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Do consumers take advantage of common pricing standards? An experimental investigation

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Abstract
Gaudeul and Sugden have hypothesized that, when some but not all competing products are priced in a common standard and when consumers are liable to make errors in cross-standard price comparisons, consumers confine their attention to common-standard offers. This 'largest common standard' (LCS) heuristic provides incentives for sellers to use common standards, and so differs from most 'consider-then-choose' decision processes by *not* exposing consumers to exploitation by sellers. We report an experimental test of this hypothesis, using choice tasks similar to those represented in the Gaudeul–Sugden model. These tasks are parameterized such that participants, given their actual cognitive abilities, would benefit by using the LCS heuristic. However, we find little evidence that this heuristic is used. Most participants use a 'dominance editing' (DE) rule which begins by eliminating transparently dominated offers. This rule incentivises sellers *not* to use common standards. Since DE is less efficient than LCS, given participants' cognitive abilities, the use of DE is evidence of overconfidence.

JEL classification codes

Keywords
shortlisting; common standard; largest common standard heuristic; dominance editing; consideration set.

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1. Introduction

For many years, psychologists and consumer researchers have been interested in two-stage *consider-then-choose* decision processes (e.g. Payne, 1976; Hauser and Wernerfelt, 1990; Hauser, 2010). Recently, economists have begun to investigate these processes too (e.g. Manzini and Mariotti, 2007; Eliaz, Richter and Rubinstein, 2011; Eliaz and Spiegler, 2011). The essential idea in these literatures is that, when a consumer faces a large choice set, he or she economises on cognitive effort by using 'quick and dirty' heuristics to select a subset of options – the *shortlist* or *consideration set* – for further investigation. The final choice is then made from that subset using a procedure which tracks the consumers' preferences more accurately but is cognitively more costly. Shortlisting heuristics are understood as procedures that screen options relative to criteria that are easily observable, psychologically salient, and (in most models) positively correlated with the consumer's actual preferences. Examples of such heuristics include eliminating options that lack some pre-determined desirable quality (Tversky, 1972), shortlisting options with recognised names (Goldstein and Gigerenzer, 2002), and shortlisting options that immediately engage attention (Eliaz and Spiegler, 2011). One of the main reasons for economists' recent interest in two-stage decision processes is the recognition that profit-seeking firms may have incentives to tailor their offers to meet consumers' shortlisting criteria rather than to satisfy their actual preferences. Viewed in this way, two-stage decision-making belongs to the apparently large class of boundedly-rational decision-making procedures which, when used by consumers, are vulnerable to exploitation by firms.

Gaudeul and Sugden (2012) have presented a model of a different kind of two-stage decision-making, with correspondingly different implications for market efficiency. In this model, shortlisting is not an attempt to pick options that are expected to score highly on the scale of the consumer's true preferences. Instead, the aim is to construct the largest set of options that can easily and accurately be compared *with one another* on that scale. In other words, the consideration set is constructed so that the second stage of decision-making can be carried out by using quick *and clean* processes. As a stylised example, consider a consumer who is trying to find the cheapest supplier of some homogeneous and storable product – say, bottled water – which she consumes at a given weekly rate. Different firms supply water in bottles of different capacities, quoting their prices *per bottle*. Thus, even if bottle capacities are declared, identifying the cheapest price *per litre* will typically require the consumer to divide prices by capacities. However, if some subset of two or more suppliers uses the same size of bottle – that is, if they use a *common standard* of pricing – finding the cheapest offer *in that subset* is a simpler operation in which errors are much less likely. If standards are uncorrelated with per litre prices and if cross-standard price comparisons are sufficiently more subject to error than within-standard comparisons, expected expenditure per litre can be minimised by confining attention to the largest set of offers that are priced in a common standard. This is the *largest common standard* (LCS) heuristic.[1] One significant feature of this heuristic is that its use by consumers incentivises (non-colluding) firms to converge on common standards. Since competition is more intense when price comparisons are less noisy, this can lead to a virtuous circle: common standards come to be signals of competitive prices, increasing the incentive for consumers to use the LCS heuristic, and so further eroding the market share of firms which do not use such standards.

Whether consumers use decision rules that favour products priced in common standards is important in relation to current discussions of 'obfuscation' in pricing. Often-cited examples of obfuscation include advertising headline prices which exclude over-priced add-ons (such as delivery charges for products bought online) or excessive charges contingent on events which customers may fail to anticipate (such as overdraft fees on bank acounts). By reducing the information content of headline prices, such practices make price comparisons more difficult and so blunt price competition (Ellison, 2005; Gabaix and Laibson, 2006; Spiegler, 2006; Ellison and Ellison, 2009). In considering regulatory responses to obfuscation, it is important to know whether, in the absence of collusion among firms, markets have self-regulating tendencies towards common pricing standards.

The current paper reports an experiment that investigates how people respond to choice tasks that are structured like those represented in Gaudeul and Sugden's model. The experiment was designed to test various implications of the hypothesis that the LCS heuristic is widely used.

The results of these tests were negative. To our initial surprise, however, we found patterns in our data that were suggestive of the effects of an alternative two-stage decision rule which, as far as we know, has not previously been investigated in the context of common pricing standards. This is the *dominance editing* (DE) rule, which is briefly discussed by Gaudeul and Sugden (2012). It uses an operation similar to one of the editing operations that are applied to lotteries in prospect theory (Kahneman and Tversky, 1979: 274–275).[2] It constructs a shortlist by eliminating offers that are transparently dominated. More specifically, an offer is eliminated if it has a higher price than some other offer that is priced in the same standard. If cross-standard comparisons are subject to error, this rule can have perverse effects on firms' market shares. If no two offers are identical, the DE rule constructs a shortlist in which each standard is represented by exactly one offer. Thus, other

[1] The LCS heuristic has some similarities with modes of reasoning that generate the *decoy* (or *asymmetric dominance*) effect (Huber et al., 1982; Shafir et al., 1993). The common feature is that, when comparing choice options that are not themselves dominated, decision-makers favour options that dominate others.

[2] In the original version of prospect theory, the method by which prospects are evaluated can sometimes allow stochastically dominated prospects to have higher values than the prospects that dominate them. Kahneman and Tversky postulate an editing operation which eliminates dominated alternatives before any prospects are evaluated.

things being equal, a firm's offer is more likely to be shortlisted, the *fewer* other offers are priced in the same standard. So if consumers use the DE rule rather than the LCS heuristic, their attempts to take advantage of the simplifying properties of a common standard provide firms with incentives to use *individuated* standards (i.e. standards that are used by only one firm).

Further analysis of our experimental data established that many participants did indeed use the DE rule. Thus, our findings provide evidence of the use of a two-stage decision rule which can obstruct the development of common pricing standards.

In Section 2, we describe the choice problems faced by consumers in the Gaudeul–Sugden model, explain how these were reproduced in our experiment, and state the hypotheses that we will test as a means of investigating how far individuals use the LCS heuristic. In Section 3, we describe the experimental design in more detail. In Section 4, we report the results of our hypothesis tests. In Section 5, we investigate the decision processes used by participants, and show that the DE rule was widely used. In the final section, we discuss some general implications of our findings.

2. Experimental design: principles

In the Gaudeul–Sugden model, a consumer faces a *choice set* of *n offers*, from which she must choose one. Each offer i can be described by a pair (p_i, s_i) where p_i is the *final price* and s_i is the *standard* in which the price is expressed. The consumer's objective is to minimise the final price paid. She observes the standard of each offer, but is not directly informed about its final price. She is given information from which the final price can be reconstructed, but that reconstruction requires her to use cognitive processes that are liable to error. These processes are modelled by means of the assumption that, for each offer i, the consumer 'observes' a *price signal* $p_i + \varepsilon$, where ε is an i.i.d. random variable with zero mean. The price signal is interpreted as the consumer's reconstruction of the final price of an offer whose actual price is p_i; ε represents error. For simplicity, and to isolate the role of the LCS heuristic, the distribution of ε is assumed to be independent both of the final price and of the standard in which the price is expressed.

One way in which the consumer can form a preference between two offers is by comparing their price signals (i.e. by attempting to reconstruct their final prices). This is the *calculating* operation. However, she is also capable of forming preferences by using another, independent mental operation, the *ranking* operation. This operation generates an accurate ordinal ranking of every pair of prices p_i, p_j for which $s_i = s_j$, but cannot rank prices that are not expressed in the same standard. If all offers are expressed in individuated standards, the consumer has to rely on the calculating operation; the best she can do is to choose the offer with the lowest price signal. But if the choice set contains at least two offers with a common standard, it is possible that the expected price she pays will be lower if she uses the LCS heuristic. The first stage of this heuristic identifies the largest (or an equal-largest) set of offers such that all offers in this consideration set have a common standard. The second stage uses the ranking operation to find the lowest final price in the consideration set.

In our experiment, participants chose from sets of alternative offers, with an incentive to find the lowest possible final price. In most of our experimental tasks, final prices were not stated directly. Instead, participants (who were not allowed to use calculating aids) were given information from which final prices could be calculated by addition and/or multiplication. For example, a final price of 10.07 'points' (the experimental currency unit) might be expressed by means of the *price details* '10.60 points × 95%'. We chose the parameters with the intention that calculating final prices would require some cognitive effort, and that participants would be likely to make some errors in these calculations (or, alternatively, would choose to rely on approximations rather than exact calculations). Notice that the error mechanism in the experiment was a property of the participants' own reasoning, not a property of an external random mechanism. Our aim was to test how human decision makers choose in situations in which they might reasonably expect *their own decision-making processes* to be subject to error.

In each task, there were 24 offers, all with the same *offer type*. For example, the offers described by the price details '10.60 points × 95%', '9.50 points × 95%' and '12.20 points × 86%' all have the type (which we will later denote 'P*D') in which the final price is described as 'original price × *y*%', where *y* is a variable. Within a given offer type, two offers have a *common standard* if an accurate ordinal comparison of them can be made simply by ranking their original prices. For example, '10.60 points × 95%' and '9.50 points × 95%' have a common standard.

The experiment used four types of task. In the *benchmark* task, the final price of each offer was identical to the original price. All other tasks used offer types in which original and final prices were different. In *all common standard* (AC) tasks, all 24 offers had a common standard. In *no common standard* (NC) tasks, all 24 offers had individuated standards. In *part common standard* (PC) tasks, eight of the 24 offers had a single common standard; the other 16 offers had individuated standards. For testing whether participants use the LCS heuristic, the PC tasks are most directly relevant. (In AC tasks, that heuristic reduces to the obvious rule of comparing all 24 original prices; in NC tasks, it is not applicable.) However, by including AC and NC tasks we were able to make independent assessments of the accuracy of participants' cross-standard and within-standard comparisons, and hence to assess the efficiency or inefficiency of the LCS heuristic, given participants' cognitive capacities.

In all tasks, the distribution of final prices was the same. Final prices were uncorrelated with standards, and so the fact that a particular offer was or was not priced using a common standard contained no information about its final price. This provided a neutral setting for investigating individuals' tendencies to use or not use the LCS heuristic. The experimental interface between participant and task was designed to allow us to track significant aspects of participants' reasoning, and thus to look for the fingerprints of heuristics that participants might be using. At the start of any task, offers were presented in a way that allowed participants to identify which, if any, used a common standard, but participants were required to make specific mouse clicks to reveal further information about specific offers. These mechanisms enabled us to track which offers were inspected in which order.

The experiment was designed to investigate whether the LCS heuristic is used in a setting in which decision makers, given their cognitive capacities, would benefit from using it (rather than using only the calculating operation). Given this objective, the validity of our experiment depends on two preconditions – that subjects have the cognitive capacity to use the LCS heuristic, and that in PC tasks, the expected payoff from using that heuristic is greater than that from using only the calculating operation. The AC and NC tasks allow us to test whether these preconditions hold. More precisely, we test the following two conditions:

> *Validation Condition 1*: In AC tasks, the average final price of chosen offers is close to the lowest final price available.

> *Validation Condition 2*: In NC tasks, the average final price of chosen offers is greater than the expected value of the lowest price in a randomly selected subset of eight offers.

Recall that in an AC task, it is possible to find the lowest final price by comparing the 24 original prices. Validation Condition 1 tests whether participants are generally able to do this. If they are, it is reasonable to infer that they also have the cognitive ability to use the ranking operation to find the lowest of the eight common-standard prices in a PC task. Now suppose that this condition is satisfied. Consider any given distribution of final prices, and any given offer type in which original and final prices are different. In a PC task based on this distribution and offer type, the expected value of the final price for a participant who uses the LCS heuristic is equal to the expected value of the lowest price in a randomly selected subset of eight offers. For a participant who ignores the common/ individuated distinction, this task is equivalent to an NC task based on the same distribution and offer type. Thus, a test of Validation Condition 2 is a test of whether, in PC tasks, participants would pay lower prices if they used the LCS heuristic than if they used only the calculating operation.

Given that the validation conditions are satisfied, the following hypotheses are implications of the assumption that, in situations in which the use of the LCS heuristic would be beneficial, it is in fact widely used:

Hypothesis 1: The average final price of chosen offers is lower in PC tasks than in NC tasks.

Hypothesis 2: In PC tasks, the proportion of common-standard offers inspected is greater than the corresponding proportion of individuated-standard offers.

Hypothesis 3: In PC tasks, the proportion of common-standard offers chosen is greater than the corresponding proportion of individuated-standard offers.

Hypothesis 4: In PC tasks, the frequency with which the optimal offer (i.e. the offer with the lowest final price) is chosen is higher if the optimal offer is common-standard than if it is individuated-standard.

Hypotheses 2, 3 and 4 are stated very conservatively. If the LCS heuristic were used by *every* participant in *every* task without *any* error, common-standard offers would be the only ones to be inspected or chosen, and the optimal offer would always be chosen if it was common-standard. It would be unrealistic to expect any specific heuristic to be used universally, but if the LCS heuristic were widely used, one would expect the asymmetries predicted by Hypotheses 2, 3 and 4 to be very marked. And were we to find significant numbers of participants who inspected only common-standard offers and who always chose the optimal offer if it was common-standard, the only credible explanation would be that those participants were using the LCS heuristic.

3. The experiment

The experiment had a within-subject design. Each participant completed ten different tasks presented in randomised order on a computer screen. In each task, a participant was given an 'endowment', and was required to buy one unit of a notional good by accepting one of 24 alternative price 'offers'. All final prices were lower than the endowment. Endowments and prices were expressed in 'payment points'. In each task, the participant was credited with payment points equal to the endowment minus the final price of the chosen offer. At the end of the experiment the computer randomly picked one of the ten tasks; the participant's earnings from the experiment were equal to her payment points from that task, converted into UK pounds using an 'exchange rate' that was specific to the task. Thus, in each task, participants had an incentive to choose the offer with the lowest price.

In every task, the money value of the endowment (converted at the task-specific exchange rate) was £32. The set of final prices, expressed in UK pounds, was the same in all tasks, except for rounding; these unrounded prices ranged from £20.270 to £28.895, in increments of £0.375. Keeping the set of final prices constant was important in allowing controlled hypothesis tests.

However, it was also important that participants did not recognise this feature of the design and use it to simplify their decision problems (for example, by remembering the value of the lowest price). Thus, although participants were told at the start of the experiment that the endowment would always have a converted value of £32, they were *not* told that the distribution of converted final prices was the same in all tasks. Nor were they told anything about these distributions other than that, in every task, the highest price was always lower than the endowment. The exchange rate was generated randomly, independently for each participant and for each task. It was expressed in the form 'x points = £1', where x was a round number in the interval $10 \leq x \leq 100$. The price details of the offers in a task were then constructed so as to be consistent with the relevant exchange rate. For example, an offer with a final price of £20.27 and the offer type P*D might appear in one task with an exchange rate of 12 points = £1 and an endowment of 384 points, and be described as 'original price = 676 points; final price = original price × 36%'. The same offer might appear in another task with an exchange rate of 43 points = £1, an endowment of 1376 points, and the description 'original price = 1063 points; final price = original price × 82%'.

In any given task, all offers were expressed in terms of the same offer type. The following four offer types were used:

(1) *Type P*: Price details are described as a single price such as:

Final price = x points

where x is a positive round number. This offer type is used only in the benchmark task. In that task, offers are differentiated only by their original prices. In tasks with this offer type, we will say that all offers have the same *price structure*.

(2) *Type P*D*: Price details are described as an original price with a percentage discount:

Original price = x points; Final price = Original price × y%

where x is a positive round number and y is a round number in the interval $0 < y < 100$. In tasks with this offer type, we will say that offers have the same price structure if and only if they have the same value of y.

(3) *Type P*D+A*: Price details are described as an original price with a percentage discount plus an add-on:

Original price = x points; Final price = Original price × y% + z points

where x and z are positive round numbers and y is a round number in the interval $0 < y < 100$. In tasks with this offer type, offers have the same price structure if and only if they have the same values of both y and z.

(4) *Type P*D1*D2*: Price details are described as an original price with two percentage discounts:

Original price = x points; Final price = Original price $\times\, y_1\% \times y_2\%$

where x is a positive round number and y_1 and y_2 are round numbers in the intervals $0 < y_1 < 100$ and $0 < y_2 < 100$. In tasks with this offer type, offers have the same price structure if and only if they have the same values of both y_1 and y_2.

Whenever two offers in the same task have the same price structure, the ranking of their final prices is necessarily the same as the ranking of their original prices. Thus, if two or more offers in a task have the same price structure, they have a common standard as defined in Section 2; if some price structure is unique to a specific offer, that offer has an individuated standard.

As explained in Section 2, the experiment used four types of task – benchmark, AC, NC and PC. There was one benchmark task, using the offer type P. Nine further tasks were constructed by crossing the AC, NC and PC task types with the P*D, P*D+A and P*D1*D2 offer types. (Since offer type P necessarily implies that all offers have a common standard, this design is fully factorial.) In PC tasks, which eight of the final prices £20.270, …, £28.895 were assigned to the common standard was determined randomly, independently for each participant. Thus, the standard in which an offer was expressed provided no information about the final price. The ten tasks used in the experiment are summarised in Table 1.

[Table 1 near here]

The four offer types were chosen to cover a range of levels of complexity. The P type is the simplest that is possible in our experimental set-up. The P*D type is unambiguously less complex than the P*D+A and P*D1*D2 types. By using tasks with different degrees of complexity, we made it more likely that each participant would face some tasks in which the problem of working out final prices was perceived as difficult but manageable. This design feature also allows us to investigate whether the decision rules that participants use are affected by the complexity of the offer type.

Each task was presented in the form of two screen pages – the *market page* and the *shopping basket page*. Screen shots of these pages are shown in Appendix B. At the start of the task, the participant saw the market page. The participant's endowment (in points) and the exchange rate between points and UK pounds were displayed at the top of the page. One panel of the page displayed 24 coloured boxes, corresponding with the 24 offers, which were described as the offers of 24 different 'firms'. The boxes were labelled 'Offer A', …, 'Offer X'. The allocation of actual offers to boxes was randomised. Boxes had the same colour if and only if the corresponding offers had the same price structure. In all other respects, colours were randomised. No details of the offers apart from the colours and the letter codes were visible.

In the market page, a participant was able to do four types of action. (1) She could single-click on an offer, in which case the offer was highlighted and a message such as 'price structure 1' would immediately appear at the bottom of the page.[3] (2) She could click more than once on an offer, in which case the relevant price details would appear at the bottom of the screen after a three-second delay. (Actions (1) and (2) could be done only for one offer at a time: if the participant clicked on a new offer, information about the price structure and/or price detail of the previous offer disappeared.) (3) Following action (1) or (2), the participant could click a 'Move into the shopping basket' button, in which case a correspondingly coloured and labelled box immediately appeared in a 'shopping basket' panel of the market page. The shopping basket had a maximum capacity of nine offers; subject to this limit, the participant could move as many offers to the basket as she wished without any time delays. (4) At any time, the participant could click a 'View the shopping basket' button, in which case she would move to the shopping basket page after a three-second delay.

In the shopping basket page, the participant could immediately see the price detail(s) of all the offers that had been moved into the basket (and had not yet been moved out), displayed in the middle of the screen. Thus, price comparisons (particularly for offers with complex price structures) could be made much more easily in the shopping basket page than in the market page, where the participant could view the price details of only one offer at a time. In this page, the participant was able to do three types of action, none of which involved any time delay. (1) She could move any offer(s) out of the basket, thus creating space to add new offers from the market page. (2) She could go back to the market page by clicking a 'Continue shopping' button. (3) She could make a final decision by clicking a 'Buy the good from firm —' button (where — was the letter identifying the chosen offer).

Because a final choice could be made only on the shopping basket page, and because offers could be compared more easily on that page, we expected participants to use the shopping basket to store offers that they perceived as potentially choiceworthy. If the shopping basket was used in this way, the evolution of its contents over the course of a task could be interpreted as the progressive building up and refinement of a shortlist, and so would be informative about participants' reasoning.

The three-second time delays served two purposes. First, the existence of short time delays replicates the fact that in real-world internet shopping there is always some time delay while opening and negotiating a website to find the price of a specific product, or going to a shopping basket page for checking out. Second, the delay mechanism was intended to encourage participants to use the shopping basket as a shortlist. If comparisons were made in the market page, there was a three-second delay for every offer inspected, but if offers were moved to the shopping basket before being compared, there was only one such delay for every batch of (up to nine) offers moved together.

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[3] Since the numbering of price structures was arbitrary, and since the colours of the boxes showed which if any offers had the same price structure, this message had no real information content. It served as an aid for any participants who had difficulty distinguishing colours.

However, no time constraints were imposed: participants were free to spend as long as they liked on any task.

Before starting the formal experiment, the experimenter read out the experimental instructions and activated all participants' computer screens to let them do a practice task. The practice task was similar to the PC tasks but with a different offer type. (This had the form: *Original price = x points; Final price = Original price* $\times y\%$ with $y > 100$.) Participants went through the practice task step by step, following the experimenter's instructions. After finishing the practice task, participants were given a questionnaire to check their understanding of the experiment. The formal experiment began only after these questions had been answered correctly. The instructions and questionnaire are reproduced in Appendix A.

4. Results: tests of the largest common standard heuristic

The experiment was conducted at the Centre for Behavioural and Experimental Social Science Laboratory at the University of East Anglia in the summer of 2013. It was implemented using z-Tree (Fischbacher, 2007). 171 participants were recruited using a campus-wide online system. Most of the participants were students from a wide range of academic disciplines, with ages ranging from 18 to 65. The experiment lasted approximately 65 minutes with an average payment of £10.76 per person. Payments ranged from £3.10 to £11.73.

Table 2 reports means, medians and standard deviations of the time used and *excess price* paid by participants in each task. 'Excess price' is defined as the final price of the offer chosen by a participant minus the lowest available final price (which was £20.27 in all tasks). The expected value of excess price for an offer chosen at random was £4.32. In all tasks, the expected value of the lowest final price in a randomly selected subset of eight offers was £20.90. Thus, for a participant who used the LCS heuristic without error in a PC task, the expected value of excess price would be £0.63. This table also reports, for each task, the percentage of participants who chose the optimal offer (i.e. the offer with the lowest final price).

[Table 2 near here]

In the benchmark task, the low mean and median values of excess price (£0.33 and £0.00 respectively) and the high proportion of optimal choices (89.5 per cent) show that most participants had little difficulty in negotiating the market and shopping basket pages and were sufficiently patient to search for the lowest price, despite the time delays built into the experimental interface. The time used in this task (mean 158 seconds, median 125 seconds) provides a useful baseline from which to measure the extra time used in making the more difficult price comparisons required by other tasks.

Time used and excess prices in the AC tasks are only slightly higher than in the benchmark task, and the proportions of optimal choices are only slightly lower. We conclude that Validation Condition 1 is satisfied. In other words, participants had the cognitive capacity to use the LCS heuristic with a high degree of accuracy. Given the complexity of the arithmetic operations required to calculate final prices in the AC tasks, it is natural to infer that most participants realised that, when offers have the same price structure, such calculations were not necessary; they simply compared original prices.

The data from NC tasks give further support to this inference. It is immediately obvious from Table 2 that participants found NC tasks much more difficult and time-consuming than AC tasks. For each of the three offer types, mean and median values of time used and excess price are much higher in NC tasks than in AC tasks, and the proportion of optimal choices is much lower. In all cases, these differences are highly significant ($p < 0.001$).[4] Since the only difference between AC and NC tasks is the presence or absence of a common standard, it is clear that the existence of a common standard makes decision-making easier and less subject to error.

In each of the three NC tasks, mean and median excess price are greater than £0.63, satisfying Validation Condition 2. More intuitively, we can ask whether a typical participant could be expected to do better in a PC task by using the LCS heuristic than by ignoring the common/individuated distinction and treating that task as if it were an NC task. From the AC data, it is reasonable to infer that the median participant would be able to use the LCS heuristic without error, leading to an expected excess price of £0.63 in a PC task. In the NC tasks, the median excess prices are slightly higher than this datum for the P*D and P*D+A offer types (£0.75 in both cases), and markedly higher for the P*D1*D2 offer type (£1.50). Comparing time used in AC and NC tasks, and given that in a PC task the LCS heuristic requires only eight offers to be inspected and ranked, it seems likely that a typical participant would also save at least three minutes in each PC task by using the LCS heuristic rather than treating these problems like NC tasks.

However, the data in Table 2 show little evidence of the use of the LCS heuristic. For each offer type, mean and median values of time used and of excess price, and proportions of optimal choices, are generally similar between PC and NC tasks. Time used is not significantly different between PC and NC tasks for any offer type. Excess price is significantly different only for the P*D offer type (where it is lower for PC tasks; $p = 0.056$). The proportion of optimal choices is significantly different only for the P*D offer type (where it is higher for PC tasks; $p = 0.029$). Thus, we find little support for Hypothesis 1.

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[4] Throughout the paper, unless otherwise stated, all within-subject tests are Wilcoxon signed rank tests, while for between-subjects comparisons we use Mann-Whitney tests. All *p*-values are two-sided. We say that results are 'significant' and report *p* values when $p < 0.10$.

Tables 3 and 4 provide more direct evidence that the LCS heuristic was not used. Table 3 reports the numbers of offers *inspected* in each task. An offer is defined to have been inspected by a participant if and only if the participant has seen its price details, either by double-clicking it on the market page or by moving it to, and viewing it in, the shopping basket page.[5] In every task, most participants inspected most (and often all) of the 24 offers. In PC tasks, the proportion of offers inspected was significantly higher for common-standard offers than for individuated-standard offers ($p < 0.001$ for each of the three offer types), consistently with Hypothesis 2, but even for individuated-standard offers the average rate of inspection was 80.1 per cent. At the individual level, the most obvious fingerprint of a participant who uses the LCS heuristic is the absence of inspections of individuated-standard offers in PC tasks. For the P*D, P*D+A and P*D1*D2 offer types respectively, only 1, 1 and 2 of the 171 participants inspected no individuated-standard offers, and only 7, 10 and 12 inspected fewer than four such offers.

[Table 3 near here]

Table 4 reports the proportions of participants who chose common-standard offers in each PC task. For a participant who ignored the common/individuated distinction, the ex ante probability of choosing a common-standard offer in a PC task would be 0.33; for a participant who used the LCS heuristic, it would be 1. The observed proportion is *less than* 0.33 in all three tasks, contrary to Hypothesis 3; this difference is significant for the P*D+A and P*D1*D2 offer types ($p < 0.001$ and $p = 0.085$ respectively in two-sided binomial tests).

[Table 4 near here]

Table 5 reports the frequency with which the optimal offer was chosen in each PC task, conditional on whether that offer was common-standard or individuated-standard. For a participant who ignored the common/individuated distinction, the ex ante probability of choosing the optimal offer would be independent of its standard; a participant who used the LCS heuristic without error would always choose the optimal offer if it was common-standard and never choose it if it was individuated-standard. In the P*D and P*D+A tasks, there is no significant difference between the two conditional frequencies. In the P*D1*D2 task, the frequency of optimal choices is much greater

[5] In each task, there was a very sharp division between participants according to whether they used 'one-click' or 'two-click' inspections. One-click participants moved offers to the shopping basket before inspecting price details; two-click participants inspected price details in the market page before deciding whether to move offers to the shopping basket (and so incurred more time delays). Overall, the split between two-click and one-click methods was approximately 60:40, but participants were somewhat more likely to use the one-click method in tasks in which price comparisons were more difficult. However, when we investigated the sequences of inspections made by participants and the evolution of the content of their shopping baskets, we found no major differences between one-click and two-click participants.

when the optimal offer is common-standard, and this difference is highly significant ($p < 0.001$). In relation to Hypothesis 4, then, the evidence is mixed.

[Table 5 near here]

Our conclusions so far can be summarised in the following results:

Result 1: There is little support for the hypothesis that buyers use the largest common standard heuristic.

Result 2: Relative to the case in which all offers have individuated standards, buyers are better able to find low prices if all offers have a single common standard. But this effect is weak or non-existent if some but not all offers have a common standard.

Result 3: When some but not all offers have a common standard, common-standard offers are more likely to be inspected than individuated-standard offers, but are less likely to be chosen.

Result 4: The evidence does not support a firm conclusion about whether, when some but not all offers have a common standard, the optimal offer is more likely to be chosen if it is common-standard than if it is individuated-standard.

5. Results: analysis of the decision process

So what decision rule(s) *did* participants use? In this Section, we examine the mouse clicks made by participants during the decision process to learn more about the decision rules they used.

The methodology for this part of our investigation was inductive, guided by conjectures formed after reflecting on the findings reported in Section 4. We were particularly interested in Result 3 which, although puzzling at first sight, seemed to us to be suggestive of the DE (dominance editing) rule, referred to in Section 1. In PC tasks, the first stage of the DE rule requires all common-standard offers to be inspected as a means of eliminating dominated offers. It would not be surprising if, in the cognitively more demanding second stage, some users of the DE rule followed satisficing or reservation-price stopping rules, analogous with those in models of rational search (Diamond, 1971; Salop and Stiglitz, 1977), rather than making exhaustive comparisons of all non-dominated offers. Such behaviour would be consistent with the observation that common-standard offers were more likely to be inspected than individuated-standard ones. However, as pointed out in Section 1, if calculating errors can occur in the second stage, the fact that only one common-standard offer survives to that stage imparts a bias towards the choice of individuated-standard offers. This is consistent with the observation that common-standard offers were less likely to be chosen.

Since we are particularly interested in the order in which participants performed different operations, our analysis focuses on the sequences of clicks made by each participant. To facilitate comparisons between participants, we define percentiles of *clicking time* separately for each participant and each task. Thus, if a given participant made a total of N clicks during a task, her tth click is assigned to the $(100t/N)$th percentile of clicking time. In the graphs that we will present, each unit of observation corresponds with a 10 percentage point interval of clicking time.

One obvious fingerprint of the DE rule is that in PC tasks, common-standard offers are inspected before individuated-standard ones. For each PC task, for each interval of clicking time, we define the *proportion of common-standard inspections* as the number of common-standard offers inspected by all participants in that interval divided by the total number of inspections. If all participants ignored the common/individuated distinction, this proportion would be 0.33 throughout, except for random variation. If all participants used the SF rule, it would be 0.33 in the early intervals and increase thereafter. If all participants used the DE rule, it would be close to 1 in the early intervals and fall thereafter. Figure 1 plots the evolution of this proportion for each PC task.

[Figure 1 near here]

The three graphs are remarkably similar. In all three PC tasks, the proportion of common-standard inspections is approximately 0.7 in the first three deciles of clicking time, decreases steadily over the next four deciles, and then levels off at values between 0.1 and 0.15. This pattern indicates a strong tendency for participants to inspect common-standard offers before individuated-standard ones.

It is natural to ask whether some participants inspected offers in the order specified by the DE rule while others inspected them randomly. To investigate this question, we looked at the number of common-standard offers in the first eight (distinct) offers inspected by each participant in each task. We found that the distributions of these numbers were strongly bimodal, with a sharp peak at eight and a much less pronounced mode in the range between one and three. In the P*D task, there were 99 (out of 171) participants for whom either seven or eight of the first eight inspected offers were common-standard. The corresponding numbers for the P*D+A and P*D1*D2 tasks were 102 and 89. The implication is that between 50 and 60 per cent of participants began PC tasks by inspecting offers in exactly, or almost exactly, the sequence implied by the DE rule, while other participants inspected the offers in approximately random order.

It is also useful to investigate how the contents of participants' shopping baskets changed over the course of each PC task. For any given offer in any given task, and for each interval of clicking time, we define the *in-basket probability* as the probability that, for a randomly selected participant and a randomly selected moment in that interval, the relevant offer is in the participant's shopping basket. Formally, for any given participant, we define *moments* $t = 1, \ldots, N$, each corresponding with one click. For each moment t, for any given offer, we define the offer's *basket status* B_t as 1 if the offer is in the shopping basket immediately after the participant's tth click and 0 if it is not. For each interval of clicking time, the probability that the offer is in the participant's shopping basket is defined as the mean value of B_t, averaged over all moments in that interval. The mean of these probabilities, averaged over all participants for a given interval of clicking time, is the relevant in-basket probability. Our analysis focuses on the evolution of the in-basket probabilities of different offers in the various tasks.

Figure 2 presents graphs of the evolution of in-basket probabilities for those AC, NC and PC tasks that used the P*D offer type. We focus on just one offer type in the interests of brevity; the corresponding graphs for the other offer types are presented in Appendix C. Unless otherwise stated, the patterns that we will identify in the P*D data are also found in the P*D+A and P*D1*D2 data (and, if task 1 is interpreted as a degenerate form of AC task, in the P data too).

[Figure 2 near here]

First, consider Figure 2a, which refers to the AC task. Offers are classified according to the ranks of their final prices, with higher ranks for lower prices. To keep the diagram uncluttered, we partition the set of 24 ranks into the sets $\{1\}$, $\{2, 3, 4\}$, $\{5, \ldots, 14\}$ and $\{15, \ldots, 24\}$. For each of these sets, we graph the average in-basket probability of the offers in that set. Notice that, over the first three intervals of clicking time, all four graphs increase at approximately the same rate, implying that offers are being moved into the basket in a more or less random fashion. This is as one would expect if participants moved offers into the basket before inspecting their price details, or if they began the task without strong prior expectations about the distribution of final prices. By the third interval, in-basket probabilities are around 0.2 (corresponding with an average of 4.8 offers in the basket). From this point on, the graphs diverge systematically. From being a random sample of the set of 24 offers, the distribution of offers in the basket becomes increasingly skewed towards higher-ranked offers. The in-basket probabilities for all but the best four offers remain low and approximately constant. In the last four intervals, in-basket probabilities for all but the best offer remain approximately constant. Only the optimal offer has a continuously increasing in-basket probability. The implication is that, over the course of the task, there is a process of *continuous sorting* in which offers are sequentially moved into the basket, compared with other offers in the basket, and then removed if judged to be inferior.

The graphs for the NC task, presented in Figure 2b, show the same qualitative patterns as those in Figure 2a. However, the sorting is less effective, reflecting the fact that price comparisons based on calculation are less accurate than those based on ranking.

Figures 2c and 2d show the evolution of in-basket probabilities for the PC task, broken down between individuated-standard offers (in Figure 2c) and common-standard offers (in Figure 2d). Since the DE rule begins by eliminating all common-standard offers other than the best, it is particularly informative to look at the evolution of the in-basket probability of the *best common-*

standard offer – that is, the offer with the lowest final price in the subset of eight offers that have a common standard. This probability is plotted as one of the graphs in Figure 2d. The remaining common-standard offers are then grouped by their ranks *in the full set of 24 offers*. (Notice that the best common-standard offer does not necessarily have rank 1 in the set of 24 offers, but that it is the only common-standard offer that can have that rank.) For consistency, Figure 2c uses an analogous grouping of individuated-standard offers.

The graphs in Figure 2c are broadly similar to those in Figure 2a and 2b: an initial stage of random accumulation of individuated-standard offers is followed by gradual (but relatively ineffective) sorting. The main difference is that the rate of accumulation in the first phase of the task is relatively low. This is consistent with the observation, reported earlier, that inspections in this phase were strongly biased towards common-standard offers – a fingerprint of the DE rule.

Given this finding, one would expect a correspondingly high rate of accumulation of common-standard offers in the first phase of the task, and this effect is clearly visible in Figure 2d. But Figure 2d shows a further DE fingerprint: after the first phase, the pattern of sorting differentiates very sharply between the best and all other common-standard offers. By the fifth interval of clicking time, the in-basket probability of the best common-standard offer is 0.59, while the corresponding probabilities of all the other common-standard offers fall sharply to around 0.1. Once this sorting phase has been completed, in-basket probabilities stay roughly constant.[6] This pattern is consistent with the hypothesis that many participants used the DE rule: they began the task by inspecting and sorting common-standard offers, finding the best and eliminating the others, and then went on to compare the best common-standard offer with individuated-standard offers.

However, if *all* participants had behaved in this way, the in-basket probabilities of common-standard offers other than the best would have been close to zero in the later intervals. Under the same assumption, and given what we have learned about the continuous sorting procedures used in the AC and NC tasks, we might also expect the in-basket probability of the best common-standard offer to fall over the later intervals. (As long as the best common-standard offer is in the basket, it is continuously subject to comparisons with individuated-standard offers to which, correctly or incorrectly, it may be judged inferior.) We conjecture that these tendencies were offset by the behaviour of the substantial minority of participants who inspected offers in approximately random order. For such participants, the in-basket probability of any given low-price offer, and hence of the best common-standard offer, is likely to increase over the course of the task.

[6] The diagrams corresponding with Figure 2d but referring to the P*D+A and P*D1*D2 offer types (presented in Appendix C) show similar patterns to those in Figure 2d, except that in the P*D+A case there is a marked fall in the in-basket probability of the best common standard offer in the second half of the task (from a maximum of 0.60 to 0.37 in the final interval).

Notice that if a participant inspects offers in random order and uses a continuous sorting procedure, she has the opportunity to use the ranking operation whenever the shopping basket contains two or more common-standard offers. If this operation is repeatedly used to remove dominated offers from the basket, and given that the calculating operation is subject to error, continuous sorting imparts a bias against the choice of common-standard offers in much the same way as the DE rule does. Thus, the patterns we have found in our PC data are broadly consistent with the conjecture that a majority of participants inspected offers in the DE order, that the other participants inspected offers at random, that continuous sorting procedures were generally used, and that the ranking operation was used to eliminate dominated offers.

This conjecture may also help to explain the mixed results of our tests of Hypothesis 4. If the optimal offer is common-standard, a participant who inspects offers in the DE order will move it into the basket early in the course of the task. The earlier it enters the basket, the longer it is exposed to the hazard of being incorrectly judged inferior to some individuated-standard offer. This effect works against Hypothesis 4. However, if sorting procedures use the ranking operation when comparing common-standard offers, an optimal offer that is common-standard will never be judged inferior to any common-standard offer, whereas an optimal offer that is individuated-standard *is* exposed to this hazard. This effect works in the same direction as Hypothesis 4.[7] The fact that common-standard offers were more likely to be inspected than individuated-standard offers (Result 3) is an additional factor working in this direction.

6. Discussion

The behaviour we have observed in this experiment reflects a combination of cognitive constraints and overconfidence. Our participants' cognitive constraints, revealed most obviously in the excess prices paid in tasks in which there were no common pricing standards, are not particularly surprising. It is well known that people often find it hard to find the lowest price when price structures are complex (Wilson and Waddams Price, 2010; Office of Fair Trading, 2011). It is more interesting that, in tasks in which some but not all offers were priced in a common standard, our participants failed to use a simple decision rule (the LCS heuristic) that was clearly within their cognitive capacities and which would have allowed them to find lower prices with considerably less expenditure of time and effort. Indeed, the majority of participants used a decision rule (the DE

[7] We explored this issue further by investigating, at the level of individual participants, the movement of optimal offers into and out of the basket. In AC tasks, optimal offers were almost never moved out of the basket, but such movements were fairly common in NC and PC tasks. Averaging over the three NC tasks, 21.1 per cent of participants moved the optimal offer out of the basket at some stage. The corresponding proportions for PC tasks were 18.1 per cent if the optimal offer was individuated-standard and 30.4 per cent if it was common-standard.

rule) whose first stage replicated the LCS heuristic by finding the best common-standard offer, but then wasted both time and money by considering offers priced in individuated standards.

We conjecture that our participants were reluctant to use (or failed to consider using) the LCS heuristic because of the counter-intuitiveness of a strategy that looks at only one in every three of the available offers. Most of our participants would have known how to carry out the arithmetic operations which, if applied correctly to all 24 offers, would be certain to identify the lowest price. It seems that they were overconfident in their ability to avoid arithmetic errors.

There is a long-standing psychological literature on the reliability of people's judgements of confidence in their own knowledge, beliefs, skills and memory. This research has found a prevailing but not universal bias towards overconfidence, particularly in relation to complex tasks (e.g. Adams and Adams, 1961; Oskamp, 1965; Lichtenstein and Fischhoff, 1977). Economists and management scientists have been particularly interested in overconfidence as a cause of excess market entry (Camerer and Lovallo, 1999), excess financial trading (Barber and Odean, 2001), and excess investment by CEOs in their firms'own projects (Malmendier and Tate, 2005). Our research suggests that overconfidence by consumers about their own cognitive abilities may make them more vulnerable to pricing practices which make rival offers difficult to compare.

However, it is possible that individuals would be more willing to use the LCS heuristic in situations in which they could rationalise it without thereby acknowledging their own cognitive failings. This might be the case, for example, if there was an explicit cost for inspecting each offer, or if a decision had to be made within an externally-imposed time constraint. The nature of the mental operations required to identify the best offer may also be significant. For example, individuals might be more relaxed about acknowledging deficiencies in spatial judgement than in arithmetic ability (or vice versa). These conjectures may help to explain differences between our results and those of an experiment reported by Crosetto and Gaudeul (2012), which found some evidence of the use of the LCS heuristic. In a typical task in Crosetto and Gaudeul's experiment, a participant had to make a decision problem within a fixed time constraint. The problem was to purchase 'paint' to cover a fixed square area. The prices of alternative paint products were described in terms of the cost of covering areas of various shapes and sizes, presented visually; in some choice problems, two or more products were priced in terms of areas with the same shape and size, thus creating a common standard.

Thus, our results should not be interpreted as an unconditional rejection of Gaudeul and Sugden's (2012) hypothesis that consumers come to decision problems with a basic propensity to use the LCS heuristic. However, these results demonstrate the existence of two factors – the psychological salience of editing operations which eliminate dominated options, and overconfidence –

which work against the use of this heuristic.   How far, or under what conditions, common pricing standards are self-sustaining remains an important open question.

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Table 1
Properties of the tasks

Task	Task type	Offer type	Number of common standard offers	Number of individuated standard offers
1	Benchmark	P	24	0
2	AC	P*D	24	0
3	AC	P*D+A	24	0
4	AC	P*D1*D2	24	0
5	NC	P*D	0	24
6	NC	P*D+A	0	24
7	NC	P*D1*D2	0	24
8	PC	P*D	8	16
9	PC	P*D+A	8	16
10	PC	P*D1*D2	8	16

Table 2
Time used, excess price paid and frequency of optimal choice in each task

Task(s)	Task type	Offer type	Time used (seconds)		Excess price paid (£)		Proportion of optimal choices (%)
			Mean (SD)	Median	Mean (SD)	Median	
1	Benchmark	P	158 (104)	125	0.33 (1.36)	0	89.5
2	AC	P*D	177 (145)	133	0.47 (1.64)	0	86.0
3	AC	P*D+A	187 (132)	143	0.50 (1.71)	0	84.8
4	AC	P*D1*D2	183 (121)	138	0.68 (2.06)	0	81.9
2-4	AC	Average	182 (73)	165	0.55 (1.50)	0	84.2
5	NC	P*D	344 (226)	305	1.62 (2.00)	0.75	26.3
6	NC	P*D+A	363 (225)	328	1.63 (2.07)	0.75	27.5
7	NC	P*D1*D2	398 (296)	355	2.47 (2.52)	1.5	20.5
5-7	NC	Average	368 (182)	367	1.90 (1.51)	1.75	24.8
8	PC	P*D	342 (256)	289	1.32 (1.94)	0.38	36.8
9	PC	P*D+A	354 (245)	304	1.69 (2.04)	0.75	21.6
10	PC	P*D1*D2	376 (243)	363	2.3 (2.44)	1.50	19.3
8-10	PC	Average	357 (166)	339	1.77 (1.37)	1.38	25.9

There are 171 observations for each task. SD = standard deviation. Where the offer type is ‘average’, we calculate the average time used and average excess price over the three relevant tasks for each of the 171 participants, and then report means, standard deviations and medians of these averages.

Table 3
Numbers of common and individuated-standard offers inspected in each task

Task(s)	Task type	Offer type	Number of CS offers inspected			Number of IS offers inspected		
			Mean (SD)	Median	%	Mean (SD)	Median	%
1	Bench-mark	P	22.6 (4.52)	24	94.3			
2	AC	P*D	22.3 (4.88)	24	93.0			
3	AC	P*D+A	22.3 (4.83)	24	92.7			
4	AC	P*D1*D2	22.4 (4.53)	24	93.1			
2-4	AC	Average	22.3 (4.53)	24	93.0			
5	NC	P*D				19.9 (6.33)	24	83.0
6	NC	P*D+A				19.8 (6.28)	24	82.4
7	NC	P*D1*D2				18.4 (6.61)	22	76.6
5-7	NC	Average				19.4 (5.38)	21.3	80.7
8	PC	P*D	7.3 (1.78)	8	91.2	13.5 (4.02)	16	84.1
9	PC	P*D+A	7.1 (2.12)	8	88.3	12.9 (4.46)	16	80.9
10	PC	P*D1*D2	7.0 (2.12)	8	87.5	12.3 (4.61)	15	76.8
8-10	PC	Average	7.1 (1.70)	8	89.0	12.9 (3.58)	14.3	80.1

There are 171 observations for each task. CS = common standard; IS = individuated-standard; SD = standard deviation.

Table 4
Numbers of participants choosing common standard offers in each PC task

Tasks	Offer type	Choices of common standard offers	%
8	P*D	50	29.2
9	P*D+A	29	17.0
10	P*D1*D2	46	26.9
8-10	Average	41.7	24.4

There are 171 observations for each task.

Table 5
Frequency of optimal choices conditional on standard of offer

Task(s)	Offer type	If optimal offer is common-standard			If optimal offer is individuated-standard		
		n	Number of optimal choices	%	*n*	Number of optimal choices	%
8	P*D	55	23	41.8	116	40	34.5
9	P*D+A	60	10	16.7	111	27	24.3
10	P*D1*D2	56	20	35.7	115	13	11.3

Averages not reported because of differences in *n* between tasks.

Figure 1

Proportion of common standard inspections over course of task for each PC task

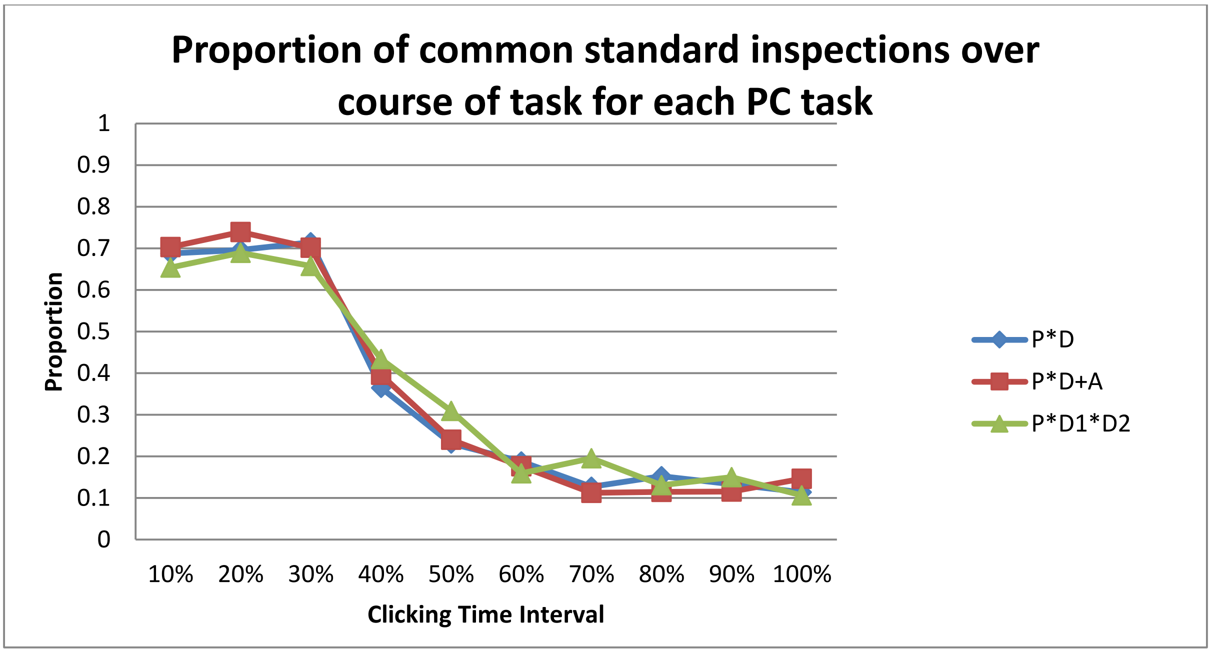
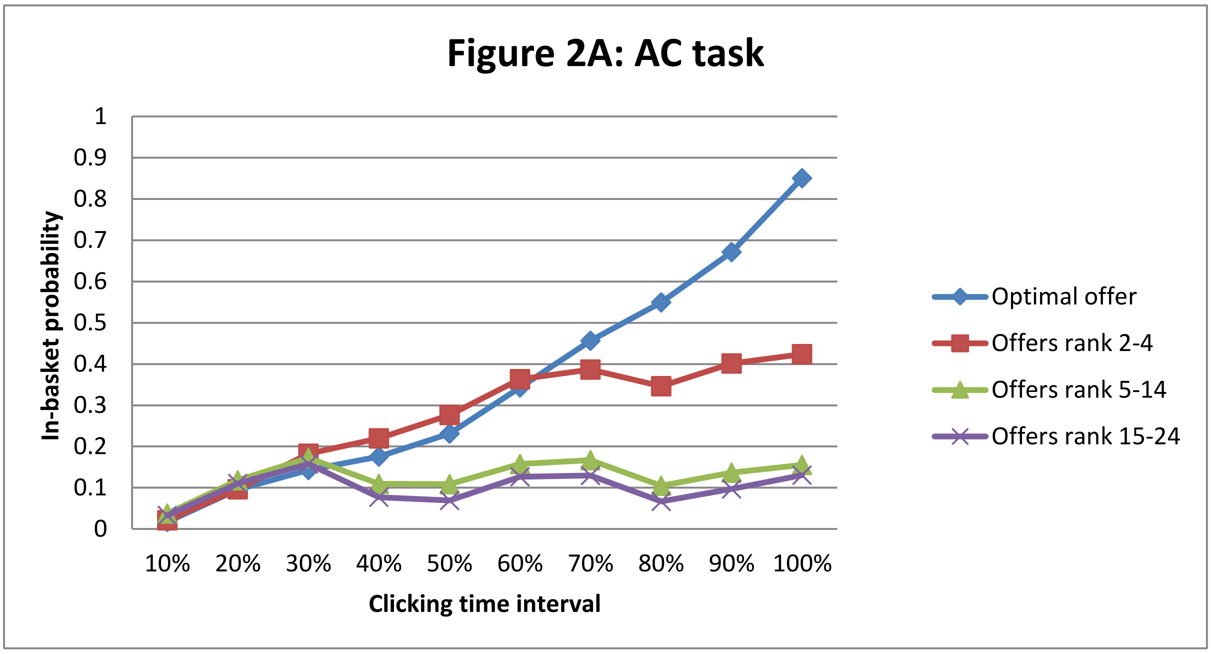
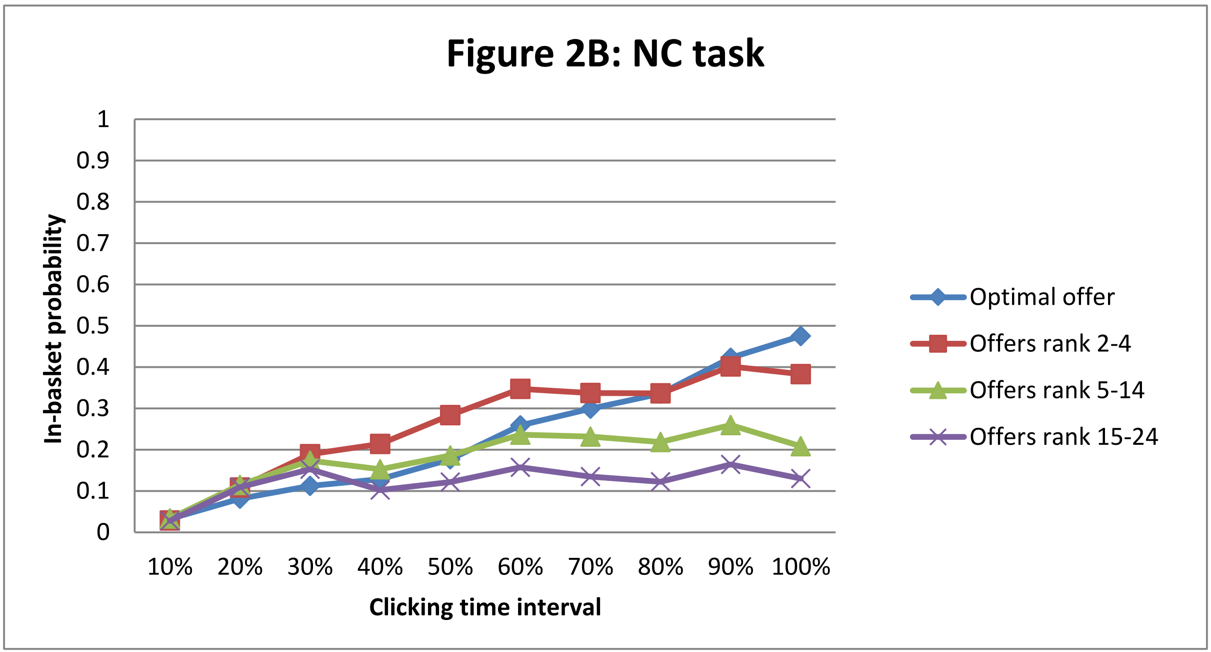


Figure 2

Evolution of contents of shopping basket for P*D offer type





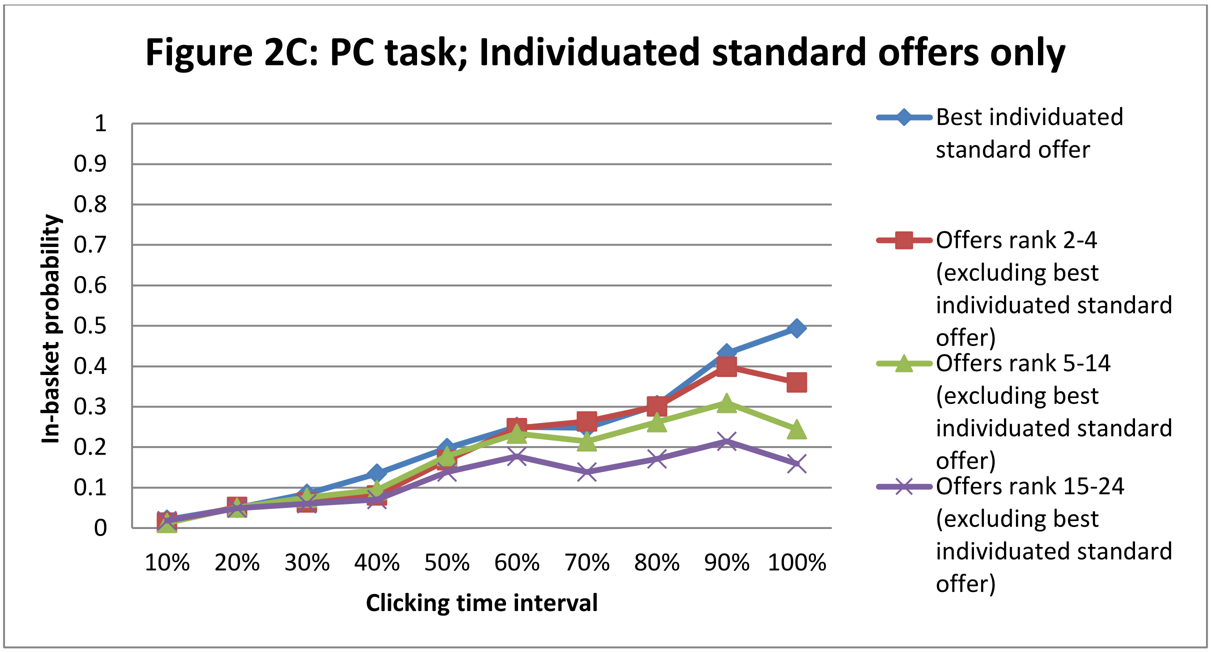


Figure 2C: PC task; Individuated standard offers only
In-basket probability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Clicking time interval
Best individuated standard offer
Offers rank 2-4 (excluding best individuated standard offer)
Offers rank 5-14 (excluding best individuated standard offer)
Offers rank 15-24 (excluding best individuated standard offer)

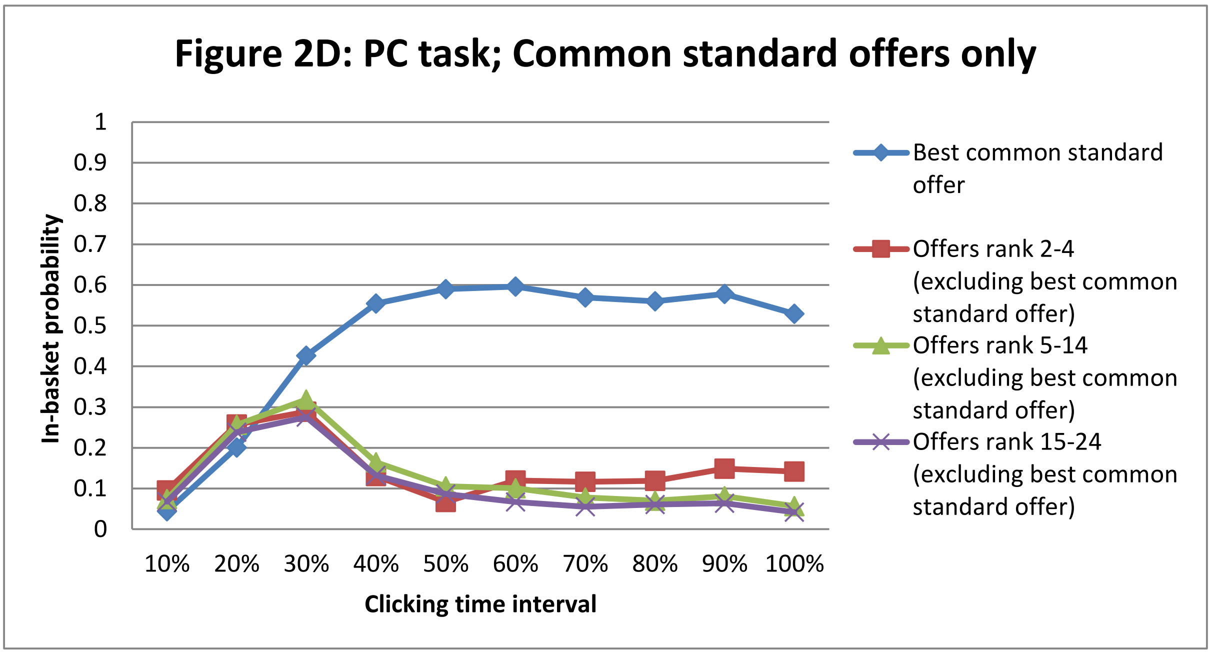


Figure 2D: PC task; Common standard offers only
In-basket probability
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Clicking time interval
Best common standard offer
Offers rank 2-4 (excluding best common standard offer)
Offers rank 5-14 (excluding best common standard offer)
Offers rank 15-24 (excluding best common standard offer)

Appendices (intended for Electronic Companion only)

Appendix A: Experimental instructions and questionnaire

Experimental instructions

Welcome to today's experiment on decision making. Today's session will begin shortly. Before we start, I have a few friendly reminders. First, to help us keep the lab neat and tidy, we ask that you do not eat or drink in the lab. Also, we ask that you turn off completely your mobile phones and other devices, as they may not be used during today's session. Please refrain from talking to other participants during the experiment. Finally, you are not allowed to use calculators, take notes or use the computer privately. Do not open any webpage or any other applications on this computer. Calculators, mobile phones, paper and pens are not allowed to be used in this experiment.

A copy of the instructions is on your desk. Please follow along as I read through the instructions. If you have a question, please raise your hand and I will come and answer it privately.

(On the desk in front of you, you will see a receipt form. DO NOT sign the receipt. You will sign the receipt form only once you have been paid.)

We are now ready to describe the nature of the tasks within the experiment.

Tasks

In the experiment, you will make decisions that involve buying goods from firms.

There are 10 tasks in this experiment. I will now describe a typical task for you.

At the beginning of each task, you are given an endowment of *game points*. Using this endowment, you must buy one unit of a good. Exactly the same good is being sold by 24 firms. Each firm offers you a price at which you can buy the good. We will call this the firm's *offer*. Each firm's offer is also in game points. Your job is to choose which firm to buy the good from. The price you pay the firm is deducted from your endowment to give your *payment points* for the round. Different firms may offer different prices, so how many payment points you earn will depend on which firm you buy the good from. However, all the prices will be less than your endowment. So, whichever firm you buy from, the number of payment points you earn will be positive.

It is in your interest to try to get as many payment points as possible in each task. At the end of the experiment, one of the 10 tasks will be selected randomly. We will find out how many payment points you earned in that task and convert them into UK pounds, using an *exchange rate*. We will pay you that amount of money, immediately after the experiment. The exchange rate between points and UK pounds may be different for different tasks. It will be shown on the screen for each task. In each task, the value of your endowment at the exchange rate will be £32.

Now I will explain more about the task.

[Activating the computer screen]

This is an example and your payment will NOT relate to this example. Please do not click anything except when I tell you to.

Each task has two pages: a "market page" and a "shopping basket page".

<u>*Market page*</u>

Now what you see is the market page.

Notice that your endowment and the exchange rate are shown on the top of the screen. It says: *"Your endowment is 64 points."* and *"The exchange rate is 2 points = £1."*

On the left hand side of the screen you can see 24 coloured boxes, "OFFER A", OFFER B"……., "OFFER X". These are the offers of a good from the 24 firms (details of the offers are not yet visible). Different colors represent different "price structures" which I will explain later.

On the right hand side of the screen you can see a "shopping basket".

On the bottom of the screen you can see two buttons: The “View the shopping basket” button on the left and the “Move into the shopping basket” button on the right.

In the market page, you can do the following four actions:

1. Discover the *price structure* used by a firm to present its offer
2. Discover the *price details* of a firm’s offer
3. Move an offer into the shopping basket
4. View the shopping basket

I will now explain these actions.

Please click ONCE on offer A. Notice that this is a red box. You can see that the offer now has a black frame round it. This tells you that you have chosen to look at this offer. The price structure of offer A is shown on the screen, below the 24 offers: it says “price structure 1”. Now, click offer A again and wait. There is a delay of 3 seconds before anything happens. Now you can see the price details of offer A, below the price structure information: “*Original price = 15 points; Final price = Original price* x *110%*”. This means that the final price is 15 points multiplied by 110%, which comes to 16.5 points. This is what you would have to pay if you bought the good from this firm. Your endowment in this task is 64 points. If you bought offer A, your payment points for this task would be 64 points – 16.5 points = 47.5 points. Please raise your hand if you have any questions.

If this was a real task, you would now be able to choose whether or not to put this offer into the shopping basket. For the purposes of this practice, let us now put this offer into the shopping basket. Click the “Move into the shopping basket” button at the bottom right of the screen. Now the offer A is moved into the shopping basket and you can see it in the shopping basket on the right side of the screen.

Now we'll look at another offer with the same price structure. Click once on offer D. Notice that this is also a red box. You can see the black frame has moved from offer A to offer D. Offer A's price structure and price details have both disappeared and offer D's price structure is now shown on the screen. Below the 24 offers, it says "price structure 1". It has the same price structure as offer A. Offers with the same colour always have the same price structure.

Click offer D again and wait for 3 seconds. Now you can see the price details of offer D: "*Original price = 20 points; Final price = Original price* x *110%*". This means that the final price is 20 points multiplied by 110%, which comes to 22 points. Your endowment in this task is 64 points. If you bought offer D, your payment points for this task would be 64 points – 22 points = 42 points. Please raise your hand if you have any questions.

Remember that offer A was Original price x 110%. Offer A and offer D have different original prices (15 points or 20 points), but in both cases the original price is multiplied by the same percentage. This is because these two offers have the same price structure. In this example, all offers which use price structure 1 consist of an original price multiplied by 110%.

Put offer D into the shopping basket by clicking the "Move into the shopping basket" button.

Now we'll look at another offer with a different price structure. Click once on offer E. Notice that this is a yellow box. Below the 24 offers, it says: "price structure 2". Offers with different colors always have different price structures.

Click offer E again and wait for 3 seconds. Now you can see the price details of offer E showing below the price structure information: "*Original price = 18 points; Final price = Original price* x *120%*". This means that the final price is 18 points multiplied by 120%, which comes to 21.6 points. Your endowment in this task is 64 points. If you bought offer

E, your payment points for this task would be 64 points – 21.6 points = 42.4 points. Please raise your hand if you have any questions.

Remember that offer A and offer D both had original prices multiplied by 110%. Offer E has an original price multiplied by 120%. This is because E has a different price structure than A and D. In this example, all offers which use price structure 2 consist of an original price multiplied by 120%.

Put offer E into the shopping basket by clicking the “Move into the shopping basket” button.

Now let us quickly put some more offers in the shopping basket. Do this for offer F, by clicking the offer once and then clicking the “Move into shopping basket” button.

And do the same for offer G.

And do the same for offer M.

And finally, do the same for offer W.

Now we will go to the shopping basket. Click “View the shopping basket” button.

Shopping basket page

After 3 seconds delay, you can see the shopping basket page.

Your endowment and the exchange rate are still shown at the top of the screen. These values stay the same throughout the task.

In the middle of the screen you can see the price details of the seven offers that you have put into the shopping basket. Notice that the shopping basket allows you to see the price details of several offers at the same time. This makes it easier to compare different offers.

On the left side of the screen, you can see a “Move offer out” button for each offer.

On the right side of the screen, you can see a “Buy the good from firm” button for each offer.

On the bottom of the screen, you can see a “Continue shopping” button.

In the shopping basket page, you can do the following three actions.

1. Move an offer out of the shopping basket
2. Continue shopping
3. Buy the good from one of the firms whose offers are in the shopping basket.

Let us move offer E out of the shopping basket. Click the “Move offer E out” button. After clicking, you can see the information of offer E, the “Move offer E out” button and the “Buy the good from firm E” button all disappear. This means that offer E has been moved out of the shopping basket.

Notice, the capacity of the shopping basket is nine. This means you cannot put more than nine offers into the shopping basket at the same time. If the shopping basket is full but you want to put some new offers into it, you must first move some old offers out of the shopping basket, and then go back to the market page.

Let us go back to the market page. Click the “Continue shopping” button.

Now you are in the market page again.

Put offer U into the shopping basket and click “View the shopping basket button”. Wait for 3 seconds.

Now you are back at the shopping basket page. You can see the price details of the offers in the basket, listed in the middle of the screen. Notice that this list includes offer U, which you just added to the basket.

If this was a real task, you would now be able to decide whether to buy the good from any one of the firms whose offers are in the shopping basket, or whether to continue shopping.

Now, look at offer A:

"*Original price = 15 points; Final price = Original price* x *110%*". This means that the final price is 15 points multiplied by 110%, which comes to 16.5 points. This is what you would have to pay if you bought the good from this firm. Your endowment in this round is 64 points. If you bought offer A, your payment points would be 64 points – 16.5 points = 47.5 points.

Now, let us assume that this is a real task and at the end of the experiment this round is randomly picked by the computer. So you would have 47.5 payment points, which would covert to UK pounds.

We know that the exchange rate in this round is 2 points = £1, so we would pay you 47.5 points / 2 = £23.75. This £23.75 is called your *final payment.* Please raise your hand if you have any questions.

Now, look at offer D:

"*Original price = 20 points; Final price = Original price* x *110%*". This means that the final price is 20 points multiplied by 110%, which comes to 22 points. Your endowment in this round is 64 points. If you bought offer A, your payment points would be 64 points – 22 points = 42 points.

Now, let us assume that this is a real task and at the end of the experiment this round is randomly picked by the computer. You would have 42 points, which would covert to UK pounds.

We know that the exchange rate in this round is 2 points = £1, so we would pay you 42 points / 2 = £21.00 and your final payment is £21.00. Please raise your hand if you have any questions.

Now, look at offer E:

"*Original price = 18 points; Final price = Original* x *120%*" This means that the final price is 18 points multiplied by 120%, which comes to 21.6 points. Your endowment in this round is 64 points. If you bought offer E, your payment points would be 64 points – 21.6 points = 42.4 points.

Now, let us assume that this is a real task and at the end of the experiment this round is randomly picked by the computer. You would have 42.4 points, which would covert to UK pounds.

We know that the exchange rate in this round is 2 points = £1, so we would pay you 42.4 points / 2 = £21.20. Please raise your hand if you have any questions.

For the purposes of this practice, let us now buy the good from any firm you want. Click a "Buy the good from firm" button at the right hand side of the screen.

If this was a real task, your payment points for this task would be your endowment minus the final price of the offer you have bought.

The practice is over.

Please answer the following questions. After finishing these questions, please raise your hand and I will come to you to check your answers… If all your answers are correct, you will be able to start the experiment.

__Questionnaire__

Questions 1 to 6: please answer each question ticking ONE box.

1. The capacity of the shopping basket is:

A. 8 offers

B. 10 offers

C. 9 offers

D. No limitation

2. At the beginning of each task, you are endowed with:

A. Payment points that convert to £32

B. Payment points that convert to £64

C. 32 payment points

D. Nothing

3. If you want to move an offer out of the shopping basket, you can do it in the

A. Market page

B. Shopping basket page

C. Both pages

D. You cannot move an offer out of the shopping basket

4. The exchange rate between payment points and UK pounds in different tasks:

A. Is always the same

B. May be different

5. Offers with the same color:

A. Have the same price structure

B. Have the same final price

C. May have different price structures and different final prices

6. Your payment is equal to:

A. The final price of the good

B. Your endowment

C. Your endowment minus the final price of the good

Questions 7 to 9: Please answer each question by filling in the blanks.

7. If your endowment is 200 points and the final price of the offer you select is:

Original price = 100 points; Final price = Original price + 20 points

then your payment points are ________.

If this is the selected round and the exchange rate is *20 points = 1 pound*, your final payment is ____ pounds

8. If your endowment is 200 points and the final price of the offer you select is:

Original price = 200 points; Final price = Original price x *60%*

then your payment points are ________.

If this is the selected round and the exchange rate is *10 points = 1 pound*, your final payment is ____ pounds.

9. If your endowment is 200 points and the final price of a selected offer is:

Original price = 100 points; Final price = Original price x *60% + 40 points*

then your payment points are ________.

If this is the selected round and the exchange rate is *50 points = 1 pound*, your final payment is ____ pounds.

Correct answers:

1: C

2: A

3: B

4: B

5: A

6: C

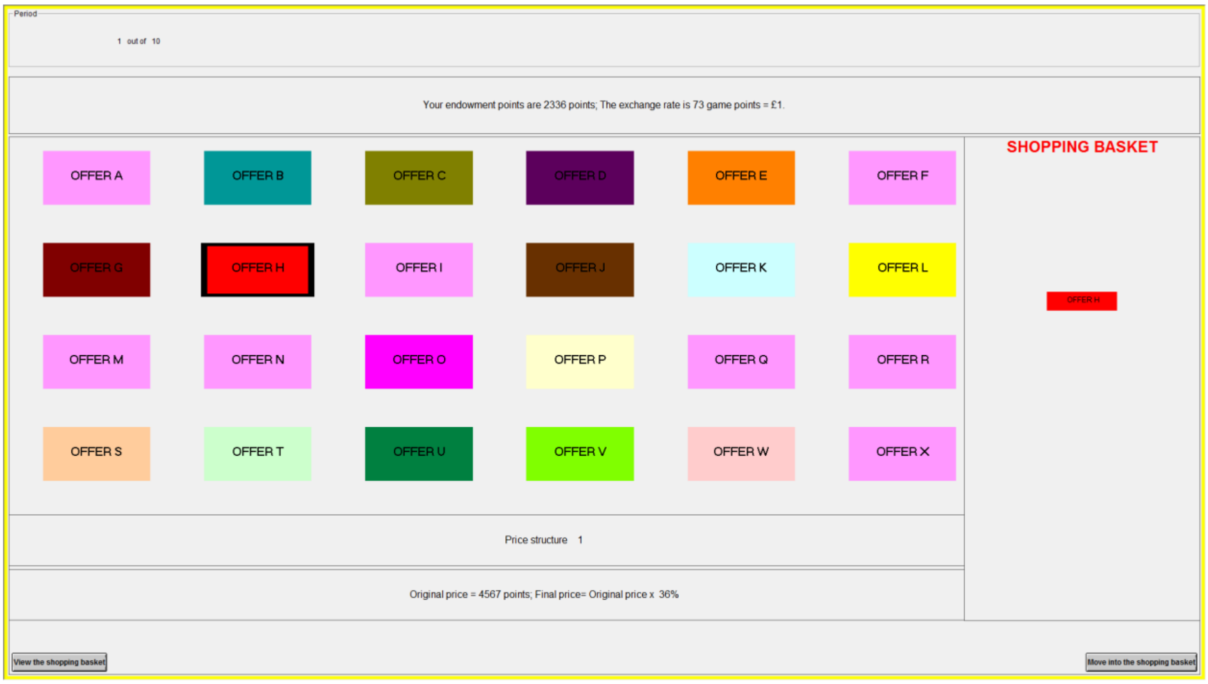
7: 80; 4

8: 80; 8

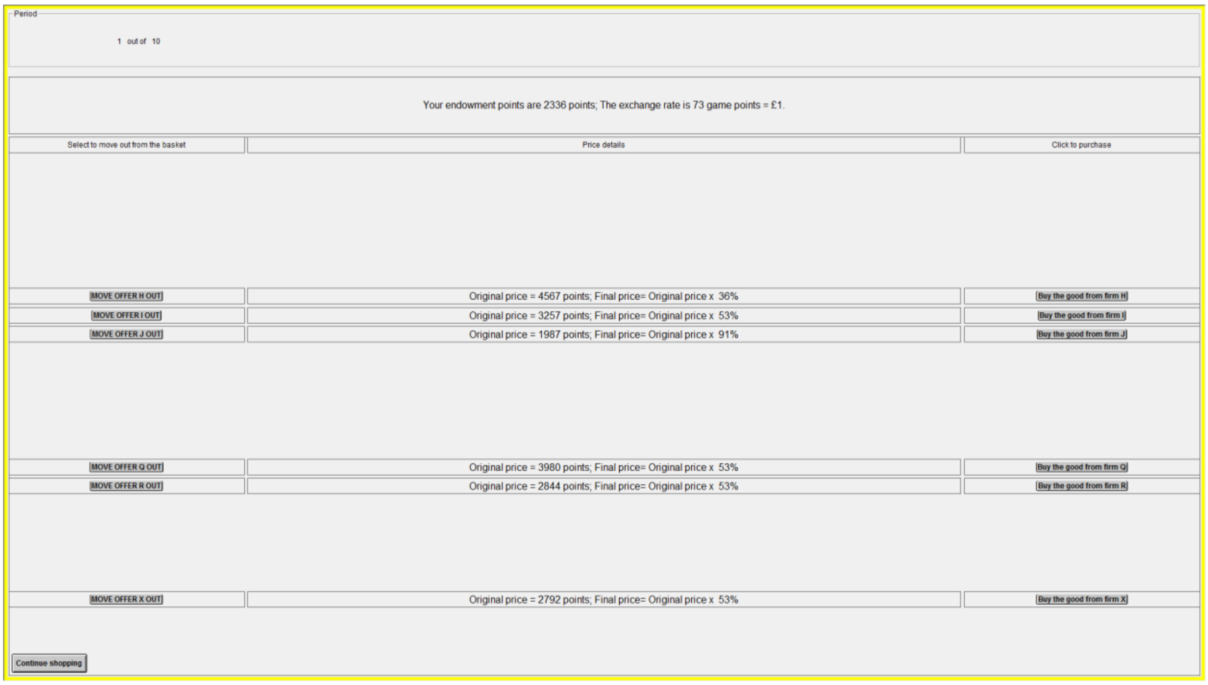
9: 100; 2

Appendix B: Typical screen shots

Marketing page



Shopping basket page



Appendix C: Evolution of contents of shopping basket for P, P*D+A, and P*D1*D2 offer types

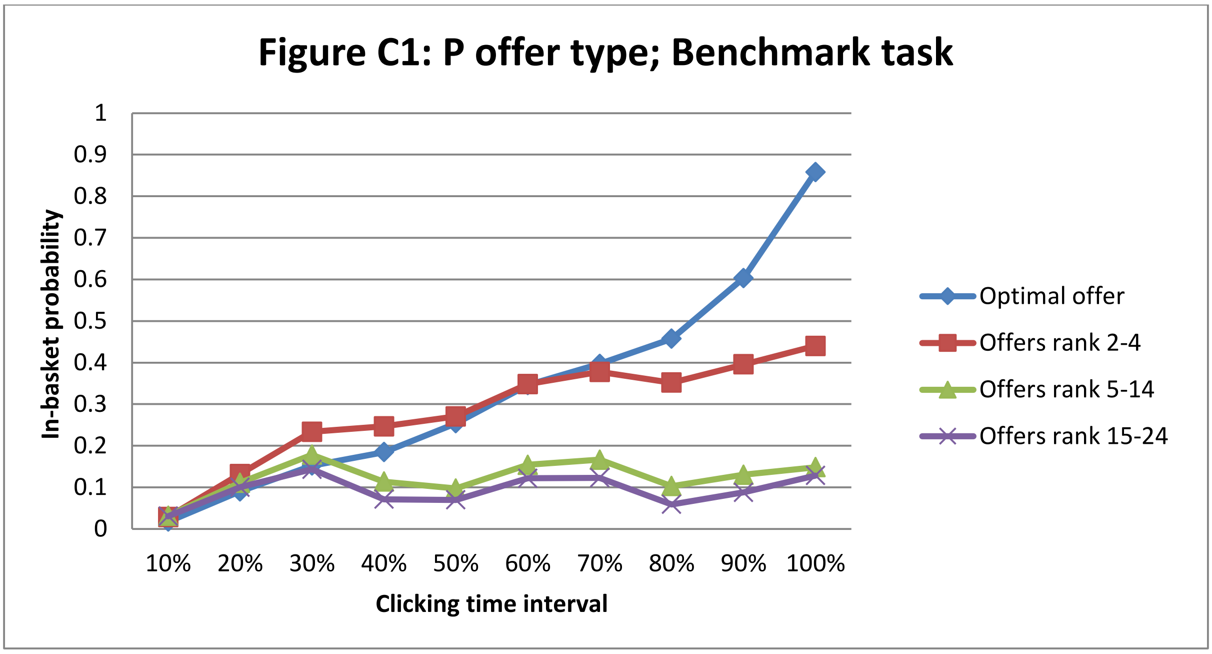


Figure C2: P*D+A offer type; AC task

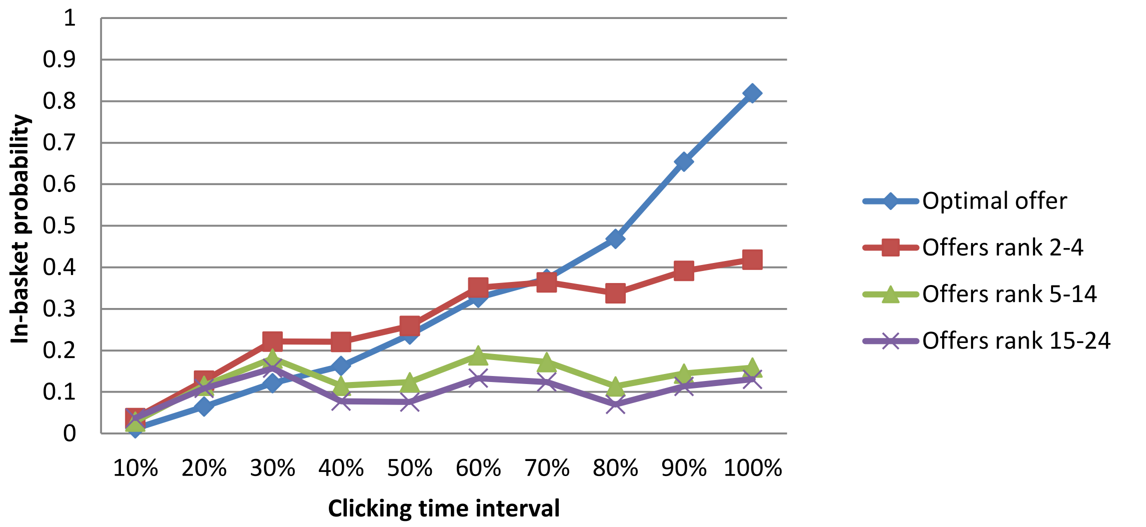
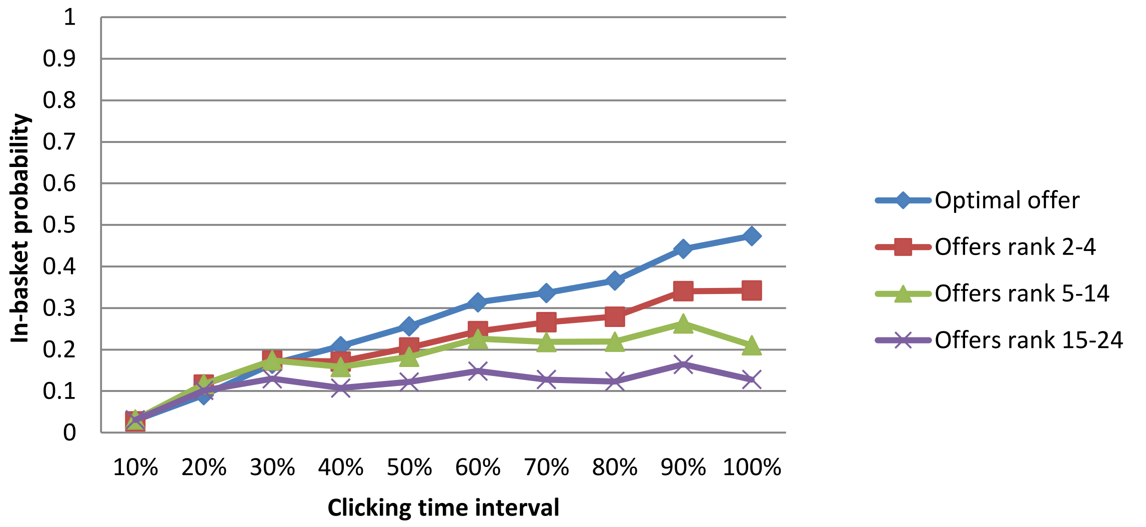


Figure C3: P*D+A offer type; NC task



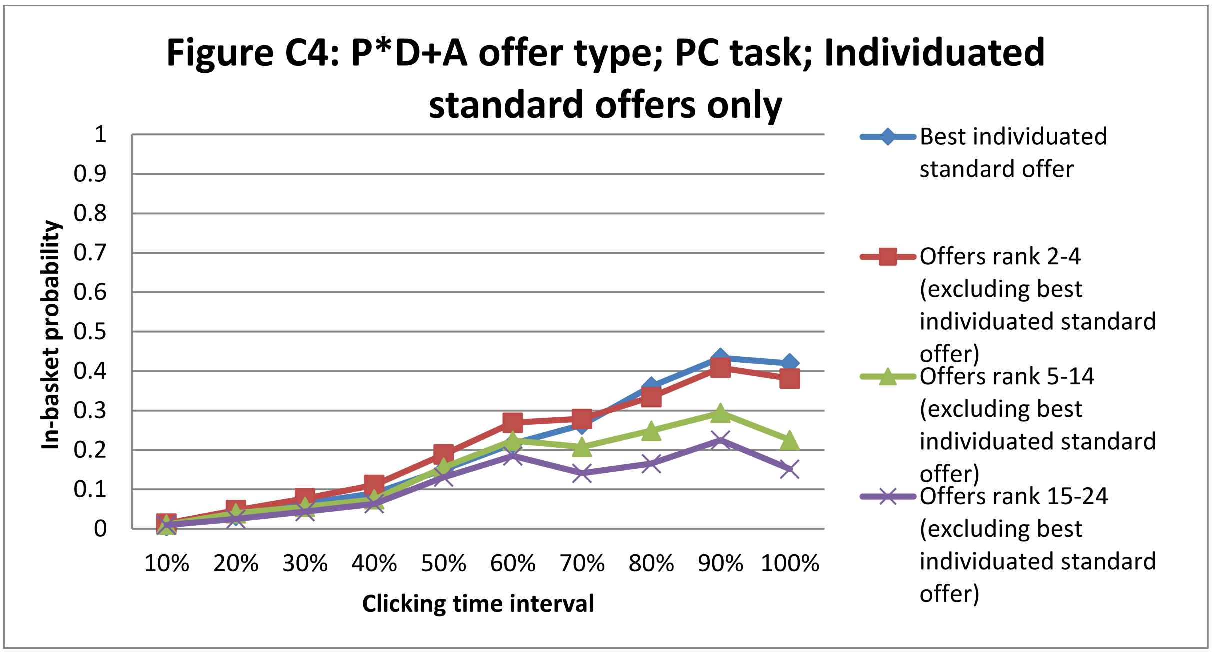


Figure C4: P*D+A offer type; PC task; Individuated standard offers only
In-basket probability
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Clicking time interval
Best individuated standard offer
Offers rank 2-4 (excluding best individuated standard offer)
Offers rank 5-14 (excluding best individuated standard offer)
Offers rank 15-24 (excluding best individuated standard offer)

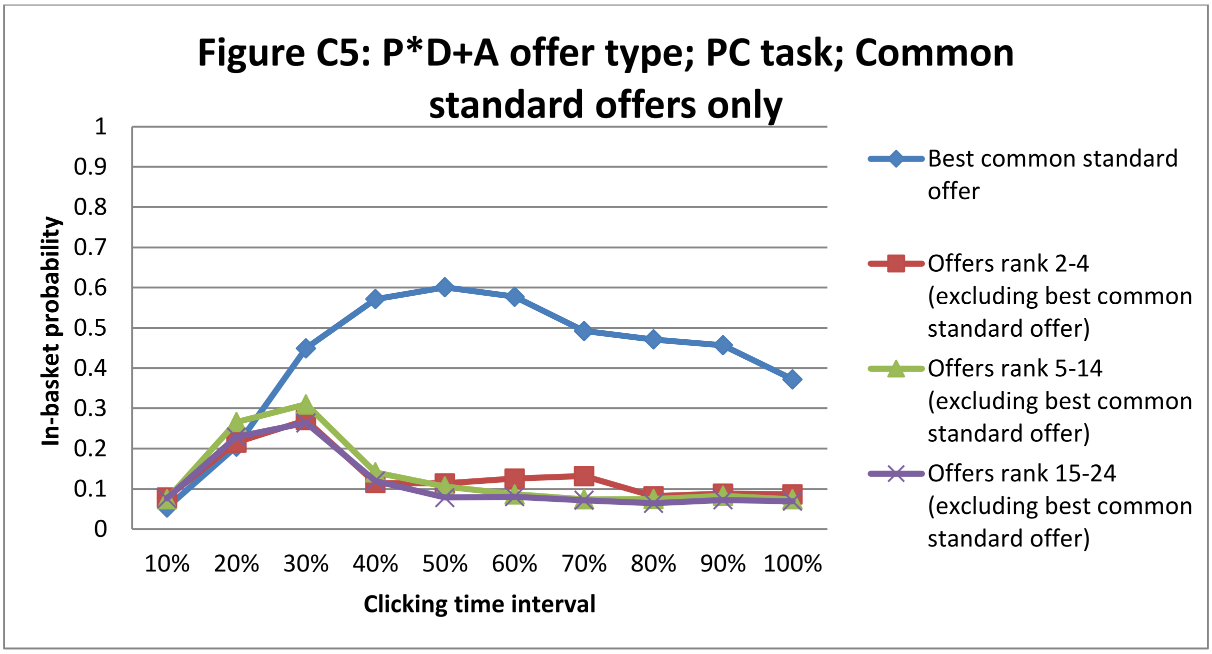


Figure C5: P*D+A offer type; PC task; Common standard offers only
In-basket probability
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Clicking time interval
Best common standard offer
Offers rank 2-4 (excluding best common standard offer)
Offers rank 5-14 (excluding best common standard offer)
Offers rank 15-24 (excluding best common standard offer)

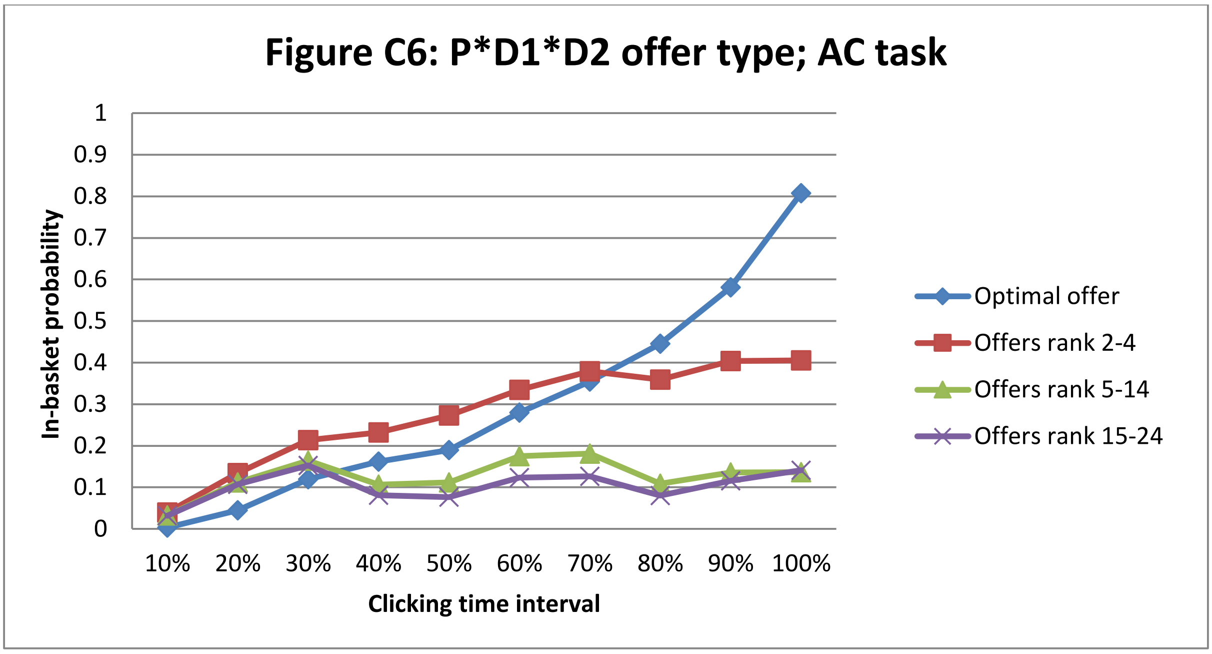


Figure C6: P*D1*D2 offer type; AC task
In-basket probability
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Clicking time interval
Optimal offer
Offers rank 2-4
Offers rank 5-14
Offers rank 15-24

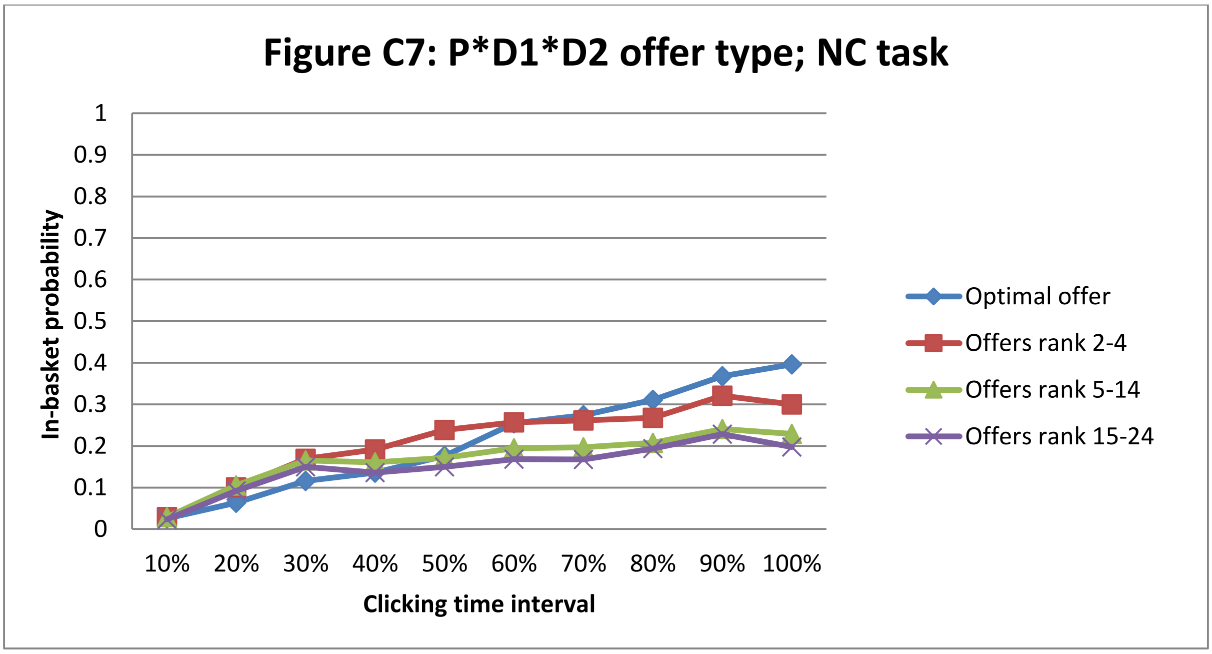


Figure C7: P*D1*D2 offer type; NC task
In-basket probability
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Clicking time interval
Optimal offer
Offers rank 2-4
Offers rank 5-14
Offers rank 15-24

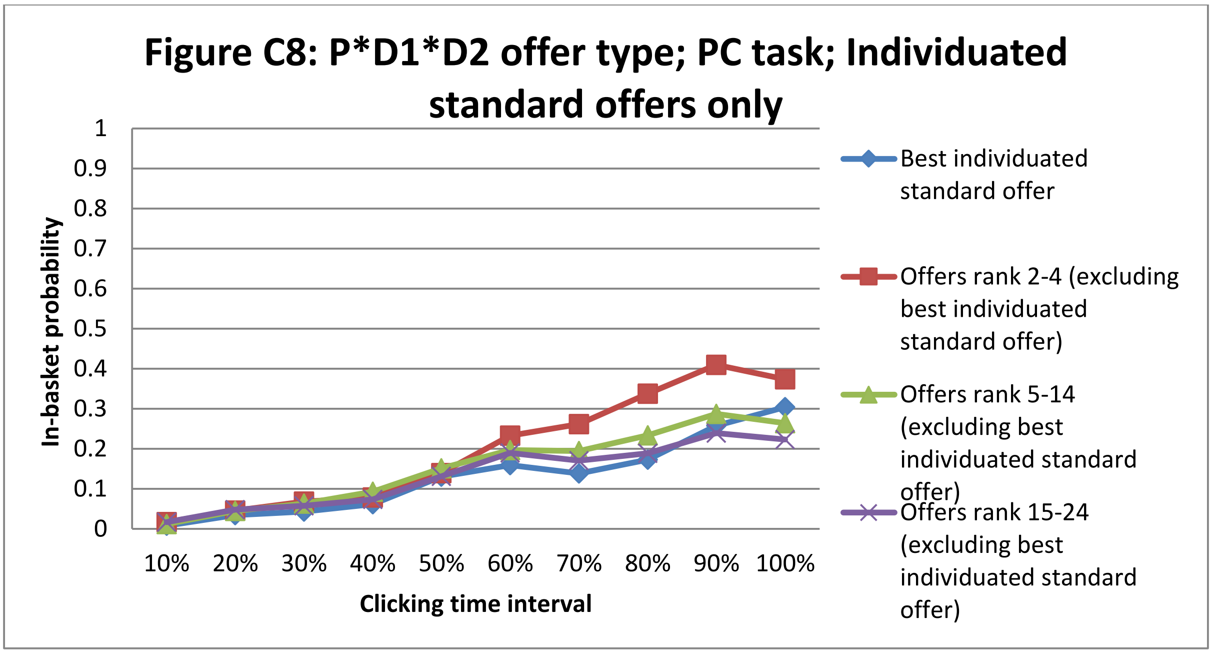


Figure C8: P*D1*D2 offer type; PC task; Individuated standard offers only
In-basket probability
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Clicking time interval
Best individuated standard offer
Offers rank 2-4 (excluding best individuated standard offer)
Offers rank 5-14 (excluding best individuated standard offer)
Offers rank 15-24 (excluding best individuated standard offer)

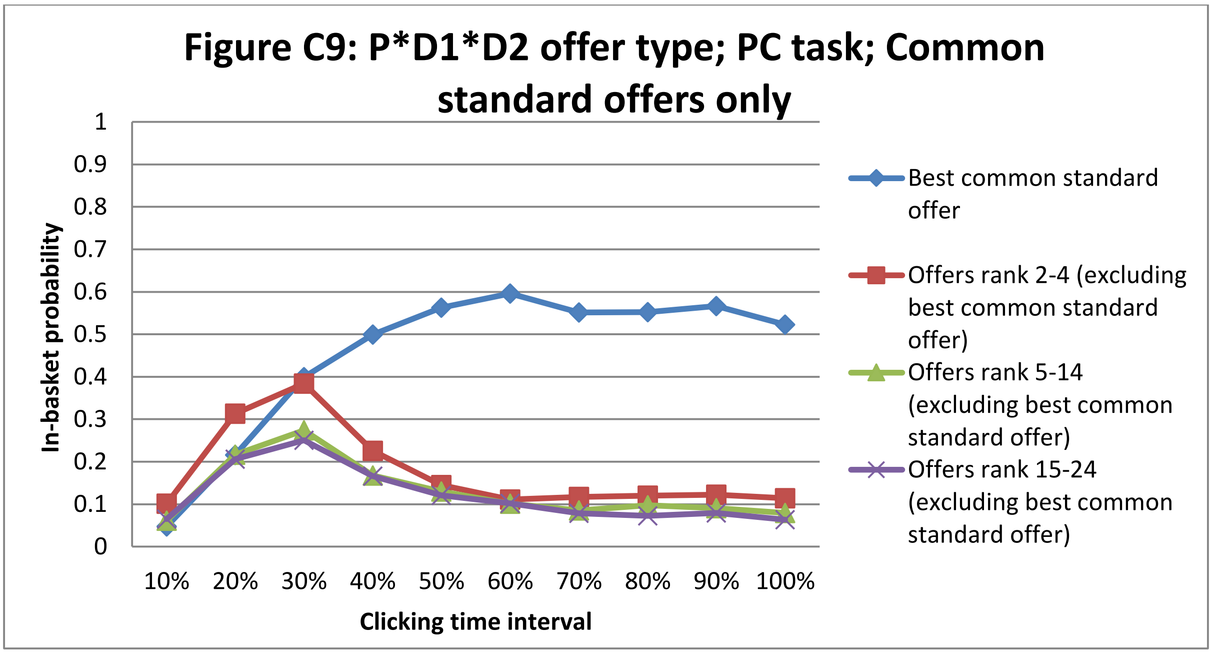


Figure C9: P*D1*D2 offer type; PC task; Common standard offers only
In-basket probability
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Clicking time interval
Best common standard offer
Offers rank 2-4 (excluding best common standard offer)
Offers rank 5-14 (excluding best common standard offer)
Offers rank 15-24 (excluding best common standard offer)