Do consumers prefer offers that are easy to compare? An experimental investigation.

Crosetto, Paolo and Gaudeul, Alexia

Max Planck Institute of Economics, Max Planck Institute of Economics

20 September 2012

Do consumers prefer offers that are easy to compare? An experimental investigation.[1]

Paolo Crosetto[2] and Alexia Gaudeul[3]

September 20, 2012

[1]We wish to thank Nicolas Berkowitsch, Alena Otto and Robert Sugden for their comments and suggestions. This paper was presented at the Max Planck Institute for Economics in Jena in April 2011, at the workshop for Experimental Methods and Economic Modeling in Capua in June 2011, at the Max Planck Institute for Human Development in Berlin in June 2011, at the International Conference of the Economic Science Association in Chicago in July 2011, at the European Conference of the Economic Science Association in Luxembourg in September 2011, at the Department of Economics, Business and Statistics (DEAS) of the University of Milan in December 2011 and at the Conference of the European Economic Association in Málaga in August 2012. The experiment's interface and randomized menu generation were programmed with Python (van Rossum, 1995). Data analysis and regressions were performed with Stata (StataCorp, 2009). Simulations were run with Octave (Eaton, 2002).

[2]Strategic Interaction Group (ESI), Max Planck Institute for Economics, Jena. email: crosetto@econ.mpg.de

[3]Strategic Interaction Group (ESI), Max Planck Institute for Economics, Jena. email: gaudeul@econ.mpg.de

Abstract

Firms can exploit consumers' mistakes when facing complex purchasing decision problems but Gaudeul and Sugden (2012) argue that if at least some consumers disregard offers that are difficult to compare with others then firms will be forced into adopting common ways to present their offers and thus make choice easier. We design an original experiment to check whether consumers' indeed favor those offers that are easy to compare with others in a menu. A sufficient number of subjects do so with sufficient intensity for offers presented in common terms to generate higher revenues than offers that are expressed in an idiosyncratic way.

Keywords: Bounded Rationality, Cognitive Limitations, Standards, Consumer Choice, Experimental Economics, Heuristics, Pricing Formats, Spurious Complexity.

JEL Codes: C91, D18, D83, L13

Behavioral economics finds that consumers have "inconsistent, context dependent preferences" and may not have "enough brainpower to evaluate and compare complicated products" (Spiegler, 2011). They "may fail to choose in accordance with what, after sufficient reflection, they would acknowledge to be their own best interests" (Gaudeul and Sugden, 2012). Low levels of consumer literacy and numeracy even in advanced economies make it very difficult for broad swathes of the population to understand how to make adequate decisions in many situations, such as when choosing how much to save for retirement, when selecting healthcare insurance, when investing in stock markets, when comparing car or computer models, *etc.* (Agarwal and Mazumder, 2010; Ayal, 2011; Bar-Gill and Stone, 2009; Lusardi, 2008; Miravete, 2003; Wilson and Price, 2010). Marketing research (Morwitz et al., 1998; Nunes, 2000; Viswanathan et al., 2005; Zeithaml, 1982) and research from behavioral economics (Ariely, 2008; Iyengar and Lepper, 2000; Iyengar et al., 2004) also give examples of how badly consumers deal with products choices in realistic purchasing scenarios. Experiments on this topic include Huck and Wallace (2010), Choi et al. (2010) and Shestakova (2011) among others.

The consumers' biases, limitations and inconsistencies may be exploited by firms. They may for example benefit from introducing spurious complexity in their contract offerings so as to deliberately obfuscate consumer choice (Carlin, 2009; Chioveanu and Zhou, 2009; Ellison, 2005; Gabaix and Laibson, 2006; Piccione and Spiegler, 2012). Sectors in which firms do so may be called "confusopolies" (Adams, 1997). Those are "a group of companies with similar products who intentionally confuse consumers instead of competing on price". Sectors in which this might be the case include telephone services, insurance, mortgage loans, banking, financial services, electricity, *etc.* In all those sectors, firms sell a relatively homogeneous product and so would make low profits if they did not introduce spurious differentiation in their offerings and thus undermine consumers' ability to make informed choices about their services and products. Recent research does find empirical evidence that firms might design their offers to exploit consumers (DellaVigna and Malmendier, 2006; Ellison and Ellison, 2009; Miravete, 2003, 2011). Kalaycı and Potters (2011) and Shchepetova (2012) also find experimental evidence that more complex offers increase firms profits.

Faced with such issues, libertarian paternalists (Camerer et al., 2003; Thaler and Sunstein, 2008) suggest regulatory intervention to impose that consumers' decision problems be framed in such a way that they reach the "correct" decision, that is, the decision they would take *absent their limitations.* However, determining what decision that would be is difficult, not to mention that even experts may not know what is best (Freedman, 2010). A complementary option is to introduce measures to educate consumers and provide them with information so they have the tools to make better choices in a wide variety of settings (Agarwal et al., 2010; Garrod et al., 2008). However, as far as possible, one would want to leave consumers free to choose as they wish and the market free to fulfill their needs as they occur (Sugden, 2004).

Gaudeul and Sugden (2012) argue that if at least some consumers disregard offers that are difficult to compare with others then firms will be forced into adopting common ways to present their offers and thus make choice easier. Consumers who discard offers that are difficult to compare with others are said to follow the common standard rule ("CS rule"). An example of how it operates goes as follows: a consumer wants to buy a fruit and is faced with the choice between two oranges and one apple. Oranges are priced at $\$0.45$ and $\$0.55$ respectively, while the price of the apple is $\$0.70$. Suppose the consumer cares only about calories and estimates the oranges to contain 35 calories each while he thinks the the apple contains 55 calories. The consumer discards the higher priced orange from his consideration set and compares the lower priced orange with the apple in terms of price per calories. From the price and calorific content of each fruit, he calculates that the lower priced orange costs $1.29 per 100 calories, while the apple costs $1.27 per 100 calories. The lower priced orange appears to cost more than the apple, but the consumer still chooses it under the CS rule. We will see this makes sense as long as the consumer is not sure about how different fruits compare in terms of calorific content (he knows he might have made mistakes in his evaluation), there is little intrinsic differences between products (he cares only about calories), and the consumer does not hold prior beliefs on the value of each product (he does not believe for example that apples are always the best deal). This rule derives strength from its simplicity, has strong behavioral foundations and can be applied in many settings, thus ensuring its evolutionary robustness. Contributing to the later, we will see that there is no need for others to follow it for it to be optimal.

To clarify our meanings, what we call a "standard" here is what others have called a "frame", that is, to paraphrase Spiegler (2011, p.151), an aspect of a product's presentation that is of no relevance to a consumer's utility and yet affects his ability to make comparisons among alternatives. This can be a price format, the language in a contract clause, but also a unit of measurement, a way of packaging a product, a technical standard, *etc.*.. Expressing an offer in terms of a common standard does *not* inherently make that offer less complex to understand. That is, a CS offer when standing on its own will not be easier to evaluate than an offer that is presented in terms of an individuated standard ("IS"). It is only when put in relation with other offers that a CS offer will be easier to evaluate than an IS offer. To take an example, the switch by Apple from PowerPC processors to Intel x86 processors in 2006 did not make the performance of Apple computers easier to evaluate, but it did make it easier to compare with the performance of most other computers. The CS rule does not therefore involve considerations of *complexity*, but of *comparability*.

Our goal in this paper is to check in an experimental setting whether consumers indeed make use of common standard information, whether being offered menus of offers with a CS improves their payoffs, whether they tend to favor offers that are easier to compare and how much they penalize non-standard offers. We focus in particular on whether their behavior is affected by the number of offers that are proposed to them or by how close offers are in terms of price. This contribution to the experimental literature on consumer decisions in complex settings is motivated, as argued above, by its implications within the field of behavioral industrial organization (Ellison, 2006; Spiegler, 2011).

We rely in this paper on data generated from a controlled laboratory setting because empirical data is not well suited for our purpose. Relying on product sales, for example, introduces various confounds: the presence of real along with spurious product differentiation; regulations that impose standards for a variety of reasons; economies of scale and network effects that encourage the convergence to a technological standard; reputation concerns that lead firms not to wish to confuse consumers; framing other than the standard adopted by the offer that may influence choice as well; habits such that the consumer chooses a product based on past purchasing behavior, and so on. Doing an experiment in the laboratory allows us to create genuine spurious complexity, that is, complexity that all consumers would agree should be irrelevant to their choice. We kept the laboratory experience close to a purchasing act by framing the experiment as a real buying decision in which the participants were asked to *buy* a product out of *menus* of *offers* with the aim of minimizing expenditure. This means that even though the task was cognitively complex and making correct choices was difficult, our subjects were still able to easily understand the task they were asked to perform.

We find that our subjects generally obtain better payoffs when a menu includes some offers that are expressed in terms of a common standard, that is, when some offers within a menu are easy to compare. We also observe that a number of consumers favor the Lower Priced of the CS offers ("LPCS"). The intensity of their preference for the LPCS ensures that products expressed in terms of a common standard generate higher revenues than others.

1 Experimental design

Our subjects were first faced with a purchasing tasks, which constitutes the core of our experiment, and then had to complete a set of control tasks and fill out a questionnaire. The next section describes the main task.

1.1 The main task

In order to explore consumer behavior when faced with a problem that is both simple to understand but complex to solve, we designed a novel purchasing task with a simple structure in which complexity was introduced in a natural way. Subjects were given a budget B to buy *gray paint* in order to cover a fixed, square area A. They were presented with menus consisting of a number of offers, each offer being expressed in terms of its price and a visual representation of the area that the paint could cover for that price. Formally, each offer was a triple (s, a, p) in which s is a shape, a is the area of the shape s, expressed as a fraction of the total area A, and p is the price of the offer. Participants were told that paint quality did not differ across offers. The subjects' payoff was what remained from their budget B once all the paint needed to cover A had been bought at the cost implied by the chosen offer. The overall price paid for the chosen offer was calculated as p/a, and the payoff for the subject was $B - p/a$.

While the task is conceptually very simple and relates to everyday activities - subjects must minimize expenditure when buying a product of standardized quality - it is also cognitively quite hard, as evaluating hidden unit prices and comparing areas of different shapes can be difficult. Presenting offers in terms of a combination of a shape and a size allowed us to introduce a relatively high level of spurious complexity in an intuitive way while drawing on an existing body of research on shape perceptions (Krider et al., 2001). The concept of a *standard* was also easily introduced within our design: two offers within a menu that shared the same shape *and* size were easy to compare in terms of price, as price was then the only remaining differentiating factor. We therefore denote in our setting an offer as being a *common standard* offer if it has an equivalent in terms of size and shape in the menu.

Since the basic task (choosing an offer within a menu) was repeated several times, we wanted to exclude by design the possibility for our subjects to learn some specific pattern in the offers. Our offers could thus take three different shapes, each of twelve possible sizes, meaning that there were 36 possible distinct standards. Prices were randomly generated, meaning that it was almost impossible for consumers to rely on past purchasing experiences within our experiment to inform their present purchasing task.

The offers' three dimensions varied in the following way:

1. The shape s could be a circle, a square, or an equilateral triangle. We considered only those three shapes so as to be able to build on the existing literature on shape comparisons (Krider et al., 2001). Broad based offers such as triangles will be preferred to squares covering the same area and those will be preferred to the compact circle offers.

2. The area a took one of 12 possible values. Normalizing A to 100, these values ranged from 10 to 43, in steps of 3.[1] The step was chosen to be big enough to allow our subjects to determine easily whether an offer was bigger than another of the same shape within a menu, while being small enough to yield a sufficient number of steps and therefore a sufficient number of different (s, a) pairs in order to minimize learning from comparisons across menus.

3. The price information conveyed to the subjects, p, was computed from randomly drawn *unit prices* (up, the cost to cover 1% of A) as $p = up \cdot a$. Unit prices were drawn from a normal distribution of mean 0.5, while standard deviation σ^2 was equal to either 0.05, which generated more distance between offers and hence an *easier* problem, or 0.01, which generated closer offers and thus made it *harder* to identify the best one. Easy menus are meant to mimic conditions when there is little competition among firms, while hard menus translate closer competition.

The offers were displayed as a gray area centered on a white background representing the total area to be painted. The triangular offers rested on their base while square offers rested on a side. The white background allowed participants to visually appreciate the size of the

[1] The size was limited to 43 as an equilateral triangle resting on a base cannot cover more than ${}^{5\times\sqrt{75}}/_{100} = 43.3\%$ of a 10×10 square.

shape with respect to the total area to be painted. This background was overlaid with a grid of thin light blue lines to ease comparison and made it possible for participant to assess if two offers of the same shape were indeed of the same size.

The offers were displayed in menus, that varied in length (*3* or *6* offers per menu). This is done to assess the impact of increasing the number of competing firms, which introduces an additional source of complexity for consumers that may actually lead to a decrease in the strenght of competition among firms (Carlin, 2009).

Menus were randomly generated under the constraint that no offer was to give a negative payoff to the participant. With respect to CS, menus could feature *no* common standard, such that a given (s, a) combination would appear only once within the menu; *one* common standard, such that two (and only two) offers featured the same (s, a) combination; or *two* common standards (only possible for menus of six offers), whereby one (s, a) combination occurred twice while another occurred thrice.

An example of a menu with three elements and a common standard (the triangle) is shown in figure 1. An example of a menu with six elements and no common standard is shown in figure 2.

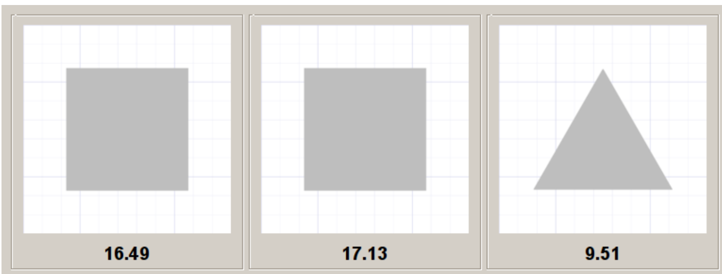


Figure 1: Screen shot of a menu with three offers and a common standard.

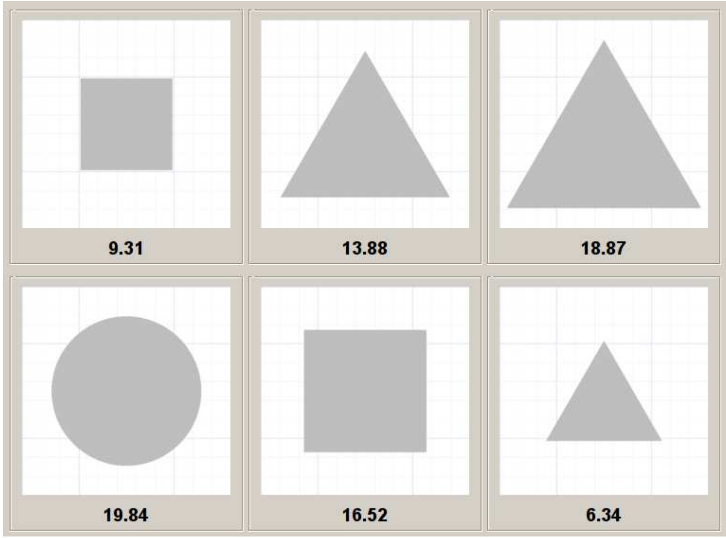


Figure 2: Screen shot of a menu with six offers and no common standard.

Each individual was faced with 80 menus, the same set for everyone but presented in a subject-specific random order. 36 menus showed three options ("3-menus"), of which 18 with one CS. 44 showed six options ("6-menus"), of which 18 with one CS and 8 with two CS (one CS with two members, the other CS with three). In each case, half of the menus were *hard* ($\sigma^2 = 0.01$) while the other half were *easy* ($\sigma^2 = 0.05$). The distribution of menus is summarized in table 1.[2]

Table 1: Distribution of menus by CS and difficulty of the problem.

		Hard menus ($\sigma^2 = 0.01$)	Easy menus ($\sigma^2 = 0.05$)
3-menu	No CS	9	9
	One CS	9	9
6-menu	No CS	9	9
	One CS	9	9
	Two CS	4	4

Given the random process governing unit price generation, the lowest priced common standard offer had a theoretical chance of being the optimal choice in $\frac{2}{3}$ of our 3-menus with a CS, in $\frac{1}{3}$ of our 6-menus with one CS and in $\frac{3}{6}$ of our 6-menus with two CS (considering only the lowest priced of the CS with 3 options). The actual realization of these chances was 56% in 3-menus, 39% in 6-menus with one CS and 63% in 6-menus with 2 CS.

The participants had up to two minutes to choose an offer from each menu and were

[2]The menus are available for visual inspection at https://people.econ.mpg.de/∼crosetto/Shapes/Menus.html.

forced to spend a minimum time of 10 seconds on each menu. The choice was performed by clicking on an offer - in which case it would be highlighted with a light green frame - and could be revised as many times as one wanted within the two minutes limit. The choice was finalized by clicking on a 'Submit' button at the bottom of the screen. If no final choice was submitted within the time limit the last highlighted offer was submitted as the final choice; if no offer had been highlighted, then the participant received a payment of 3 euros for that trial, which was less than the minimum payment a participant could get even if he made the worst choice out of all our menus.[3]

The participants were given feedback after each menu. This feedback reminded them of the price of their chosen offer, told them the resulting expenditure to paint A, as well as their payoff in terms of budget minus expenditure. The participants were not given the possibility to automatically store and retrieve their payoffs from previous rounds, but were provided with pencil and paper and some did record their payoffs. After the feedback dialog, they were given a new budget B and shown the next menu. The participants knew the total number of menus was 80 and were reminded of their progress along the experiment.

1.2 Control tasks

Once finished with the main task, the participants were exposed to a set of non-incentivized visual perception and computational skills tasks to control for their ability to perform the main task. No minimum time was enforced and the participants could skip any question within each task.[4] Three different set of tasks were chosen:

1. *Shape size comparisons*: The participants were asked to give their estimate of the relative size of a shape (rectangles, circles and triangles) with respect to another. Each of four comparison had to be done within a time limit of one minute.

2. *Mathematical operations.* The participants were asked to solve three sets of 10 operations (sum, subtraction, multiplication, divisions).[5] Each set had to be completed within one minute.

3. *Simple problems*: The participants were asked to solve four simple problems, testing

[3] Only one participant failed to submit a decision within the time limit, and this only once, in that case highlighting no offer.

[4] Only one participant did so.

[5] The sets were generated using Mail Goggles's GMail Labs app by Jon Perlow and were graded in terms of difficulty. See http://gmailblog.blogspot.com/2008/10/new-in-labs-stop-sending-mail-you-later.html

their understanding of the concept of area, of how an area relates to its dimensions, and how a number can be translated from one standard to another (here, a currency). Each problem had to be solved within two minutes.

Once done with the control tasks, the participants filled in a short demographic questionnaire. They were finally asked to guess what the experiment was about - to check for demand effects - and to rate their level of motivation during the experiment. Finally, each participant individually drew a number from 1 to 80 from an urn and was paid according to the result of her purchasing decision in the period corresponding to that number.

Our whole experiment was computerized. The experimental software, the menu generator and the script we used to collect and organize the raw data were programmed in Python (van Rossum, 1995).[6] The German instructions, as well as their English translation, are available upon request.

2 The common standard rule and its generalization

In his choice, the consumer may take into account a number of criteria involving the perceived unit prices of offers, their shape, their position and their belonging to a CS. Let us consider how a consumer might go about a "covert sequential elimination process" as per Tversky (1972), based on perceived unit price and belonging to a CS. Denote $u\hat{p}_{ij} = up_i + e_{ij}$ the perceived unit price of offer i by consumer j (the "signal"). up_i is the unit price of offer i, while e_{ij} is an error term, which is independent across offers in a menu and across consumers. How large the error term will be on average will depend on the consumer's accuracy and on how difficult it is to compare offers *across* standards. As for whether an offer belongs to a CS or not, this matters because prices are directly comparable *within* a standard, so the consumer can identify the Lowest Priced Common Standard offer ("LPCS") with high accuracy.[7] A consumer who only considers signals for his choice will choose the offer with the lowest signal and will not consider whether that offer may be dominated by another offer expressed in terms of the same standard. This is what we call the *Naive* rule. A variant on

[6]Different python modules were needed to develop the experimental software: wxpython was used for the graphical user interface, and two community-contributed packages, svgfig and polygon, were used for creating and managing the shapes. The experimental software (menu and shape generators and analyzers, user interface) and its documentation, as well as the raw data and the script used to collect and organize them are available upon request.

[7]We will consider the possibility that a consumer may make mistakes in choosing among CS even if he is aware of their existence, though one may alternatively argue that choosing a higher priced CS offer means the consumer does not take account of CS information.

the Naive rule adds a second step whereby the consumer checks if the offer he chose after the first step based on signals may not be dominated by another offer expressed in the same standard, and if so, revises his choice to the dominant offer. This is what we call the *Signal First* heuristic. The reverse steps, *i.e.* first eliminate dominated offers within a standard, and then compare the dominant CS offers with those expressed in terms of an IS based on their signal, is called *Dominance Editing*. Finally, a rule based only on belonging to a CS, which we call the *CS rule*, consists in choosing $\arg\min_{i \in CS} p_i$ (the LPCS) if a CS exists and revert to the Naive rule otherwise. The consumer not only avoid the higher priced of the common standard offers but choose the LPCS and disregard individuated standard ("IS") offers. There are many reasons why we would expect consumers to follow such a rule:

1. *Statistically*, if one assumes that prices are i.i.d. across offers and offers are assigned to a CS at random, then the LPCS is lower priced in expectation than other offers. As in the Monty-Hall problem (Friedman, 1998), there is information gained from being told that an option is dominated.

2. *Behaviorally*, consumers have been shown to be subject to the asymmetric dominance effect (Ariely, 2008, Chapter 1), so that when faced with three offers, one being dominated by another, that other will be chosen more often than if the dominated offer was not present. Another way to call this effect in the field of decision theory is the "attraction effect", which is a type of context effect (Huber and Puto, 1983).

3. *From learning*: Gaudeul and Sugden (2012) argue that consumers are better off choosing among CS offers when firms are strategic agents in a competitive setting, subject to at least some agents following the CS rule. This learning is made easier by the applicability of the common standard rule to many environments, so that consumers who learned from one environments that CS offers are lower priced than other offers will apply this insight generally. Consumers ought therefore to learn to choose CS offers over time (Sugden, 1986; Fudenberg and Levine, 1998).

4. *For simplicity*, as agents faced with complex choices tend to follow simple heuristics, often with good results (Gigerenzer and Brighton, 2009). In this case, an offer being unambiguously better than another provides "one good reason" to choose it (Gigerenzer and Goldstein, 1999).

The CS rule, based on multiple foundations, can thus be generalized across many settings and is likely to be more robust than rules that hold only in some settings (Sugden, 1989) or that can be justified in only one way. We believe this rule is at work in a wide variety of consumer choice problems. Its simplicity and intuitive appeal make it particularly interesting for economists interested in consumer behavior and heuristics, marketing, consumer protection and the competitive process. Note that we are not wedded to one particular explanation for why consumers might prefer CS offers: we are only interested in determining if they do so and if so, to what extent. Indeed, the main reason we are interested in this possible consumer bias is that we believe that it could drive firms into making their offers less difficult to compare and thus encourage the efficient working of competitive markets. Our setting provides a lower bound for the CS effect, in so far as any competitive effect justifying the use of the rule is excluded by design since offers are not determined through a competitive process.

The Threshold rule. Following the CS rule is strictly optimal in the context of Gaudeul and Sugden (2012) as IS offers are systematically higher priced than CS offers in a competitive setting where firms can choose their standard, so that even an IS offer with a very good signal should be rejected. However, the CS rule is not optimal in the context of our experiment as offers are randomly generated rather than the result of a competitive process. It is better for a consumer to follow a more general *Threshold rule*, which we present below, in our setting. The Threshold rule functions as follows: determine the LPCS, denoted $k \equiv \underset{i \in CS}{\arg\min}\, p_i$ if there is a CS and then choose $l(v_j) = \underset{i \notin CS}{\arg\min}\,(\hat{up}_k, \hat{up}_i \times v_j)$, *i.e.* the price of all IS options is multiplied by v_j, with v_j depending on consumer j's preference for $(v_j > 1)$ or against $(v_j < 1)$ the LPCS. We will call v_j a threshold and the optimal choice of threshold is $v_j^* = \underset{v_j}{\arg\min} E(up_{l(v_j)})$. Its level depends on the consumer's accuracy in assessing the unit price of offers in a menu, with less accurate consumers benefiting from adopting higher thresholds v_j. Threshold $v_j = 1$ corresponds to eliminating dominated offers and choosing based on the signals from the remaining offers (this is Dominance Editing), while threshold $v_j \to \infty$ corresponds to the CS rule.

To put this in behavioral terms, the consumer who adopts a threshold $v_j > 1$ does not reject IS offers out of hand, but penalizes them, that is, he does not follow his first impression $(\hat{up}_{ij})$ of the price of the IS offer, but rather revises it upwards when comparing it to his perception of the price of common standard offers. In other terms, the consumer applies a certain dose of skepticism to his evaluation of an offer that is expressed in uncommon terms, and will choose to buy it only if it seems sufficiently better than the best of those offers that are expressed in common terms – that is, if its unit price appears to be lower by a factor of at least $1 - 1/v_j$ compared to the apparent unit price of the LPCS.

To make this clearer, let us come back to the example on page 2. We saw that under the CS rule, the consumer would always choose the orange. Under the Threshold rule, the consumer will choose the orange only if his threshold v is more than $1.29/1.27 = 1.016$.

A consumer's optimal threshold depends on his accuracy in assessing offers, with less accurate consumers being better off adopting higher thresholds. For example, a consumer who makes considerable mistakes obtains $B - E(a)$ in expectation under the Naive rule (he chooses essentially at random), which is less than $B - E(\min(a, b))$, his expected payoff under the CS rule.

We performed simulations with Octave (Eaton, 2002) to determine the optimal threshold v to use under the Threshold rule as a function of consumers accuracy.[8] We modeled e_{ij} as following a normal distribution with mean zero and variance σ^2, which we varied between 0 and 0.2. In the same way as in our experiment, products unit prices up_i followed a normal distribution with mean 0.5 and variance 0.01 (hard menus), and 0.05 (easy menus) and B was set to 60. Consumer choice was simulated according to the Naive rule as well as according to the Threshold rule, with the optimal threshold v calculated for every level of σ^2 — less accurate consumers benefit from adopting higher thresholds. Their average payoff for each rule was calculated over 2 million menu draws so as to achieve good accuracy.[9]

The following graphs show payoffs in the four situations in our experimental setting, that is depending on whether the consumer has a choice among three or six options, and whether menus are easy or hard. Also shown on a separate scale is the optimal threshold v^* for each value of the error term.

[8] Program available upon request.

[9] The ranking of payoffs by rules is quite robust as differences in payoffs are significant even for much smaller draws.

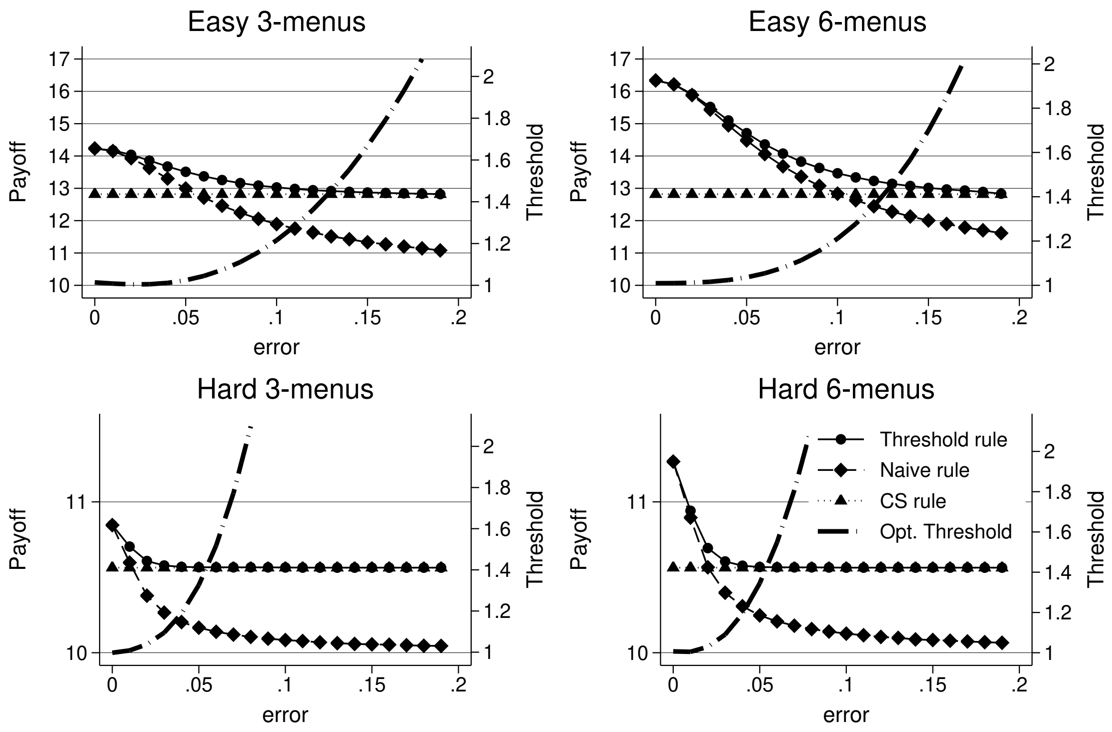


Figure 3: Consumer payoffs by choice rules and optimal thresholds, by menu length and difficulty.

As can be seen in figure 3, payoff decreases as consumers become less accurate in their choice (higher σ^2), except for the CS rule since consumers always choose correctly among CS offers and thus obtain $B - E(\min(a, b))$. The Threshold rule outperforms the CS and Naive rules and converges towards the CS rule for less accurate consumers as can be seen from the rising level of the optimal threshold v as σ^2 increases. Following the CS rule obtains higher payoffs than the Naive rule as long as consumers are not too accurate. This is so especially when menus are hard as then even high levels of accuracy may result in mistakes. From this graph, one can infer a consumer's accuracy from the average payoff he attained when facing menus with no common standard, and from this accuracy determine the threshold he ought to use when facing offers with a CS.

Other possible influences on consumer choice. Consumers may be subject to other influences in their choices and we will need to control for those. Biases may come from following alternative possible rules as follows:

- The *budget rule* chooses $\arg\,\min p_i$. This is a rule that favors small packages, or equivalently lower priced items. While this does not make sense in our setting, this rule may be imported from other settings where for example the consumer faces a binding budget constraints (Viswanathan et al., 2005). Alternatively, a *bulk purchasing rule* would favor big packages, as offers in big packages are usually better deals than those in small packages.

- The *lexicographic rule* may favor the first offers in the lexicographic order in the menu – maybe because the consumer is satisficing rather than optimizing (Simon, 1955) or simply because he does not have time to consider all offers. Alternatively, a consumer may also favor the last offers in the menu if he tends to remember (and choose) the last option he read from a list.

- Finally, consumers may favor some shapes over others because they appear larger, as evidenced in Krider et al. (2001). As evoked before, broad based offers such as triangles will be preferred to squares covering the same area and those will be preferred to the compact circle offers.

3 Results

Our experiment took place at the laboratory of the Max Planck Institute in Jena in June 2011. The experiment involved 202 students over 8 sessions, each with 24 to 27 subjects. Our subjects were asked for their age, gender, field of study, year of study, motivation in completing the tasks, and also what they thought the experiment was about (in order to control for demand effects). All subjects were students. When asked what they thought the experiment was about after going through it, most subjects guessed we wanted to assess their abilities to take account of both price and area to identify the best offer in our menus. Some wondered if we wanted to identify what shapes were perceived as more attractive, but no subject mentioned that some offers were expressed in terms of a common standard.

Table 2: Summary statistics.

Variable	Mean	Median	Std Dev.	Skewness	Min	Max	N
Age	23.65	23.00	3.69	2.31	18.00	47.00	202
Gender	0.65	1.00	0.48	-0.64	0.00	1.00	202
Score in shape comparisons	0.25	0.25	0.10	0.35	0.05	0.58	201
Score in simple problems	2.78	3.00	0.96	-0.27	1.00	4.00	202
Score in mathematical tasks	20.92	21.50	2.93	-1.45	6.00	25.00	202
Reported motivation	6.29	7.00	2.28	-0.67	0.00	10.00	202
Payoff	11.44	11.48	0.41	-0.80	9.88	12.28	202
Time spent per menu	19.67	18.34	6.36	1.30	11.66	46.27	202

The average age of our subjects was 24, ranging from 18 to 47 (Table 2). 65% of our subjects were women. The average motivation of our subjects, on a scale from 0 to 10, was 6, with a median motivation of 7 and 75% of our subjects having motivation more than 5, the middle point. The monotony of the tasks did not therefore result in noticeable discontent. Speed of choice for each menu and each subject was also recorded. Subjects took 20 seconds on average to make each choice (they could not make a choice before 10 seconds had elapsed). Time spent on each menu was longer for menus with more options and declined over time (from an average of 36 seconds for the first choice to 16 for the last).

There were three control tasks. In the shape comparison task, we computed individual performance as the average of $|\text{guess} - \text{true value}|/\text{true value}$. On average, people were 25% off the true value, with a minimum of 5% and a maximum of 58%. In the mathematical tasks, we coded answers as either right or wrong. On average, subjects got 21 of the 25 calculations right, with only two obtaining less than half of the calculations right, and 7 of them obtaining all of them right. Finally, in the simple problems, only about 62% answered more than half of the questions correctly. Performance in the different control tasks were significantly and positively correlated, though not highly (correlation coefficients were around 0.35). Women performed less well than men in all control tasks.

3.1 Did individuals benefit from the presence of a common standard?

Overall, consumers made about 39% of their choices optimally, that is, choosing the offer with the lowest unit price. In only 21 of the 80 menus did a majority of the consumers make the optimal choice. In other terms, most consumers were wrong for most menus.[10] Table 3 shows how often consumers made the optimal choice depending on the length of the menu, its difficulty and whether the menu included one CS, two CS or no CS. The presence of a CS significantly improved accuracy in consumer choices, except in the case of hard 6-menus. Consumers were also more likely, as designed, to choose the best option when the menu was easy.

Table 3: Optimal choices by menu length, difficulty and presence of a CS.

		Hard menus			Easy menus		
		Mean	Std Dev	N	Mean	Std Dev	N
3-menu	No CS	35.48%	47.86%	1818	45.27%	49.79%	1818
	One CS	46.42%*	49.89%	1818	64.63%*	47.82%	1818
6-menu	No CS	27.89%	44.86%	1818	24.70%	43.14%	1818
	One CS	21.45%*	41.06%	1818	38.44%*	48.66%	1818
	Two CS	40.97%*(*)	49.21%	808	41.34%(*)	49.27%	808

* Difference significant at 5% level *vs.* one row above, Wilcoxon rank-sum test.

(*) Difference significant *vs.* two rows above.

We did not find any effect of the presence of a CS in a menu on the speed with which consumers took a decision, except in the case of easy 3-menus where the presence of a CS reduced time spent from 18 to 16 seconds on average. Subjects took on average 5 seconds more to reach a decision among 6-menus than among 3-menus, but did not reach faster decisions when the menu was easy (except again in the case of easy 3-menus).

Let us now consider whether higher accuracy in choices led individuals to obtain higher payoffs when a menu included CS offers. The following table displays individual payoffs by menu length, difficulty and presence of a CS (Table 4).

[10]Looking at menus where consumers performed particularly badly, one finds that they mistakenly chose smaller size options, triangles, options to the end of the lexicographic order, or the LPCS when the IS was actually better. This last point underlines an important fact about the CS rule: while following it maximizes average payoffs for a consumer that is prone to making mistakes, it does *not* lead to the correct choice for each individual choice instance.

Table 4: Payoffs by menu length, difficulty and presence of a CS.

		Hard menus			Easy menus		
		Mean	Std Dev	N	Mean	Std Dev	N
3-menu	No CS	10.41	0.92	1818	11.02	4.56	1818
	One CS	10.45	0.96	1818	13.34*	3.96	1818
6-menu	No CS	10.14	0.81	1818	11.97	4.11	1818
	One CS	10.04*	0.98	1818	13.84*	5.48	1818
	Two CS	10.78*(*)	0.87	808	12.78(*)	4.34	808

* Difference significant at 5% level *vs.* one row above, Wilcoxon rank-sum test.
(*) Difference significant *vs.* two rows above.

This table can be read in conjunction with another table that indicates how those payoffs translate in terms of how close they are to the maximum available payoff in each menu. Table 5 thus reports the average of the ratio $(\mathrm{up}^{\max} - \mathrm{up}^{\mathrm{chosen}})/(\mathrm{up}^{\max} - \mathrm{up}^{\min})$ over individuals and menus in each category. We normalize the difference between the worst choice and the consumer's choice as shown because we want to be able to compare performance between easy and hard menus, where the difference between the worst and the best choice within a menu will be smaller on average. We call this the performance ratio. A value of 0 would indicate the consumers always made the worst choice, while a value of 1 would indicate they always made the best choice.

Table 5: Performance ratio by menu length, difficulty and presence of a CS.

		Hard menus			Easy menus		
		Mean	Std Dev	N	Mean	Std Dev	N
3-menu	No CS	0.597	0.447	1818	0.607	0.448	1818
	One CS	0.592	0.419	1818	0.794*	0.324	1818
6-menu	No CS	0.683	0.353	1818	0.682	0.321	1818
	One CS	0.545*	0.364	1818	0.735*	0.299	1818
	Two CS	0.735*(*)	0.323	808	0.759*(*)	0.365	808

* Difference significant at 5% level *vs.* one row above, Wilcoxon rank-sum test.
(*) Difference significant *vs.* two rows above.

Subjects obtained a payoff of 11.44 ECU on average (1 ECU=0.8 €), and their performance ratio was 0.66. No participant obtained payoffs that were significantly less than 10.22, which is what they would have obtained had they chosen at random within our menus, and only 8 obtained payoffs that were not significantly greater than this. Subjects therefore seem to have made considered choices. As could be expected from statistical arguments, individuals obtained higher payoffs with 6-menus and with easy menus.

Participants obtained significantly higher payoffs and performed significantly better when a menu was easy and included a CS, while the effect of the presence of a CS in hard menus was either not significant or slightly negative. The presence of a CS did not therefore benefit consumers when prices were already close together, but worked to the advantage of consumers when prices varied more widely among options, which would be the case when firms are not in close competition. The CS effect would therefore be at play when it matters most.

Panel regressions of payoffs on individual and menu characteristics are shown inTable 11 on page 36. A Breusch and Pagan Lagrange multiplier test for random effect indicates that there are no significant difference across units so that one can rely on the results of a pooled regressions (OLS). Compared to the base case (Easy 3-menus with no CS), individuals obtained higher payoffs when the menu displayed 6 options and when the menu included CS offers. Payoffs were smaller when the menu was hard. Looking at cross-effects, one sees that making a 6 menus harder negates the benefit of having more choice, and making a menu with a CS harder negates the benefits of having a CS. Finally, the gain from including CS offers in a 6-menu are mainly due to the presence of a CS rather than from having more options. Individuals improved their payoffs with experience ("order" variable). Older people obtained lower payoffs, while those with higher scores in the mathematical and practical consumption problems, or with higher motivation, obtained higher payoffs. Time spent choosing an offer within each menus did not appear to have a significant effect overall, though individuals who spent more time on average obtained higher payoffs (*cf.* between effects regression) while they obtained lower payoffs on those tasks on which they spent more time than their average (*cf.* fixed effects regression).[11] There was no sign of a significant individual effect, that is, no individual seemed to perform better than others above and beyond what could be predicted from their gender and scores in control tasks. We also checked that there was low correlation between residuals and variables in the model.

[11] We checked also if there was some quadratic effect in terms of time spent. Indeed, time spent could increase payoffs but fastest times (inattention) and slowest times (difficulty) could obtain lower payoffs. While coefficients were of the correct sign, they were not significant.

3.2 Did individuals favor the lower priced of the common standard offers?

Table 6 shows that the LPCS was chosen about 57% of the time within our 3-menus,[12] about as often as the LPCS was the lower priced product (56%). This was less often than if consumers followed the CS rule, whereby the LPCS would always be chosen. However, the IS was disfavored as it was chosen less often than if consumers always chose the lowest priced product (37% of the time while it was the lowest price in 44% of the menus). In the case of 6-menus with one CS, the LPCS was chosen about 26% of the time in 6-menus with only one CS, which was less often than optimal (39%). The IS on the other hand was chosen more often than optimal (18% vs. 15%). Finally, the lower priced of the larger CS (the one with three members) was chosen more often than the lower priced of the smaller CS in 6-menus with two CS, (40% vs. 33%), but less often than optimal (62%), and the IS was chosen more often than optimal.

Table 6: Choice frequencies by menu length and presence of a CS.

		LPCS	HPCS	IS	LPSCS	HPSCS	MPLCS
3-menu	No CS			33.33%			
	One CS	56.71%	5.86%	37.40%			
	Lowest priced	*55.56%*	*0.00%*	*44.44%*			
6-menu	No CS			16.67%			
	One CS	25.55%	3.52%	17.73%			
	Lowest priced	*38.89%*	*0.00%*	*15.28%*			
	Two CS	40.41%	2.35%	17.33%	32.67%	2.97%	4.27%
	Lowest priced	*62.50%*	*0.00%*	*12.50%*	*25.00%*	*0.00%*	*0.00%*

Notes: In the case of 6-menus with two CS, the LPCS is the Lower Priced of the Larger CS (the one with three members), the HPCS is the Higher Priced of the Larger CS, and the MPLCS is the Middle Priced of the Larger CS. The LPSCS is the Lower Priced of the Smaller CS (the one with two members) and the HPSCS is the Higher Priced of the Smaller CS. In 6-menus with one CS, the IS choice frequency is calculated by averaging across the four IS offers.

In the aggregate, consumers do not appear to follow a Naive rule since most of them took account of the presence of a CS by discarding higher priced CS offers. The LPCS was chosen more often than any other offer. A number of consumers appear to have avoided IS offers in 3-menus although higher sales by the LPCS in 6-menus appear to have occured mainly because of diversion away from the dominated CS offer rather than because consumers consistently avoided IS offers. All the same, even in that case, diversion was mainly towards lower priced common standard offers rather than sales being equally distributed across IS and LPCS.

[12] Differences across hard and easy menus are not significant and are therefore not reported.

Figure 5 on page 37 displays the distribution of the frequency with which individuals in our sample chose the lower priced of the common standard offers. This is disaggregated by menu length and difficulty, and by whether the menu included one or two CS in the case of 6-menus. In each graph, the first reference line to the left indicates the proportion of choices of the LPCS that would be consistent with consumers following a Naive rule, i.e. choosing among options as if there was no CS. In the case of 3-menus, this corresponds to 33%, and in the case of 6-menus to 17%. The second reference line corresponds to the proportion of choices of the LPCS that would be consistent with consumers doing Dominance Editing, that is, eliminating the dominated CS offer and comparing the LPCS with the IS offers. This would lead the LPCS to be chosen 50% of the time in 3-menus, 20% of the time in 6-menus with one CS and 33% of the time in 6-menus with two CS. The third reference line corresponds to the proportion of choices of the LPCS that would be consistent with consumers following the Signal First heuristic, that is, first assessing options based on their signal, and then transferring their preliminary choice of a dominated CS offer onto the LPCS. This would lead the LPCS to be chosen 67% of the time in 3-menus, 33% of the time in 6-menus with one CS and 50% of the time in 6-menus with two CS (for the CS with more options). Like the CS and the Threshold rule, the Signal First heuristic thus results in the LPCS gaining a large advantage on IS offers. Anybody to the left of the first reference line can be said to disfavor CS offers, those between the two first reference lines do not either favor or penalize CS offers while those to the right of the last reference line can be said to favor CS offers vs. IS ones. One sees that a significant proportion of subjects favor the LPCS *vs.* the IS offer in 3-menus, especially if the menu is easy. However, the proportion of such consumers is smaller in 6-menus with a CS. Preference for the LPCS in 6-menus with two CS is more pronounced.

One cannot however rely on such descriptive statistics to assert with certainty that a portion of consumers favored CS offers, since the results we showed could be due to chance. Our random draw of offers, their price, shape, size, position in the menu, could be the driver behind our results. This is why we perform regressions that are designed to correct for possible biases due to the elements mentioned above.

Predicting consumer choice when there is a common standard. We perform maximum likelihood estimation with three different models of consumer choice among option: the alternative-specific conditional logit and probit models and the mixed logit model which allows for preference heterogeneity for all the attributes. The probit model is fitted by using maximum simulated likelihood implemented by the Geweke-Hajivassiliou-Keane (GHK) algorithm (Greene and Hensher, 2003). The Halton sequence is used to generate the point sets used in the quasi-Monte Carlo integration of the multivariate normal density, while optimization is performed using the Berndt-Hall-Hall-Hausman procedure (Berndt et al., 1974). The mixed logit model is fitted by using maximum simulated likelihood (Train, 2003) and the estimation was performed with the user-written `mixlogit` command for Stata (Hole, 2007). Estimation makes use of the sandwich estimator of variance, except when performing the probit regressions with 6-menus as convergence was not achieved otherwise.

The outcome for each menu is one of 3 or 6 options. Options are identified by their position in the menu, and by whether they are the LPCS, HPCS or an IS in menus with a CS. The dependent variable is the choice of the consumer among alternatives and the independent variables include the unit price of the option, its shape, its size and its position. Since shapes that extend more broadly in space are preferred (see Krider et al., 2001), we create a variable coding shapes from most to least attractive: a triangle is assigned a value of 1, a square a value of 2 and a circle a value of 3.[13] The variable "position" is coded by lexicographic position in the menu, from 1 if the option is in the top left corner to 6 if it is in the bottom right corner in a 6-menu, otherwise to 3 for the option to the right in a 3-menu. As per a remark in Hole (2007), we include no alternative-specific constants in our models, which is "common practice when the data come from so-called unlabeled choice experiments, where the alternatives have no utility beyond the characteristics attributed to them in the experiment." We will also cross unit price with case specific variables such as gender and scores in the control tasks to determine whether individual characteristics make our subjects more or less sensitive to price signals (other individual characteristics such as age and educational background do not vary sufficiently in our sample). We also consider a menu specific variable (whether the menu was "hard" or "easy") and variables that are both menu and case specific (the order in which a specific menu was presented to an individual and the time that individual spent deciding on this menu).

Whether a subject avoids the HPCS or prefers the LPCS vs. the ISs may depend on their individual characteristics so that we introduce case-specific variables (here, a case is an individual) along with alternative-specific variables to determine choice among alternatives.

[13]We also ran the same regressions with each shape being a dummy variable. This did not influence the results.

Our case specific variables are scores in the mathematical, shape comparison and simple problems, along with gender, time spent choosing within a menu and motivation. We also consider whether facing a hard menu makes it more likely to favor the LPCS as following a simple heuristic may be more likely if there appears to be little difference in prices between options. Finally, we consider whether the LPCS was next to the HPCS on the same row in the menu since it is easier to notice there is a CS if CS options are close together.

Formally, denote y^o_{ijm} the utility of option j in menu m for individual i, and denote $y_{ijm} = 1$ if that option is chosen. We will have $y_{ijm} = 1$ if $y^o_{ijm} > y^o_{itm}$ for all $t \neq j$ in menu m, 0 else. Latent utility y^o_{ijm} takes the form $y^o_{ijm} = \alpha\, up_{jm} + \omega \times up_{jm} \times \Omega_i + \mu \times up_{jm} \times M_m + \lambda_j \times \Omega_i + \theta_j \times M_m + \beta\,\text{shape}_{jm} + \gamma\,\text{size}_{jm} + \phi\,\text{position}_{jm} + u_{ijm}$. An option is coded in terms of whether it is the LPCS, the HPCS or an IS offer. Ω_i is a $q \times 1$ vector of case-specific variables, the same variables being assumed to influence the choice for each option, ω is a $1 \times q$ vector of parameters, M_m is a $h \times 1$ vector of menu-specific variables while μ is a $1 \times h$ vector of parameters. λ_j is a $1 \times q$ vector of parameters, different for each alternative as case-specific variables are assumed not to influence the choice of each alternative in the same way. Similarly, θ_j is a $1 \times h$ vector of parameter translating the influence of menu characteristics on the choice of an alternative. u_{ijm} is a random variable of mean 0 that follows either a logistic or a normal distribution. We constrain λ_j and θ_j to be the same for all four IS options in 6-menus with a CS. Model selection using the AIC finds that all of the alternative specific variables ought to be used, while only score in the shape comparison and in the mathematical tasks, along with gender and whether a menu is hard or easy, ought to be used as case-specific variables. Results are reported in table 7.

Table 7: Regressions with a CS, 3 and 6-menus.

		(1) Logit 3-menus	(2) Probit 3-menus	(3) MixLogit 3-menus	(4) Logit 6-menus	(5) Probit 6-menus	(6) MixLogit 6-menus	(7) Logit 6-m 2 CS	(8) Probit 6-m 2 CS	(9) MixLogit 6-m 2 CS
main	unit price (up)	−14.5806***	−9.5842**	−15.5821***	−19.2308***	−6.9231***	−19.6781***	−11.6973***	−1.9796	−12.2147**
		(−4.99)	(−2.71)	(−4.65)	(−11.03)	(−4.85)	(−9.62)	(−4.09)	(−0.28)	(−3.63)
	up × shape task	−5.0589	−4.1344	−5.2897	17.5590**	5.8729*	18.0310*	6.4474	1.0936	7.1735
		(−0.48)	(−0.61)	(−0.45)	(2.85)	(2.53)	(2.49)	(0.64)	(0.27)	(0.59)
	up × hard menu	16.4312***	10.9950**	16.8252***	15.0242***	4.7505***	16.0361***	8.8646	−1.2748	10.2190
		(3.90)	(3.29)	(3.44)	(4.72)	(3.44)	(5.17)	(0.88)	(−0.25)	(0.99)
	position	−0.0543+	−0.0463+	−0.0489	0.0696***	0.0325***	0.0656***	0.0205	0.0028	0.0303
		(−1.75)	(−1.94)	(−1.59)	(6.42)	(3.94)	(6.08)	(0.84)	(0.21)	(1.16)
	shape	−0.2062***	−0.1465**	−0.2333***	−0.3682***	−0.1332***	−0.4286***	−0.6777***	−0.0766	−0.7630**
		(−5.21)	(−2.61)	(−4.96)	(−14.56)	(−4.84)	(−10.18)	(−9.49)	(−0.28)	(−10.17)
	size	−0.0007	−0.0004	0.0009	−0.0058**	−0.0019*	−0.0062+	−0.0447***	−0.0036	−0.0370**
		(−0.21)	(−0.16)	(0.20)	(−3.21)	(−2.04)	(−1.70)	(−5.87)	(−0.28)	(−3.73)
HPCS	score shape task	1.9492*	1.4973**	1.9687*	2.7203*	1.1523**	2.7527*	−0.1989	0.0525	−0.2176
		(2.44)	(2.73)	(2.12)	(2.48)	(2.78)	(2.45)	(−0.12)	(0.04)	(−0.12)
	score math	−0.0096	−0.0113	−0.0090	0.0675+	0.0239	0.0689+	−0.0776+	−0.0508	−0.0756
		(−0.41)	(−0.69)	(−0.30)	(1.87)	(1.61)	(1.85)	(−1.71)	(−0.97)	(−1.41)
	gender	−0.4832**	−0.2882**	−0.4819*	−0.8498***	−0.3015***	−0.8506***	−1.3970***	−0.8411*	−1.3944**
		(−3.24)	(−2.74)	(−2.43)	(−4.30)	(−3.43)	(−3.66)	(−4.06)	(−2.45)	(−3.71)
	hard menu	−0.1681	−0.1401	−0.1995	−0.5105*	−0.0970	−0.5341**	−0.3825	0.2909	−0.4529
		(−1.03)	(−0.90)	(−1.34)	(−2.55)	(−1.08)	(−2.58)	(−0.94)	(0.61)	(−1.10)
	close CS	−0.4200+	−0.1512	−0.4122*	−0.1289	0.0471	−0.1133	−0.2745	−0.4255	−0.2341
		(−1.95)	(−0.97)	(−1.98)	(−0.50)	(0.46)	(−0.45)	(−0.78)	(−1.03)	(−0.61)
	constant	−1.5065*	−1.7151***	−1.4918*	−2.9550**	−1.7752***	−2.9806**	0.2745	−1.1791	0.2397
		(−2.42)	(−3.67)	(−1.97)	(−3.25)	(−3.40)	(−3.23)	(0.22)	(−0.73)	(0.16)
IS	score shape task	−0.2998	−0.3094	−0.4166	0.0294	0.1489	0.0205	0.1574	0.0123	0.1212
		(−0.77)	(−1.07)	(−0.94)	(0.06)	(0.87)	(0.04)	(0.18)	(0.11)	(0.15)
	score math	0.0248+	0.0188+	0.0284	0.0054	0.0016	0.0062	0.0078	0.0004	0.0103
		(1.84)	(1.74)	(1.54)	(0.37)	(0.27)	(0.36)	(0.29)	(0.13)	(0.30)
	gender	−0.2679***	−0.1628*	−0.3129**	−0.2517**	−0.1132**	−0.2657**	−0.3562*	−0.0368	−0.3590*
		(−3.45)	(−2.23)	(−3.18)	(−2.80)	(−2.78)	(−2.69)	(−2.30)	(−0.28)	(−2.25)
	hard menu	0.0105	−0.0190	−0.0386	−0.4933***	−0.1580***	−0.4923***	0.6969**	0.0083	0.5104*
		(0.13)	(−0.34)	(−0.45)	(−5.46)	(−3.43)	(−5.51)	(3.03)	(0.15)	(1.96)
	close CS	−0.7851***	−0.5384**	−0.8847***	0.2557*	0.0519	0.2872**	0.4785**	−0.0070	0.6749**
		(−6.39)	(−2.94)	(−7.38)	(2.36)	(1.16)	(2.65)	(2.65)	(−0.22)	(3.21)
	close SCS							−0.2762	0.0985	−0.2752
								(−0.69)	(0.27)	(−0.71)
	constant	0.0291	−0.0573	0.0736	0.1316	0.0202	0.0741	−1.2370+	−0.0573	−1.3206
		(0.08)	(−0.23)	(0.15)	(0.35)	(0.13)	(0.17)	(−1.73)	(−0.25)	(−1.53)
SD	shape			0.3763***			0.4722***			0.2567*
				(7.63)			(10.60)			(2.38)
	size			0.0363***			−0.0428***			0.0650**
				(8.18)			(−11.42)			(7.39)
	N	10851	10851	10851	21708	21708	21708	9648	9648	9648
	ll	−2919.5938	−2917.2251	−2850.6984	−5617.2643	−5564.1585	−5450.2711	−2078.6207	−2057.6991	−2055.1065

t statistics in parentheses + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Base outcome is the LPCS. Not reported in the table are coefficients on case specific variables for the higher and lower priced of the options that are part of the CS with two options and for the middle priced of the CS with three options in 6-menus with two CS. Whether CS options were close within a CS was deemed to influence choice only within that CS and vs. the IS option.

In terms of alternative-specific variables, subjects tend to prefer lower priced options, "broader" shapes, and smaller sized options (equivalently, those with lower displayed prices). One can notice that prices being close together (hard menus) makes consumers less sensitive to price. Case-specific variables show that consumers tend to avoid the HPCS: the parameter on the constant term for that option is negative and highly significant. Individuals that are worse at the shape comparison tasks are more likely to choose the HPCS, maybe because they find it difficult to compare the area and shape of all options and thus do not notice the presence of a CS. It is however only women who display an aversion to the IS *vs.* the LPCS. Aversion to the IS is encouraged when the presence of a CS is more obvious, i.e. when the CS options are next to each other – there is a negative impact of the dummy variable taking value one if CS options are close in 3-menus (the impact is not consistent across logit and probit regressions in the case of 6-menus). Whether the menu is hard also encourages individuals in rejecting the IS option, at least in 6-menus with one CS (results in the case of 6-menus with two CS are not consistent across logit and probit regressions).

In conclusion, only women appear to favor the LPCS when choosing among options. This might explain why women managed to obtain higher payoffs than men in this experiment even though they were less good at those control tasks that predicted higher payoffs.

3.3 How strong was the common standard effect?

It is difficult to quantify the strength of the Common Standard effect from the results presented up to now. We seek to know how much of an advantage a LPCS offer gains compared to an offer expressed in terms of an individuated standard. We simulate in this part how consumers would make choice among menus with a CS based on their choices when there is no CS. We first perform regressions to explain consumer choice when there is no CS, and then apply predictions from that setting to the case where there is a CS, assuming consumers apply the Threshold rule. We determine what thresholds best predicts consumer choice, which can be interpreted as the price penalty applied to non-standard offers.

3.3.1 Consumer choice when there is no common standard

We adopt the same model as for predicting choice when there is a CS. Latent utility y^o_{ijm} takes the form $y^o_{ijm} = \alpha\, up_{jm} + \omega \times up_{jm} \times \Omega_i + \mu \times up_{jm} \times M_m + \beta\, \text{shape}_{jm} + \gamma\, \text{size}_{jm} + \phi\, \text{position}_{jm} + u_{ijm}$ with u_{ijm} a random variable of mean 0 that follows either a logistic or a normal distribution. Ω_i is a $q \times 1$ vector of case-specific variables while ω is a $1 \times q$ vector of parameters. M_m is a $h \times 1$ vector of menu-specific variables while μ is a $1 \times h$ vector of parameters. As before, j is the option, m is the menu and i is the individual.

We find that a model that takes into account all the alternative specific variables (price, position in menu, shape, area size) minimizes the Akaike Information Criterion ("AIC"). In addition to those, one menu specific variable was consistently significant across menu length (whether the menu was easy or hard) and one case specific variable turned out to be significant for 3-menus (performance in the shape comparison task). Results are shown in table 8. Subjects tend to prefer options that have a lower unit price, "broader" shapes, and smaller sized options (equivalently, those with lower displayed prices). There is no consistent tendency for consumers to favor either options at the beginning or at the end of the menu. Subjects with low performances in the shape comparison task were understandably less affected by unit price in their choice, and subjects were more sensitive to unit price in hard menus.

The log-likelihood is much lower in 6-menus than in 3-menus, which means that the choices from 6-menus are considerably less accurately predicted with our model than from 3-menus (there was the same number of choices to make from within each menu type). This means there is more randomness in consumer choice within 6-menus, probably because it is more difficult to compare 6 offers than 3 offers as this requires holding more information into one's working memory.

Results from the mixed logit model indicate there is significant variation in the extent to which an option's shape and size influenced consumers. However, the influence of an option's position did not appear to vary across subjects. We can conclude that our participants have some bias that may be explained by their use of a budget rule (choose lower priced, that is, smaller sized, options) and of a shape rule (prefer triangles to square to circle). However, the marginal effect of an increase in unit price is much higher than that of any other variables (not reported).

3.3.2 What threshold best describes aggregate behavior?

We use the estimation results from the mixed logit regressions done for the case where there is no CS to predict choice when there is a CS. If the consumer is Naive, his choice will be predicted by applying parameter estimates from the model with no CS to the data with CS, which obtains estimates $(p^{Na}_{LPCS}, p^{Na}_{HPCS}, p^{Na}_{IS})$ for the probabilities to choose the LPCS, HPCS

Table 8: Regressions with no CS, 3 and 6-menus.

	(1) Logit 3-menus	(2) Probit 3-menus	(3) MixLogit 3-menus	(4) Logit 6-menus	(5) Probit 6-menus	(6) MixLogit 6-menus
main						
unit price (up)	−18.7200***	−16.2710***	−20.2468***	−16.2815***	−6.6052***	−17.4617***
	(−6.89)	(−6.87)	(−6.91)	(−8.49)	(−6.19)	(−7.67)
up × hard menu	−9.7361**	−11.7958***	−10.2537**	−24.3972***	−9.6439***	−26.9113***
	(−2.86)	(−3.50)	(−3.14)	(−6.63)	(−4.77)	(−7.19)
up × score shape task	20.7627*	14.2704+	20.9114*	10.8997	4.1976*	13.4579
	(2.24)	(1.77)	(2.23)	(1.53)	(1.96)	(1.61)
position	0.0656*	−0.0916+	0.0671**	0.0053	0.0240	0.0046
	(2.56)	(−1.95)	(2.63)	(0.53)	(1.22)	(0.44)
shape	−0.3621***	−0.3705***	−0.3961***	−0.3339***	−0.1509***	−0.3958***
	(−12.05)	(−11.55)	(−9.21)	(−14.52)	(−6.58)	(−9.54)
size	−0.0121***	−0.0108***	−0.0137***	−0.0019	−0.0002	−0.0019
	(−5.28)	(−4.19)	(−4.03)	(−0.92)	(−0.23)	(−0.41)
SD						
shape			0.3836***			0.4549***
			(9.81)			(9.48)
size			0.0352***			0.0537***
			(8.39)			(11.81)
N	10854	10854	10854	21708	21708	21708
ll	−3757.4104	−3747.6265	−3689.0559	−6103.5141	−6042.2092	−5881.8136

t statistics in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: One subject did not perform the shape comparison task, so the regressions are based on 201 subjects choosing among 18 menus with no CS.

and IS respectively. If he follows the CS rule, he will choose the LPCS. If he follows the Threshold rule then the probability he chooses the LPCS is $p^{Th}_{LPCS} = p^{Na}_{LPCS}(LPCS, IS \times v)$, which is to be interpreted as the probability a Naive consumer would choose the LPCS if his choice was restricted to either the LPCS or the IS and the price of the IS was multiplied by a factor v. We computed for each consumer the threshold v_j that maximizes their maximum likelihood. Behavior of subjects with a high value of v_j is close to following the CS rule, while that of those with low v_j is close to Dominance Editing, that is, eliminating dominated offers from one's consideration set and comparing remaining offers based on their signals.[14] One can similarly predict the choices made by a consumer following the Signal First heuristic.

Compared to predictions based on the Naive rule, the Threshold rule makes use of two additional degrees of freedom as it requires information about what is the CS and requires estimating the threshold used by the subjects. This will be taken into account by comparing rules using the Akaike Information Criterion.

In mathematical terms, the likelihood function is $f(y, \theta) = \prod_{t=1}^{N} \prod_{j=1}^{M} p_{tj}^{y_{tj}}$ with t denoting the menu, N the total number of menus presented to consumers, j denoting the option, M the number of options, and $y_{tj} = 1$ iff $y_t = j$, 0 otherwise, whereby y_t is the consumer's choice. $p_{tj} = \Pr(y_t = j)$ is the predicted probability, which depends on the rule we assume for consumers' choice, so for example $p_{tj} = 1$ iff j is the LPCS and the consumer is assumed to follow the CS rule. y is the vector of choices and θ are the parameters determining the choice among options.

Table 9 reports the log-likelihood, the values of the AIC and of the Bayesian information criterion ("BIC") for each rule, for 3 and 6-menus.[15] The last column contains the value of threshold v that maximizes the log-likelihood for the Threshold rule. The number v reported there is to be interpreted as "consumers appear to consider IS options as v times more expensive when they are presented next to CS options than when they are presented next to other IS options". This measures the price penalty applied to IS options when compared to the LPCS. For more interpretation of this number, see the detailed explanation in section 2.

[14] The rules above predict that the HPCS will never be chosen. However, as we saw, this is not the case in our data. One therefore has to take account that some consumers choose the HPCS. We therefore do a separate regression so as to determine the probability p_{LPCS} with which the LPCS is chosen among CS offers. Note that in this case, only the offer's position and its price may determine the choice, along with some case-specific variables, since both shape and area are the same in a CS. One then modifies the formulas above as follows: In the case of the CS rule: $p^{CS}_{LPCS} = p_{LPCS}$ and $p^{CS}_{HPCS} = 1 - p_{LPCS}$ and in the case of the Threshold rule: $p^{Th}_{LPCS} = p_{LPCS} p^{Na}_{LPCS}(LPCS, IS \times v)$, $p^{Th}_{HPCS} = (1 - p_{LPCS}) p^{Na}_{HPCS}(HPCS, IS \times v)$ and $p^{Th}_{IS} = 1 - p^{Th}_{LPCS} - p^{Th}_{HPCS}$. Formulas are slightly longer in the case of 6-menus but can be inferred from the above.

[15] We only study 6 menus with one CS.

Table 9: Rules scores, aggregate behavior.

		Naive	Signal First	Dominance Editing	Threshold Heuristic	v
3-menus	LL	$-3\,484$	$-2\,994$	$-3\,073$	$-2\,984$	1.05
	df	8	9	9	10	
	AIC	6 984	6 006	6 164	5 988	
	BIC	7 034	6 062	6 220	6 050	
	N	3 618	3 618	3 618	3 618	
6-menus	LL	$-5\,954$	$-5\,769$	$-5\,788$	$-5\,762$	1.04
	df	8	9	9	10	
	AIC	11 924	11 556	11 594	11 544	
	BIC	11 974	11 612	11 650	11 606	
	N	3 618	3 618	3 618	3 618	

The Threshold rule gives the best predictions for both menu lengths. In terms of threshold, an IS offer suffers a 4 to 5% price penalty compared to the LPCS offer, which is a considerable amount. Assuming consumers follow the Signal First heuristic or do Dominance Editing does not either attain better values in the AIC or BIC criteria. The Naive rule is clearly rejected in all cases so consumers clearly do take CS information into account.

When mapping payoffs by menu length and difficulty in the case with no CS (table 4) to the predictions from our simulations (Graph 3), the standard error of the consumers' error term when assessing unit prices appears to have been be about 0.15, in which case the optimal threshold v_j would be between 1.2 and 1.4, which is a lot more than the 1.04-1.05 threshold determined above. This indicates perhaps that they were over-confident in their ability to make accurate choices. We check this in the following by determining thresholds individual by individual and comparing this to optimal thresholds given individual accuracy determined from choice among menus with no CS.

3.3.3 What threshold did consumers use individually, and did they choose their threshold rationally?

The above techniques were used to determine what thresholds is consistent with behavior of our subjects and what rule best predicted consumers choice (based on the AIC), individual by individual. The following graph relates average payoffs obtained by subjects in menus with no CS to the threshold that best predicted their choice (based on the log-likelihood) when choosing within menus with a CS. Sujects whose behavior was best predicted by the Threshold rule (based on the AIC) are represented with squares, by the Naive rule with circles, by Dominance Editing with exes and by the Signal First heuristic by crosses. We super-impose on this graph the optimal choice of threshold for a consumer with the accuracy implied by his average payoff when faced with menus with no CS.[16] The graph for 3-menus can be read as follow: Consider point (105,11), which represents a consumer who obtained a payoff of 11 in 3 menus with no CS and used a threshold of 1.05 in 3 menus with a CS. The curve indicates that a threshold of 1.20 would have been the optimal choice for this consumer.

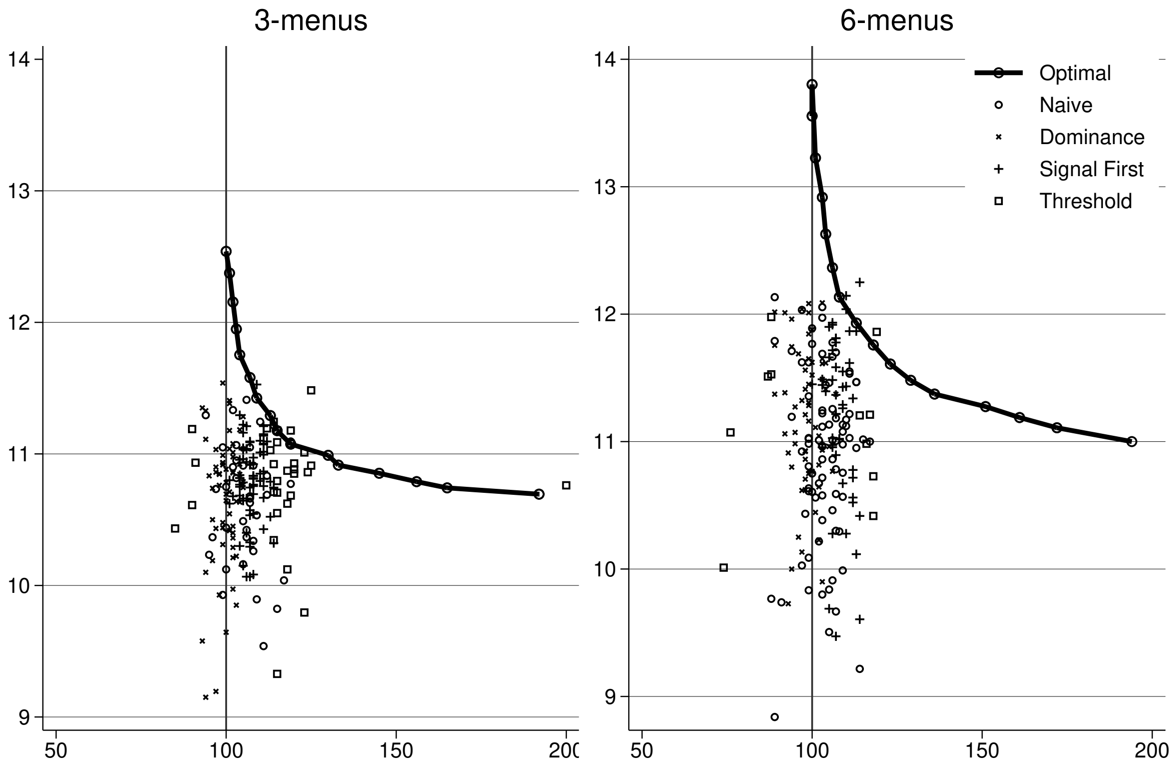


Figure 4: Optimal vs. best predicting threshold in 3 and 6-menus.

In terms of payoffs, and whether considering 3-menus or 6-menus with a CS, we find that consumers whose behavior is best predicted by the Naive rule tend to obtain significantly lower payoffs than consumers whose behavior was consistent with Dominance Editing, and consumers who were assigned to the Threshold rule (and adopted a positive threshold) obtained significantly higher payoffs than all others.

In terms of thresholds used by individuals, theory presented in this paper would predict

[16] We computed the optimal threshold to be used when the consumer knows the distribution of price variances across menus but does not know, when presented with a menu, whether the menu has high or low price variance, as this seems more reasonable to us. That is, with reference to part 2, expectation in the formula determining v_j^* is taken over all menus of a specific length.

that a rational consumer who is beset by an inability to assess offers accurately ought to be using higher thresholds than those used by subjects that are more accurate. Accuracy can be estimated by the payoffs consumers obtained when faced with menus with no CS. Those who obtained higher average payoffs in those menus are more accurate. As can be seen in the graph, we find no relation between payoffs when faced with menus with no CS and the threshold used by the consumer. Furthermore, almost all points on the graph above are below the optimal line, meaning that thresholds were lower than optimal. This is the case even for those consumers whose behavior is best predicted by the Threshold rule. Assuming they indeed consciously followed the Threshold rule, it may be that they chose thresholds that were too low because they were overconfident in their own ability to choose the best offers based on signals alone, or they did not make the link between their accuracy and the threshold they ought to be using. We checked whether behavior was consistent with consumers using higher thresholds over the course of the experiment by re-running estimates of the threshold they used excluding the first 20 menus each consumer was faced with. We did not find significant change. We also confirmed that our classification by rules used was consistent across 3 and 6-menus (based on the Pearson χ^2).

4 Conclusion

We found that menus with a common standard improved the ability of our subjects to make optimal choices among offers in a menu. Our subjects also obtained higher payoffs when a menu featured a common standard as long as price differences across offers were relatively large. The presence of a CS thus benefited consumers most when prices varied more widely among options, which would be the case when firms are not in close competition. The CS effect would therefore be strongest at play when it matters most. Subjects took into account the presence of common standard offers by avoiding dominated CS offers. Most of the sales that would have gone to dominated CS offers if consumers relied only on price information went to the lowest priced of the common standard offers. Even though the presence of a CS effectively meant higher priced CS offers were discarded from the consumers' consideration set, thus lowering competition among remaining offers, offers expressed in terms of an individuated standard did not gain sales compared to a situation with no CS. We showed that, everything else being equal, a number of our subjects favored the lower priced of the common standard offers over offers expressed in individuated terms. However, this effect was driven by the choice of women against offers expressed in terms of an individuated standard. The effect was more pronounced when common standard offers were presented close to each other. Very few consumers were savvy enough to penalize IS offers to a sufficient extent. They should have given a higher penalty to offers that were not easily comparable with others given their inability to make accurate choices. However, consumers' aggregate behavior still favored offers that were expressed in terms of a common standard. Indeed, offers expressed in terms of an individuated standard suffered an overall *price penalty of 4 to 5% compared to common standard offers.*

Preference for the lowest priced of the common standard offers was less robust in 6-menus than in 3-menus, as the LPCS was chosen less often than would be optimal in 6-menus (see discussion of table 6). It might be that "too much choice" worked towards negating the common standard effect, either because it made it more difficult for consumers to identify offers that were expressed in terms of a common standard, or because they were less confident in the logic of favoring just one offer, the lower priced of the CS offers, when that meant disregarding many IS options. From this, one can infer that the common standard effect which is hypothesized in Gaudeul and Sugden (2012) may be effective in fighting against the introduction of *spurious complexity* by those firms that wish to confuse consumers, but it may not be effective in counteracting the introduction of *spurious variety*, whereby firms would pursue what we could call *frame proliferation* when faced with the threat of the emergence of a common standard. For a common standard effect to work in markets where firms multiply the options to choose from, firms ought therefore to be able to advertise their use of a common standard. This is where complications occur since the claim to be following a "common standard" may be difficult to verify and there are myriads of ways in which a standard can be debased. For example, if the common standard is in terms of the dimension of the product's packaging, then firms might decide not to fill it properly. If it is in terms of weight, and in the case of food, then managers may lower the quality of the product and mask this by adding more spices. There is therefore a role for regulatory authorities that promote and monitor the use of standards and mandate the disclosure of the information that enters into the definition of that standard.

Lead towards future work. We would like to examine in future work whether the extent of consumers' preference for CS offers is enough to drive a process of convergence towards the adoption of common standards by firms in a competitive market. Our data is encouraging in that respect (Table 10). The lower priced of the CS offers in our menus generated significantly higher revenue than offers expressed in terms of an individuated standard. Indeed, revenue from a LPCS offer was 0.27 on average when there were three options, much more than revenue of 0.18 for IS offers, and 0.12 on average when there were six options and one CS, much more again than revenue of 0.09 for IS offers. Those differences were significant in a statistical sense as well.

Table 10: Revenue by menu length and presence of a CS.

		LPCS	HPCS	IS	LPSCS	HPSCS	MPLCS
3-menu	No CS			0.1643			
	One CS	0.2725	0.0298	0.1786			
6-menu	No CS			0.0816			
	One CS	0.1190	0.0176	0.0860			
	Two CS	0.1891	0.0121	0.0875	0.1570	0.0154	0.0212

Note: See table 6 for the meaning of the headers in the case of 6-menus with two CS.

Since the lower priced of the CS offers generated significantly higher revenues than others, a firm would prefer to adopt a CS and undercut its rivals rather than maintaining an individuated standard. Furthermore, consumers who favored CS offers gained higher payoffs than others. While this may not necessarily translate into a process of convergence to a CS as hypothesized in Gaudeul and Sugden (2012), the conditions are therefore in place for this to be so.

Nomenclature

CS Common Standard

HPCS Higher Priced Common Standard Offer

IS Individuated Standard

LPCS Lowest Priced of the Common Standard offers

References

Adams, S. (1997). *The Dilbert Future.* HarperCollins. (ref. p. 1).

Agarwal, S., G. Amromin, I. Ben-David, S. Chomsisengphet, and D. D. Evanoff (2010, May). Learning to cope: Voluntary financial education and loan performance during a housing crisis. *American Economic Review 100*(2), 495–500. (ref. p. 2).

Agarwal, S. and B. Mazumder (2010). Cognitive abilities and household financial decision making. Working Paper 2010-16, Federal Reserve Bank of Chicago. (ref. p. 1).

Ariely, D. (2008). *Predictably Irrational.* HarperCollins. (ref. p. 1 and 10).

Ayal, A. (2011). Harmful freedom of choice: Lessons from the cellphone market. *Law and Contemporary Problems 74*, 91–133. (ref. p. 1).

Bar-Gill, O. and R. Stone (2009). Mobile misperceptions. *Harvard Journal of Law & Technology 23*(1), 49–118. (ref. p. 1).

Berndt, E. K., B. H. Hall, R. E. Hall, and J. A. Hausman (1974). Estimation and inference in nonlinear structural models. *Annals of Economic and Social Measurement 3*(4), 653–655. (ref. p. 21).

Camerer, C., S. Issacharoff, G. Loewenstein, T. O'Donoghue, and M. Rabin (2003). Regulation for conservatives: Behavioral economics and the case for "asymmetric paternalism". *University of Pennsylvania Law Review 151*(3), pp. 1211–1254. (ref. p. 1).

Carlin, B. I. (2009, March). Strategic price complexity in retail financial markets. *Journal of Financial Economics 91*(3), 278–287. (ref. p. 1 and 6).

Chioveanu, I. and J. Zhou (2009). Price competition and consumer confusion. *MPRA Paper No. 17340*. (ref. p. 1).

Choi, J. J., D. Laibson, and B. C. Madrian (2010). Why does the law of one price fail? An experiment on index mutual funds. *Review of Financial Studies 23*(4), 1405–1432. (ref. p. 1).

DellaVigna, S. and U. Malmendier (2006, June). Paying not to go to the gym. *American Economic Review 96*(3), 694–719. (ref. p. 1).

Eaton, J. W. (2002). *GNU Octave Manual.* Network Theory Limited. (ref. p. 1 and 12).

Ellison, G. (2005, May). A model of add-on pricing. *The Quarterly Journal of Economics 120*(2), 585–637. (ref. p. 1).

Ellison, G. (2006). Bounded rationality in industrial organization. In T. P. Richard Blundell, Whitney K. Newey (Ed.), *Advances in economics and econometrics: theory and applications. Ninth World Congress of the Econometric Society,* Volume 2. Cambridge University Press. (ref. p. 3).

Ellison, G. and S. F. Ellison (2009). Search, obfuscation, and price elasticities on the Internet. *Econometrica 77*(2), 427–452. (ref. p. 1).

Freedman, D. H. (2010). *Wrong: Why experts keep failing us.* Little, Brown and Company. (ref. p. 2).

Friedman, D. (1998). Monty Hall's three doors: Construction and deconstruction of a choice anomaly. *The American Economic Review 88*(4), 933–946. (ref. p. 10).

Fudenberg, D. and D. K. Levine (1998). *The Theory of Learning in Games.* MIT Press. (ref. p. 10).

Gabaix, X. and D. Laibson (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics 121*(2), 505–540. (ref. p. 1).

Garrod, L., M. Hviid, G. Loomes, and C. W. Price (2008). Assessing the effectiveness of potential remedies in consumer markets. Report 998, Office of Fair Trading. (ref. p. 2).

Gaudeul, A. and R. Sugden (2012). Spurious complexity and common standards in markets for consumer goods. *Economica 79*, 209–225. (ref. p. 1, 2, 10, 11, 31, and 32).

Gigerenzer, G. and H. Brighton (2009). Homo Heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science 1*, 107–143. (ref. p. 10).

Gigerenzer, G. and D. G. Goldstein (1999). Betting on one good reason: The take the best heuristic. In G. Gigenrenzer, P. M. Todd, and The ABC Research Group (Eds.), *Simple heuristics that make us smart*, Chapter 4, pp. 75–95. Oxford University Press. (ref. p. 10).

Greene, W. H. and D. A. Hensher (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological 37*(8), 681 – 698. (ref. p. 21).

Hole, A. R. (2007). Fitting mixed logit models by using maximum simulated likelihood. *The Stata Journal 7*(3), 388–401. (ref. p. 21).

Huber, J. and C. Puto (1983). Market boundaries and product choice: Illustrating attraction and substitution effects. *Journal of Consumer Research 10*(1), 31–41. (ref. p. 10).

Huck, S. and B. Wallace (2010). The impact of price frames on consumer decision making. Report 1226, Office of Fair Trading. (ref. p. 1).

Iyengar, S. S., G. Huberman, and W. Jiang (2004). How much choice is too much?: Contributions to 401(k) retirement plans. *Pension design and structure New lessons from behavioral finance 401*, 83–95. (ref. p. 1).

Iyengar, S. S. and M. R. Lepper (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology 79*, 995–1006. (ref. p. 1).

Kalaycı, K. and J. Potters (2011). Buyer confusion and market prices. *International Journal of Industrial Organization 29*(1), 14 – 22. Special Issue: Experiments in Industrial Organization. (ref. p. 1).

Krider, R. E., P. Raghubir, and A. Krishna (2001). Pizzas: π or square? Psychophysical biases in area comparisons. *Marketing Science 20*(2), 405–425. (ref. p. 4, 5, 14, and 21).

Lusardi, A. (2008). Financial literacy: An essential tool for informed consumer choice? Working Paper 14084, National Bureau of Economic Research. (ref. p. 1).

Miravete, E. J. (2003). Choosing the wrong calling plan? Ignorance and learning. *American Economic Review 93*(1), 297–310. (ref. p. 1).

Miravete, E. J. (2011). Competition and the use of foggy pricing. *American Economic Journal - Microeconomics*. Forthcoming. (ref. p. 1).

Morwitz, V., E. Greenleaf, and E. J. Johnson (1998). Divide and prosper: Consumers' reaction to partitioned prices. *Journal of Marketing Research 35*, 453–463. (ref. p. 1).

Nunes, J. C. (2000). A cognitive model of people's usage estimations. *Journal of Marketing Research 37*(4), 397–409. (ref. p. 1).

Piccione, M. and R. Spiegler (2012). Price competition under limited comparability. *The Quarterly Journal of Economics 127*(1), 97–135. (ref. p. 1).

Shchepetova, A. (2012, February). Strategic limitation of price comparison by competing firms: An experimental study. Working Paper, Toulouse School of Economics. (ref. p. 1).

Shestakova, N. (2011). Understanding consumers' choice of pricing schemes. Working paper, University of Vienna. (ref. p. 1).

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics 69*(1), 99–118. (ref. p. 14).

Spiegler, R. (2011). *Bounded rationality and industrial organization.* Oxford University Press. (ref. p. 1, 2, and 3).

StataCorp (2009). *Stata Statistical Software: Release 11.* College Station, TX: StataCorp LP. (ref. p. 1).

Sugden, R. (1986). *The Economics of Rights, Cooperation and Welfare.* Blackwell. (ref. p. 10).

Sugden, R. (1989). Spontaneous order. *The Journal of Economic Perspectives 3*(4), 85–97. (ref. p. 11).

Sugden, R. (2004). The opportunity criterion: Consumer sovereignty without the assumption of coherent preferences. *American Economic Review 94*(4), 1014–1033. (ref. p. 2).

Thaler, R. H. and C. R. Sunstein (2008). *Nudge.* Yale University Press. (ref. p. 1).

Train, K. (2003). *Discrete choice methods with simulation.* Cambridge: Cambridge University Press. (ref. p. 21).

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review 79*(4), 281–299. (ref. p. 9).

van Rossum, G. (1995, April). Python reference manual. CWI Report CS-R9525. (ref. p. 1 and 9).

Viswanathan, M., J. A. Rosa, and J. E. Harris (2005). Decision making and coping of functionally illiterate consumers and some implications for marketing management. *Journal of Marketing 69*, 15–31. (ref. p. 1 and 14).

Wilson, C. M. and C. W. Price (2010). Do consumers switch to the best supplier? *Oxford Economic Papers*. (ref. p. 1).

Zeithaml, V. A. (1982). Response to in-store price information environments. *The Journal of Consumer Research 8*(4), 357–369. (ref. p. 1).

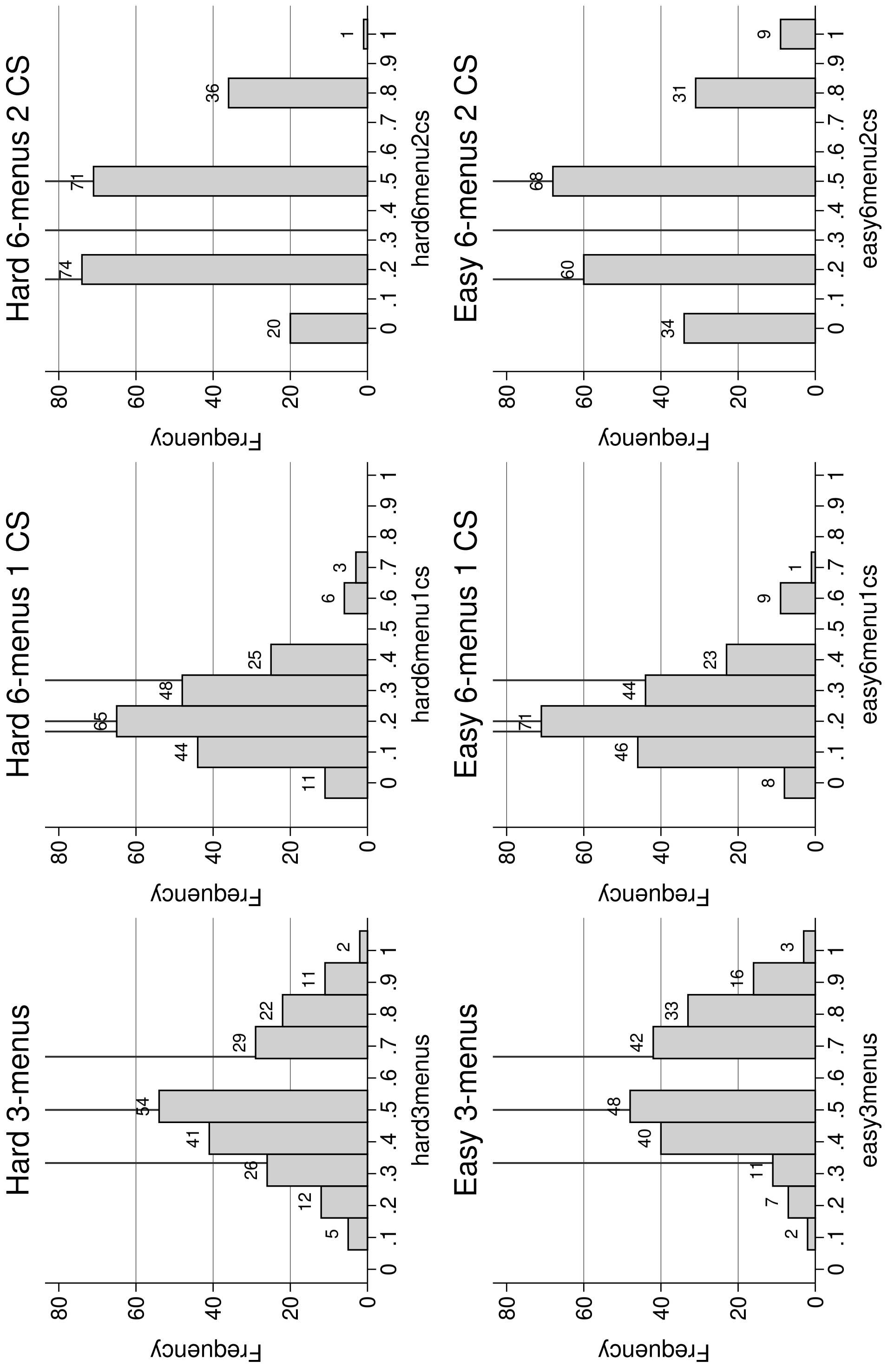
A Determinants of payoffs

Table 11: Regression of payoffs on menu and individual characteristics.

	(1) OLS	(2) Between effects	(3) Fixed effects	(4) Random effects
6-menu	0.9452^{***}		0.9849^{***}	0.9452^{***}
	(9.35)		(9.59)	(9.35)
hard menu	-0.6188^{***}		-0.6200^{***}	-0.6188^{***}
	(-10.15)		(-10.19)	(-10.15)
CS	2.3045^{***}		2.2896^{***}	2.3045^{***}
	(26.30)		(26.14)	(26.30)
6-menu×hard	-1.2046^{***}		-1.2055^{***}	-1.2046^{***}
	(-11.75)		(-11.83)	(-11.75)
6-menu×CS	-0.7680^{***}		-0.7625^{***}	-0.7680^{***}
	(-5.44)		(-5.43)	(-5.44)
hard×CS	-2.2658^{***}		-2.2519^{***}	-2.2658^{***}
	(-23.08)		(-23.01)	(-23.08)
6-menu×hard×CS	0.8466^{***}		0.8407^{***}	0.8466^{***}
	(5.59)		(5.60)	(5.59)
order	0.0027^{*}		0.0016	0.0027^{*}
	(2.20)		(1.27)	(2.20)
gender	0.0780	0.0693		0.0780
	(1.24)	(1.24)		(1.24)
age	-0.0272^{**}	-0.0233^{**}		-0.0272^{**}
	(-2.88)	(-3.25)		(-2.88)
shape task	-0.1948	-0.0987		-0.1948
	(-0.68)	(-0.36)		(-0.68)
score problems	0.0884^{**}	0.0680^{*}		0.0884^{**}
	(2.91)	(2.25)		(2.91)
score math	0.0181^{+}	0.0184^{+}		0.0181^{+}
	(1.72)	(1.91)		(1.72)
motivation	0.0207^{+}	0.0212^{+}		0.0207^{+}
	(1.67)	(1.89)		(1.67)
time	-0.0011	0.0221^{***}	-0.0091^{***}	-0.0011
	(-0.52)	(5.47)	(-3.51)	(-0.52)
Constant	10.8294^{***}	10.8288^{***}	11.1272^{***}	10.8294^{***}
	(30.70)	(34.43)	(127.67)	(30.70)
N	16080	16080	16080	16080
ll	$-4.192e+04$	-73.4482	$-4.180e+04$	
df	15.0000	7.0000	8.0000	15.0000

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Preference for the common standard, by menus and individuals



Note: In the case of 6-menus with two CS, the statistic is for choices of the lower priced of the larger common standard (the one with three members).

Figure 5: Choice of the lower priced common standard offer, as a percentage of all choices among menus with a common standard, by menus and individuals.