

# **Partitioned Pricing Research**

## **A behavioural experiment**

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A study for the Office of Fair Trading by London Economics, Dr Charlotte Duke and Dr Miriam Sinn, and University College London, Professor Steffen Huck and Dr Brian Wallace

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## **FOREWORD BY CHRIS WALTERS**

This report was commissioned by the Office of Fair Trading (OFT) from London Economics in association with Dr Steffen Huck and Dr Brian Wallace (University College London). It examines the impact of partitioned pricing on consumer decision-making.

Consumers may face prices from retailers that are split into more than one component, for example a base price and then an additional fee for administration, handling or post and packaging. Where the additional fee is presented to the consumer at the same time as the base price, pricing is said to be partitioned. Where the additional fee is revealed at a later stage in the buying process than the base price, pricing is said to be dripped. This report focuses on partitioned pricing, the OFT having previously commissioned analysis of 'drip' pricing.

This report presents the results of a controlled laboratory experiment which compared the impact of different pricing partitions with non-partitioned pricing, and explored the circumstances under which partitioned pricing would be most likely to affect consumer decisions and possibly cause harm to consumers. A key finding is that transparency and clarity of price partitions and the total price of a product or service have a significant impact on consumer decisions and welfare even when all the price components are displayed at the same time.

The views in this paper are those of authors and do not necessarily reflect the views of the OFT. This paper is not intended to constitute guidance on consumer or competition law or the exercise of the OFT's enforcement functions. Rather the aim of the report is to develop and review some evidence on this interesting issue and promote economic debate in this area.

This report is part of the OFT's Economic Discussion Paper series. If you would like to comment on the paper, please write to me, Chris Walters, at the address below. The OFT welcomes suggestions for future research topics on all aspects of UK competition and consumer policy.

Dr Chris Walters  
Chief Economist  
Office of Fair Trading,  
Fleetbank House,  
2-6 Salisbury Square  
London EC4Y 8JX  
[chris.walters@oft.gsi.gov.uk](mailto:chris.walters@oft.gsi.gov.uk)

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## DEFINITIONS

'Drip pricing' frame	Price frame in which the respondents see only part of the full price up front and one price increment is dripped through the buying process (for example, on subsequent pages of a website).
'Presentation' frame	Price frame in which the price is split into two partitions (base and extra part) and the extra part (or second partition) is presented in a different font to the base and at a different position on the screen.
'Three partitions no total' frame	Price frame in which the price is split into three partitions, and the total cost is not displayed (for example, £7 + £2 + £1)
'Two partitions no total' frame	Price frame in which the price is split into two partitions, and the total cost is not displayed (for example, £7 + £3)
'Two partitions with total' frame	Price frame in which the price is split into two parts (base plus one extra part) and the total cost is displayed (for example, £7 + £3 = £10)
Behavioural biases	Systematic deviations from the classical economic decision making framework of full rationality and unlimited cognitive ability.
Consumer welfare	In our context consumer welfare is measured by the payoff respondents receive in the experiment which directly translates into monetary earnings.
Optimal behaviour	The behaviour which maximises payoff, irrespective of any behavioural biases.
Over-search	Searching, when the optimal response would be to purchase without further search.

Purchasing errors	Purchasing a positive number of goods, but not the optimal number. For example, purchasing two goods, when purchasing one would have been optimal.
The baseline frame	Straight per-unit pricing. This will be the benchmark relative to which the other pricing strategies will be compared
Under-search	Not searching, when the optimal response would be to search further.
Welfare loss/ Consumer detriment	This is the amount of expected payoff the respondent missed out on because they made a decision which deviated from the optimal behaviour.

Clustered standard errors	Allows the standard errors to be grouped which therefore allows for intra-group correlation. In our case standard errors are clustered at the respondent level, meaning that standard errors can be correlated within respondent, but not between respondents.
OLS regression	An Ordinary Least Squares (OLS) is a method for estimating the unknown parameters in a linear regression model. This method minimizes the sum of squared vertical distances between the observed responses in the dataset and the responses predicted by the linear approximation.
Probit regression	A probit regression is a type of regression where the dependent variable can only take two values, for example zero or one.

# 1 EXECUTIVE SUMMARY

- 1.1 This report presents a controlled economic experiment that analyses the impact of how prices are framed on consumer behaviour. This report looks at 'partitioned pricing', which is where the price is split into multiple components, and includes a form of drip pricing.
- 1.2 The experiment was designed to compare the impact of these pricing practices on consumer decision making with a baseline where sellers use clear per-unit prices. It was also designed so that the results of this experiment can be compared to the results of a previous experiment conducted by London Economics for the OFT, 'The impact of price frames on consumer decision making' (2010), which formed part of the OFT study 'Advertising of Prices' (2010)<sup>1</sup> (henceforth referred to as the 2010 study). One of the main results of the 2010 study was that drip pricing can lead to significant welfare loss for consumers. The aim of the current study is to understand if other forms of partitioned pricing also lead to consumer detriment.

## The price frames

- 1.3 The price frames tested in this controlled experiment are the following:

A '*baseline*' frame in which consumers see straight per-unit prices (for example £10)

'*Two partitions with total*' in which the price is split up into two partitions (base plus one extra part) and the total cost is also displayed (for example, £7 + £3 = £10)

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<sup>1</sup> [http://www.offt.gov.uk/shared\\_offt/market-studies/AoP/OFT1291.pdf](http://www.offt.gov.uk/shared_offt/market-studies/AoP/OFT1291.pdf)

'*Two partitions no total*' in which the price is split into two partitions, but the total cost is not displayed (for example, £7 + £3)

'*Drip pricing*' where the respondents see only part of the full price up front and one price increment is dripped through the buying process (for example, on subsequent pages of a website).<sup>2</sup>

'*Presentation*' in which the price is split into two partitions (base and extra part) and the extra part (or second partition) is presented in smaller font next to the 'Buy' button instead of in the same font size next to the base price.

'*Three partitions no total*' in which the price is split into three partitions (base plus first extra part plus second extra part), but the total cost is not displayed (for example, £7 + £2 + £1).

## Experiment design

- 1.4 The experiments were conducted at the University College London (UCL) Experimental Laboratory, and used 145 respondents drawn from across the UCL student population. Each respondent participated in the unit-pricing baseline, the drip pricing and one of the other partitioned pricing frames.
- 1.5 Respondents participated in 30 rounds of the experiment, with each respondent experiencing each of their three frames 10 times.<sup>3</sup> This repetition allows respondents to learn about the experiment and adapt their behaviour. This allows us to determine whether experience has any impact on outcomes. We discuss the effect of learning below.

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<sup>2</sup> In the 2010 study the drip pricing frame had 3 partitions (the base price plus two drips). In this current study drip pricing has 2 partitions (the base price plus one drip).

<sup>3</sup> The order of the frames was completely randomised.

- 1.6 There were two shops in the experiment, allowing respondents to search for a second offer by 'travelling' to the second shop if they did not want to purchase at the price given at the first shop. The same price frame was used at each shop and there was a search cost associated with travelling between these shops.<sup>4</sup>
- 1.7 The full design is presented in detail in Chapter 3.

## Results

- 1.8 Standard economic theory predicts that consumers are fully rational and that how prices are framed should not affect their decisions. However, this controlled experiment finds further evidence that the way prices are framed does matter for consumer decision making and welfare. In particular, we find evidence that consumers reduce search effort under most price frames we investigate and that under some of the price frames they also make more mistakes in search and purchasing behaviour as compared to straight unit pricing (the baseline).
- 1.9 We use a number of measures to compare outcomes across the price frames relative to the identified optimal strategy. Each measure is explained in detail in Chapter 4. Here we provide an overview.

## *Welfare and errors*

- 1.10 The first measure we use to compare outcomes is consumer welfare. As in the 2010 study, we analyse the earnings

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<sup>4</sup> The experiment is incentivised in the sense that the choices respondents make during the experiment affect their monetary earnings in pounds sterling in the experiment. Respondents earned on average £15.50 plus a £5 fixed participation payment. This ensures that respondents behave the same way during the experiment as they would in the real world while shopping online. Respondents have an incentive to pay close attention to the task at hand and they aim to maximise their experimental earnings the same way shoppers aim to maximise their utility when shopping in the real world. This is called saliency in experimental design.

respondents made in the experiment relative to the earnings they would have made if they had behaved in a fully optimal way.<sup>5</sup> This measure is the 'consumer welfare loss'.

1.11 The next set of measures we use are errors in purchasing behaviour, and errors in search. Purchasing errors are defined as purchasing a positive number of goods, but not purchasing the optimal number. For example, purchasing two goods when purchasing one would have been optimal. Search errors occur when respondents either search 'too much' or 'too little'. For example, buying goods at the first shop visited instead of continuing to search at the next shop. Or, continuing to search when buying without further search would have been optimal.

1.12 When considering the effects of the different price frames on behaviour within this controlled experiment, two points should be taken into account. These are:

- Within controlled experiments respondents will tend to search more than in real world markets. This is because respondents explore the experimental environment and they are focused on completing the tasks within the experiment. This is common in all controlled experiments.
- The findings from controlled experiments are asymmetric. Asymmetry in this context means that if respondents in the simplified experiment environment have difficulties with the tasks, then we can expect that consumers will have greater difficulties in the real world. However, if we find that respondents in the experiment do not suffer any problems with

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<sup>5</sup> Optimal behaviour is the behaviour a fully rational respondent with no limits to their computational power would follow. Using the measure of optimal behaviour allows us to quantitatively assess to what extent the different price frames impact upon optimality. This measure is used in controlled experiments to investigate relative effects on behaviour of different practices, interventions and policies.

the tasks in the experiment then we cannot say that consumers will also have no problems in the real world where the environment is more complex. This asymmetry is also is magnified by the use of a 'smart' respondent group in controlled laboratory experiments.<sup>6</sup>

- 1.13 In this context, if we find consumer welfare loss in the experiment it indicates that it is likely to occur in the real world. However, due to the nature of the experiment the results are likely to underestimate the true impact on consumer welfare loss. Consequently in the real world there may still be potential for consumer welfare loss even if this is not found in the experiment.<sup>7</sup> This is particularly the case when we find that the price frame significantly affects consumer behaviour as discussed below.
- 1.14 We consider each of the price frames and their effect on consumer welfare, purchase errors and search errors in turn.
- 1.15 First, we find clear evidence that drip pricing is the price frame that affects consumer behaviour the most. It is strongly associated with more errors in general, more purchasing errors and significantly less search effort. The finding that drip pricing leads to more overall errors confirms the findings from the 2010 study, showing that a reduction from two drips to one drip still leads to an increase in errors. That is overall errors and specifically purchasing errors.<sup>8</sup>

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<sup>6</sup> University student respondent pools have on average higher cognitive abilities than the general population as a whole. In this experiment we find that cognitive abilities have a strong influence on welfare and errors made within the experiment. Therefore, we would expect that this 'biased' smart respondent group to do better at the tasks than the average consumer.

<sup>7</sup> A further discussion of this can be found in paragraphs 3.8, 14.9 to 14.12 and further in the discussion of external validity in Section 5.

<sup>8</sup> Although the experiment did not find evidence of consumer welfare loss arising from drip pricing with one drip, for the reasons outlined previously we would expect the experiment to underestimate the effect on consumer welfare. Consequently we might expect that, due to its

- 1.16 We find evidence that the 'presentation' frame leads to higher consumer welfare loss than the straight per unit baseline frame. In the 'presentation' frame respondents' earnings were 22% lower than if they had followed the optimal strategy.<sup>9</sup> This is particularly striking as the presentation frame was a simple change in the position and font size of the partition (see Figure 3.3). Both parts of the price were shown to respondents on the same screen, and the screen did not include any other features that may have distracted the respondent.
- 1.17 We observe that the 'two partitions no total' price frame also has a significant impact on consumer behaviour. The evidence shows that this frame leads to more general errors, more search errors and overall lower search effort in comparison to the baseline.
- 1.18 In the context of this experiment, this reduction in search effort turned out to improve decision making in some instances. Since respondents in experiments tend to search more than in the real world, we often observed over-search and this tendency to over-search was reduced by the price frames. However, in the real world over-searching is very unlikely to be a problem. Indeed under-searching is more likely to be prevalent in the real world, and; as a result, the reduction in search effort under price frames is likely to be unambiguously negative in the real world.

### ***Learning and IQ***

- 1.19 If we consider respondents' behaviour over time, we can assess if any learning happens and if errors decline and respondents' payoffs increase as respondents become more experienced.

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overall affect on consumer behaviour, that drip pricing with one drip would cause consumer welfare loss in the real world.

<sup>9</sup> In comparison earnings under the baseline were 10% lower than if they had followed the optimal strategy.

- 1.20 We find strong evidence that respondents learn over time, making fewer errors, taking less time to make a decision and obtaining higher welfare. This suggests that when people make similar decisions regularly, errors in decision-making due to the use of price frames may decline as they become more experienced.
- 1.21 However, in the real world we would expect less learning than in this experiment as there will be greater variation in the price framing and time between decisions will be greater. In addition, the fact that consumers learn over time creates incentives for sellers to vary their pricing strategies over time. Similarly, the fact that consumer detriment is greatest when consumers encounter a pricing strategy for the first time gives sellers an incentive to continually develop new pricing strategies.
- 1.22 We also observe that respondents who score highly on an aptitude test (IQ test) also obtain higher welfare and make fewer mistakes throughout all price frames.
- 1.23 This suggests that consumers with lower computational abilities may suffer more harm from the use of price frames.

### ***Comparison to the Advertising of Prices study***

- 1.24 When the data from this experiment is combined with the experiment conducted for the 2010 study we are able to compare the welfare effects of the different pricing frames.
- 1.25 The previous study was run with a different set of respondents; however the experiment set-up was identical.
- 1.26 We find that 'drip pricing with two drips' is the most detrimental to consumers. The next most detrimental is 'presentation' frame, where the two partitions are not presented clearly together, and third is 'time limited offers'.

- 1.27 When we control for which study the observation comes from, we find that respondents performed better in the baseline in the current study compared to the 2010 study, despite these two frames being identical. The better performance in the baseline in this study is likely due to the fact that the frames in this experiment are easier and very similar. This means that respondents are likely to learn faster and across the frames improving their overall performance.<sup>10</sup>

### ***Behavioural forces***

- 1.28 As in the 2010 study we find that drip pricing turns consumers who tend to search too much into consumers who tend to search too little.<sup>11</sup> In this study the number of drips was reduced from two to only one, thereby making the cost associated with the drip as small as possible. The additional cost imposed on respondents by being in the 'drip pricing' frame is in fact only an additional click (there were no time delays between drips) and as such, behaviour cannot be explained by increases in cost of search or sunk costs.
- 1.29 Rather the data suggests that respondents' willingness to pay for the good increases between seeing a low base price and seeing the additional 'shipping' charges. This is in line with loss aversion and the endowment effect.<sup>12</sup>
- 1.30 In the case of 'two partitions no total' frame where the total price is not calculated for the respondent we find reduced search effort and this leads to increased search errors in this frame. This observed effect may arise due to (i) the requirement to add together two numbers increases perceived search cost and respondents, in

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<sup>10</sup> Learning across frames was possible as the order was completely randomised.

<sup>11</sup> Over-searching is a common occurrence in such laboratory experiments because respondents have a very limited environment, are entirely focused on the task and generally have a lot of time to complete each task. As a result, respondents tend to explore the limited environment fully which may result in more search than optimal.

<sup>12</sup> This is discussed in greater detail in paragraph 4.74 in Section 4.

turn, respond to this by searching less; and (ii) the larger partition (first part of the price) may be acting as an anchor and respondents focus less on the second, smaller part of the price and on the (total) final price.

- 1.31 When the presentation of the partitions is changed and the smaller (second) part of the price is not presented next to the first part, but instead in small font before the 'Buy' button, welfare declines and there are more errors in purchasing behaviour relative to the baseline. The most likely explanation for this is that the second part of the price is easier to miss and respondents are therefore more likely to make cognitive errors. In addition any anchoring effect on the first part of the price is also likely to be more pronounced when the second part is not presented prominently.
- 1.32 Overall, any action that increases the prominence of prices and reduces the cognitive requirement for consumers to remember and mentally sum prices will help consumers.

## **Sellers**

- 1.33 Shops in this experiment were computerised, with the prices being randomly drawn from a price range, and as such they did not react within the experiment environment to the behaviour of the consumers.<sup>13</sup> There were two shops in the experiment, allowing respondents to search for a second offer by 'travelling' to the second shop if they did not want to purchase at the price given at the first shop. We observe that the overall sales volume of both shops taken together is similar across the different frames. The effect on shops of the different price frames is in the distribution of sales. We find that the first shop visited gains in all price frames considered. Therefore, firms may engage in activities to encourage consumers to visit their shops first when elaborate pricing frames are used.

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<sup>13</sup> It is possible to have both consumers and firms active in experiments.

## External Validity

- 1.34 This experiment was designed in such a way that the external validity of any evidence of consumer detriment is maximised. That is, any pricing frames found to lead to consumer detriment in the experiment are also likely to result in consumer detriment when they are used in a real market situation. However, this also implies that absence of consumer detriment caused by pricing frames in the experiment cannot be taken as absence of consumer detriment in the real market place if the same pricing strategy were used.
- 1.35 An educated respondent pool was asked to make straightforward purchasing decisions in an extremely simple decision making environment in which all of the decision makers' attention was on the task at hand. Even the price frames themselves were implemented in the most basic fashion possible with no distractions and with the final screen always displaying the full price.
- 1.36 As a result, when we find good performance in the experiment, we cannot extrapolate this finding to the real world in which the environment is not nearly as simplistic and in which a much wider range of consumers is involved. However, at the same time we can feel very confident that where we do find evidence of consumer detriment, purchasing errors and search errors, that this is likely to be the case also in the real world.
- 1.37 An additional implication of this design choice is that all effects found in this experiment are likely to underestimate the true effect of these pricing practices in the real world.
- 1.38 In conclusion, we believe that results from this experimental study have external validity when it comes to assessing consumer detriment, search errors and purchasing errors.

## Summary of main findings

The main findings for each price frame, as discussed above, are summarised in Table 1.1.

**Table 1.1: Summary of main findings**

Price frame	Significantly more errors	Significantly less search	Significant consumer welfare losses	1st shop benefits	Behavioural biases
Drip pricing	Yes	Yes	No	Yes	Endowment effect/loss aversion
Two partitions with total	No	Yes	No	Yes	Cognitive errors
Two partitions no total	Yes	Yes	No	Yes	Cognitive errors/higher search cost
Presentation	Yes	No	Yes	Yes	Cognitive errors
Three partitions no total	No	No	No	Yes	Cognitive errors

Note: The measure 'significantly more errors' shows if respondents made more search or purchasing errors relative to the baseline price frame. 'Significantly less search' shows if respondents search behaviour was affected by the price frames. 'Significant consumer welfare losses' shows if actual earnings compared to optimal earnings in each price frame are less than actual earnings compared to optimal earnings in the baseline. 'First shop visited benefits' reports if the distribution of sales in this experiment is to the advantage of the 1<sup>st</sup> shop visited under each price frame. 'Behavioural biases' shows which behavioural bias is causing actual behaviour to differ from optimal behaviour in each price frame.

## 2 INTRODUCTION

- 2.1 The way in which prices are framed has received surprisingly little attention from economists despite the abundance of different pricing strategies employed by sellers throughout the world. Sometimes goods are on offer (cheaper prices for a limited time, permanently reduced prices, 'buy one get one free' offers, etc) and sometimes they are not on offer. Other times sellers inform you that you should hurry because the stock is low.
- 2.2 The OFT's study on the Advertising of Prices (2010) made a first step towards testing the effects of price frames by studying, with a controlled laboratory experiment, if the way in which prices are framed affects consumer behaviour. This study found significant effects of various price frames on consumer choice and consumer welfare. The current study builds on this previous work by analysing additional price frames and by attempting to shed further light on the mechanisms which drive consumer behaviour under the various frames.
- 2.3 The experiment in the 2010 study analysed the following price frames:
- (1) straight per unit pricing (the baseline)
  - (2) a sales frame (for example, 'was £2 now is £1')
  - (3) complex pricing ('3 for 2')
  - (4) time-limited offers ('£1 only today')
  - (5) baiting sales ('£1 while stock lasts' – with the possibility that consumers may face a much higher price because the initial stock was only very small); and
  - (6) drip-pricing (where the final price is only revealed after two 'drips', for example by revealing that there is a shipping and handling fee only some time into the purchasing process).
- 2.4 While all price frames studied affected consumer choice, drip-pricing stood out as being particularly detrimental to consumers. Drip-pricing is a form of partitioned pricing. A partitioned price is one which includes at least two parts (for example, £8 + £2 as opposed to £10).

- 2.5 This study explicitly looks at the effects of 'partitioned pricing' in order to disentangle the effect of initially withholding part of the price from the consumer and the effect of splitting the price into several partitions.
- 2.6 The study isolates the effect of each price frame. That is, each price frame is tested on its own. In real-life markets some of these frames might appear at the same time, further complicating the task of comparing prices for consumers.
- 2.7 In order to explore the effects of partitioned pricing on consumer decision-making, we run a controlled laboratory experiment with exactly the same set-up as the 2010 study.
- 2.8 In this study we investigate the following price frames:
- (1) The same benchmark of straight unit pricing as in the 2010 study.
  - (2) A simplified 'drip pricing' frame (with only one drip as opposed to two 'drips' so that the complete price is revealed after one drip, for example, £8 on the first screen and an additional £2 dripped on the second screen).
  - (3) 'Two partitions with total' frame in which the price is split up into two partitions and the total price is also displayed (for example, £8 + £2 = £10).
  - (4) 'Two partitions no total' frame in which the price is split into two partitions, but the total price is not displayed (for example, £8 + £2).
  - (5) 'Presentation' frame in which the price is split into two partitions and the smaller partition is presented in a smaller font next to the 'Buy' button instead of next to the first partition and no total was presented (Figure 3.4).
  - (6) 'Three partitions with no total' frame in which the price is split into three partitions, but again the total price is not displayed (for example, £7 + £2 + £1).
- 2.9 Our main result is that partitioned pricing does affect consumer behaviour in the experiment. The 'presentation' frame is the only price frame which is associated with significantly lower welfare; however, the

search and purchasing behaviour of respondents is affected by several price frames and especially by drip pricing.

- 2.10 In particular, we find strong evidence that the price frames lead to less search effort by respondents. As will be discussed in more detail, the treatments are only very minor modifications of the baseline and the respondent pool is highly educated, which suggests that any results found in this experimental setting are likely to be much stronger in the real world.
- 2.11 Exactly as in the Advertising of Prices study, respondents are UCL students registered on a database for economics experiments who participate in a sequence of one-person decision tasks that mirror the repeated purchasing of different goods. Before we go into the detail of the experimental design it is perhaps useful to offer an overview of how the experiment works.
- (1) Respondents work on their own on a computer screen, and are rewarded for their performance. Specifically, they receive a monetary payoff<sup>14</sup> for each unit of each good they buy but, of course, they also have to pay the price that the shops charge.
  - (2) In the entire experiment there are always two shops. Before the respondent visits a shop (and sees the prices on offer), these shops are entirely identical.
  - (3) Since respondents play the role of consumers, they have to choose which shop to visit first. They then need to decide if they want to buy at the first shop, and how many units of the good they want to buy; or, to return home. Once the respondent has returned home they have the choice to visit the second shop.
  - (4) Respondents can 'travel' between the two shops as many times as they like.

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<sup>14</sup> Reflecting consumption utility; the satisfaction one derives from the consumption of a good.

- (5) 'Travelling' to a shop involves some (monetary) search costs reflecting the time costs of search on the internet or the actual travel costs in the case of visiting physical stores. Respondents were timed throughout the experiment.
- 2.12 Our main experimental manipulation is how prices are framed when the consumer respondent arrives at a shop. In our baseline respondents see simple per-unit prices. The five more elaborate price frames that we analyse are then modelled on price frames used in the field.
- 2.13 With this experiment we can examine the effect of price frames on consumers in two ways. First, we can simply examine whether price frames have an effect on consumer welfare (reflected in the experiment by respondents' total pay in UK pounds).
- 2.14 The second way of looking at our data is by comparing actual choices with the optimal strategy. This allows us to identify errors in consumer decision making and how they are triggered by the different price frames. A more detailed analysis of errors also allows us to identify where in the process errors occur, which is important for understanding the root causes of the consumer detriment.
- 2.15 Section 3 of the report discusses the precise setup and design of the experiment (which is called the experiment environment). Section 4 presents the results of the experiment and the behavioural drivers. In Section 5 we discuss the implications of our findings for markets outside the laboratory.

### 3 THE EXPERIMENT

#### The experimental environment

- 3.1 The task is to analyse all of the five pricing practices (plus a baseline with straight unit pricing) in a way that allows the OFT to compare consumer decision making between the different practices and the baseline as well as the pricing frames analysed in the experiment which formed part of the Advertising of Prices study (2010).
- 3.2 In order to ensure comparability with the 2010 study, the original experimental environment was used. This means that the price frames analysed in this experiment are comparable to the price frames in the 2010 study.
- 3.3 As in the 2010 study, we needed an environment with multiple shops in which multiple units of at least one good can be purchased. We opted to include all these facets in the simplest manner. The philosophy behind this is that we want to minimise the noise in decision making that originates from the complexity of the basic environment. The simpler the basic environment, the sharper will be the results of the price-frame comparison.
- 3.4 The implications of a simple environment for applicability outside the laboratory will be highly asymmetric. That is, if we found that respondents do well in the simplified experiment environment, it would be hard to transfer this finding to real world markets. However, if we found that respondents in this very simple environment are doing badly, we know that in more complicated real-life environments the problems are likely to be at least as severe, if not more.<sup>15</sup>

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<sup>15</sup> Of course, markets have a certain tendency to correct themselves. For example, firms could establish a reputation for not using certain confusing practices. We discuss these issues in a section below devoted to the external validity of our study.

- 3.5 Our basic environment is designed in the following way. There are two shops, both of which sell a good that the consumer wishes to buy. At the start of each round, the consumer is at the home screen. The consumer can go back and forth between his home and the two shops as often as he likes and buy units of the good at the shops (up to four units in total). He does not know the price of the good at either shop until he visits it.
- 3.6 All goods are of the same quality. Again this allows us to focus on the pure effect of the frames. In many real-life markets prices may serve as a quality signal which renders the decision problems much more complicated and confounds the issue of price framing.
- 3.7 In the baseline, each shop draws a random price from a price interval.<sup>16</sup> For the purposes of explanation, the price interval is between 60 and 120 (in the experiment the range was sometimes different, but could always be normalised to this interval). Both shops draw their prices from a uniform distribution over this interval. That is, all prices between 60 and 120 are equally likely.
- 3.8 Exogenous prices have the crucial advantage of easing comparability between treatments. There are, of course, consequences for the interpretation of our experiment. Clearly, in an environment where firms can adjust prices optimally the effects of any suboptimal consumer behaviour would presumably be more pronounced. For example, in such a setting firms may select the partition or drip size which maximizes firm revenue at the expense of the consumer. Or alternatively, firms could optimally diversify their pricing strategy in order to surprise shoppers with different pricing strategies as often as possible. In this sense, exogenous prices help us compare treatments but imply that we will underestimate the consumer detriment because firms are static and do not respond to consumer behaviour.

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<sup>16</sup> The price interval is selected before the experiment begins. The respondents are told what the price interval is at the beginning of the experiment.

- 3.9 The consumer has a utility (payoff) function with decreasing marginal utility.<sup>17</sup> For the first unit he buys he receives a payoff of 120, for the second unit 80, for the third unit 20, and for the fourth unit 10. So the total payoff for buying one, two, three or four units is 120, 200, 220 or 230 respectively. Notice that the consumer should never buy more than two units as the marginal utility of the third unit is smaller than the lowest possible price of 60. Notice also that we never allow the purchase of more than 4 units.
- 3.10 Each time the consumer travels to a shop he has to pay some search/travel costs,  $c$ . The search costs vary in the experiment, being randomly chosen each round. Specifically, we examine three different levels of  $c$ , low (2), medium (6), and high (12).
- 3.11 The decision process a consumer must therefore undertake is summarised in the box below and a simple schematic diagram of the process is reproduced in the subsequent figure.

### Box 1: Consumer decision making process

I can go to shop 1 or shop 2 to buy up to 4 units of the good available in this time period. Whenever I go to a shop, I incur a travel cost which will be deducted from the points I receive when I purchase a unit of the good. The two shops have different prices but employ the same price frame. I can only find out what price each shop is selling a unit of the good at by travelling to the shop. At the home screen (see Figure A.1 in the annex for a screen shot of the home screen), I can see that the travel cost is 2 per journey in this time period.

I will go to a shop. Suppose I choose to go to Shop 1. I see a price of 105 (as in Figure A.2). I know that I receive 120 points from buying 1 unit, for 2 units I receive 200 points, and for 3 units I receive 220. So the additional points (my

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<sup>17</sup> Marginal utility is the additional satisfaction (payoff) the consumer derives if he buys and consumes another unit of the good in question. Marginal utility decreases as the consumer gets, and consumes, more units of the good.

marginal utility) are 80 and 20 for buying the second and third unit.

I have already incurred a travel cost of 2 points. Therefore if I buy 1 unit at 105, my earnings will be  $120 - 105 - 2 = 13$  points. If I buy two units at this shop, then my earnings will be  $200 - 105 * 2 - 2 = -12$  points. If I buy 3 units at this shop, then my earnings are  $220 - 3 * 105 - 2 = -97$  points.

If instead I choose to go to Shop 2 to find out the price of the good there, I will incur another travel cost (for travelling from home to Shop 2). This means my travel costs, for visiting the two shops, will be  $2 * 2 = 4$ . To make it worth my while, the price at Shop 2 will need to be lower than at Shop 1. If the price at shop 2 is higher than shop 1, then I may want to come back to shop 1 again. In this instance I will incur a third travel cost meaning my total travel cost will be  $2 * 3 = 6$ .

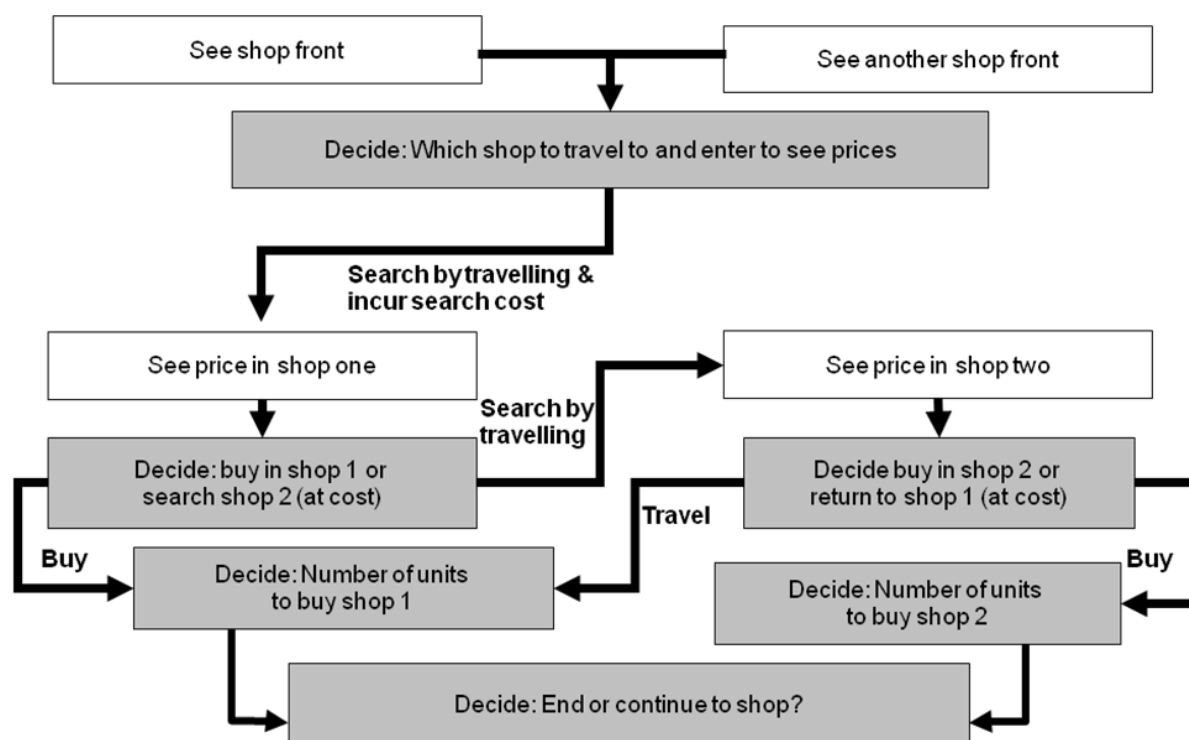
Looking at the price range, the lowest possible price is 60 and the highest is 120. I have observed 105 for a unit at Shop 1. If I choose not to visit Shop 2, then it will be best to buy 1 unit at Shop 1 (because I get 13 points, better than -12 or -97).

Should I go to Shop 2? Well, the price at Shop 1 is quite high and so it is likely that the price at Shop 2 will be lower. If it is at least 2 points lower (i.e. lower than 103), then I will more than cover the extra travel cost. This is quite likely. Even if it is higher than Shop 1, I can always come back to Shop 1 and have only lost the cost of two extra trips (a cost of 4 points).

So, I will go to Shop 2 and see the price there. Once there, I will do the same calculations as I have just done here to decide the optimal number of units to buy (or whether it is better to go back to Shop 1).

Figures A.3, A.4, A.5, and A.6 show the buying and results process. For simplicity, suppose rather than visit Shop 2, I chose to buy 2 units at Shop 1 and then end the round. I must confirm my purchase – see Figure A.3. If I confirm my purchase, I successfully buy 2 units (at 105 each) – see Figure A.4. If I then go home and click “I’m done” on the home screen to finish the period, I am prompted to confirm my decision – Figure A.5. Upon confirmation of my exit, the results are shown – see Figure A.6.

**Figure 3.1: Consumer decision process in the baseline treatment**



## The implementation of the pricing practices

- 3.12 The experiment studies five different pricing practices and compares these practices to a baseline of straight per-unit prices. As described previously, in this baseline treatment, consumers see the per-unit price a shop charges once they visit this shop. This price stays constant within one round. That is, if the consumer returns to the shop he will still get the same price. This holds for both shops. Notice that we design the experiment in a way such that both shops always employ the same type of price framing.
- 3.13 The set up of the 'two partitions with total' frame is very close in design to the baseline frame. Final sale prices are determined in exactly the same way. However, the way in which they are

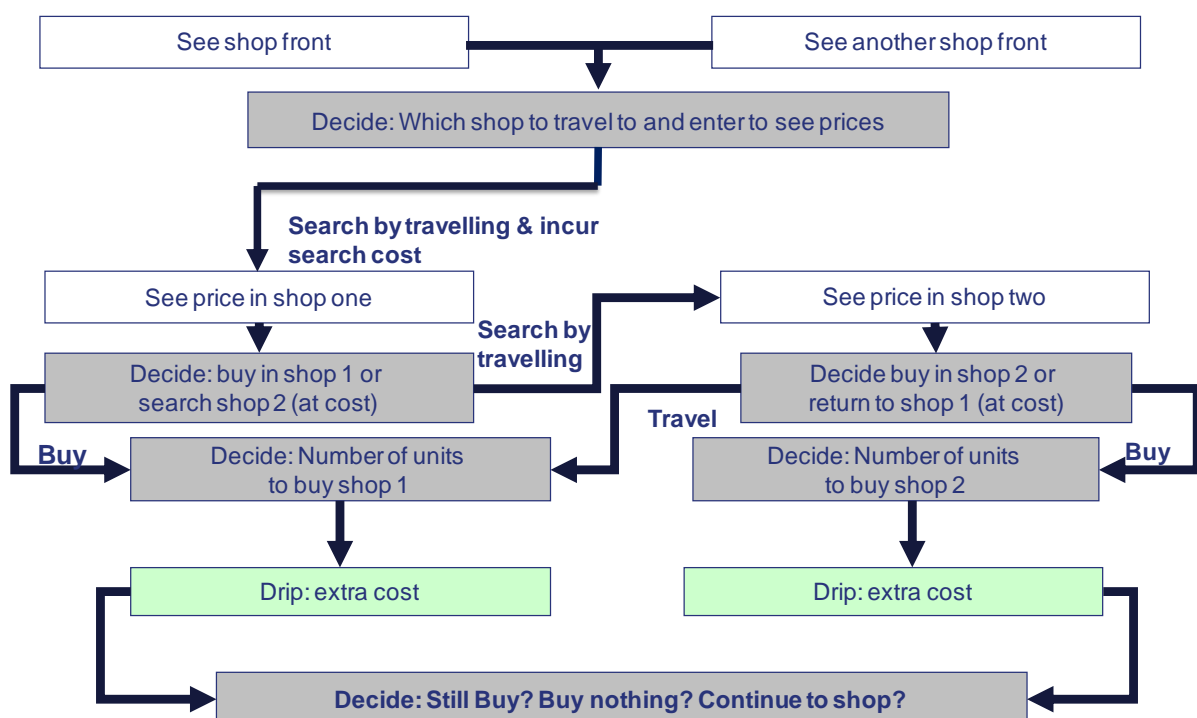
displayed is slightly modified: the final price is split into two components which will be displayed individually together with the total amount. For example,  $\pounds 54 + \pounds 6 = \pounds 60$ . Respondents in the baseline scenario and those in the 'two partitions with total' pricing scenario therefore see the same final selling price, but there is additional (and in the context of this experiment entirely meaningless) information available which consists of the extra part of the final selling price. The extra price part is randomly chosen to be between 5% and 15% of the total selling price and will be labelled as 'shipping fee'. The remainder of the total selling price is the base price.

- 3.14 The consumer decision making process in the 'two partitions with total' is therefore identical to that of the baseline shown in Figure 3.1 above.
- 3.15 The 'two partitions no total' scenario is identical to the 'two partitions with total' scenario with the exception that the total sale price is removed from the home screen. Respondents therefore have less information than in the previous two scenarios as they have to make the addition themselves to arrive at the final sale price. The final sale price is shown on the final screen where they confirm their purchase.
- 3.16 Again, the consumer decisions making process is identical to that of the baseline shown in Figure 3.1.
- 3.17 Drip pricing is also virtually identical to the baseline. Actual selling prices are determined in precisely the same manner. This time, however, consumers learn about the selling price only in drips. Once they visit a shop, they see a base price (with no mention of additional charges). Once they decide to buy one or multiple units, they see a 'drip' and need to click 'ok' to proceed. If they do so, they see the total price (and its decomposition into base price plus drip price) and they need to click one more time to confirm their purchase. So the only difference to the baseline is that respondents need to click one more time to learn the actual selling price. As

mentioned above, actual selling prices are determined in precisely the same way as in the baseline. The actual selling price is then decomposed by the computer into the base and the drip. Again, the drip is randomly chosen to be between 5% and 15% of the selling price and is labelled as 'shipping fee'. The base price is the remainder.

3.18 Figure 3.2 shows a schematic of the consumer decision making process in the 'drip pricing' frame.

**Figure 3.2: Consumer decision making process in the 'drip pricing' frame**

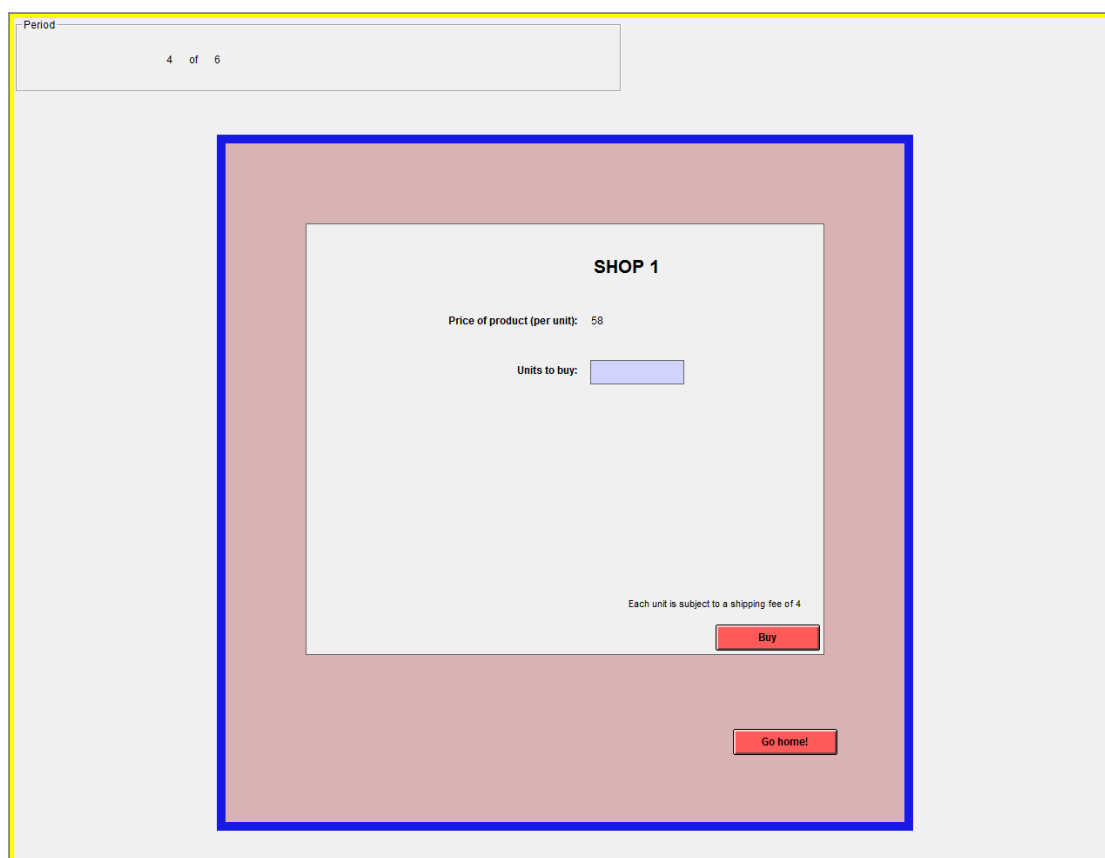


3.19 The 'presentation' frame is the same as the 'two partitions no total pricing' frame, but in this scenario the extra price part is displayed in a different position and in different font. As shown in Figure 3.3 below – the text displayed by the 'Buy' button reads 'Each unit is subject to a shipping fee of 4'.<sup>18</sup> Therefore, the position and

<sup>18</sup> The precise fee varies between decisions in the experiment.

prominence of the extra price part is different from the partitioned pricing frames where the extra price part is in the same font and sits alongside the first price part.

**Figure 3.3: Screenshot of shop 1 in the 'presentation' frame**



- 3.20 Finally, the 'three partitions no total' pricing frame is set up exactly as the 'two partitions no total' frame, with the only difference being that the final selling price is split into *two* extra parts, for example, £42 + £6 + £12. The following split is used: the first extra part is randomly chosen to be between 5% and 15% of the selling

price, and the second extra part is randomly chosen to be between 10% and 20% of the selling price.<sup>19</sup>

- 3.21 The consumer decision making process in the 'three partitions no total' is also identical to that of the baseline shown in Figure 3.1 above.

### **The consumer's optimal search strategy**

- 3.22 The consumer's optimal strategy is the same regardless of the price frame. The only thing that determines optimal search behaviour is the final selling price and the search costs, both of which are identical in each price frame.
- 3.23 The first decision is to choose one of the two shops to visit first. As there is no history and no information about the two shops, this is inevitably a random (and, hence, meaningless) decision.<sup>20</sup> So, without loss of generality, we can call the shop the consumer chooses first 'shop 1'.
- 3.24 Once the consumer is at shop 1, he can see the unit price that the shop charges in this period. He can then either buy as many units as he wants (up to a maximum of 4) or he can also decide not to buy and return to the home screen empty-handed. He can then travel to shop 2 (or indeed go back to shop 1 but that would, of course, not be reasonable as no new information would be revealed), again paying the travel/search costs,  $c$ . At shop 2 the same rules apply. That is, the consumer learns the unit price charged at shop 2 and can buy as many units as he desires. Again, he can also return empty-handed and, if he desires, return to shop

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<sup>19</sup> This split was selected to be consistent with Advertising of Prices study in which the first partition/drip was randomly chosen to be between 5% and 15% of the selling price, and the second partition/drip was randomly chosen to be between 10% and 20% of the selling price.

<sup>20</sup> This changes in the presence of some advertising, as in our previous treatment on baiting implemented as part of the 2010 study.

1. He can, of course, also return to shop even if he has bought some units already, either at shop 2 or even at shop 1, but, as is easy to see, that would also not be rational.
- 3.25 We can analytically derive the optimal consumer search strategy. The optimal search strategy is what a fully rational, risk-neutral consumer should do. Here we summarise the solution. The theory is presented in detail in Annex B.
- 3.26 As can be seen in Annex B, working out the optimal strategy is no trivial task. Given the time constraints in the experiment, it is practically impossible that any respondent could have worked out the optimal strategy. As a result, respondents had to intuitively form expectations and make decisions in the experiment, as they would have to do in the real-world.
- 3.27 Notice first that the marginal utilities and prices used in this experiment mean that it is only ever optimal to buy one or two units in total. The marginal utility of the third unit is always less than the price. This can be seen in Table 3.5 below.
- 3.28 At shop 1, there are two cut-off prices,  $p'$  and  $p''$ .  $p'$  is the cut-off for buying one unit or two units and  $p''$  is the cut-off for buying at shop 1 or searching more by visiting shop 2.
- 3.29 If the price at shop 1,  $p_1$ , is above  $p''$ , then the consumer will not buy at shop 1, but rather go to shop 2 and see what the price is there. The consumer may return to shop 1 later, depending on the price at shop 2 and the prevailing search costs.
- 3.30 If  $p_1$  is below  $p''$ , the consumer will do all their shopping at shop 1. If  $p_1$  is below  $p'$ , the consumer will buy two units at shop 1 and end the round. If  $p_1$  is above  $p'$  he will buy one unit at shop 1 and end the round.
- 3.31 As described above, in case of a price  $p_1$  above  $p''$ , the consumer will travel to shop 2. There are four different possibilities that can then arise: (i) He can buy two units at shop 2 and end the round.

(ii) He can buy one unit at shop 2 and end the round. (iii) He can decide not to buy at shop 2 and return to shop 1 to buy two units there. (iv) He can decide not to buy at shop 2, return to shop 1 and buy one unit there.

- 3.32 Which of these four options is optimal depends on the search costs and the two prices  $p_1$  and  $p_2$ . The higher the search costs, the higher the cut-off  $p''$ . Table 3.1 shows the cut-offs for the search costs we have implemented.

**Table 3.1:  $p''$  cut-off values**

Search cost	Cut-off
$c = 2$	74.5
$c = 6$	86.3
$c = 12$	97.8

Note: This is for the price range [60,120]

## Experimental procedures

- 3.33 A total of 145 respondents participated in this experiment. Each respondent was confronted with the baseline frame, 'drip pricing' and one of the four partitioned pricing frames. Respondents played for thirty rounds, ten for each type of price frame. The sequence in which they faced the different frames was randomised. We opted against a full factorial design (i.e. mixing all combinations of the frames) as the partitioned pricing frames were too similar and there was a consequent risk of spill over of effects between the frames which would have biased the comparison of behaviour between frames.
- 3.34 In order to enhance attention (and make sure that each round was viewed as a truly new round) we scaled payoffs in four different ways. Specifically, respondents faced four different goods, GREEN, ORANGE, BLUE and RED. Utilities and prices for each good were

obtained from the model above through different ways of up scaling (the model above details the utilities and prices for RED). This ensures that the basic problem is always identical, regardless of the specific goods respondents could buy. The search cost was randomly chosen each period from low, medium and high. The actual payoff, price and search costs are given in Table 3.5.

**Table 3.5: Parameters for different goods**

Product	C (search costs)	0 units	1 unit	2 units	3 units	4 units	Price Range
GREEN	1,3,6	0	60	100	110	115	30 to 60
ORANGE	1,3,6	0	80	140	170	195	50 to 80
BLUE	2,6,12	0	110	180	190	190	50 to 110
RED	2,6,12	0	120	200	220	230	60 to 120

3.35 In addition to the 30 rounds of the experiments, each respondent undertook:

1. a pre-experiment test to ensure that they understood the experimental instructions
2. a 12 question IQ test (incentivised)
3. a personality questionnaire; and
4. a feedback questionnaire about the experiment.

3.36 Experimental sessions lasted on average 130 minutes and average earnings were approximately £20, which included a £5 show-up fee.

## 4 EXPERIMENTAL RESULTS

- 4.1 In our analysis, we proceed as follows. We first study whether price frames have any effect on consumer welfare. To make treatments comparable we define losses in consumer welfare relative to what consumers could have achieved under optimal behaviour. In a second step, we employ econometrics to analyse errors in behaviour, distinguishing errors in search and errors in purchasing. Finally, we will zoom in more closely on search patterns and purchasing behaviour, in order to understand what the root causes of poor performance are and how they relate to known behavioural phenomena.

### Consumers

#### Consumer welfare

- 4.2 We first turn to the question of whether or not price frames matter for consumer welfare.
- 4.3 In order to do this, we take, for each of the 4350 observations we have, the difference between the actual achieved payoff and the payoff that would have resulted from following the optimal decision rule. We call this variable the consumer's loss. If a consumer could have achieved a payoff of 87 under optimal behaviour but only achieved a payoff of 69 then their loss is  $87 - 69 = 18$ . Often we look at the average loss a consumer has made in a particular environment, which is simply calculated as the arithmetic mean of all the losses in all rounds.
- 4.4 Additionally, we compute a further welfare indicator; the extra loss relative to the baseline loss. This is computed as follows. For each respondent we have three average loss variables, one for the baseline, and two for the two price frames encountered. The extra loss a respondent incurred under a price frame is then simply defined as the difference between the average loss in this price frame and the average loss in the baseline. We can then also

compute the extra loss made on average by all respondents under a particular price frame. This difference-in-difference approach controls for both different earning potentials under different frames and respondent-specific differences in performance levels.

- 4.5 Table 4.1 shows both loss and extra loss for all price frames and the baseline. One unit of loss translates to £0.02 in each round of the experiment. So, for example, the average loss under the 'drip pricing' frame of 3.76 translates into a monetary loss of £0.75 over ten rounds in which drip pricing is experienced. Given average earnings of £15 on top of the show-up fees over thirty rounds, this equals a loss of 15 percent of what respondents make on average in ten rounds. Likewise, in the presentation frame the monetary loss relative to optimal behaviour is £1.43, which equates to a 29 percent loss of what respondents make on average in the ten rounds.

**Table 4.1: Consumer welfare under the various price frames**

Frame number	Frame	Loss	Extra Loss
1	Baseline	4.05	0
7	2 Partitions with total	3.47	1.24
8	2 Partitions no total	2.90	-3.24* *
9	Drip pricing	3.76	-0.29
10	Presentation	7.16	2.34*
11	3 Partitions no total	2.77	-0.28

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

Extra loss = Average loss under a frame – average loss under the baseline frame (at the respondent level)

- 4.6 For each price frame, we test whether the average performance is significantly different from the baseline performance. Differences are significant for the 'two partitions no total' frame and for the 'presentation' frame. For the former, the significance level is 5% and for the latter it is 10%. The direction of the effect however is mixed, with respondents in the 'two partitions no total' frame experiencing higher welfare than under the baseline and

respondents in the 'presentation' frame experiencing a welfare loss relative to the baseline.

- 4.7 This mixed result is surprising at first glance, however the simple comparison between welfare under each price frame shown in Table 4.1 does not account for a number of factors: it is possible that respondents in certain price frames happen to be more intelligent, more focused or that they simply were luckier than respondents in other price frames. As a result, we ran ordinary least squares (OLS) regressions of prices, search costs, the scaling factor and the different price frames (where each frame is captured by a binary dummy with the baseline serving as the reference), aptitude and experimental period (which captures the effects of learning) on negative welfare loss (i.e. welfare relative to the baseline treatment). Table 4.2 below shows the estimated marginal effects; standard errors were clustered at the respondent level in order to account for dependencies resulting from repeated measurement.
- 4.8 The table is to be read as follows: each coefficient indicates by how much welfare was affected by this particular variable, holding all other variables constant. That is, controlling for aptitude, luck<sup>21</sup> and learning, respondents performed worse in the 'presentation' frame as welfare there was lower than in the baseline frame. In all other price frames welfare was not significantly different from that in the baseline.<sup>22</sup>

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<sup>21</sup> p1 and p2 control for luck in the experiment, since a low price is a lucky draw while a high price is an unlucky draw.

<sup>22</sup> It is worth noting that while the direction of the welfare effect of the price frames is positive except for the presentation frame, each point estimate is very far from being statistically different from zero. Similarly the magnitude of each point estimate is significantly smaller than on the 'd10 presentation' dummy. Hence, the positive point estimates on the other price frames are likely due to noise only and are neither statistically nor economically relevant.

**Table 4.2: The effects of price frames, learning and aptitude on welfare**

Variable	Coefficient	Standard error
p1 (price at 1st shop visited)	-0.046	0.014***
p2 (price at 2nd shop visited)	0.097	0.020***
c (search cost)	-0.056	0.066
High value	-0.002	0.004
d7 (2 partitions with total)	0.003	0.008
d8 (2 partitions no total)	0.009	0.009
d9 (drip pricing)	0.002	0.005
d10 (presentation)	-0.019	0.011*
d11 (three partitions no total)	0.007	0.007
aptitude	0.007	0.002***
period	0.003	0.000***

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

- 4.9 However, as respondents were undergraduate university students, entirely focused on the experiment, one can expect that individuals who are not as highly qualified or individuals who are more distracted may perform worse. In fact, there is strong evidence that respondents who performed better on the aptitude questions also have significantly higher welfare in the experiment. This can be seen by noting that the coefficient on aptitude in the regression table above is positive and highly significant at the 1% level.
- 4.10 Similarly, there are strong effects due to learning. As respondents play the game several times, they receive significantly higher payoffs. This can be seen by looking at the coefficient on the variable period which is positive and significant. This means that in later periods, respondents' welfare was higher.

- 4.11 In addition, it should be noted that welfare comparisons are biased against finding welfare effects because even respondents who make a 'wrong' choice, for example by purchasing an item at the first shop although the optimal decision would have been to travel to the second shop, may get lucky. That is, the realisation of the price at the second shop, had they optimally travelled there, could have been worse than the price at the first shop. As a result, any comparison in welfare will be biased towards zero since respondents who acted optimally can get unlucky and respondents who did not act optimally can get lucky.
- 4.12 As a result, there are some arguments for why in the context of this study it might be more important to focus on errors rather than overall performance. In addition to being biased towards zero, welfare comparisons are also very sensitive to the precise parameters chosen in the experiment. For example, the losses would have been much bigger if the value of the goods had been higher.<sup>23</sup>
- 4.13 The same argument holds for the experiment in the Advertising of Prices study, yet because the price frames in the 2010 study were more complex and more diverse, there were strong welfare effects. As this study tests more subtle nuances across price frames, this bias towards zero is more consequential.
- 4.14 The following section therefore analyses errors in consumer behaviour in detail.

### ***Errors in consumer behaviour***

- 4.15 There are generally two types of errors respondents can make in our experiment: Errors in their search activity and errors in

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<sup>23</sup> The scaling of the goods 'red', 'green' and 'blue' captures to what extent the relative magnitude of the payoffs affects behaviour. Namely, we answer the question "are respondents more likely to make mistakes when the stakes are high". However, if we scaled all parameters in the experiment by 10, we would also find 10 times the welfare loss.

purchasing behaviour. Errors in search activity occur where a consumer makes more or fewer visits to the shops than what is optimal. Specifically, there are two types of search errors. A consumer makes a search error if he buys at the present shop but should optimally have continued his search, we term this under-search. Or, vice versa, if he continues his search but should have optimally bought at the present shop, we term this over-search. Errors in purchasing behaviour occur where respondents do not buy the optimal amount of the good. For example, they buy one unit when it would be optimal to buy two units given prices and marginal utilities of consumption. Notice that search and purchasing errors can also occur together, for example, when a consumer buys one unit at the first shop while according to the optimal strategy he should have bought two units at the second.

- 4.16 In order to gain a preliminary understanding on errors in decision-making, we examine each of the 4350 rounds played by our 145 respondents. Whenever the observed behaviour in a given round departs from the optimal decision rule, we classify the round as a round with an error. We then regress errors on prices, search costs, the scaling factor and the different price frames (where each frame is captured by a binary dummy with the baseline serving as the reference). We use probit regressions and again we cluster the standard errors at the respondent level. Table 4.3 shows the estimated marginal effects.
- 4.17 The way to read Table 4.3 is the following: the estimated coefficients show if respondents in the experiment either searched 'too much' or 'too little' or bought 'too many' or 'too few' units (overall errors) than was optimal in the relevant price frame as compared to the overall errors that respondents made in the baseline treatment with straight per unit pricing.

**Table 4.3: Probit estimation of errors in decision making**

Variable	Coefficient	Standard Error
p1 (price at 1st shop visited)	0.053	0.063
p2 (price at 2nd shop visited)	0.117	0.051**
c (search cost)	0.132	0.213
Highvalue (the scaling; Green, Blue, Orange or Red goods)	-0.007	0.014
d7 (2 partitions with total)	-0.033	0.033
d8 (2 partitions no total)	0.054	0.030*
d9 (drip pricing)	0.037	0.018**
d10 (presentation)	0.031	0.028
d11 (three partitions no total)	0.018	0.033
period	-0.004	0.001***
aptitude	-0.026	0.006***

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%. Marginal effects at the sample mean are reported.

- 4.18 We observe significantly more errors in the 'two partitions no total' frame (at 10% significance level) and in the 'drip pricing' frame (5% significance). The significant effect seen in the 'drip pricing' frame confirms the result of the 2010 study, showing that a reduction from two drips to only one drip still leads to an increase in error rate when compared to the baseline. The magnitude of the effect however is lower than in the 2010 study (3.7% more errors in drip pricing, relative to the 14% found in the 2010 study and 5.4% in the 'two partitions no total' frame).
- 4.19 The smaller effect size is likely due to the fact that overall the pricing frames in this study are simpler and easier to understand for respondents. The drip pricing has been simplified from two to one drip and the partitioned pricing frames are simpler than the baiting sales, complex pricing or time limited offers seen in the 2010 study. In addition to these direct effects, there is a secondary effect of the simpler price frames due to faster learning: as the price frames are more similar to each other, respondents' learning

from one frame carries over to other frames. As a result, overall error making is reduced.

### **Errors in purchasing behaviour**

- 4.20 This sub-section analyses the quality in choices by looking at purchasing behaviour only. The next sub-section will look in greater detail at the errors in search behaviour. Errors in purchasing behaviour occur when respondents buy a suboptimal number of units. While determining the optimal number of units is a rather simple task (it just requires a very basic understanding of the marginal utility/pay-off table) the decision about search is more demanding.
- 4.21 We define a purchasing error as 'purchasing a positive but incorrect number of units at one shop, regardless of the correctness of search'. Therefore Table 4.4 can be read in the following way: The estimated coefficients show if respondents in the experiment either bought 'too many' units or 'too few' units than was optimal.
- 4.22 The 'drip pricing' frame emerges as resulting in significantly more purchasing errors than the baseline frame at 0.05% significance with 3% more errors. Respondents also made 2% more purchasing errors in the 'presentation' frame and this finding is significant at the 10% level.

**Table 4.4: Probit estimation of errors in purchasing behaviour**

Variable	Coefficient	Standard error
p1 (price at 1st shop visited)	-0.010	0.039
p2 (price at 2nd shop visited)	-0.068	0.030**
c (search cost)	0.236	0.118**
Highvalue (the scaling; Green, Blue, Orange or Red goods)	-0.005	0.009
d7 (2 partitions with total)	-0.025	0.017
d8 (2 partitions no total)	-0.002	0.018
d9 (drip pricing)	0.031	0.012***
d10 (presentation)	0.023	0.015*
d11 (3 partitions no total)	0.016	0.024
Period	-0.003	0.001***
aptitude	-0.013	0.003***

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%. Marginal effects at the sample mean are reported.

- 4.23 Again there is clear evidence that respondents with higher levels of aptitude make significantly fewer errors and that playing the game repeatedly also results in a reduction of errors.

### Errors in search behaviour

- 4.24 This sub-section studies in greater detail how the pricing frames affected the number of search errors made by respondents. Errors in search occur whenever a consumer continues his search while the optimal strategy prescribes immediate purchase or vice versa.
- 4.25 However before analysing the optimality of search behaviour, it is worth noting that respondents in experiments tend to search more than in real-life markets. As respondents have nothing else to do but play the game, they are likely to explore the limited space available to them to the fullest. As a result, we are likely to see significantly more search in this experiment than what one would expect to see in the real world.

- 4.26 The analysis of the 2010 study has been replicated and the results of this are shown in Table 4.5 below. No clear pattern emerges from this analysis and the only price frame which shows a significantly different number of search errors relative to the baseline is the 'two partitions no total' pricing frame. Under this price frame respondents made on average 5% more search errors than under the baseline frame.

**Table 4.5: Probit estimation of errors in search behaviour**

Variable	Coefficient	Standard error
p1 (price at 1st shop visited)	-0.023	0.063
p2 (price at 2nd shop visited)	0.193	0.044***
c (search cost)	-0.180	0.223
Highvalue (the scaling; Green, Blue, Orange or Red goods)	-0.009	0.012
d7 (2 partitions with total)	-0.023	0.027
d8 (2 partitions no total)	0.050	0.027*
d9 (drip pricing)	0.005	0.016
d10 (presentation)	-0.006	0.026
d11 (3 partitions no total)	0.005	0.027
period	-0.002	0.001***
aptitude	-0.015	0.005***

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%. Marginal effects at the sample mean are reported.

- 4.27 Again, there is evidence that respondents who performed better on the aptitude test perform better in the experiment and make fewer search errors and that playing the game repeatedly also results in fewer mistakes, that is there is evidence of learning.

- 4.28 However, these aggregate findings disguise what is happening at a finer level. Search errors can be broken down into two types: under-search, where the respondent did not search enough and over-search, where the respondent searched more than would have been optimal.
- 4.29 Table 4.6 below displays errors in under-search. In the 'two partitions no total' frame and in the 'drip pricing' frame, respondents under-searched significantly more and these results are significant at the 10% and 5% level respectively. Table 4.7 displays the regression results studying over-searching. The 'drip pricing' and 'two partitions with total' frames are both associated with significantly less over-searching.
- 4.30 The results of both regressions therefore indicate that the various pricing frames result in less search effort. This finding is particularly strong once again for drip pricing.
- 4.31 In some instances reducing search turns out to be optimal in this experimental setting. As outlined previously<sup>24</sup>, respondents have a tendency to search more in experiments than in real-world markets and therefore sometimes reducing search effort in the experiment can work out to be beneficial for the respondent. In other instances however, insufficient search results unambiguously in welfare loss.

**Table 4.6: Probit estimation under-search**

Variable	Coefficient	Standard error
p1 (price at 1st shop visited)	0.314	0.040***
p2 (price at 2nd shop visited)	0.095	0.034***

<sup>24</sup> For example, see paragraphs 1.13 and 1.19 in the executive summary outlining in greater detail why respondents in experiments tend to over-search and why we expect this not to be the case in the real-world.

c (search cost)	-0.357	0.167**
Highvalue (the scaling; Green, Blue, Orange or Red goods)	0.029	0.010***
d7 (2 partitions with total)	0.008	0.023
d8 (2 partitions no total)	0.038	0.025*
d9 (drip pricing)	0.026	0.013**
d10 (presentation)	0.023	0.023
d11 (3 partitions no total)	0.018	0.027
period	0.001	0.001*
aptitude	-0.007	0.005

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%. Marginal effects at the sample mean are reported.

**Table 4.7: Probit estimation over-search**

Variable	Coefficient	Standard error
p1 (price at 1st shop visited)	-0.315	0.045***
p2 (price at 2nd shop visited)	0.093	0.031***
c (search cost)	0.153	0.129
Highvalue (the scaling; Green, Blue, Orange or Red goods)	-0.038	0.008***
d7 (2 partitions with total)	-0.031	0.013**
d8 (2 partitions no total)	0.011	0.023
d9 (drip pricing)	-0.019	0.010**
d10 (presentation)	-0.023	0.016
d11 (3 partitions no total)	-0.010	0.015

period	-0.003	0.001 * * *
aptitude	-0.006	0.003 * *

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%. Marginal effects at the sample mean are reported.

- 4.32 This analysis was extended to look at how the size of the partition affected over-search and under-search (see Annex D for a full discussion). However, we found little evidence that the partition size had any effect on search behaviour.

## The lessons so far

- 4.33 We have seen clear evidence that identifies drip pricing as the price frame which affects consumer behaviour the most. While there is no evidence from this experiment that drip pricing leads to a reduction in welfare (as measured by participants' payoffs in the experiment), it is strongly associated with more errors in general, more purchasing errors and significantly less search effort.
- 4.34 There is evidence that the 'presentation' frame has caused a reduction in welfare and significantly more purchasing errors.
- 4.35 Finally, the 'two partitions no total' price frame also results in more general errors, more search errors and overall lower search effort.
- 4.36 In order to better understand the behavioural forces that are the root cause of poor consumer decision making we will now study search and purchasing behaviour in much finer detail.

## Zooming in

- 4.37 We will next zoom into the actual choices made in order to better understand the patterns observed in the data.
- 4.38 Here only results of the baseline price frame will be presented in detail while the effect in the other price frames will be discussed collectively. The detailed analysis of the remaining price frames can be found in Annex C.

- 4.39 Table 4.8 shows all the observations we have for our respondents at the first shop in the baseline. The rows indicate what would have been optimal, the columns what has actually been chosen. So, the first row ('0') in the table indicates all situations where the optimal strategy prescribes further search (the purchase of 0 units at the first shop). The second row contains all cases where consumers should have bought 1 unit and the third all cases where consumers should have bought 2 units. The columns indicate the actual number of units purchased.
- 4.40 Overall, the results of the baseline frame are strikingly similar to those of the baseline frame in the 2010 study. While Table 4.8 shows that respondents do generally very well in this situation (77.9% of all choices are optimal relative to 78.6% in the 2010 study) it also confirms two interesting asymmetries which were also found in the 2010 study.
- 4.41 First of all, it shows that errors are typically search errors while purchasing errors are much rarer. In this study 87.8% of all errors are search errors relative to 90.5% in the 2010 study.<sup>25</sup>
- 4.42 The second asymmetry occurs within the class of search errors. While respondents do not buy in 85.3% (86.8% in the 2010 study) of all cases when it is optimal to continue to search ( $690/809 = 0.853$ ), they buy optimally only in 68.5% of all cases (68.3% in the 2010 study) where it is optimal to buy ( $[98 + 340]/[180 + 459] = 0.685$ ). In other words, there is a clear tendency to over-search.<sup>26</sup> This is particularly dramatic when

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<sup>25</sup> Search errors are: a) when the respondent should have bought zero units at the first shop but instead bought a positive number of units, this is under-search; and, b) when the respondent should have bought a positive number of units at the first shop but bought zero units, this is over-search.

<sup>26</sup> In controlled experiment environments we do expect respondent to explore the environment and therefore even in the baseline treatment it is not unexpected to observe some over-search.

respondents should optimally buy just one unit. In this case only 54.4% (50.8% in previous experiment) of choices are correct.<sup>27</sup>

**Table 4.8: Optimal v actual choices at the first shop visited in 'baseline'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>690</b>	<i>92</i>	<i>26</i>	<i>1</i>	0	809
	1	<u>74</u>	<b>98</b>	<i>7</i>	0	1	180
	2	<u>88</u>	29	<b>340</b>	2	0	459
	Total	852	219	373	3	1	1448

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

- 4.43 Next we look at what happens at the second shop (where we only track those respondents who went there optimally).<sup>28</sup> Again, the findings here reflect what was found in the 2010 study.
- 4.44 The rate of optimal behaviour here is 90.1% (86.7% in the 2010 study) even higher than at the first shop. This partly reflects that it is an easier decision (as now all uncertainty has been resolved and all prices are known) but is also due to a selection effect. After all, the table only contains those respondents who have already made one correct decision. The asymmetries also largely disappear (there are 29 search errors and 48 purchase errors). There is no clear result of over-search or under-search once consumers have reached

<sup>27</sup> Namely,  $(98/180 = 0.544)$ .

<sup>28</sup> Notice that the number of cases in all tables that show behaviour at the second shop does not always coincide with number of cases in the (0,0) box of the first-shop tables. This is due to the fact that in some instances respondents did not buy at all.

the second store although there is more over-search (20 over-searches and 9 under-searches, that is, 6.1% of all people who should have continued to search did not do so).

**Table 4.9: Optimal v actual choices at the second shop visited in 'baseline'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>139</b>	9	0	0	0	148
	1	<u>17</u>	<b>249</b>	15	0	5	286
	2	<u>3</u>	14	<b>231</b>	1	4	253
	Total	159	272	246	1	9	687

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

- 4.45 In the other price frames, this pattern of over-searching disappears and we find that respondents are on average as likely to under-search as they are to over-search. Depending on the price frame, the rate of optimal search and purchasing behaviour is also slightly lower than it is the case in the baseline.
- 4.46 Table 4.10 summarises the percentage of optimal decisions, the percentage of over- and under-search and the percentage of respondents who make purchasing errors. We see that particularly for the price frames 'two partitions no total', 'drip pricing' and 'presentation' respondents under-search more frequently. The phenomenon of reduced over-search is particularly stark in the 'presentation' frame where only 16% of respondents over-search relative to 25% in the baseline treatment.

**Table 4.10: Summary of optimal decision making and errors made at the first shop**

	percentage optimal decision	percentage over-search	percentage under-search	percentage purchasing error
Baseline	78%	25%	15%	11%
2 partitions with total	82%	21%	15%	10%
2 partitions no total	73%	26%	21%	14%
Drip pricing	78%	18%	20%	15%
Presentation	77%	16%	21%	17%
3 partitions no total	79%	22%	16%	11%

Note: numbers do not sum to 100% because respondents can make both purchasing and search errors and because not all respondents were in a position to over-search/under-search (for example, if the optimal decision is to search, then it is not possible to over-search, but it is possible to under-search. So for the baseline the percentage under-search =  $(92 + 26)/809 = 0.146$ ).

4.47 Table 4.11 below shows the same summary statistics for decisions made at the second shop. As outlined previously, respondents make significantly fewer mistakes at the second shop, partly due to the fact that the decision is much easier and also partly due to the fact that only those who travelled to the second shop optimally are considered.

**Table 4.11: Summary of optimal decision making and errors made at the second shop**

	percentage correct	percentage over-search	percentage under-search	percentage purchasing error
Baseline	90%	4%	6%	7%
2 partitions with total	90%	3%	9%	7%
2 partitions no total	88%	5%	14%	8%
Drip pricing	82%	5%	16%	14%
Presentation	83%	6%	7%	12%
3 partitions no total	88%	6%	3%	7%

Note: numbers do not sum to 100% because respondents can make both purchasing and search errors and because not all respondents were in a position to over-search/under-search (for example, if the optimal decision is to search, then it is not possible to over-search, but it is possible to under-search.)

## Decision times

- 4.48 This sub-section studies how the amount of time respondents take to make a decision (i.e. the decision time) affects outcomes. In Annex E we look at the differences in decision times across frames and find that respondents take significantly longer to make decisions when confronted with the 'two partitions no total' frame, the 'drip pricing' frame and the 'three partitions no total frame'.<sup>29</sup> We find evidence that when respondents confirm a purchase they only take a cursory glance at the confirmation screen. Finally we find evidence that for the 'three partitions no total' frame some respondents use the confirmation screen as an easy way to find out the total price without having to do the calculations themselves, which may indicate why this frame did not appear to cause purchasing or search errors.
- 4.49 Next, we analyse whether or not the amount of time taken to complete the purchase in any way correlates with the respondent's payoff and therefore welfare. This is not straightforward to do because we expect the price frames to simultaneously affect welfare and the amount of time respondents will require to make a decision. This is particularly clear in the case of drip-pricing where respondents have to click through one additional screen which necessarily requires somewhat more time. Hence, looking only at the welfare effects of spending more time on a decision is likely to pick up some of the treatment effect of prices being framed differently.
- 4.50 As a result, we use standardised deviations in each of the price frames. That is, for each treatment we normalize the amount of time a respondent takes to complete the task relative to the mean

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<sup>29</sup> It should be noted that the 'drip pricing' frame involves one additional screen (the drip screen) which may be the main driver of this significant result.

in that treatment.<sup>30</sup> If in some treatments respondents take longer *in general* to complete the task or if in some treatments the variance in the decision time is greater, this will not affect our results.

- 4.51 We then ran an ordinary least squares regression with the standardised deviation in welfare on the left hand side and the prices at the two shops, the cost of searching, the value of the good, the price frame dummies, aptitude, period and the standardised deviation of the amount of time taken to complete the purchase. The results are shown in Table 4.12 below<sup>31</sup>.

**Table 4.12: The effects of decision time on welfare**

	Variable	Standard error
p1 (price at 1st shop visited)	-0.294	0.096***
p2 (price at 2nd shop visited)	0.737	0.150***
c (search cost)	-0.425	0.472
Highvalue (the scaling; Green, Blue, Orange or Red goods)	0.006	0.029
d7 (2 partitions with total)	-0.013	0.080
d8 (2 partitions no total)	-0.005	0.064
d9 (drip pricing)	0.002	0.034
d10 (presentation)	0.042	0.046
d11 (3 partitions no total)	-0.022	0.063
Standardized deviation of decision time	-0.123	0.033***
aptitude	0.040	0.015***
period	0.011	0.003***

<sup>30</sup> That is: standardised time = ((time taken) – (average time taken in this treatment))/(standard deviation of time taken in that treatment).

<sup>31</sup> The point estimates of the treatment effects are all small in magnitude and none are statistically significant. Therefore, we see no variation in welfare across treatments in this specification.

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

- 4.52 The results shown in Table 4.12 above indicate that respondents who take, relatively speaking, longer to complete the purchase do worse on average. It is worth noting that this result is robust to controlling for aptitude. However, our aptitude variable will not capture all the variation in ability and skill in the sample. That is, as we show in Annex E (Table E.1), respondents who perform worse in the IQ questions also tend to take longer in the experiment, and those with lower aptitude also have lower welfare (Table 4.2).<sup>32</sup>
- 4.53 This result is probably due to the fact that respondents who are less certain about whether or not to purchase take longer and are also less likely to make the correct decision. This is particularly likely when the price seen at the shop is close to the cut-off value. In this case the decision to purchase or not to purchase is most difficult and as a result also likely to require more time and more likely to be incorrect.
- 4.54 Table 4.13 below shows that respondents who take longer to make a decision are also more likely to make errors (either purchasing or search errors). Again, this is likely due to the fact that respondents take more time when the decision is most difficult, which would also be the case in the real-world markets.

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<sup>32</sup> Similarly, including an interaction term between “aptitude” and “time taken” in the regression shown in Table 4.24 shows that respondents with high aptitude levels who spend a long time on one decision perform better than respondents with low aptitude levels who spend a long time on one decision.

**Table 4.13: Probit estimation on the effects of decision time on errors**

	Variable	Standard error
p1 (price at 1st shop visited)	0.040	0.059
p2 (price at 2nd shop visited)	0.120	0.050**
c (search cost)	0.112	0.210
Highvalue (the scaling; Green, Blue, Orange or Red goods)	-0.011	0.014
d7 (2 partitions with total)	-0.032	0.032
d8 (2 partitions no total)	0.051	0.030*
d9 (drip pricing)	0.036	0.018**
d10 (presentation)	0.033	0.028
d11 (3 partitions no total)	0.018	0.030
Standardized deviation of decision time	0.035	0.012***
aptitude	-0.025	0.007***
period	-0.002	0.001**

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%. Marginal effects at the sample mean are reported.

## IQ and learning

- 4.55 Given that the decision environment in this experiment is not completely trivial and given that respondents take the same kind of decisions repeatedly, there is, just as in real life, ample scope for learning. In this sub-section we discuss whether there is any evidence for learning and whether learning is different across the different price frames.
- 4.56 The regressions presented above include a linear time trend and the results of the respondent's aptitude test. The aptitude score is between 0 and 12. Respondents who either have higher IQ or who are more focused and motivated are likely to perform better on this aptitude test.

- 4.57 Throughout almost all regressions both linear time trend and aptitude are highly significant in explaining errors made. Respondents make fewer errors as they repeat the exercise and respondents who score more highly on the aptitude test make fewer errors as well.
- 4.58 Interestingly however, this is not the case for the regressions studying under-search. In this regression, respondents are likely to make *more* errors as the experiment progresses (presumably fatigue with the experiment sets in and as a result respondents search less and therefore under-search more frequently). Aptitude also had no significant effect on the likelihood of under-searching in the experiment. Higher scores on the aptitude test are correlated with fewer over-search errors.
- 4.59 Welfare is found to be increasing in the second half of the experiment under all price frames (including the baseline). This is shown in the following table where we report welfare loss in the 1<sup>st</sup> and 2<sup>nd</sup> half of the experiment sessions by price frame.

**Table 4.14: Welfare loss across 1st and 2nd half of the experiment sessions**

Frame	1 <sup>st</sup> half	2 <sup>nd</sup> half	Average
Baseline	6.09	2.01	4.05
2 partitions with total	3.65	3.30	3.47
2 partitions no total	4.53	1.26	2.90
Drip	4.96	2.55	3.76
Presentation	11.02	3.30	7.16
2 partitions no total	3.62	1.92	2.77

## **Sellers**

- 4.60 In our analysis we have so far focussed on the effect of price frames on consumer behaviour and welfare although we had some results that pointed towards the effect on firms and, generally, the two are of course closely linked.

- 4.61 While shops were completely computerized it is still interesting to ask how their performance is affected by price frames. Price frames that perform well for the shops are not necessarily those that are detrimental for consumers. Some price frames could hurt both buyers and sellers. Of course, one would expect that in a market environment mainly those price frames are used that actually improve sellers' performance.
- 4.62 The table below shows the average number of units sold by the two shops under the different price frames as well as average turnover. The table also contains units sold and turnover for the entire industry. These industry performance indicators are perhaps the most important ones as a specific shop is, in our experiment, equally likely to become the first or the second shop.

**Table 4.15: Average number of units sold by the two shops**

Frame	Units shop 1	Units shop 2	All units (Industry indicator)	Sales revenue shop 1	Sales revenue shop 2	Total sales revenue
Baseline	.92	.62	1.54	71	49	120
2 partitions with total	.86	.66	1.52	67	53	120
2 partitions no total	.98	.58	1.56	76	45	121
Drip	.96	.56	1.52	75	45	120
Presentation	.94	.59	1.53	74	48	122
3 partitions no total	.97	.53	1.5	75	43	118

- 4.63 However, the table above does not account for the different prices encountered by respondents under each pricing frame. The table below replicates the above table relative to optimal behaviour.
- 4.64 Here we see a slight bias towards the first shop in the baseline, which is magnified by all the other price frames, in particular the 'drip pricing' and the 'presentation' frame.

- 4.65 Interestingly, the numbers on relative sales revenue is identical for the three partitioned treatments. In each of the three partitioned pricing treatments, the first shop had a positive sales revenue equal to 4 and the second shop a negative sale revue of -4 (relative to what would have happened under optimal behaviour of the subjects). We therefore see that the first shop benefited from the partitioned pricing frames, yet overall sales were no higher than under optimal behaviour.

**Table 4.16: Average effect of price frames on sellers**

Frame	Units shop 1	Units shop 2	All units (Industry indicator)	Sales revenue shop 1	Sales revenue shop 2	Total sales revenue
Baseline	.01	-.01	0	2	0	2
2 partitions with total	.02	-.06	-0.04	4	-4	0
2 partitions no total	.03	-.03	0	4	-4	0
Drip	.09	-.09	0	9	-6	3
Presentation	.11	-.09	0.02	12	-7	5
3 partitions no total	.03	-.05	-0.02	4	-4	0

### Comparison to price frames in the Advertising of Prices study

- 4.66 In a next step, we combined the data obtained from this experiment with the data obtained from the 2010 study. As the set up was identical, we can directly compare the results of the two studies and run regressions on the combined dataset.
- 4.67 Table 4.17 shows the welfare effects of each of the pricing frames in direct comparison to each other. This table reports the coefficients of an OLS regression, estimating the effects of each of the pricing frames, while controlling for price at the first shop, price at the second shop, search cost, value of the product and a dummy variable for the study (equal to zero if the observation is taken from the previous study and equal to one if it is from the current study).

- 4.68 We see that the frame 'drip pricing – two drips' remains the most detrimental to consumer welfare out of all the price frames analysed as the coefficient on 'd3 drip pricing – two drips' is large and significant. The second largest significant coefficient is found on the 'presentation' frame and finally, the third most detrimental price frame for consumers is the 'time limited offers' price frame.
- 4.69 Interestingly, we also see that the coefficient on the dummy variable for the study is significant and positive. Therefore, subjects on average performed better in the baseline treatment of this study than they did in the baseline treatment of the previous study, despite these two treatments being completely identical. This finding is likely due to the fact that overall the price frames in this study were much easier to understand than those in the previous study. As a result, subjects learned faster which in turn led to better results in the baseline treatment. In other words, the better performance in the baseline treatment is likely due to spill-over effects from the other treatments.

**Table 4.17 Welfare effects of all pricing frames (combined with data from previous experiment)**

Variable	Coefficient	Standard error
p1 (price at 1 <sup>st</sup> shop visited)	-0.066	0.012***
p2 (price at 2 <sup>nd</sup> shop visited)	0.094	0.015***
c (search cost)	-0.035	0.057
Highvalue (the scaling; Green, Blue, Orange or Red goods)	0.003	0.004
d2 (complex pricing)	-0.012	0.007*
d3 (drip pricing – two drips)	-0.040	0.012***
d4 (baiting)	-0.002	0.009
d5 (sales)	-0.010	0.011
d6 (time limited offers)	-0.016	0.008*
d7 (two partitions with total)	0.005	0.009
d8 (two partitions no total)	0.009	0.009

d9 (drip pricing – one drip)	0.003	0.005
d10 (presentation)	-0.025	0.012**
d11 (three partitions no total)	0.010	0.007
Study	0.014	0.008*

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

## Behavioural forces at work

- 4.70 We conclude our empirical analysis of consumer behaviour by reflecting on what the data tell us about behavioural forces at work. We briefly discuss each of the five pricing practices under investigation.
- 4.71 Drip pricing: As in the 2010 study, we have again seen that drip pricing turns consumers who tend to search too much into consumers who tend to search too little. This was already surprising in the 2010 experiment where respondents had to click through two drips; however this time we reduced the number of drips to only one. That is, the total price is just one extra mouse click and consumers can see the total price very clearly before they make their final purchasing decision.
- 4.72 The objective cost of going through the drip is very close to zero (just the one click – there was no time delay). Accordingly, it is completely implausible to attribute the change in behaviour to increased costs of search and sunk costs. In principle, consumers might *rationaly* decide to accept higher prices after being led through complicated drips if they were to expect equally costly practices elsewhere. Accepting a higher price at the first outlet would after all avoid the costs of clicking through a labyrinth at a competing outlet. Notice that this is an entirely rational response and has nothing to do with the so-called sunk cost fallacy where consumers ignore that they cannot recover the costs of (failed) activities and, consequently may 'throw good money after bad'. Here the extra search costs are so tiny that any explanation along the sunk costs line is simply not justified. Rather the data suggests

that respondents' willingness to pay for the good increases between seeing a low base price and seeing the additional 'shipping' charges, which is in line with loss aversion and the so-called endowment effect.<sup>33</sup> Consumers who decide to buy the product at the low price experience a shift in their reference point as they already imagine departing with the good. Changing the initial decision, that is, giving up the good that is already in the virtual basket would be perceived as a loss. This loss can be avoided by purchasing the product despite an increased price.

- 4.73 Two partitions with total: This frame is extremely close to the benchmark frame and unsurprisingly we did not see many large effects of this treatment. The only difference to the baseline is the addition of a meaningless split of the price while still displaying the total price and indeed respondents in this treatment mostly behave the same way as they do in the baseline treatment.
- 4.74 Two partitions no total: this frame is somewhat more complicated than the previous partitioned pricing frame as it requires respondents to add up two numbers. Indeed we find some evidence that this increases errors and in particular search errors and leads to reduced search effort. There are two possible explanations for this finding: First, having to sum two numbers indirectly increases the search cost and respondents respond to this by searching less. In order to compare prices effectively, respondents not only have to pay the monetary search cost 'c', but they also have to mentally add two prices at each shop and remember the sum at each shop. Second, the larger price partition may act as a price anchor resulting in respondents paying less attention to the final price.
- 4.75 Three partitions no total: This treatment is a simple extension of the above treatment. Instead of dividing the price into two partitions, it has been divided into three separate partitions. Surprisingly,

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<sup>33</sup> This is similar to the findings of previous researchers such as Morwitz, Greenleaf and Johnson (1998), and Hossain and Morgan (2006).

respondents make neither more errors, nor have lower welfare in this frame than in the baseline frame. In fact, out of all the pricing frames, this one is most similar to the baseline. There are again two possible explanations why this is the case. The first explanation is that the task of adding three numbers was too complicated for many respondents, so they simply used the final check-out screen (where they see the final price added up for them) instead of doing the calculation themselves. In fact, we do see evidence of exactly this happening when examining the decision times in detail (see above for more detail on decisions times). We also found that respondents reported doing this in the qualitative feedback they provided at the end of the experiment. The second explanation could be that with three partitions respondents also pay more attention and there is no anchoring effect. If one small number is added to one large number, the respondent may focus on the large number while disregarding the (additional) smaller number. In the case of three numbers being added, however, there is no one large price anchor and as a result respondents have to calculate the sum.

- 4.76 'Presentation' frame: the 'presentation' frame is identical to the two partitions frame with the exception that the smaller partition is not included directly next to the other partition, but instead is included in a small box before the 'Buy' button. This treatment was associated with lower welfare and more errors in purchasing behaviour. The most likely explanation is that, in addition to all the behavioural drivers listed in the two partition frames, the second partition was easier to miss and respondents therefore were more likely to make cognitive errors by simply 'missing' the second partition. Similarly any anchoring effect on the first part of the price is also likely to be more pronounced when the second partition is more hidden.

## Summary

4.77 In Table 4.18 we attempt a summary of our main findings, indicating for each price frame how it impinges on welfare and errors, how it affects stores and which kind of behavioural bias (if any) can be identified to be driving the data.

**Table 4.18: Summary of main findings**

	Significant welfare losses	Significantly more errors	Significantly less search	1 <sup>st</sup> shop benefits	Behavioural biases
Drip pricing (1 drip)	No	Yes	Yes	Yes	Endowment effect/loss aversion
Two partitions with total	No	No	Yes	Yes	Cognitive errors
Two partitions no total	No	Yes	Yes	Yes	Cognitive errors/ higher search cost
Presentation	Yes	Yes	No	Yes	Cognitive errors
Three partitions no total	No	No	No	Yes	Cognitive errors

## 5 EXTERNAL VALIDITY AND IMPLICATIONS FOR NON-LABORATORY MARKETS

- 5.1 External validity for studies of this nature is typically highly asymmetric. Both simplification and stylisation of the decision problems and the highly selected respondent pool imply that we are more likely to observe good or even optimal performance in the laboratory than in the field under real world conditions. This implies that whenever we find close to perfect performance, external validity is severely limited. If student respondents do well in a simple task it is hard to conclude that the general population would do well in a more complicated real-world environment. However, if a highly selected student sample does badly in a simple decision environment that also offers scope for repetition and learning, it would be very surprising if the general population did much better in the real world.
- 5.2 Given this asymmetry, the design choices we took carried certain risks. We designed a very simple search environment that was, given our requirement (multiple units, two stages), as simple as possible. It would have been difficult to design a simpler environment. Similarly, the implementation of the price frames was typically simple and respondents could experience them repeatedly in an almost identical manner. The risk of these design choices was that we might have found close to optimal performance in all treatments in which case we would have learned very little from this study.
- 5.3 The alternative strategy to design a more complicated environment would have entailed different risks. In more complicated environments decision errors and noise would invariably increase and accordingly it would be more difficult to detect differences between treatments for given sample sizes.
- 5.4 However, as we have documented we have observed differences between treatments. The results on drip pricing stand out. Being 'just one click away' from the baseline, its effects on search

patterns and performance are surprising. It is likely that the effects that stem from loss aversion or the endowment effect will be even stronger in the real world where drip mechanics are more elaborate and it is more time consuming to reach a stage where full prices are clearly visible. On top of that, more elaborate drips will also increase the true costs of searching for the price, which will enhance the effects from loss aversion. Similarly, we have not tried to optimise the drip sizes and it would be highly unlikely if we had, by accident, stumbled across the most effective drips. Once again, this suggests that, if anything, we might still underestimate the true effect of drip pricing.

- 5.5 The same thing can be said about the other partitioned pricing practices examined in this study. Out of the partitioned pricing frames considered here, the 'presentation' frame is maybe closest, yet simpler, to what one might expect to see in real-life markets and this was the treatment in which we saw negative welfare effect for respondents in the experiment. In real-life markets, where presentation is more complex, this is likely to be an even bigger problem for consumers. In the experiment we placed the second price part right next to the 'Buy' button and there were no other distractions on the screen. Hence, our findings in all 'partitioned' pricing frames are likely to underestimate consumer detriment.
- 5.6 Given our basic design choices and selection of respondents the observation holds, of course, more generally: there is a built-in tendency to underestimate consumer detriment for all price frames.
- 5.7 In our experiment, both price frames and prices themselves are exogenously fixed while in real markets they are chosen. Given our data it appears clear that certain price frames will allow firms to charge higher prices (in particular those that trigger loss aversion and the endowment effect as these effects are akin to increased willingness to pay or an outward shift of the demand curve). Consumers would then suffer in two ways: first from their direct negative consequences we measure in this experiment *and* second from the higher prices.

- 5.8 One aspect of endogenous choice of price frames that we have not studied at all is that sellers in the same market might choose different price frames which make price comparisons much harder.<sup>34</sup> This situation is also known as ‘confusopoly’: firms making price structures unnecessarily confusing, thereby making it difficult for consumers to evaluate rival offers. As a result, firms avoid having to compete on price.<sup>35</sup> With added confusion from a greater variety of price frames, consumers might actually suffer from the entry of additional sellers.
- 5.9 On the other hand firms may elect to not use price frames that annoy customers. Firms may seek to establish a reputation for not using annoying practices, such a drip pricing.
- 5.10 While we can neither validate nor reject these theoretical predictions we can make some inferences about how our findings on relevant behavioural biases would impact on markets. Clearly, the strongest force that causes consumer detriment in our experiment is the endowment effect or loss aversion. Consumers’ imagination of owning a good shifts their willingness to pay. We observe strong evidence of this in drip pricing. In the field there will be many other practices that play on these effects. If the consumer tries out a product in a shop it will give him some objective information about how the product handles but it also makes envisaging ownership easier and what we have seen here is that envisaging ownership is all that is needed to increase willingness to pay.
- 5.11 There are, of course, many institutional and physical details that will matter for the effect of these practices in non-laboratory markets. For example, it might be easier to encourage the

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<sup>34</sup> As Chioveanu and Zhou (2009) show these effects can even overturn standard intuition on how the number of firms in a market relates to consumer welfare.

<sup>35</sup> <http://oft.gov.uk/OFTwork/public-markets/choice-and-competition/Confusopoly/>

imagination of ownership for some goods than for others. By thinking about the product characteristics that make imagination of ownership easier, we could then derive comparative static predictions about in which markets we would expect to observe certain price frames more frequently.

- 5.12 Summarising, let us stress however again that we have good reason to believe in the general external validity of our results – that these practices do cause consumer detriment and that what we identify in the laboratory is probably rather the tip of the iceberg as there are many aspects of real-life markets that will accentuate the problems we document here. Although inevitably there are also likely to be some factors in real life which will mitigate concerns about practices (even when frames are complex) such as the desire for firms to build reputation, and consumers to learn about honest firms.

## A SCREEN SHOTS FROM THE EXPERIMENT

Figure A.1: Home Screen in baseline

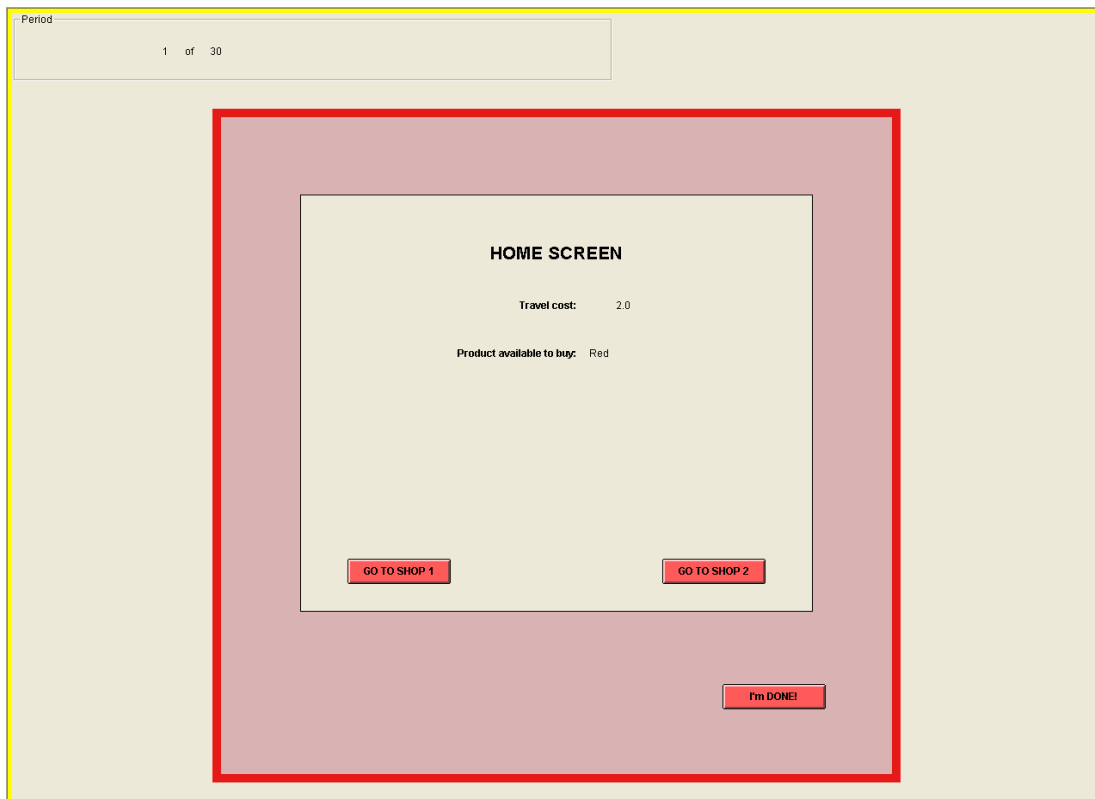


Figure A.2: Shop 1 screen in baseline

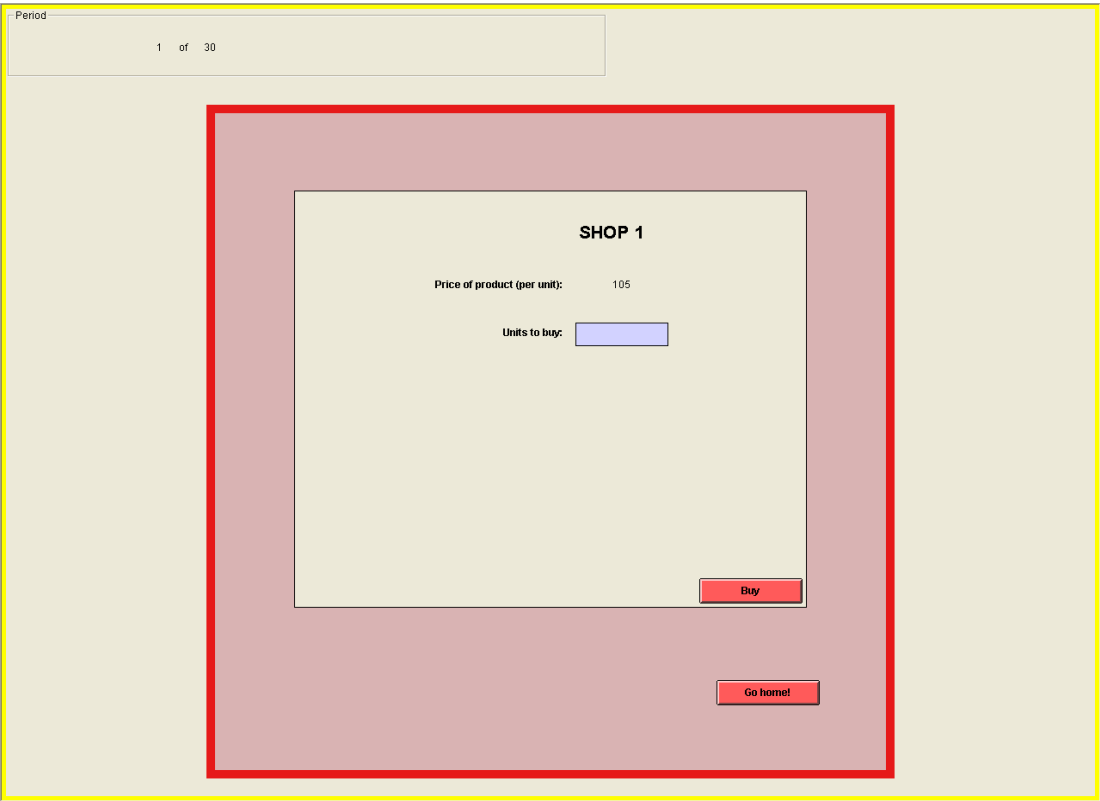


Figure A.3: Purchase confirmation dialogue in baseline

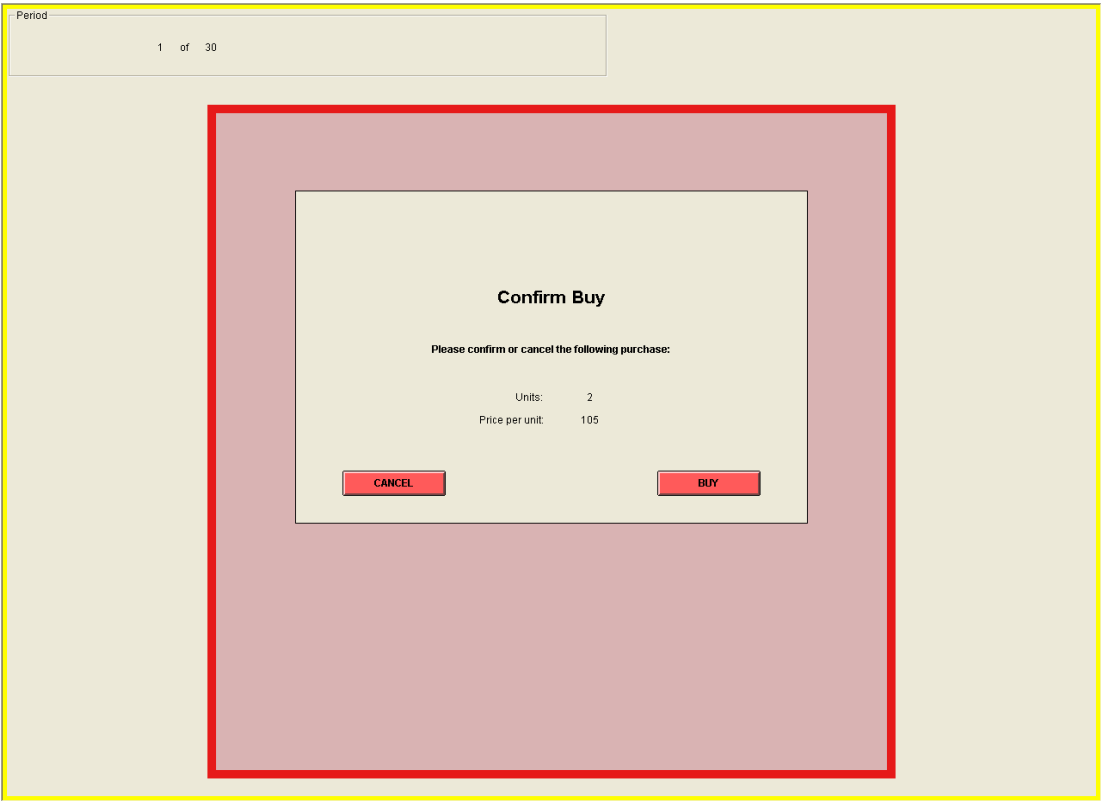


Figure A. 4: Purchase notification



**Figure A.5: Confirm exit from period**

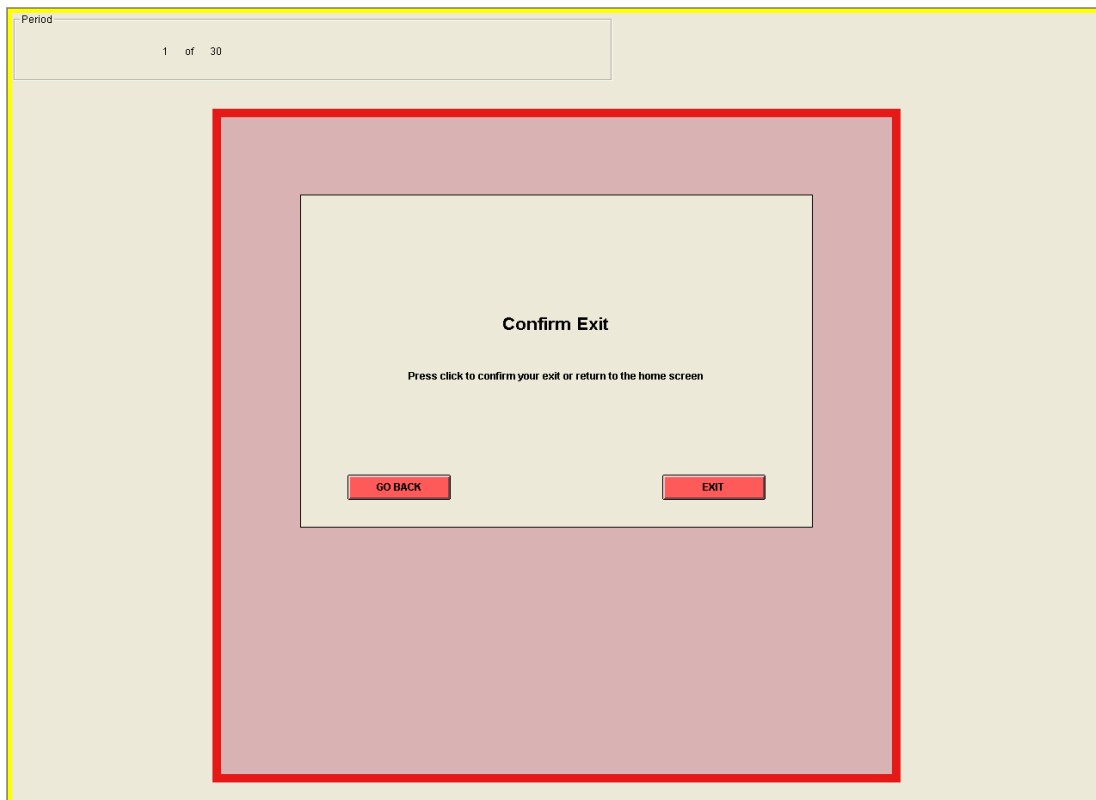


Figure A.6: Results screen

Period

1 of 30

RESULTS

Units purchased:2

Total Points:200

Buying costs:210

Number of shop visits:1

Travel Costs:2.0

Earnings this period:-12.0

OK

**Figure A.7: Shop screen in 2 partitions with total frame**

Period

1 of 6

SHOP 1

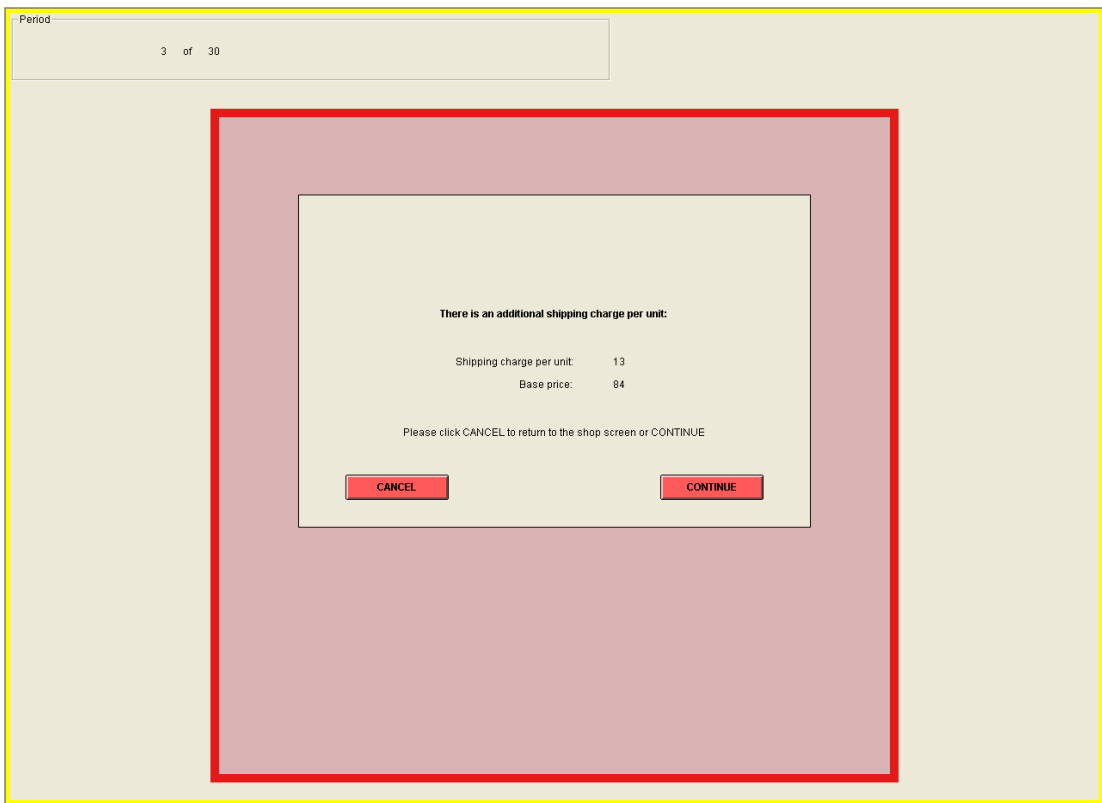
Price of product (per unit): 29 plus 5 shipping = 34

Units to buy:

Buy

Go home!

Figure A.8: Drip screen



**Figure A.9: Confirmation in 'drip pricing' frame**

[illegible]

**Figure A.10: Shop screen in 2 partitions with no total frame**

Period

2 of 6

SHOP 1

Price of product (per unit): 62 plus 9 shipping

Units to buy:

Buy

Go home!

**Figure A.11: Shop screen 'presentation' frame**

The diagram illustrates a shop screen layout with three nested frames. The outermost frame is yellow and contains a header bar at the top with the text "Period" and "4 of 6". Inside this is a light gray frame, which contains a darker gray frame. The innermost frame is titled "SHOP 1" and contains the following elements: "Price of product (per unit): 58", a label "Units to buy:" followed by a light blue input field, the text "Each unit is subject to a shipping fee of 4", a red "Buy" button, and a red "Go home!" button.

Period 4 of 6

**SHOP 1**

Price of product (per unit): 58

Units to buy:

Each unit is subject to a shipping fee of 4

Buy

Go home!

**Figure A.12: Shop screen in 3 partitions with no total frame**

Period

5 of 6

SHOP 1

Price of product (per unit): 55 plus 10 shipping plus 11 handling

Units to buy:

Buy

Go home!

## B OPTIMAL SEARCH STRATEGY

### Baseline model optimum search strategy

#### 1 Introduction & Assumptions

In this document, we derive the optimal search and purchasing strategy for the baseline pricing strategy.

Suppose the travel costs are  $c < 1/3$ . Without loss of generality, suppose the buyer goes to shop 1 and observes price  $p_1$  drawn from  $(1/2, 1)$ .

In general, there are two strategies that we need to consider:

Strategy 1: stay at shop 1 and buy some number of units.

Strategy 2: go to shop 2 and observe price  $p_2$ . If  $p_2$  is low enough, stay there and buy some number of units and otherwise come back to shop 1 and buy some number of units (i.e. two potential cases).

We split the analysis up into three sections, firstly finding the best search and buying strategy for the case  $p_1 \in (1/2, 2/3)$ , secondly finding the best search and buying strategy for case where  $p_1 \in (2/3, 1)$  and finally deriving the optimal overall strategy.

#### 2 Low price in shop 1: $p_1 \in (1/2, 2/3)$

##### 2.1 Strategy 1

Buy 2 units at shop 1 to give a payoff of  $\pi = 5/3 - 2p_1$ .

##### 2.2 Strategy 2

At shop 2, there are two cases:

*Case 1:*  $p_2 \in (1/2, 2/3)$  which occurs with probability  $1/3$ . Stay at shop 2 if:

$$\frac{5}{3} - 2p_2 \geq \frac{5}{3} - 2p_1 - c \quad \Rightarrow \quad p_2 < p_1 + \frac{c}{2} \quad (1)$$

If  $p_1 > 2/3 - c/2$ , then inequality (1) will always hold, the buyer will always stay at shop 2, the expected price at shop two will be  $= (1/2 + 2/3)/2 = 7/12$  and the expected profit will be  $5/3 - 2 * 7/12 - c = 1/2 - c$ .

If  $p_1 < 2/3 - c/2$  and inequality (1) holds, then the expected price  $p_2$ , given that they are staying, will be half way between  $1/2$  and  $p_1 + c/2 = 1/2(1/2 + p_1 + c/2)$ . So  $\pi = 5/3 - 2p_2 - c = 7/6 - p_1 - 3c/2$ . The overall probability that  $p_2 < p_1 + c/2$  is  $6(p_1 + c/2 - 1/2)$ .

Alternatively, the probability that inequality (1) doesn't hold, given that  $p_1 < 2/3 - c/2$  is  $1 - 6(p_1 + c/2 - 1/2)$  and the expected payoff in this case is the payoff from returning to shop 1, which is  $5/3 - 2p_1 - 2c$ .

Summary:

1. If  $p_1 > 2/3 - c/2$  buyer will stay at shop 2 with probability 1 and get  $E(\pi) = 1/2 - c$ .
2. If  $p_1 < 2/3 - c/2$  and (1) holds, buyer will stay at shop 2 and get  $E(\pi) = 7/6 - p_1 - 3c/2$ . Probability =  $6(p_1 + c/2 - 1/2)$ .
3. If  $p_1 < 2/3 - c/2$  and (1) does not hold, buyer will return to shop 1 and  $E(\pi) = 5/3 - 2p_1 - 2c$ . Probability =  $1 - 6(p_1 + c/2 - 1/2)$ .

Case 2:  $p_2 \in (2/3, 1)$  which occurs with probability  $2/3$ . Stay at shop 2 if:

$$1 - p_2 \geq \frac{5}{3} - 2p_1 - c \Rightarrow p_2 < 2p_1 + c - \frac{2}{3} = p_2^* \quad (2)$$

Let us find for what values of  $p_1$ ,  $p_2^*$  is in the given range.  $p_2^* > 2/3$  if  $p_1 > 2/3 - c/2$  and  $p_2^* < 1$  if  $p_1 < 5/6 - c/2$ . The latter is always met. But the former is not necessarily always met.

If  $p_1 < 2/3 - c/2$ , then go back to shop 1 with probability 1 to get  $\pi = 5/3 - 2p_1 - 2c$ .

If  $p_1 > 2/3 - c/2$  then stay if inequality (2) is satisfied.

$$\begin{aligned} \Pr((2) \text{ holds}) &= \Pr(p_2 < 2p_1 + c - 2/3) \\ &= \frac{(2p_1 + c - 2/3) - 2/3}{1 - 2/3} = 6p_1 + 3c - 4 \end{aligned}$$

$$\Pr((2) \text{ does not hold}) = \Pr(p_2 > 2p_1 + c - 2/3) = 5 - 6p_1 - 3c$$

If inequality (2) holds, then expected price,  $p_2 = 1/2 * (2p_1 + c - 2/3 + 2/3) = p_1 + c/2$ . Hence expected profit if buyer stays is  $1 - p_1 - 3c/2$ . The expected

profit if you return is  $\pi = 5/3 - 2p_1 - 2c$ .

Summary:

1. If  $p_1 < 2/3 - c/2$  buyer go back to shop 1 with probability 1 and get  $E(\pi) = 5/3 - 2p_1 - 2c$ .
2. If  $p_1 > 2/3 - c/2$  and (2) holds, buyer will stay at shop 2 and get  $E(\pi) = 1 - p_1 - 3c/2$ . Probability =  $6p_1 + 3c - 4$ .
3. If  $p_1 > 2/3 - c/2$  and (2) does not hold, buyer will return to shop 1 and  $E(\pi) = 5/3 - 2p_1 - 2c$ . Probability =  $1 - (6p_1 + 3c - 4)$ .

### 3 High price in shop 1: $p_1 \in (2/3, 1)$

#### 3.1 Strategy 1

Buy 1 unit to give a payoff of  $\pi = 1 - p_1$ .

#### 3.2 Strategy 2

In shop 2, there are two cases:

*Case 1:*  $p_2 \in (1/2, 2/3)$  which occurs with probability  $1/3$ . As  $p_2 < p_1$ , clearly stay at shop 2, with an expected price of  $(1/2 + 2/3)/2 = 7/12$ , and get an expected profit of  $\pi = 5/3 - 2p_2 - c = 1/2 - c$ .

Summary:

1. Stay at shop 2, buy 2 units with  $E(\pi) = 1/2 - c$

*Case 2:*  $p_2 \in (2/3, 1)$  which occurs with probability  $2/3$ . Stay at shop 2 if:

$$1 - p_2 \geq 1 - p_1 - c \Rightarrow p_2 < c + p_1 \quad (3)$$

Suppose  $p_1 > 1 - c$ . Then (3) is automatically satisfied, so stay at shop 2 and  $p_2$  is unrestricted and expected price is  $(1 + 2/3)/2 = 5/6$  so expected profit is  $1 - p_2 - c = 1/6 - c$ .

Suppose instead  $p_1 < 1 - c$ . Then the probability that (3) is satisfied is:

$$Pr(p_2 < p_1 + c) = \frac{p_1 + c - 2/3}{1 - 2/3} = 3(p_1 + c - 2/3)$$

The expected price is then  $(p_1 + c + 2/3)/2$ , so the expected profit is  $(2/3 - p_1/2 - 3c/2)$ . The alternative is to return to shop 1 and get a payoff of  $1 - p_1 - 2c$ .

1. If  $p_1 > 1 - c$  stay at 2 with probability 1 and get  $E(\pi) = 1/6 - c$ .
2. If  $p_1 < 1 - c$  and (3) holds, buyer will stay at shop 2 and get  $E(\pi) = 2/3 - p_1/2 - 3c/2$ . Probability =  $3(p_1 + c - 2/3)$ .
3. If  $p_1 < 1 - c$  and (3) does not hold, buyer will return to shop 1 and  $E(\pi) = 1 - p_1 - 2c$ . Probability =  $1 - 3(p_1 + c - 2/3)$ .

## 4 Optimal overall search strategy

We have derived the optimal strategies for the various combinations of eventualities. We now combine these to produce the optimal overall strategy, having observed  $p_1$ .

### 4.1 $p_1 \in (1/2, 2/3)$

#### 4.1.1 $p_1 < 2/3 - c/2$

Stay at shop 1 if:

$$\frac{5}{3} - 2p_1 > \frac{1}{3}(6(p_1 + \frac{c}{2} - \frac{1}{2})(\frac{7}{6} - p_1 - \frac{3c}{2}) + (1 - 6(p_1 + \frac{c}{2} - \frac{1}{2}))(\frac{5}{3} - 2p_1 - 2c)) + \frac{2}{3}(\frac{5}{3} - 2p_1 - 2c)$$

This simplifies to:

$$2p_1^2 - 2p_1 + 2cp_1 + \frac{c^2}{2} - 3c + \frac{1}{2} < 0$$

Completing the square and solving yields the condition on  $p_1$  to stay at shop 1:

$$p_1 < \frac{1}{2} - \frac{c}{2} + \sqrt{c}$$

#### 4.1.2 $p_1 > 2/3 - c/2$

Stay at shop 1 if:

$$\frac{5}{3} - 2p_1 > \frac{1}{3}(\frac{1}{2} - c) + \frac{2}{3}((6p_1 + 3c - 4)(1 - p_1 - \frac{3c}{2}) + (1 - (6p_1 + 3c - 4))(\frac{5}{3} - 2p_1 - 2c))$$

This simplifies to:

$$4p_1^2 - \frac{14p_1}{3} + c^2 + 4cp_1 - \frac{13c}{3} + \frac{25}{18} < 0$$

Completing the square and solving yields the condition on  $p_1$  to stay at shop 1:

$$p_1 < \frac{7}{12} - \frac{c}{2} + \frac{1}{12}\sqrt{72c-1}$$

## 4.2 $p_1 \in (2/3, 1)$

### 4.2.1 $p_1 > 1 - c$

Stay at shop 1 if:

$$1 - p_1 > \frac{1}{3} * \left(\frac{1}{2} - c\right) + \frac{2}{3}\left(\frac{1}{6} - c\right) \Rightarrow p_1 < c + \frac{13}{18}$$

Otherwise, go to shop 2 and stay there.

### 4.2.2 $p_1 < 1 - c$

Stay at shop 1 if:

$$1 - p_1 > \frac{1}{3}\left(\frac{1}{2} - c\right) + \frac{2}{3}\left(3\left(p_1 + c - \frac{2}{3}\right)\left(\frac{2}{3} - \frac{p}{2} - \frac{3c}{2}\right) + \left(1 - 3\left(p_1 + c - \frac{2}{3}\right)\right)\left(1 - p_1 - 2c\right)\right)$$

This simplifies to:

$$1 - p_1 > c^2 + 2cp - 3c + p^2 - 2p + \frac{23}{18} \Rightarrow c^2 + 2cp - 3c + p^2 - p + \frac{5}{18} < 0$$

Completing the square and solving yields the condition on  $p_1$  to stay at shop 1:

$$\left[p_1 + \left(c - \frac{1}{2}\right)\right]^2 < 2c - \frac{1}{36} \Rightarrow p_1 < \frac{1}{2} - c + \frac{1}{6}\sqrt{72c-1}$$

## C ZOOMING IN ON SEARCH AND PURCHASING BEHAVIOUR

C.1 Here we outline in detail what happens to respondents' search and purchasing behaviour under each of the price frames.

### Two partitions with total

C.2 Table C.1 below shows the optimal and actual choices respondents made under the 'Two partitions with total' frame. The number of respondents making the optimal decision is higher than in the baseline at 81.6%. There are 30 errors of over-searching and 33 errors of under-searching, indicating that, unlike in the baseline treatment, these two errors are equally prevalent.

**Table C.1: Optimal v actual choices at the first shop visited in '2 partitions with total'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>194</b>	<i>30</i>	<i>3</i>	0	0	227
	1	<u>18</u>	<b>18</b>	1	0	0	37
	2	<u>12</u>	4	<b>90</b>	0	0	106
	Total	224	52	94	0	0	370

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

C.3 At the second shop once again the ratio of correct decisions is even higher (and nearly identical to that in the baseline) with 90.2% of respondents making the optimal choice. There are only very few observations, as there were few respondents optimally travelling to the second shop, meaning that it is difficult to compare over- and under-searching. Nonetheless also here over- and under-searching appear roughly equally important with four respondents under-searching and five over-searching.

**Table C.2: Optimal v actual choices at the second shop visited in '2 partitions with total'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>43</b>	<i>4</i>	0	0	0	47
	1	<u>3</u>	<b>70</b>	4	0	0	77
	2	<u>2</u>	5	<b>62</b>	0	1	70
	Total	48	79	66	0	1	194

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

## Two partitions no total

C.4 Under the 'two partitions no total' only 73.3% of choices at the first shop are optimal relative to 78% in the baseline. Again, there are no clear patterns of over- or under-searching unlike in the baseline treatment confirming that this particular frame has resulted in a general reduction in search.

**Table C.3: Optimal v actual choices at the first shop visited in '2 partitions no total'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>151</b>	<i>33</i>	<i>7</i>	<i>0</i>	<i>1</i>	192
	1	<u>21</u>	<b>28</b>	1	0	0	50
	2	<u>23</u>	9	<b>85</b>	1	0	118
	Total	195	70	93	1	1	360

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

- C.5 The ratio of optimal to non-optimal choices at the second store is lower under this price frame than under the baseline frame. Eighty-eight percent of choices are optimal relative to 90% in the baseline frame. Once again, the number of over and under-searches at the second shop is negligible.

**Table C.4: Optimal v actual choices at the second shop visited in '2 partitions no total'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>31</b>	<i>5</i>	0	0	0	36
	1	<u>6</u>	<b>44</b>	2	0	0	52
	2	0	4	<b>58</b>	0	1	63
	Total	37	53	60	0	1	151

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

## Drip pricing

- C.6 Table C.5 shows the choices at the first shop for drip pricing, with one drip. In this frame 77.6% of all choices at the first shop were optimal relative to the 77.9% seen in the baseline. This is significantly higher than the rate of optimal decision making observed in the previous experiment (70.9%) with two drips as opposed to one.
- C.7 Under drip pricing respondents optimally do not buy when it is optimal to continue searching in 79.9% of the cases, which is slightly less than the 85% in the baseline. However they do buy the optimal number of units in 74.7% of all cases where the correct decision to buy a positive

number of units.<sup>36</sup> This proportion is significantly more than the 68.5% who did so in the baseline treatment.

C.8 That is, we again see evidence that the extent of over-searching has been reduced relative to the baseline frame. This can also be seen by noting that 164 respondents bought at the first shop when searching would have been optimal (under-search), but only 112 respondents searched when purchasing either one or two units would have been optimal (over-search).

C.9 This represents a clear shift from the baseline frame in which over-search was more common than under-search.

**Table C.5: Optimal v actual choices at the first shop visited in '1 drip'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>652</b>	<i>131</i>	<i>33</i>	0	0	816
	1	<u>52</u>	<b>124</b>	27	0	0	203
	2	<u>60</u>	18	<b>349</b>	2	1	430
	Total	764	273	409	2	1	1449

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

C.10 Table C.6 below summarizes the choices made at the second shop where 81.5% of respondents chose optimally, significantly less than the 90% seen in the baseline frame.

<sup>36</sup> Namely,  $([124 + 349]/[203 + 430] = 0.747)$

**Table C.6: Optimal v actual choices at the second shop visited in '1 drip'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>103</b>	<i>17</i>	<i>1</i>	<i>0</i>	<i>1</i>	122
	1	<u>27</u>	<b>234</b>	35	0	0	296
	2	<u>1</u>	32	<b>196</b>	0	2	231
	Total	131	283	232	0	3	649

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

## Presentation

C.11 Under the 'presentation' frame 76.7% of respondents made the optimal choice at the first shop relative to the 77.9% in the baseline. As in the drip price frame, there is clear evidence of more under-searching than over-searching in the data (45 under-search and 23 over-search).

**Table C.7: Optimal v actual choices at the first shop visited in 'presentation'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>168</b>	<i>41</i>	<i>2</i>	<i>1</i>	<i>1</i>	213
	1	<u>14</u>	<b>26</b>	5	0	0	45
	2	<u>9</u>	9	<b>82</b>	0	2	102
	Total	191	76	89	1	3	360

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

**Table C.8: Optimal v actual choices at the second shop visited in 'presentation'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>26</b>	<i>1</i>	<i>1</i>	0	0	28
	1	<u>8</u>	<b>68</b>	9	0	0	85
	2	<u>1</u>	5	<b>44</b>	2	2	54
	Total	35	74	54	2	2	167

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

### Three partitions no total

C.12 Under the three partitions no total frame 78.9% of choices was optimal and here under and over-searching appear equally prevalent.

**Table C.9: Optimal v actual choices at the first shop visited in '3 partitions no total'**

		Actual choice					
		0	1	2	3	4	Total
Optimal choice	0	<b>166</b>	<i>26</i>	<i>5</i>	0	0	197
	1	<u>12</u>	<b>32</b>	3	0	0	47
	2	<u>24</u>	6	<b>86</b>	0	0	116
	Total	202	64	94	0	0	360

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search.

**Table C.10: Optimal v actual choices at the second shop visited in '3 partitions no total'**

		Actual choice					
--	--	---------------	--	--	--	--	--

		0	1	2	3	4	Total
Optimal choice	0	<b>39</b>	<i>1</i>	0	0	0	40
	1	<u>6</u>	<b>65</b>	5	0	0	76
	2	<u>1</u>	5	<b>42</b>	1	0	49
	Total	46	71	47	1	0	165

Note: Bold figures are 'optimal' decisions. Figures in 'italics' are under-search; and, figures 'underlined' are over-search

## D EFFECT OF PARTITION SIZE

### The effect of the size of the partition

- D.1 The previous analysis has shown that the various price frames result in a reduction in search effort. Here we discuss whether the size of the partition (or the drip) also affected respondents' behaviour. In order to do so, we ran several OLS regressions which included the size of the partition or drip (expressed as a percentage of the overall price) as a dependent variable. These regressions focus only on the treatments with two partitions and therefore the treatment with three partitions has been excluded from this analysis. The size of the partition/drip randomly varied between 5% and 15% of the total selling price.
- D.2 Table D.1 shows the results of the regression analysing to what extent under-search occurring at the first shop has been affected by the price at the first shop, the scaling of the product, the search cost, the treatments, aptitude and learning and the size of the partition (or drip in the case of drip pricing).
- D.3 The findings indicate that a larger partition size has no significant effect on under-search which can be seen by the fact that the coefficient on 'partition size' is not significant. Similarly Table D.2 below shows the results of the same regression for over-search. A larger partition size is associated with less over-search, however the result again is not statistically significant.

**Table D.1: The effect of the size of the partition on under-search at the first shop**

Variable	Coefficient	Standard error
p1 (price at 1st shop visited)	0.227	0.043***
Highvalue (the scaling; Green, Blue, Orange or Red goods)	0.034	0.009***

c (search cost)	-0.058	0.164
Partition size	-0.183	0.129
d7 (two partitions with total)	0.031	0.031
d8 (two partitions no total)	0.063	0.035 *
d9 (drip pricing)	0.054	0.025 **
d10 (presentation)	0.061	0.037
period	0.001	0.001 **
aptitude	-0.008	0.005

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

**Table D.2: The effect of the size of the partition on over-search at the first shop**

Variable	Coefficient	Standard error
p1 (price at 1st shop visited)	-0.395	0.044 ***
Highvalue (the scaling; Green, Blue, Orange or Red goods)	-0.025	0.008 ***
c (search cost)	0.398	0.118 ***
Partition size	-0.049	0.106
d7 (two partitions with total)	-0.013	0.020
d8 (two partitions no total)	0.017	0.029
d9 (drip pricing)	-0.019	0.018
d10 (presentation)	-0.031	0.018 *
period	-0.002	0.001 ***
aptitude	-0.005	0.003

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

D.4 At first glance, we therefore do not find any evidence that the size of the partition affects search behaviour. However, the above regression

examined the effect of partition size in all price frames and cannot distinguish if partition size has a different effect in different treatments.

- D.5 In order to test whether or not partition size matters in any single treatment, the following regression includes interaction terms between the partition size and each of the treatments. This allows us to see if the size of the partition affects behaviour differently under different price frames. If this were the case, we would expect to see a significant coefficient on the interaction term.
- D.6 Results in Table D.3 and D.4 reveal an interesting effect of the size of the partition in the 'presentation' frame. The results show that the 'presentation' frame overall results in more under-search (positive and significant coefficient on the variable 'd10 (presentation) '). However, we see that as the size of the partition increases, under-search is reduced (negative and significant coefficient on the interaction term 'd10 (presentation) \* partition size').
- D.7 This result is rather intuitive and in line with expectations: Having a small additional cost right before clicking 'Buy' reduces search efforts. However, a large additional fee before clicking 'Buy' stands out and prompts the shopper to search further. This is particularly the case in the presentation frame because the additional fee is not presented directly next to the base price.
- D.8 Results for over-search, shown in Table D.3, are also in line with this finding. The presentation frame itself resulted in less over-search (negative and significant coefficient on 'd10 (presentation frame) ' and as the partition size increases over-search increases (although the coefficient on the interaction term is not statistically significant).

**Table D.3: The effect of the size of the partition between treatments on under-search at the first shop**

	Coefficient	Standard error
p1 (price at 1st shop visited)	0.227	0.043***
Highvalue (the scaling; Green, Blue, Orange or Red goods)	0.034	0.009***

c (search cost)	-0.056	0.164
d7 (2 partitions with total)	0.053	0.058
d8 (2 partitions no total)	0.054	0.044
d9 (drip pricing)	0.033	0.027
d10 (presentation)	0.170	0.089*
d7 (2 partitions with total) *		
partition size	-0.320	0.283
d8 (2 partitions no total) *		
partition size	-0.128	0.230
d9 (drip pricing) * partition		
size	-0.035	0.154
d10 (presentation) * partition		
size	-0.729	0.335**
period	0.001	0.001**
aptitude	-0.008	0.005

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

**Table D.4: The effect of the size of the partition between treatments on over-search at the first shop**

	Coefficient	Standard error
p1 (price at 1st shop visited)	-0.395	0.044***
Highvalue (the scaling; Green, Blue, Orange or Red goods)	-0.025	0.008***
c (search cost)	0.397	0.118***
d7 (2 partitions with total)	-0.013	0.034
d8 (2 partitions no total)	0.009	0.035
d9 (drip pricing)	-0.013	0.022
d10 (presentation)	-0.042	0.023*
d7 (2 partitions with total) *		
partition size	-0.048	0.259
d8 (2 partitions no total) *		
partition size	-0.002	0.193
d9 (drip pricing) * partition		
size	-0.089	0.136

d10 (presentation) * partition		
size	0.068	0.272
period	-0.002	0.001 * * *
aptitude	-0.005	0.003

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

## E DECISION TIMES

- E.1 This annex studies how the amount of time respondents take to make a decision (i.e. the decision time) varies by price frame and by respondent characteristics. Table E.1 shows the results of an OLS regression which analyses how the average time taken depends on the price at the first shop, the price at the second shop, the cost of searching, whether or not it was a high value good, the type of pricing strategy used, the aptitude of the respondent and any learning effects. Standard errors are again clustered at the respondent level.
- E.2 The estimated coefficients can be interpreted as follows: the price, either at the first or the second shop, has no statistically significant effect on the amount of time respondents take to arrive at a decision. Higher search costs however lead respondents to spend more time contemplating their decision. Similarly, respondents contemplate their purchasing decisions longer when the good has a higher value (both these results are statistically significant at the 1 % level). In regard to the price frames, respondents take significantly longer in the 'two partitions no total', the drip pricing and the 'three partitions no total' frames (again, results are significant at the 1 % level). Comparing these three price frames against each other, we see that respondents take the longest in the 'drip pricing' frame, followed by 'three partitions no total' and finally in the 'two partitions no total' frame. Respondents did not take significantly longer in the 'two partitions with total' frame and the 'presentation' frame as compared to the baseline.
- E.3 However, it should be noted that the 'drip pricing' frame includes one more screen than the other price frames and as a result respondents necessarily will take longer to complete the task under this frame. Below, we study the time respondents take for each individual action, which allows us to study how long respondents spend between each individual mouse click. Table E.1 also allows us to see that respondents who score higher on the aptitude test generally take less time to complete a task (however as discussed below this does not suggest that 'speeding' through a task leads to a better outcome). Similarly, there is

also strong evidence that respondents get faster at the task as they repeat it several times.

**Table E.1: Decision time by pricing strategy and respondent characteristics**

	Variable	Standard error
p1 (price at 1st shop visited)	-2.395	2.655
p2 (price at 2nd shop visited)	-1.626	2.565
c (search cost)	55.691	12.313***
Highvalue (the scaling; Green, Blue, Orange or Red goods)	2.562	0.732***
d7 (2 partitions with total)	1.403	1.710
d8 (2 partitions no total)	6.011	1.741***
d9 (drip pricing)	12.422	0.794***
d10 (presentation)	1.430	1.826
d11 (3 partitions no total)	9.901	1.793***
aptitude	-1.071	0.541**
period	-1.347	0.057***

Note: Stars indicate significant differences to baseline, \* 10%, \*\* 5%, \*\*\* 1%

E.4 We next turn to each individual action to see where respondents spend most of their time. After having travelled to a shop the first decision respondents have to make is whether to purchase an item or to go back home. Table E.2 below summarises the median amount of time respondents take for each of these decisions under each price frame.

**Table E.2: Mean amount of time taken to make the first decision at the first shop**

	Go home	Buy
Benchmark	4.805 (687)	14.937 (760)
d7 (2 partitions with total)	6.583 (215)	24.648 (155)
d8 (2 partitions no total)	7.442 (181)	28.844 (179)

d9 (drip pricing)	5.086	16.24
	(523)	(925)
d10 (presentation)	7.0045	21.7465
	(180)	(180)
d11 (3 partitions no total)	15.491	23.2675
	(164)	(196)

Note: number of observations in parentheses

- E.5 In all price frames except the 'three partitions no total' frame, respondents take on average between five and seven seconds to decide not to purchase anything at this store but to go back home. Respondents take much longer to decide not to purchase anything and instead go home when the price consists of three separate partitions.
- E.6 For the decision to purchase, on the contrary, there is a much clearer distinction between treatments, although the average time taken to purchase the item in the baseline and the 'drip price' frames are the lowest.
- E.7 In a next step we analyse the amount of time respondents take for the next decision, the decision to confirm their purchase or to cancel the process. Respondents who selected to 'buy' items on the first screen are prompted with either a confirmation screen, or in the case of 'drip pricing', a second price screen followed by the confirmation screen. The mean decision time taken for each of these actions is summarised in Table E.3 below.

**Table E.3: Mean amount of time taken to confirm a purchase or to cancel**

	Confirm after first drip	Cancel after first drip	Confirm purchase	Cancel
Benchmark			1.817	1.576
			(582)	(178)
d7 (2 partitions with total)			1.6145	4.929
			(152)	(3)

d8 (2 partitions no total)			1.966	4.618
			(170)	(9)
d9 (drip pricing)	6.521	6.7155	2.59	5.741
	(567)	(358)	(532)	(35)
d10 (presentation)			2.106	13.1355
			(174)	(6)
d11 (3 partitions no total)			2.698	5.912
			(163)	(33)

Note: number of observations in parentheses

- E.8 Several things stand out in this table: First, the average amount of time taken to confirm a purchase is very short across all treatments, suggesting that respondents only had a cursory glance at the confirmation screen.
- E.9 Second, a very large number of respondents cancel their purchase in the benchmark pricing frame (30% of all respondents) and in the 'three partitions no total' frame (20% of all respondents).
- E.10 For the 'three partitions no total' frame, it is possible that some respondents learnt to use the confirmation screen instead of adding up the partitions themselves.<sup>37</sup> This could also explain why respondents who choose to 'buy' on the first screen on average do not take longer in the 'three partitions no total' frame than in all the other frames while respondents who choose to 'go home' take longer in this price frame (Table E.3 above).
- E.11 For the benchmark treatment a likely explanation of why there are so many cancellations is that respondents were testing whether or not they were in the 'drip pricing' frame before contemplating the purchase. That is, before even considering the offer, respondents wanted to see if this

---

<sup>37</sup> This is confirmed in the qualitative comments provided by a number of respondents at the end of the experiment.

was the full price or if the full price would be revealed on the next page.<sup>38</sup>

- E.12 In order to check the possibilities outlined above we can look at how long respondents take to click the first 'Buy' button conditional on whether or not they confirm the purchase on the following screen. For example, we can see if respondents who cancelled at the confirmation screen took more or less time to decide to purchase in the first place.
- E.13 Table E.4 below shows respondents who went to cancel the purchase in the benchmark treatment only took 6.6 seconds to decide to purchase relative to 18.6 seconds taken by respondents who confirmed their purchase. This clearly indicates that respondents who were quick to choose to buy were also significantly more likely to cancel the purchase. There are two explanations for this: either respondents who act too quickly make more mistakes and therefore have to cancel more frequently, or respondents deliberately choose very quickly on the first screen in order to identify the pricing strategy.
- E.14 Exactly the same pattern can be seen in the 'three partitions no total price' frame, where respondents who cancel the purchase only took 7.3 seconds to decide they want to purchase the item, while respondents who confirmed their purchase took 21.2 seconds to decide they want to purchase. This supports the theory suggested above that respondents use the confirmation screen in place of adding up the partitions themselves.

**Table E.4: The median amount of time taken on the decision to 'purchase' conditional on the following decision.**

	confirm after first drip	Cancel after first drip	Confirm purchase	Cancel purchase
Benchmark			18.6335	6.599

<sup>38</sup> The treatments were randomised and therefore some respondents would have experienced the drip pricing frame before they experienced the baseline frame.

			582	178
d7 (2 partitions with total)			24.796	7.94
			152	3
d8 (2 partitions no total)			29.391	13.416
			170	9
d9 (drip pricing)	19.562	12.402	19.679	14.008
	567	358	532	35
d10 (presentation)			21.661	32.690
			174	6
d11 (3 partitions no total)			26.208	7.348
			163	33

## **F      FEEDBACK QUESTIONNAIRE**

Here are the questions that we asked the respondent in the questionnaire. Note that not all respondents received all parts of question 3.

1. Did you feel the instructions were clear?
2. What was your strategy during the experiment (in terms of shops to visit, where to purchase and number of units to buy)?
3. Do you have any comments on the shopping experience where you encountered a:
  - a. [partitioned pricing] Do you have any comments on the shopping experience where the price was split into more than one component, but all displayed on the same screen?
  - b. [drip pricing] Do you have any comments on the shopping experience a situation where you needed to add shipping charge after choosing how many units to buy?
4. Were there any aspects of the shopping experience that you enjoyed? Please explain what and why.
5. Were there any aspects of the shopping experience that you found annoying? Please explain what and why.
6. How did the experiment, pricing practices you encountered and your behaviour mirror/reflect your experience of shopping?
7. How old are you in years?
8. Which gender are you?
9. What subject, if any, are you studying?
10.      Any other comments.

## **G PERSONALITY TEST**

The personality survey consisted of the following statements. Subjects had to choose how strongly they agreed or disagreed with them.

I am somebody who:

1. Is often worried.
2. Is communicative and talkative.
3. Works systematically and thoroughly.
4. Has original ideas.
5. Is sometimes a little tough on others.
6. Tends to be lazy.
7. Becomes nervous easily.
8. Is sociable and can let their hair down.
9. Values artistic experiences.
10. Can forgive others.
11. Is reserved.
12. Has a vivid imagination.
13. Treats others respectfully and politely.
14. Is relaxed and can cope with stress easily.
15. Solves tasks efficiently and effectively.

Developed by Schupp and Gerlitz , DIW German Institute for Economic Research, 2005.

## G REGRESSION DETAILS

Variables used in regressions:

Dependent variables:

diff\_u. This is the welfare loss

var err "Indicator variable for errors made". These are either search or purchasing errors.

var err\_n\_3 "Indicator variable for error in the number units bought". These are purchasing errors.

err\_v "Indicator variable for in search ".

undersearch "indicator variable for when the optimal strategy would have been to search but the subject did not do so"

oversearch "indicator variable for when the subject searched, although the optimal strategy would have been not to"

undersearch\_at\_1 "indicator variable for when the optimal strategy at shop 1 would have been to search, but the subject did not do so"

oversearch\_at\_1 "indicator variable for when the optimal strategy at shop 1 would have been to not search, but the subject did search"

time "overall amount of time taken by the subject to complete the task"

Independent variables:

subject: Subject number

price\_strategy: Pricing strategy (1=baseline, 2=complex, 3=drip, 4=bait, 5=reference, 6=time limited)

p1: Price at first shop visited

p2: Price at second shop visited

c: Search cost

highvaluegood: Dummy for whether the good was high value

aptitude: Aptitude (0 = worst, 12 = best)

d7 = dummy for partitioned pricing with total

d8 = dummy for partitioned pricing no total

d9 = dummy for drip pricing

d10 = dummy for presentation

d11 = dummy for three partitions no total

period: the experimental period, time trend

aptitude: number of correct responses in the aptitude test

drip\_proportion: the relative size of the partition (or drip) with respect to the overall price

d7drip\_proportion: interaction between dummy for price frame 7 and the relative size of the partition

d8drip\_proportion: interaction between dummy for price frame 8 and the relative size of the partition

d9drip\_proportion: interaction between dummy for price frame 9 and the relative size of the partition

d10drip\_proportion: interaction between dummy for price frame 10 and the relative size of the partition

## Welfare regression

This is an ordinary least squares regression studying the welfare effects of the various pricing frames, learning and aptitude.

### Reported in Table 4.2: The effects of price frames, learning and aptitude on welfare

reg diff\_u p1 p2 c highvalue d7 d8 d9 d10 d11 aptitu period, cluster(subject)

Linear regression

Number of obs = 4350

F( 11, 144) = 7.02

Prob > F = 0.0000

R-squared = 0.0524

Root MSE = .13568

(Std. Err. adjusted for 145 clusters in subject)

-----						
	Robust					
diff_u	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----						
	+					
p1	-.0458058	.0140087	-3.27	0.001	-.0734949	-.0181166
p2	.0965433	.0196042	4.92	0.000	.0577941	.1352925
c	-.0563246	.0655867	-0.86	0.392	-.1859616	.0733124
highvaluegood	-.0017313	.0040756	-0.42	0.672	-.0097871	.0063245
d7	.0027322	.0083949	0.33	0.745	-.013861	.0193254
d8	.0087422	.0091176	0.96	0.339	-.0092793	.0267637
d9	.002476	.0045287	0.55	0.585	-.0064754	.0114274
d10	-.0190262	.0105117	-1.81	0.072	-.0398033	.001751
d11	.00721	.0067319	1.07	0.286	-.006096	.020516
aptitude	.0066801	.0019642	3.40	0.001	.0027977	.0105626
period	.0025171	.0003893	6.47	0.000	.0017477	.0032865
_cons	-.1726482	.0309132	-5.58	0.000	-.2337504	-.111546
-----						

## Error regressions

This is the probit regression studying the effects of the various pricing frames, learning and aptitude on errors made (search and purchasing combined).

### Reported in Table 4.3: Probit estimate of errors in decision making

```
dprobit err p1 p2 c highvaluegood d7 d8 d9 d10 d11 period aptitude , cluster(subject )
```

```
Iteration 0: log pseudolikelihood = -2678.1013
```

```
Iteration 1: log pseudolikelihood = -2619.2878
```

```
Iteration 2: log pseudolikelihood = -2619.2515
```

```
Iteration 3: log pseudolikelihood = -2619.2515
```

```
Probit regression, reporting marginal effects      Number of obs = 4350
```

```
Wald chi2(11) = 53.31
```

```
Prob > chi2 = 0.0000
```

```
Log pseudolikelihood = -2619.2515
```

```
Pseudo R2 = 0.0220
```

```
(Std. Err. adjusted for 145 clusters in subject)
```

	Robust						
err	dF/dx	Std. Err.	z	P> z	x-bar	[ 95% C.I. ]	
p1	.0528824	.062546	0.84	0.398	.751469	-.069705 .17547	
p2	.117427	.0510072	2.29	0.022	.751421	.017455 .217399	
c	.1321746	.2130066	0.62	0.535	.055467	-.285311 .54966	
highva~d*	-.0068923	.0142258	-0.48	0.628	.489655	-.034774 .02099	
d7*	-.032993	.0334669	-0.96	0.337	.085057	-.098587 .032601	
d8*	.0540669	.0304089	1.83	0.067	.082759	-.005533 .113667	
d9*	.0367288	.0181124	2.05	0.041	.333333	.001229 .072228	
d10*	.0308853	.0280618	1.12	0.264	.082759	-.024115 .085885	
d11*	.0183086	.0325784	0.57	0.570	.082759	-.045544 .082161	
period	-.0041291	.0008819	-4.66	0.000	15.5	-.005858 -.002401	
aptitude	-.0255955	.0060262	-4.27	0.000	9.83448	-.037407 -.013784	
obs. P	.3057471						
pred. P	.3020209 (at x-bar)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1

z and P>|z| correspond to the test of the underlying coefficient being 0

This is a probit regression estimating the effects of the various pricing frames, aptitude and learning on purchasing errors.

#### Reported in Table 4.4: Probit estimation of errors in purchasing behaviour

```
dprobit err_n_3 p1 p2 c highvaluegood d7 d8 d9 d10 d11 period aptitude if err_n_1==0 &
err_n_2==0, clust
> er(subject )
```

```
Iteration 0: log pseudolikelihood = -1237.966
Iteration 1: log pseudolikelihood = -1175.2506
Iteration 2: log pseudolikelihood = -1174.2753
Iteration 3: log pseudolikelihood = -1174.2745
Iteration 4: log pseudolikelihood = -1174.2745
```

```
Probit regression, reporting marginal effects      Number of obs = 4226
              Wald chi2(11) = 89.18
              Prob > chi2  = 0.0000
Log pseudolikelihood = -1174.2745      Pseudo R2   = 0.0514
```

(Std. Err. adjusted for 145 clusters in subject)

	Robust						
err_n_3	dF/dx	Std. Err.	z	P> z	x-bar	[ 95% C.I. ]	
p1	-.0103705	.0390915	-0.27	0.790	.749744	-.086988 .066248	
p2	-.0681963	.0302206	-2.29	0.022	.751274	-.127428 -.008965	
c	.2361882	.1179721	2.04	0.041	.055182	.004967 .467409	
highva~d*	-.0047734	.0086193	-0.56	0.578	.490535	-.021667 .01212	
d7*	-.0253943	.0167181	-1.29	0.196	.085897	-.058161 .007372	
d8*	-.0018906	.0181381	-0.10	0.918	.083531	-.037441 .033659	
d9*	.031192	.0116688	2.82	0.005	.332466	.008322 .054062	
d10*	.0233629	.0148272	1.68	0.092	.082111	-.005698 .052424	
d11*	.0157287	.0243762	0.68	0.494	.082584	-.032048 .063505	
period	-.0026366	.0005374	-4.61	0.000	15.6235	-.00369 -.001583	
aptitude	-.0128891	.0025312	-5.06	0.000	9.8398	-.01785 -.007928	
obs. P	.0858968						
pred. P	.0763913 (at x-bar)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| correspond to the test of the underlying coefficient being 0

This is a probit regression estimating the effects of the various pricing frames, aptitude and learning on search errors.

### Reported in Table 4.5: Probit estimation of errors in search behaviour

```
dprobit err_v p1 p2 c highvaluegood d7 d8 d9 d10 d11 period aptitude , cluster(subject )
```

```
Iteration 0: log pseudolikelihood = -2342.8272
```

```
Iteration 1: log pseudolikelihood = -2309.645
```

```
Iteration 2: log pseudolikelihood = -2309.6149
```

```
Probit regression, reporting marginal effects      Number of obs = 4350
```

```
Wald chi2(11) = 40.67
```

```
Prob > chi2 = 0.0000
```

```
Log pseudolikelihood = -2309.6149      Pseudo R2 = 0.0142
```

```
(Std. Err. adjusted for 145 clusters in subject)
```

		Robust					
err_v	dF/dx	Std. Err.	z	P> z	x-bar	[ 95% C.I. ]	
p1	-.0228096	.0628299	-0.36	0.717	.751469	-.145954 .100335	
p2	.1925231	.0436799	4.37	0.000	.751421	.106912 .278134	
c	-.1804767	.2228838	-0.81	0.418	.055467	-.617321 .256368	
highva~d*	-.0092752	.0118911	-0.78	0.437	.489655	-.032581 .014031	
d7*	-.0234881	.0266404	-0.86	0.392	.085057	-.075702 .028726	
d8*	.0495116	.0266524	1.94	0.052	.082759	-.002726 .101749	
d9*	.0054331	.0156778	0.35	0.728	.333333	-.025295 .036161	
d10*	-.0062522	.0255516	-0.24	0.808	.082759	-.056332 .043828	
d11*	.0051257	.0273723	0.19	0.851	.082759	-.048523 .058775	
period	-.0022379	.0008357	-2.65	0.008	15.5	-.003876 -.0006	
aptitude	-.0151121	.0045736	-3.34	0.001	9.83448	-.024076 -.006148	
obs. P	.2294253						
pred. P	.2263367	(at x-bar)					

(\*) dF/dx is for discrete change of dummy variable from 0 to 1

z and P>|z| correspond to the test of the underlying coefficient being 0

The following two regressions study the effects of the pricing frames, aptitude and learning on under and over-search respectively.

### Reported in Table 4.6: Probit estimation under-search

dprobit undersearch p1 p2 highvaluegood c d7 d8 d9 d10 d11 period aptitude, cluster(subject )

Iteration 0: log pseudolikelihood = -1600.1042  
 Iteration 1: log pseudolikelihood = -1537.062  
 Iteration 2: log pseudolikelihood = -1536.3157  
 Iteration 3: log pseudolikelihood = -1536.3155

Probit regression, reporting marginal effects      Number of obs = 4350  
    Wald chi2(11) = 140.18  
    Prob > chi2 = 0.0000  
 Log pseudolikelihood = -1536.3155              Pseudo R2 = 0.0399

(Std. Err. adjusted for 145 clusters in subject)

	Robust						
unders~h	dF/dx	Std. Err.	z	P> z	x-bar	[	95% C.I. ]
p1	.3137767	.0397078	9.79	0.000	.751469	.235951	.391603
p2	.0945135	.0343214	2.69	0.007	.751421	.027245	.161782
highva~d*	.029086	.0095821	3.11	0.002	.489655	.010305	.047867
c	-.3565839	.1673238	-2.20	0.028	.055467	-.684532	-.028635
d7*	.0076922	.0225035	0.35	0.727	.085057	-.036414	.051798
d8*	.0379447	.0248189	1.68	0.094	.082759	-.0107	.086589
d9*	.0258612	.0125844	2.09	0.037	.333333	.001196	.050526
d10*	.0229633	.0231868	1.04	0.298	.082759	-.022482	.068409
d11*	.0177768	.0265523	0.70	0.484	.082759	-.034265	.069818
period	.0010444	.0006051	1.75	0.080	15.5	-.000142	.00223
aptitude	-.0074451	.0050129	-1.50	0.133	9.83448	-.01727	.00238
obs. P	.1204598						
pred. P	.1105612	(at x-bar)					

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
 z and P>|z| correspond to the test of the underlying coefficient being 0

## Reported in Table 4.7: Probit estimation over-search

```
. dprobit oversearch p1 p2 highvaluegood c d7 d8 d9 d10 d11 period aptitude, cluster(subject )
```

```
Iteration 0: log pseudolikelihood = -1497.9095
Iteration 1: log pseudolikelihood = -1406.9906
Iteration 2: log pseudolikelihood = -1405.2395
Iteration 3: log pseudolikelihood = -1405.2374
```

```
Probit regression, reporting marginal effects      Number of obs = 4350
              Wald chi2(11) = 183.86
              Prob > chi2   = 0.0000
Log pseudolikelihood = -1405.2374      Pseudo R2   = 0.0619
```

(Std. Err. adjusted for 145 clusters in subject)

	Robust						
overse~h	dF/dx	Std. Err.	z	P> z	x-bar	[ 95% C.I. ]	
p1	-.3153993	.0449157	-9.01	0.000	.751469	-.403432	-.227366
p2	.09349	.030509	3.09	0.002	.751421	.033694	.153287
highva~d*	-.037974	.0084953	-4.43	0.000	.489655	-.054624	-.021324
c	.1529671	.1288636	1.20	0.231	.055467	-.099601	.405535
d7*	-.0308698	.0134646	-2.02	0.043	.085057	-.05726	-.00448
d8*	.0112091	.0230019	0.51	0.612	.082759	-.033874	.056292
d9*	-.0193458	.0096281	-1.96	0.050	.333333	-.038217	-.000475
d10*	-.0226042	.0160028	-1.33	0.185	.082759	-.053969	.008761
d11*	-.010055	.015459	-0.63	0.527	.082759	-.040354	.020244
period	-.0030069	.0005701	-5.05	0.000	15.5	-.004124	-.00189
aptitude	-.0064999	.0032999	-2.00	0.045	9.83448	-.012968	-.000032
obs. P	.1089655						
pred. P	.0946566 (at x-bar)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| correspond to the test of the underlying coefficient being 0

This ordinary least squares regression shows the effects of the various pricing frames, aptitude and learning on the amount of time respondents take in the experiment.

### Reported in Table 4.12: Decision time by pricing strategy and respondent characteristics

```
reg time p1 p2 c highvaluegood d7 d8 d9 d10 d11 apt period, cluster(subject)
```

```
Linear regression               Number of obs = 36085
                               F( 11, 144) = 70.74
                               Prob > F   = 0.0000
                               R-squared   = 0.1477
                               Root MSE = 32.17
```

(Std. Err. adjusted for 145 clusters in subject)

-----							
		Robust					
time		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----							
	+						
	p1	-2.395136	2.655372	-0.90	0.369	-7.643678	2.853406
	p2	-1.625605	2.564604	-0.63	0.527	-6.694738	3.443527
	c	55.69136	12.31294	4.52	0.000	31.3539	80.02881
highvaluegood		2.562226	.7323397	3.50	0.001	1.114702	4.00975
	d7	1.402822	1.70981	0.82	0.413	-1.976747	4.78239
	d8	6.011174	1.741127	3.45	0.001	2.569707	9.452641
	d9	12.42208	.7938041	15.65	0.000	10.85307	13.9911
	d10	1.430172	1.825531	0.78	0.435	-2.178126	5.038471
	d11	9.901356	1.793196	5.52	0.000	6.35697	13.44574
aptitude		-1.071069	.5405559	-1.98	0.049	-2.139518	-.0026196
period		-1.347346	.0565675	-23.82	0.000	-1.459156	-1.235536
_cons		66.16946	5.927553	11.16	0.000	54.45321	77.88572
-----							

The following OLS regression studies how welfare correlates with the amount of time taken in the experiment, while controlling for pricing frame, aptitude and learning.

**Reported in Table 4.16: the effects of decision time on welfare**

```
reg std_diff_u p1 p2 c highvaluegood d7 d8 d9 d10 d11 std_time apt period ,
cluster(subject)
```

Linear regression	Number of obs =	4350
	F( 12, 144) =	7.10
	Prob > F	= 0.0000
	R-squared	= 0.0593
	Root MSE	= .97067

(Std. Err. adjusted for 145 clusters in subject)

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
std_diff_u	p1	-.2938987	.0957454	-3.07	0.003	-.4831467	-.1046508
	p2	.7372118	.15017	4.91	0.000	.4403895	1.034034
	c	-.4247698	.4719541	-0.90	0.370	-1.357623	.508083
highvaluegood		.006357	.0294167	0.22	0.829	-.0517874	.0645014
	d7	-.0126278	.0798498	-0.16	0.875	-.1704569	.1452014
	d8	-.0048678	.0640075	-0.08	0.939	-.1313836	.1216479
	d9	.0020485	.0338839	0.06	0.952	-.0649255	.0690226
	d10	.0416961	.0463144	0.90	0.369	-.0498478	.1332399
	d11	-.0216411	.0628003	-0.34	0.731	-.1457706	.1024883
	std_time	-.1234356	.0330942	-3.73	0.000	-.1888487	-.0580224
	aptitude	.0397832	.0145191	2.74	0.007	.0110851	.0684812
	period	.0108886	.0025671	4.24	0.000	.0058145	.0159626
	_cons	-.8735379	.2396109	-3.65	0.000	-1.347147	-.3999289

The following OLS regression studies how the amount of time taken in the experiment correlates with whether or not the respondent made an error.

**Reported in Table 4.17: The effects of decision time on errors**

Linear regression

Number of obs = 4350  
F( 12, 144) = 4.77  
Prob > F = 0.0000  
R-squared = 0.0321  
Root MSE = .45395

(Std. Err. adjusted for 145 clusters in subject)

			Robust				
	err	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
	p1	.0404569	.0590138	0.69	0.494	-.0761884	.1571021
	p2	.1198527	.0503754	2.38	0.019	.0202819	.2194235
	c	.112284	.2095537	0.54	0.593	-.3019147	.5264826
highvaluegood		-.0107547	.0141278	-0.76	0.448	-.0386793	.0171699
	d7	-.0319771	.031988	-1.00	0.319	-.0952039	.0312496
	d8	.0510585	.0295005	1.73	0.086	-.0072514	.1093684
	d9	.0357472	.0175694	2.03	0.044	.00102	.0704744
	d10	.0326532	.0276348	1.18	0.239	-.021969	.0872753
	d11	.0175132	.0300349	0.58	0.561	-.0418532	.0768795
	std_time	.0354033	.012378	2.86	0.005	.0109372	.0598694
	aptitude	-.0249242	.0067064	-3.72	0.000	-.0381799	-.0116684
	period	-.0022002	.0010439	-2.11	0.037	-.0042636	-.0001369
	_cons	.44597	.0944251	4.72	0.000	.2593317	.6326083

The following regression studies the effect of the size of the partition (or drip) on under-search

### Reported in Table D.1 The effect of the size of the partition on under-search at the first shop

```
dprobit undersearch_at_1 p1 highvaluegood c drip_proportion d7 d8 d9 d10 period aptitude if
price_strat
> egy !=11, cluster(subject )
```

```
Iteration 0: log pseudolikelihood = -1318.9151
Iteration 1: log pseudolikelihood = -1267.03
Iteration 2: log pseudolikelihood = -1266.3988
Iteration 3: log pseudolikelihood = -1266.3986
```

```
Probit regression, reporting marginal effects      Number of obs = 3990
              Wald chi2(10) = 96.91
              Prob > chi2  = 0.0000
Log pseudolikelihood = -1266.3986      Pseudo R2   = 0.0398
```

(Std. Err. adjusted for 145 clusters in subject)

	Robust						
unders~1	dF/dx	Std. Err.	z	P> z	x-bar	[ 95% C.I. ]	
p1	.2268608	.0428422	6.02	0.000	.752414	.142892 .31083	
highva~d*	.0341659	.0093746	3.74	0.000	.493233	.015792 .05254	
c	-.0582517	.1641834	-0.36	0.721	.055535	-.380045 .263542	
drip_p~n	-.1826113	.1293132	-1.42	0.156	.08804	-.436061 .070838	
d7*	.0306879	.0306619	1.09	0.277	.092732	-.029408 .090784	
d8*	.0634774	.0351399	2.11	0.035	.090226	-.005396 .13235	
d9*	.0540215	.0247878	2.29	0.022	.363409	.005438 .102605	
d10*	.0606443	.0374098	1.87	0.062	.090226	-.012678 .133966	
period	.0011467	.0005725	2.03	0.042	15.5145	.000025 .002269	
aptitude	-.007976	.0048525	-1.66	0.096	9.7995	-.017487 .001535	
obs. P	.1025063						
pred. P	.0935833 (at x-bar)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| correspond to the test of the underlying coefficient being 0

The following regression studies the effect of the size of the partition (or drip) on over-search

## Reported in Table D.2 The effect of the size of the partition on over-search at the first shop

```
dprobit oversearch_at_1 p1 highvaluegood c drip_proportion d7 d8 d9 d10 period aptitude if
price_strate
> gy !=11, cluster(subject )
```

```
Iteration 0: log pseudolikelihood = -1229.8822
Iteration 1: log pseudolikelihood = -1109.5782
Iteration 2: log pseudolikelihood = -1104.071
Iteration 3: log pseudolikelihood = -1104.0257
Iteration 4: log pseudolikelihood = -1104.0257
```

```
Probit regression, reporting marginal effects      Number of obs = 3990
              Wald chi2(10) = 283.26
              Prob > chi2  = 0.0000
Log pseudolikelihood = -1104.0257      Pseudo R2   = 0.1023
```

(Std. Err. adjusted for 145 clusters in subject)

	Robust						
overse~1	dF/dx	Std. Err.	z	P> z	x-bar	[ 95% C.I. ]	
p1	-.394903	.0441786	-13.72	0.000	.752414	-.481491 -.308315	
highva~d*	-.0248399	.0076933	-3.14	0.002	.493233	-.039919 -.009761	
c	.3979477	.1179835	3.54	0.000	.055535	.166704 .629191	
drip_p~n	-.0494017	.1062165	-0.46	0.643	.08804	-.257582 .158779	
d7*	-.0128152	.019648	-0.61	0.540	.092732	-.051325 .025694	
d8*	.0169015	.0285513	0.64	0.524	.090226	-.039058 .072861	
d9*	-.0189702	.0180105	-1.03	0.302	.363409	-.05427 .01633	
d10*	-.0307919	.0177785	-1.46	0.143	.090226	-.065637 .004053	
period	-.0023344	.0005264	-4.25	0.000	15.5145	-.003366 -.001303	
aptitude	-.0048189	.0031225	-1.57	0.117	9.7995	-.010939 .001301	
obs. P	.0924812						
pred. P	.0688909 (at x-bar)						

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| correspond to the test of the underlying coefficient being 0

The following probit regression studies the effect of the size of the partition (or drip) between treatments on under-search at the first shop.

### Reported as Table D.3: The effect of the size of the partition between treatments on under-search at the first shop

```
dprobit undersearch_at_1 p1 highvaluegood c d7 d8 d9 d10 d7 drip_proportion d8drip_proportion
d9drip_pro
> portion d10drip_proportion period aptitude if price_strategy !=11, cluster(subject )
```

```
Iteration 0: log pseudolikelihood = -1318.9151
Iteration 1: log pseudolikelihood = -1265.274
Iteration 2: log pseudolikelihood = -1264.514
Iteration 3: log pseudolikelihood = -1264.5133
```

```
Probit regression, reporting marginal effects      Number of obs = 3990
              Wald chi2(13) = 105.07
              Prob > chi2  = 0.0000
Log pseudolikelihood = -1264.5133      Pseudo R2    = 0.0412
```

(Std. Err. adjusted for 145 clusters in subject)

		Robust					
unders~1	dF/dx	Std. Err.	z	P> z	x-bar	[ 95% C.I. ]	
p1	.2266728	.0427127	6.04	0.000	.752414	.142957 .310388	
highva~d*	.0343014	.00939	3.75	0.000	.493233	.015897 .052705	
c	-.0556298	.1640158	-0.34	0.733	.055535	-.377095 .265835	
d7*	.0525109	.0575209	1.04	0.298	.092732	-.060228 .16525	
d8*	.0536284	.0436575	1.40	0.161	.090226	-.031939 .139196	
d9*	.0326956	.0271509	1.24	0.214	.363409	-.020519 .08591	
d10*	.1703863	.0892444	2.46	0.014	.090226	-.00453 .345302	
d7drip~n	-.3195811	.2825762	-1.14	0.255	.012717	-.87342 .234258	
d8drip~n	-.1282599	.2302489	-0.56	0.578	.012708	-.579539 .32302	
d9drip~n	-.0349919	.1536646	-0.23	0.820	.050201	-.336169 .266185	
d10dri~n	-.7292665	.335407	-2.18	0.029	.012414	-1.38665 -.071881	
period	.0011471	.0005708	2.04	0.041	15.5145	.000028 .002266	
aptitude	-.0079637	.0048694	-1.66	0.098	9.7995	-.017507 .00158	
obs. P	.1025063						
pred. P	.0932526	(at x-bar)					

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| correspond to the test of the underlying coefficient being 0

The following probit regression studies the effect of the size of the partition (or drip) between treatments on over-search at the first shop.

**Reported as Table D.4: The effect of the size of the partition between treatments on over-search at the first shop**

```
dprobit oversearch_at_1 p1 highvaluegood c drip_proportion d7 d8 d9 d10 period aptitude if
price_strate
> gy !=11, cluster(subject )
```

```
Iteration 0: log pseudolikelihood = -1229.8822
Iteration 1: log pseudolikelihood = -1109.5782
Iteration 2: log pseudolikelihood = -1104.071
Iteration 3: log pseudolikelihood = -1104.0257
Iteration 4: log pseudolikelihood = -1104.0257
```

```
Probit regression, reporting marginal effects      Number of obs = 3990
              Wald chi2(10) = 283.26
              Prob > chi2  = 0.0000
Log pseudolikelihood = -1104.0257      Pseudo R2   = 0.1023
```

(Std. Err. adjusted for 145 clusters in subject)

-----								
	Robust							
overse~1	dF/dx	Std. Err.	z	P> z	x-bar	[	95% C.I.	]
-----+-----								
p1	-.394903	.0441786	-13.72	0.000	.752414	-.481491	-.308315	
highva~d*	-.0248399	.0076933	-3.14	0.002	.493233	-.039919	-.009761	
c	.3979477	.1179835	3.54	0.000	.055535	.166704	.629191	
drip_p~n	-.0494017	.1062165	-0.46	0.643	.08804	-.257582	.158779	
d7*	-.0128152	.019648	-0.61	0.540	.092732	-.051325	.025694	
d8*	.0169015	.0285513	0.64	0.524	.090226	-.039058	.072861	
d9*	-.0189702	.0180105	-1.03	0.302	.363409	-.05427	.01633	
d10*	-.0307919	.0177785	-1.46	0.143	.090226	-.065637	.004053	
period	-.0023344	.0005264	-4.25	0.000	15.5145	-.003366	-.001303	
aptitude	-.0048189	.0031225	-1.57	0.117	9.7995	-.010939	.001301	
-----+-----								
obs. P	.0924812							
pred. P	.0688909 (at x-bar)							
-----								

(\*) dF/dx is for discrete change of dummy variable from 0 to 1  
z and P>|z| correspond to the test of the underlying coefficient being 0

