Are Consumers Fooled by Discounts? 
An Experimental Test in a Consumer Search Environment 

Ralph-C Bayer and Changxia Ke
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Abstract
In this paper we investigate experimentally if people search optimally and how price promotions influence search behavior. We implement a sequential search task with exogenous price dispersion in a baseline treatment and introduce discounts in two experimental treatments. We find that search behavior is roughly consistent with optimal search but also observe some discount biases. If subjects don’t know in advance where discounts are offered the purchase probability is increased by 19 percentage points in shops with discounts, even after controlling for the benefit of the discount and for risk preferences. If consumers know in advance where discounts are given then the bias is only weakly significant and much smaller (7 percentage points).

Keywords: Consumer Search Theory, Search Cost, Price Promotion

JEL codes: D82, D83, C91

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1 Introduction

Price promotions (like discounts and rebates) are ubiquitous. “Buy one, get one free”, “30 percent more for the same price”, “Save four Cents per liter”, “Half price”, or “Happy hour” are some catch phrases we encounter every day. The persistence of the phenomenon of price promotions suggests that it works as consumers react with increased purchases. Per se this is not surprising at all, as any economist would agree that for most goods (i.e. Non-Giffen goods) lower prices should lead to higher demand. Marketing research has produced a large amount of evidence though that consumers react differently to identical discounts that are framed differently (see the meta analysis on how discounts work by Krishna et al. 2002), which is not consistent with standard economic theory. These findings suggest that there might be a discount effect beyond the pure price effect, which might differ depending on how a discount is framed. Generally, the marketing literature shows that the frame of discounts might impact on the perceived savings, the estimate of product quality, the accuracy with which savings are calculated and the expected price distribution in the market place (Grewal et al. 1998; Darke and Chung 2005; Inman et al. 1990; Kim and Kramer 2006; Sinha and Smith 2000), all of which should be purchase relevant.

In this paper we use an experimental setting in order to test if there is a discount effect, even if we exclude factors such as expected quality of the good and the believed price distribution. In other words, is there an effect that induces humans to buy the same good at the same net price more frequently if the price results from a discount? Such an exercise is of interest, as it allows for a clean test if subjects actually are prone to be exploited by discounts. The typical marketing study cannot properly evaluate this question, as often no real purchase decisions are observed and beliefs about the market distribution of prices for the good are not controlled for.

In our experiments we implement a standard finite price-search task with and without discounts. In a standard price-search task consumers have demand for one unit of a good. Initially, the consumers do not know the prices different shops charge. They only know the over-all price distribution shop offers are drawn from. In order to find out about the prices subjects can visit different shops at a cost. The crucial
decision of a shopper is to determine at which shop and at which price she stops searching and buys the unit of the good she demands.

We employ three treatments designed to investigate the impact of discounts. In a base line treatment subjects are engaged in the standard search task. In two other treatments we introduce discounts. The specific environments of the two discount search tasks are guided by reality. In the *Known-Discount* treatment subjects know *ex-ante* which of the ten shops offer discounts. The real-world equivalents to this treatment are fuel shopper dockets and discount stores. Fuel shopper dockets (widely observed in Australia) work as follows. Shoppers receive a docket from their supermarket (if they spend at least a certain amount on groceries), which entitles them to a discount (typically 4 Cents) per liter of fuel if purchased at certain petrol stations. Our treatment emulates the situation of a motorist, who has a docket and knows which petrol stations offer the discount. She does not know the actual prices though. The treatment is also similar to the situation where a shopper knows that there are some regular and some discount shops (such as factory outlets) but does not know the actual prices offered.

In the second treatment with discounts (*Random-Discount*) the shopper does not know if a particular shop offers a discount before visiting. The shopper knows the probability of a shop offering a discount though. This treatment is comparable with the real-world situation of a shopper sampling different stores along a shopping strip without any previous information. When designing our experiments we conjectured that the impact of discounts might differ across these two treatments. A bias toward buying more often in shops offering discounts (at identical net prices) could arise for different reasons in the two treatments. If subjects don’t know where discounts are offered they might be positively surprised once they enter a shop that offers a discount, which could lead to a purchase impulse. In the situation where a shopper knows where there are discounts the shops who offer them might be focal and subjects might turn down good prices on the way as they want to get to a discount shop.

Our results are as follows. Over all, the search behavior in all treatments is roughly consistent with expected value maximization. About 70 percent of all se-
quences of search and purchase decisions do not violate expected value maximization. If we allow for heterogeneous risk preferences (risk-love and aversion) then only about ten percent of subjects clearly violate rationality. Contrary to other studies we do not find the fraction of subjects with behavior consistent with risk-aversion to be significantly larger than the fraction of subjects with risk-loving behavior.

There are differences across treatments with respect to decidedly irrational behavior. We use a multilevel mixed-effects Logit regression in order to explore these differences. By comparing the impact of discounts on search behavior, while controlling for the objective expected benefit from searching and discounts, heterogeneity in risk preferences, learning effects and demographics we can identify discount biases. We observe the stronger discount bias in the Random-Discount treatment. Subjects ceteris paribus are about 19 percentage points more likely to buy at a shop offering a discount than from a shop without a discount when they do not know ex-ante which shops offer a discount. This is strong evidence that unexpected discounts lead to a large decision bias resulting in impulsive purchases. If a consumer knows ex-ante which shops offer discounts then the effect is much smaller. The purchase probability only increases by about 7 percentage points compared to that in a shop without a discount. This increase is only weakly significant. Shops that are focal as they are known to offer a discount (or because shoppers own a discount voucher for them) only have a small effect on shoppers’ propensity to buy there, once the benefit from the discount is controlled for.

The remainder of the paper is organized as follows. In Section 2 we review the related literature from search theory and experiments and motivate our approach by looking at some marketing literature. In Section 3 we lay out the design of the experiment and its implementation. In Section 4 we illustrate the optimal stopping rule and the calculation of reservation prices. In Section 5 we provide our major findings. Section 6 offers a conclusion.
2 Related literature

Consumer-search theory dates back to “The economics of information” (Stigler 1961). This seminal paper is motivated by the perception that the so-called “law of one price” in a perfectly competitive market does not exist in the real world. Stigler attributes the ubiquitous price dispersion to consumers’ costly search behavior in a world where information asymmetry prevails. Since then, research has developed rapidly, with the aim to describe optimal search rules in different settings and to apply them in more complex micro and macroeconomic models.

In conventional search models a rational and potentially risk-neutral buyer searches for the lowest price for a certain product among dispersed prices in the market. The buyers may have some knowledge of the price distribution in the market without knowing the individual prices charged by each seller. Obtaining this specific information is costly. The main objectives of these models are to characterize the optimal stopping rule and to predict how it changes in response to the variations of the following major parameters:


2. Search strategies adopted by consumers. Examples are fixed sample size search (FSS; e.g., Manning and Morgan 1982), sequential search (SS; e.g., Kohn and Shavell 1974; Bikhchandani and Sharma 1996), or variable sample size search (VSS; e.g., Morgan and Manning 1985). While FSS and VSS might be more applicable than SS in a job search scenario, SS is more realistic and hence more popular in consumer search models. Our experiment follows this convention.

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1There also exists a large literature on search theory in job-seeking scenarios (e.g., Lippman and McCall 1976). However, we only focus on consumer search theory in this paper.

2Consumers can draw multiple samples simultaneously in the FSS model, whereas in SS models they have to search one by one. As a generalization of both FSS and SS, the VSS model gives the consumers the highest degree of flexibility such that consumers search sequentially, but with the freedom to vary the sample size from period to period.
3. The availability of recall for previously rejected price offers (e.g., Karni and Schwartz 1977; Bikhchandani and Sharma 1996).

4. Search duration – infinite time horizon versus finite time horizon.

Regardless of which of these assumptions are made, the optimal stopping rule characterized in these papers share some general properties. Rational (and potentially risk-neutral) expected utility maximizers will maximize their expected utility when the expected net gain of one additional search is equal to the marginal search cost. Following this optimal rule, there exists a cutoff reservation price, which makes consumers indifferent between accepting the lowest price available and searching further. Consumers should keep searching until they find a price equal to or less than this reservation price. In infinite time horizon settings where consumers can search as long as they like, the reservation price is constant. Therefore, consumers never reject a price offer and go back after a few searches if every decision they make follows the optimal reservation price rule. In finite time horizons, the reservation price increases over time due to a reduced number of not-yet-uncovered offers. In general, the reservation price increases with an increase in the cost of search and the degree of risk aversion, or a decrease in price dispersion if the consumer is risk-averse.

Considering the popularity of search models and their frequent application in economic modelling, it is important to know whether consumers actually search according to the reservation price rule. Also, given the difficulty in gathering empirical data on the search process, experimental studies are especially valuable.

In the earliest experimental studies, Schotter and Braunstein (1981) and Braunstein and Schotter (1982) investigate whether individuals in an infinite time horizon search according to an optimal reservation wage rule in a job market context. They show that the search behavior is generally consistent with the reservation-wage hypothesis and responds to parameter changes (of search cost, risk preferences, price dispersion, availability of recall, searcher’s knowledge of the price distribution, the existence of a minimum wage, etc.) in the direction theory predicts.

One inconsistency observed by Schotter and Braunstein is a decreasing reservation wage, compared to the constant reservation wage predicted in an infinite horizon
search model. Cox and Oaxaca (1989) suggest that this might due to the subjects’ perception of searching infinitely being unrealistic. Hence they test a finite time horizon model with a maximum of 20 searches. Subjects on average search optimally 77% of the time if risk-neutrality is assumed and 94% of the searches terminate optimally according to a model allowing for risk aversion. In a follow-up experiment, Cox and Oaxaca (1992) ask subjects to pre-commit to a reservation wage according to which acceptances and rejections are made on their behalf. Direct tests on the stated reservation wages reject risk-neutrality in favor of risk-aversion.

Kogut (1990; 1992) investigates consumer search behavior when the price distribution is known, in both infinite and finite time horizons. The focus of his two papers is on recall behavior. He finds that people recall a third of the time in the infinite horizon even though it is never optimal to do so. In addition, subjects stop searching too early even if risk aversion is assumed. He attributes the substantial under-search to the subjects not being able to ignore sunk search cost. In the finite time horizon, subjects recall roughly 30% of the time, where the amount of recall varies with the search cost. However, Kogut concludes that the decisions made by the subjects are still generally consistent with rational choice.³

In our paper, we adopt a sequential search model with a finite time horizon as the baseline environment. The search task we implement in the laboratory differs from the previous experimental studies in the following aspects. First, recall is allowed to a certain extent but leads to costs. In previous studies, recall (of previously rejected prices) *per se* does not associate with any explicit cost when it is available. This assumption could be true for Internet shopping. However, in physical markets where sellers spread spatially, it always takes time (or transportation cost) to move from one seller to another. In this circumstance, we believe that costly recall is a more realistic assumption. Second, subjects are allowed to move freely both forwards and backwards like in a real shopping scenario until the maximum number of moves is exhausted. More specifically, subjects can move forwards to a new shop or move backwards to a previous shop. Subjects can also reverse the direction as many

³Instead of testing the optimal stopping rule, Hey (1982; 1987), Moon and Martin (1990; 1996) and Sonnemans (1998) focus on discovering the heuristic rules used by the subjects in experimental search tasks.
times as they like (within the bounds of the finite number of moves). The last scenario is obviously irrational and inefficient, but it is feasible and observable in the real world. Therefore, our design realistically simulates the scenario of consumers shopping along a road or a mall. Last, and most importantly, our focus is to find out how discounts may bias consumer search behavior rather than to simply test the optimal stopping rule. Moreover, as recall can only be rational in very rare cases (which only twice occurred in 1580 price sequences), this design provides a simple test for clearly irrational behavior.

Our paper also relates to and shares the research question with marketing studies on how price presentation affects consumers’ perceived savings from price promotions and thereby influences their probability to purchase a certain product. Krishna et al. (2002) provide a meta-analysis of 20 studies by looking at different dimensions of price promotion. The study shows that the buyers’ perception of the promotional value is influenced by both price framing effects (e.g., whether a reference price is provided) and situational effects (e.g., whether the price promotion is on a national brand or a generic brand). For example, both absolute discounts and percentage discounts increase consumers’ perceived savings, while percentage discounts have a bigger impact. The typical methodology used in these studies is to survey student subjects on their perceived savings of a particular price framing and ask them either to rate their likelihood to purchase or to make real purchase decisions. Conclusions are drawn by comparing the rating or the behavior of subjects across different price framing formats.

Typically, studies in this tradition suffer from lack of control. Important factors (like buyers’ valuation, quality or attributes of the product) are usually not appropriately controlled for in order to allow for a clean isolation of price-framing effects. In addition, subjects are usually asked to make hypothetical (or sometimes real) decisions in isolation, whereas buyers in reality usually search for the best deal among different sellers under uncertainty. Our design (i.e. introducing discounts into an experimental search environment) provides the control and incentives necessary for a clean analysis of the effects of discounts on individuals’ purchase decisions. On the one hand, consequences of subjects’ decisions are real, as their payoff depends
on them. On the other hand, we are able to control for subjects’ beliefs about the quality of the good and for their beliefs about the price distribution in the market place.

3 Experimental design

In what follows we will provide details of our experimental design and its implementation. We start with the structure and parameters of the search environment. The search task we implemented in the baseline treatment (referred to as No-Discount) can be formally defined as follows:

1. The individual is actively seeking the lowest price offered in a market, where there are \( N (= 10) \) sellers (or shops) numbered from 1 to 10.

2. The exact price offered by each seller is not available to the buyer. However, the buyer is informed that sellers will draw their prices randomly and independently from the same uniform distribution with p.d.f \( f(p) = 1/(p - \bar{p}) \), \( \bar{p} = 75 \), and \( \bar{p} = 175 \).

3. The only way to learn the price charged by particular shops is to physically visit them in sequence. Moving from one shop to another causes costs of \( c = 5 \).

4. If the buyer moves away from a seller but later goes back to that seller then she will find the price unchanged. In other words, recall of previously rejected price offers is permitted.

5. Recall is also costly in this experiment, which differentiates our setting from other commonly used search models. In the existing literature recall is either not available or available for free. We assume that the cost of going back to the last shop passed is the same (i.e., \( c \)) as the cost of moving from that shop to the current one. The more shops visited after that shop, the longer is the distance needed to travel back to it and hence the cost of recall is higher.

6. The buyer can at most make ten moves (forwards or backwards) due to some implicit budget (or time) constraint.
7. The buyer’s payoff is equal to her valuation of the purchased product \((v = 200)\) less the net price paid and the total cost spent on searching and recalling (i.e., \(n \times c\), whereas \(n\) is the total number of moves made by the individual). The first price quote is free in a standard search model, whereas it is costly in ours.

In our two experimental treatments, the search task is identical to the baseline treatment except that some shops may offer discounts to customers. Each shop in the experimental treatments has an *ex-ante* probability of one-third of offering a discount on its posted price. The discount \(d\) is equal to 15 monetary units. Draws are independent across shops. In one treatment, the draw in a particular shop (if this shop offers a discount) is revealed only if the buyer reaches that shop. In the other treatment, the draws (if a discount is offered) of all ten shops are revealed before the search process starts. We call the former the *Random-Discount* treatment, and the latter the *Known-Discount* treatment. This design makes it possible to not only explore the discount effect on consumer search behavior, but also to check if the effect varies with the level of information on discounts revealed to the buyers.

In order to communicate the situation in the experimental treatments to the subjects we provided the following information in addition to the common information explaining the search task from above. Subjects in the experimental treatments were informed that outlets are associated with one of three different colors – blue, red and green. Subjects were also informed of the color of a shopper docket they held. Furthermore, they were told that they are entitled to a discount in all shops where the color matches their docket. In the *Known-Discount* treatments subjects knew the colors of the ten shops in advance. In the *Random-Discount* treatment, they were only told that for any shop all three colors are equally likely. Subjects could only find out if they were eligible for a discount once they had entered a particular shop.

The search task was programmed in z-Tree (Fischbacher 2007) and the experimental sessions were conducted at AdLab, the Adelaide Laboratory for Experimental Economics. In total, 158 university students participated – 53, 57 and 48 in the *No-Discount*, *Random-Discount* and *Known-Discount* treatments, respectively. Subjects were randomly assigned to sessions and repeated participation was not
possible. In each session, the same search task was repeated ten times with new prices drawn randomly and independently for each subject.\textsuperscript{4}

At the beginning of each session, subjects were given comprehensive written instructions along with the opportunity to ask clarifying questions. At the end of each session, subjects completed a computerised questionnaire, which asked for some demographic characteristics (which we use as controls in our analysis). Experimental earnings were converted into Australian Dollars using an exchange rate of 100 Experimental Dollars yielding 1.25 Australian Dollars. On average, subjects earned AUD 10.20 for about 30 minutes of their time. Given that our sessions were quite short, we conducted this experiment together with other unrelated experiments, which were also incentivized by real money. A whole session lasted around 1.5 hours.

4 The optimal stopping rule

Despite the modifications we made to the conventional search model, the calculation of the optimal stopping rule still follows the same reasoning. The individual in this search task faces a dynamic decision-making problem under uncertainty. In each shop, the subject has to decide whether to stop and accept the current offer, recall at a previously visited shop, or keep searching (with the chance of finding better prices). The first two choices lead to certain payoffs, while the last choice causes uncertainty, where the payoff is drawn from a probability distribution. Therefore, an expected-utility maximizer should compare the (expected) utilities attached to the different options. Whenever the expected utility given by “search” exceeds the maximum available utility from “stop” or “recall”, the search should continue. Following this principle, the optimal rule consists of a set of reservation prices containing one at each point in the finite time horizon. Whenever the actual price at a certain point is below the reservation price the optimal decision is to stop, and to keep searching otherwise. The reservation price increases with the number of searches

\textsuperscript{4}Fixed, pre-drawn price sequences are used in some previous studies, as they can simplify the analysis and also increase the power of statistical tests. We used random draws, as this provides more variation. The large number of observations we have overcomes the test-power problem.
conducted. The intuition is simple. The more prices are sampled, the less shops with potentially low prices are left. A consumer should accept a higher price if the likelihood of finding a low price in the future is reduced.

We start with the baseline model to illustrate the optimal stopping rule for the case of risk-neutrality. For expositional reasons we do not allow a consumer to recall at a shop previously visited.\textsuperscript{5} Suppose a risk-neutral shopper arrives (without having made any mistakes before) at the penultimate shop. Then the decision whether to go to the last shop or to buy from the penultimate shop depends on whether the profit from buying $V(N - 1, p_{N - 1})$ is greater or smaller than the expected profit from searching $EV(N - 1)$. Let $i \in [1, 2, ..., N]$ denote the location of the shop along the street and $p_i$ denotes the price charged at shop $i$. A consumer is indifferent if

$$V(N - 1, p_{N - 1}) = EV(N - 1), \text{ or}$$

$$v - p_{N - 1} - (N - 1)c = \int_{p}^{\infty} (v - p - Nc) \, dF(p)$$

The price $p_{N - 1}$ solving this equation is the reservation price $R(N - 1)$ for shop $N - 1$:

$$R(N - 1) = \int_{p}^{\infty} pdF(p) + c$$

At lower prices than $R(N - 1)$ the consumer will buy and for prices higher than $R(N - 1)$ the consumer will go to the last shop. For our experimental parametrization, e.g., the reservation price for the penultimate period, which is period nine, is therefore 130, the price expectation for shop ten plus the search cost.

To find the reservation prices for earlier periods one can simply use the recursive structure and iterate backwards. So a consumer, who arrives at shop $N - 2$, knows that she will accept all prices below $R(N - 1)$ but will go on searching otherwise if she moves to shop $N - 1$. Then taking the expectation over the profits made in these two events gives $EV(N - 2)$ which can be compared to the profit of buying at

\textsuperscript{5}In our experimental setting recall is possible to some extent but hardly ever optimal. Only in two out of 1580 price sequences recall was ever optimal. In principle it is straightforward to include recall. The notation becomes quite messy though. The reserve prices of the optimal stopping rule with recall do not change significantly.
shop $N - 2$. The indifference condition can be used to solve for $R(N - 2)$, and so on.

The general recursive structure for solving for the reservation prices can be written using an indifference condition and a Bellman-type equation:

$$R(i) := \{ p_i \in [p, \bar{p}] : V(i, p_i) = EV(i) \}$$

$$EV(i) = \int_{p}^{R(i+1)} V(i + 1, p) dF(p) + \int_{R(i+1)}^{\bar{p}} EV(i + 1) dF(p)$$

The first integral of $EV(i)$ in Equation 5 is the expected payoff if the search terminates in shop $i + 1$ weighted by the probability that this happens. The second integral is the expected continuation value if search continues in shop $i + 1$ weighted by its probability of occurrence. As a result, the cutoff price $R(i)$ is a function of all the future cutoff prices. To solve for the optimal reservation price at each stage we need to solve a series of recursive equations starting with the last shop.

The general form of the optimal stopping rule derived through the cutoff prices in equations 4 and 5 also applies to the experimental treatments where discounts are given. The differences here are that a) whenever a discount is encountered the prices in the equations above have to be replaced by the net prices and b) that the expected price distributions featuring in the continuation value have to take into account the likelihood of a discount in the Random-Discount treatment and the known discounts in the Known-Discount treatment.

To find the optimal stopping rule we used the software Mathematica and calculated the expected continuation values $EV(i)$ and net reservation prices $R(i)$ at each point starting in the last period. The values for the No-Discount and Random-Discount treatments are shown in Table 1.\(^7\) Note that the optimal stopping rule in the treatment, where subjects in advance know the location of the shops offering discounts depends on the actual location of shops with discounts. Given the number

\(^6\)The reservation price in the last shop has to be set to $\bar{p}$, as further search is not possible.

\(^7\)Moving backwards (i.e. recall) is typically not optimal if a subject has not violated expected value maximisation before. The only occasions where moving backwards can be optimal are extremely unlikely and can only happen in period eight or nine. In our sample we observed only two price draws out of 1580 where recall was actually optimal. For this reason recalls are ignored in the table.
of the discount offers and their varying locations, we observe 463 different sequences in the Known-Discount treatment. We calculated the optimal stopping rules for all of these sequences but do not explicitly report them here for obvious reasons.\(^8\)

<table>
<thead>
<tr>
<th>i</th>
<th>EV(i)</th>
<th>R(i)</th>
<th>EV(i)</th>
<th>R(i)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>87.667</td>
<td>107.334</td>
<td>93.384</td>
<td>101.616</td>
</tr>
<tr>
<td>2</td>
<td>82.330</td>
<td>107.670</td>
<td>88.021</td>
<td>101.979</td>
</tr>
<tr>
<td>3</td>
<td>76.828</td>
<td>108.172</td>
<td>82.485</td>
<td>102.515</td>
</tr>
<tr>
<td>4</td>
<td>71.072</td>
<td>108.928</td>
<td>76.685</td>
<td>103.315</td>
</tr>
<tr>
<td>5</td>
<td>64.918</td>
<td>110.082</td>
<td>70.475</td>
<td>104.525</td>
</tr>
<tr>
<td>6</td>
<td>58.116</td>
<td>111.872</td>
<td>63.601</td>
<td>106.399</td>
</tr>
<tr>
<td>7</td>
<td>50.194</td>
<td>114.806</td>
<td>55.582</td>
<td>109.418</td>
</tr>
<tr>
<td>8</td>
<td>40.125</td>
<td>119.875</td>
<td>45.375</td>
<td>114.625</td>
</tr>
<tr>
<td>9</td>
<td>25</td>
<td>130</td>
<td>30</td>
<td>125</td>
</tr>
</tbody>
</table>

Table 1: Expected continuation values and reservation prices.

5 Results

In this section we present our results. The most important findings are as follows. Overall, the observed search behavior is largely consistent with the optimal behavior under risk-neutrality. We do not observe systematic under-search patterns found in previous studies. Subjects did exercise recall, which is typically suboptimal. The recall rate is substantially lower than the 30% reported by Kogut (1990; 1992) though. The introduction of discounts significantly reduces the fraction of behavior consistent with optimal behavior under risk-neutrality. Subjects seem to be less inclined to search further when the shop they are in offers a discount, even if the surplus gained through the discount is controlled for by considering the net price. This effect is much stronger if subjects do not have \textit{ex-ante} information on who is going to offer a discount. In what follows we provide the details of our analysis.

We first compare actual search behavior to the optimal search strategy under risk neutrality. Then we use a multilevel mixed-effects logistic regression to investigate the impact of discount vouchers on search behavior.

\(^8\)The optimal rules and the Mathematica code can be obtained on request from the authors. 
\(^8\)R(i)_{net} is the net reservation price, namely the price minus the discount.
5.1 Comparison with the prediction under risk-neutrality

Assuming risk-neutrality, we can calculate the maximum available payoff and the expected continuation value, conditional on the prices and the discount information given at each point of the search task. The optimal decision at each stage of the search task, and hence the optimal search path (or duration), can be determined. Comparing the actual behavior with the theoretically optimal behavior, we can state our first result.

**Result 1:** Among the 4387 decisions made by the subjects, 85% of the decisions are consistent with the optimal stopping rule under risk neutrality.

<table>
<thead>
<tr>
<th></th>
<th>Observed-Buy</th>
<th>Observed-Search</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>%</td>
<td>Obs.</td>
</tr>
<tr>
<td>Optimal</td>
<td>1291</td>
<td>29.4</td>
<td>2438</td>
</tr>
<tr>
<td>Non-optimal</td>
<td>287</td>
<td>6.5</td>
<td>371</td>
</tr>
<tr>
<td>Total</td>
<td>1578</td>
<td>35.9</td>
<td>2809</td>
</tr>
</tbody>
</table>

Table 2: Actual versus optimal decisions under risk neutrality.

Table 2 provides a comparison between the observed and the optimal behavior for every individual decision. Of the 4387 decisions made by the subjects, 1291 of the purchase decisions and 2438 of the search decisions are optimal. In 287 decisions when subjects stopped, a rational risk-neutral agent would have kept searching. In the remaining 371 decisions where subjects searched, a risk-neutral searcher would have stopped. Similar to findings in previous studies, the subjects seem to follow the optimal stopping rule reasonably well.

Besides looking at each individual decision, we can look at a full search tasks that include multiple decisions. The first question we ask is if a subject in a particular search task exactly follows the search path predicted by theory. In the case that a subject deviates from the prescribed path we can further ask if a subject keeps searching for too long or stops too early.

**Result 2:** Among 1580 search tasks, subjects followed the optimal paths for risk-neutral agents in 70.2% of tasks.

Table 3 reports the fraction of actual search paths that are optimal, or too short, or too long. Seventy percent of observed search paths are optimal. This number
Table 3: Observed search paths and optimal paths under risk neutrality.

<table>
<thead>
<tr>
<th></th>
<th>Optimal-path</th>
<th>Undersearch-path</th>
<th>Oversearch-path</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>74.9%</td>
<td>12.1%</td>
<td>14.0%</td>
</tr>
<tr>
<td>Random-D</td>
<td>69.6%</td>
<td>18.8%</td>
<td>11.6%</td>
</tr>
<tr>
<td>Known-D</td>
<td>65.6%</td>
<td>20.2%</td>
<td>14.2%</td>
</tr>
<tr>
<td>Aggregate</td>
<td>70.2%</td>
<td>17.0%</td>
<td>12.8%</td>
</tr>
</tbody>
</table>

is slightly lower than what is reported (77%) by Cox and Oaxaca (1989). This difference could be due to the increased complexity induced by the provision of discounts in the two experimental treatments. This will be further discussed in due course. The remaining 29.8% of observations deviate from the optimal path; 17.0% of the search paths are too short (undersearch) and 12.8% are too long (oversearch). A common finding in the literature is that subjects search too little, which is mostly explained as risk-averse behavior. In our experiment the inconsistent behavior seems to stem from heterogeneous risk preferences, as well as some noise in the decision-making process. The theoretically inconsistent search patterns show a strong serial correlation. We find one-third of the subjects always searched for too long, one-third always searched too little, and the remaining third shows both types of inconsistency. This is consistent with the view that two-thirds of the subjects, who deviated from the path that maximizes expected profit are not risk-neutral, while one-third made noisy decisions. Hence, about 10% of subjects behaved noisily and in a way that is not consistent with expected utility maximization.

**Result 3:** The provision of discount vouchers significantly reduces the rate of theoretically consistent behavior. The impact of the level of information revealed to the subjects on the rate of theoretically consistent behavior tends to be negative and is weakly significant.

The disaggregate success rates in Table 3 show that 74.9%, 69.6% and 65.6% of the paths exactly match the optimal paths in the No-Discount, Random-Discount and Known-Discount treatments, respectively. Proportion tests suggest that the success paths in both Random-Discount and Known-Discount treatments are strictly lower than that in the base treatment ($p = 0.026$ and $p < 0.001$, respectively). The success rate in the Known-Discount treatment is smaller and only weakly significant.
in the *Random-Discount* treatment (*p* = 0.082). Observing the composition of inconsistent search patterns, we find a significant increase of undersearch paths in the two experimental treatments (18.8% and 20.2% versus 12.1% in the treatment without discounts). This suggests that discounts bias the subjects towards buying early without appropriately considering the benefits of a further search. As this analysis cannot control for risk preferences, we will further explore this effect in the next subsection, where we provide a proper econometric analysis.

**Result 4**: *Subjects exercise recall in 112 (7%) cases, which is considerably less often than in previous studies (30%).*

<table>
<thead>
<tr>
<th></th>
<th>Optimal</th>
<th>Undersearch</th>
<th>Oversearch</th>
<th>Aggregate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>0%</td>
<td>21.9%</td>
<td>78.1%</td>
<td>28.6%</td>
</tr>
<tr>
<td>Random-D</td>
<td>2.4%</td>
<td>50.0%</td>
<td>47.6%</td>
<td>37.5%</td>
</tr>
<tr>
<td>Known-D</td>
<td>2.6%</td>
<td>36.9%</td>
<td>60.5%</td>
<td>33.9%</td>
</tr>
<tr>
<td>Aggregate</td>
<td>1.8%</td>
<td>37.5%</td>
<td>60.7%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Note: Percentages are calculated based on a total of 112 recalled-paths

Table 4: A summary of search patterns where recall was exercised.

In finite time horizon search tasks the reservation prices increase with the number of shops visited, and hence recall might be optimal on some occasions. When recall is costly as in our setting, optimal behavior rarely allows for recall. We had exactly two price draws, where recall was optimal at one of the stages. As shown in Table 4, on aggregate only 1.8% of the recalls are optimal, 60.7% of the recalls are observed in oversearch and 37.5% in undersearch situations. Non-optimal recall clearly suggests irrational behavior that might be caused by regret. The disaggregate ratios show that most (78.1%) of the recall happened after oversearching in the base treatment, which is consistent with regret. This percentage reduces to 47.6% and 60.5% in the *Random-Discount* and *Known-Discount* treatments, respectively. The recall along undersearch paths increases from 21.9% in the *No-Discount* treatment to 50% and 36.9% in the *Random-Discount* and *Known-Discount* treatments. The observed shift in the composition of irrational recall behavior (i.e., oversearch-recall or undersearch-recall) also hints at the existence of discount effects.
5.2 The impact of discounts

The analysis above suggests that there is a discount effect. For a proper test we now turn to individual decision data. In what follows we estimate the influence of different variables (discounts among them) on the search decisions of individuals. Recall that we observe the decisions of one individual in different shops and in different periods. Periods here refers to the ten different search tasks with up to ten decisions each. We use the panel structure to control for unobserved heterogeneity across subjects and across search tasks by allowing for random effects on these two levels. We arrive at a multilevel mixed-effects Logit regression. The dependent variable is binary (with 0 and 1 corresponding to “stop” and “search”, respectively).\(^9\)

So we estimate the probability of subject \(s\) to keep searching in the \(p^{th}\) search task and in shop \(i\) conditional on some covariates \(X\):

\[
\text{logit} \{ \Pr(\text{search}_{spi} = 1) \} = \beta_0 + \beta X_{spi} + \mu_s + \nu_{sp} + \varepsilon_{spi} \quad (6)
\]

The random effect on the subject level is denoted as \(\mu_s\) and \(\nu_{sp}\) represents the subject-task-level random effect.

The covariates (listed below) include treatment dummies, and its interaction with discount dummies, expected search benefit, search duration and individual characteristics.

- **No-D, Random-D, Known-D** are the treatment dummies; **No-D** is the base category.

- **\(EB_{\text{search}}\)** is the expected net benefit from search. It is calculated at each decision point using the expected continuation value minus the maximum available payoff if a subject decided to stop there.

- **Discount_Random-D** is a dummy variable indicating that a subject is in the **Random-D** treatment and a discount is offered in the current shop.

\(^9\)The reason we use “stop” rather than “buy” is that “stop” is the aggregate of both “buy” and “recall” decisions. The decisions after a subject has decided to go back are not included in the regression, as recall is a clear indication for erroneous behavior.
• Discount_Known-D is a dummy variable indicating that a subject is in the Known-D treatment and a discount is offered in the current shop.

• i(shop) is the search duration, measured as the number of the shop the subject has arrived at.

• Male is a gender dummy, which is equal to 1 for male participants.

• Age25, Age26-30 and Age31-40 is a set of dummies indicating the subjects’ age range. Age25 is the base category.

• Maths is a dummy variable capturing whether or not a subject has a good background in mathematics (measured as the level of high school maths that the subject has taken), with 0 indicating a low level.

• Arts, Comm/Fin, Economics, Engineering, Law, Medicine, Science, and Other are dummies which categorize subjects according to the course they are enrolled in. Arts is the base category; Comm/Fin is the abbreviation for Commerce/Finance.

Before presenting the regression results, we need to explain why this regression allows us to identify a discount bias if it exists. Basically, our task is the following. We want to see if a person, who gets a discount at a certain shop, is more likely to buy there even if we control for a) the savings from the discount and b) for individual risk preferences. Assume for instance that all subjects were expected value maximizers as in our theoretical benchmark. Then adding the expected benefit from searching (given net prices and net expected prices), which we denote by $EB_{search}$, as a covariate would control for the benefit, while heterogeneous risk preferences would not be an issue. However, this is not enough when we have subjects with heterogenous risk preferences. The more risk-averse a person is the lower the search probability should be in any given situation. So we have to control for the characteristics of a given situation that are relevant with respect to risk and also allow for subjects’ heterogeneous propensity to search in general. Our subject and subject-task-level random effects accomplish the latter. Including the expected benefit from searching and also the search duration $i(shop)$ are sufficient for the former.
The inclusion of the search duration is necessary, as decision situations with the same expected benefit from searching but at different shop locations are only equivalent for expected value maximizers but not for expected utility maximizers. The closer a subject gets to the end of the street, the higher the risk becomes, as there are less and less shops. Therefore, we would expect a negative impact of the search duration on the probability of an additional search if subjects are risk-averse. Including \( i(\text{shop}) \) controls for this.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>( \partial y / \partial x )</th>
<th>Variable</th>
<th>Coefficient</th>
<th>( \partial y / \partial x )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.611</td>
<td>(1.023)</td>
<td>i(\text{shop})</td>
<td>-0.231***</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Random-D*</td>
<td>-0.165</td>
<td>(0.386)</td>
<td>Maths*</td>
<td>-0.374</td>
<td>(0.412)</td>
</tr>
<tr>
<td>Known-D*</td>
<td>-0.048</td>
<td>(0.410)</td>
<td>Comm/Fin*</td>
<td>0.037</td>
<td>(1.029)</td>
</tr>
<tr>
<td>( \text{EB} \text{search} )</td>
<td>0.177***</td>
<td>(0.010)</td>
<td>Economics*</td>
<td>0.937</td>
<td>(1.083)</td>
</tr>
<tr>
<td>Discount_Random-D*</td>
<td>-0.978***</td>
<td>(0.232)</td>
<td>Engineering*</td>
<td>0.387</td>
<td>(1.054)</td>
</tr>
<tr>
<td>Discount_Known-D*</td>
<td>-0.393*</td>
<td>(0.233)</td>
<td>Law*</td>
<td>-0.156</td>
<td>(1.203)</td>
</tr>
<tr>
<td>Male*</td>
<td>-0.268</td>
<td>(0.381)</td>
<td>Medicine*</td>
<td>1.063</td>
<td>(1.149)</td>
</tr>
<tr>
<td>Age26-30*</td>
<td>-0.907</td>
<td>(1.007)</td>
<td>Science*</td>
<td>0.372</td>
<td>(1.130)</td>
</tr>
<tr>
<td>Age31-40*</td>
<td>-0.537</td>
<td>(0.847)</td>
<td>Other*</td>
<td>0.282</td>
<td>(1.491)</td>
</tr>
<tr>
<td>Random-effect:</td>
<td>Group var.</td>
<td>Estimation</td>
<td>Std.Err.</td>
<td>[95% Conf. Interval]</td>
<td></td>
</tr>
<tr>
<td>level-1</td>
<td>Id</td>
<td>1.649</td>
<td>(0.161)</td>
<td>1.361</td>
<td>1.997</td>
</tr>
<tr>
<td>level-2</td>
<td>Period</td>
<td>1.493</td>
<td>(0.193)</td>
<td>1.159</td>
<td>1.925</td>
</tr>
</tbody>
</table>

Log likelihood=-1341.111; Wald chi2(16) = 405.30; Prob>chi2 = 0.0000

*\( \partial y / \partial x \) is for discrete change of a dummy variable from 0 to 1; ***significant at 0.001

Table 5: Multilevel mixed-effects logistic estimation of search probabilities.

As shown in Table 5, the search probability tends to increase with the expected benefit from searching. The marginal effect of \( \text{EB} \text{search} \) (at its mean), measured as the change in the likelihood of a subject searching, is 0.028 for an increase by one currency unit. This is reassuring. We also have the expected sign for the search duration. Getting one shop closer to the end reduces the propensity to search by 4 percentage points. This hints at subjects on average being risk-averse. Other
control variables that might explain part of the risk preferences (like age, gender etc.) are not significant. Furthermore, we do not find any differences in search behavior across treatments for shops without discounts, which validates our design.

We observe a large level of heterogeneity in risk preferences. The intra-class correlation for the same subject calculates as 0.33. The correlation for choices of the same subject in the same task is even higher with 0.6. Both correlations are highly significantly different from zero.\(^\text{10}\) On the one hand this provides a good justification for using a multi-level model. On the other hand this shows a very high degree of consistency of the choices of subjects across shops within tasks and still some consistency of subjects across tasks. This suggests that subjects do not choose randomly but follow decision rules that are influenced by risk preferences. These decision rules change somewhat with repetition of the search task due to learning and experience. The changes are systematic in the sense that initially more risk-averse subject tend to stay more risk-averse than initially less risk-averse subjects. These results above show that our empirical model is well specified. We can now proceed to our main objective, which is to determine if there is a discount bias.

**Result 5:** Subjects exhibit discount biases. The bias is large (19 percentage points) and strongly significant in the Random-D treatment but smaller (about 7 percentage points) and only weakly significant in the Known-D treatment.

The discount bias is stronger in a situation where a shopper does not know \textit{ex-ante} that a shop will offer a discount. Once at a shop with a discount, the surprise and the positive feeling of receiving a discount have a strong positive impact on the purchase decision. The effect of discounts is relatively small when consumers know already in advance which shops offer discounts. This means that subjects are only to a small extent prone to pass by shops with good prices, because they have

\(^{10}\)A likelihood-ratio test rejects the hypothesis that an ordinary logit explains the data equally well as our mixed-level model \((p < 0.0001)\).
a discount voucher for a shop further down the road.

6 Conclusion

We reported on an experiment inspired by the marketing literature that shows that discounts and the exact framing have an impact on consumers’ propensity to buy a good. We use a consumer-search environment in order to investigate if a discount bias exists after controlling for many aspects marketing studies do not control for. Using a search task with discounts enabled us to fix the beliefs about the product quality, induced the value of the good and held the beliefs about the price distribution in the market place constant. This design increased the level of control compared to marketing studies considerably. Furthermore, the search environment was made salient by using real money to incentivize subjects’ experimental search and purchase decisions. The main result of our experiments was that even with this high level of control a discount bias survives. In the Random-D treatment a discount increased the purchase probability by 19 percentage points even after controlling for benefits and risk preference. We conjecture that this bias is due to positive emotions arising from entering a shop and realizing that a discount is offered.

We found a small (about seven percent) and only weakly significant discount effect for situations where the identity of shops offering discounts is known in advance. This suggests that the surprise effect is important for large discount biases to exist. However, it also suggests that there might still be some (smaller) discount effect that is caused by focal attraction of shops, where the consumer knows ex-ante that she will receive a discount. It remains to be mentioned that the existence of discount biases we found does not mean that consumers behave extremely randomly and irrationally. We found that a large majority of search and purchase sequences in a particular search task (70.2 percent) are consistent with expected value maximization. Allowing for heterogenous risk preferences increases the fraction of rationalizable behavior even further. Only about ten percent of our subjects made decisions that were clearly irrational.
References


A Experimental Instructions

A.1 No-Discount treatment

Thank you for participating in the experiment. Please ensure that you read the instructions carefully and refrain from talking or discussing the experiment with others during the experiment. If you have any questions, please ask one of us, and we will answer your questions individually to the best of our ability. The amount of money you earn depends on your performance in the game. 100 points of profit in the game equates to 1.25 Australian Dollars.

You are playing a shopping game. You need to buy a certain good, which is worth 200 points to you (your valuation of the good). Prices vary from outlet to outlet, with the prices ranging from 75 to 175. Any price between 75 and 175 has equal chance of occurring at any outlet you visit. You don’t know prices at outlets until you visit them. There are ten outlets arranged along a line, and it costs you 5 to move from one outlet to another. You will begin at outlet 1 on the left side of the line and begin moving to the right. You have to travel to the next outlet to learn its price, and it will cost you 5 to discover the price at the first outlet. Once you have moved forwards you have the option to move forwards again to a new outlet, or backwards to a previous outlet. You have a maximum of ten moves to buy the good.

The money you can earn is calculated by:

\begin{align*}
\text{Profit} &= \text{Final Price} - \text{25} \\
&= \text{Final Price} - \text{25}
\end{align*}
\[ \text{Profit} = \text{Valuation} - \text{price paid} - (\text{number of moves} \times \text{travel cost}) \]

The game will begin at outlet 1, which will offer you the chance to buy at their price, or you can go to the next outlet for a cost of 5. At the outlet, you can choose either ‘buy here’, ‘go to the next outlet’, or you can ‘go back to the previous outlet’. The price at an outlet previously visited will not change if you go back to it. The game will finish when you buy your good. If you have moved ten times and not bought anything, you will make zero profit, and the game will end. At the end of the game you will be shown on the screen how much profit you made from that round.

The game will be played ten times, and the prices and colors of outlets are randomly determined in each new game. Tickets cannot be kept from one game to the next.

Thank you again for participating in our experiment, and please do not hesitate to ask if you have any questions.

A.2 Random-Discount treatment

Thank you for participating in the experiment. Please ensure that you read the instructions carefully and refrain from talking or discussing the experiment with others during the experiment. If you have any questions, please ask one of us, and we will answer your questions individually to the best of our ability. The amount of money you earn depends on your performance in the game. 100 points of profit in the game equates to 1.25 Australian Dollars.

You are playing a shopping game. You need to buy a certain good, which is worth 200 points to you (your valuation of the good). Prices vary from outlet to outlet, with the prices ranging from 75 to 175. Any price between 75 and 175 has equal chance of occurring at any outlet you visit. You don’t know prices at outlets until you visit them. There are ten outlets arranged along a line, and it costs you 5 to move from one outlet to another. You will begin at outlet 1 on the left side of the line and begin moving to the right. You have to travel to the next outlet to learn its price, and it will cost you 5 to discover the price at the first outlet. Once you have moved forwards you have the option to move forwards again to a new outlet,
or backwards to a previous outlet. You have a maximum of ten moves to buy the
good.

The money you can earn is calculated by:

\[ \text{Profit} = \text{Valuation} - \text{price paid} - (\text{number of moves} \times \text{travel cost}) \]

In this game some outlets offer you discounts. There are three different color
outlets: blue, red, and green. You will start with one ticket, which you can redeem
at matching color outlet for a discount of 15 off the price of your good. You can
still buy from any outlet you find. You know that all color outlets occur with equal
chance. This means that there is a one in three chance that the next outlet will be
the same color as your ticket.

The game will begin at outlet 1, which will offer you the chance to buy at their
price, or you can go to the next outlet for a cost of 5. At the outlet, you can choose
either ‘buy here’, ‘go to the next outlet’, or you can ‘go back to the previous outlet’.
The price at an outlet previously visited will not change if you go back to it. The
game will finish when you buy your good. If you have moved ten times and not
bought anything, you will make zero profit, and the game will end. At the end of
the game you will be shown on the screen how much profit you made from that
round.

The game will be played ten times, and the prices and colors of outlets are
randomly determined in each new game. Tickets cannot be kept from one game to
the next.

Thank you again for participating in our experiment, and please do not hesitate
to ask if you have any questions.
A.3 Known-Discount treatment

Thank you for participating in the experiment. Please ensure that you read the instructions carefully and refrain from talking or discussing the experiment with others during the experiment. If you have any questions, please ask one of us, and we will answer your questions individually to the best of our ability. The amount of money you earn depends on your performance in the game. 100 points of profit in the game equates to 1.25 Australian Dollars.

You are playing a shopping game. You need to buy a certain good, which is worth 200 points to you (your valuation of the good). Prices vary from outlet to outlet, with the prices ranging from 75 to 175. Any price between 75 and 175 has equal chance of occurring at any outlet you visit. You don’t know prices at outlets until you visit them. There are ten outlets arranged along a line, and it costs you 5 to move from one outlet to another. You will begin at outlet 1 on the left side of the line and begin moving to the right. You have to travel to the next outlet to learn its price, and it will cost you 5 to discover the price at the first outlet. Once you have moved forwards you have the option to move forwards again to a new outlet, or backwards to a previous outlet. You have a maximum of ten moves to buy the good.

![Outlets along the line]

The money you can earn is calculated by:

$$Profit = Valuation - price ~paid - (number ~of ~moves \times ~travel ~cost)$$

In this game some outlets offer you discounts. There are three different color outlets: blue, red, and green. You will start with one ticket, which you can redeem at matching color outlet for a discount of 15 off the price of your good. You can still buy from any outlet. When you begin the game the computer will show a chart on the screen displaying the color of each outlet 1 through 10.

The game will begin at outlet 1, which will offer you the chance to buy at their
price, or you can go to the next outlet for a cost of 5. At the outlet, you can choose either ‘buy here’, ‘go to the next outlet’, or you can ‘go back to the previous outlet’. The price at an outlet previously visited will not change if you go back to it. The game will finish when you buy your good. If you have moved ten times and not bought anything, you will make zero profit, and the game will end. At the end of the game you will be shown on the screen how much profit you made from that round.

The game will be played ten times, and the prices and colors of outlets are randomly determined in each new game. Tickets cannot be kept from one game to the next.

Thank you again for participating in our experiment, and please do not hesitate to ask if you have any questions.