Discounts and Consumer Search Behavior: The Role of Framing

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Discounts and Consumer Search Behavior: The Role of Framing*

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Abstract

We implement a simple two-shop search model in the laboratory with the aim of testing if consumers behave differently in equivalent situations, where prices are displayed either as net prices or as gross prices with discounts. We compare search behavior in base treatments (where both shops post net prices without discounts) to discount treatments (where either the first shop or the second shop posts gross prices with separate discount offers). We find that subjects search less in both treatments with discount frames irrespective where the discount is offered. We argue that this bias results from subjects basing their decisions on salient characteristics of the situation rather than on objective price distributions.

Keywords: Consumer Search, Price Framing, Price Discounts, Competition

JEL codes: D82, D83, C91, L13

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1 Introduction

Retail-price promotions are ubiquitous in modern markets. Motivated by different marketing strategies, promotions can take various forms: in-store price discounts, coupons, mail-in rebates, everyday lowest price guarantees, etc. The promotions are usually accompanied by extensive and costly advertisement campaigns. The ultimate goal of these measures is to increase sales, and more importantly to increase sellers’ profits. Price promotions may simply create more demand due to the lower resulting prices. Price promotions may also increase profits through intertemporal price discrimination. Temporary price promotions lead to buyers facing different prices for the same product over time. Economic theories suggest that sellers can under certain circumstances extract more surplus from consumers with different product valuations by using temporary discounts.\footnote{Conlisk et al. (1984), Gul et al. (1986), Bagnoli et al. (1989), Sobel (1991) and Dudey (1996) investigate situations where monopolists can successfully and profitably discriminate. Sobel (1984), Gale (1993), Dana Jr. (1998) and Bayer (2010) show that intertemporal price discrimination can also occur in more competitive markets.}

It is not surprising that genuine price reductions increase sales. However, a look at the large literature in marketing science on the effects of differently framed price promotions suggests that not only the resulting net price but also the way a price is presented might influence purchase decisions. In an early study, Inman et al. (1990) find that some customers react to promotion announcements or signals (e.g. attaching an “everyday lowest price” tag) even without further evidence that a real price cut has taken place. Krishna et al. (2002) provide a meta-analysis of 20 publications on how price presentation affects consumers’ perceived savings and thereby influences their probability to purchase a certain product. The study shows that the buyers’ perception of the promotion 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). Kim and Kramer (2006) find that individuals, who do not enjoy exerting calculation effort (i.e. having a low need for cognition) fail to accurately calculate net prices. Consequently, these individuals are less likely to buy if prices are listed as gross prices with separate
relative discounts, and more likely to buy if prices are partitioned as base prices plus surcharges than individuals who are inclined to exert more calculation effort.

These studies suggest that there might be a pure price-framing effect. We are interested in the effect of pure price framing in a search environment. For this purpose we need to control for the actual savings from discounts and the expected prices in all shops selling the same product. This is very difficult to achieve in hypothetical choice studies or in the field. For this reason we use laboratory experiments. Moreover, we employ the simplest possible environment capturing the essence of the consumer’s decision problem. If one assumes that increased complexity leads to larger decision biases, then the results from our experimental study can be seen as a lower bound for the real impact of price framing. In other words, if we find price-framing effects in our very simple decision task, then we can be confident that they also exist in the real world, where purchasing decisions are much more complex.

An other advantage of laboratory experiments is that we can control for important factors like buyers’ valuation, quality or attributes of the product and beliefs about price distributions in the market place, which is difficult in the field.

We employ a two-shop search model, where we manipulate the price framing across treatments. In a baseline search model, two shops sell a homogeneous product and independently draw their prices from given price distributions. A consumer has a given valuation for the product and wants to buy one unit of it. The consumer is in shop one initially and observes the price charged there. The price charged in shop two is unknown to the shopper. She is aware of the distribution the price is drawn from though. The subject has to decide if she want to pay some search cost and move to shop two. Once arrived at shop two, the price there is revealed to the shopper, who can decide to buy or to exit the market. Recalling the price at shop one after searching is not possible. The same decision task is repeated 20 times with the prices being newly drawn from the according distributions.

In this simple setup we present the same search task in three different ways: without any discounts, with a discount frame in shop one and with a discount frame in shop two. Equivalence of the search task across the three different framing conditions is achieved by shifting the gross price distributions to offset the discounts.
such that the net price distributions of both shops are the same for all frames. If subjects are unaffected by the price framing, then behavior in these three conditions should be identical. In addition, we vary the net price distributions of the two shops. This variation serves as a robustness check of the framing effects if they exist. For each price frame, we have three different treatments with the expected net price in the second shop being higher, equal or lower than that in the first shop. This $3 \times 3$ design allows for a clean isolation of the pure framing effect of price discounts.\footnote{There exist quite some experimental studies investigating costly search behavior (e.g. Schotter and Braunstein 1981; Braunstein and Schotter 1982; Kogut 1990; Kogut 1992; Cox and Oaxaca 1989; Cox and Oaxaca 1992; Grether et al. 1988; David and Holt 1996; Abrams et al. 2000; Cason and Friedman 2003; Cason et al. 2005; Morgan et al. 2006; Cason and Datta 2006; Cason and Datta 2010). However, none of them looks at the price-framing effects of discounts.}

Search decisions of rational buyers should depend on the net price offered in shop one, the search cost and the net price distribution in shop two. As the search decision is essentially a binary choice between a fixed offer from shop one and a lottery offer from shop two (as in e.g. Holt and Laury 2002), buyers’ risk preferences also play an important role in the decision process. In order to be able to identify potential price-framing effects and discount biases we structurally estimate risk-preference parameters and the size of biases. We find that risk-preference parameters are stable over time and across different levels of search incentives. This provides some evidence that our model is properly specified.

More importantly, we find discount biases in both treatments. Consumers tend to over-value a discount that is provided in the initial shop, while they do not sufficiently value a discount provided by the shop the subjects does not yet know the price of. Both biases can be explained by salience. A discount is clearly salient when it is provided where a consumer is, whereas it is not if it is offered in a shop that the consumer has not yet entered. As a consequence in both treatments with discounts lead consumers to search less for given initial prices than in the treatment without discounts. The discount biases are initially of the same size (about a third of the discount). In later periods the discount bias for shop one tends to disappear, while it is persistent for discounts offered in the second shop.

The main insight from our paper is the following. Both observed price-framing
effects reduce the consumers’ propensity to search. This suggests that firms can use discount frames without actually reducing net prices in order to reduce the competitiveness of markets. According to our findings, discount frames reduce the search intensity, which gives more market power to the firms that use them. By exploiting the price-framing effects on search firms are able to sustain higher net prices in general. This is good news for firms but bad news for those who are concerned with consumer welfare and allocating efficiency.

The remainder of this paper is organized as follows. In Section 3, we describe the experimental design and the standard theoretical predictions for the underlying model. In Section 4 we provide summary statistics on buyers’ decisions. In Section 5 we report on a structural maximum likelihood estimation of discount bias and risk parameter, followed by a discussion on potential explanations. Finally, we offer some concluding remarks in Section 6.

2 Related field experiments

Most of the marketing studies referred to above typically suffer from some methodological problems. Firstly, the experiments are often not properly incentivized. Secondly, the results often rely on survey questions, hypothetical choices or recalled data. Some recent experiments related to our laboratory experiments have overcome these problems. In a fully incentivized auction experiment, Morwitz et al. (1998) find that partitioned prices can increase demand. Participants also recall lower prices if they were previously presented with prices containing multiple components. In a nice field experiment on eBay, Hossain and Morgan (2006) manipulate the opening bid and the shipping cost, while keeping the total reserve price constant. The study shows that the final sale price is higher when the opening bid is relatively low (and shipping cost are relatively high) than when the relation between opening bid and shipping cost is reversed. Furthermore, in a follow-up online auction experiment, Brown et al. (2010) study whether firms should disclose or shroud shipping costs. They find that disclosing small shipping cost, or shrouding high shipping cost increases revenue. Using scanner data in supermarkets, Chetty et al. (2009) establish
that consumers respond more strongly to a tax increase if the tax is printed on the price tag than if it is added at the register. These studies provide field evidence that price presentation matters.

Our study complements the existing literature by adding a so far neglected dimension – consumer search. The decision to purchase a certain good or not, typically does not only depend on the price (and its framing) in a single shop. It should also be relevant how a consumer perceives the price relative to expected prices for the same good charged by other shops. A consumer will buy the good from a certain shop if it is perceived to be relatively cheap there. If it is perceived as relatively expensive, then the shopper might visit other shops and search for a lower price as long as the associated search cost is not too high. Since price framing affects consumers’ perception of net prices (established by the studies mentioned above), it can be expected that it also impacts on search decisions. We use a laboratory environment here, since it is difficult to impossible to control for shoppers’ beliefs about expected prices in other shops.

If price presentation really impacts on search decisions, then price framing becomes an economically important phenomenon. In a world where consumers are not perfectly informed about prices and have to spend time, effort and money to gather information, the way consumers search has a strong impact on the market power of firms and their pricing behavior.\(^3\) Search intensity (as induced by search cost, price expectations, and other things) influences the market prices in equilibrium. Ceteris paribus, the more consumers are inclined to search, the stronger is the pressure to compete on price. Prices decrease and welfare increases with higher search intensity (Stahl 1989, Robert and Stahl 1993).

\section{Experimental design}

Often, search models and the computation of the resulting optimal stopping rule are quite complex. In this experiment, our aim is to test neither theoretical search

\footnote{In an extreme case, costly consumer search is even leading to monopoly outcomes (Diamond 1971).}
models nor the computation ability of our subjects. Therefore, we chose an extremely simple search environment, which minimizes the calculation effort required by subjects. This enables us to look for the existence of pure price framing effects. By keeping the environment as simple and transparent as possible we stack the deck against finding biases stemming from price framing. So if we find price-framing effects in our simple artificial world, then we would also expect them to present in the real world, which is much more complex. Our treatments consist of variations of the following simple search task.

3.1 A two-shop search task

Subjects are asked to buy one unit of a homogeneous good which is worth \( v \) monetary units to them. There are two shops (1 and 2) selling this good. The price offered by each shop is randomly and independently drawn from uniform distributions. The subjects know the price distributions of both shops in advance, but not the particular prices offered by each shop. Following the convention in search theory, the price draw in shop 1, is given to the subjects for free. After observing this price \( p_1 \) subjects face three options: (1) Exit, which yields zero profit; (2) Buy at \( p_1 \), the payoff is equal to the valuation \( v \) less the net price \( p_{1_{\text{net}}} \); (3) Search (i.e., the subject pays a search cost \( c \) to visit shop 2 and to learn the price \( p_2 \) charged there). Recall is not possible. Once search is chosen the price in shop one is no longer available. After having chosen search, subjects can decide either to (a) Buy at \( p_2 \) (the profit is given by \( v - p_{2_{\text{net}}} - c \) where \( p_{2_{\text{net}}} \) is the net price offered by shop two), or (b) Exit with a loss of \( c \).

3.2 Treatments

Building on this baseline search task, our experiment consists of nine treatments. The buyers’ valuation \( (v = 200) \) and the search cost \( (c = 5) \) are held constant across all treatments. The nine treatments result from a three-step variation in the two dimensions of price framing and price distributions. Table 1 summarizes the parameter values used in each treatment. On the horizontal dimension in Table 1,
we have three different frames *No-D*, *Shop1-D*, and *Shop2-D*, which correspond to “there is no discount in any shop”, “only shop one offers a discount” and “only shop two offers a discount.” On the vertical dimension in Table 1, we have three different search incentive levels denoted as *L-Incentive*, *M-Incentive* and *H-Incentive*, where *L*, *M*, *H* stand for low, medium and high, respectively. Loosely speaking, the *ex ante* search incentive and hence the search intensity increases if the expected price in shop two decreases, while everything else is constant. In the *M-Incentive* treatments (*T4*, *T5*, *T6*), the net-price distributions of both shops are the same (both uniformly distributed on the interval [75, 175]). In the *L-Incentive* treatments (*T1*, *T2*, *T3*) the net-price distribution of shop one is stochastically dominated by that of shop two (uniform on [60, 160] in shop one versus [75, 175] in shop two). The relationship is reversed in the *H-Incentive* treatments (*T7*, *T8*, *T9*), where a lower expected net-price is assigned to shop two. The variation on search incentives (namely through shifts of the net-price distributions where the shops draw their prices from) serves as a robustness check of a framing effect if it exists.

<table>
<thead>
<tr>
<th></th>
<th>No-D</th>
<th>Shop1-D</th>
<th>Shop2-D</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>L-Incentive:</strong></td>
<td></td>
<td>T1:</td>
<td>T2:</td>
</tr>
<tr>
<td></td>
<td></td>
<td><em>p1</em>∈[60,160]</td>
<td><em>p1</em>∈[75,175]</td>
</tr>
<tr>
<td></td>
<td></td>
<td><em>p2</em>∈[75,175]</td>
<td><em>p2</em>∈[75,175]</td>
</tr>
<tr>
<td><strong>M-Incentive:</strong></td>
<td></td>
<td>T4:</td>
<td>T5:</td>
</tr>
<tr>
<td></td>
<td></td>
<td><em>p1</em>∈[75,175]</td>
<td><em>p1</em>∈[90,190]</td>
</tr>
<tr>
<td></td>
<td></td>
<td><em>p2</em>∈[75,175]</td>
<td><em>p2</em>∈[75,175]</td>
</tr>
<tr>
<td><strong>H-Incentive:</strong></td>
<td></td>
<td>T7:</td>
<td>T8:</td>
</tr>
<tr>
<td></td>
<td></td>
<td><em>p1</em>∈[75,175]</td>
<td><em>p1</em>∈[90,190]</td>
</tr>
<tr>
<td></td>
<td></td>
<td><em>p2</em>∈[60,160]</td>
<td><em>p2</em>∈[60,160]</td>
</tr>
</tbody>
</table>

Note: *v* = 200, *c* = 5, *p1* and *p2* are drawn from *uniform* distributions. 
*d1* and *d2* is the among to discount offered in shop 1 and 2, respectively.

Table 1: Price intervals by shop and treatment.

Within a search incentive level, the search task in each of the three treatments is essentially the same. The price frames do not change the net-price distributions in both shops. Take the *M-Incentive* treatments (*T4*, *T5*, *T6*) as an example. In the *No-D* treatment (*T4*) neither shop offers a discount. Prices are randomly and independently drawn from uniform distributions. Subjects see the first price and
then make their decisions. The price they see is the price they pay. In the *Shop1-D* treatment (*T5*), the search task follows the same procedure as that in the *No-D* treatments except that subjects are told in advance that shop one always offers a discount (*d₁ = 15*), which will be deducted from the price. At the same time, the gross price distribution in shop one is moved up by 15 monetary units to [90, 190]. This shift exactly offsets the benefit of the discount offered. Similarly, in the *Shop2-D* treatment (*T6*), subjects were told in advance that shop two always offers a discount of *d₂ = 15*. The gross price distribution in shop two is shifted upwards by 15 units to offset the discount. Consequently, the underlying decision problem across the different price frame is identical within the *M-Incentive* treatment. The same manipulation is used for the *L-Incentive* and the *H-Incentive* treatments. The variation on price frames (while holding the net price distributions constant) will be used to identify the price-framing effects of discounts.

### 3.3 Benchmark predictions

There are three theoretical predictions for the behavior of rational buyers. Firstly, *exit* is obviously a strictly dominated option in both stages. In all treatments, *buy* generates a positive profit even if the highest possible price is drawn, whereas *exit* yields non-positive profits. Secondly, as illustrated above the search problems (in different price-discount frames) are objectively identical when the search incentive is held constant. Note that this implies that a subject, who is not affected by framing, should use the same decision rule for all decision problems within one incentive condition, regardless of her risk preferences. So the search intensity *S* (i.e. the fraction of search decisions) should be identical within an incentive condition. Lastly, as we increase the *ex ante* incentive to search while holding the price framing constant the search intensity *S* should increase. These predictions are summarized in Table 2.
\begin{table}
\centering
\begin{tabular}{ lccc }
& \text{No-D} & \text{Shop1-D} & \text{Shop2-D} \\
\hline
\text{L-Incentive}: & $S_1 = S_2 = S_3$ & \land & \land \\
\text{M-Incentive}: & $S_4 = S_5 = S_6$ & \land & \land \\
\text{H-Incentive}: & $S_7 = S_8 = S_9$ & \land & \land \\
\hline
\end{tabular}
\caption{Predicted relations between search intensities across treatments.}
\end{table}

3.4 Experimental procedure

The search task was programmed and implemented in the laboratory using z-Tree (Fischbacher 2007). We conducted all experimental sessions at AdLab, the Adelaide University Laboratory for Experimental Economics. In each session, one treatment was randomly assigned to each subject. Within a treatment the same search task was repeated 20 times. The price distributions and the availability of the discount were not changed throughout a treatment. The procedure, the search task and the payoffs were explained to the subjects in written instructions (see samples in the Appendix). The subjects were paid privately at the end of their session according to their performance (Experimental Dollars were converted into Australian Dollars at a given exchange rate). In total, 293 university students from various disciplines participated in the experiment. Subjects had no experience with similar tasks in the laboratory and earned on average AUD 9.2 (about $10 US) in approximately 30 minutes.\footnote{We combined our experiment with some other totally unrelated experiments. It took 1.5 to 2 hours in total for the whole session, in which the search task was always run at the beginning.}

4 A first look at search behavior

It is encouraging that in our 5860 search tasks subject only chose exit in 0.6\% of the cases in shop one and in 3.3\% of the cases in shop two. We conclude from the small proportion of obviously irrational behavior that the subjects in general understood the search task. We now turn to the decision we are mostly interested in – the search decision. Table 3 provides a summary of search fractions across treatments.
Compared to the theoretical predictions on search intensity given in Section 3.3, our results are mixed. In the *L-Incentive* treatments, the average fraction of buyers, who search is 38.43% (*No-D*), 35.63% (*Shop1-D*) and 34.66% (*Shop2-D*). The search intensity increases to 54.46%, 48.67% and 45.71% in the *M-Incentive* treatments, and further increases to 58.39%, 58.89% and 57.92% in the *H-Incentive* treatments. The variation of search frequencies along the incentive dimension is as predicted. Higher search incentives lead to more searching. However, comparing the search fractions at the same incentive level, we do not observe identical search intensities across different price frames.

<table>
<thead>
<tr>
<th>Incentive Level</th>
<th>No-D</th>
<th>Shop1-D</th>
<th>Shop2-D</th>
</tr>
</thead>
<tbody>
<tr>
<td>L-Incentive</td>
<td>38.43%</td>
<td>35.63%</td>
<td>34.66%</td>
</tr>
<tr>
<td>M-Incentive</td>
<td>54.46%</td>
<td>48.67%</td>
<td>45.71%</td>
</tr>
<tr>
<td>H-Incentive</td>
<td>58.39%</td>
<td>58.89%</td>
<td>57.92%</td>
</tr>
</tbody>
</table>

Table 3: A summary of search intensity across treatments.

Note that the unconditional search fractions do not give a conclusive picture. The fractions do not condition on the prices drawn in shop one, which should be the main determinant of search behavior. For this reason we investigate how the search intensities relate to the prices in shop one and compare this within the same incentive level. Figure 1 plots the relation between smoothed search fractions and the net price in shop one for a given level of search incentives.\(^5\) We provide the same graphs separately for the data from the first and the second half of the experiment. The left panel of the graph shows that in the first ten periods subjects searched more in the *No-D* treatments (in solid lines) than in the *Shop1-D* (in dashed lines) or *Shop2-D* treatments (in dotted lines). This is true for all incentive levels. Initially both discount frames – regardless of where the discount is given – reduce the search intensity at given net prices in shop one. The difference becomes smaller in the second half of the experiment, as the right panel shows. But there is still less searching if

\(^5\)For the graphs we used locally weighted scatterplot smoothing (LOWESS, Cleveland 1979 ) with bandwidth 0.8.
the discount is offered in the shop with the unknown price (Shop2-D treatments) than in the other two framing conditions. However, it is hard to tell from the graphs if the search intensity is still significantly different between the Shop2-D frame, the discount in shop one (Shop1-D) and the net price frame (No-D).

Overall the aggregate results provide some support for the existence of price-framing effects on consumer search behavior. At the same time there is also some support for the theoretical predictions, as the search intensity increases with the incentives to search. Also, the differences along the price-frame dimension appear to become smaller in the second half of the experiment. Given these findings on the aggregate level, we believe that it is worthwhile to further explore the price-framing effect using a more in-depth analysis that allows for proper statistical tests.
5 Structural estimation

Our experiments implement a model of consumer search under uncertainty. The search decision is essentially an individual decision under risk, i.e., a binary choice between a fixed payment offered by shop one and a lottery offered by shop two. The decision may depend on the price and discount offered by the first shop, the price distribution and discount offered at the second shop, on the search cost and also on the risk preferences of the consumer. In our analysis estimating risk preferences is crucial, as they are unobserved, while the other determinants have been controlled for. Previous experimental studies aiming to test search theory, typically compare observed behavior to the theoretical predictions under risk-neutrality. This approximation can greatly reduce the computational demands for solving complex search models, especially when the time horizon is finite. However, risk neutrality is a strong assumption. Our simple design allows us to relax this assumption and conduct a structural estimation of underlying risk-aversion coefficients and discount biases. The estimation is based on expected utility theory (EUT) and the noisy probabilistic choice model proposed by Holt and Laury (2002).

5.1 An expected-utility maximizer’s decision rule

We assume that the utility function is given by $u(x) = x^r$ (for $x > 0$), where $x$ is the monetary payoff and $r$ is the risk parameter to be estimated. A utility function of this form exhibits constant relative risk aversion (CRRA). We believe that CRRA is appropriate, as the stakes in our experiment are moderate. Decisions in gambles that do not significantly change an individual’s lifetime wealth can be appropriately described by CRRA. The risk parameter $r$ implies a proclivity to risk if $r > 1$, risk-neutrality if $r = 1$, and risk-aversion if $r < 1$.

The consumers in our experiments have to choose between a safe payoff from buying (yielding an utility $U(B)$) and a lottery over the prices at shop two resulting in an expected utility $EU(S)$ from searching. We allow for discount dependent biases $b_1$ and $b_2$, where the subscript indicates whether the discount is given in shop one or two. Our discount biases can be interpreted as the money equivalent for by
how much the consumer overvalues the savings from the discount. A negative bias is interpreted as the money equivalent for by how much the subjects undervalue the savings provided by the discount.

Denoting the discount as \( d \) (i.e. 15 in our experiments) the values of \( U(B) \) and \( EU(S) \) can be calculated as follows:

\[
U(B) = \begin{cases} 
[200 - (p_1 - (d + b_1))]^r & \text{if Shop1-D} \\
[200 - p_1]^r & \text{else}
\end{cases} ,
\]

\[
EU(S) = \begin{cases} 
\int_p^\infty f(p) [200 - (p_1 - (d + b_2)) - 5]^r dp & \text{if Shop2-D} \\
\int_p^\infty f(p) [200 - p_1 - 5]^r dp & \text{else}
\end{cases} .
\]

The function \( f(p) \) is the density of the price distribution; \( p \) and \( \overline{p} \) are the minimum and maximum prices. Given the uniform distributions we adopt (with \( f(p) = 1/a, a = \overline{p} - p = 100 \)), \( EU(S) \) can be expressed as

\[
EU(S) = \begin{cases} 
\frac{(195 - p + d + b_2)^r + 1}{100(r+1)} & \text{if Shop2-D} \\
\frac{(195 - \overline{p})^r + 1}{100(r+1)} & \text{else}
\end{cases} .
\]

A rational expected utility maximizer always chooses the option, which yields the higher expected utility. The probability of search in this case is a step function:

\[
prob(S \mid p_1, d, b_1, b_2) = \begin{cases} 
1 & \text{if } EU(S) > U(B) \\
0 & \text{if } EU(S) \leq U(B)
\end{cases} .
\]

Figure 1 shows that there is no clear cutoff price in the data. Therefore we are allowing individuals to make some decision errors. We still expect that the probability of search increases with the difference between \( EU(S) \) and \( U(B) \) though. A simple probabilistic decision rule capturing this is:

\[
prob(S \mid p_1, d, b_1, b_2) = \frac{EU(S)^{\frac{1}{r}}}{U(B)^{\frac{1}{r}} + EU(S)^{\frac{1}{r}}},
\]

\[
prob(B \mid p_1, d, b_1, b_2) = 1 - prob(S \mid p_1, d, b_1, b_2).
\]

This formulation is flexible with respect to the likelihood of errors. As the noise
\( \mu \) in the decision process increases, subjects will become less sensitive to payoff differences between the two alternatives and hence the randomness of the decision increases. In the extreme case, where \( \mu \) approaches infinity, the probability of search will approach one-half, regardless of the values of \( U(B) \) and \( EU(S) \). Subjects make purely random choices when the noise is infinitely large. On the other hand, when \( \mu \) approaches 0 the probability of choosing the option associated with the higher (expected) utility approaches one and the decision maker becomes fully rational as defined by (4). With Equations (1), (3), (5) and (6) we have a model of noisy consumer search that can easily be put to the data. The probability of search depends on known variables (net price in shop one, the net-price distribution in shop two) and on unknown parameters \( \mu, r, b_1, b_2 \), which we will estimate.

5.2 Estimation equation and results

Our main focus is to estimate by how much consumers over or under-value a discount in a given shop (i.e., \( b_1 \) or \( b_2 \)) and whether a potential bias is persistent or vanishes over time. For this reason we specify the biases as constants with an additive dummy variable for the last ten periods \( D_{T10+} \):

\[
b_i = \begin{cases} 
    b_{0i} + \phi_i D_{T10+} & \text{if Shop}_i-D \\
    0 & \text{else}
\end{cases}
\]  

In addition, we specify the risk-preference parameter such that we can control for individual heterogeneity in risk preferences and also check the robustness of our model specification. We allow the risk parameter to be a function of individual characteristics, as well as search incentives and a time dummy:

\[
r = r_0 + \beta D_{\text{characteristics}} + \gamma D_{\text{incentives}} + \theta D_{T10+}
\]  

\( D_{\text{characteristics}} \) is a set of variables including a gender dummy (\textit{Male}), dummies for different age groups (\textit{Age26\text{-}}, \textit{Age26-30}, \textit{Age30\text{+}}), dummies for students from different disciplines (\textit{Science}, \textit{Comm/Fin (Commerce/Finance)}, \textit{Economics}, \textit{Engineering}, \textit{Law}, \textit{Medicine}, \textit{Arts} and \textit{Other}), and a dummy variable \textit{Math} (indicating
if a student has taken advanced high-school math). $D_{incentives}$ is a set of dummy variables ($L$-Incentive, $M$-Incentive and $H$-Incentive) that indicates of which of the three different incentive conditions the observation was taken.

Moreover, it is reasonable to assume that subjects get better at the task as the experiment progresses (i.e., subjects learn and gradually make fewer errors). For this reason we allow the noise parameter $\mu$ to have a time trend:

$$\mu = \mu_0 + \delta Period$$

$$\hat{\mu} = \hat{\mu}_0$$

Table 4: Estimation results of the discount biases, risk and noise parameters.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Variable</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_{01}$</td>
<td>5.855***</td>
<td>$b_{02}$</td>
<td>-5.575**</td>
</tr>
<tr>
<td></td>
<td>(2.133)</td>
<td></td>
<td>(2.265)</td>
</tr>
<tr>
<td>$D_{T10}^+$</td>
<td>-3.501*</td>
<td>$D_{T10}^+$</td>
<td>-2.882</td>
</tr>
<tr>
<td></td>
<td>(1.938)</td>
<td></td>
<td>(2.003)</td>
</tr>
<tr>
<td>$\hat{r}$</td>
<td>$r_0$(constant) 1.243***</td>
<td>Engineering 0.399</td>
<td>(0.379) (0.319)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$D_{T10}^+$ -0.138</td>
<td>Medicine 0.783***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$M$-Incentive -0.177</td>
<td>Economics 0.484</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$H$-Incentive -0.274</td>
<td>Commerce/Finance 0.738**</td>
</tr>
<tr>
<td>Male</td>
<td>0.008</td>
<td>Law</td>
<td>1.377***</td>
</tr>
<tr>
<td></td>
<td>(0.186)</td>
<td></td>
<td>(0.432)</td>
</tr>
<tr>
<td>Maths</td>
<td>0.655***</td>
<td>Arts</td>
<td>0.805**</td>
</tr>
<tr>
<td></td>
<td>(0.241)</td>
<td></td>
<td>(0.370)</td>
</tr>
<tr>
<td>Age26-30</td>
<td>0.203</td>
<td>Other</td>
<td>0.176</td>
</tr>
<tr>
<td></td>
<td>(0.284)</td>
<td></td>
<td>(0.451)</td>
</tr>
<tr>
<td>Age30</td>
<td>0.068</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.355)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\mu}$</td>
<td>$\mu_0$(constant) 0.393***</td>
<td>Period -0.012***</td>
<td>(0.053) (0.002)</td>
</tr>
</tbody>
</table>

Note: Log-Likelihood=-1867.51; Wald $\chi^2_0=3.26^*$; No. of Obs.=5827; 293 clusters.

Robust Std.Err. in parentheses,*p-value<0.1; **p-value<0.05; ***p-value<0.01
subjects from risk lovers. The risk parameter of a base-category subject is around 1.243, which is close to risk neutrality. We find that risk preferences are stable over time and across the conditions with different search incentives. The coefficients on the dummy variables $D_{T_{10}+}$, $M$-Incentive and $H$-Incentive are not significant. There is considerable heterogeneity in risk preferences. Subjects with better Maths background, studying Medicine, Commerce/Finance, Law and Arts are willing to take more risk.

The estimated noise parameter $\mu$ starts off with 0.4 in the first period. As expected, the amount of noise in the decision process significantly decreases over time as subjects become familiar with the task. By period 20, $\mu$ has decreased to about 0.15, which indicates a very reasonable level of rationality. The stability of risk preference over time and across search-incentive levels and the declining noise are findings one expects for a properly specified model. This gives some support that the choice of utility function and controls is appropriate.

We now turn to the first part of Table 4 and concentrate on discount biases. A discount initially offered in shop one leads to behavior as if the discount were about 5.9 units larger than it actually is. This bias is substantial, since its size is more than a third of the actual discount of 15 units. If the discount is offered in shop 2, then subjects behave as if they under-value the discount by 5.6 units. Comparing the discounts as perceived by the consumers, leads to the observation that a discount offered in a shop which is already visited by the consumer is seen as providing more than twice the savings as the same discount in a shop that is not visited yet. Regardless where the discount is offered, consumers are less inclined to search in both discount treatments.

However, the discount bias disappears over time for discount vouchers offered in the first shop. In the second half of the experiment the discount bias for shop one is reduced by 3.5 units. The remaining bias is not significantly different from zero anymore ($p > 0.16$, Chow test). For discounts given in shop two the situation is different. There the (negative) discount bias does not disappear. The change in the

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Note that this only applies to the baseline group (i.e. female science students aged 26 or younger, having not studied higher level math in high school, playing in the $L$-incentive and $No-D$ treatment in the first ten periods).
second half of the experiment is not significant but rather hints at a strengthening than a weakening discount bias.

The result of a negative and persistent bias for shop two seems surprising, as it implies that the knowledge that there are discounts in shop two does not, as one might expect, lure people into searching more. On the contrary, knowing that shop two offers discounts persistently reduces the propensity to search compared to the situation where shop two posts net prices. One plausible explanation for our finding is that the saliency of discount vouchers is location dependent. Suppose that subjects use short-cuts when they take decisions.\textsuperscript{7} In order to save cognitive resources a subject gathers the salient characteristics of a situation and makes decisions based on them. Then in our Shop1-D treatments the discount is clearly salient, as a subject experiences it before making a choice. This might lead to subjects (at least initially) overvaluing the discount in their decision.\textsuperscript{8} Less search than in the No-D is the consequence. However, it is not very difficult to learn that using the discount in the first shop as a salient characteristic for the search decision is not very sensible. The calculation of the net price is very easy, since there are no distributions involved once they see the first price, and only a simple subtraction is needed. Consequently, experience leads to a shift from the discount to the net price as the decision relevant characteristic and the discount bias disappears over time.

In the Shop2-D treatments circumstances are different. The discount is not salient, since it is not yet experienced. The immediate focus goes to the risk of searching. The risk of searching comes from not knowing the price in the second shop and is represented by the price distribution, which becomes salient. The expected net price and the impact of the discount are not properly taken into account. Consequently, consumers search less in Shop2-D than in No-D. This phenomenon is more persistent than that in the Shop1-D case, as it needs more cognitive energy to

\textsuperscript{7}Think e.g. of Gigerenzer’s concept of an adaptive toolbox for decision making (Gigerenzer 2001).

\textsuperscript{8}This contradicts some of the marketing literature (e.g., Gupta and Cooper 1992, Obermiller and Spangenberg 1998) which finds that consumers are skeptical about discounts and tend to underestimate their value. The different findings show how important it is to control for beliefs about price distributions.
learn that the focus on the gross price leads to distortions in the decision. The net price in the second shop with a discount is partly unknown at the time of decision and cannot just be computed as $p_{2\text{net}} = p_2 - d$.

Our design allows us to see whether subjects really focus on the gross price and ignore the discount offer in the second shop, when a discount is offered. Take treatments 1, 4 and 9. Treatments 1 and 4 are treatments without discounts, where the price distribution for the second shop is uniform over the range of 75 to 175. Treatment 9 is the high-incentive treatment with a discount in shop 2, where the gross price (not taking into account the discount) is also uniformly distributed on 75 to 175. If our suspicion that subjects mainly focus on the gross distribution in the latter treatment is correct, then search behavior for given prices in shop one (where there are no discounts in all three treatment) should be identical.\textsuperscript{9} This can be assessed graphically by plotting the smoothed relationship between search

\textsuperscript{9}An expected utility maximiser would search more in this treatment, of course.
fractions and initial prices, as done earlier. Figure 2 shows that there is virtually no difference between search rules, which gives some support for our claim that the discounts in shop two are not taken into account. An estimation including only the data from treatments 1, 4 and 9, (which can be obtained on request from the authors) also shows that there is no significant difference in search behavior between the treatment with a discount ($T_9$) and those without ($T_1, T_4$).

6 Conclusion

Retailers regularly post gross prices and at the same time announce discounts instead of just posting net prices. This paper examines the impact of the discount frame on search behavior. A two-stage search model was used in the laboratory for this purpose. We designed our experimental treatments such that the search tasks were theoretically identical across different price frames. We compared two types of experimental treatments (in which the price in either of the shops was presented as a gross price with a discount) to their corresponding baseline treatments (where prices in both shops were given as net prices). To achieve this we shifted the gross-price distributions, such that the net price distributions were identical. A structural estimation revealed that subjects’ behavior exhibited a discount bias. Subjects searched less, when discounts are present regardless where the discount was offered. The bias disappeared with experience if the discount was offered in the shop where the consumer knew the price already. In contrast, the bias persisted if the discount was offered in the shop that the consumers had not yet visited. We conclude that firms can reduce the competitiveness of their markets by framing prices as discounts. Discounts generally reduce search intensity, which is positively related to the competitiveness of the outcome in a market.

\footnote{There is an increasing body of evidence showing that people tend to avoid risk in more complex choices or decision-making problems under uncertainty (Huck and Weizsacker 1999, Mador et al. 2000, Sonsino et al. 2002, Wilcox (1993), Johnson and Bruce (1998)). Hence, our results might also be explained by complexity aversion, since a two-shop search task is essentially a binary lottery choice experiment with a slight complication in the discount treatments.}
References


A Experimental Instructions (online appendix possible)

A.1 M-Incentive & No-D treatment

Thank you for participating in this experiment. Please read the instructions carefully. This is important, as your earnings will depend on your performance. Please note that you are not allowed to communicate with other participants during the experiment. If you do not obey this rule we may exclude you from the experiment. If you have any questions, please raise your hand. We will come to answer your questions individually.

The currency in this game is called E-Dollars. At the end of the game we will convert the E-Dollars you have earned in the game to real money. The exchange rate is 100 E-Dollars = 0.6 Australian Dollars.

• Your task

Suppose you want to buy one unit of a certain good. You value the good at 200 E-Dollars. Your profit will either be this valuation (200 E-Dollars) minus the price you pay for the good if you decide to buy, or zero if you do not buy the good.

There are two shops, which may sell at different prices. The prices at each shop are determined randomly and independently. However, you do not know the prices until you have arrived at a particular shop. The only things you know in advance are that the price is drawn according to the rules given below. Moving from shop 1 to 2 will lead to a search cost of 5 E-Dollars.

The prices at both shops will be in the range between 75 and 175 E-Dollars, where all prices are equally likely. You can think of the following: Shopkeeper one draws randomly from an urn with balls numbered 75 to 175. The number of the ball he draws is the price. Shopkeeper two has his own urn with balls numbered 75 to 175, where he draws from.

The game’s timing is as follows:

1. You arrive at shop 1 and observe the price at shop 1 ($P_1$). You have three options:
(a) EXIT, the game ends and your profit is zero.
(b) BUY HERE, the game ends and your profit is $200 - P_1$.
(c) GO TO THE NEXT SHOP, you learn the price of the second shop ($P_2$) and incur search cost of 5 E-Dollars.

2. If you have chosen to go to the next shop you learn the price charged by the second shop ($P_2$). You have two options now, which both end the game:

(a) EXIT, with a total profit of $-5$.
(b) BUY, which gives you a total profit of $200 - P_2 - 5$. Note that $-5$ represents the cost of moving from shop 1 to shop 2.

The diagram below summarizes the game:

<table>
<thead>
<tr>
<th>Stage 1</th>
<th>Stage 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observe $p_1$:</td>
<td>1: Exit (profit = 0)</td>
</tr>
<tr>
<td>2: Buy (profit = $200 - p_1$)</td>
<td>3: Search (i.e., go to shop 2, observe $p_2$)</td>
</tr>
</tbody>
</table>

- Repetition

You will play 20 of these games in succession. Note that the prices are newly drawn in each of the games. The prices are independent across games. Prices are not influenced by the prices of the previous game. If you have any questions please raise your hand. We will come and answer your question.

A.2 M-Incentive & Shop1-D treatment

Thank you for participating in this experiment. Please read the instructions carefully. This is important, as your earnings will depend on your performance. Please note that you are not allowed to communicate with other participants during the experiment. If you do not obey this rule we may exclude you from the experiment.
If you have any questions, please raise your hand. We will come to answer your questions individually.

The currency in this game is called E-Dollars. At the end of the game we will convert the E-Dollars you have earned in the game to real money. The exchange rate is 100 E-Dollars = 0.6 Australian Dollars.

- **Your task**

Suppose you want to buy one unit of a certain good. You value the good at 200 E-Dollars. Your profit will either be this valuation (200 E-Dollars) minus the price you pay for the good if you decide to buy, or zero if you do not buy the good.

There are two shops, which may sell at different prices. The prices at each shop are determined randomly and independently. However, you do not know the prices until you have arrived at a particular shop. The only things you know in advance are that the price is drawn according to the rules given below, and that you will be granted a discount of 15 E-Dollars at the first shop (because you have got a rebate voucher). You also know that moving from shop 1 to 2 will lead to a search cost of 5 E-Dollars.

The price at shop 1 is in the range between 90 and 190 E-Dollars, where all prices are equally likely. You can think of the following: Shopkeeper one draws randomly from an urn with balls numbered 90 to 190. The number of the ball he draws is the price. The price at shop 2 is in the range between 75 and 175 E-Dollars, where all prices are equally likely. Shopkeeper two has his own urn with balls numbered 75 to 175, where he draws from.

The game’s timing is as follows:

1. You arrive at shop 1 and observe the price at shop 1 ($P_1$). You have three options:

   (a) **EXIT**, the game ends and your profit is zero.

   (b) **BUY HERE**, the game ends and your profit is $200 - P_1 + 15$. Note that $+15$ represents the discount if you buy from the first shop.
(c) **GO TO THE NEXT SHOP**, you learn the price of the second shop \( (P_2) \) and incur search cost of 5 E-Dollars.

2. If you have chosen to go to the next shop you learn the price charged by the second shop \( (P_2) \). You have two options now, which both end the game:

   (a) **EXIT**, with a total profit of \(-5\).

   (b) **BUY**, which gives you a total profit of \(200 - P_2 - 5\). Note that \(-5\) represents the cost of moving from shop 1 to shop 2.

The diagram below summarizes the game:

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<tr>
<th>Stage 1</th>
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</tr>
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<tbody>
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<td>Observe ( p_1 ):</td>
<td></td>
</tr>
<tr>
<td>1: Exit ( (profit = 0) )</td>
<td></td>
</tr>
<tr>
<td>2: Buy ( (profit = 200 - p_1 + 15) )</td>
<td></td>
</tr>
<tr>
<td>3: Search (i.e., go to shop 2, observe ( p_2 ))</td>
<td>3.1: Exit ( (profit = -5) )</td>
</tr>
<tr>
<td></td>
<td>3.2: Buy ( (profit = 200 - p_2 - 5) )</td>
</tr>
</tbody>
</table>

**Repetition**

You will play 20 of these games in succession. Note that the prices are newly drawn in each of the games. The prices are independent across games. Prices are not influenced by the prices of the previous game. If you have any questions please raise your hand. We will come and answer your question.

**A.3 M-Incentive & Shop2-D treatment**

Thank you for participating in this experiment. Please read the instructions carefully. This is important, as your earnings will depend on your performance. Please note that you are not allowed to communicate with other participants during the experiment. If you do not obey this rule we may exclude you from the experiment. If you have any questions, please raise your hand. We will come to answer your questions individually.

The currency in this game is called E-Dollars. At the end of the game we will convert the E-Dollars you have earned in the game to real money. The exchange rate is 100 E-Dollars =0.6 Australian Dollars.
• Your task

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The game’s timing is as follows:

1. You arrive at shop 1 and observe the price at shop 1 ($P_1$). You have three options:

   (a) EXIT, the game ends and your profit is zero.

   (b) BUY HERE, the game ends and your profit is $200 - P_1$.

   (c) GO TO THE NEXT SHOP, you learn the price of the second shop ($P_2$) and incur search cost of 5 E-Dollars.

2. If you have chosen to go to the next shop you learn the price charged by the second shop ($P_2$). You have two options now, which both end the game:

   (a) EXIT, with a total profit of $-5$. 

A-5
(b) **BUY**, which gives you a total profit of $200 - P_2 + 15 - 5$. Note that $-5$ represents the cost of moving from shop 1 to shop 2, while the $+15$ is the discount if you buy from the second shop.

The diagram below summarizes the game:

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<td>1: Exit ($profit = 0$)</td>
<td>3.1: Exit ($profit = -5$)</td>
</tr>
<tr>
<td>2: Buy ($profit = 200 - p_1$)</td>
<td>3.2: Buy ($profit = 200 - p_2 + 15 - 5$)</td>
</tr>
<tr>
<td>3: Search (i.e., go to shop 2, observe $p_2$)</td>
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- **Repetition**

You will play 20 of these games in succession. Note that the prices are newly drawn in each of the games. The prices are independent across games. Prices are not influenced by the prices of the previous game. If you have any questions please raise your hand. We will come and answer your question.