



The University of Adelaide  
School of Economics

Research Paper No. 2010-21  
October 2010

## **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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16th August 2010

## Abstract

We implement a simple two-shop search model in the laboratory with the aim to investigate if consumers behave differently in equivalent situations, where prices are displayed either as net prices or as gross prices with discounts. We compare treatments, where we either depict the known price of the first shop or the initially uncertain price of the second shop as a gross price with a discount, with treatments without discounts. We find that subjects search less in both treatments with discounts. Hence, we conclude that retailers can use this framing effect in order to reduce the competitiveness in their market, since decreased search intensities dampen competitive pressure.

*Keywords:* Consumer Search, Price Framing, Price discounts, Competition

*JEL codes:* D82, D83, C91, L13

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\*We want to thank the Faculty of Professions at the University of Adelaide for generous financial support. Mickey Chan's able research assistance is gratefully acknowledged. We are also grateful for helpful comments by Charles Noussair, Pablo Guillen, Simon Gächter and participants at various conferences and workshops.

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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, etc. The different forms of price promotions share at least two characteristics. Firstly, the promotional price is only available for some limited time. When the promotion is over, the goods revert to their regular (higher) prices. Therefore, at different times the buyer may be charged different prices on identical products due to a sellers' intertemporal price variation. Secondly, the promotional price is usually presented alongside the regular (full) price. Sellers often post the regular price with a discount in either percentage terms (e.g., "20% off the marked price") or absolute value (e.g., "\$10 off"). Economists have mainly devoted their research to explaining the first feature of price promotion, believing that random variation of underlying demand or cost conditions is not a sufficient explanation for price variations. Most theories concerned explain the variations with intertemporal price discrimination, where sellers vary their prices extracting more surplus from consumers with different product valuations.<sup>1</sup>

The second common characteristic of price promotions, the discount frame, is typically ignored by economists. The reason for this is simple. The behavior of a rational informed consumer with stable preferences should not depend on how the price is framed. Why is it then that firms typically do not just show the net price? Do buyers react differently if sellers post regular prices with discounts rather than simply post the reduced net prices? To answer these questions this paper investigates if the framing of prices affects consumer-search behavior. We further ask if consumer's reactions to price promotions offer an explanation to why firms typically prefer to display gross prices with discounts instead of net prices. We make use of the methodology of experimental economics for our purpose.

Understanding consumers' reactions to price framing (as gross or net prices) is

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<sup>1</sup>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.

important. If consumers are not immune to the framing of prices then this has an impact on how we should judge firms' use of the discount frame. We mainly think of the impact on consumers' price-search behavior here. In a world where consumers are not *ex ante* perfectly informed about prices and have to spend time, effort and sometimes also money to learn what different sellers charge for the same product, the way consumers search has a strong impact on the market power of firms. Just think of the extreme example of costly consumer search leading to local monopolies in the Diamond (1971) model. In models with consumer search and advertising, the search intensity (as induced by search cost, price expectations, and other things) has a strong impact on pricing behavior. *Ceteris paribus* the more consumers are inclined to search the stronger is the pressure to compete on price. Prices decrease and welfare increases with the search intensity (Butters 1977, Stahl 1989, Robert and Stahl 1993). Our question becomes now the following: does price framing impact on consumer behavior when they search for the lowest price? If yes, does it increase search intensity or reduce the intensity? The latter would provide a rationale for why firms use the discount frame. A decreased search intensity reduces price elasticities of demand, and *ceteris paribus* higher prices are more sustainable.

For obvious reasons there is a large literature on the impact of price framing in marketing. Marketing researchers focus on comparing the effectiveness of different forms of price promotions in boosting sales. Krishna et al. (2002) provide a meta-analysis of 20 publications on how price presentation affects consumers' perceived savings from price promotions 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). 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 some lack of control. Important factors like buyers' valuation, quality or attributes

of the product or beliefs about prices distributions in the market place are usually not appropriately controlled for. Hence, a clean isolation of the framing effect is not possible in these studies. The findings indicate that price framing might have an impact though. Therefore, we implement an extremely simple search environment with price framing in the laboratory that provides the maximum amount of control and makes a clean separation of price-framing effects possible.

The search environment we implement is borrowed from economic consumer-search theory. Theoretical papers determine optimal search rules of a rational decision maker searching for the lowest among dispersed offers in different environments (Stigler 1961; Kohn and Shavell 1974; Gastwirth 1976; Rothschild 1974; Manning and Morgan 1982; Morgan and Manning 1985). Regardless of differing environmental assumptions in these papers, the optimal search rule is always based on a comparison of expected benefits from searching (the possibility to find a lower price) and the cost associated with search (e.g., shoe-leather cost). In order to maximize experimental control we choose the simplest of all search environments in this tradition. A consumer with a given valuation for a good is at a shop and knows the price charged there, which has been drawn from a known distribution. The decision is now either to buy or to go to a second shop where the price is yet unknown. The distribution the price in the second shop was drawn from is known though. Moving to the next shop is costly, and once the consumer has moved the offer of the initial shop is not available anymore. This search task basically becomes a choice between a certain payout and a lottery (as in e.g. Holt and Laury 2002). In this setup it is possible to frame the exactly same search task in three different ways: without any discounts, with a discount frame in the initial shop and with a discount frame in the second shop. Equivalence of the search task across the three different framing conditions can be achieved by shifting the price distributions to offset the discounts. If subjects are unaffected by the discount frame then behavior in these three conditions should be identical.

We also vary the price distributions of both shops to check if the relative price reputation of the shops interacts with the effect of price framing on search behavior. For each type of price framing, we have three different treatments with the expected

price in the second shop being higher, equal and lower than that in the first shop. This  $3 \times 3$  design allows us to test: (i) if price framing changes consumer behavior; (ii) how expectations about the relative expected prices between the initial and second shop impact on search and (iii) if there are interaction effects between framing and relative expected prices. To our knowledge this is the first experiment that can cleanly answer these questions.<sup>2</sup>

In order to be able to identify potential price-framing effects we structurally estimate the risk-preferences from our data with the null hypothesis that there are no differences across our nine treatments, as this is what standard theory predicts. We find that risk parameters vary across treatments with different price frames, while they do not significantly differ between treatments with different relative expected prices within a price-frame. The latter observation gives us some confidence that our structural model is properly specified, whereas the former observation provides evidence for price-framing effects.<sup>3</sup> We find two interesting price-framing effects. Firstly, compared to the scenario without discounts, a discount framing in the initial shop reduces the subjects' inclination to take risk and go to the second shop even when the net prices are identical. This effect is larger in early periods of our experiment and is significantly reduced in later rounds. We conjecture that a discount being offered at shop, where a consumer already is, has strong salience and leads to the consumer putting a large value on it, while experience reduces the salience. Secondly, consumers are inclined to take *less* risk if the second shop is known to offer a discount than in the equivalent treatment without discounts. This effect is persistent and does not disappear with repetition. At first one might find this result odd, as intuition might suggest the opposite: consumers being lured to the second shop by discounts. It makes perfect sense if one thinks about salience though. The expected gross price is higher in the second shop (by the amount of the discount). Since the consumer has to decide while not being in the second shop (i.e. having

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<sup>2</sup>There exist some experimental studies which implement similar search models in the laboratory (e.g. Schotter and Braunstein 1981; Braunstein and Schotter 1982; Kogut 1990; Kogut 1992; Cox and Oaxaca 1989; Cox and Oaxaca 1992). These experiments were only designed for testing if subjects adhere to optimal search rules typically assuming risk-neutrality.

<sup>3</sup>It remains a philosophical question whether the price framing effect leads to biased behavior or if it impacts on risk-preferences.

not yet experienced the discount), the salience of the discount is low compared to that of the gross price distribution. The value of the discount in the future shop is undervalued and the search intensity is reduced.

The main insight from our paper is that both the price-framing effect of discounts in shops that are visited and that of discounts in shops consumers consider to visit point in the same direction. The use of the discount frame reduces the inclination of consumers to take risk and to search for a better price. So firms using the discount frame without actually reducing net prices are able to reduce the competitiveness of markets, as it reduces the price elasticity of demand through a reduced search intensity of consumers.

The remainder of this paper is organized as follows. In Section 2, we describe the experimental design and the standard theoretical predictions for the underlying model. In Section 3 we provide summary statistics of buyers' decisions. In Section 4 we report on the structural estimation of the risk preferences using maximum likelihood estimation, followed by a discussion of explanations for the framing effect in Section 5. Finally, we offer some concluding remarks in Section 6.

## 2 The experiment

Typically, search models and the computation of the resulting optimal stopping rule can be quite complex. In this experiment, our aim is to test neither the theoretical search models nor the computation ability of our subjects. Therefore, we chose an extremely simple search environment in order to minimize the calculation effort required by subjects. The treatments consist of variations of a simple search task.

### 2.1 A baseline search task

Subjects are asked to buy one unit of a homogeneous good which is worth  $v$  monetary units to them. There exist two sequentially located shops (1 and 2), selling this good. The price offered by each shop is randomly and independently drawn from commonly known 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 quoted in shop 1, once it is determined, 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 to be paid. Note that depending on the specific treatment, the net price subjects have to pay may equal  $p_i$  (when shop 1 does not offer a discount) or  $p_1 - d_1$ , where  $d_1$  denotes a discount offered by shop 1.
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 1 is no longer available. After *search* subjects face two further choices:
  - (a) *Buy at  $p_2$* . The profit is given by  $v - p_2 - c$  in the treatments where shop 2 does not offer a discount and as  $v - (p_2 - d_2) - c$  otherwise.
  - (b) *Exit* with a loss of  $c$ .

## 2.2 Treatments

Built upon on this baseline search task, our experiment consists of nine treatments (Table 1). The buyers' valuation ( $v = 200$ ) and the search cost ( $c = 5$ ) are held constant across all treatments. The prices offered by both shops are drawn from uniform distributions, which serves the purpose of keeping the search problem as simple as possible. The nine treatments result from a three-step variation in the two dimensions of price framing and price distributions.

Along the first dimension, we can classify the three different types of treatments as *No-D*, *Shop1-D*, and *Shop2-D*, which correspond to “there is no discount in any shop”, “only shop 1 offers a discount” and “only shop 2 offers a discount.” The *No-D* treatments ( $T1, T4, T7$ ) implement the baseline search model with different incentives for search, which come from the different price distributions used. In the *Shop1-D* treatments ( $T2, T5, T8$ ) a discount of  $d_1 = 15$  is granted in shop 1, while in shop 2 no discount applies. Compared to the treatments without any discount the

|  | No-D  | Shop1-D<br>(d <sub>1</sub> =15)                   | Shop2-D<br>(d <sub>2</sub> =15)                   |
|--|---|---|---|
| L-Incentive:   | T1:<br>$p_1 \in [60, 160]$<br>$p_2 \in [75, 175]$ | T2:<br>$p_1 \in [75, 175]$<br>$p_2 \in [75, 175]$ | T3:<br>$p_1 \in [60, 160]$<br>$p_2 \in [90, 190]$ |
| M-Incentive:   | T4:<br>$p_1 \in [75, 175]$<br>$p_2 \in [75, 175]$ | T5:<br>$p_1 \in [90, 190]$<br>$p_2 \in [75, 175]$ | T6:<br>$p_1 \in [75, 175]$<br>$p_2 \in [90, 190]$ |
| H-Incentive:   | T7:<br>$p_1 \in [75, 175]$<br>$p_2 \in [60, 160]$ | T8:<br>$p_1 \in [90, 190]$<br>$p_2 \in [60, 160]$ | T9:<br>$p_1 \in [75, 175]$<br>$p_2 \in [75, 175]$ |
| $v = 200, c = 5, p_1$ and $p_2$ are drawn from <i>uniform</i> distributions. |   |   |   |

Table 1: A summary of the parameter values by treatment.

gross price distributions in shop 1 are moved up by 15 monetary units. This exactly offsets the discount. In the *Shop2-D* treatments (*T3*, *T6*, *T9*) the discount of 15 monetary units applies to purchases in shop 2 and the gross price distributions are again shifted, such that the discount is perfectly offset. As the price distributions and the discounts are communicated to the subjects, the underlying decision problems across the framing conditions are identical within the same incentive category, as the net price distributions are identical.

On the other dimension, we vary the incentive to search by shifting the relative location of the price distributions in shop 1 and 2. The three different incentive categories are 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 increases if the relative expected price in shop 2 decreases while everything else is constant. In *M-Incentive* treatments (*T4*, *T5*, *T6*), the net-price distributions from which the two shops draw their prices are both uniform on the interval [75, 175]. In the *L-Incentive* treatments (*T1*, *T2*, *T3*) the net-price distribution of shop 1 is stochastically dominated by that of shop 2 (uniform on [60, 160] in shop 1 versus [75, 175] in shop 2). This relationship is reversed in the *H-Incentive* treatments (*T7*, *T8*, *T9*), where a lower expected net-price is assigned to shop 2. This design makes it possible to isolate the impact of price framing on search decisions for the three different incentive categories. The variation of the incentive to search is useful for the identification of interaction effects between framing and expectations.

## 2.3 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 that we distributed in advance. 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, 226 university students from various disciplines participated in the experiment. They earned on average 9.2AUD in approximately 30 minutes.<sup>4</sup> The subjects had no experience with similar tasks in the laboratory and repeated participation was not allowed.

## 2.4 The benchmark predictions

Before we report our findings, it is important to illustrate the theoretical predictions of a rational buyer’s behavior as a benchmark. Firstly, *exit* is obviously a strictly dominated option in both stages given the parameter values we applied. In all treatments, *buy* generates a positive profit even if the highest possible price is drawn, whilst *exit* gives either 0 or  $-5$ . We included this apparently dominated option as a low-level rationality check. Secondly, as illustrated in the section on treatment design, 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 unaffected by framing effects should use the same decision rule for all decision problems within one incentive condition, regardless of her risk preferences. Denoting the expected search intensity (fraction of search) in treatment  $j$  as  $S_j^*$ , equalities  $S_{T1}^* = S_{T2}^* = S_{T3}^*$ ,  $S_{T4}^* = S_{T5}^* = S_{T6}^*$  and  $S_{T7}^* = S_{T8}^* = S_{T9}^*$  should hold if

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<sup>4</sup>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.

the risk preferences of subjects are distributed identically across treatments, which we ensure by randomly assigning subjects to treatments. Lastly, as we increase the *ex ante* incentive to search while holding the price framing constant,  $S_j^*$  should increase accordingly. Therefore, inequalities  $S_{T1}^* < S_{T4}^* < S_{T7}^*$ ,  $S_{T2}^* < S_{T5}^* < S_{T8}^*$  and  $S_{T3}^* < S_{T6}^* < S_{T9}^*$  should hold. These relationships are summarized in Table 2.

|   | No-D                     | Shop1-D                  | Shop2-D                |
|---|--------------------------|--------------------------|------------------------|
| L-Incentive:  | $S_{T1}^* =$<br>$\wedge$ | $S_{T2}^* =$<br>$\wedge$ | $S_{T3}^*$<br>$\wedge$ |
| M-Incentive:  | $S_{T4}^* =$<br>$\wedge$ | $S_{T5}^* =$<br>$\wedge$ | $S_{T6}^*$<br>$\wedge$ |
| H-Incentive:  | $S_{T7}^* =$             | $S_{T8}^* =$             | $S_{T9}^*$             |
| $S_j^*$ : predicted search intensity in treatment $j$ |                          |                          |                        |

Table 2: The predicted relations of search intensities across treatments.

### 3 A first look at search behavior

Before we investigate individual search behavior, we first present an overview over observed decisions. Among 4520 observations, we observe 20 (i.e., 0.44%) instances of exits in shop 1. We also observe a small amount of irrational exits in the second stage (69 out of 2338, 2.95%). We conclude from the small proportion of obviously irrational behavior that the subjects in general understood the search task.

Compared to the three theoretical predictions made in Section 2.4, the average search behavior shows certain regularities, which do not perfectly agree with theory. We find that although the search intensity in general increases as the incentive to search increases, we do not observe identical search intensities across different price presentations, when the search incentive is held constant. The observed search intensity generally increases as the price expectation for shop 2 (relative to that of the shop 1) decreases. In the *L-Incentive* treatments, the average fraction of buyers who search is 40.91% (*No-D*), 44.44% (*Shop1-D*) and 32.94% (*Shop2-D*). This fraction generally increases to 54.46%, 48.67% and 45.71% in the *M-Incentive* treatments, respectively, and further increases to 58.39%, 58.89% and 57.92% in the *H-Incentive* treatments, respectively. The variation of search frequencies along

the incentive dimension therefore roughly follows the theoretical prediction. Higher search incentives lead to more searching. This is reassuring. However, comparing the search fractions within the incentive dimension shows that they are not necessarily the same. Note that the unconditional search fractions do not necessarily give a conclusive picture, as they cannot account for different draws of the prices in shop 1 across treatments. For this reason we investigate how the search intensities relate to the prices in shop 1 and compare this within the same incentive level.

Figure 1 plots the relation between smoothed search fractions and the net price in shop 1 for a given level of search incentives.<sup>5</sup> 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 than in the *Shop1-D* or *Shop2-D* treatments. This is true for all incentive levels. Initially both discount frames – regardless of where the discount is given – seem to reduce the search intensity at given net prices in shop 1. The difference becomes smaller in the second half of the experiment, as the right panel shows. But there is still less searching if the discount is offered in the shop with the unknown price (*Shop2-D* treatments) than in the other two framing conditions. It is hard to tell from the graphs if the searching intensity is still different between the *Shop2-D* frame, with the discount in shop one (*Shop1-D*) and the net price framing (*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 and the differences along the price-frame dimension appear to become smaller in the second half of the experiment. In the next section we provide a more in-depth analysis, which exploits that under standard assumptions the search decision should depend only on the observed price in shop 1, the price distribution in shop 2 and the risk preferences of the subject.

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<sup>5</sup>For the graphs we used locally weighted scatterplot smoothing (LOWESS, Cleveland 1979 ) with bandwidth 0.8.

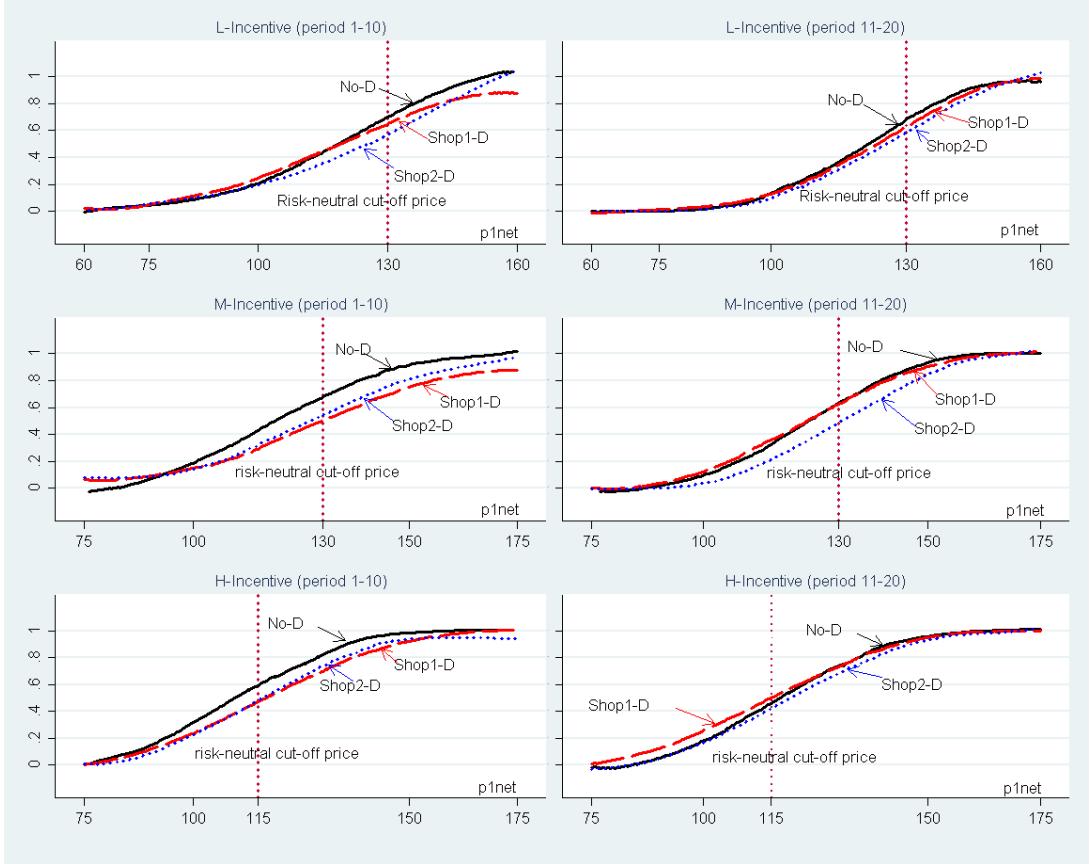


Figure 1: Lowess smoothing probability of search by treatment and period

## 4 Structural estimation of risk preferences

Our experiments implement a model of consumer search under uncertainty. The cutoff price (i.e., the lowest price in shop 1 where a consumer decides to search) depends on the price distribution at the second shop, search cost and the risk preferences of the consumer. In our analysis uncovering 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 their observations to the theoretical predictions under risk-neutrality. This approximation can greatly reduce the computational demand in 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. The estimation is based on expected utility theory (EUT) and the noisy probabilistic choice model proposed by Holt and

Laury (2002). In our estimation we allow the risk-aversion coefficient to depend on subject characteristics and on treatments. Significantly different risk parameters across treatments then provide evidence for price-framing effects.

#### 4.1 An expected utility maximizer's decision rule

We assume that the utility function is defined 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 risk proclivity (being risk loving) for  $r > 1$ , risk-neutrality for  $r = 1$ , and risk-aversion for  $r < 1$ .

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 2 resulting in an expected utility  $EU(S)$  from searching.<sup>6</sup> The values of  $U(B)$  and  $EU(S)$  are calculated according to the following expressions:

$$U(B, p_{1net}) = (200 - p_{1net})^r, \quad (1)$$

$$EU(S) = \int_{\underline{p}}^{\bar{p}} f(p) [200 - p_{2net} - 5]^r dp. \quad (2)$$

Here  $f(p)$  denotes the density function of the price distribution;  $\underline{p}$  and  $\bar{p}$  are the lower and upper bounds of the price distribution and  $p_{1net}$  and  $p_{2net}$  are the net prices charged. The density function of our uniform distribution is given by  $f(p) = \frac{1}{a}$ , where  $a = \bar{p} - \underline{p} = 100$ . Therefore,  $EU(S)$  can be expressed as a function of the unknown risk parameter  $r$ :

$$EU(S) = \frac{(195 - \underline{p})^{r+1} - (195 - \bar{p})^{r+1}}{100(r + 1)} \quad (3)$$

A rational expected utility maximizer should always choose the option which

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<sup>6</sup>The utility from buying also depends on  $p_{1net}$ . We omit this in the text to enhance readability.

yields the higher expected utility. The probability of search in this case is a step function:

$$prob(S | p_{1net}) = \begin{cases} 1 & \text{if } EU(S) > U(B, p_{1net}) \\ 0 & \text{if } EU(S) \leq U(B, p_{1net}) \end{cases} \quad (4)$$

If we allow individuals to make decision errors then we would at least expect that the probability of search increases with the difference, i.e.,  $EU(S) - U(B)$ . A simple probabilistic decision rule capturing this is:

$$prob(S | p_{1net}) = \frac{EU(S)^{\frac{1}{\mu}}}{U(B, p_{1net})^{\frac{1}{\mu}} + EU(S)^{\frac{1}{\mu}}} \quad (5)$$

$$prob(B | p_{1net}) = 1 - prob(S | p_{1net}) \quad (6)$$

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 make decisions more randomly. To the extreme, if  $\mu$  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 with higher (expected) payoff approaches 1 and the decision maker becomes fully rational. With Equations (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 1, the net-price distribution in shop 2) and on the two unknown parameters  $\mu$  and  $r$ , which we will estimate.

## 4.2 Maximum likelihood estimation

Assuming that subjects make decisions according to the probabilistic choice rule stated above, the risk parameter  $r$  and the noise parameter  $\mu$  can both be estimated using maximum likelihood estimation. As we are interested in how search behavior is influenced by price framing, we allow the risk parameter to vary across treatments. To control for the impact of individual characteristics of our subjects, we also allow

the risk parameter to vary with demographic variables such as age, gender and background in mathematics. In addition, as we repeat the same task 20 times, we also include time effects and their interactions with treatments to capture the potential behavioral changes over time. 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 change over time (*Period*). The estimation equations for  $\hat{r}$  and  $\hat{\mu}$  are given in Equations (7) and (8), followed by explanations of the independent variables.

$$\begin{aligned}\hat{r} = & \hat{r}_0 + (\hat{r}_{Discount} \times Discount) + (\hat{r}_{Incentive} \times Incentive) \\ & + (\hat{r}_{Characteristics} \times Charactistics) + (\hat{r}_{T_{10+}} \times T_{10+}) \\ & + (\hat{r}_{Disc*T_{10+}} \times (Disc * T_{10+})) + (\hat{r}_{Inc*T_{10+}} \times (Inc * T_{10+}))\end{aligned}\quad (7)$$

$$\hat{\mu} = \hat{\mu}_0 + (\hat{\mu}_{Period} \times Period) \quad (8)$$

- *Discount* is a set of dummies indicating from which price-framing condition the observation is taken (*No-D*, *Shop1-D*, *Shop2-D*). The base treatment is the *No-D* treatment. This set of dummies is included in order to test if price framing alters the subjects' underlying risk preferences.
- *Incentive* is a set of dummy variables (*L-Incentive*, *M-Incentive* and *H-Incentive*), which indicates the three different incentive conditions from which the observations were taken. *L-Incentive* treatments are omitted in the estimation as the base category. This set of dummies can be used to test if shifting the price distribution in shop 2 alters risk preferences.<sup>7</sup>
- *Characteristics* is a set of dummies and categorical variables, which contain information on the subjects. This set of variables is included mainly as a control. *Male* is a dummy variable to control for gender differences, where

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<sup>7</sup>Note that a systematic persistent effect could also point into the direction of mis-specification of the utility function. We will discuss this in a later section.

female is the base group. *Age* is a categorical variable which classifies the subjects into three age groups: *Age26<sup>-</sup>*, *Age26-30*, *Age30<sup>+</sup>*. The group *Age26<sup>-</sup>* contains the majority of observations and is used as base group. *Math* is a dummy variable to define whether or not a subject has a good background in mathematics (measured as the level of high school math the subject has taken). *Course* is a categorical variable which divides the subjects into students of *Science*, *Comm/Fin (Commerce/Finance)*, *Economics*, *Engineering*, *Law*, *Medicine*, *Arts* and *Other*. *Science* is used as the base group.

- The last category of dummy variables is the time dummy and its interactions with the treatment dummies.  $T_{10+}$  is a dummy variable to distinguish the observations in the last ten periods from those in the first ten periods. In addition,  $Disc^*T_{10+}$  and  $Inc^*T_{10+}$  are two sets of dummies generated by interacting treatment dummies with the time dummy. They are  $No-D^*T_{10+}$ ,  $Shop1-D^*T_{10+}$ ,  $Shop2-D^*T_{10+}$  in the former set and  $L-Incentive^*T_{10+}$ ,  $M-Incentive^*T_{10+}$  and  $H-Incentive^*T_{10+}$  in the latter set. The first interaction in each group is omitted in the estimation.

### 4.3 Estimation results

The estimation results are presented in Table 3. The standard errors allow for error clustering within a subject. Recall that an increase in the risk parameter  $r$  indicates a higher propensity to take risks, where  $r = 1$  (risk neutrality) separates risk-averse subjects ( $r < 1$ ) from risk lovers ( $r > 1$ ). The risk parameter of a base-category subject is around 1.415, which indicates risk-seeking, while the resulting risk coefficient for the second half of the experiment is not significantly different from risk neutrality anymore ( $p > 0.96$ ).<sup>8</sup> The estimated noise parameter starts off with 0.276 in period one. This value is much higher than the value (0.134) estimated by Holt and Laury (2002) for the binary lottery choice task. This is not surprising, since the search task itself is more complex than just making binary lottery choices. The

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<sup>8</sup>However, this only applies to those who are 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.

amount of noise in the decision process significantly decreases over time (*Period*) as subjects become familiar with the task. In period 20, the estimated noise parameter is 0.116, which indicates a very reasonable level of rationality.

|   | Variable                     | Coefficient          | Variable             | Coefficient          |
|---|------------------------------|----------------------|----------------------|----------------------|
| $\hat{r} =$   | $\hat{r}_0$ (constant)       | 1.415***<br>(0.342)  | Math                 | 0.469***<br>(0.161)  |
|   | Shop1-D                      | -0.784***<br>(0.236) | Age26-30             | 0.100<br>(0.192)     |
|   | Shop2-D                      | -0.756***<br>(0.224) | Age30 <sup>+</sup>   | 0.044<br>(0.244)     |
|   | Shop1-D*T <sub>10+</sub>     | 0.566**<br>(0.256)   | Engineering          | 0.215<br>(0.230)     |
|   | Shop2-D*T <sub>10+</sub>     | 0.346<br>(0.237)     | Medicine             | 0.552***<br>(0.212)  |
|   | M-Incentive                  | -0.277<br>(0.190)    | Economics            | 0.200<br>0.303       |
|   | H-Incentive                  | 0.071<br>(0.207)     | Commerce/Finance     | 0.455**<br>(0.223)   |
|   | M-Incentive*T <sub>10+</sub> | 0.370<br>(0.229)     | Law                  | 0.974***<br>(0.313)  |
|   | H-Incentive*T <sub>10+</sub> | -0.336<br>(0.230)    | Arts                 | 0.516**<br>(0.261)   |
|   | T <sub>10+</sub>             | -0.401<br>(0.300)    | Other                | 0.120<br>(0.273)     |
|   | Male                         | 0.029<br>(0.126)     |                      |                      |
| $\hat{\mu} =$   | $\hat{\mu}_0$ (constant)     | 0.276***<br>(0.032)  | Period               | -0.008***<br>(0.276) |
|   | Log-Likelihood               | -1862.98             | Wald $\chi^2_{(20)}$ | 65.22***             |
| Robust standard error in parentheses, * $p$ -value < 0.1; ** $p$ -value < 0.05; *** $p$ -value < 0.01 |                              |                      |                      |                      |

Table 3: Estimation results of the risk and the noise parameters.

The estimation also shows that subjects' risk preferences do vary with different price frames. Subjects behave as if they are more risk averse in both *Shop1-D* and *Shop2-D* treatments than those who are in the equivalent *No-D* treatments. The estimated risk parameter is 0.784 lower in *Shop1-D* treatments and 0.756 lower in *Shop2-D* treatments, when compared with that of the *No-D* treatments. These differences are large and statistically significant at the 1% level. A base subject in the *No-D* treatment (who is slightly risk loving) would pay 6.1 Dollars for a 50:50

gamble between receiving zero and ten Dollars. A base subject in one of the price-framing treatments (with an  $r$  of approximately 0.65) would only be willing to pay about 3.4 Dollars for the same gamble.

However, this difference in willingness to take risks diminishes as subjects become more familiar with the price framing. In the *Shop1-D* treatments, the impact on the risk parameter due to discount framing is reduced to 0.218 in the second half of the experiment (periods 11 to 20). A Chow Test reveals that the remaining effect on of discount framing in the first shop is not significantly different from zero anymore ( $p > 0.27$ ). In the *Shop2-D* treatments the framing effect is more persistent. The coefficient of  $Shop2-D * T_{10+}$  offsets only 46% (0.346) of the total framing effect (0.756). The impact of the discount frame in shop 2 on the risk-preference parameter remains highly significant ( $p < 0.025$ ) in the second half of the experiment.

This result seems surprising, as it implies that the knowledge that there are discounts in shop 2 does not, as one might expect, lure people into searching more. On the contrary, knowing that shop two offers discounts persistently reduces the search intensity compared to the situation where shop 2 posts net prices. The effect of the equivalent upwards shift of the price distribution seems to be stronger than that of the promised discount.

Along the other dimension of our treatment design, we find that risk preferences are relatively stable to changes on relative price expectations. There are no significant differences in the estimated risk-parameters across incentive levels. This is the case for both the first and last ten periods. The estimation also shows that risk preferences tend to vary with some individual characteristics. Subjects who have better math backgrounds are more risk-loving ( $r$  is around 0.469 higher). Subjects who study Commerce/Finance, Arts, Law and Medicine seem to be more risk-loving than those who study Engineering, Science, Economics and other subjects.

## 5 Discussion

The subjects behave as if their risk preferences were influenced by the price-framing conditions when the price expectations and everything else are held constant. Hold-

ing the net price constant means that the subjects who faced identical tasks showed systematically different risk preferences depending on how prices were framed. This raises the question if our CRRA formulation could be the reason for this. This is not the case, as any valid expected utility function would detect this difference, since the underlying choice tasks were identical. Furthermore, subjects respond to the variation on relative price expectations in a way that is consistent with our choice of parametric utility function. As we have seen above there is no significantly different behavior within a discount frame but across incentive condition. Just varying the net price distributions in shops 1and 2 does not influence the risk coefficient. This result provides support for our specification of the utility function, as well as for the robustness of the framing effect.

In what follows we discuss what might have led to the surprising result that subjects consistently searched less if the price was framed as a shop 2 discount. We will offer two explanations, one more complex explanation – “complexity aversion”, and a simple one – “shifts in salient characteristics”. The observed price-framing effect may be caused by a variety of potential psychological factors. One explanation could be “complexity aversion”. There is an increasing body of evidence showing that people tend to avoid risk in more complex choices in decision-making problems under uncertainty. In a simple binary lottery choice experiment, Huck and Weizsacker (1999) find that subjects select the lottery with higher expected value (EV) in general, but deviate from EV maximization more frequently as the lotteries become more complex (i.e., the number of outcomes in the lotteries increases). This is especially the case when the number of outcomes are different in two lotteries. Subjects tend to choose the less complex lottery. Similar results are also found in a multi-period lottery experiment based on discounted EUT. Mador et al. (2000) show that subjects’ willingness to pay for a simple but inferior multi-period lottery can be significantly higher than that of a superior but more complicated lottery in first-price auctions. Moreover, Sonsino et al. (2002) demonstrate that subjects’ choice behavior is affected by complexity in two ways: (i) subjects are less likely to choose an alternative as the relative complexity of that alternative increases; and (ii) the noise in the decision-making process increases with the absolute complexity

of the choice.

Instead of focussing on the complexity of choice alternatives (Huck and Weizsäcker 1999, Mador et al. 2000 and Sonsino et al. 2002), Wilcox (1993) and Johnson and Bruce (1998) investigate the behavioral impact of the complexity of whole decision problems. In their studies subjects are also shown to be complexity averse. Our results are consistent with this finding. Our two-shop search task is essentially a binary lottery choice experiment with a slight complication in the discount treatments. The baseline treatment *No-D* requires a binary choice between a fixed payment and a lottery payment that is determined by the price distribution in shop 2. Instead of maximizing the expected value, the subjects' objective here is to minimize the expected payment. Framing the price in either of the two shops as a gross price distribution with a discount increases the complexity of the whole search problem, as discounts add one more dimension to the decision problem. Facing more complex discount frames, subjects in the *Shop1-D* and *Shop2-D* treatments tend to stick with the safe alternative (i.e., pick the fixed payment) more often. This can be seen from our structural estimation, as risk preference coefficients for these two treatments are lower, initially.

However, as subjects gain more experience with the task they gradually better understand the real consequences of the gross price framing. Depending on where the discount is offered, the price framing increases the complexity of the search problem by different amounts. Hence, the speed of this learning process differs across the discount treatments. Compared to the baseline treatment, *Shop1-D* is not much more complex because a constant only has to be subtracted from a known number. Overcoming complexity aversion should be quick. Indeed, we find that the framing effect disappears in the second ten rounds in this treatment. In contrast, the *Shop2-D* treatment requires the subjects to subtract a constant from a known distribution (i.e., shifting the distribution), which adds much more complexity. Consequently, we observe the framing effect to be more persistent. The magnitude is reduced in the second half of the experiment, but it does not vanish.

Despite complexity-aversion being a potentially plausible explanation, we favour

another one. Suppose subjects use short-cuts in order to make their decisions.<sup>9</sup> 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. 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. Consequently, experience leads to a shift from the discount to the net price as decision relevant.

In the *Shop2-D* treatments things are different. The discount is not salient as 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 learn that the focus on the gross price leads to distortions in the decision. So is the net price in the second shop with a discount partly unknown at the time of decision and cannot just be computed as  $p_{2net} = p_2 - d$ .

Our design allows us to see whether subjects really focus on the gross price in the second shop, when there 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 only focus on the gross distribution in the latter treatment then search behavior for given prices in shop 1 (where there are no discounts in all three treatment) should be identical. This can be assessed graphically in the same manner as earlier in this

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<sup>9</sup>Think e.g. of Gigerenzer's concept of an adaptive toolbox for decision making (Gigerenzer 2001).

paper. Figure 2 shows that there is virtually no difference between search rules.

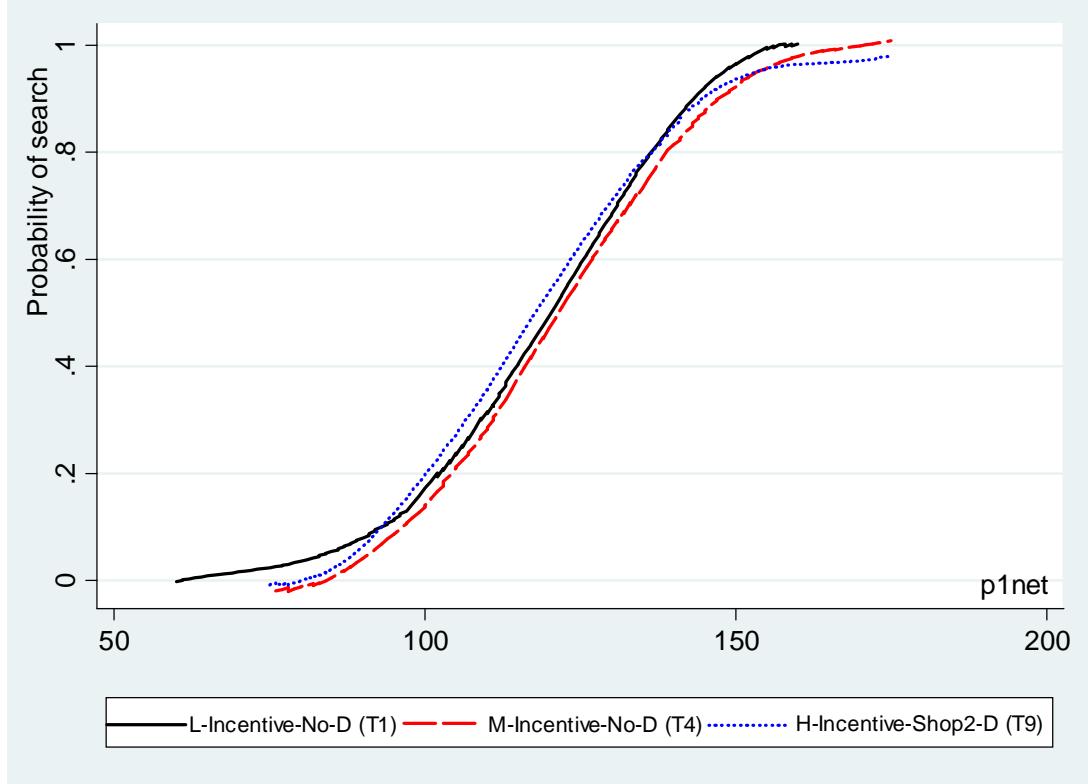


Figure 2: Lowess smoothing probability of search for T1, T4 and T9

## 6 Conclusion

Retailers regularly post gross prices and at the same time announce discounts instead of just posting net prices. This paper examined the impact of the discount frame on search behavior. A two-stage search model was used in the laboratory for this purpose. We designed the 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). The distributions where prices were drawn from were adjusted in a way that the decision problem was identical in all three frames. Revealed risk preferences show significant framing effects according to a structural estimation under the assumption of constant relative risk-aversion. We found that

people became less inclined to search if there were discounts. This reduction in search intensity was independent of which shop actually offered the discount. With experience the framing effect disappeared if the discount was offered in the shop where the consumer knew the price already. The effect was persistent though if the discount was offered in the shop that the consumers had not visited yet. Consequently, discount framing persistently reduced search intensity. We conclude that firms can reduce the competitiveness of their markets by framing prices as discounts, as search intensity is positively related to competitiveness of markets.

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# A Experimental Instructions

## A.1 *M-Incentive & No-Discount 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 second 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 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:

|                 | Stage 1  | Stage 2  |
|-----------------|--|--|
| Observe $p_1$ : | 1: Exit ( <i>profit</i> = 0)<br>2: Buy ( <i>profit</i> = $200 - p_1$ )<br>3: Search (i.e., go to shop 2, observe $p_2$ ) → | 3.1: Exit ( <i>profit</i> = $-5$ )<br>3.2: Buy ( <i>profit</i> = $200 - p_2 - 5$ ) |

- **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-Discount 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 second 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:

|                 | Stage 1   | Stage 2  |
|-----------------|---|--|
| Observe $p_1$ : | 1: Exit ( <i>profit</i> = 0)<br>2: Buy ( <i>profit</i> = $200 - p_1 + 15$ )<br>3: Search (i.e., go to shop 2, observe $p_2$ ) → | 3.1: Exit ( <i>profit</i> = $-5$ )<br>3.2: Buy ( <i>profit</i> = $200 - p_2 - 5$ ) |

### • 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-Discount 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 second 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 **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. The price at shop **2** is in the range between **90** and **190** E-Dollars, where all prices are equally likely. Shopkeeper two has his own urn with balls numbered 90 to 190, 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  $200 - P_2 + 15 - 5$ . 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:

|                 | Stage 1  | Stage 2   |
|-----------------|--|---|
| Observe $p_1$ : | 1: Exit ( <i>profit</i> = 0)<br>2: Buy ( <i>profit</i> = $200 - p_1$ )<br>3: Search (i.e., go to shop 2, observe $p_2$ ) → | 3.1: Exit ( <i>profit</i> = $-5$ )<br>3.2: Buy ( <i>profit</i> = $200 - p_2 + 15 - 5$ ) |

- **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.