The Joy of Shopping: Thrill of the Hunt*

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Abstract

People sometimes enjoy the thrill of the hunt, which implies search can generate joy in addition to costs. For example, some customers say they enjoy searching for unique items such as vintage T-shirts or unusual flavors of a snack food, and managers at warehouse stores, discount stores, thrift stores, and some online selling platforms say they design their store format to produce a treasure hunt experience. We develop a model in which customers enjoy searching for a treasure. We derive the optimal product price and hunt difficulty level for a company that sells treasures such as unique thrifted clothes. For products with low intrinsic value, the seller sets price equal to product value and makes the search process difficult enough that some customers leave the store without finding a product to buy. Search utility then motivates customers to travel to the store and participate in the hunt.

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1 Introduction

Throughout human history, whether in romantic pursuits, pirate adventures, or English fox hunts, people have enjoyed the thrill of the hunt. In these examples, hunting for treasure provides inherent joy in addition to the joy of possessing the treasure. In the modern retail context, a large body of academic research has shown that many customers say shopping also produces "the excitement of the hunt," and these customers agree with statements such as "Shopping is a thrill to me," and "In certain second-hand outlets, I feel rather like a treasure hunter" (Babin et al. 1994, Arnold and Reynolds 2003, Jones et al. 2006, Guiot and Roux 2010).

For example, some customers say they visit discount stores like T.J. Maxx, warehouse stores like Costco, and thrift stores like Goodwill and Salvation Army partly because they enjoy the thrill of hunting unique or exciting items to purchase, and managers of these stores explicitly say they design their retail format to produce a treasure hunt experience (Mitchell 2018, Wahba 2024). The appendix contains examples with images of this type of retail format that makes the search process a fun and exciting challenge. For any given customer, the search process may be a joy in some retail situations but a cost in others. For example, a customer who enjoys searching for a vintage T-shirt with the name of her favorite singer may dread time spent searching for a new power cord for her computer. From a managerial perspective, any given retailer has some customers who enjoy search and others who consider search costly.

An important example of treasure hunting in a retail context occurs in the used clothing market, which is growing rapidly, with global revenues expected to increase from $141 billion in 2021 to $230 billion in 2024 (ThreadUp 2024). Even wealthy shoppers now visit Goodwill stores, thrift shops, and online markets to buy used clothing, which is also known as thrifted or pre-loved fashion (Rao 2023, Bass 2024). Thrift shopping is especially popular with Gen Z, as both male and female customers of all income levels have made thrift shopping a frequent and important part of their lifestyle (Huber 2020). As a young thrift shopping fan wrote, “While it’s a common theme to see a group of teen boys on a Friday afternoon at the mall or a park, today, they are just as likely to be at the vintage shop, or the thrift, scouring for the best second-hand find. The fact is, thrifting is thriving right now” (Kramer 2024).

Customers often mention the thrill of searching for a unique item as an important motivation for thrift shopping (Hughes et al. 2024). Although customers also buy used clothes for other reasons, such as low prices and environmental sustainability, anecdotal and empirical evidence suggests the joy of a treasure hunt is a primary motivation for many customers. For example, a thrift industry executive stated that customers “like the thrill of the hunt” (Pandey 2021). A thrift shopper said in a news interview, “Younger people find it fun, like a game. A hunt for something unique,” (Sicurella 2021) and another shopper said, “I’ll never stop loving the rush of adrenaline that I get when I enter a thrift store not knowing what I’m going to find that day” (Huber 2020).

Stores sell thrifted clothing through a variety of selling formats, which differ in how easy it is to find products. Some clothing manufacturers buy and resell the brand’s used clothes in their own store or on their own website, making the search process easy for customers. For example, fast fashion company H&M has a store in New York City that sells pre-loved H&M clothes (Walk-Morris 2024). Alternatively, customers can visit thrift shops, where clothes are hidden among a variety of brands, styles, and sizes of clothing, so it takes significantly longer to find an item a customer wants to buy. The marketing manager of a Goodwill store that is popular with fashion influencers stated, “It’s always a treasure hunt. A lot of people don’t know what they’ll find from one rack to the next” (Mitchell 2018).

Thrifting websites like Poshmark, Depop, and The Realreal, as well as general selling platforms like eBay and Mercari, also differ in how easy the website’s search function makes it to find the particular brand, style, and size of clothing a customer desires (Huynh 2023). Some of these websites buy and resell used clothes themselves, whereas others have become a popular form of social media where users search, browse, and comment on clothing offered by millions of other users. In addition, some websites allow users to livestream fashion shows in which they present one article of clothing at a time to followers who can write comments and purchase items (Braun 2023, Gu et al. 2024). A fashion journalist wrote that searching for used clothes on these websites provides "a slot machine-style pleasure" (Snapes 2021).

In addition to thrift stores and thrifted clothing websites, other retailers also offer a treasure hunt experience. Stores like Costco and T.J. Maxx sell a constantly changing and unpredictable inventory of products. For example, Costo buys a limited quantity of rare cosmetics, jewelry, food items, and other unusual products that it stocks in random locations throughout a few stores so that customers experience the thrill of discovering these special items, a policy that the Costco chief merchandising officer says creates a "treasure hunt" for customers (Wahba 2024).

Consistent with this anecdotal evidence from customers, managers, and the popular press, there is also a large body of academic research showing that some people engage in hedonic shopping, which is motivated mostly by the shopping experience rather than by product purchases. The seminal paper on hedonic shopping by Babin et al. (1994) in *Journal of Consumer Research*, entitled "Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value," develops a survey-based scale for measuring the value that a shopping trip provides to customers because of their enjoyment of the shopping experience rather than because of the products they purchase. Subsequent research uses surveys and lab experiments to study purchase behavior of hedonic shoppers (Jones et al. 2006, Scarpi 2012), conditions in which customers engage in hedonic shopping (Childers et al. 2001, Scarpi 2021), and their motivations for doing so (Arnold and Reynolds 2003). An important finding from this literature is that hedonic shoppers enjoy the search process. In particular, hedonic shopping is strongly correlated with positive responses to the survey items "Shopping is a thrill to me" (Arnold and Reynolds 2003), and "During the trip, I felt the excitement of the hunt" (Babin et al. 1994, Jones et al. 2006). Furthermore, some customers visit thrift stores for hedonic shopping (Bardhi and Arnould 2005), and these shoppers tend to agree with the survey item, "In certain second-hand outlets, I feel rather like a treasure hunter" (Guiot and Roux 2010).

This paper develops a formal model of a treasure hunt. In our model, a treasure is a product that is unique and exciting to hunt, so customers enjoy searching for it. At each moment during the treasure hunt, a customer decides whether to continue searching, considering both the probability of finding treasure and also marginal search utility, which initially is positive but decreases over time and eventually becomes negative. If the customer finds a treasure, for example, a unique shirt that complements her outfit well, she acquires the treasure and stops searching. We derive the optimal stopping rule, the probability of finding a treasure before the customer stops searching, and the total expected utility from the treasure hunt. If the treasure is easy to find, the customer has a high probability of finding treasure quickly but low expected utility from the joy of the search. If the treasure is more difficult to find, the customer has higher expected utility from the joy of search but a lower probability of finding treasure before she decides to stop searching.

We allow the company designing the treasure hunt to decide the price of products and the ease of search, which is reflected in the instantaneous probability of finding treasure. The company would like to maximize profits from selling the product, which depends on the number of people who both visit the store to participate in the treasure hunt and then find a treasure.

If the treasure has low value, the company sets price equal to product value and makes the treasure difficult to find, and the thrill of search provides an incentive to participate in the treasure hunt. If the treasure has high value, the company sets price below product value and makes the treasure somewhat easier to find, and both search utility and the value of the treasure itself provide an incentive to participate in the treasure hunt.

Our paper makes two key contributions. First, we formally model customers' intrinsic joy from treasure hunting, thus providing insight into the thrifted fashion market that has rapidly expanded during the past decade. In particular, if the value of a firm's products is relatively low and a sufficient fraction of customers enjoy search, we show that the firm should set price high enough to extract the full value of the product, and it should rely on search utility to attract customers to the store. In fact, real world thrift stores have significantly increased their prices to generate more revenues from shoppers motivated by the treasure hunt experience they offer (Gallagher 2022, Warren 2023), and Goodwill stores now set prices for some used clothing items that are higher than prices of similar new clothes at Walmart and Target (Duley 2023).

Another contribution is to show how a well-designed thrift shop can benefit from customers' enjoyment of treasure hunts to motivate people to buy used clothes, even if customers do not explicitly value environmental sustainability. This finding illustrates that marketing tactics can help promote sustainability, which is an important policy goal (Yalcin et al. 2020). For example, a recent report found that an estimated 92 million tons of textile waste arrive in landfills each year worldwide, and only about 12% of material used in clothing is currently recycled (State of Matter 2023).

Section 2 discusses related literature. Section 3 presents the main model. Section 4 presents analysis of the main model, and section 5 contains several model extensions. Section 6 concludes. Appendix A displays examples of in-person and online thrifted clothing sellers. Appendix B contains formal proofs of all results.

2 Related Literature

In classic search models, search is costly, and conditional on the quality and price of the product they purchase, customers prefer to minimize time spent searching (e.g., Diamond 1971, Weitzman 1979). Some search models include a segment of customers who consider search costly and another segment with zero search cost (Varian 1980, Narasimhan 1988). In other models, search involves experimenting with an alternative that has a lower expected payoff (Adam 2001, Ke and Villas-Boas 2019). There is also literature on dynamic search for product information when search is costly (e.g., Branco et al. 2012, Gu and Liu 2013, Ke et al. 2023). In our paper, customers enjoy search, and the firm's strategy accounts for customers' search utility. In particular, we develop a continuous time dynamic model with search utility that is initially positive.

Previous literature has also used continuous time models to study other marketing decisions such as sales force compensation (Rubel and Prasad 2016), product positioning (Villas-Boas 2018), and influencer endorsements (Nistor et al. 2024). Using a model with continuous time allows us to derive expected search time and search utility as a function of the ease of finding treasure.

Previous literature has shown that competing firms may want to make price information difficult to find in order to soften price competition (Stahl 1989, Ellison and Ellison 2009). By contrast, in our paper, we show the firm should make it easy for customers to find price information but somewhat difficult to find a product that is a good fit. Furthermore, our model involves a single retailer designing its store format to generate search utility for its customers, as opposed to competing retailers trying to soften price competition.

Our model is related to two streams of behavioral research. One research stream uses interviews, surveys, and simulations to understand different motivations for shopping. Some people shop mostly for the pleasure of the shopping experience itself, and these customers say shopping provides a sense of excitement, discovery, and adventure (Babin et al. 1994), as well as a chance to socialize and relieve stress (Arnold and Reynolds 2003). In such situations, people enjoy the thrill of hunting for a product to purchase (Jones et al. 2006). However, in other situations, the main goal of shopping is to quickly and efficiently purchase products that meet a customer's needs (Childers et al. 2001). In our model, customers visit a thrift store both for the joy of the shopping experience and for the intrinsic value of products. We also consider a model extension in which a segment of customers does not enjoy search and shops only because of intrinsic product value.

In addition, behavioral lab experiments and surveys have shown that people savor the anticipation of an enjoyable event, and they sometimes prefer to delay such an event to prolong this anticipation utility (Elster and Loewenstein 1992). For example, people say they would prefer to wait a period of time before experiencing certain desired events (such as a kiss from one's favorite celebrity, or a fancy meal) rather than experience them immediately (Loewenstein 1987). Furthermore, the emotional experience of anticipating an event is more intense than post-event emotional experiences (Van Boven and Ashworth 2007). Consumers experience the highest levels of enjoyment with medium-length waits, which are long enough for them to enjoy anticipation, but not so long that annoyance occurs (Chan and Mukhopadhyay 2010). In our model, customers derive utility from searching for treasure, and an increase in search time needed to find treasure can lead to greater utility from the shopping trip, although the marginal utility of search declines over time as customers grow tired of shopping.

Previous literature has developed behavioral industrial organization models (Goldfarb et al. 2012, Heidhues and Kőszegi 2018) that incorporate effects such as context-dependent preferences (Orhun 2009), desire for uniqueness or conformity (Amaldoss and Jain 2005), and fairness concerns (Cui et al. 2007, Selove 2019). These papers study different phenomena than we do, but our paper is related in that we also incorporate findings from behavioral literature into a formal model.

There is literature on the circular economy that involves reusing or recycling products (D'Adamo et al. 2022, Luukkonen et al. 2024). For example, Ek Styvén and Mariani (2020) examines consumers' incentives to buy secondhand fashion on platforms, and Buehler et al. (2023) study product design when consumers account for the environmental impact of product disposal. By contrast, in our paper, consumers buy thrifted fashion not because of an altruistic motive to preserve the environment but because of their joy of searching for a unique product.

Previous literature has studied the impact of a second-hand market on manufacturers' strategic decisions and outcomes. Shulman and Coughlan (2007) shows that a retailer-operated used-goods market for durable goods such as textbooks can lead to a higher manufacturer profit by enhancing consumer valuations for new goods and also by treating used goods sales as a price discrimination tool. Yin et al. (2010) shows that a retailer-operated used-good market allows the manufacturer to charge a higher price for its new product and so suppresses the manufacturer's incentive for product upgrades, but competition from a peer-to-peer used goods market reverses these effects. Some research also considers contexts in which a used good has a higher value than a new product (Tan 2022, Zhao et al. 2024). Liao and Kuksov (2023) examines the effect of speculators who buy new products in the first period when consumers are uncertain about their valuation and resell the products in the second period when consumer uncertainty is resolved. Whereas these studies explore value depreciation or appreciation of a second-hand product, we study thrifted fashion goods when consumers enjoy treasure hunting for these products.

Our study is also related to literature on fashion goods. Existing studies have examined how a fashion product can be used to signal high social status and how fashion cycles arise in equilibrium (e.g., Karni and Schmeidler 1990, Pesendorfer 1995, Yoganarasimhan 2012). In contrast with these studies, we do not model fashion as a signaling tool but rather as both a product and an experience with enjoyment from search.

3 Model

We first describe the decisions and profit function of the firm in the model, and we then describe the decisions and utility function of consumers.

3.1 Firm

A store sells products that have intrinsic value V, where $V > 0$. The firm decides the price p of each product and the rate μ at which a customer who visits the store discovers a product with good fit, for example, clothes that are the correct size and her preferred style. We refer to a product that is a good fit for a given customer as a "treasure." We allow any rate of treasure discovery $\mu \geq 0$.[1] To ensure positive demand and profits, the firm will optimally set price such that $0 < p \leq V$.

The firm can increase the rate μ of treasure discovery, for example, by having employees sort clothes by brand, size, and color. Sorting on all of these attributes makes treasure easy to find, whereas leaving clothes unsorted or sorting on only some attributes makes treasure harder to find. As another example, the firm can ensure it maintains a consistent, predictable stock of inventory which helps make finding treasure easy, or it can acquire whatever products are currently available to the store at low cost, resulting in unpredictable inventory and greater difficulty of finding treasure. In reality, making the treasure easier to find (increasing μ) can be costly, but we allow the firm to choose any level of μ at no cost to illustrate that it may prefer a difficult treasure hunt even if it could make the treasure easier to discover a no cost.

The firm maximizes total profits from product sales, and we normalize the firm's cost to acquire and sell a product to zero.

3.2 Customers

Customers derive value V from a product with a good fit (a treasure) and zero value from a profit with a poor fit. Given $p > 0$, consumers will only purchase a product with good fit. Before visiting the store, customers observe both p and μ.[2] However, customers do not observe their fit with any given product until they travel to the store and conduct a search, which implies all consumers have the same expected utility from conducting a treasure hunt once they arrive at the thrift store.

We consider a unit mass of consumers, with each having unit demand for treasure. Consumers' transportation cost to visit the thrift store is uniformly distributed on the interval $[0, 1]$. A consumer will visit the store as long as the expected benefit from visiting exceeds the cost. Letting U denote the expected utility of the treasure hunt,

[1] The expected search time to find a treasure is $\frac{1}{\mu}$ for all $\mu > 0$, and as $\mu \to \infty$ search time approaches zero. See the following section on customer search behavior for more detail.

[2] We later consider the case in which customers do not learn price until after they discover a treasure.

including both expected search utility and expected utility from buying treasure, the number of customers who travel to the store and participate in the treasure hunt equals U for all $U \in [0, 1]$.

After traveling to the store, a customer can search for treasure over time $t \in [0, \infty)$. At each moment t, the customer decides whether to continue the search to maximize her expected utility, considering both search utility and the expected value of finding a treasure. Note that the heterogeneous transportation cost consumers incur to visit the store becomes a sunk cost after they arrive at the store, so this travel cost does not affect their decisions during treasure hunting. Below we provide detailed specifications of a representative consumer's treasure hunting process.

The search process provides a consumer with utility that initially has positive value $\alpha + \beta(V - p)$ per unit of time, where $\alpha > 0$ and $\beta > 0$. This marginal search utility decreases linearly over time as the customer grows tired of shopping. For notational simplicity, we scale time units so the rate of decrease in marginal search utility is one, and the total instantaneous search utility at time t is:

$$s(t) = \alpha + \beta(V - p) - t \tag{1}$$

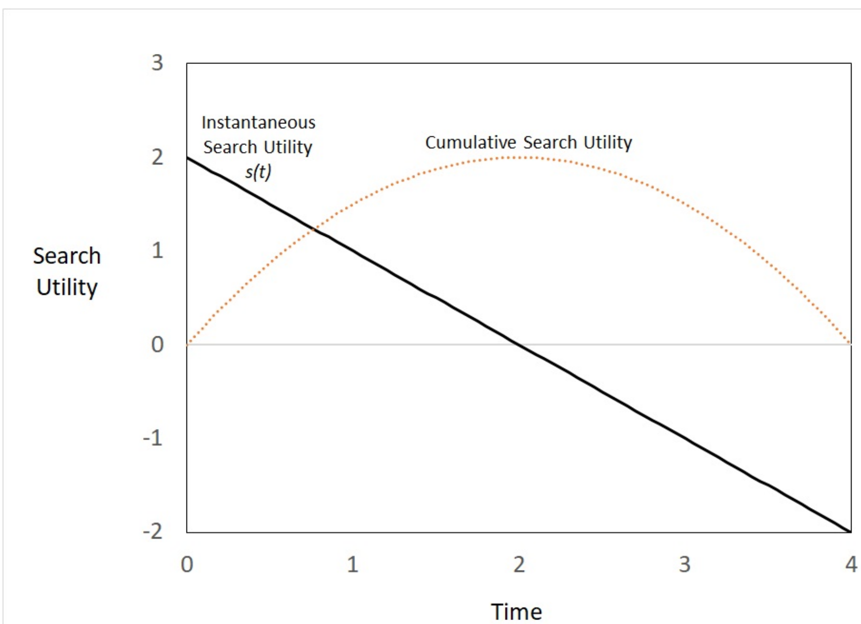
The function $s(t)$ reflects instantaneous search utility per unit of time at time t, that is, the current joy of search the customer experiences at the time. Our setup implies a positive instantaneous utility at $t = 0$ as the consumer starts the search, that is, $s(0) = \alpha + \beta(V - p) > 0$. Note that α represents the constant in this search utility expression and β reflects the degree to which search utility increases with the net value of the treasure.[3] Equation (1) implies search is enjoyable while $t < \alpha + \beta(V - p)$, that is, during the first $\alpha + \beta(V - p)$ units of time that a customer is shopping. However, the customer grows increasingly tired of shopping, and after $\alpha + \beta(V - p)$ units of time, her marginal utility of search becomes negative. For parsimony, in this

[3]We are conducting experiments to measure the functional form of search utility, and preliminary results indicate this utility is not very sensitive to changes in net product value, that is, β is relatively small.

main model, we let all customers enjoy search. We later present a model extension in which one segment of customers initially enjoys search ($\alpha > 0$ and $\beta > 0$), but another segment of customers considers search costly and prefers to find the product as quickly as possible ($\alpha = \beta = 0$).

The total utility of searching from time zero until a given time x, without finding treasure during this time interval, is the integral over the instantaneous search utility: $\int_{t=0}^{x}(\alpha+\beta(V-t)-t)dt = [\alpha+\beta(V-t)]x-\frac{1}{2}x^2$. This total search utility is maximized by setting $x = \alpha + \beta(V - t)$, that is, by searching while search is still enjoyable, and then stopping search when it is no longer enjoyable. Figure 1 depicts instantaneous and total cumulative search utility as a function of time for initial search utility $\alpha + \beta(V - t) = 2$.

Figure 1. Instantaneous and Cumulative Search Utility ($\alpha + \beta(V - t) = 2$)



As a customer searches, she finds a treasure, which provides utility of $V - p$, according to a Poisson process with rate μ, so the probability of finding a treasure during a small period of time of length dt is given by μdt. Once the consumer finds a treasure, she stops the search. A larger μ makes it easier to find a product that fits, so in expectation consumers have a shorter search time before finding treasure. In particular, the expected time required to find a treasure is $\frac{1}{\mu}$ for all $\mu > 0$.

3.3 Game Sequence

To summarize, the model timing is the following:

1. The seller decides the price p and rate of finding treasure μ, and customers observe these decisions.

2. Customers decide whether to travel to the store.

3. Customers who travel to the store decide at each time $t \in [0, \infty)$ whether to continue searching for treasure.

Table 1 summarizes model notation, including some variables introduced later in the paper. [The current draft solves the model for $\beta = 0$, and we are working on extending the model to more general functional form of search utility.]

Table 1. Model notation

t	Time
a	Initial utility from search per unit of time
$s(t) = a - t$	Instantaneous utility from search at time t
V	Value of product
p	Price of product
μ	Rate of discovering treasure
$t^* = a + \mu(V - p)$	Optimal time to stop search
$q = 1 - e^{-\mu t^*}$	Equilibrium probability of finding treasure after traveling to the store
U	Customer's total expected utility from the treasure hunt

4 Analysis

We solve the game through backward induction. We first solve the subgame with customers' treasure hunting decisions for a given price and treasure discovery rate. This analysis allows us to derive a customer's optimal search strategy and expected utility from the treasure hunt. We then derive the store's optimal strategy to maximize its profits.

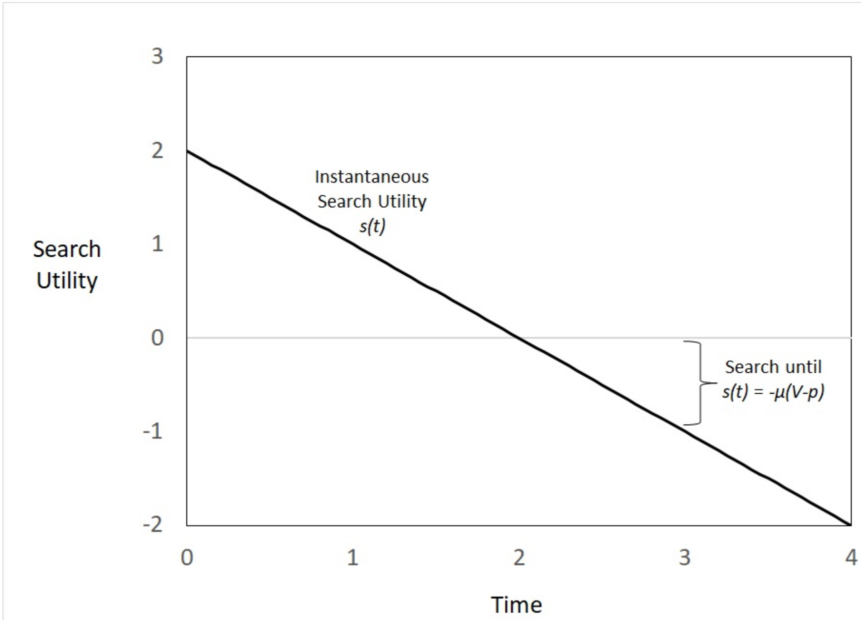
4.1 Consumers' Treasure Hunting Decisions

Conditional on visiting the store, a customer decides at each time t whether to continue searching for treasure. Once she finds a treasure, she has no further utility from search, and she no longer desires another treasure, so she acquires the treasure and stops searching. If the customer has not yet found a treasure, her optimal strategy is to continue searching if the instantaneous utility from search plus the value of a possible treasure discovery is positive, that is, if $a - t + \mu(V - p) \geq 0$. Given that the utility from the search process decreases over time, once this term becomes negative it will only continue to decrease, so there is no reason to continue searching. The appendix formally proves the following lemma.

Lemma 1. *A customer's optimal strategy is to search either until she finds a treasure or until time* $t^* = a\mu^{\phi} + \mu(V - p)$.

The customer searches while the marginal utility from search is positive (until $t = a$) and then continues searching for a period of time when the marginal utility from search is negative (when $t > a$) because of the ongoing possibility of finding the treasure. Figure 2 provides a visual depiction of this optimal search strategy for $a = 2$, $\mu = 1$, and $V - p = 1$, which implies it is optimal to search until $t = 3$.

Figure 2. Optimal Search Strategy ($a = 2$; $\mu = 1$; $V - p = 1$)



The probability that a customer stops search without finding treasure is the probability of zero Poisson arrivals with rate μ over a length of time t^*, which is given by $e^{-\mu t^*}$. If we let q denote the probability she finds a treasure, and we insert the value for t^* above, we have:

$$q = 1 - e^{-\mu(a\mu^{\phi}+\mu(V-p))} \tag{2}$$

This equilibrium probability q that the customer finds a treasure increases in the initial utility of search a, the rate of finding treasure μ, and the value of treasure $V - p$.

We now compute the customer's expected utility from the shopping experience. Her expected utility from the treasure itself is $q(V - p)$, which is the probability of finding the treasure times the value of the treasure. The expected utility from the joy of search is $\int_{t=0}^{t^*} e^{-\mu t}(a\mu^{\phi} - t)dt$, which is found by integrating over the instantaneous utility from search times the probability of searching until a given point in time. The proof of the following proposition solves this integral and computes total expected utility from the treasure hunt.

Proposition 1. *A customer's expected utility from the treasure hunt is given by the following equation.*

$$U = (1 - e^{-\mu t^*})(V - p) + \frac{a}{\mu^{(1-\phi)}}(1 - e^{-\mu t^*}) - \frac{1}{\mu^2}(1 - e^{-\mu t^*} - \mu t^* e^{-\mu t^*}) \tag{3}$$

The first term represents expected utility from the treasure itself, whereas the second and third terms represent expected search utility. In order to perform comparative statics, we need to consider the effect of each model parameter on all three components of utility. The following corollary states comparative statics results.

Corollary 1. *The expected utility from the treasure hunt increases with the value of treasure $V - p$ and increases with initial search utility a, but may either increase or decrease with the ease of finding treasure μ.*

An increase in the value of the treasure increases expected utility from the treasure itself. An increase in the search utility parameter increases expected utility from search. By contrast, an increase in the ease of finding treasure has two opposing effects. First, an easier hunt increases the probability of finding the treasure, which increases expected utility from the treasure itself. Second, an easier hunt makes it more likely for the customer to find the treasure faster, which can reduce expected utility from search. The net effect can go in either direction, and in some cases, a more difficult hunt (lower μ) increases total expected utility from the treasure hunt.[4]

[4] These parameters also affect the optimal search time t^*. However, the envelope theorem implies that this change in t^* has only a second-order effect on the customer's utility, and we can perform comparative statics while holding t^* constant.

If there was no positive search utility ($a = 0$), the second term in (3) would equal zero. The first and third terms of (3) are maximized by letting the treasure discovery rate $\mu \to \infty$, so customers immediately find treasure with no search cost. In other words, if customers did not enjoy search, the firm would want to make finding treasure as easy as possible, so everyone who visits the store finds a treasure and customers do not incur search costs.

However, with positive search utility ($a > 0$), utility from the treasure hunt is greatest if the firm sets a finite treasure discovery rate to provide customers with joy of search. The appendix proves that Proposition 1 has the following corollary.

Corollary 2. *For any $a > 0$, there is a finite treasure discovery rate μ that maximizes expected utility from the treasure hunt.*

Consumers' transportation costs are uniformly distributed on $[0, 1]$, so the number of customers who visit the thrift store is equal to the expected utility from the treasure hunt. Therefore, Corollary 2 implies a firm that wishes to maximize foot traffic to the store should make the treasure hunt at least somewhat challenging so customers who visit the store experience the joy of search. Section 5.2 provides additional analysis of the objective of maximizing foot traffic.

In order to maximize profits, the seller needs to consider foot traffic, the price of treasure, and the probability that a customer finds treasure conditional on visiting the store. In the next section, we characterize the seller's optimal strategy to maximize profits from selling treasures.

4.2 Firm's Treasure Selling Strategy

The firm's objective is to choose price p and ease of finding treasure μ to maximize the following profit function.

$$\pi = pUq \tag{4}$$

The number of people U who visit the store is equal to the expected utility of the treasure hunt as stated in (3), and the probability q of finding treasure is given by (2), both of which are functions of p and μ.

The firm's strategy must account for interactions in the effect of p and μ on profits. If the firm lowers its price, then the value of treasure to customers $(V-p)$ increases, which implies that an increase in the treasure discovery rate has a larger incremental impact on customers' expected utility from finding treasure. However, an increase in $(V-p)$ also causes customers to search longer (increases t^*), which implies that setting a higher treasure discovery rate has a smaller incremental impact on the probability of finding treasure. As a result of these various interactions in the effect of p and μ on U and q, a decrease in product price can either increase or decrease the firm's optimal treasure discovery rate (see the numerical example below).

In order to solve this multivariate optimization problem, we first focus on cases in which the product has either low or high intrinsic value V, and we derive closed form results for the firm's optimal strategy in both cases. We then numerically solve for the optimal strategy for intermediate product values.

If we hold μ constant, the partial derivative of profits with respect to p is the following:[5]

$$\frac{\partial \pi}{\partial p} = Uq + p\left[\frac{dU}{dp}q + \frac{dq}{dp}U\right] \tag{5}$$

If we hold p constant, the partial derivative of profits with respect to μ is the following:

$$\frac{\partial \pi}{\partial \mu} = p\left[\frac{dU}{d\mu}q + \frac{dq}{d\mu}U\right] \tag{6}$$

Motivated by the example of thrift stores such as Goodwill selling used clothes, we now solve the firm's profit-maximization problem for products with low value.

[5]We take total derivatives of U and q with respect to p to reflect that customers' search time t^* changes with p, and this change in t^* has a first-order effect on q.

Given the constraint $p \leq V$, as $V \to 0$ the second term in (5) also approaches zero. However, even for very low product value, a customer is always willing to search at least until time a because of search utility, so the utility U from the treasure hunt is always at least $\int_{t=0}^{a} e^{-\mu t}(a-t)dt$, and the probability of finding treasure is always at least $1 - e^{-\mu a}$. Therefore, the term Uq does not approach zero even for low product value, and for small values of V, the derivative (5) is strictly positive for all $p \in [0, V]$, which implies the profit maximizing price is $p = V$. The intuition is that, when the product has low value, the firm is not able to raise the price until the point that profits begin to decrease in price. Therefore, the optimal strategy is to set price to extract the full value of the product, and search utility then provides the motivation for customers to visit the store and participate in the treasure hunt. In this case, the optimal values of p and μ to maximize profits are found by setting $p = V$ and by choosing the optimal μ given this value of p.

When the firm sets price equal to product value, all of the customer utility from the treasure hunt comes from the joy of search. Therefore, customers search until they find a treasure or until time a, that is, they search while search is still enjoyable. In this case, an easier treasure hunt decreases expected utility from the treasure hunt by making it more likely for a customer to find treasure quickly. However, an easier hunt also increases the probability of a given customer finding treasure. The firm's optimal choice of μ balances these two effects. Formally, when the firm sets $p = V$, the optimal search time is $t^* = a\mu^{(1+\phi)}$, the probability of finding treasure is $q = 1 - e^{-a\mu^{(1+\phi)}}$, and the utility of the treasure hunt is $U = \frac{a}{\mu^{(1-\phi)}} - \frac{1}{\mu^2}(1 - e^{-a\mu^{(1+\phi)}})$. Therefore, the profit function becomes:

$$\pi(\mu, p = V) = V(1 - e^{-a\mu^{(1+\phi)}})\left[\frac{a}{\mu^{(1-\phi)}} - \frac{1}{\mu^2}(1 - e^{-a\mu^{(1+\phi)}})\right] \tag{7}$$

Making the substitution $g(\mu) = \frac{1-e^{-a\mu^{(1+\phi)}}}{\mu}$, this profit function equals $V(ga\mu^{\phi} - g^2)$, which is maximized by setting $g = \frac{a\mu^{\phi}}{2}$ so optimal profits are $\frac{Va^2}{4}$. The optimal choice of μ solves the following equation to set $g = \frac{a\mu^{\phi}}{2}$:

$$1 - e^{-a\mu^{(1+\phi)}} = \frac{a\mu^{(1+\phi)}}{2} \tag{8}$$

This equation is solved by $a\mu^{(1+\phi)} \approx 1.6$. As the search utility parameter a increases, the profit-maximizing seller makes the treasure hunt more difficult (reduces μ), so the term $a\mu^{(1+\phi)}$ stays constant. Furthermore, if we define q^* as the probability of a given customer finding treasure when (8) is satisfied, we have $q^* = 1 - e^{-\mu a} \approx 0.80$ and the optimal value of μ is $\frac{2q^*}{a}$.

The appendix proves the following proposition, which formalizes these results.

Proposition 2. *If V is sufficiently small, the firm sets $p = V$ and sets μ such that (8) is satisfied, which implies $\mu = \frac{2q^*}{a}$. The equilibrium probability that a customer who visits the store finds treasure is $q^* \approx 0.8$.*

This optimal strategy attracts visitors to the store based purely on the search utility of treasure hunting. This strategy arises in equilibrium when products have low value. In this case, the firm sets price equal to product value and makes the treasure hunt difficult enough that about 80% of customers who visit the store find a treasure. This 80% rule holds quite generally, and as long as the marginal utility of search decreases linearly over time and the number of customers who visit the store is proportional to expected utility from the treasure hunt, a seller of low-value products designs its treasure hunt such that about 80% of customers who visit the store find a treasure.[6]

[6]For example, if the unit transportation cost to visit the store is k instead of one, then the number of customers who visit the store is $\frac{U}{k}$, so (7) becomes $\frac{1}{k}V(1 - e^{-\mu a})\big[\frac{a}{\mu} - \frac{1}{\mu^2}(1 - e^{-\mu a})\big]$, and the profit-maximizing solution is still $\mu a \approx 1.6$, which implies $q = 1 - e^{-\mu a} \approx 0.80$.

As a real world example to illustrate these findings, suppose a group of college students spend the day thrift shopping for vintage T-shirts. Their utility from the shopping experience may be greater than their utility from a T-shirt, and their cost of time spent driving to the thrift store may be more significant than the price of a T-shirt. In other words, the benefits and costs of the treasure hunt experience are sometimes much larger than the benefit and price of the treasure itself. In such situations, a difficult treasure hunt allows customers to spend time experiencing the thrill of the hunt.

We now consider the case of products with high value, such as stores selling high-end vintage items or consignment shops that are selective about which products they accept for trade-in. As $V \to \infty$, we show the firm sets price low enough that the probability of finding treasure approaches one. The intuition for this result is that, as product value and profit margins increase, the firm chooses to set price below product value in order to attract more foot traffic to the store. As a result, $V - p$ increases, which causes customers to search longer. As the time customers are willing to search grows larger, the probability of a given customer finding treasure approaches one.

In this case, the firm chooses μ to maximize customers' expected search utility. The firm would like to make the treasure hunt difficult enough that customers have some expected joy of search, but not so difficult that customers are likely to need to continue searching after search utility becomes negative. Formally, as $q \to 1$, expected utility from the treasure hunt approaches $U = (V - p) + \frac{a}{\mu} - \frac{1}{\mu^2}$, and profits approach $\pi = pU$. In this case, to solve for the optimal μ, we take the derivative $\frac{dU}{d\mu} = -\frac{a}{\mu^2} + \frac{2}{\mu^3}$, which equals zero for $\mu = \frac{2}{a}$. This value of μ maximizes expected utility from the treasure hunt and sets $U = V - p + \frac{a^2}{4}$. Inserting this value of U into the profit function pU, we find the optimal price is $\frac{V}{2} + \frac{a^2}{8}$.

The appendix formally proves these results.[7]

Proposition 3. *As $V \to \infty$, the firm's optimal strategy lets $p \to (\frac{V}{2} + \frac{a^2}{8})$ and $\mu \to \frac{2}{a}$. The equilibrium probability that a customer who visits the store finds treasure approaches one.*

This strategy attracts visitors to the store based on both expected utility from search and expected surplus from purchasing treasure. This strategy arises in equilibrium when the products have high value. Under this strategy, the optimal treasure discovery rate satisfies $\mu a \to 2$, which is a higher treasure discovery rate than that in the low-value case (where $\mu a \approx 1.6$). That is, for high-value products, the firm designs an easier treasure hunt. In the low-value case, the firm makes treasure difficult to discover, and about 20% of customers leave the store without finding treasure. By contrast, for high-value products, the firm sets price below value, and the value of the product itself is the primary factor that motivates people to visit the store. Customers are willing to keep searching long after search utility becomes negative, and almost everyone who visits the store will find a treasure. In this case, the firm designs a treasure hunt that is challenging enough to provide some expected search utility, but still easy enough that people are likely to discover treasure while their search utility remains positive.

Even for high-value products, the seller does not want to make the treasure hunt too easy. Based on the optimal treasure discovery rate $\mu = \frac{2}{a}$, the expected search time to find a treasure is $\frac{a}{2}$, and a customer's expected utility from the joy of search is $\frac{a^2}{4}$. The seller makes the treasure hunt easy enough that almost everyone who visits the store finds a treasure, but still difficult enough that search utility is a significant component of the customer's expected utility from the treasure hunt.

[7] This proposition states results as $V \to \infty$. Therefore, instead of a standard Hotelling line with a unit mass of customers, we let the firm be located at the endpoint of a ray that extends infinitely in the other direction, which implies the number of customers who visit the store is U for all $U \geq 0$.

Propositions 2 and 3 both imply that the search utility parameter a affects the firm's optimal treasure hunt design. We obtain the following corollary.

Corollary 3. *For both low-value and high-value products, an increase in the search utility parameter implies the firm designs a more difficult treasure hunt. That is, the optimal μ decreases with a for both low V and high V.*

If customers enjoy searching for a seller's products, the firm should create a challenging treasure hunt to provide customers with search utility. For example, some thrift shops sort clothes by type, size, and color (Brennan 2023), but other shops create a more challenging hunt by offering "shelves upon shelves of unsorted clothes" (Russo 2020). Thrift shops can also create a challenging treasure hunt by accepting a wide range of donations, so shoppers need to search through a variety of products to find treasures. For example, Goodwill stores accept donations of most items that are in good enough condition to sell without needing repairs (Hadero 2021), whereas other thrift sellers like Buffalo Exchange and ThreadUp create a somewhat easier treasure hunt because they are more selective about which products they sell (Raynor 2017).

We have derived closed-form results for the seller's profit-maximizing strategy given low and high values of V. To illustrate results for these values and also for intermediate levels of product value, we now present a numerical example. We solve for the seller's optimal strategy for $a = 1$ and $V \in [0, 1.5]$. For each value of V, we compute expected profits over a grid of possible values of μ and p and select the (μ, p) pair that maximizes profits.

Figure 3. Treasure discovery rate
and product price that maximize profits

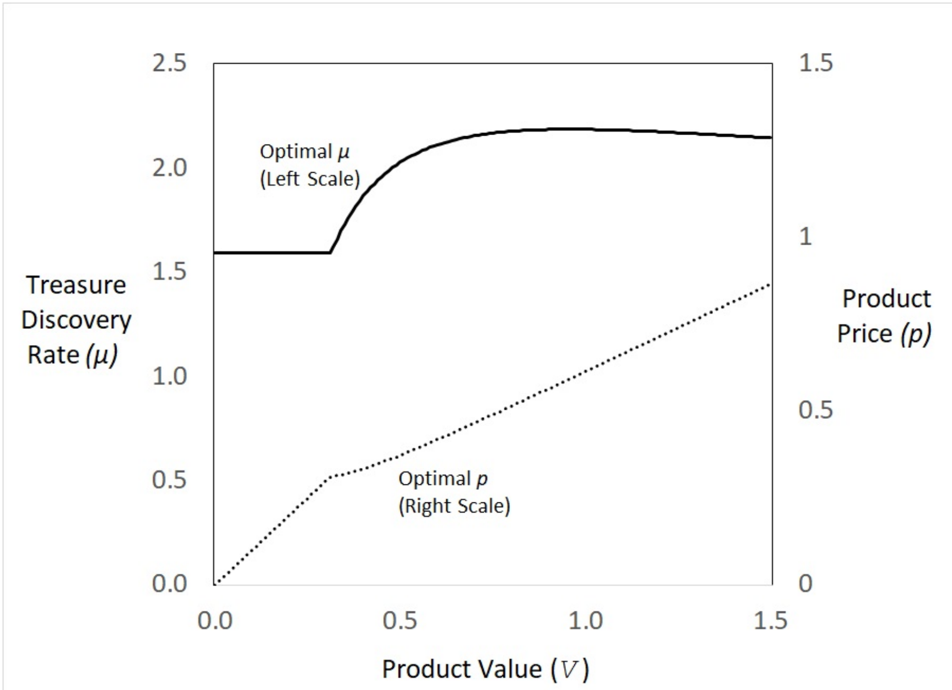


Figure 3 presents the optimal μ and p as a function of V. As stated in Proposition 2, for low values of V, the firm sets $\mu = 1.6$ and $p = V$, so the utility of the treasure hunt comes entirely from the joy of search. After V is greater than approximately 0.31, the firm begins increasing μ and setting $p < V$, so the utility of the treasure hunt comes partly from the value of the product itself. As stated in Proposition 3, for large V, $\mu \to 2$ and $p \to \frac{V}{2} + \frac{1}{8}$.

As V grows large enough that the firm sets price below product value, the firm also begins increasing the treasure discovery rate. This result occurs because a higher treasure value $(V - p)$ implies the treasure discovery rate has a larger impact on customers' expected utility from finding treasure. However, for $V = 0.95$, the optimal treasure discovery rate is $\mu = 2.2$, and as V increases further, μ declines. As μ affects both foot traffic and the probability of finding treasure, the firm sets the treasure discovery rate above the level that maximizes foot traffic in order to increase the probability that a customer finds treasure. As V grows very large, the probability of finding treasure approaches one as customers are willing to search longer because of the value of the treasure itself. Therefore, the firm's strategy converges to value of μ that maximizes foot traffic, that is, $\mu = 2$. Thus, the optimal μ first increases and then decreases with V.

5 Model Extensions

5.1 Customer Search for Price Information

Our main model allows customers to observe price before they decide whether to travel to the store. For example, the firm may advertise its prices, or customers may have learned the price of each type of good based on previous visits to the store. Therefore, the firm can set price below value to help provide an incentive to travel to the store.

We now extend the model to study the case in which customers learn the price of a product only after they search and observe the price tag on a particular item. In this case, customers rationally expect the firm to set price to extract the full value of the product. We continue to allow customers to observe the treasure discovery rate before they visit the store, for example, based on online reviews or store reputation. The appendix formally proves this result.

Proposition 4. *If customers observe μ before visiting the store but observe p only after inspecting a given product, the firm sets $p = V$ and $\mu = \frac{2q^*}{a}$ for all values of V.*

As an intermediate case, if customers learn price after traveling to the store but before searching for treasure, the firm sets price equal to value for larger product values than in the main model, but still sets price below value for sufficiently high product value to provide an incentive to search longer. Among these possible timing set-ups, profits are weakly greater if customers learn price before visiting the store than for the other possible set-ups, as the firm can then commit to a low price to provide an incentive to visit the store.

Our results imply profits are maximized if the store informs customers about prices before they travel to the store. Thus, the store creates a treasure hunt that allows customers to search for a product with good fit, but the store does not want to require customers to search for price information. In practice, many thrift shops have signs announcing the price of each type of product they sell (see the appendix for an example). However, some of the basic insights of our model still hold if customers learn price only after they find treasure, in which case customers visit the thrift shop for the thrill of the hunt.

5.2 Maximizing Foot Traffic

We now consider the alternative objective of designing a treasure hunt to maximize foot traffic to the store.

In our model, the number of customers who visit the store is equal to the expected utility from the treasure hunt. Therefore, a seller may want to maximize customers' expected utility if its goal is to build foot traffic to its store to cross-sell other products. For example, Costco selects some products as treasure hunt items, which are hidden throughout the store, in order to attract customers who then buy other items (Wahba 2024). The results in this section illustrate that a difficult treasure hunt can help accomplish the goal of maximizing foot traffic.

If the firm wants to maximize customers' utility from the treasure hunt, it should set price to the minimum acceptable level, for example, equal to the marginal cost of the product. In this extension, we take price as given and focus on the optimal treasure discovery rate. For a given price, the firm makes treasure more difficult to find if its goal is to maximize expected utility rather than profits. Formally, profits are given by pUq, and the probability q of finding treasure increases with μ. A firm that maximizes profits considers the effect of μ on both U and q, whereas a firm that maximizes utility considers on the effect on U.

The appendix formally proves this result.

Proposition 5. *For a given product price, the firm makes treasure harder to find (sets a lower μ) if its goal is to maximize foot traffic rather than profits from selling treasure.*

We now present numerical examples to illustrate how the ease of finding treasure affects expected utility. We compare results for treasures with low versus high value, with the search utility parameter set to $\alpha = 1$.

Figure 4 presents results for a treasure with relatively low value ($V - p = 0.2$). As the treasure becomes easier to find (μ increases), the expected utility from the joy of search decreases because the customer expects to find the treasure faster and therefore derives less total pleasure from the search process. However, an increase in μ increases the equilibrium probability of finding the treasure, so the expected utility from finding the treasure increases. For this low-value treasure, the effect of μ on search utility is more significant than its effect on the utility from finding treasure, and the total expected utility from the treasure hunt is greatest if the treasure is difficult to find, that is, if μ is low.

In particular, for the example in Figure 4, the expected utility from the treasure hunt is maximized when $\mu = 0.49$. For this value of μ, the customer's equilibrium probability of finding the treasure is $q = 1 - e^{-0.49(1+0.49*0.2)} = 0.42$. For this low-value treasure, the expected total utility the customer derives from the treasure hunt is greatest when the treasure is difficult to find so she only has a 42% chance of finding the treasure before she stops searching. This challenging treasure hunt provides the customer with high expected utility from search.

Figure 5 presents results for a treasure with higher value ($V - p = 0.5$). For this high-value treasure, the total expected utility from the treasure hunt is greatest if the treasure is easier to find, that is, if μ is high. In particular, for this example, the expected utility from the treasure hunt is maximized when $\mu = 1.74$. For this value of μ, the customer's equilibrium probability of finding the treasure is $q = 1 - e^{-1.74(1+1.74*0.5)} = 0.96$. The expected total utility the customer derives from the treasure hunt is greatest if the treasure is easy enough to find so she has a 96% chance of finding the treasure before she stops searching. This easier treasure hunt provides the customer with some expected utility from search, but the main source of utility is from finding the treasure itself.

For a Poisson process with arrival rate μ, the expected time until the first arrival is $\frac{1}{\mu}$. If the time units are hours, for the numerical example in Figure 4, expected utility from the treasure hunt is greatest if it would take an average of $\frac{1}{0.49} = 2.04$ hours or about 122 minutes to find a treasure. For such a difficult treasure hunt, the customer has a high probability of stopping search before she finds treasure. By contrast, for the example in Figure 5, expected utility is greatest if it would take an average of $\frac{1}{1.74} = 0.57$ hours or about 34 minutes to find a treasure, and the customer is very likely to find treasure before she stops searching.

Figure 4. Utility from hunting for low-value treasure ($V - p = 0.2$; $a = 1$)

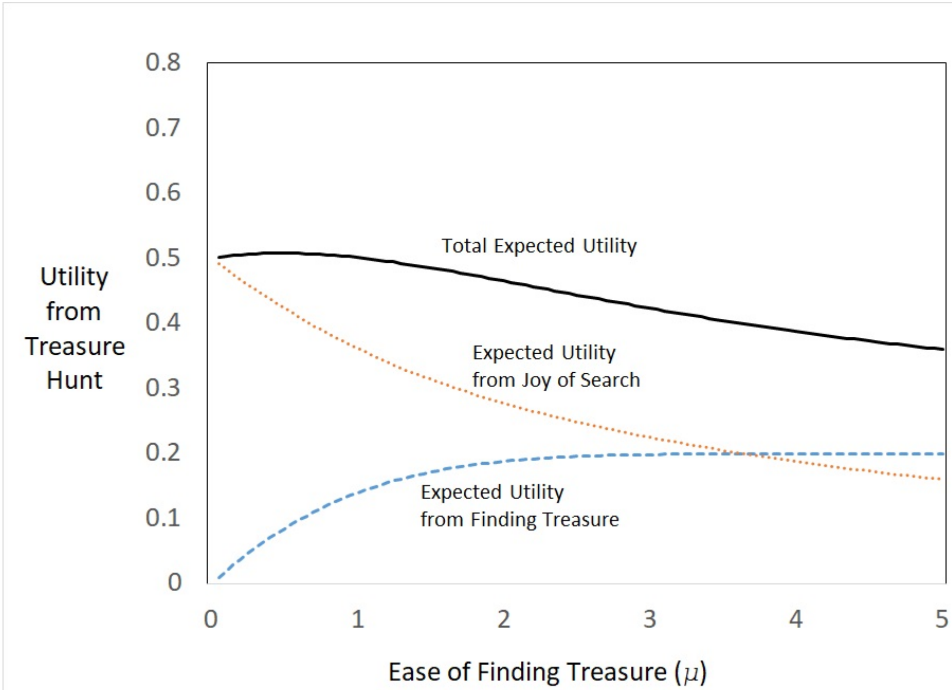
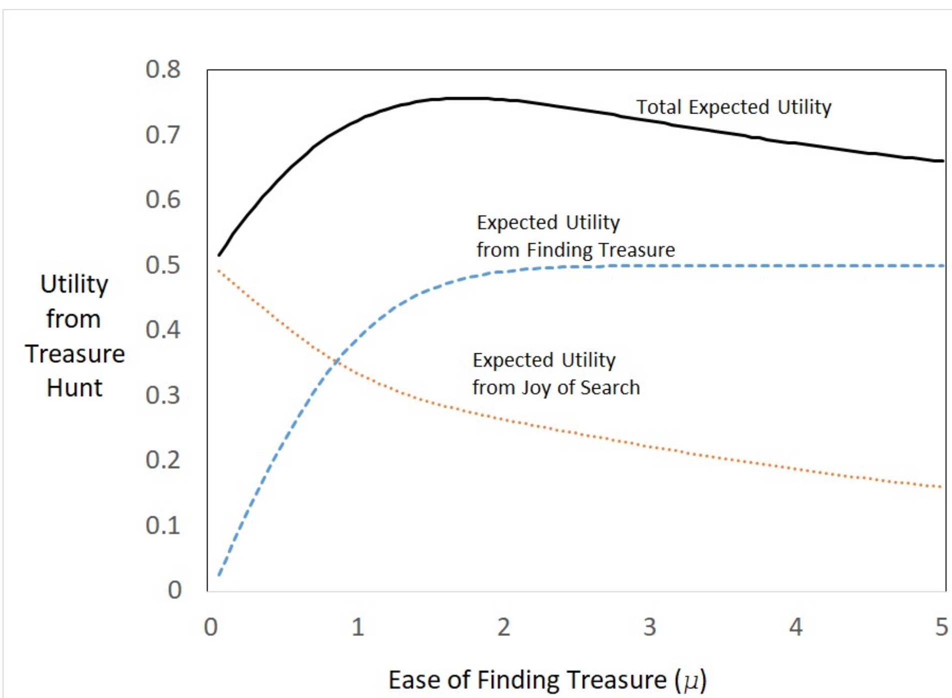


Figure 5. Utility from hunting for high-value treasure ($V - p = 0.5$; $a = 1$)



5.3 Customers Who Do Not Enjoy Search

Babin et al. (1994) find that some customers participate in hedonic shopping and enjoy long shopping trips, whereas other customers prefer to find a product that meets their needs as quickly as possible. We now extend the main model to allow for a segment of customers who do not enjoy search.

A fraction γ of customers have the same instantaneous search utility as in the main model, that is, $s(t) = a - t$. The remaining fraction $(1 - \gamma)$ have no positive search utility and experience only search costs, so their instantaneous search utility is $\widehat{s}(t) = -t$. Both customer types are uniformly distributed along the Hotelling line, and we let $0 < \gamma < 1$.

For small V, customers who do not enjoy search have little reason to visit the store because they derive no utility from search and low utility from the product even if its price approaches zero. In this case, the firm's optimal strategy is to serve only customers who do enjoy search and set the same price and treasure discover rate as in the main model, that is, $p = V$ and $\mu = \frac{2q^*}{a}$.

For large V, both customer types visit the store in equilibrium, motivated by the value of the product itself. The firm's optimal strategy balances the preferences of these two customer segments. Customers who enjoy search prefer a somewhat difficult treasure hunt so they derive search utility, whereas customers who do not enjoy search prefer an easy treasure hunt so they avoid search costs. We show that the optimal treasure discover rate is $\mu = \frac{2}{\gamma a}$. The firm makes treasure more difficult to find if there is a large fraction γ of customers who enjoy search and if these customers have high initial utility a from search.

The following proposition states these results formally.

Proposition 6. *If V is sufficiently small, the firm sets $p = V$ and $\mu = \frac{2q^*}{a}$, and it serves only customers who enjoy search. As $V \to \infty$, the firm serves both customer* *types, and sets* $p \to \left[\frac{V}{2} + \frac{(\gamma a)^2}{8}\right]$ *and* $\mu \to \frac{2}{\gamma a}$.

For low-value products, the firm sets price equal to product value and serves only customers who enjoy search. Consistent with this theoretical finding, real world thrift stores appeal to Gen Z, who have free time for shopping and high utility from search (Huber 2020, Pandey 2021, Sicurella 2021).

For high-value products, the firm serves both customer types. In this case, given that some customers do not enjoy search, the firm to set a higher treasure discovery rate and a lower price than in the main model.

6 Conclusion

We develop a model in which customers enjoy searching for a product to purchase, and this search utility declines over time during the search process. A profit-maximizing seller decides its price and treasure discovery rate and intentionally makes products somewhat difficult to find so that customers derive joy from search. For a low-value product, the firm sets its price equal to product value and makes the treasure hunt difficult enough that some customers leave the store without finding treasure. The joy of search motivates customers to visit the store and participate in the treasure hunt. For a high-value product, the firm sets price below product value, and customers visit the store partly for the joy of search and partly for the value of the product itself. We also study the objective of maximizing utility from the treasure hunt, and we extend the model to allow for competition between a thrift store and a traditional retailer and to allow for a segment of customers who do not enjoy search.

Our model helps explain why some high-income customers make frequent visits to thrift stores and spend hours searching for used clothing items to purchase. These customers enjoy the search process and consider it a valuable form of entertainment.

Thrift stores design their retail experience to generate high search utility and ensure customers spend significant time in the store hunting through clothes that are unsorted on attributes like brand, size, and style. These stores have raised prices to capture some of the value of the treasure hunt experience they offer, and customers visit the thrift stores because they derive particularly high search utility from hunting for an unexpected treasure among racks of used clothes.

Future research could extend our model in several ways. If customers derive more search utility or more value if the product is rare, then making treasure difficult to discover further enhances the utility customers derive from a treasure hunt by reducing the number of people who discover treasure. Future research could explicitly incorporate this effect of product uniqueness into the model. It would also be interesting to study how search utility in the used clothing market affects the incentives of makers of new clothes, including their decisions about the quality and quantity of clothes to produce, and to explore the effects of new and used clothing sales on environmental sustainability. Future research could also incorporate positive search utility into traditional search models in which customers visit multiple stores while searching for a product, and could explore how the joy of search affects equilibrium outcomes in these models.

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Appendix A: Treasure Hunt Examples

Thrift Store Tables with Unsorted Clothes

Retrieved July 13, 2024, https://www.yelp.com/biz/the-collection-by-casa-teresa-orange-2

Thrift Store with Posted Prices, and Partially Sorted Clothes

Photos taken June 19, 2024, Salvation Army in Orange, CA

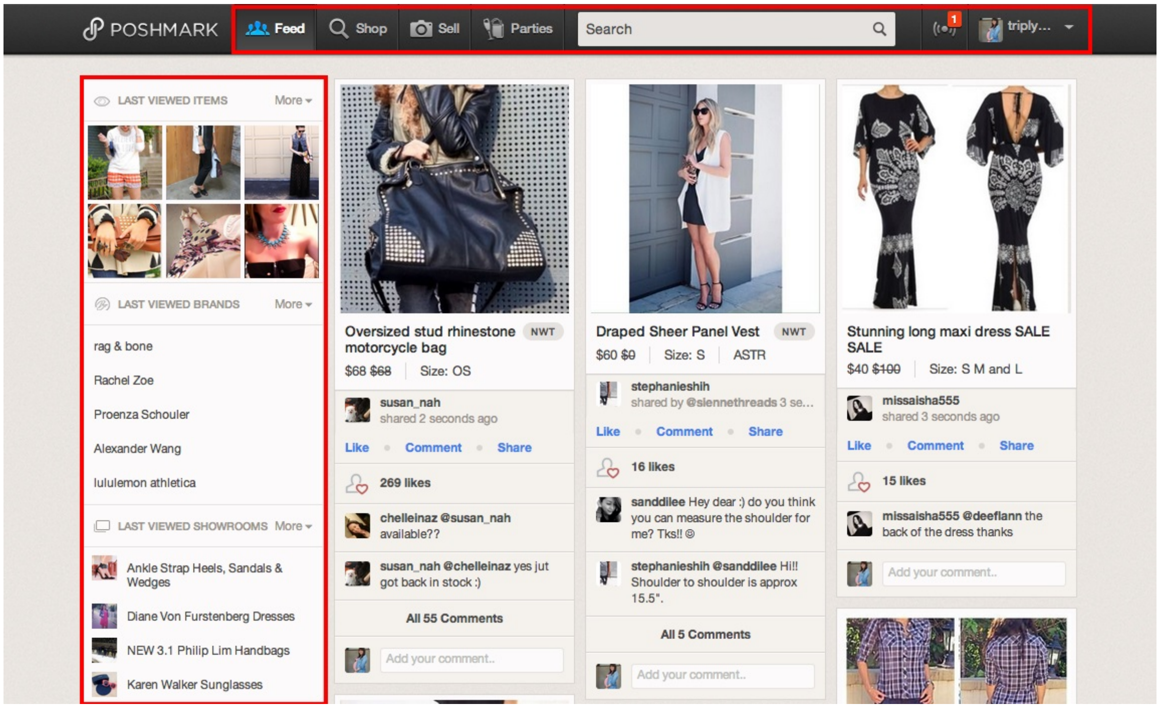
Weekly Treasure Hunt Items at Costco

Retrieved August 11, 2024

https://www.reddit.com/r/Costco/comments/ye4kea/costco_opening_in_my_country_tomorrow_can_someone/

https://emailtuna.com/costco.com/44109

Thrifted Clothing Online Platform



Retrieved July 13, 2024, https://blog.poshmark.com/wp-content/uploads/2013/10/feed-poshmark.png

Appendix B: Proofs

Proof of Lemma 1

We first show it cannot be optimal to stop search at time $\widehat{t}$ if treasure has not yet been discovered, where $\widehat{t} < t^* = a + \mu(V - p)$. We show that at such time $\widehat{t}$ it would be optimal to continue searching for an additional length of time ϵ. As $\epsilon \to 0$, the search utility of this continued search converges to $(a - \widehat{t})\epsilon$ and the probability of discovering treasure during this additional search period converges to $\mu\epsilon$. Therefore, continued search generates positive expected utility if $a - \widehat{t} + \mu(V - p) > 0$, which is true for any $\widehat{t} < t^*$. Similarly, it cannot be optimal to continue search until any stopping time $\widehat{t}$ that is greater than t^*. For such a $\widehat{t}$, the customer could increase expected utility by stopping search sooner at time $\widehat{t} - \epsilon$. Thus, the optimal stopping time cannot be less than or greater than t^*. QED

Proof of Proposition 1

For stopping time t^*, the probability of discovering treasure is $1-e^{-\mu t^*}$, so a customer's expected utility from discovering and buying treasure is $(1 - e^{-\mu t^*})(V - p)$.

For all $t \in [0, t^*]$, the probability that the customer continues searching until time t is $e^{-\mu t}$, and instantaneous search utility is $a - t$. Therefore, expected search utility from the treasure hunt is $\int_{t=0}^{t^*} e^{-\mu t}(a-t)dt$. We first compute the search utility component $\int_{t=0}^{t^*} ae^{-\mu t}dt$, which is $-\frac{a}{\mu}(e^{-\mu t^*} - e^0) = \frac{a}{\mu}(1 - e^{-\mu t^*})$.

Next, note the antiderivative of $-te^{-\mu t}$ is $\frac{t}{\mu}e^{-\mu t} + \frac{1}{\mu^2}e^{-\mu t} + C$. Therefore, we can compute the search cost component $\int_{t=0}^{t^*} -te^{-\mu t}dt$, which is $\frac{t^*}{\mu}e^{-\mu t^*} + \frac{1}{\mu^2}e^{-\mu t^*} - \frac{1}{\mu^2}$.

Adding all three components, we have the total expected utility of the treasure hunt: $(1 - e^{-\mu t^*})(V - p) + \frac{a}{\mu}(1 - e^{-\mu t^*}) - \frac{1}{\mu^2}(1 - e^{-\mu t^*} - \mu t^* e^{-\mu t^*})$. QED

Proof of Corollary 1

The derivative of U with respect to $V-p$ is $1-e^{-\mu t^*}$, and the derivative of U with respect to a is $\frac{1}{\mu}(1-e^{-\mu t^*})$. Both of these derivatives are strictly positive, so expected utility increases with $V-p$ and a. The numerical examples in section 5.2 illustrate that U can either increase or decrease with μ. Furthermore, customers choose stopping time t^* to maximize expected utility U. Therefore, the envelope theorem implies we can perform comparative statics of U on model parameters while holding t^* constant, as the effect of each parameter on the optimal t^* has only a second order effect on U. QED

Proof of Corollary 2

Differentiating (3), we find the derivative of utility with respect to the treasure discovery rate:

$$\frac{dU}{d\mu} = t^* e^{-\mu t^*}\left(V - p + \frac{a}{\mu} - \frac{2}{\mu^2} - \frac{t^*}{\mu}\right) + (1 - e^{-\mu t^*})\left(\frac{-a}{\mu^2} + \frac{2}{\mu^3}\right) \tag{9}$$

As $\mu \to \infty$, the entire first expression has order $e^{-\mu t^*}$, whereas the terms in the second expression have order $\frac{1}{\mu^2}$ and $\frac{1}{\mu^3}$, respectively. Therefore, (9) converges to $\frac{-a}{\mu^2}$, which is negative. Thus, for large μ, we have $\frac{dU}{d\mu} < 0$, which implies U must be maximized by a finite value of μ. In particular, the only possible optimal solutions are either $\mu = 0$ or a value of μ that solves the first-order-condition by setting (9) equal to zero. QED

Proof of Proposition 2

We first solve for the optimal μ given $p = V$, and we then show it is in fact optimal to set $p = V$ if product value is sufficiently low.

For $p = V$, we have $t^* = a$, and expected utility is:

$$U = \frac{a}{\mu}(1 - e^{-\mu a}) - \frac{1}{\mu^2}(1 - e^{-\mu a} - \mu a e^{-\mu a}) = \frac{a}{\mu} - \frac{1}{\mu^2}(1 - e^{-\mu a}) \tag{10}$$

The profit function is:

$$\pi = pUq = V\left[\frac{a}{\mu} - \frac{1}{\mu^2}(1 - e^{-\mu a})\right](1 - e^{-\mu a}) \tag{11}$$

Making the substitution $g(\mu) = \frac{1-e^{-\mu a}}{\mu}$, this profit function becomes $V(ag - g^2)$, which is maximized by setting $g = \frac{a}{2}$, which implies $\pi = V\frac{a^2}{4}$. We will show this equation has a unique solution that maximizes profits. As $\mu \to 0$, the numerator and denominator of g both approach zero. Furthermore, the derivative of the numerator with respect to μ approaches a and the derivative of the denominator approaches one. Therefore, as $\mu \to 0$, we have $g \to a$, which implies $\pi \to 0$. Furthermore, as $\mu \to \infty$, we have $g \to 0$, which also implies $\pi \to 0$.

To see that a unique value of μ maximizes profits, note the condition $g = \frac{a}{2}$ implies $1 - e^{-\mu a} - \frac{\mu a}{2} = 0$. Setting $\mu = 0$ solves this equation, but as noted above, $\mu = 0$ cannot be the profit-maximizing solution. Furthermore, $\frac{d^2}{d\mu^2}(1 - e^{-\mu a} - \frac{\mu a}{2}) = -a^2 e^{-\mu a}$, so this function is strictly concave and can have at most one other zero, which must be the optimal solution. We find numerically that this solution is $\mu a \approx 1.6$.

We now show that the firm sets $p = V$ if V is sufficiently small. The partial derivative of profits with respect to price is $Uq + p[\frac{dU}{dp}q + \frac{dq}{dp}U]$. Taking derivatives of the terms in brackets, we have $\frac{dU}{dp} = -(1 - e^{-\mu t^*}) = -q$ and $\frac{dq}{dp} = -\mu^2 e^{-\mu t^*}$, which implies:

$$\frac{\partial \pi}{\partial p} = Uq - p\left[q^2 + \mu^2 e^{-\mu t^*} U\right] \tag{12}$$

We now derive a lower bound on (12), which we use to derive a sufficient condition for this derivative to be positive for all $p \in [0, V]$. We have shown above that, for $p = V$, the firm can choose μ such that $Uq = \frac{a^2}{4}$. Reducing p increases both U and q, so for all $p \leq V$ the firm's optimal choice of μ implies $Uq \geq \frac{a^2}{4}$. To derive bounds on the other terms, note $p \leq V$ and $q^2 \leq 1$. Furthermore, the term $\mu^2 e^{-\mu t^*} \leq \mu^2 e^{-\mu a}$, and the latter expression is maximized by setting $\mu = \frac{2}{a}$, so an upper bound on this expression is $\frac{4}{a^2}e^{-2}$. The expected utility is bounded by $U \leq V + \frac{a^2}{2}$, which is the utility the customer would derive from buying the treasure at price zero after searching exactly until time a. Inserting these bounds into (12), we have:

$$\frac{\partial \pi}{\partial p} \geq \frac{a^2}{4} - V\left[1 + \frac{4}{a^2}e^{-2}V + 2e^{-2}\right] \tag{13}$$

If V is small enough to make (13) positive, the derivative of profits with respect to price is positive for all $p \in [0, V]$, so the firm sets $p = V$ to maximize profits. For $a = 1$, (13) is positive if $V \leq 0.18$. Note this condition is sufficient to guarantee $p = V$ in equilibrium but stronger than necessary. A necessary condition is that (12) is positive at the equilibrium value of all variables, that is, $Uq = \frac{a^2}{4}$, $p = V$, $q = q^*$, $t^* = a$, and $\mu = \frac{2q^*}{a}$. Inserting these values into (12) and simplifying the resulting expression, we find a necessary condition for the firm to set $p = V$ in equilibrium is $\frac{a^2}{4} - Vq^* \geq 0$. For $a = 1$, this condition holds if $V \leq 0.31$. QED

Proof of Proposition 3

We first show that, as $V \to \infty$, the firm's optimal price must satisfy $(V - p) \to \infty$. Based on this result, we then compute the optimal μ, which we use to compute the optimal p.

The derivative of profits with respect to price given by (12) can be written as:

$$\frac{\partial \pi}{\partial p} = U(q - p\mu^2 e^{-\mu(a+\mu(V-p))}) - pq^2 \tag{14}$$

In equilibrium, this derivative cannot be negative, or the firm could increase profits by reducing its price. Furthermore, as $p \to \infty$, this derivative is negative unless the term $\mu^2 e^{-\mu(a+\mu(V-p))}$ approaches zero. One possible solution would be to let $(V-p)$ stay bounded and let $\mu \to 0$, which also implies $q \to 0$. However, we will show that this proposed strategy cannot be optimal. Taking the derivative of profits with respect to μ, we have:

$$\frac{\partial \pi}{\partial \mu} = p\left[\frac{dU}{d\mu}q + \frac{dq}{d\mu}U\right] \tag{15}$$

As $\mu \to 0$, the first term in brackets approaches zero, and the second term approaches aU. The derivative is positive, and $\mu \to 0$ cannot be optimal because the firm could increase profits by raising μ. Furthermore, letting $(V-p)$ stay bounded and $\mu \to \infty$ cannot be the optimal strategy, as that would imply the second term in (14) diverges to negative infinity while the first term stays bounded, and in any case letting $\mu \to \infty$ cannot be optimal as (15) becomes negative for sufficiently large μ. Thus, the only possible solution is setting price such that $(V-p) \to \infty$, which implies $U \to \infty$ and the term $\mu^2 e^{-\mu(a+\mu(V-p))}$ approaches zero.

We now compute the optimal μ based on (15). We first compute the derivative of q with respect to μ:

$$\frac{dq}{d\mu} = (a + 2\mu(V-p))e^{-\mu(a+\mu(V-p))} \tag{16}$$

Because U has order V, the negative exponential term implies as $(V-p) \to \infty$, we have $\frac{dq}{d\mu}U \to 0$. Taking the derivative of each term in (3) shows that, as $(V-p) \to \infty$, we have $\frac{dU}{d\mu}q \to \frac{-a}{\mu^2} + \frac{2}{\mu^3}$. Thus, the optimal μ satisfies $\mu \to \frac{2}{a}$, which maximizes Uq.

We now compute the optimal price. As $V \to \infty$, $(V-p) \to \infty$, and $\mu \to \frac{2}{a}$, profits approach $p(V - p + \frac{a^2}{4})$. This profit function is maximized by letting $p \to \frac{V}{2} + \frac{a^2}{8}$. QED

Proof of Corollary 3

Proposition 2 states that $\mu = \frac{2q*}{a}$ for products with low value, and Proposition 3 states that $\mu \rightarrow \frac{2}{a}$ for products with high value. In both cases, an increase in a leads to a proportional decrease in μ, so that μa stays constant. QED

Proof of Proposition 4

After discovering treasure, a customer's willingness to pay for the treasure is V. Because customers do not observe price until after they discover the treasure, the actual price cannot affect their decisions to travel to the store or search, and these decisions are based on price expectations rather than the actual price. Furthermore, in equilibrium, expectations must equal the actual price that the firm optimally chooses. For any given search behavior, the firm's optimal price is to set $p = V$ to extract the full value of the product, and customers rationally expect this price. The derivation of the optimal μ is the same as in the main model for the case of $p = V$. QED

Proof of Proposition 5

For a given price, Corollary 2 states that utility is maximized by a finite μ. We show that the firm sets a strictly greater μ if its objective is to maximize profits. We allow any price that satisfies $0 < p \leq V$, which implies profits are positive.

Let μ^* denote the largest value of μ that maximizes utility. If there are multiple optimal solutions, that is, multiple values of μ that maximize utility, then μ^* generates the greatest profits among these values and greater profits than any smaller μ because q increases with μ. Suppose μ^* is zero. For this treasure discovery rate, q is zero and profits are zero. Therefore, profits are increased by setting a higher value of μ. If μ^* solves the first-order condition for utility-maximization, then for $\mu = \mu^*$, we have $\frac{d\pi}{d\mu} = p\big(q\frac{dU}{d\mu} + U\frac{dq}{d\mu}\big) = p\big(U\frac{dq}{d\mu}\big) > 0$. The derivative is positive, which implies profits are increased by setting a higher value of μ. In both cases, any value of μ that maximizes profits must be strictly greater than μ^*. QED

Proof of Proposition 6

As in the main model, the utility U for customers who enjoy search is given by (3). Let $\widehat{U}$ denote the expected utility from the treasure hunt for customers who do not enjoy search, which is given by (3) with $a = 0$. Similarly, the probability q of finding treasure for customers who enjoy search is given by (2), and the probability of finding treasure for customers who do not enjoy search is $\widehat{q} = 1 - e^{-\mu^2(V-p)}$.

The firm's objective is to choose p and μ to maximize $\pi = p[\gamma U q + (1-\gamma)\widehat{U}\,\widehat{q}]$.

As $V \to 0$, we have $\widehat{U} \to 0$ and $\widehat{q} \to 0$, but U and q do not approach zero because of positive search utility for the segment of customers who enjoy search. Therefore, the profit function approaches $\gamma p U q$, which is a constant times the profit function in the main model, so the optimization problem for this extension is equivalent to the main model and has the same solution as in Proposition 2 for sufficiently small V. This solution sets $p = V$, which implies only customers who enjoy search visit the store.

As V grows large, the same logic as in the proof of Proposition 3 implies the firm sets price such that $(V - p) \to \infty$, and we have $q \to 1$ and $\widehat{q} \to 1$. The number of units of treasure sold then approaches $\gamma U + (1-\gamma)\widehat{U} = (V-p) + \frac{\gamma a}{\mu} - \frac{1}{\mu^2}$. Differentiating with respect to μ and solving the first-order condition, we find this function is maximized by setting $\mu = \frac{2}{\gamma a}$. Inserting this value of μ into the profit function, we have $\pi = p\Big(V - p + \frac{(\gamma a)^2}{4}\Big)$, which is maximized by setting $p = \frac{V}{2} + \frac{(\gamma a)^2}{8}$. QED