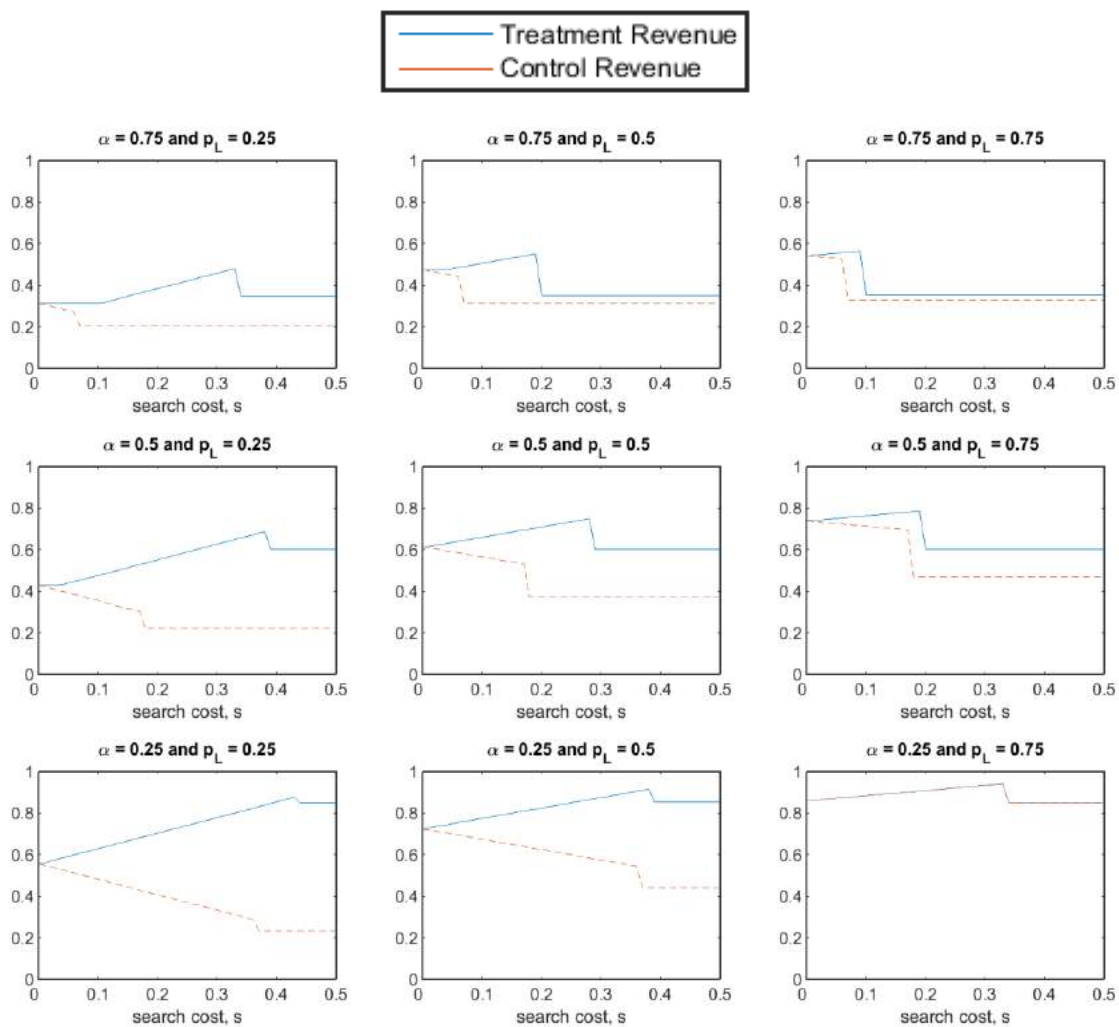


Figure W4: Revenue Comparison for  $\epsilon_L \sim Unif[0, 1]$ ,  $\epsilon_H \sim Unif[0.1, 1.1]$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$



**Figure W5: Conversion Comparison for  $\epsilon_L \sim Unif[0, 1]$ ,  $\epsilon_H \sim Unif[0.2, 1.2]$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**

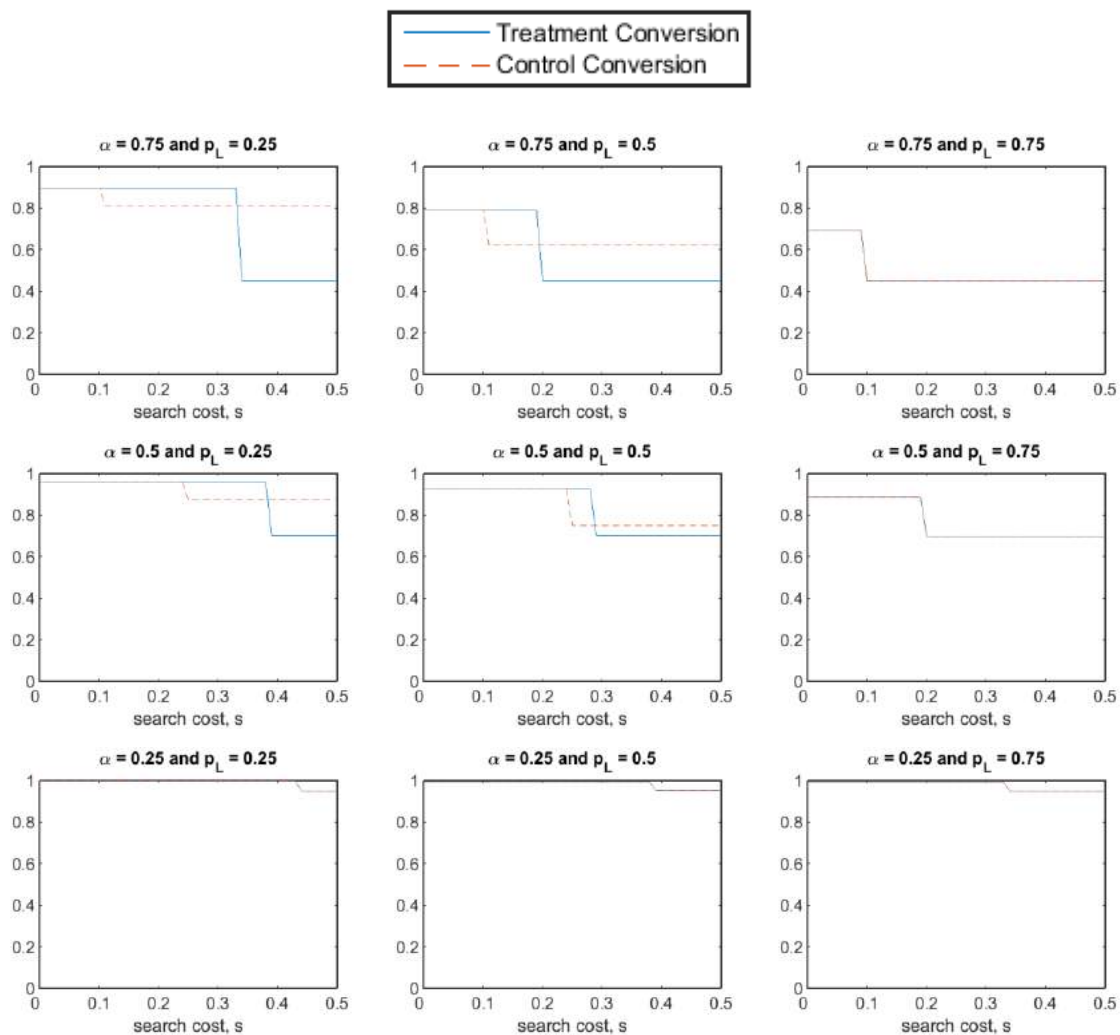


Figure W6: Revenue Comparison for  $\epsilon_L \sim Unif[0, 1]$ ,  $\epsilon_H \sim Unif[0.2, 1.2]$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$

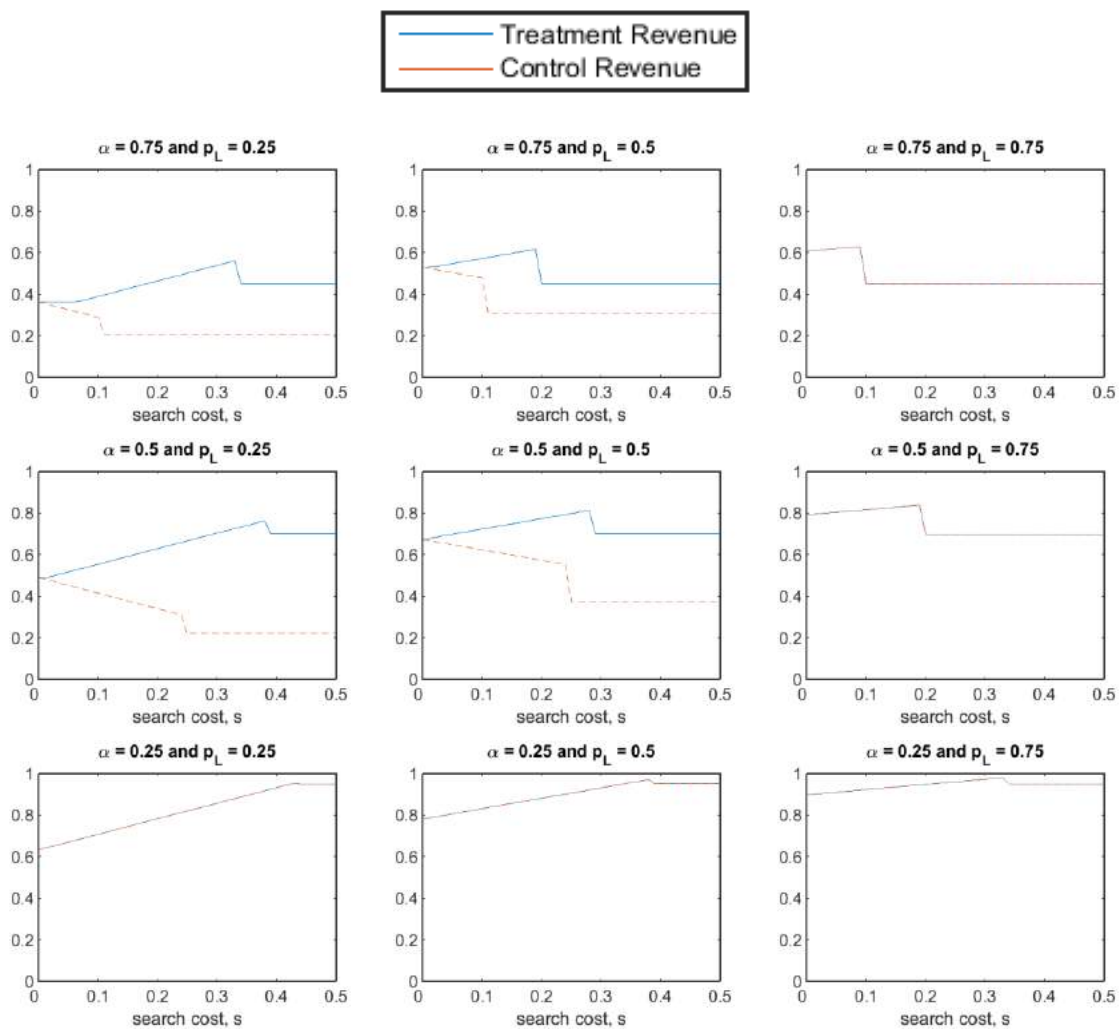


Figure W7: Conversion Comparison for  $\epsilon_L \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  
 $\epsilon_H \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$

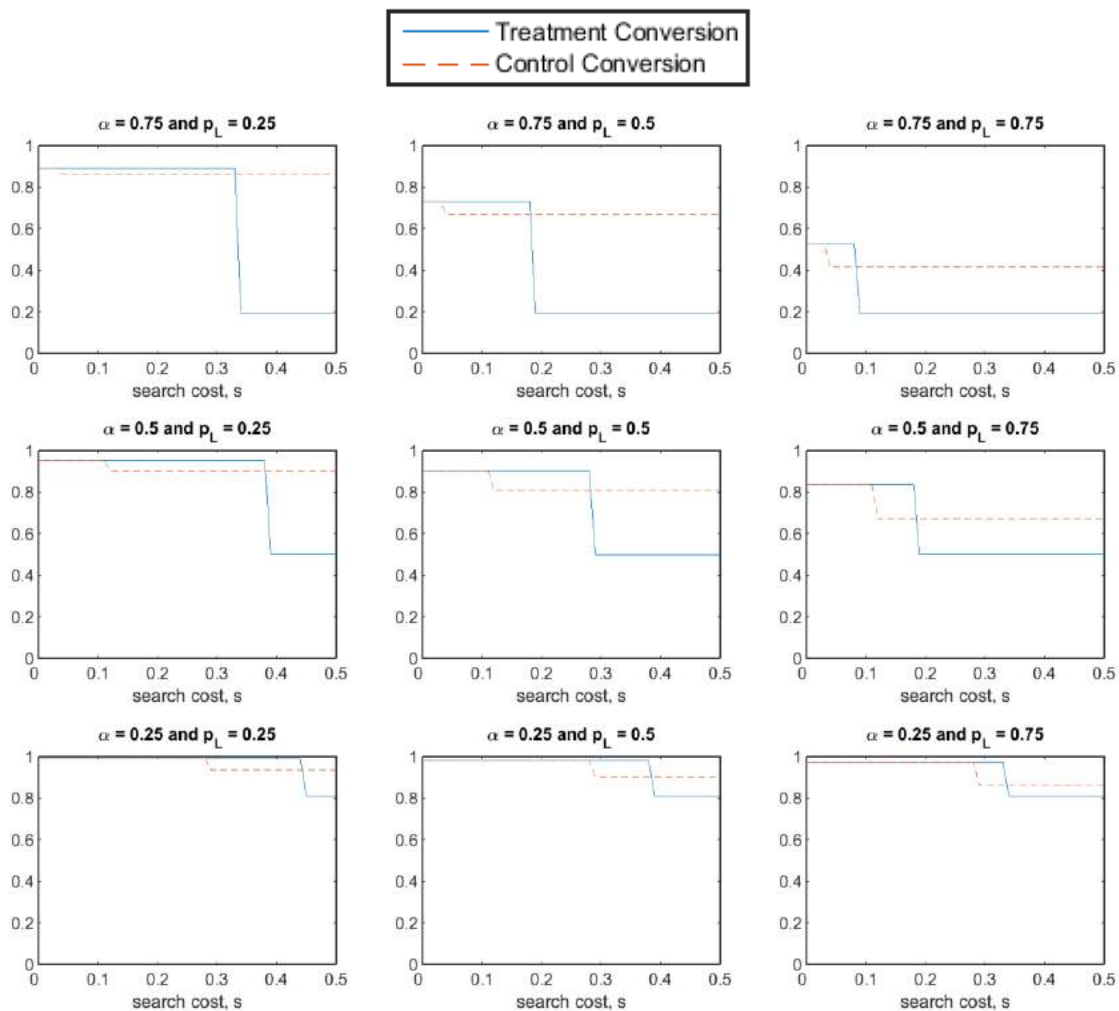


Figure W8: Revenue Comparison for  $\epsilon_L \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,

$\epsilon_H \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$

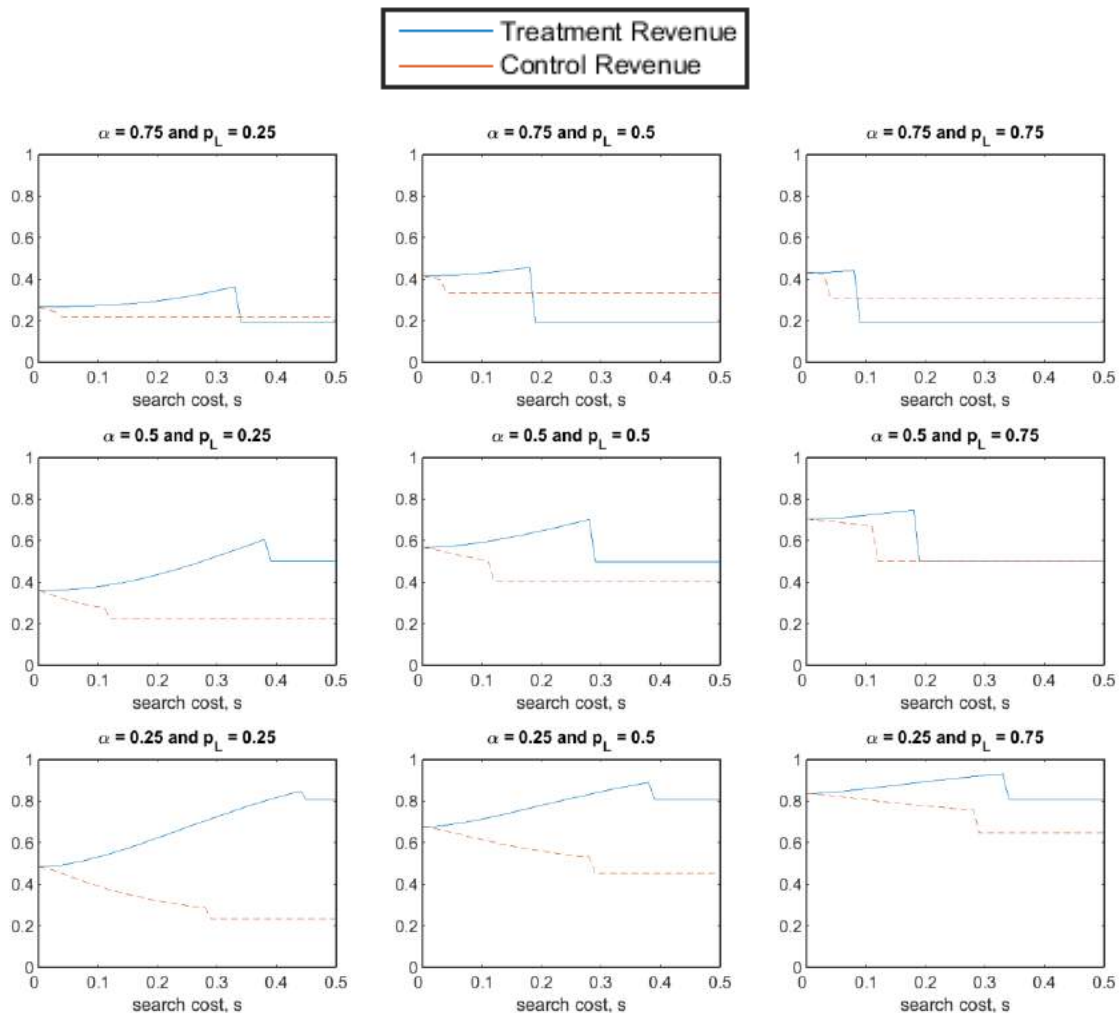


Figure W9: Conversion Comparison for  $\epsilon_L \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  
 $\epsilon_H \sim \text{Normal}\left(\mu = 0.6, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$

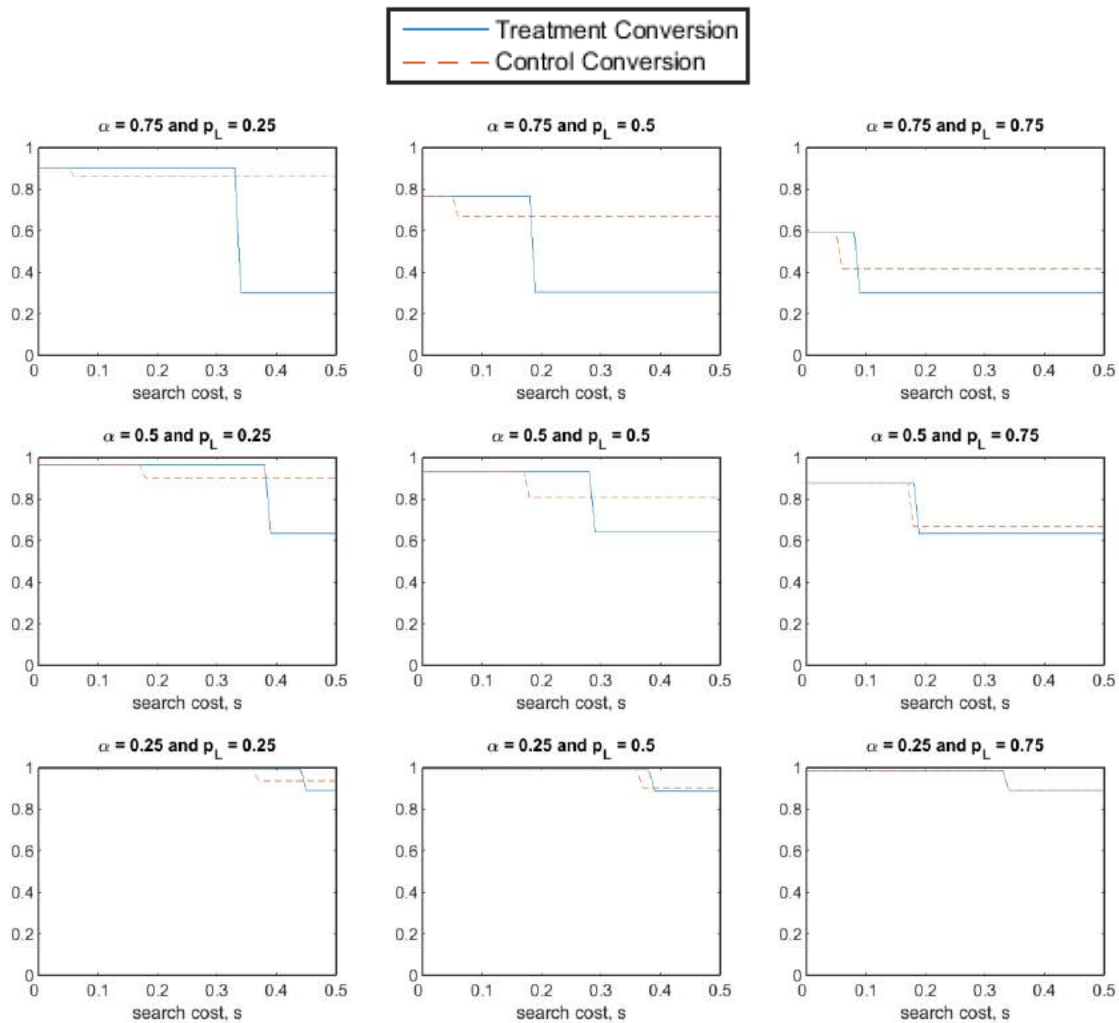
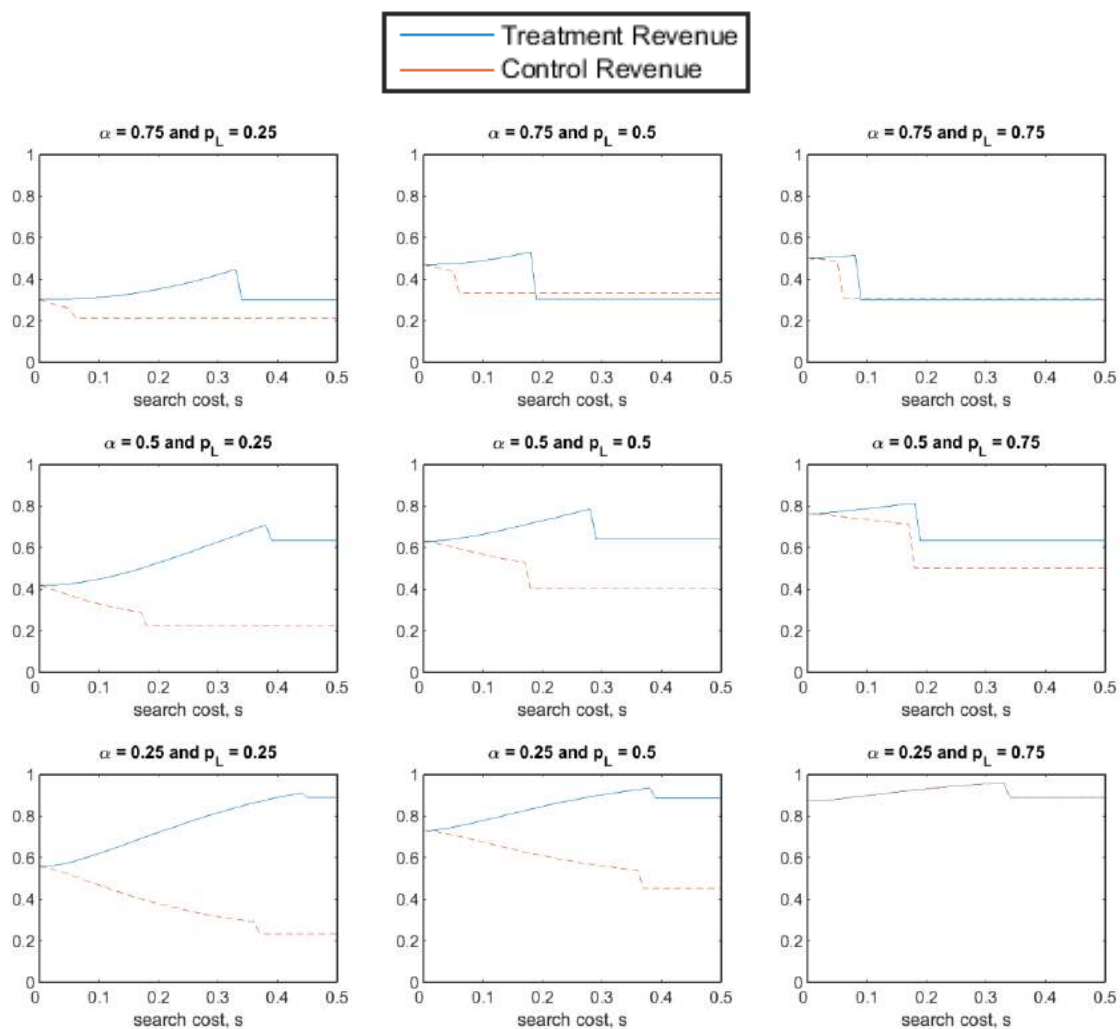




Figure W10: Revenue Comparison for  $\epsilon_L \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,

$\epsilon_H \sim \text{Normal}\left(\mu = 0.6, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$



**Figure W11: Conversion Comparison for  $\epsilon_L \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  
 $\epsilon_H \sim \text{Normal}\left(\mu = 0.7, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**

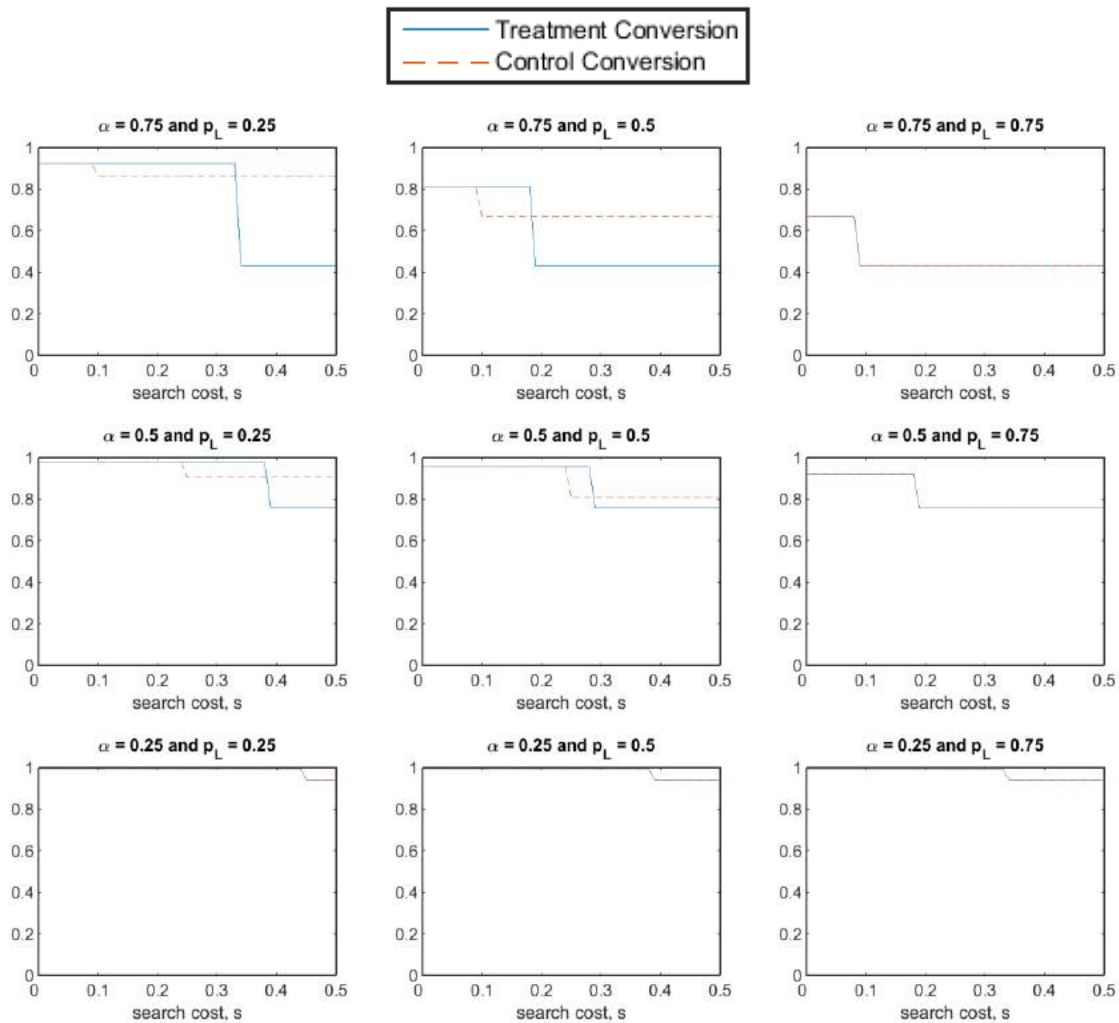
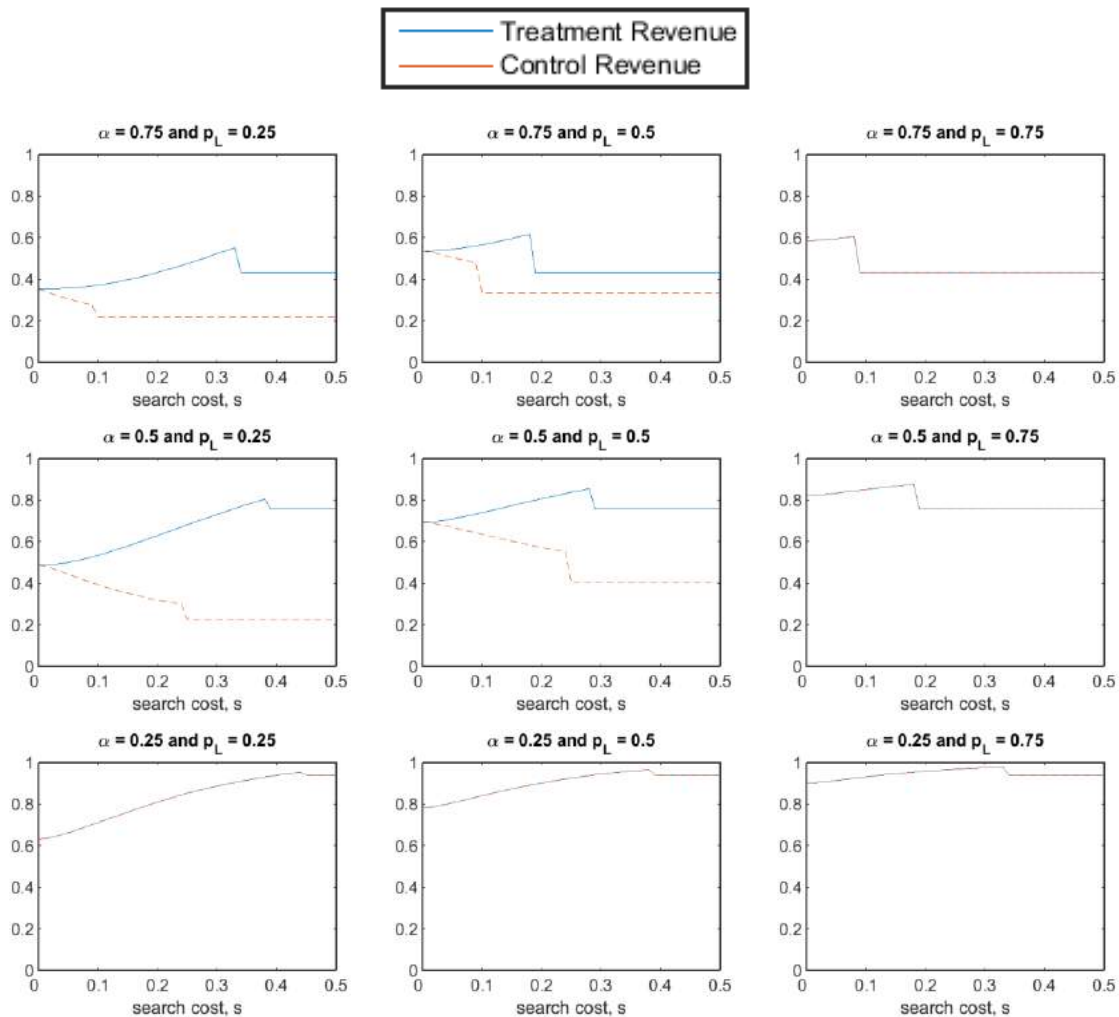


Figure W12: Revenue Comparison for  $\epsilon_L \sim \text{Normal}\left(\mu = \frac{1}{2}, \sigma = \sqrt{\frac{1}{12}}\right)$ ,

$\epsilon_H \sim \text{Normal}\left(\mu = 0.7, \sigma = \sqrt{\frac{1}{12}}\right)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$



**Figure W13: Conversion Comparison for  $\epsilon_L \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  
 $\epsilon_H \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**

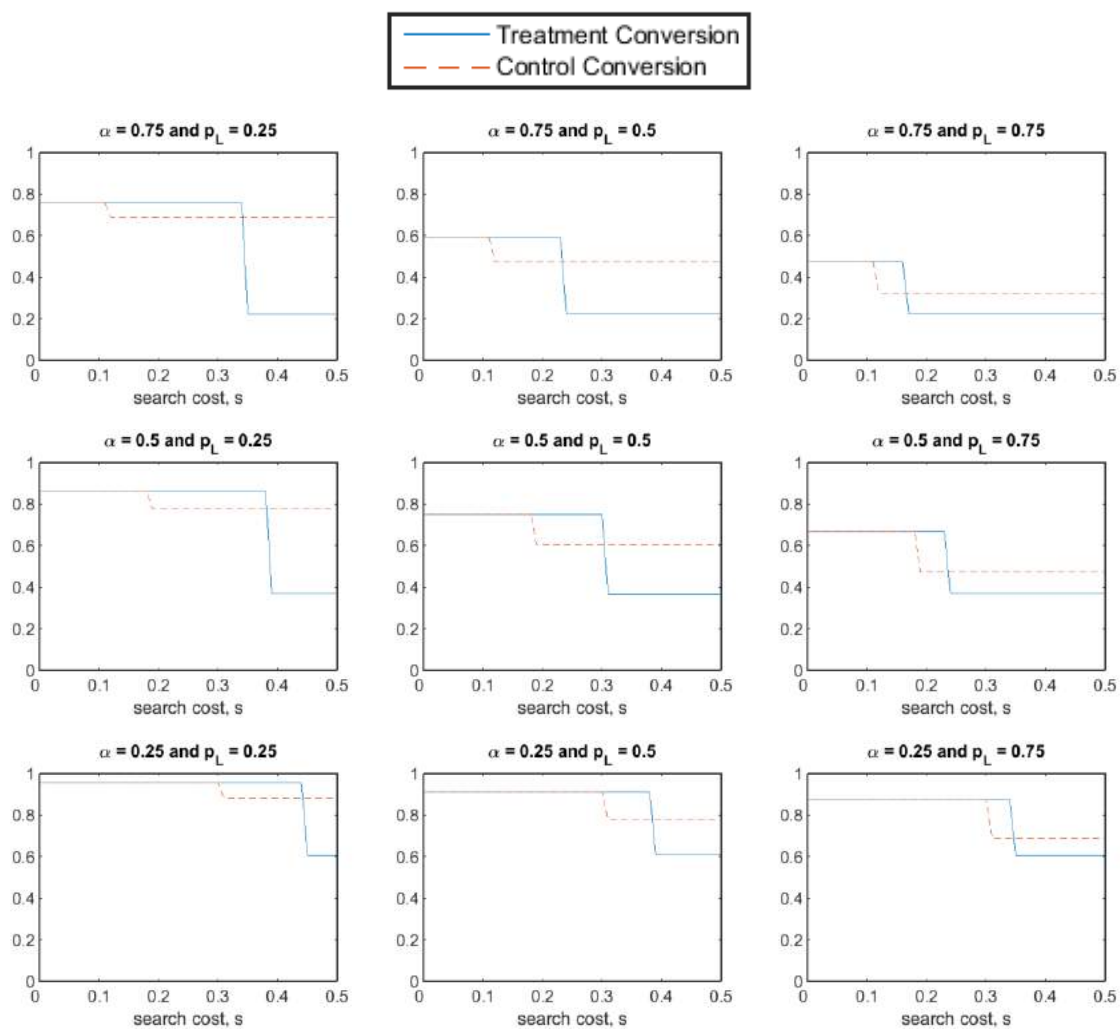
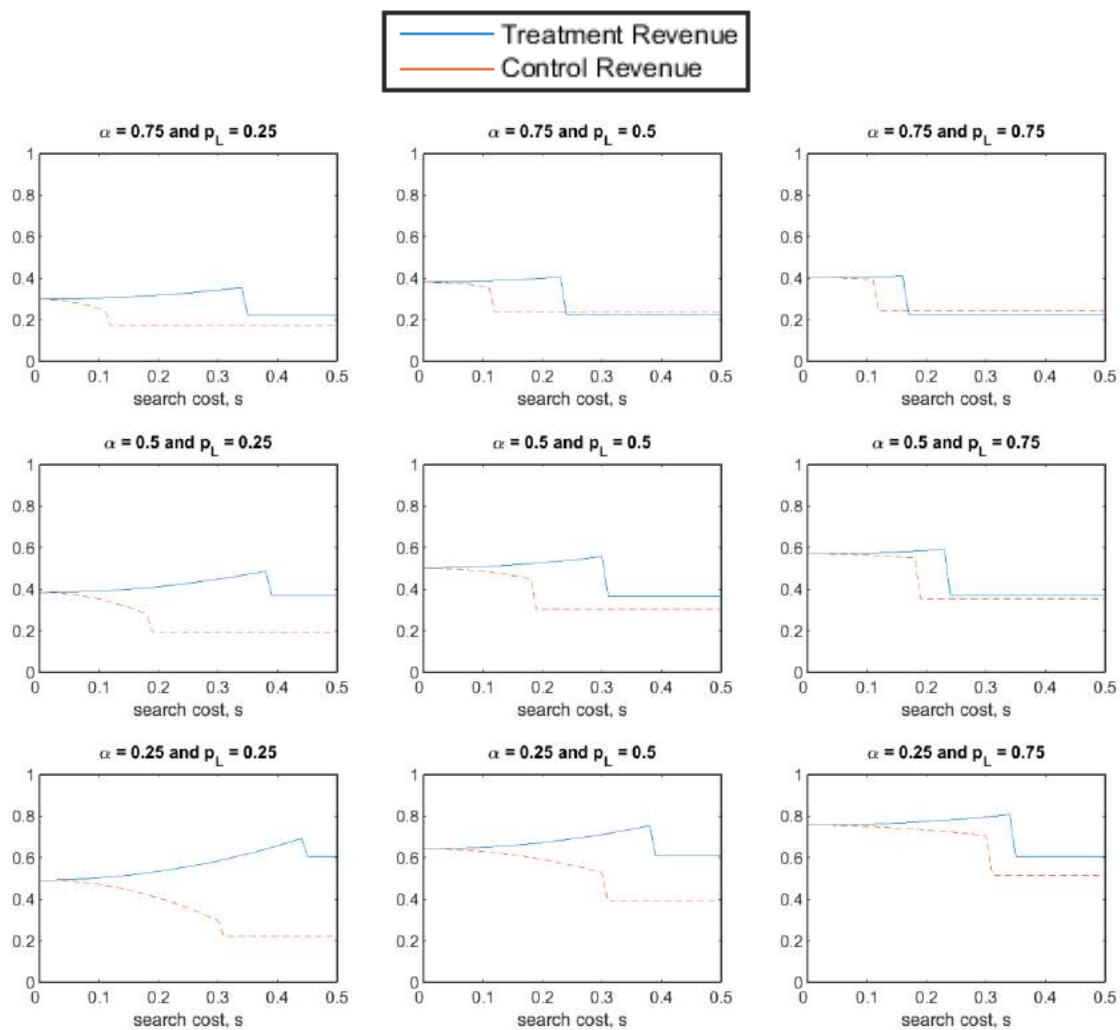
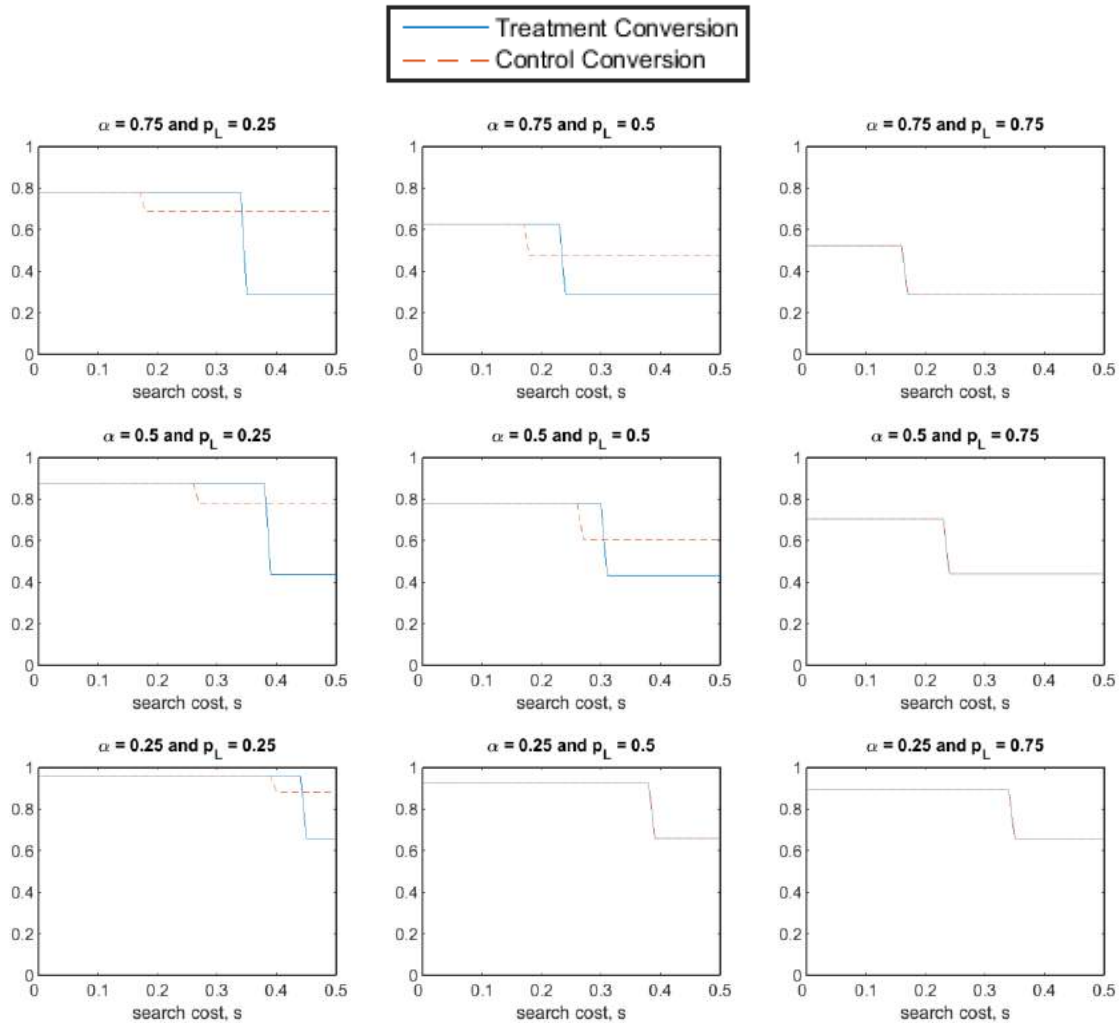


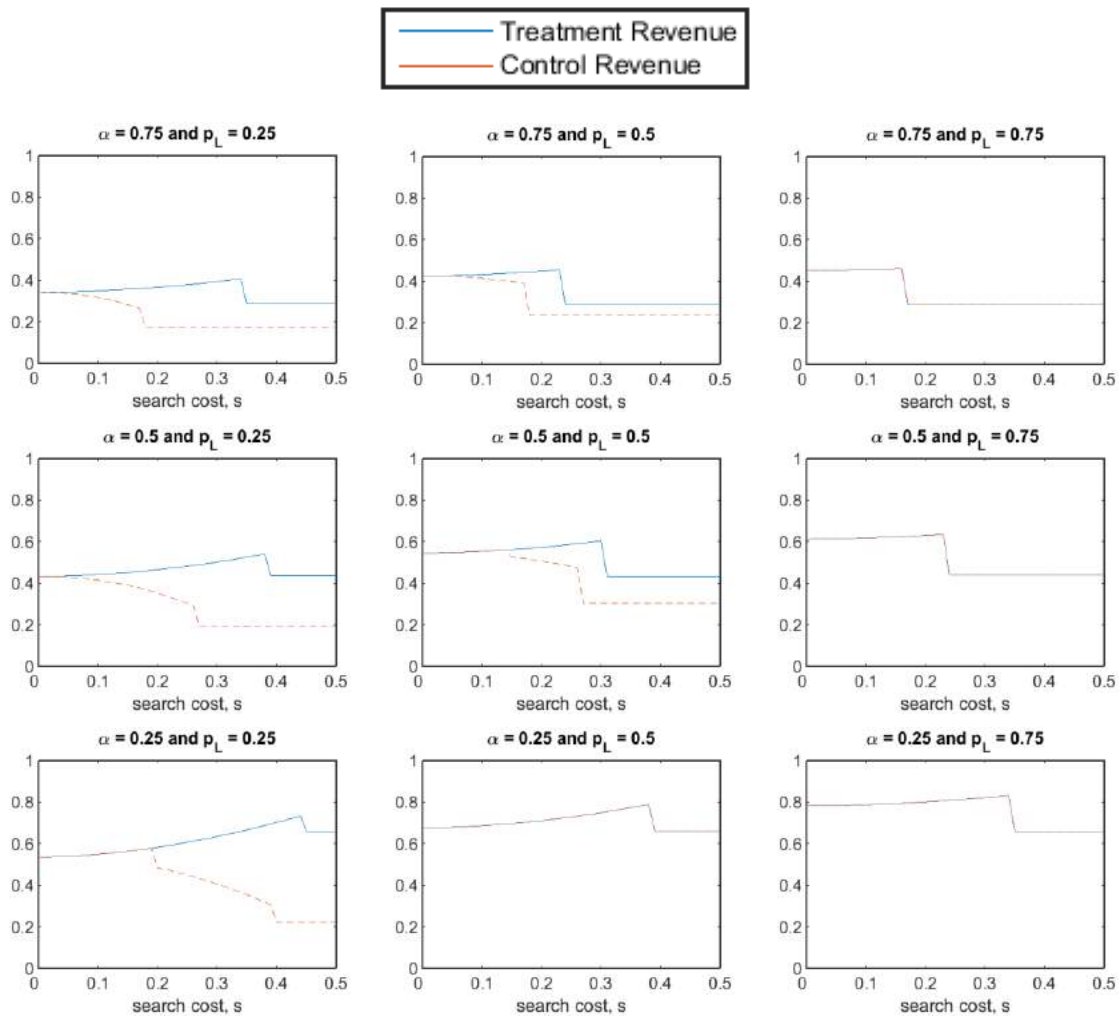
Figure W14: Revenue Comparison for  $\epsilon_L \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  
 $\epsilon_H \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$



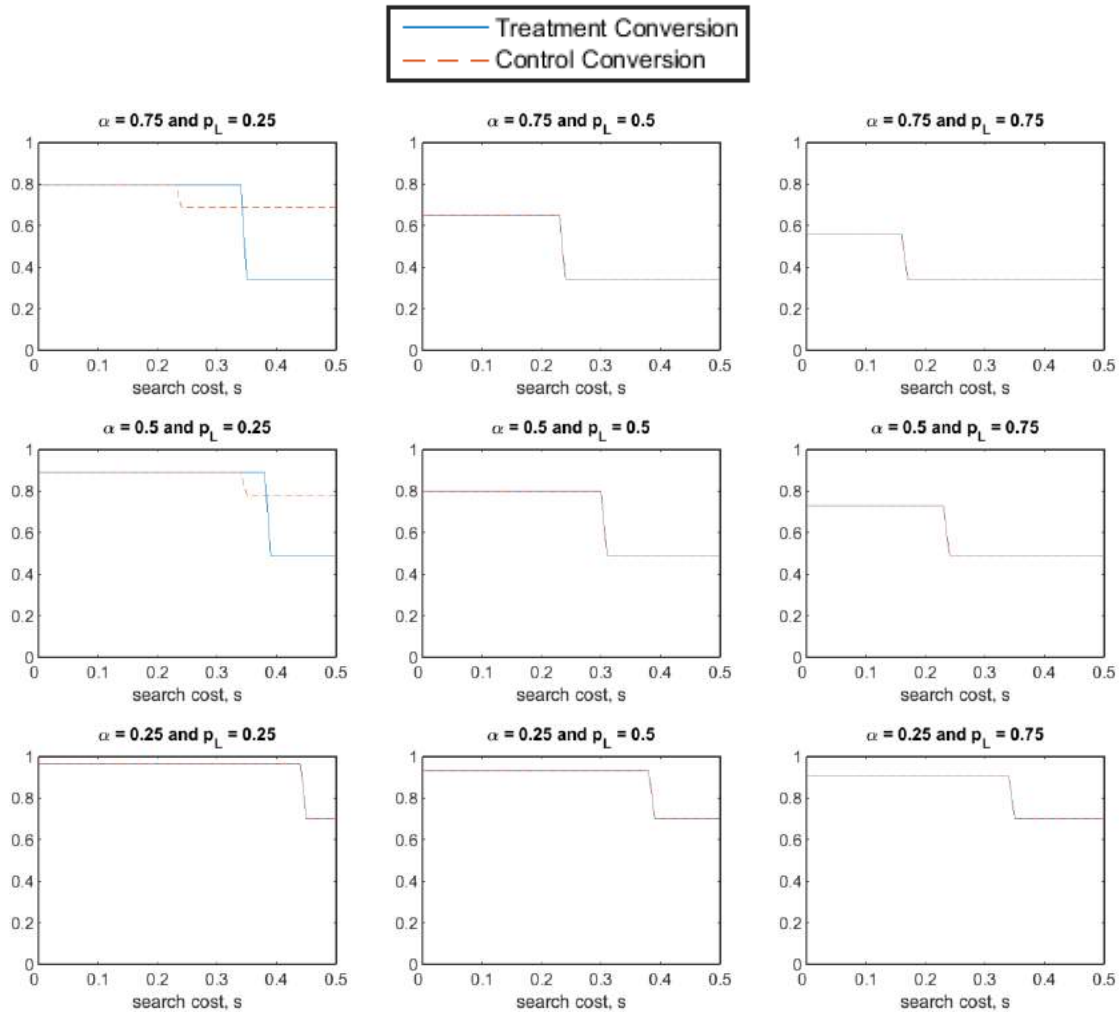
**Figure W15: Conversion Comparison for  $\epsilon_L \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  
 $\epsilon_H \sim \text{Exponential}(\mu = 0.6)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**



**Figure W16: Revenue Comparison for  $\epsilon_L \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  
 $\epsilon_H \sim \text{Exponential}(\mu = 0.6)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**

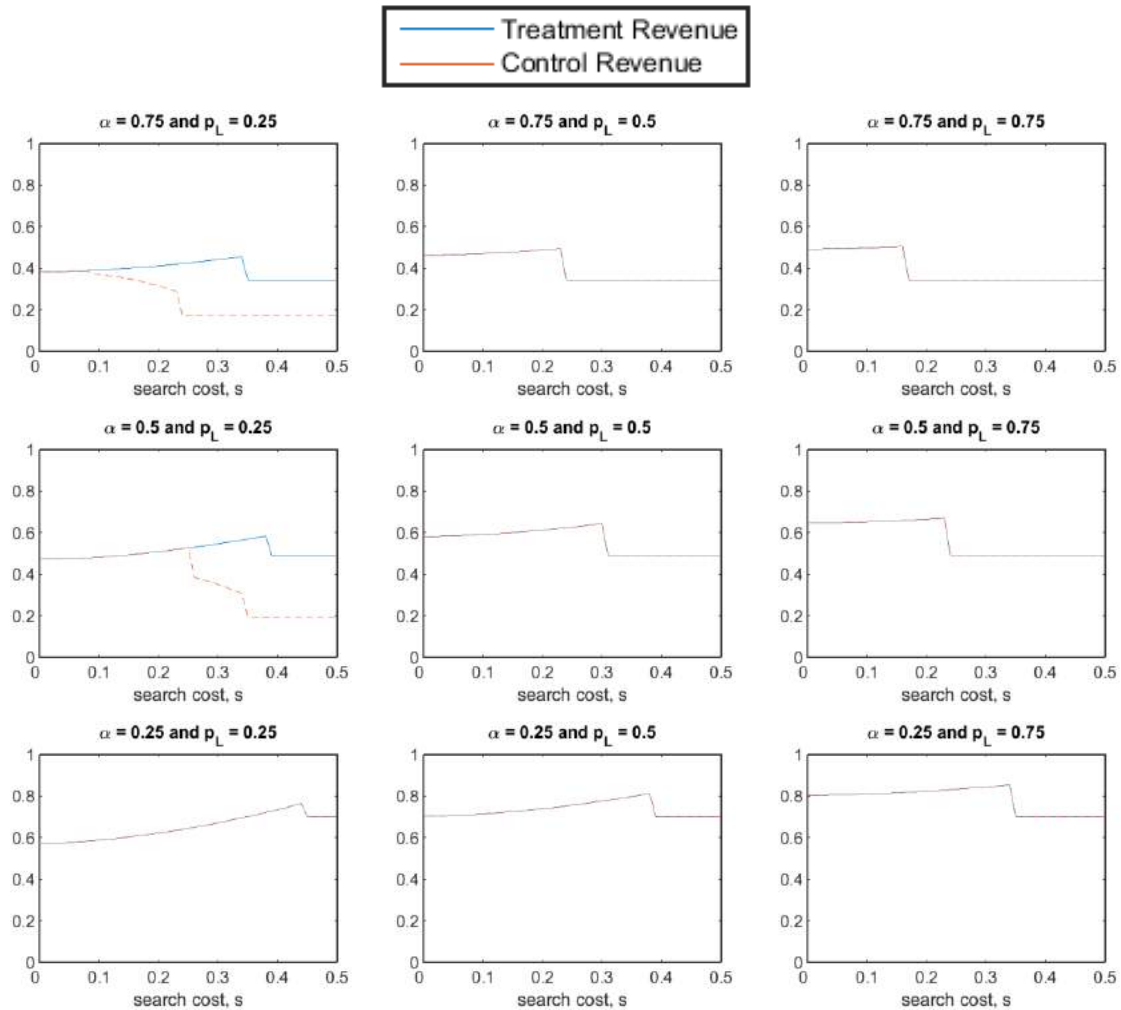


**Figure W17: Conversion Comparison for  $\epsilon_L \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  $\epsilon_H \sim \text{Exponential}(\mu = 0.7)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**





**Figure W18: Revenue Comparison for  $\epsilon_L \sim \text{Exponential}(\mu = \frac{1}{2})$ ,  
 $\epsilon_H \sim \text{Exponential}(\mu = 0.7)$ ,  $p_H = 1$ , and varying  $p_L$ ,  $\alpha$ , and  $s$**



**WEB APPENDIX E: Additional Tables and Figures**

**Table W3: Randomization checks for Field Experiment I**

	<b>Sample size</b>	<b>Ages 18-24</b>	<b>Chrome browser</b>	<b>Windows system</b>	<b>Visited on Thursday</b>
<b>Control</b>	26014	4234	19538	23931	6319
<b>Treatment 1</b>	26199	4268	19616	23985	6452
<b>Treatment 2</b>	26343	4284	19732	24116	6348
<b>Treatment 3</b>	26049	4380	19622	23893	6420
<b>p-value</b>		0.2469	0.6042	0.2079	0.3845

H<sub>0</sub>: Proportions are equal across all conditions.

**Table W4: Margin measurements in Field Experiment I**

	<b>No. of items sold</b>	<b>Average product margin</b>	<b>p-value</b>	<b>Gross margin</b>
<b>Control</b>	681	141.68 (9.14)		96,483.48
<b>Treatment 1</b>	695	174.20 (13.23)	0.0441	121,070.70
<b>Treatment 2</b>	712	287.20 (28.09)	0.0000	204,488.30
<b>Treatment 3</b>	589	211.00 (28.49)	0.0143	124,280.30

H<sub>0</sub>: value is equal to that in the control condition. Gross margin is the sum of product margin over items sold in each condition.

**Table W5: Randomization checks for validation experiment**

	Sample size	No. of Female	Average Age	CLV	No. of transactions	Newsletter frequency
<b>Group 1</b>	123,346	86,032	31.22	6,169.42	3.92	1.72
<b>Group 2</b>	123,342	86,166	31.13	6,015.13	3.82	1.72
<b>p-value</b>		0.5486	0.0698	0.3875	0.2235	0.9968

H<sub>0</sub>: value is equal to that in the control condition. CLV is computed as the sum of all previous basket sizes.

**Table W6: Randomization checks for Field Experiment II**

	Sample <sup>15</sup>	No. of new users	No. of ages 18-24	Used Chrome browser	Used Windows system	Visited on Thursday
<b>Control</b>	68,343	42,692	13,396	49,893	53,996	16,388
<b>Treatment 1</b> <b>No outlet and sale links</b>	70,058	43,679	13,629	51,025	55,675	16,424
<b>Treatment 2</b> <b>No discount markers</b>	70,025	43,549	13,645	50,673	55,423	16,465
<b>Treatment 3</b> <b>No discount sorting</b>	69,859	43,734	13,696	50,722	55,315	16,435
<b>Treatment 4</b> <b>No discount banners</b>	69,825	43,740	13,624	50,736	55,199	16,482
<b>p-value</b>		0.3880	0.9342	0.0874	0.2381	0.1425

H<sub>0</sub>: Proportions are equal across five groups.

<sup>15</sup> The null that the number of subjects in the control condition is not equal to 20% of the total number of subjects, or that the number of subjects in the five groups are not equal, cannot be rejected at  $p < 0.01$ . We have investigated possible sources for sampling discrepancies with the firm and its third-party testing platform but have found no satisfying explanations. Tests of balance find no significant differences between groups in available variables; hence, we argue that any systematic departures from assignment with equal probabilities has not resulted in observably selected samples.

**Table W7: Profitability for Field Experiment II**

	No. of items sold	Average product margin	p-value	Average percent margin	p-value	Gross margin
<b>Control</b>	2,709	225.64 (6.33)		0.23		611,246.31
<b>Treatment 1 No outlet and sales links</b>	3,268	215.51 (5.01)	0.2043	0.25	0.0159	704,302.19
<b>Treatment 2 No discount markers</b>	3,295	218.23 (5.70)	0.3840	0.2472	0.0883	719,059.63
<b>Treatment 3 No discount sorting</b>	3,171	221.49 (5.65)	0.6245	0.2464	0.0959	702,355.94
<b>Treatment 4 No discount banners</b>	3,625	220.78 (5.46)	0.5616	0.2527	0.0119	800,344.38

H<sub>0</sub>: Value is equal to that in the control condition.

**Table W8: Repeat visits by consumers in the treatment conditions**

<i>Dates</i>	<i>Control</i>		<i>No outlet and sale links</i>		<i>No discount markers</i>		<i>No discount sorting</i>		<i>No discount banners</i>	
	Visits	Conv	Visits	Conv	Visits	Conv	Visits	Conv	Visits	Conv
<i>Jun 1 - Jun 15</i>	68343	1.98%	70058	2.28%	70025	2.29%	69859	2.30%	69825	2.45%
<i>Jun 16 - Jun 30</i>	14157	5.88%	15205	6.15%	15337	5.73%	15167	5.70%	15302	7.07%
<i>Jul 1 - Jul 15</i>	10461	6.10%	11649	6.03%	11393	6.42%	11281	6.60%	11497	7.44%
<i>Jul 16 - Jul 31</i>	9058	9.03%	9870	8.11%	9956	7.63%	10037	7.91%	9962	9.13%
<i>Aug 1 - Aug 15</i>	7560	7.34%	8290	7.25%	8308	6.91%	8295	7.15%	8501	7.15%
<i>Aug 16 - Aug 31</i>	6367	7.81%	6815	7.18%	7025	6.28%	6918	6.79%	7091	7.63%
<i>Sep 1 - Sep 15</i>	5288	6.92%	5635	6.87%	5928	6.55%	5921	7.52%	5905	7.50%
<i>Sep 16 - Sep 30</i>	4922	6.85%	5306	6.20%	5553	6.86%	5569	6.12%	5520	8.13%
<i>Oct 1 - Oct 15</i>	4549	6.70%	4945	7.46%	5073	7.71%	5045	7.49%	5101	8.10%
<i>Oct 16 - Oct 31</i>	4364	7.03%	4658	7.11%	4784	7.48%	4771	7.76%	4755	7.38%
<i>Nov 1 - Nov 15</i>	3824	6.88%	4065	7.23%	4186	7.12%	4275	5.89%	4253	7.05%
<i>Nov 16 - Nov 30</i>	2931	6.28%	3308	7.04%	3414	5.27%	3342	5.69%	3294	7.13%
<i>Dec 1 - Dec 15</i>	3654	8.95%	4019	8.43%	4002	8.67%	4191	7.92%	3992	8.37%
<i>Dec 16 - Dec 31</i>	1764	6.58%	1889	5.93%	1985	6.25%	1980	6.92%	1970	5.43%

For all subsequent time periods after the duration of the experiment (June 1-15, 2016), the proportion of consumers revisiting is significantly higher in each treatment than in the control with  $p < 0.01$ . Conversion (conv) is the number of transactions divided by the number of visits. Note that the website reverts to the control condition after June 15, 2016 for all consumers.

**Table W9: Regression analysis of Field Experiment II**

<b>VARIABLES</b>	(1)	(2)	(3)
Treatment 1: No outlet and sales links	-0.00926* (0.00549)	-0.00966* (0.00549)	-0.0128** (0.00646)
Treatment 2: No discount markers	-0.0156*** (0.00548)	-0.0161*** (0.00548)	-0.0210*** (0.00647)
Treatment 3: No discount sorting	-0.0116** (0.00553)	-0.0117** (0.00553)	-0.0128** (0.00644)
Treatment 4: No discount markers	-0.0144*** (0.00537)	-0.0147*** (0.00537)	-0.0141** (0.00628)
New customer		0.0108*** (0.00363)	
Total past spending			-7.75e-06*** (9.49e-07)
Number of previous orders			-0.000415*** (0.000132)
Customer age			-2.80e-06*** (5.33e-07)
Male			0.0134*** (0.00506)
Constant	0.182*** (0.00406)	0.179*** (0.00418)	0.235*** (0.00849)
Observations	16,068	16,068	11,197
R-squared	0.001	0.001	0.013

Standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table W10: Conversion for new and existing customers in Field Experiment II**

	<b>New customers</b>	<b>Existing customers</b>
<b>Control</b>	541 (1.07%)	940 (3.84%)
<b>Treatment 1 No outlet and sales links</b>	695 (1.37%) <sup>***</sup>	1,037 (4.15%) <sup>***</sup>
<b>Treatment 2 No discount markers</b>	701 (1.37%) <sup>***</sup>	1,043 (4.16%) <sup>***</sup>
<b>Treatment 3 No discount sorting</b>	662 (1.31%) <sup>***</sup>	1,076 (4.29%) <sup>***</sup>
<b>Treatment 4 No discount banners</b>	752 (1.48%) <sup>***</sup>	1,111 (4.43%) <sup>***</sup>

H<sub>0</sub>: value is equal to that in the control condition. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

In each cell, the top entry is the number of transactions and the bottom entry (in parentheses) is the conversion.

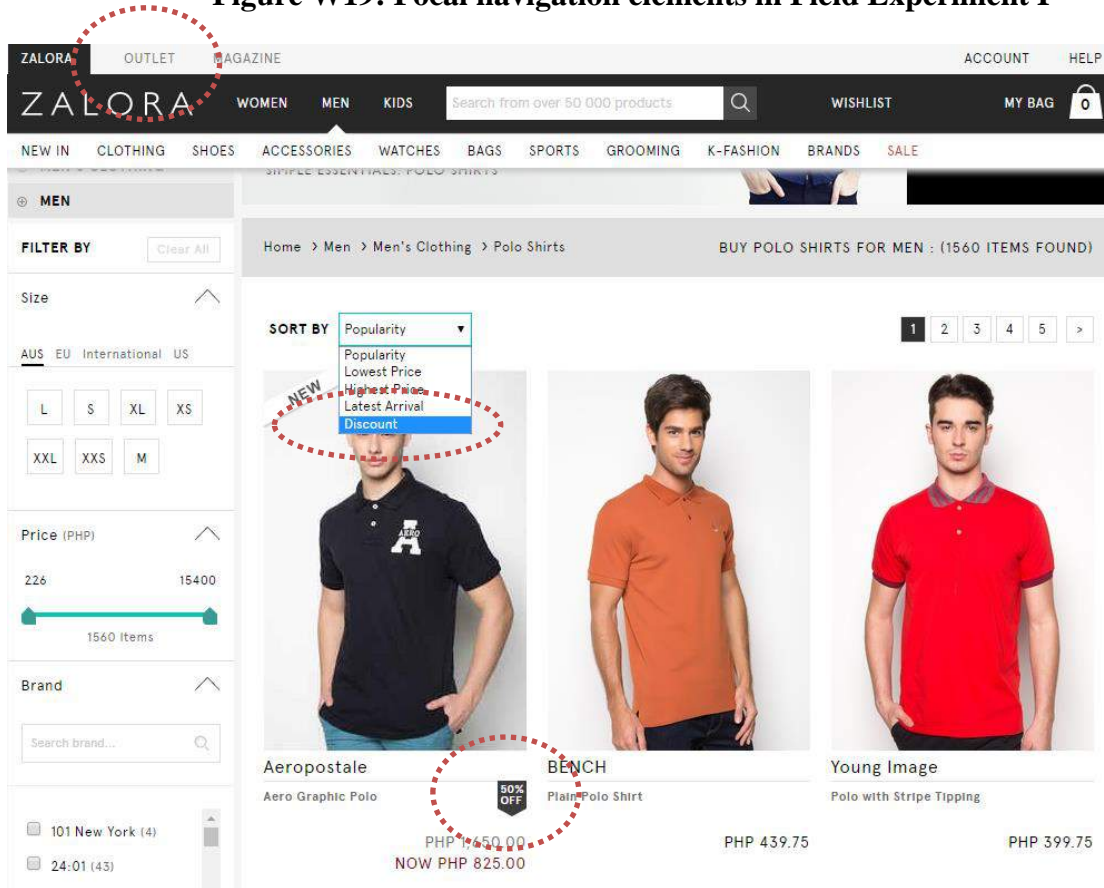
Roughly two-thirds of visitors to the website are new customers.

**Table W11: p-values for pairwise comparisons in Table 4**

<b>H<sub>0</sub></b>	<b>Control</b>	<b>Treatment 1 No outlet and sale links</b>	<b>Treatment 2 No discount markers</b>	<b>Treatment 3 No discount sorting</b>	<b>Treatment 4 No discount banners</b>
<b>Low = Medium</b>	0.04	0.00	0.00	0.00	0.00
<b>Medium = High</b>	0.00	0.00	0.00	0.00	0.00
<b>Low = High</b>	0.00	0.00	0.00	0.00	0.00

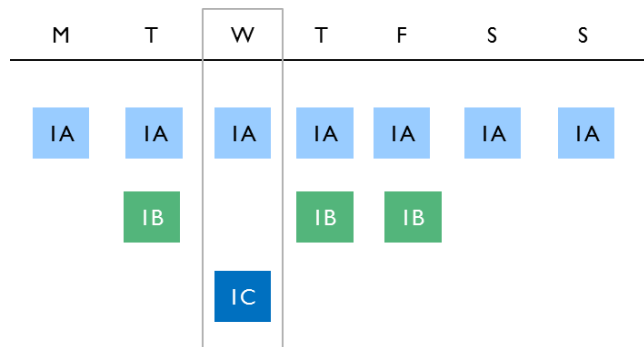
Each cell contains the p-value concerning the null hypothesis that the difference between the two price sensitivity bins indicated in the leftmost column for the given treatment group is zero.

**Figure W19: Focal navigation elements in Field Experiment I**



In Field Experiment II, we remove the SALE button as well.

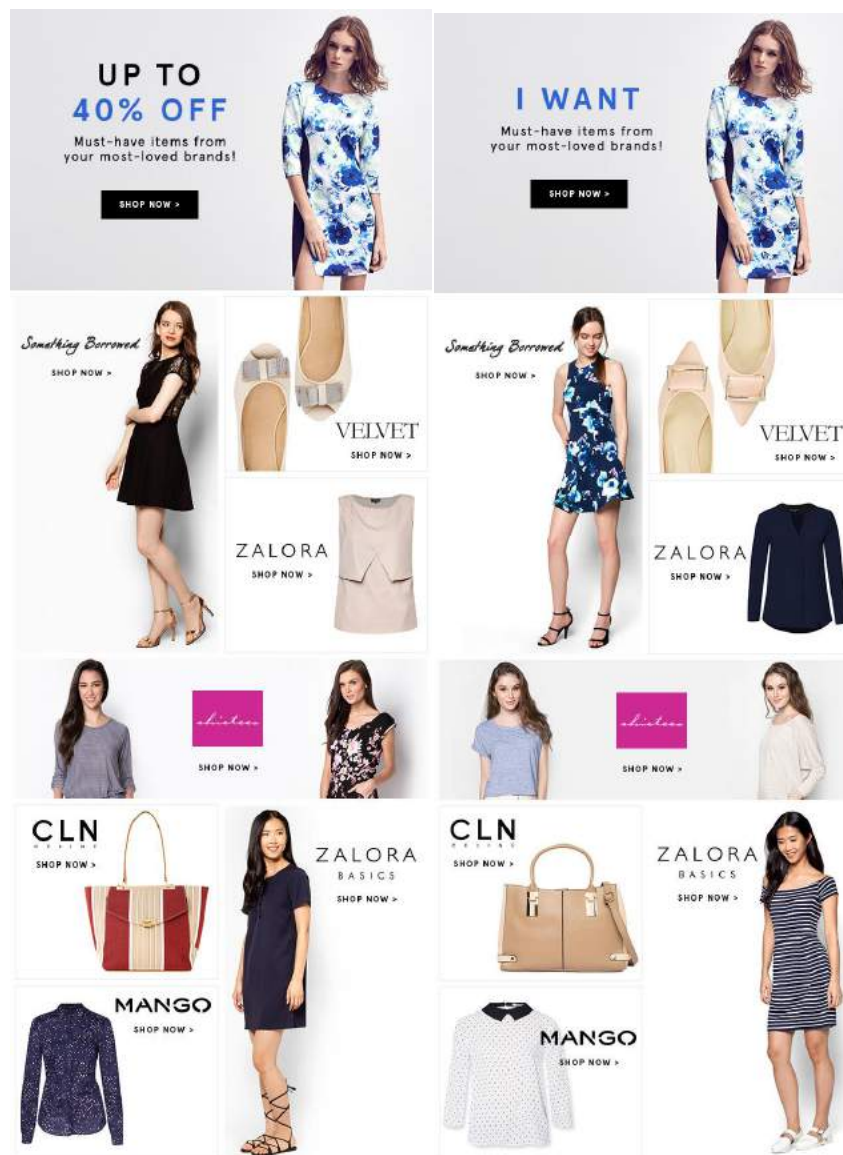
**Figure W20: Regular newsletter schedule**



This diagram is taken from internal company documents. Customers who subscribe to the email newsletter opt to receive them daily, three times a week, or once a week.



**Figure W21: Examples of discount and non-discount email newsletters**



This pair of newsletters is representative of the array of discount- and non-discount newsletters sent out in the validation experiment. Product categories differed between days, as did newsletters sent to male and female recipients. These are two out of a total of 22 unique newsletters sent out during the experiment.

Figure W22: Examples of discount banners

The image shows a screenshot of the Zalora website homepage. At the top, there is a navigation bar with the Zalora logo, menu categories (WOMEN, MEN, KIDS), a search bar, and utility icons (notifications, heart, shopping cart). Below the navigation bar, there are service icons: '3 DAYS FREE RETURNS', 'FREE DELIVERY ABOVE P999', 'CASH ON DELIVERY', and 'CALL 025 888 0777'. A 'DOWNLOAD & SHOP ON OUR APP' button is also present.

The main visual is a large banner featuring a woman and a man. Below the image are two buttons: 'SHOP WOMEN >' and 'SHOP MEN >'.

Below the main banner is a section titled 'THIS WEEK ON ZALORA' containing three promotional cards:

- FINAL CALL:** A card with a green background and a red border. Text includes 'FINAL CALL', 'THIRD TED MAY', 'UP TO 80% OFF', and lists brands: MANGO, RIVER ISLAND, ZALORA, GABRI. Below the card is the text: 'FINAL CALL - Up to 80% off your favourite brands!'.
- EXCLUSIVELY ON ZALORA:** A card with a black and white photo of a person at a gym. Text includes 'IVY PARK' and 'Beacon's newly launched active wear line.' Below the card is the text: 'EXCLUSIVELY ON ZALORA - Beacon's newly launched active wear line.'
- DESIGNERS' COLLECTION:** A card with a dark background. Text includes 'FROM THE RUNWAY TO YOUR WARDROBE', 'FASHION FESTIVAL \* ZALORA', and 'SHOP THE COLLECTION'. Below the card is the text: 'DESIGNERS' COLLECTION - Pre-Order Designer Collection from the latest season of Manila Fashion Festival.'

Below these cards is a section titled 'DISCOVER MORE' containing two more promotional cards:

- ZALORA OUTLET:** A card with a light background and a red border. Text includes 'ZALORA OUTLET', 'UP TO 80% OFF', 'YOUR FAVORITE BRANDS!', and 'ZALORA OUTLET'.
- ZALORA App:** A card with a blue and white background. Text includes 'DOWNLOAD THE NEW ZALORA App', 'GET 15% OFF', 'USE CODE: ZLAPP15', and 'APP STORE' and 'GOOGLE PLAY' logos. Below the card is the text: 'ZALORA MAGAZINE'.

## WEB APPENDIX F: Proofs

### Proof of Lemma 1

Recall that  $x_j = \epsilon_{j'} - \alpha p_{j'} + \alpha p_j$  such that

$$\int_{\epsilon_j = \epsilon_{j'} - \alpha p_{j'} + \alpha p_j}^{\infty} (\epsilon_j - \alpha p_j - \epsilon_{j'} + \alpha p_{j'}) f_j(\epsilon_j) d\epsilon_j = s.$$

As is common in the search literature, we define  $x_j - \alpha p_j$  to be the reservation utility for product  $j$ ; the consumer will search product  $j$  if and only if  $\epsilon_{j'} - \alpha p_{j'} < x_j - \alpha p_j$ . For  $\epsilon_j \sim_{iid} Unif[0, 1]$ , it can be shown that  $x_L = x_H = 1 - \sqrt{2s}$ .

We prove Lemma 1 separately for different ranges of the search cost,  $s$ , which dictate the consumer's search behavior. Note that a customer has a positive probability of searching product  $j$  only if her expected benefit of searching  $j$  exceeds her search cost  $s$ , i.e. if

$$s \leq \int_{\epsilon_j=0}^1 \max\{0, \epsilon_j - \alpha p_j\} d\epsilon_j = \int_{\epsilon_j=\alpha p_j}^1 (\epsilon_j - \alpha p_j) d\epsilon_j = \frac{1}{2}(1 - \alpha p_j)^2.$$

Furthermore, if the customer views product  $H$  first, she will always choose to incur the search cost  $s$  to view product  $L$  if the search cost is sufficiently small, specifically, if

$$P(\epsilon_H > x - \alpha p_L + \alpha p_H) = 0 \text{ which occurs when } x \leq 1 + \alpha p_L - \alpha p_H \text{ (equivalently, } s \leq \frac{1}{2}(\alpha p_H - \alpha p_L)^2).$$

Although  $\frac{1}{2}(\alpha p_H - \alpha p_L)^2 \leq \frac{1}{2}(1 - \alpha p_L)^2$ , we may have  $\frac{1}{2}(\alpha p_H - \alpha p_L)^2 \leq \frac{1}{2}(1 - \alpha p_H)^2$  or  $\frac{1}{2}(\alpha p_H - \alpha p_L)^2 \geq \frac{1}{2}(1 - \alpha p_H)^2$ . Each of these two scenarios leads to four regions on the continuum of possible search costs. Figure WF.1 illustrates these regions and maps them to cases in the proof that follows.

$$\text{Case (a): } s \leq \min\{\frac{1}{2}(1 - \alpha p_H)^2, \frac{1}{2}(\alpha p_H - \alpha p_L)^2\}$$

In this case, the search cost is small enough such that after viewing the first product  $j$ , the customer will choose to incur the search cost to search product  $j' \neq j$  with positive probability.

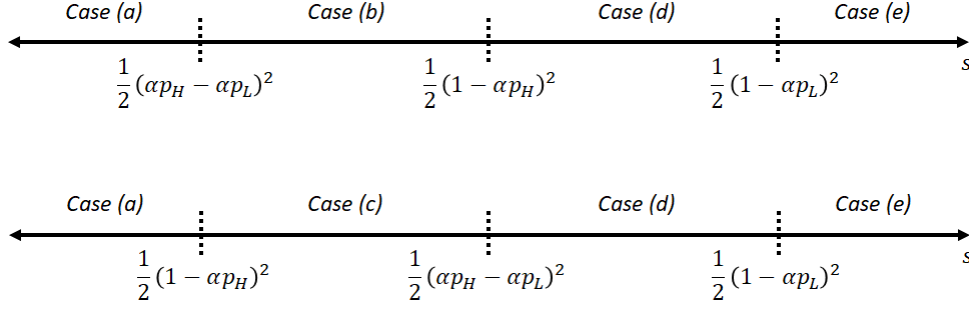


Figure WF.1: Possible regions of search costs as a function of parameters.

When the customer views the high-priced product first ( $j = H$ ), the condition

$s \leq \frac{1}{2}(\alpha p_H - \alpha p_L)^2$  tells us that the customer will always choose to incur the search cost to search product  $L$ , regardless of her realization of  $\epsilon_H$ . In such case, we have

$$\begin{aligned} \mathbb{E}[U^H] &= \mathbb{E}[\epsilon_L - \alpha p_L | \epsilon_L - \alpha p_L \geq \max\{0, \epsilon_H - \alpha p_H\}] P(\epsilon_L - \alpha p_L \geq \max\{0, \epsilon_H - \alpha p_H\}) \\ &\quad + \mathbb{E}[\epsilon_H - \alpha p_H | \epsilon_H - \alpha p_H \geq \max\{0, \epsilon_L - \alpha p_L\}] P(\epsilon_H - \alpha p_H \geq \max\{0, \epsilon_L - \alpha p_L\}) - s. \end{aligned} \quad (1)$$

We next present expressions for each of the terms above.

$$\begin{aligned} &\mathbb{E}[\epsilon_L - \alpha p_L | \epsilon_L - \alpha p_L \geq \max\{0, \epsilon_H - \alpha p_H\}] P(\epsilon_L - \alpha p_L \geq \max\{0, \epsilon_H - \alpha p_H\}) \\ &= \int_{\epsilon_L=1-\alpha p_H+\alpha p_L}^1 \int_{\epsilon_H=0}^1 (\epsilon_L - \alpha p_L) d\epsilon_H d\epsilon_L + \int_{\epsilon_L=\alpha p_L}^{1-\alpha p_H+\alpha p_L} \int_{\epsilon_H=0}^{\epsilon_L-\alpha p_L+\alpha p_H} (\epsilon_L - \alpha p_L) d\epsilon_H d\epsilon_L \quad (2) \\ &= \frac{1}{3} - \alpha p_L + \frac{1}{2}\alpha p_H + \frac{1}{2}(\alpha p_L)^2 - \frac{1}{2}(\alpha p_H)^2 + \frac{1}{6}(\alpha p_H)^3 \end{aligned}$$

$$\begin{aligned} &\mathbb{E}[\epsilon_H - \alpha p_H | \epsilon_H - \alpha p_H \geq \max\{0, \epsilon_L - \alpha p_L\}] P(\epsilon_H - \alpha p_H \geq \max\{0, \epsilon_L - \alpha p_L\}) \\ &= \int_{\epsilon_H=\alpha p_H}^1 \int_{\epsilon_L=0}^{\epsilon_H-\alpha p_H+\alpha p_L} (\epsilon_H - \alpha p_H) d\epsilon_L d\epsilon_H \quad (3) \\ &= \frac{1}{3} - \alpha p_H + \frac{1}{2}\alpha p_L + (\alpha p_H)^2 - \alpha p_L \alpha p_H - \frac{1}{3}(\alpha p_H)^3 + \frac{1}{2}\alpha p_L (\alpha p_H)^2 \end{aligned}$$

Combining these expressions, we get

$$\begin{aligned}\mathbb{E}[U^H] &= \frac{2}{3} - \frac{1}{2}\alpha p_L - \frac{1}{2}\alpha p_H + \frac{1}{2}(\alpha p_L)^2 + \frac{1}{2}(\alpha p_H)^2 - \frac{1}{6}(\alpha p_H)^3 \\ &\quad - \alpha p_L \alpha p_H + \frac{1}{2}\alpha p_L (\alpha p_H)^2 - \frac{1}{2}(1-x)^2\end{aligned}\quad (4)$$

On the other hand, when the customer views the low-priced product first ( $j = L$ ), her positive probability of searching  $j' = H$  is strictly less than one. Here, we have (for  $j = L$  and  $j' = H$ )

$$\begin{aligned}\mathbb{E}[U^j] &= \mathbb{E}[\epsilon_j - \alpha p_j | \epsilon_j - \alpha p_j \geq x - \alpha p_{j'}] P(\epsilon_j - \alpha p_j \geq x - \alpha p_{j'}) \\ &\quad + \mathbb{E}[\epsilon_j - \alpha p_j | \epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_j - \alpha p_j \geq \max\{0, \epsilon_{j'} - \alpha p_{j'}\}] \\ &\quad * P(\epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_j - \alpha p_j \geq \max\{0, \epsilon_{j'} - \alpha p_{j'}\}) \\ &\quad + \mathbb{E}[\epsilon_{j'} - \alpha p_{j'} | \epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_{j'} - \alpha p_{j'} \geq \max\{0, \epsilon_j - \alpha p_j\}] \\ &\quad * P(\epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_{j'} - \alpha p_{j'} \geq \max\{0, \epsilon_j - \alpha p_j\}) \\ &\quad - s(1 - P(\epsilon_j - \alpha p_j \geq x - \alpha p_{j'})).\end{aligned}\quad (5)$$

The first conditional expectation represents the expected utility the customer gains from purchasing product  $j$  without searching product  $j'$ ; in this case, the utility that the customer gains from product  $j$  exceeds the reservation utility  $x - \alpha p_{j'}$ . The second and third conditional expectations represent the customer's utility (omitting search cost) if she searches product  $j'$  and chooses to purchase product  $j$  or  $j'$ , respectively. The final term reflects the customer's disutility in search cost when she chooses to search product  $j'$ . We next present expressions for each of the conditional expectations and probabilities above.

$$P(\epsilon_j - \alpha p_j \geq x - \alpha p_{j'}) = 1 - (x - \alpha p_{j'} + \alpha p_j) \quad (6)$$

$$\begin{aligned}
\mathbb{E}[\epsilon_j - \alpha p_j | \epsilon_j - \alpha p_j \geq x - \alpha p_{j'}] &= \frac{1}{1 - (x - \alpha p_{j'} + \alpha p_j)} \int_{\epsilon_j = x - \alpha p_{j'} + \alpha p_j}^1 (\epsilon_j - \alpha p_j) d\epsilon_j \\
&= \frac{1}{2}(1 + x - \alpha p_{j'} - \alpha p_j)
\end{aligned} \tag{7}$$

$$\begin{aligned}
&P(\epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_j - \alpha p_j \geq \max\{0, \epsilon_{j'} - \alpha p_{j'}\}) \\
&= \int_{\epsilon_j = \alpha p_j}^{x - \alpha p_{j'} + \alpha p_j} \int_{\epsilon_{j'} = 0}^{\epsilon_j + \alpha p_{j'} - \alpha p_j} d\epsilon_{j'} d\epsilon_j \\
&= \frac{1}{2}(x - \alpha p_{j'})(x + \alpha p_{j'})
\end{aligned} \tag{8}$$

$$\begin{aligned}
&\mathbb{E}[\epsilon_j - \alpha p_j | \epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_j - \alpha p_j \geq \max\{0, \epsilon_{j'} - \alpha p_{j'}\}] \\
&= \frac{2}{(x - \alpha p_{j'})(x + \alpha p_{j'})} \int_{\epsilon_j = \alpha p_j}^{x - \alpha p_{j'}} \int_{\epsilon_{j'} = 0}^{\epsilon_j + \alpha p_{j'} - \alpha p_j} (\epsilon_j - \alpha p_j) d\epsilon_{j'} d\epsilon_j \\
&= \frac{(x - \alpha p_{j'})(2x + \alpha p_{j'})}{3(x + \alpha p_{j'})}
\end{aligned} \tag{9}$$

$$\begin{aligned}
&P(\epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_{j'} - \alpha p_{j'} \geq \max\{0, \epsilon_j - \alpha p_j\}) \\
&= \int_{\epsilon_{j'} = \alpha p_{j'}}^1 \int_{\epsilon_j = 0}^{\alpha p_j} d\epsilon_j d\epsilon_{j'} + (1 - x)(x - \alpha p_{j'}) + \int_{\epsilon_{j'} = \alpha p_{j'}}^x \int_{\epsilon_j = \alpha p_j}^{\epsilon_{j'} - \alpha p_{j'} + \alpha p_j} d\epsilon_j d\epsilon_{j'} \\
&= \alpha p_j(1 - \alpha p_{j'}) + (1 - x)(x - \alpha p_{j'}) + \frac{1}{2}(x - \alpha p_{j'})^2
\end{aligned} \tag{10}$$

$$\begin{aligned}
&\mathbb{E}[\epsilon_{j'} - \alpha p_{j'} | \epsilon_j - \alpha p_j \leq x - \alpha p_{j'} \cap \epsilon_{j'} - \alpha p_{j'} \geq \max\{0, \epsilon_j - \alpha p_j\}] \\
&= \frac{\int_{\epsilon_{j'} = \alpha p_{j'}}^{x - \alpha p_{j'}} \int_{\epsilon_j = 0}^{\epsilon_{j'} - \alpha p_{j'} + \alpha p_j} (\epsilon_{j'} - \alpha p_{j'}) d\epsilon_j d\epsilon_{j'} + \int_{\epsilon_{j'} = x}^{1 - \alpha p_{j'}} \int_{\epsilon_j = 0}^{x - \alpha p_{j'} + \alpha p_j} (\epsilon_{j'} - \alpha p_{j'}) d\epsilon_j d\epsilon_{j'}}{\alpha p_j(1 - \alpha p_{j'}) + (1 - x)(x - \alpha p_{j'}) + \frac{1}{2}(x - \alpha p_{j'})^2} \\
&= \frac{(x - \alpha p_{j'})^2(\frac{1}{3}(x - \alpha p_{j'}) + \frac{1}{2}\alpha p_j) + \frac{1}{2}(x - \alpha p_{j'} + \alpha p_j)((1 - \alpha p_{j'})^2 - (x - \alpha p_{j'})^2)}{\alpha p_j(1 - \alpha p_{j'}) + (1 - x)(x - \alpha p_{j'}) + \frac{1}{2}(x - \alpha p_{j'})^2}
\end{aligned} \tag{11}$$

$$s(1 - P(\epsilon_j - \alpha p_j \geq x - \alpha p_{j'})) = s(x - \alpha p_{j'} + \alpha p_j) \quad (12)$$

After algebraic manipulations of Equations (6)-(12), we have the following simplified expression for  $\mathbb{E}[U^j]$ :

$$\begin{aligned} \mathbb{E}[U^j] = & \frac{1}{2} - \alpha p_j + x \alpha p_j - x \alpha p_{j'} - \alpha^2 p_j p_{j'} + \frac{1}{2} x^2 + \frac{1}{2} \alpha^2 p_j^2 + \frac{1}{2} \alpha^2 p_{j'}^2 \\ & - \frac{1}{2} x^2 \alpha p_j + \frac{1}{2} x^2 \alpha p_{j'} - \frac{1}{3} x^3 - \frac{1}{6} \alpha^3 p_{j'}^3 + \frac{1}{2} \alpha^3 p_{j'}^2 p_j \end{aligned} \quad (13)$$

With the expression for  $\mathbb{E}[U^H]$  in (4) and  $\mathbb{E}[U^L]$  in (13), we next define

$$\begin{aligned} \tilde{U}(x, \alpha p_L, \alpha p_H) \triangleq \mathbb{E}[U^L] - \mathbb{E}[U^H] = & \frac{1}{3} - x + x^2 - \frac{1}{2} \alpha p_L + x \alpha p_L - x \alpha p_H - \frac{1}{3} x^3 \\ & - \frac{1}{2} x^2 \alpha p_L + \frac{1}{2} x^2 \alpha p_H - \frac{1}{6} (\alpha p_L)^3 + \frac{1}{2} \alpha p_H + \frac{1}{6} (\alpha p_H)^3 \end{aligned} \quad (14)$$

and we want to show that this is non-negative.

$$\frac{\partial \tilde{U}}{\partial x}(x, \alpha p_L, \alpha p_H) = (\alpha p_H - \alpha p_L)(x - 1) - (x - 1)^2 \leq 0, \quad (15)$$

and therefore,

$$\tilde{U}(x, \alpha p_L, \alpha p_H) \geq \tilde{U}(\alpha p_H, \alpha p_L, \alpha p_H)$$

since the conditions on the search cost  $s$  correspond to  $x \leq \alpha p_H$ . Define

$$\begin{aligned} l(\alpha p_L, \alpha p_H) \triangleq & \tilde{U}(\alpha p_H, \alpha p_L, \alpha p_H) \\ = & \frac{1}{3} - \frac{1}{2} \alpha p_H - \frac{1}{2} \alpha p_L + \alpha p_L \alpha p_H - \frac{1}{2} (\alpha p_L) (\alpha p_H)^2 - \frac{1}{6} (\alpha p_L)^3 + \frac{1}{3} (\alpha p_H)^3. \end{aligned} \quad (16)$$

We have

$$\frac{\partial l}{\partial \alpha p_L}(\alpha p_L, \alpha p_H) = -\frac{1}{2}(\alpha p_H - 1)^2 - \frac{1}{3}(\alpha p_L)^2 \leq 0, \quad (17)$$

which implies that  $l(\alpha p_L, \alpha p_H)$  is decreasing in  $\alpha p_L$ . Since  $\alpha p_L \leq \alpha p_H$ ,

$$\mathbb{E}[U^L] - \mathbb{E}[U^H] \geq l(\alpha p_L, \alpha p_H) \geq l(\alpha p_H, \alpha p_H) = -\frac{1}{3}(x - 1)^3 \geq 0, \quad (18)$$

which concludes the proof of this case.

$$\text{Case (b): } \frac{1}{2}(\alpha p_H - \alpha p_L)^2 \leq s \leq \frac{1}{2}(1 - \alpha p_H)^2$$

In this case, the search cost is small enough such that after viewing the first product  $j$ , the customer will choose to incur the search cost to search product  $j' \neq j$  with positive probability  $< 1$ . Here, we have  $\mathbb{E}[U^L]$  and  $\mathbb{E}[U^H]$  as defined in Equation (13) from case (a). Next, we define

$$\begin{aligned} \tilde{U}(x, \alpha p_L, \alpha p_H) \triangleq \mathbb{E}[U^L] - \mathbb{E}[U^H] &= \alpha p_H - \alpha p_L - 2x\alpha p_H + 2x\alpha p_L + x^2\alpha p_H - x^2\alpha p_L \\ &\quad - \frac{1}{6}(\alpha p_H)^3 + \frac{1}{6}(\alpha p_L)^3 + \frac{1}{2}(\alpha p_H)^2(\alpha p_L) - \frac{1}{2}(\alpha p_L)^2(\alpha p_H) \end{aligned} \quad (19)$$

and we want to show that this is non-negative.

$$\frac{\partial \tilde{U}}{\partial x}(x, \alpha p_L, \alpha p_H) = 2(x - 1)(\alpha p_H - \alpha p_L) \leq 0, \quad (20)$$

and therefore,

$$\tilde{U}(x, \alpha p_L, \alpha p_H) \geq \tilde{U}(1 + \alpha p_L - \alpha p_H, \alpha p_L, \alpha p_H)$$

since the conditions on the search cost  $s$  correspond to  $x \leq 1 + \alpha p_L - \alpha p_H$ . Define



$$\begin{aligned}
l(\alpha p_L, \alpha p_H) &\triangleq \tilde{U}(1 + \alpha p_L - \alpha p_H, \alpha p_L, \alpha p_H) \\
&= \frac{5}{6}(\alpha p_H)^3 - \frac{5}{6}(\alpha p_L)^3 - \frac{5}{2}(\alpha p_L)(\alpha p_H)^2 + \frac{5}{2}(\alpha p_L)^2(\alpha p_H).
\end{aligned} \tag{21}$$

We have

$$\frac{\partial l}{\partial \alpha p_L}(\alpha p_L, \alpha p_H) = -\frac{5}{2}(\alpha p_L - \alpha p_H)^2 \leq 0, \tag{22}$$

which implies that  $l(\alpha p_L, \alpha p_H)$  is decreasing in  $\alpha p_L$ . Since  $\alpha p_L \leq \alpha p_H$ ,

$$\mathbb{E}[U^L] - \mathbb{E}[U^H] \geq l(\alpha p_L, \alpha p_H) \geq l(\alpha p_H, \alpha p_H) = 0, \tag{23}$$

which concludes the proof of this case.

$$\text{Case (c): } \frac{1}{2}(1 - \alpha p_H)^2 \leq s \leq \frac{1}{2}(\alpha p_H - \alpha p_L)^2$$

In this case, if the customer views product  $L$  first, the search cost is prohibitively large such that she would never incur a search cost to search product  $H$ . We have

$\mathbb{E}[U^L] = \mathbb{E}[\max\{0, \epsilon_L - \alpha p_L\}] = \frac{1}{2}(1 - \alpha p_L)^2$ . However, if the customer views product  $H$  first, the search cost is small enough such that she will always choose to search product  $L$ , regardless of her realization of  $\epsilon_H$ , and her utility is as defined in Equation (4). We define

$$\begin{aligned}
\tilde{U}(x, \alpha p_L, \alpha p_H) &\triangleq \mathbb{E}[U^L] - \mathbb{E}[U^H] = \frac{1}{3} - \frac{1}{2}\alpha p_L + \frac{1}{2}\alpha p_H - \frac{1}{2}(\alpha p_H)^2 \\
&\quad + \frac{1}{6}(\alpha p_H)^3 + \alpha p_L \alpha p_H - \frac{1}{2}(\alpha p_L)(\alpha p_H)^2 - x + \frac{1}{2}x^2
\end{aligned} \tag{24}$$

and we want to show that this is non-negative.

$$\frac{\partial \tilde{U}}{\partial x}(x, \alpha p_L, \alpha p_H) = x - 1 \leq 0, \tag{25}$$

and therefore,

$$\tilde{U}(x, \alpha p_L, \alpha p_H) \geq \tilde{U}(\alpha p_H, \alpha p_L, \alpha p_H)$$

since the conditions on the search cost  $s$  correspond to  $x \leq \alpha p_H$ . Define

$$\begin{aligned} l(\alpha p_L, \alpha p_H) &\triangleq \tilde{U}(\alpha p_H, \alpha p_L, \alpha p_H) \\ &= \frac{1}{3} - \frac{1}{2}\alpha p_L - \frac{1}{2}\alpha p_H + \frac{1}{6}(\alpha p_H)^3 + \alpha p_L \alpha p_H - \frac{1}{2}(\alpha p_L)(\alpha p_H)^2. \end{aligned} \quad (26)$$

We have

$$\frac{\partial l}{\partial \alpha p_L}(\alpha p_L, \alpha p_H) = -\frac{1}{2}(1 - \alpha p_H)^2 \leq 0, \quad (27)$$

which implies that  $l(\alpha p_L, \alpha p_H)$  is decreasing in  $\alpha p_L$ . Since  $\alpha p_L \leq 2\alpha p_H - 1$ ,

$$\begin{aligned} \mathbb{E}[U^L] - \mathbb{E}[U^H] &\geq l(\alpha p_L, \alpha p_H) \\ &\geq l(2\alpha p_H - 1, \alpha p_H) = \frac{5}{6} - \frac{5}{2}\alpha p_H + \frac{5}{2}(\alpha p_H)^2 - \frac{5}{6}(\alpha p_H)^3 \geq 0, \end{aligned} \quad (28)$$

which concludes the proof of this case.

$$\text{Case (d): } \max\{\frac{1}{2}(1 - \alpha p_H)^2, \frac{1}{2}(\alpha p_H - \alpha p_L)^2\} \leq s \leq \frac{1}{2}(1 - \alpha p_L)^2$$

In this case, if the customer views product  $L$  first, the search cost is prohibitively large such that she would never incur a search cost to search product  $H$ . We have

$\mathbb{E}[U^L] = \mathbb{E}[\max\{0, \epsilon_L - \alpha p_L\}] = \frac{1}{2}(1 - \alpha p_L)^2$ . However, if the customer views product  $H$  first, the search cost is small enough such that she will choose to search product  $L$  with positive probability  $< 1$ , and her expected utility is as defined in Equation (13) for  $j = H, j' = L$ . We want to show

$$\begin{aligned}
\mathbb{E}[U^H] &= \frac{1}{2} - \alpha p_H + x \alpha p_H - x \alpha p_L - \alpha^2 p_H p_L + \frac{1}{2} x^2 + \frac{1}{2} \alpha^2 p_H^2 + \frac{1}{2} \alpha^2 p_L^2 \\
&\quad - \frac{1}{2} x^2 \alpha p_H + \frac{1}{2} x^2 \alpha p_L - \frac{1}{3} x^3 - \frac{1}{6} \alpha^3 p_L^3 + \frac{1}{2} \alpha^3 p_L^2 p_H \\
&\leq \frac{1}{2} (1 - \alpha p_L)^2 = \mathbb{E}[U^L]
\end{aligned} \tag{29}$$

Rearranging terms, this inequality can be rewritten as

$$\begin{aligned}
f(x, \alpha p_L, \alpha p_H) &\triangleq -\frac{1}{3} x^3 + \frac{1}{2} x^2 - x \alpha p_L + x \alpha p_H + \frac{1}{2} x^2 \alpha p_L - \frac{1}{2} x^2 \alpha p_H - \frac{1}{6} (\alpha p_L)^3 \\
&\quad + \alpha p_L - \alpha p_H + \frac{1}{2} (\alpha p_H)^2 + \frac{1}{2} (\alpha p_L)^2 \alpha p_H - (\alpha p_L)(\alpha p_H) \leq 0
\end{aligned} \tag{30}$$

We have

$$\frac{\partial f}{\partial x} = (1 - x)(x - \alpha p_L) + \alpha p_H(1 - x) \geq 0, \tag{31}$$

where the inequality holds because our conditions on  $s$  equate to the following conditions on  $x$ :

$\alpha p_L \leq x \leq \min\{\alpha p_H, 1 + \alpha p_L - \alpha p_H\}$ . This means that for any  $\alpha p_L$  and  $\alpha p_H$ ,  $f(x, \alpha p_L, \alpha p_H)$

is increasing in  $x$ . Thus, in order to show  $f(x, \alpha p_L, \alpha p_H) \leq 0$ , it suffices to show

$$f(\min\{\alpha p_H, 1 + \alpha p_L - \alpha p_H\}, \alpha p_L, \alpha p_H) \leq 0.$$

Consider each of the following two subcases:

*Case (d.1):*  $\alpha p_H \leq 1 + \alpha p_L - \alpha p_H$

In this subcase, we want to show  $f(\alpha p_H, \alpha p_L, \alpha p_H) \leq 0$ . Let

$$\begin{aligned}
g(\alpha p_L, \alpha p_H) &\triangleq f(\alpha p_H, \alpha p_L, \alpha p_H) = -\frac{5}{6} (\alpha p_H)^3 + 2(\alpha p_H)^2 - 2(\alpha p_L)(\alpha p_H) \\
&\quad + \frac{1}{2} (\alpha p_L)(\alpha p_H)^2 + \frac{1}{2} (\alpha p_L)^2 (\alpha p_H) - \frac{1}{6} (\alpha p_L)^3 + \alpha p_L - \alpha p_H
\end{aligned} \tag{32}$$

We will first argue that  $g(\alpha p_L, \alpha p_H)$  is increasing in  $\alpha p_L$  and will subsequently use this to

complete the proof.

$$\frac{\partial g}{\partial \alpha p_L}(\alpha p_L, \alpha p_H) = -2\alpha p_H + \frac{1}{2}(\alpha p_H)^2 + \alpha p_L \alpha p_H - \frac{1}{2}(\alpha p_L)^2 + 1 \quad (33)$$

This expression is decreasing in  $\alpha p_H$  because

$$\frac{\partial^2 g}{\partial \alpha p_L \partial \alpha p_H}(\alpha p_L, \alpha p_H) = -2 + \alpha p_H + \alpha p_L \leq 0. \quad (34)$$

Thus  $\frac{\partial g}{\partial \alpha p_L}(\alpha p_L, \alpha p_H)$  achieves its minimum value when  $\alpha p_H$  is at its maximum value, which for the conditions in this subcase is when  $\alpha p_H = \frac{1}{2}(1 + \alpha p_L)$ . This gives us

$$\frac{\partial g}{\partial \alpha p_L}(\alpha p_L, \alpha p_H) \geq \frac{\partial g}{\partial \alpha p_L}(\alpha p_L, \frac{1}{2}(1 + \alpha p_L)) = \frac{1}{8}(1 - \alpha p_L)^2 > 0. \quad (35)$$

Therefore  $g(\alpha p_L, \alpha p_H)$  is increasing in  $\alpha p_L$ . Noting  $\alpha p_L \leq \alpha p_H$ , we have

$$g(\alpha p_L, \alpha p_H) \leq g(\alpha p_H, \alpha p_H) = 0 \quad (36)$$

which concludes the proof of this subcase.

*Case (d.2):*  $\alpha p_H \geq 1 + \alpha p_L - \alpha p_H$

In this case, we want to show  $f(1 + \alpha p_L - \alpha p_H, \alpha p_L, \alpha p_H) \leq 0$ . Let

$$\begin{aligned} h(\alpha p_L, \alpha p_H) \triangleq f(1 + \alpha p_L - \alpha p_H, \alpha p_L, \alpha p_H) &= \frac{1}{6}(1 + \alpha p_L - \alpha p_H)^3 - \frac{1}{6}(\alpha p_L)^3 \\ &\quad - (\alpha p_L)^2 + (\alpha p_L)(\alpha p_H) - \frac{1}{2}(\alpha p_H)^2 + \frac{1}{2}(\alpha p_L)^2(\alpha p_H) \end{aligned} \quad (37)$$

We will first argue that  $h(\alpha p_L, \alpha p_H)$  is increasing in  $\alpha p_L$  and will subsequently use this to complete the proof.

$$\frac{\partial h}{\partial \alpha p_L}(\alpha p_L, \alpha p_H) = \frac{1}{2}(1 + \alpha p_L - \alpha p_H)^2 - \frac{1}{2}(\alpha p_L)^2 - 2\alpha p_L + \alpha p_H + (\alpha p_L)(\alpha p_H) \quad (38)$$

This expression is increasing in  $\alpha p_H$  because

$$\frac{\partial^2 h}{\partial \alpha p_L \partial \alpha p_H}(\alpha p_L, \alpha p_H) = \alpha p_H \geq 0. \quad (39)$$

Thus  $\frac{\partial h}{\partial \alpha p_L}(\alpha p_L, \alpha p_H)$  achieves its minimum value when  $\alpha p_H$  is at its minimum value, which for the conditions in this subcase is when  $\alpha p_H = \frac{1}{2}(1 + \alpha p_L)$ . This gives us

$$\frac{\partial h}{\partial \alpha p_L}(\alpha p_L, \alpha p_H) \geq \frac{\partial h}{\partial \alpha p_L}(\alpha p_L, \frac{1}{2}(1 + \alpha p_L)) = \frac{1}{4}(1 - \alpha p_L)^2 + \frac{1}{2} > 0. \quad (40)$$

Therefore  $h(\alpha p_L, \alpha p_H)$  is increasing in  $\alpha p_L$ . Noting  $\alpha p_L \leq 2\alpha p_H - 1$ , we have

$$h(\alpha p_L, \alpha p_H) \leq h(2\alpha p_H - 1, \alpha p_H) = \frac{5}{6}(\alpha p_H)^3 - \frac{5}{2}(\alpha p_H)^2 + \frac{5}{2}\alpha p_H - \frac{5}{6} \leq 0 \quad (41)$$

which concludes the proof of this subcase.

$$\text{Case (e): } s \geq \frac{1}{2}(1 - \alpha p_L)^2$$

In this case, the search cost is large enough such that the customer would only consider the initial product viewed for purchase and would never incur a search cost to search the second product. We simply have for  $j \in \{L, H\}$

$$\mathbb{E}[U^j] = \mathbb{E}[\max\{0, \epsilon_j - \alpha p_j\}] = \frac{1}{2}(1 - \alpha p_j)^2.$$

Since  $p_L \leq p_H$ , we have  $\mathbb{E}[U^L] \geq \mathbb{E}[U^H]$ .

### Proof of Theorem 1

We prove each statement separately below.

*Theorem 1(i):*

Consider a customer who may face two possible scenarios: one scenario where she views product  $L$  first and the other scenario where she views product  $H$  first. We will argue that she will either purchase a product in both scenarios (could be different products) or not purchase a product in either scenario. This implies that conversion (purchase probability) is the same for both scenarios and, together with Lemma 1, implies that conversion would be the same regardless of if a customer was in the control or treatment group.

Note that since  $s \leq \frac{1}{2}(1 - \alpha p_H)^2$ , a customer will always choose to search the second product before choosing not to buy either product, i.e. the customer will purchase a product if  $\max\{\epsilon_j - \alpha p_j, \epsilon_{j'} - \alpha p_{j'}\} \geq 0$ . There are 4 possible search and purchase outcomes to consider, given the customer viewed product  $j$  first.

1. *The customer purchases product  $j$  without searching product  $j'$ .* This implies  $\max\{\epsilon_j - \alpha p_j, \epsilon_{j'} - \alpha p_{j'}\} \geq \epsilon_j - \alpha p_j \geq 0$ , and thus the customer also would have purchased a product if she were to have viewed product  $j'$  first.
2. *The customer purchases product  $j$  after searching product  $j'$ .* This implies  $\max\{\epsilon_j - \alpha p_j, \epsilon_{j'} - \alpha p_{j'}\} = \epsilon_j - \alpha p_j \geq 0$ , and thus the customer also would have purchased a product if she were to have viewed product  $j'$  first.
3. *The customer purchases product  $j'$ .* This implies  $\max\{\epsilon_j - \alpha p_j, \epsilon_{j'} - \alpha p_{j'}\} = \epsilon_{j'} - \alpha p_{j'} \geq 0$ , and thus the customer also would have purchased a product if she were to have viewed product  $j'$  first.
4. *The customer does not purchase either product.* This implies  $\max\{\epsilon_j - \alpha p_j, \epsilon_{j'} - \alpha p_{j'}\} < 0$ , and thus the customer also would not have purchased either product if she were to have viewed product  $j'$  first.

*Theorem 1(ii):*

In this case, a customer who views product  $L$  first will never choose to search product  $H$ , whereas a customer who views product  $H$  first will always choose to search product  $L$  before choosing not to buy either product.

If a customer who views product  $L$  first purchases product  $L$ , we have  $\max\{\epsilon_L - \alpha p_L, \epsilon_H - \alpha p_H\} \geq \epsilon_L - \alpha p_L \geq 0$ , and thus the customer also would have purchased a product if she were to have viewed product  $H$  first.

Now consider a customer who views product  $H$  first and the following 4 possible search and purchase outcomes:

1. *The customer purchases product  $H$  without searching product  $L$ .* With positive probability,  $\epsilon_L - \alpha p_L < 0$ , and thus the customer would not have purchased a product if she were to have viewed product  $L$  first.
2. *The customer purchases product  $H$  after searching product  $L$ .* With positive probability,  $\epsilon_L - \alpha p_L < 0$ , and thus the customer would not have purchased a product if she were to have viewed product  $L$  first.
3. *The customer purchases product  $L$ .* This implies  $\epsilon_L - \alpha p_L \geq 0$ , and thus the customer also would have purchased product  $L$  if she were to have viewed product  $L$  first.
4. *The customer does not purchase either product.* This implies  $\epsilon_L - \alpha p_L < 0$ , and thus the customer also would not have purchased a product if she were to have viewed product  $L$  first.

Thus we have  $d^L < d^H$ , and together with Lemma 1, this implies conversion would be greater if the customer was in the treatment group.

*Theorem 1(iii):*

In this case, the search cost is so large that a customer who views product  $j$  first will never choose to search product  $j'$ , for  $j \in \{L, H\}$ . This gives us

$$d^L = 1 - \alpha p_L > 1 - \alpha p_H = d^H, \quad (42)$$

and together with Lemma 1, this implies conversion would be greater if the customer was in the control group.

### **Proof of Theorem 2**

We prove Theorem 2 separately for different ranges of the search cost,  $s$ .

$$\text{Case (a): } s \leq \frac{1}{2}(1 - \alpha p_H)^2$$

We first prove that  $d_H^H \geq d_H^L$ , i.e. the demand for product  $H$  will be greater when the customer views product  $H$  first. It suffices to show that a customer who views product  $L$  first and purchases product  $H$  would also have purchased product  $H$  if she viewed product  $H$  first. Note that in order for a customer who views product  $L$  first to purchase product  $H$ , she must have searched product  $H$  and thus we know  $\max\{\epsilon_H - \alpha p_H, \epsilon_L - \alpha p_L\} = \epsilon_H - \alpha p_H$ . If instead the customer were to view product  $H$  first, she would either purchase product  $H$  without searching product  $L$ , or would search product  $L$  and then purchase product  $H$  since  $\max\{\epsilon_H - \alpha p_H, \epsilon_L - \alpha p_L\} = \epsilon_H - \alpha p_H$ .

We next compare revenues:

$$\begin{aligned} d_L^L p_L + d_H^L p_H &= (d^L - d_H^L) p_L + d_H^L p_H = (d^H - d_H^L) p_L + d_H^L p_H \\ &\leq (d^H - d_H^H) p_L + d_H^H p_H = d_L^H p_L + d_H^H p_H, \end{aligned} \quad (43)$$

where the second equality holds because  $d^H = d^L$  from Theorem 1, and the inequality holds because  $p_L < p_H$  and  $d_H^H \geq d_H^L$ . Together with Lemma 1, this concludes our proof for this case.

$$\text{Case (b): } \frac{1}{2}(1 - \alpha p_H)^2 < s \leq \frac{1}{2}(1 - \alpha p_L)^2$$



In this case, we have

$$d_L^L p_L + d_H^L p_H = d^L p_L < d^H p_L < d_L^H p_L + d_H^H p_H, \quad (44)$$

where the first inequality follows from Theorem 1 and the second inequality follows from  $p_H > p_L$ . Together with Lemma 1, this concludes our proof for this case.

*Case (c):*  $s > \frac{1}{2}(1 - \alpha p_L)^2$

In this case, note that  $d^j = d_j^j = 1 - \alpha p_j$  and thus the expected revenue of a customer who views product  $j$  first is  $(1 - \alpha p_j)p_j$ . This is a parabola maximized at  $p_j = \frac{1}{2\alpha}$ , and thus the expected revenue is largest for a customer who views product  $L$  first if and only if

$|(1 - \alpha p_L)p_L - \frac{1}{2\alpha}| \leq |(1 - \alpha p_H)p_H - \frac{1}{2\alpha}|$ ; together with Lemma 1, this concludes our proof of this case.

### **Proof of Theorem 3**

Similar to the proof of Theorem 1, we prove each statement separately below. Note that a customer has a positive probability of searching the second product  $j$  only if her expected benefit of searching  $j$  exceeds her search cost  $s$ , i.e. if

$$s \leq \int_{\epsilon_j = -\infty}^{\infty} \max\{0, \epsilon_j - \alpha p_j\} f_j(\epsilon_j) d\epsilon_j = \int_{\epsilon_j = \alpha p_j}^{\infty} (\epsilon_j - \alpha p_j) f_j(\epsilon_j) d\epsilon_j.$$

*Theorem 3(i):*

Since  $s \leq \min \left\{ \int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L, \int_{\epsilon_H = \alpha p_H}^{\infty} (\epsilon_H - \alpha p_H) f_H(\epsilon_H) d\epsilon_H \right\}$ , a customer will always choose to search the second product before choosing not to buy either product, i.e. the customer will purchase a product if  $\max\{\epsilon_j - \alpha p_j, \epsilon_{j'} - \alpha p_{j'}\} \geq 0$ . The proof for this statement is identical to that of Theorem 1(i).

*Theorem 3(ii):*

In this case, a customer who views product  $L$  first will never choose to search product  $H$ , whereas a customer who views product  $H$  first will always choose to search product  $L$  before choosing not to buy either product. The proof for this statement is identical to that of Theorem 1(ii).

*Theorem 3(iii):*

The proof for this case is identical to the proof for case (ii) after swapping  $L$  and  $H$ .

*Theorem 3(iv):*

In this case, the search cost is so large that a customer who views product  $j$  first will never choose to search product  $j'$ . This gives us

$$d^j = \int_{\epsilon_j = \alpha p_j}^{\infty} f_j(\epsilon_j) d\epsilon_j, \quad (45)$$

and thus the product that maximizes this quantity will lead to greater demand if viewed first.

#### **Proof of Theorem 4**

We prove Theorem 4 separately for different ranges of the search cost,  $s$ .

$$\text{Case (a): } s \leq \min \left\{ \int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L, \int_{\epsilon_H = \alpha p_H}^{\infty} (\epsilon_H - \alpha p_H) f_H(\epsilon_H) d\epsilon_H \right\}$$

The proof of this case is identical to the proof of case (a) in Theorem 2, where  $d^H = d^L$  from Theorem 3.

$$\text{Case (b): } \int_{\epsilon_H = \alpha p_H}^{\infty} (\epsilon_H - \alpha p_H) f_H(\epsilon_H) d\epsilon_H < s \leq \int_{\epsilon_L = \alpha p_L}^{\infty} (\epsilon_L - \alpha p_L) f_L(\epsilon_L) d\epsilon_L$$

In this case, we have

$$d_L^L p_L + d_H^L p_H = d^L p_L < d^H p_L < d_L^H p_L + d_H^H p_H, \quad (46)$$

where the first inequality follows from Theorem 3 and the second inequality follows from  $p_H > p_L$ .