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Chapter 1

Introduction

Traditional economic theory is based on a model of perfectly rational individual decision maker. She is able to maximize her utility at no computational cost regardless of the complexity of the decision problem. She might have budget constraints and limited information but she has no bounds on her cognitive abilities. Her judgment is perfect.

Descriptive validity of this model has been criticized since at least Simon (1955) and several modifications and alternatives to the model have been proposed. A growing literature in behavioral economics models boundedly rational behavior that has been extensively documented by experiments. Models that assume individuals to make errors in choosing strategies in games (McKelvey and Palfrey, 1995), where individuals use mental accounts (Thaler, 1985) or have limited levels of strategic reasoning (Camerer et al., 2004) have been proposed. However, despite the recognition of bounded rationality of economic agents, the implications of bounded rationality for markets have largely been ignored.

One of the reasons for this ignorance is most economists' belief in the markets' power to regulate irrational behavior. For example Becker (1962) argues that "households may be irrational and yet markets quite rational" by showing that downward-sloping demand functions and upward-sloping supply functions can be derived from "irrational" agents' that choose randomly subject to a budget constraint. This belief in the markets' power to eliminate irrationality is perpetuated by experimental research that shows the ability of double auction markets in aggregating information and producing allocatively efficient outcomes (Smith 1962, Plott 1982). Supporting this general belief, Levitt and List (2007) argue that one cannot easily generalize the findings of anomalies from the lab to real world markets since in real markets stakes are higher and participants in each market are self selected motivated professionals.

An emerging literature in behavioral industrial organization challenges the belief that bounded rationality is irrelevant for markets. This literature shows that self interested firms in competitive markets might have incentives to take advantage of the bounded rationality of consumers. For example, in a theoretical model Gabaix and Laibson (2006) show that firms charge above-marginal cost prices for add-ons when some consumers do not pay attention to these add-ons. In similar vein, Heidhues and Koszegi (2010) show in a model of a competitive credit market that present biased borrowers who are non-sophisticated end up overborrowing and paying high penalties for late payments and suffer large welfare losses. So far this literature has remained largely theoretical and the models have not been empirically tested.

This thesis aims to make an empirical contribution to the behavioral industrial organization literature. The purpose of the thesis is to examine the implications of bounded rationality of buyers for market outcomes. In particular, I examine how complexity affects buyers' ability to make choices and whether sellers have incentives to supply excess complexity in markets. In this regard, I examine how prices and buyer surplus are affected by complexity in markets and also analyze the effects of increased competition in these markets where sellers can obfuscate buyers using complexity.

To answer the questions raised above, I use laboratory experiments. The laboratory environment allows me to have control over several factors that are very hard, if not impossible, to control in the field. First, by inducing the preferences of buyers in the lab I am able to distinguish decision errors from choices that reveal preference. Second, the laboratory setting allows me to create a complexity mechanism that has no other purpose than obfuscating buyers. In the field it is very hard to distinguish between genuine product differentiation or price discrimination from spurious complexity. And finally by using simulated buyers in the lab I am able to control the degree of buyer rationality and test alternative theories.

The thesis includes four substantive chapters each based on an individual paper. Each paper revolves around the common theme of the effects of complexity on decision making in a market setting but addresses a distinct research question.

In Chapter 2, I examine experimentally whether the complexity of loan contract terms leads to more narrow bracketing. In the experiment subjects are confronted with loans that differ in both value (benefits) and repayment (costs). First they choose a loan; next they choose among the different repayment alternatives this loan offers. I conduct two studies. In the first study, the treatments vary on whether the loan value terms or the repayment terms of all options are complex. The results show that complex contract terms increase the tendency to choose a high valued loan, disregarding the (unfavorable) repayment alternatives this loan offers. Moreover, this effect is stronger in case the repayment terms are complex than in case the loan value terms are complex. This finding is in line with the hypothesis based on narrow bracketing, which argue that complexity in the repayment terms would increase subjects tendency to bracket narrowly and choose on the basis of loan values alone. In a second study, I allow the repayment alternatives of some loans to be complex while other options' repayments are simple. The results show that making the high valued loan's repayments more complex makes that loan more attractive. This result suggests that firms with inferior loans might have incentives to obfuscate the repayment schedules of their loans. This chapter contributes to our understanding of the relationship between complexity and narrow bracketing as well as problems in credit markets such as excessive borrowing from credit cards and over-indebtedness.

In Chapter 3, we[1] employ a price setting duopoly experiment to examine whether buyer confusion increases market prices. Each seller offers a good to buyers who have homogeneous preferences. Sellers decide on the number of attributes of their good and set prices. The number of attributes bears no cost to the sellers and does not affect the value of the good to the buyers but adds complexity to buyers' evaluation of the goods.

The experimental results indicate that the buyers make more suboptimal choices and that prices are higher when the number of attributes of the goods is higher. Moreover, prices and profits are higher than those in a benchmark treatment with perfectly rational (robot) buyers. Another interesting result is the

[1]This chapter is based on Kalaycı and Potters (2010).

finding that even though the cost of making mistakes for an individual may be relatively little, these mistakes pose externalities on all buyers by reducing the price elasticity of demand. The paper also makes an important methodological contribution by developing an original complexity mechanism that can create buyer confusion with neither affecting the quality of the good nor creating actual search costs. I apply this mechanism to price complexity in Chapter 4.

Chapter 4 reports an experiment that examines the effects of price complexity on market prices. In my experimental posted-offer markets, each seller offers an identical good to buyers with homogeneous preferences. First, sellers simultaneously decide on the price and the tariff structure of their good, then buyers make their choices among the goods. Each seller can choose to have a one, two or three-part tariff. The tariff structure affects neither the value nor the price of the good. However, having a higher number of tariffs makes it harder for buyers to calculate the price of the good.

Main results show that high priced sellers choose high complexity more often when demand is simulated in accordance with the model of Carlin (2009). However, the evidence is mixed when the buyers are human subjects. Importantly, prices are higher when the sellers can confuse buyers using price complexity than when the sellers interact with perfectly rational robot buyers.

The paper documents significant price effects of the use of the price complexity mechanism which has important policy relevant implications, especially for consumer protection. In addition, by conducting a series of experiments I unravel the weaknesses of the theoretical model proposed by Carlin (2009). The results suggest that it is important to model the bounded rationality of the buyers in a more realistic way rather than following a reduced form approach.

Chapter 5 examines the effects of competition in experimental posted-offer markets where sellers can confuse buyers. I report two studies. The first study is based on the experiment in Chapter 3, where sellers offering heterogeneous goods can obfuscate buyers by means of spurious product differentiation. The other study is based on the experiment in Chapter 4. In this study sellers offer identical goods and make their prices unnecessarily complex by having multi-part tariffs. I vary the level of competition by having treatments with two- and three sellers. The results from both studies show that average complexity created by a seller is not affected by the number of sellers, which contrasts with what has been suggested by earlier literature (Gabaix and Laibson, 2004; Carlin, 2009). In addition, market prices are lower and buyer surplus is higher when there are three rather than two sellers in a market. The results in Chapter 5 imply that sellers' ability to confuse buyers is by itself not a concern against increasing competition in markets.

Chapter 2

Complexity and Narrow Bracketing in Credit Choice

2.1 Introduction

Policy makers are becoming increasingly concerned about the abundance and complexity of the decisions that consumers have to make. For example, in promoting the Credit Card Act, the White House (2009) states that "Americans need a healthy flow of credit in our economy, but for too long credit card contracts and practices have been unfairly and deceptively complicated, often leading consumers to pay more than they reasonably expect"[1]. Despite this concern of policy makers complexity has not been recognized by mainstream economists as a problem. Traditional economic theory assumes that rational actors make accurate decisions at zero cognitive cost and in no time. The complexity of the decision problem does not affect the degree of rationality and everyone is assumed to be equally capable of solving any optimization problem, however complex the problem is. Although a growing literature demonstrates systematic biases in decision making, most of these biases are interpreted to be independent of the complexity of the decision environment, and modeled as such.

One common bias in decision making is narrow bracketing, which can be defined as making choices by considering the consequences of choices in isolation

[1] http://www.whitehouse.gov/the_press_office/Fact-Sheet-Reforms-to-Protect-American-Credit-Card-Holders/

instead of considering them together (Read et al., 1999). Narrow bracketing has been suggested to explain phenomena such as the equity premium puzzle (Benartzi and Thaler, 1995), the popularity of state lotteries (Haisley et al., 2008), and the stock market participation puzzle (Barberis et al., 2006). Although the consequences of narrow bracketing have been researched the conditions under which people bracket narrowly are not fully understood. Narrow bracketing has been shown to be induced by framing options as separate choices (Tversky and Kahneman, 1981) and by increasing the frequency of feedback (Gneezy and Potters, 1997). Another possible determinant of narrow bracketing is the complexity of the decision environment. As Read et al. (1999) argue broad bracketing is cognitively more demanding than narrow bracketing. In this regard, complexity of a decision problem is likely to affect whether an individual brackets broadly or narrowly.

In this paper, I test the conjecture that complexity in a choice task leads to more narrow bracketing in decision making. In addition, I inquire whether increasing the complexity of a particular option can make that option more attractive. This second question is particularly important in understanding whether firms have incentives to obfuscate their products and whether there is a case for consumer protection regarding this.

To answer these questions I conduct two experimental studies in which the decision tasks are framed as choices between loans. In the first study, the subjects choose among three loans L^H, L^M and L^L, where each loan $L^k = \left(a^k, R^k\right)$ is characterized by a loan value a^k and a set of repayment alternatives R^k, $k \in \{H, M, L\}$. Subjects make decisions in two stages; first they choose one of the three loans, L^k, and then they choose one of the repayment alternatives $r \in R^k$, which that loan offers. The payoff to the subject is equal to $\pi = a^k - r$. So, the maximum payoff from choosing loan k is $\pi^k = a^k - min(r|r \in R^k)$. The contract terms for the three loans are as follows: $a^H > a^M > a^L$, $R^H = \{r_1, r_2, r_3\}$, $R^M = \{r_2, r_3, r_4\}$, $R^L = \{r_3, r_4, r_5\}$ where $r_1 > r_2 > r_3 > r_4 > r_5$. Loan L^H, (High), offers the highest value but also has the highest repayment. Loan L^M, (Medium), offers the medium value but also has the medium repayment. Loan L^L, (Low), offers the lowest value but also has the lowest repayment. The parameters are chosen such that the Medium loan offers a better deal than either the High or the Low loan: $\pi^k = a^k - min(r_j)$ and $\pi^M > \pi^H = \pi^L$. The Medium option offers a 10% higher payoff than the other two options.

The experimental variations are on the complexity of the loan values or on the complexity of the repayments. In the treatment "SIMPLE" both the loan values and the repayment alternatives of all options are presented in a simple form. In the treatment "COMPLEX REPAYMENT" , the repayment alternatives of all options are presented in a form that requires the subjects to find the weighted sum of three payment components to calculate the actual repayment. Complexity is introduced in similar vein in the treatment "COMPLEX VALUE", where the loan value of all options consist of three components the weighted sum of which equals the actual loan value.

In the experiment, broad bracketing would lead to choosing the loan k that maximizes $a^k - min(r|r \in R^k)$ whereas narrow bracketing results in first choosing k that maximizes a^k and then choosing the repayment r_j in R^k. Since in SIMPLE broad bracketing is cognitively not very demanding subjects are expected to choose the Medium option that offers the highest maximum payoff. In COMPLEX REPAYMENT broad bracketing requires calculation of all the repayment alternatives whereas narrow bracketing is straightforward. Therefore, subjects are more likely to choose the High option in COMPLEX REPAYMENT than they are in SIMPLE. Similarly, broad bracketing is cognitively demanding in COMPLEX VALUE, however narrow bracketing is not as easy in COMPLEX VALUE as it is in COMPLEX REPAYMENT. In this regard I hypothesize that the increase in the choice frequency of the High option will be higher in COMPLEX REPAYMENT than in COMPLEX VALUE.

The results of the first study show that complexity both in the loan value and in the repayment alternatives, leads to sub-optimal decision making. Compared to the benchmark treatment where both the loan and the repayment are displayed in a simple form, subjects choose the Medium option which gives the highest payoff less frequently in the complex treatments. The more interesting result is that complexity in the repayment alternatives leads to a larger increase in choices for the High option than for the Low option, whereas COMPLEX VALUE, leads to a similar increase in the choice frequency of the High and the Low option. In line with the hypothesis, COMPLEX REPAYMENT leads to a larger increase in the choice frequency of the High option than COMPLEX VALUE.

A question that follows the result that complexity of the loan terms of all options may induce narrow bracketing is whether narrow bracketing of the subjects can be manipulated by a single actor in the market. For example, can a single bank increase the sales of an inferior loan by making it more complex? In the second study, I vary the complexity of individual loan options allowing some of them to be simple while others are complex. The setup is the same as in the first study. In addition to COMPLEX REPAYMENT and SIMPLE I ran two other treatments. In HIGH COMPLEX only the repayment of the High option was presented in a complex form. In the other treatment called MEDIUM SIMPLE, the repayment of the High and the Low options were complex while the Medium option was simple. Comparison of HIGH COMPLEX with SIMPLE allows us to see whether a firm offering the High option can unilaterally increase the sales of that option. Similarly, by comparing MEDIUM SIMPLE with COMPLEX REPAYMENT we can see whether it is a best-response for the firm offering the Medium option to make that option's repayment more simple.

When the number of options that have a complex repayment increases, broad bracketing becomes cognitively more demanding relative to narrow bracketing. For example, a broad bracketing subject needs to calculate the weighted sum of the payment components in all three repayment alternatives in the High option to be able to find out the best option in HIGH COMPLEX. Therefore, subjects are more likely to bracket narrowly in HIGH COMPLEX and choose the High option than in SIMPLE. Similarly, in MEDIUM SIMPLE broad bracketing requires less cognitive resources than it does in COMPLEX REPAYMENT since the subject doesn't need to calculate the actual repayment of the Medium option in MEDIUM SIMPLE. Therefore, subjects are more likely to bracket narrowly and choose the High option in in COMPLEX REPAYMENT than in MEDIUM SIMPLE. In this regard, I hypothesize that the choice frequency of the High option will be higher in HIGH COMPLEX than it will be in SIMPLE and higher in COMPLEX REPAYMENT than it will be in MEDIUM SIMPLE.

The results of the second study show that the High option is chosen more in HIGH COMPLEX than in SIMPLE. This result shows that narrow bracketing can be induced even by only making the High (but sob-optimal) option's repayment schedule more complex while leaving the other options' repayment schedules simple. This finding suggests that firms have incentives to obfuscate the loan options that have larger immediate rewards but are actually inferior to competing options. I also find that subjects choose the Medium option more in MEDIUM SIMPLE, where only the Medium option's repayment schedule is simple, than in COMPLEX REPAYMENT, where all the options repayment schedules are complex.This suggests that firms that have superior loans are likely to shy away from obfuscating their loans.

The results from both studies show the importance of complexity in decision making. Not surprisingly, complexity leads to lower payoffs and makes subjects spend more time in making decisions. In particular, when the payoff elements that are at a later stage are more complex subjects are more likely to bracket narrowly. This latter finding is particularly important for understanding the conditions under which narrow bracketing determines behavior.

The results also help us understand problems in credit markets such as excessive borrowing on credit cards and over-indebtedness. Financial products are in general very complicated even to many experts and firms often put emphasis on the immediate rewards of credit products by delaying payments and fees in the first year etc. while obscuring the implied interest rates, loads and fees that the borrower will incur in the future. The finding that an individual lender may have an incentive to obfuscate its own product raises concerns regarding the markets' ability to self govern such practices.

The results from the experiment are in line with the literature in consumer inattention to non-salient features of products. Hossain and Morgan (2006) show that buyers underestimate the shipping costs on eBay auctions. Similarly, Chetty et al. (2009) show that consumers react more to price changes than they do to equivalent changes in sales taxes that are less transparent. Ausubel (1999) finds similar results in a field experiment using direct mail credit card solicitations. He finds that recipients of credit card solicitations overrespond to the introductory interest rate relative to the duration of the introductory offer and to the post introductory interest rate. My results complement this literature by showing that the non-salience of unattractive product features can be enhanced by making them more complicated.

The current paper also contributes to a more practical literature in public economics on developing policies to assist small investors in financial markets. Complexity of financial products has been recognized to be a problem for investors and policies to improve the financial literacy of investors have been proposed. Bertrand and Morse (2009) find that information that helps people think less narrowly about the cost of payday borrowing reduces the take-up of payday loans, loans which are typically very costly to the borrower in the long run. However, not every disclosure policy is effective. Beshears et al.. (2010) find that the U.S. Securities and Exchange Commission's Summary Prospectus, which simplifies mutual fund disclosure, has no effect in portfolio choices and fails to avoid sales loads. My paper suggests that policies that focus on simplifying the non-salient future elements of loan contracts are more likely to help investors make better decisions.

The remainder of the paper is organized as follows. In Section 2, I describe the design of the experiment, formulate the hypothesis and report the results for Study 1. Similarly in Section 3, I present and discuss Study 2. Finally, Section 4 concludes.

2.2 Study 1

Experiment

The experiment is an individual choice task where subjects make choices among different loan options $L^k = \left(a^k, R^k\right)$. Subjects make decisions in two stages. In the first stage, subjects choose between three loan options. In the second stage, subjects choose among repayment alternatives R^k for the particular loan that they have chosen in the first stage. Each loan has three possible repayment alternatives $r \in R^k$, which are observable to the subject in the first stage. The payoff of each subject is the loan value minus the repayment she chooses.

$$\text{Payoff} = \text{Value of the Loan - Repayment Amount}$$

Subjects have 120 seconds in the first stage and 60 seconds in the second stage and both of these time limits are binding. If subjects fail to make a decision at any stage they get 0 points for that period. Also, subjects are not allowed to proceed to the next stage before the time ends. This is implemented in order to prevent subjects from trying to finish a period early and leave the lab sooner.

There are three loan options that the subjects choose from. The first option L^H is called the “High option” since it offers the highest loan value a^H, but not the highest maximum payoff π^H. The maximum payoff π^k, for an option refers to the loan value a^k, minus the cheapest repayment alternative $min(r_j)$, for that loan.The second option L^M, is the “Medium option” which has the second highest loan value and the highest maximum payoff. The third option L^L, is called the “Low option” and it has the lowest loan value and the lowest possible repayment and the same maximum payoff as the High option. The exact numbers that the options are derived from are depicted below:

Table 2.1: Base numbers

	Loan value	Repayment options	Maximum payoff
High option	73	49 45 43	30
Medium option	67	45 43 34	33
Low option	61	43 34 31	30

Notice that $a^H > a^M > a^L$, $R^H = \{r_1, r_2, r_3\}$, $R^M = \{r_2, r_3, r_4\}$, $R^L = \{r_3, r_4, r_5\}$ where $r_1 > r_2 > r_3 > r_4 > r_5$ and $\pi^M > \pi^H = \pi^L$.

In the experiment the loan options are labeled as Loan A, Loan B and Loan C, and repayment alternatives as Repayment X, Repayment Y and Repayment Z for each loan. The numbers shown to participants are derived from the base numbers in Table 2.1 above using a scale factor.

In Study 1, there are three treatments: SIMPLE, COMPLEX REPAYMENT and COMPLEX VALUE. In SIMPLE both the value of the loan and the repayment for each option consists of a single number. Figure2.1 displays a sample screen for the loan choice in SIMPLE [2].

Loan	Value
Loan A	7300
Loan B	6700
Loan C	6100

Please make a choice among the above 3 Loans. In the 2nd stage you will have to make a choice between 3 repayment options. The repayment options you will get depends on the Loan you choose now. Below you can find the details of all the repayment options for each Loan.

Repayment options for Loan A	Payment amount
Repayment X	4900
Repayment Y	4500
Repayment Z	4300
Repayment options for Loan B	**Payment amount**
Repayment X	4500
Repayment Y	4300
Repayment Z	3400
Repayment options for Loan C	**Payment amount**
Repayment X	4300
Repayment Y	3400
Repayment Z	3100

Figure 2.1: Loan choice in SIMPLE

In COMPLEX REPAYMENT the value of the loan is a single number as in SIMPLE while the repayment for every alternative consists of three items: A standard fee, a percentage amount and a bonus discount. Figure 2.2 gives a sample of the way in which complex repayments alternatives are presented to subjects. For example, the repayment of alternative X in Figure 2.2 is equal to $4600 + 0.07 * 7300 - 1627 = 3484$.

[2]See Appendix for instructions and an example screen-shot for the repayment choice in SIMPLE.

Repayment	Payment Details
Repayment X	A standard Fee of 4600, a percentage fee of %7 of the value of the Loan you have chosen minus a bonus of 1627 .
Repayment Y	A standard Fee of 4800, a percentage fee of %5 of the value of the Loan you have chosen minus a bonus of 2005 .
Repayment Z	A standard Fee of 4700, a percentage fee of %3 of the value of the Loan you have chosen minus a bonus of 583 .

Figure 2.2: Sample COMPLEX REPAYMENT

COMPLEX VALUE differs from SIMPLE in how the loan values are displayed. Each loan value consists of three items: A standard amount, a percentage amount, and a tax credit. For example, the loan value for choosing Loan A in Figure 2.3 equals $11928 + 0.07 * 13440 - 605 = 12264$. The repayment in COMPLEX VALUE is a single number as in SIMPLE.

Loan	Details for the Value of the Loan
Loan A	A standard amount of 11928, plus a percentage amount of %7 of 13440 minus a tax of 605 .
Loan B	A standard amount of 11760, plus a percentage amount of %5 of 12432 minus a tax of 1126 .
Loan C	A standard amount of 12096, plus a percentage amount of %3 of 9408 minus a tax of 2130 .

Figure 2.3: Sample COMPLEX VALUE

The treatment conditions are summarized in Table 2.2 below.

Table 2.2: Treatments

Treatment	Loan value	Repayment alternatives
SIMPLE	Simple	Simple
COMPLEX REPAYMENT	Simple	Complex
COMPLEX VALUE	Complex	Simple

The experiment employs a within subject design. Subjects play each treatment condition 4 times. The assignment of the High, Medium and Low options to Loans A, B, C and the repayment alternatives to Repayments X, Y, Z are randomized by the computer in each period[3]. In each period the base numbers shown in Table 2.1 are multiplied by a scale factor, which is randomly drawn from uniform distribution [1000, 2000]. The purpose of this is to make the choice task more challenging and to disguise the base numbers.

The experiment was run at Tilburg University's CentERLab in June 2010. The experiment was programmed and conducted with the software zTree (Fischbacher 2007). 35 subjects in two sessions (18+17) participated in the study. The subjects were students at Tilburg University who were recruited through e-mail lists of students interested in participating in experiments. Upon arrival participants were randomly seated behind computers. The instructions were displayed on their computer screen and read aloud by the experimenter. The experiment started when all subjects indicated that they read and understood the instructions. Earnings were denoted in points and transferred to cash at a rate of 7000 points = 1 EUR. The experimental sessions lasted about 75 minutes and subjects on average earned about 15 Euros. At the end of the experiment a short questionnaire was run.

Hypothesis

In the experiment, if an individual brackets broadly she chooses the loan option that maximizes $\pi^k = a^k - min(r_j | r_j \in R^k)$. This would result in choosing the Medium option, which offers the highest maximum payoff. On the other hand, a narrow bracketing individual considers the loan value and repayment decisions as separate decisions and chooses the loan option that maximizes a^k. This would lead to choosing the High option, which offers the highest loan value.

Read et al. (1999) argue that narrow bracketing is a consequence of cognitive capacity limitations, for example in attention (Kahneman, 1973), memory (Baddeley, 1986), and analytical processing (Simon, 1957). In the experiment, choosing a loan by narrow bracketing requires the comparison of a^1, a^2 and a^3. Broad bracketing however is cognitively more demanding. Choosing a loan by broad bracketing requires the individual to first find the minimum repayment al-

[3]In order to prevent subjects from learning the ranking of the payoffs of the three loans (Medium > High = Low), over the course of the 12 rounds, there also were 9 rounds with different rankings. Data from these rounds are not used in the analysis.

ternative $min(r_j|r_j \in R^k)$ for each loan option, then to calculate the payoff for each option $\pi^k = a^k - min(r|r \in R^k)$, and finally to compare the payoffs π^1, π^2 and π^3.

While narrow bracketing is easier than broad bracketing in most situations, relative ease of these two ways of bracketing depends on the complexity of the decision problem. Narrow bracketing is cognitively as easy in COMPLEX REPAYMENT as it is in SIMPLE since in both treatments the subject only needs to compare the loan values which are all presented in a simple form. On the other hand, increasing the complexity of the repayments makes broad bracketing cognitively more demanding. As such, broad bracketing requires more cognitive resources in COMPLEX REPAYMENT than it does in SIMPLE. This makes narrow bracketing relatively easier in COMPLEX REPAYMENT than it is in SIMPLE. Therefore, an individual is more likely to bracket narrowly in COMPLEX REPAYMENT and choose the High option than she does in SIMPLE.

In COMPLEX VALUE narrow bracketing is cognitively more demanding than it is in SIMPLE, since comparing a^1, a^2 and a^3 requires the calculation of these values. However, compared to SIMPLE broad bracketing is cognitively more demanding in COMPLEX VALUE as well. In this regard it is unclear whether individuals would bracket more narrowly in COMPLEX VALUE compared to SIMPLE.

While in COMPLEX VALUE both narrow and broad bracketing become cognitively more demanding in COMPLEX REPAYMENT only broad bracketing becomes more demanding. Since a narrow bracketing individual will choose the High option, this would imply that the High option will be chosen more in COMPLEX REPAYMENT than in COMPLEX VALUE.

Hypothesis 1*: Compared to* SIMPLE, COMPLEX REPAYMENT *will lead to a larger increase in the choice frequency of the High option than it will in* COMPLEX VALUE.

Results

In this section I present the results from the experiment. Observations where the subjects fail to make a decision on time are dropped from the analysis. Treatment effects are examined with a Wilcoxon-matched pairs signed rank test using each subjects average score over all repetitions as the unit of observation. Reported p-values in parenthesis are based on two sided tests.

Figure 2.4 shows the average choice frequency of each option, High, Medium and Low, for all 3 treatments. The first block is for SIMPLE, the second block is for COMPLEX REPAYMENT and the third block is for COMPLEX VALUE treatments.

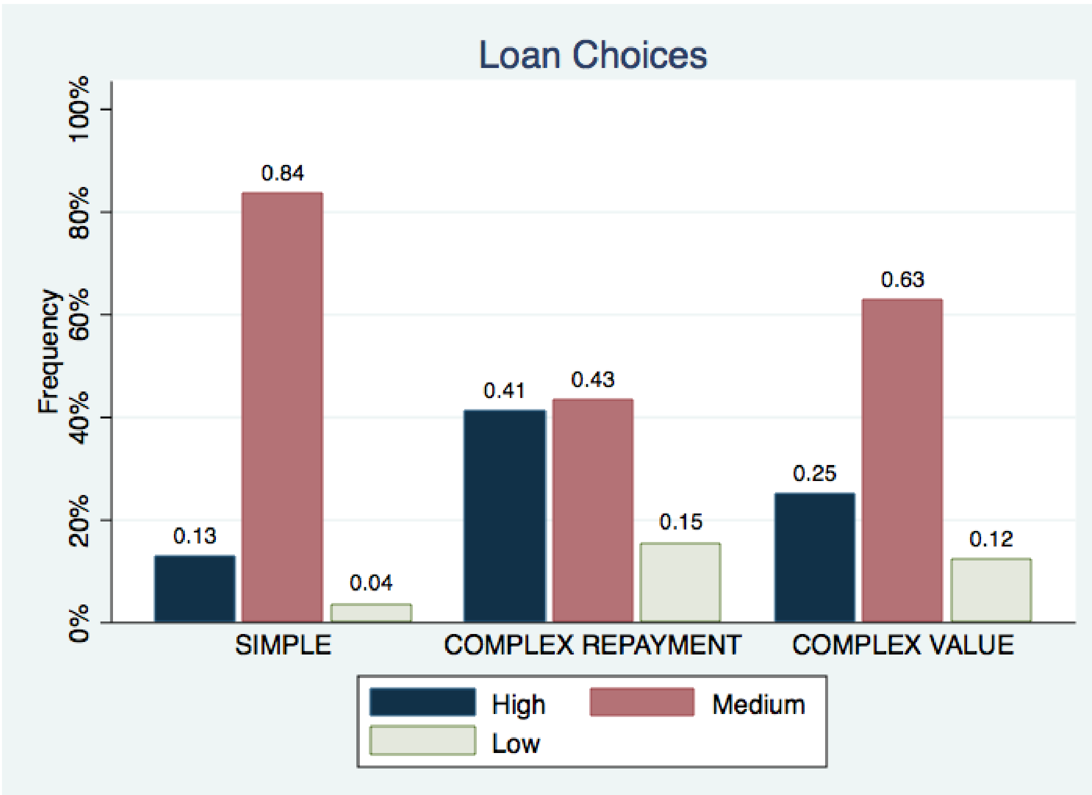


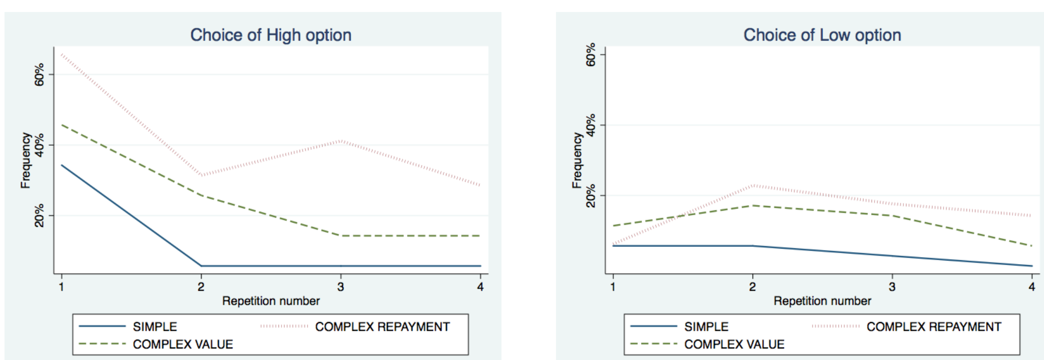
Figure 2.4: Loan choices over treatments

The second column in the first block of Figure 2.4 shows that in SIMPLE, subjects choose the Medium option, which is the optimal choice, about 84% of the time. The High option is chosen 13% of the time, while the Low option is chosen about 4%. The differences between all 3 choice frequencies is significant.

The second block in Figure 2.4 shows that in COMPLEX REPAYMENT subjects on average choose the High option about 40%, Medium option 42% and the Low option 15% of the time. There is a a strong effect of COMPLEX REPAYMENT on choices. Compared to SIMPLE, COMPLEX REPAYMENT increases the choice frequencies both of the High option and the Low option. The increase in the High option is 14%- points larger than the increase in the Low option and this difference is statistically significant (p-value=0.03). This finding supports the argument that COMPLEX REPAYMENT leads to more narrow bracketing, as an equal increase in the High and the Low option would be explained by an increase in random decision errors.

In COMPLEX VALUE subjects on average choose the High option about 25%, Medium option 63% and the Low option 12% of the time. Compared to SIMPLE, COMPLEX VALUE leads to an increase in the choice frequency of the High option by 12%-points, while it increases the choice frequency of the Low option by 8%-points. Statistically these two changes are not different (p-value=0.72).

Hypothesis 1 relates to the difference between the increase (of 27%-points) in choice frequency of the High option in COMPLEX REPAYMENT relative to SIMPLE and the increase (of 12% points) in the choice frequency of the High option in COMPLEX VALUE relative to SIMPLE. A Wilcoxon signed rank test using changes in each individuals' average frequency of High option choice from SIMPLE to COMPLEX REPAYMENT and COMPLEX VALUE shows that this difference is statistically significant (p-value<0.02), supporting Hypothesis 1. This result shows that COMPLEX REPAYMENT leads to more narrow bracketing than COMPLEX VALUE does.



(a) (b)

Figure 2.5: High and Low options' choice frequencies over time

Figure 2.5 displays the development of the choice frequencies of the High and the Low option over time. Over the course of 4 repetitions subjects choose both the High option and the Low option less and less, while the frequency of the Medium option increases. However, the complexity effect remains even at the last repetition. Subjects choose the High option more when the repayments or the loan values are more complex. In the first repetition COMPLEX REPAYMENT increases the average choice frequency of the High option from 34% in SIMPLE to 60%. In the last repetition, the average choice frequency of the High option increases from 6% in SIMPLE to 29% in COMPLEX REPAYMENT. Similarly, the choice frequency of the High option diminishes over time in COMPLEX VALUE. In COMPLEX VALUE, the average choice frequency of the High option falls from 45% in the first repetition to 14% in the last repetition.

The Medium option offers the highest maximum payoff and the results presented so far demonstrate that complexity leads the subjects to choose the Medium option less often. It follows naturally that complexity leads to lower payoffs. Subjects earn 12%-point less in COMPLEX REPAYMENT than in SIMPLE. COMPLEX VALUE leads to a relatively lower loss, 2%. Complexity not only leads to lower payoffs but also to higher decision times. Choosing a loan in COMPLEX REPAYMENT requires on average 36.1 seconds more than it does in SIMPLE. Similarly, subjects take 31.1 seconds more in COMPLEX VALUE than they do in SIMPLE.

The results from Study 1 show that complexity leads to suboptimal decisions, therefore to welfare loss for the subjects. In particular, COMPLEX REPAYMENT biases decision makers towards the High option. This is an important finding that helps us understand the scope of narrow bracketing behavior and environmental determinants of bracketing. A question that follows this finding is whether creditors would find it profitable to make the contract terms of their loans more complex. To answer this question, a second study is conducted using the complex repayment method in Study 1.

2.3 Study 2

Experiment

Study 1 shows that when the repayment of all the options are complex subjects bracket narrowly and choose the High option. However, it is unclear whether such complexity would arise endogenously in a market. For example, would a bank offering the Medium option make the repayment of this option complex? And while complexity benefits the High option can the bank increase the uptake of that loan if that is the only option in the market that has complex repayment?

Study 2 replicates SIMPLE and COMPLEX REPAYMENT treatments of Study 1, and adds two treatments. This study focuses on the relative effects of complex repayment on the attractiveness of options. In the first additional treatment, called HIGH COMPLEX, only the repayments for the High option is complex while the repayments for the Low and Medium options are simple. In the second additional treatment, called MEDIUM SIMPLE, the repayments for the High and the Low options are complex while the Medium option's repayment is simple. To distinguish the treatments better I call the treatment where all options' repayments are simple "ALL SIMPLE" and the treatment where the repayments of all options are complex "ALL COMPLEX" in this study. The treatment conditions in Study 2 are summarized in Table 2.3 below.

The motivation for running HIGH COMPLEX is to compare it with ALL SIMPLE and to examine whether an unilateral change in the complexity of the High option's repayment change this option's choice frequency. Similarly, by comparing MEDIUM SIMPLE with ALL COMPLEX we can examine whether making the repayment of the Medium option more simple affects its choice frequency.

Similar to Study 1, within subject design is employed but this time each treatment is repeated 3 times instead of 4. However, due to a programming error the actual number of repetitions turned out to be 3,3,2 and 4 for ALL SIMPLE, HIGH COMPLEX, MEDIUM SIMPLE and ALL COMPLEX, respectively.

Table 2.3: Treatments in Study 2

	Loan value	Repayment alternatives		
Treatment		High option	Medium option	Low option
ALL SIMPLE	Simple	Simple	Simple	Simple
HIGH COMPLEX	Simple	Complex	Simple	Simple
MEDIUM SIMPLE	Simple	Complex	Simple	Complex
ALL COMPLEX	Simple	Complex	Complex	Complex

The experiment was run at Tilburg University's CentERLab in June 2010. 32 subjects in two sessions participated in the study. Overall, the procedure was the same as in Study 1. The experimental sessions lasted about 80 minutes and subjects on average earned about 16 Euros.

Hypothesis

In Study 2, there are two main questions of interest. First, how does a unilateral change in the complexity of the High option affect its demand? And second, how would a unilateral change in the complexity of the Medium option affect the demand for that option?

To answer the first question one needs to compare the choice frequency of the High option in HIGH COMPLEX with the same frequency in ALL SIMPLE. As Study 1 shows there is a link between the level of complexity in repayments and the tendency to bracket more narrowly. In Study 2 the level of complexity between treatments is determined by the number of options that have complex repayments. In HIGH COMPLEX there is one option with complex repayments while there is none in ALL SIMPLE.Therefore it is harder to bracket broadly in HIGH COMPLEX than it is in ALL SIMPLE, while narrow bracketing is cognitively as easy in HIGH COMPLEX as it is in ALL SIMPLE. This implies that an individual is more likely to bracket narrowly and choose the High option in HIGH COMPLEX than in ALL SIMPLE. As such, a unilateral increase in the complexity of the High option's repayment will increase the demand for that option.

Hypothesis 2a*: The choice frequency of the High option will be higher in* HIGH COMPLEX *than in* ALL SIMPLE.

Answering the second question, how a unilateral change in the complexity of the Medium option affects its demand, requires the comparison of MEDIUM SIMPLE with ALL COMPLEX. Since the number of options with complex repayment is larger it is harder to bracket broadly in ALL COMPLEX than it is in MEDIUM SIMPLE, while narrow bracketing is as easy in both treatments. This implies that an individual is more likely to bracket broadly and choose the Medium option in MEDIUM SIMPLE than in ALL COMPLEX.

Hypothesis 2b*: The choice frequency of the Medium option will be higher in* MEDIUM SIMPLE *than in* ALL COMPLEX.

Results

As mentioned in the design section due to an error in the program the number of observations per treatment are unbalanced. In order to be able to make an accurate comparison across treatments only the data for the first two repetitions are used. Main results are not qualitatively different if the data for the 3rd repetition is added when available. As in Study 1, treatment effects are examined with a Wilcoxon-matched pairs signed rank test using each subjects average score from the first two repetitions as the unit of observation.

Figure 2.6 shows the average choice frequencies for each option for all 4 treatments. The first block in Figure 2.6 shows that in ALL SIMPLE subjects on average choose the High option about 3%, Medium option 95% and the Low option 2% of the time. In HIGH COMPLEX the High option is chosen at 25% of the time, while the Medium option is chosen at 70% and the Low option is chosen at 5% of the time. Meanwhile, in MEDIUM SIMPLE the High option is chosen at 17%, the Medium option at 70% and the Low option at 5% of the time. And finally, in ALL COMPLEX subjects on average choose the High option about 38%, Medium option 44% and the Low option 17% of the time. Notice that the first and the last block of Figure 2.6 displays a similar picture to Figure 2.4 for Study 1; increasing the complexity of the repayment of all options leads to an increase in the choice frequency of the High option.

According to Hypothesis 2a the High option will be chosen more often in HIGH COMPLEX than in ALL SIMPLE. Comparison of the second block with the first block in Figure 2.6 shows that High option is chosen 22%-points more in

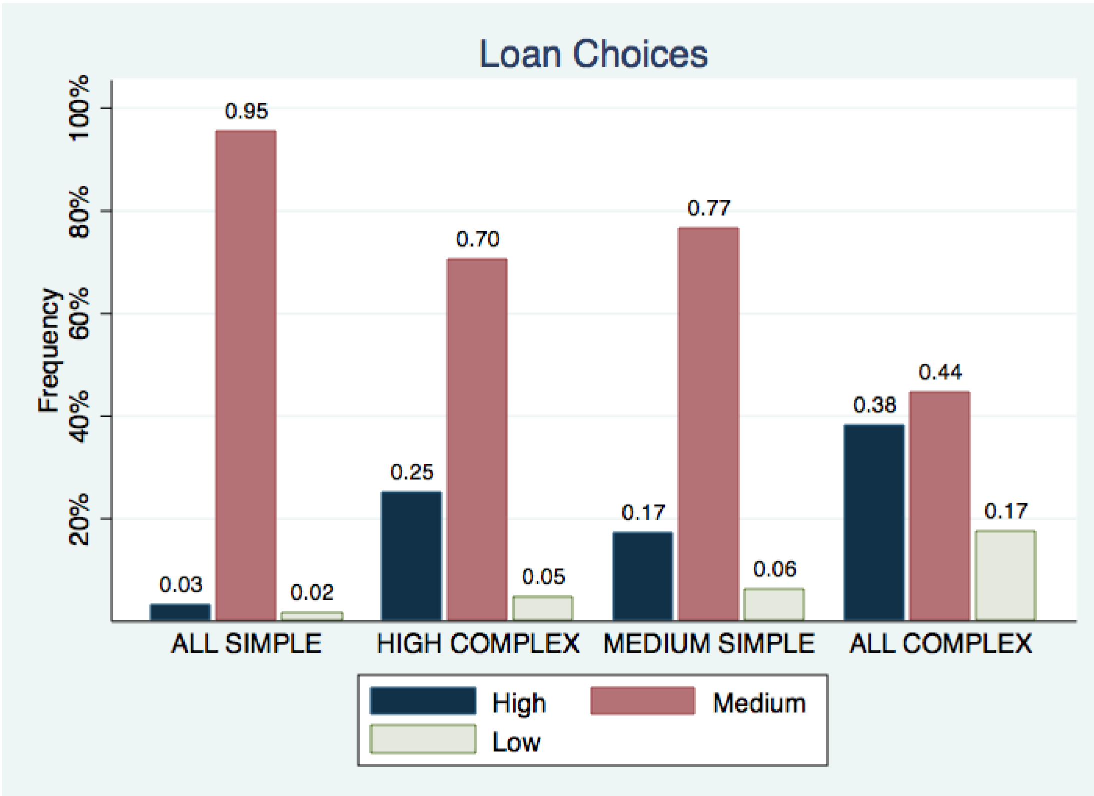
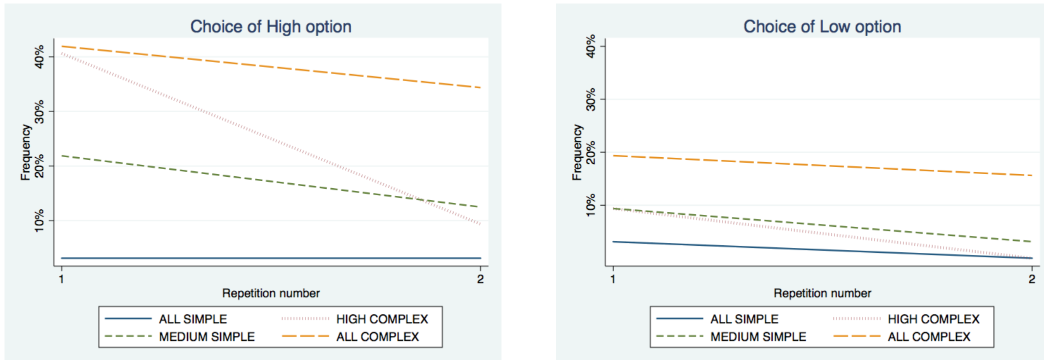


Figure 2.6: Loan choices over treatments

HIGH COMPLEX than in ALL SIMPLE (p-value<0.01). This result shows that the High option benefits from unilaterally making its repayment more complex.

According to Hypothesis 2b the Medium option will be chosen more often in MEDIUM SIMPLE than in ALL COMPLEX. Comparing the third block with the last block in Figure 2.6 shows that the Medium option is chosen 33% less in ALL COMPLEX than in MEDIUM SIMPLE (p-value<0.01). This result shows that the Medium option benefits from unilaterally making its repayment more simple[4].

[4]The argument that increasing the number of options with complex repayment leads to more narrow bracketing provides more testable implications than the two hypotheses that are being tested in this section. The fact that the choice frequency of the High option is higher in ALL COMPLEX than in HIGH COMPLEX and that it is higher in MEDIUM SIMPLE than it is in ALL SIMPLE is in line with this argument. However, the third block in Figure 6 shows that the High option is chosen at about 8% less in MEDIUM SIMPLE than in HIGH COMPLEX while the difference is not significant.(p-value= 0.17). This finding requires an alternative explanation than the ones provided in this paper. One possible explanation is that the complexity difference between MEDIUM SIMPLE and HIGH COMPLEX treatments is not



(a) (b)

Figure 2.7: High and Medium choice frequencies over time

Figure 2.7 displays the development of the choice frequencies of the High and the Low option over time. The choice frequency of both the High and the Low option are lower in the second repetition. However, treatment effects are qualitatively similar in both repetitions. The High option is chosen most frequently in ALL COMPLEX and least frequently in ALL SIMPLE in both repetitions. This shows that the influence of complexity on decision making is not eliminated by experience.

As in Study 1, results from Study 2 shows that complexity is costly for individuals in terms of both payoff and time. In HIGH COMPLEX subjects' on average earn 5% less than they earn in ALL SIMPLE. The lowest earnings are in ALL COMPLEX; subjects earn 15% less than they earn in ALL SIMPLE. As in Study 1, complexity not only leads to lower payoffs but also to higher decision times. Subjects spend 35.1 seconds more in choosing their loans in HIGH COMPLEX and 36.4 seconds more in MEDIUM SIMPLE than in ALL SIMPLE, while ALL COMPLEX requires the most amount of time.

very large. This is supported by the decision time data as subject spend a similar amount of time in these two treatments.

2.4 Conclusion

Conducting two studies I show that complexity of a decision task leads to suboptimal decision-making. Particularly, when all the options' payoff elements that are at a later stage are more complex individuals appear to bracket narrowly. In addition, an inferior option that is more attractive in the salient short run elements can be made more attractive by obfuscating its less attractive long run features. The results show that it is important to take into account the complexity of decision tasks in modeling economic behavior.

On a more practical level, the results in this paper suggest that there may be a case for consumer protection in complex markets, such as markets for credit and insurance. First of all since these markets are inherently complex and many small investors are financially illiterate they are more likely to bracket narrowly and focus on short-term gains rather than having a long-term outlook. Second of all, financial companies may not have the incentives to simplify the decision environment for investors since this enables them to sell back-loaded products at high profit margins. My results suggest that banks that have inferior loans are likely to make their loans attractive in the immediate terms while obfuscating the non-salient repayment elements by having commissions and multiple fees.

Although this paper is on individual decision-making, extensions to market behavior are crucial for evaluating the significance of the results. There is a growing literature in behavioral industrial organization that examines how markets might respond the bounded rationality of consumers (See Della Vigna, 2009 for a review). For example, Kalaycı and Potters (2011) show in a market experiment that sellers obfuscate the quality of their products and this leads to higher market prices. The results in this paper suggest that obfuscation is a best response for back-loaded credit products but dynamic strategies in the long run and equilibrium implications for prices and welfare require further research.

Appendix

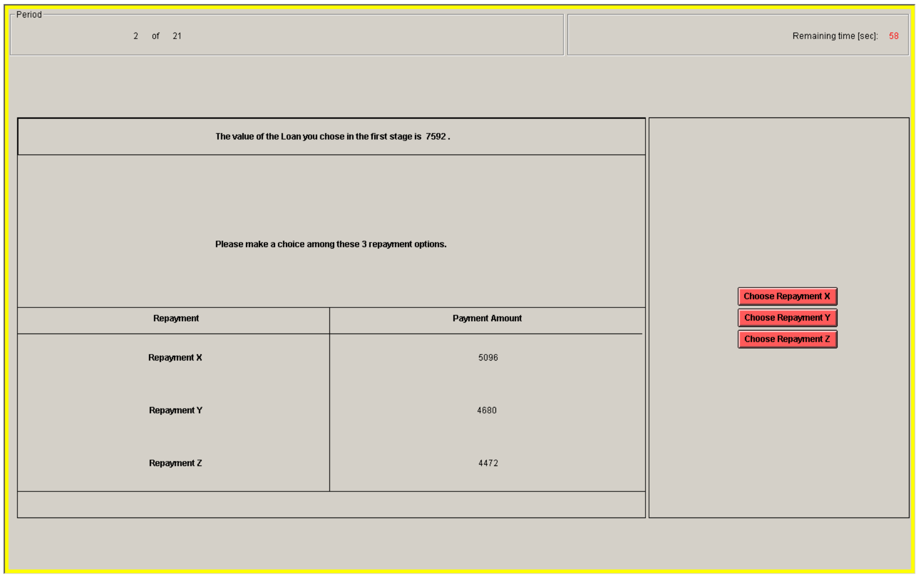


Figure 2.8: Example screen shot for repayment choice

Instructions

This session is part of an experiment in the economics of decision making. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money. At the end of the session your earnings will be paid to you in cash and in private. The amount you earn will depend on the decisions you make.

There are a number of people in this room who are participating in this session. It is important that you do not talk to any of the other people in the room until the session is over. Please TURN OFF your electronic devices such as phones and music players.

The session will consist of 24 periods, in each of which you can earn points. At the end of the experiment you will be paid an amount based on your total point earnings from all 24 periods. Points will be converted to cash using an exchange rate of 7000 points = 1 Euro. There will not be any show-up fee paid. Notice that the more points each individual earns, the more cash they will receive at the end of the session.

Each period in the experiment consists of two stages. In the first stage you make a choice among 3 Loans, each of which earns you the Value of the Loan. In the 2nd stage you get to choose between Repayment schedules for the Loan you have chosen in the 1st stage. Notice that the Repayment options for each Loan is different, therefore the options you have in the 2nd stage depends on your choice in the 1st stage. Your payoff for the period will be equal to the Value of the Loan minus the Repayment amount.

PAYOFF = VALUE of the Loan - REPAYMENT Amount

At the first stage of a period you will have a time limit of 120 seconds (2 minutes). The time limit for the 2nd stage will be 60 seconds (1 minute). Both of these time limits are strictly BINDING. If you do not make a choice in the time limit at any of the two stages in a period, you will get zero points for that period. However, even if you make a choice quicker than the allocated time limit for that stage you will have to wait until the time limit expires before you move to the next screen. You will see a waiting screen in the meantime.

When you have read the instructions carefully and are ready please click the

OK button. After everyone in the session clicks OK the experiment will start.

If you have any questions please raise your hand, the experimenter will come to answer your question.

Chapter 3

Buyer Confusion and Market Prices[1]

> "Buyers' ignorance and sales techniques catering to buyers' ignorance are perhaps an even more important source of oligopoly power [than economies of scale]." Tibor Scitovsky (1950)

3.1 Introduction

Some products seem so complex that it is difficult for consumers to make good choices. Mobile phones, for example, have over 30 attributes listed on comparison websites (date of introduction, color, dimensions, weight, camera megapixels, resolution, flash light, memory size, capacity, battery time, band type, WAP, bluethooth, USB, ringtones, video, organizer, etc.), and typically two selected phones differ on about half of the attributes. It is not trivial to rank some of the attributes (Is HSDPA better than UMTS?), and even if one has a strict preference on the attributes (HSDPA is better than UMTS), still one needs to make complex trade-offs (Do I want HSDPA or more megapixels; longer battery life or more capacity?) and decide whether these differences in the attributes make up for the price difference. Why are products so complex?

[1]This chapter is based on Kalaycı and Potters (2011).

The main reason for product complexity is product differentiation. Different people have different preferences so firms provide differentiated products. The more heterogeneous the consumers are, the more complex the products become. However, some 50 years ago already, Scitovsky (1950) proposed an additional reason. He suggested that buyer confusion may be an important source of market power. If buyers find it hard to assess and compare the value of different products this may reduce the price elasticity of demand. This, Scitovsky argued, may give sellers an incentive to emphasize the extent to which products differ and stress their technical, chemical or functional complexity. This raises some important questions. Does buyer confusion lead to higher prices? Do sellers have incentives to make it harder for buyers to compare products?

Although these questions have not received much attention in the literature there are some theoretical models suggesting that the answers are affirmative. Perloff and Salop (1985) show that price-cost margins are increasing in the degree of product differentiation, and that this holds irrespective of whether the differences between products are ”real” or ”spurious”. Gabaix and Laibson (2004) extend this analysis by showing that firms have incentives to make products inefficiently complex if this causes consumers to evaluate the utility of products with more noise. In similar vein, Spiegler (2006) shows that if goods have multiple dimensions and consumers cannot evaluate all of them firms will have incentives to make it hard from consumers to compare the value of the goods. Finally, Carlin (2009) presents a model in which firms choose excessively complex pricing structures in order to confuse consumers and increase mark-ups. The common intuition underlying these models is that buyer confusion reduces the price elasticity of demand which allows firms to increase prices.

In the present paper we use a laboratory experiment to address the questions raised above. A unique advantage of experiments in this respect is that it is possible to distinguish spurious from real product differentiation; something which is hardly possible in the field. Another advantage of the laboratory is that buyers' preferences can be induced so that it is possible to assess whether buyers make optimal or suboptimal decisions, and to examine how this is affected by the decisions of the sellers. What is not possible in the lab - nor in the field - is to precisely control or induce the cognitive limitations of the buyers and the rate at which this leads to confusion and decision errors. Theoretical models make very specific parametric assumptions here.[2] To implement such assumptions would only be possible by using simulated buyers. A key feature of our experiment, however, is that we use human subjects as buyers who are, at least potentially, prone to "real" cognitive limitations. We are interested to see whether sellers anticipate and exploit these cognitive limitations.

We set up a price setting duopoly experiment in which each seller offers a good to two identical buyers. The two goods differ in quality. The sellers first decide on the number of attributes of their goods and then set prices. The number of attributes can be costlessly varied by the sellers and does not affect the quality or utility of the good to buyers. Choosing a higher number of attributes, however, makes it more difficult for the buyers to assess the quality of the good. The experimental results indicate that buyers make more suboptimal choices when the number of attributes chosen by the sellers is higher. Most importantly, sellers' prices are increasing in the number of attributes. Moreover, prices and profits are higher than those in a benchmark treatment with perfectly rational (robot) buyers. These results provide strong support for Scitovsky's (1950) argument that buyer confusion leads to higher prices. Apparently, the intuition behind this argument is so strong that even inexperienced student subjects in their role of sellers adhere to it.

From several markets there is evidence that consumers are not always well informed about price and quality differences of products and do not always make optimal decisions. Hall (1997) reports that only 3% of desktop printer buyers claim that they know the costs of printing per page. A field experiment by Bertrand et al. (2010), finds that bank clients who responded to offers for a short-term loan, were not just responsive to the interest rate but also to "irrelevant" marketing features such as the inclusion of a woman's photo on the offer letter and the number of different loan types mentioned. Wilson and Waddams Price (2010) report that in the UK electricity market consumers who switch between suppliers appropriated only a quarter to a half of the maximum gains available while 20-

[2]For example, Gabaix and Laibson (2004) assume that consumers perceive the utility of each good with a random error which is drawn from the same distribution for all goods. Spiegler (2006) assumes that consumers evaluate multi-dimensional goods on the basis of a random selection of one dimension only.

30% of the consumers actually reduced their surplus as a result of switching. Frank and Newhouse (2008) conclude that the complexity of the Medicare Part D prescription drug support plan in the U.S. has caused many beneficiaries to choose suboptimal insurance schemes. There is also evidence that consumers are susceptible to exploitation by firms. For example, Chetty et al (2009) find that consumers under-react to taxes that are not salient, i.e. when the advertised price is not inclusive of taxes. Hossain and Morgan (2006) and Brown et al. (2010) show that buyers underestimate the shipping costs on eBay auctions. Choi et al. (2010) show that investors fail to minimize on mutual fund fees (for a recent review, see DellaVigna, 2009).

There is also substantial experimental evidence showing that making good decisions is difficult when the choice problem is complex. Decision makers often resort to relatively simple choice heuristics in those cases (Payne, Bettman, Johnson, 1993, Besedes et al., 2009). These studies, however, do not examine how buyers' cognitive limitations affect the marketing strategies and prices of sellers, which is the focus of the present paper. The experimental paper closest to our paper is Sitzia and Zizzo (2009). They conduct a posted-offer market experiment with a monopolist offering either simple or complex lotteries. They results show that the quantity demanded is higher for complex products, suggesting potential consumer exploitability. They find no evidence for the influence of complexity on prices. In the experiment of Sitzia and Zizzo (2009), however, there is no competition.

There are also other theoretical models of obfuscation not based on bounded rationality (e.g., Ellison and Wolitzky, 2009, Wilson, 2010). It may be possible to interpret the "search costs" in these models as the "decision making costs". However, we believe such an approach has certain problems. In search models fully rational buyers decide whether to search or not taking the benefits and costs of search into account. The counterpart of this in a bounded rationality framework would be that buyers decide whether to evaluate a certain product by taking into account the cost of making such evaluation. However, this would require the assumption that the boundedly rational buyers are fully rational in assessing whether to evaluate a good or not, which is somewhat problematic (see Wilson, 2010, for additional arguments).

The remainder of the paper is organized as follows. In the next section we present a simple model illustrating Scitovsky's (1950) intuition for the environment we use in our experiment. Our experiment uses vertically differentiated products which differs from the symmetric models mentioned above (Gabaix and Laibson, 2004, Spiegler 2006, Carlin, 2009). The main reason is that in the experiment we allow for learning by means of repetition and information feedback. This might be problematic in case products have the same quality. After some repetitions, the buyers might find out that it does not really matter what they buy since all goods essentially have the same quality. In Section 3 we outline the design of the experiment. Section 4 presents the results and, finally, Section 5 concludes.

3.2 The model

In this section we develop a duopoly model with vertically differentiated products and boundedly rational buyers with homogeneous preferences. The basic setup of our model follows the one-sided information version of Anderson and Renault (2009). Heterogeneity in consumer preferences with respect to products in their model is replaced in our model with heterogeneity in decision accuracy. The main difference is that we allow the sellers to influence the degree of buyer's decision errors by manipulating product complexity (much in line with Gabaix and Laibson, 2004).

The model consists of three decision stages. In the first stage the two sellers simultaneously decide on the complexity of their goods, conditional on the exogenous quality levels. In the second stage they simultaneously set their prices. Finally, the buyers make their purchasing decisions.

Using backward induction, we first determine the demand schedule of the buyers for given complexity, price and quality levels. Using this demand schedule we generate the expected profit functions of the sellers and solve for the optimal pricing strategies. Lastly, we find the equilibrium product complexity levels for each seller given the pricing strategies.

Demand and profit functions

The buyers have homogeneous preferences and purchase one unit of good from either Seller 1 or Seller 2, with corresponding utilities:

$$u_i = v_i - p_i, \quad i = 1, 2 \tag{1}$$

where v_i and p_i are the quality and the price of seller i, respectively. For simplicity we normalize the demand to unit demand and consider a representative buyer.

Define $Q = v_1 - v_2$ as the quality advantage and $\Delta = u_1 - u_2 = Q - p_1 + p_2$ as the net value advantage of Seller 1 over Seller 2. Without loss of generality we assume that Seller 1 sells the good with the higher quality, i.e. $Q \geq 0$.

The behavioral element in our model is the vulnerability of the buyer to making decision errors. We assume that the buyer perceives the difference between the utilities $u_1 - u_2$ only with some noise ε. This noise is a random variable with support $[-b, b]$, density function $f(x)$ and distribution $F(x)$, where b is the sellers' decision variable. For simplicity we assume that $F(x)$ is uniform continuous. Therefore, the buyer purchases from Seller 1 if $\Delta + \varepsilon > 0$, and from Seller 2 if $\Delta + \varepsilon < 0$ and is indifferent if $\Delta + \varepsilon = 0$. The symmetry of f implies $F(\Delta) = 1 - F(-\Delta)$. We consider a covered market, that is, the buyer is assumed to buy one unit. Permitting zero purchases adds unnecessary complications to the model, without qualitatively affecting the results.

Expected demand for Seller 1 is equal to the probability that the buyer purchases from Seller 1: $Prob = (\Delta + \epsilon > 0) = 1 - F(-\Delta) = F(\Delta)$. Similarly, expected demand for Seller 2 is equal to $Prob(\Delta + \epsilon < 0) = F(-\Delta)$. We assume that sellers have no costs. Hence, the expected profits of Seller 1 and Seller 2, respectively, are:

$$\begin{aligned} \pi_1(p_1, p_2) &= p_1 F(\Delta) \\ \pi_2(p_1, p_2) &= p_2 F(-\Delta) \end{aligned} \tag{2}$$

Equilibrium Prices

Sellers set prices to maximize profits, given the exogenous quality levels, v_1 and v_2, and the noise distribution characterized by b. This yields the following first order conditions for Seller 1 and Seller 2, respectively:

$$\begin{aligned} F(\Delta) - p_1 f(\Delta) &= 0 \\ F(-\Delta) + p_2 f(-\Delta) &= 0 \end{aligned} \tag{3}$$

The equilibrium prices and profits that follow from these first order conditions, taking into account non-negativity constraints, are summarized in the following proposition:

Proposition 1. If $b \leq \frac{Q}{3}$, equilibrium prices are $p_1^* = Q - b$ and $p_2^* = 0$, implying that Seller 1 gets the whole demand and makes profits $\pi_1^* = Q - b$ and Seller 2 makes zero profits $\pi_2^* = 0$. If $b > \frac{Q}{3}$, equilibrium prices are $p_1^* = \frac{Q}{3} + b$ and $p_2^* = -\frac{Q}{3} + b$. Both sellers make positive profits with $\pi_1^* = \frac{1}{2b}(b + \frac{Q}{3})^2$ and $\pi_2^* = \frac{1}{2b}(b - \frac{Q}{3})^2$.

Proof. See Appendix A. □

Note first that if $b = 0$ we get the standard (Bertrand) equilibrium prices, where Seller 1 charges a price equal to the quality difference Q. As long as the noise is small relative to the quality difference ($b \leq Q/3$), Seller 1 reduces her price with an increase in noise in order to ascertain that the boundedly rational buyer always buys from her.

The scenario is different when the noise can be large relative to the quality advantage. In this case capturing the whole market with certainty is no longer the most profitable strategy for Seller 1. She can enjoy higher profits when sharing the market with Seller 2 and cashing in on the positive effect of the noise on prices. In this case, also Seller 2 has positive expected demand since the maximum level of noise is larger than the utility difference, i.e. $b > \Delta = Q - (p_1^* - p_2^*) = \frac{Q}{3}$. Importantly, in this regime the prices of both sellers are increasing in the buyer's rate of confusion (characterized by b).

Equilibrium Complexity

An important aspect of our model is that the sellers can affect the noise experienced by the buyer when evaluating the sellers' offers. We assume that seller i chooses b_i, and that $b = b_1 + b_2$. Recall that buyer noise (ε) is a random variable following a uniform distribution with support $[-b, b]$. Together the sellers determine the support and hence the variance of the noise distribution (as in Gabaix and Laibson, 2004). There can be various interpretations for b_i such as the complexity of the price schedule (Carlin 2009), spurious product differentiation (Perloff and Salop 1985), or product complexity (Gabaix and Laibson, 2004). Our experimental implementation is closest to the latter interpretation.

Anticipating the equilibrium prices that arise in the second stage, sellers determine their product complexity $b_i \in [0, \bar{b}]$ where $b = b_1 + b_2$ in order to maximize their expected profits $\pi_i(p_1^*(b), p_2^*(b)) = \pi_i(p_1^*(b_1 + b_2), p_2^*(b_1 + b_2))$.

Proposition 2. Seller 2 chooses maximum complexity $b_2^* = \bar{b}$. Seller 1's choice of complexity depends on the value of Q relative to $\bar{b}$. If $\bar{b} \leq \frac{Q}{\mu}$, Seller 1 chooses $b_1^* = 0$; if $\bar{b} > \frac{Q}{\mu}$, Seller 1 chooses $b_1^* = \bar{b}$ (where $\mu = \frac{12}{2+\sqrt{2}} > 3$).

Proof. See Appendix A. □

Choosing maximum complexity is a (weakly) dominant strategy for Seller 2. Without buyer noise Seller 2 will have zero expected demand and whenever he has positive expected demand his profits are positively related to the noise variance (see the second regime in Proposition 1). The decision problem for Seller 1 is more intricate. If the maximum level of noise that Seller 2 can generate unilaterally is small relative to the quality difference ($\bar{b} < Q/\mu$), Seller 1 prefers not to add to the noise ($b_1^* = 0$). In this case the noise distribution ($b = b_1^* + b_2^* = \bar{b}$) ensures that the pricing stage of the game will be in the first regime of Proposition 1 (since $\bar{b} < Q/\mu < Q/3$) where Seller 1 captures the whole market. However, if the level of noise that Seller 2 can bestow on the buyer is sufficiently large ($b_2^* = \bar{b} > Q/\mu$), it is in Seller 1's interest to choose the maximum level of noise as well ($b_1^* = \bar{b}$). In this case the noise distribution ($b = b_1^* + b_2^* = 2\bar{b}$) ensures that the pricing stage of the game will be in the second regime of Proposition 1 (since

$2\bar{b} > 2Q/\mu > Q/3$) where both sellers' prices (and profits) are increasing in the noise variance (characterized by b).

Hypotheses

Summarizing, the model suggests that when the goods are vertically differentiated, not only the low quality seller, but also the high quality seller may have an incentive to increase buyer confusion and raise price in response. This will be the case in particular if the level of noise the low quality seller can generate is sufficient to prevent the high quality seller from capturing the whole market. If, however, the maximum level of noise the low quality seller can create is low relative to the quality difference then the high quality seller will have a weaker incentive to obfuscate than the low quality seller. What is a relatively low or high level of noise depends on the rate at which buyers make suboptimal decisions. Since in the experiment we use human buyers who, at least potentially, make errors due to cognitive limitations, this is something we cannot control precisely. Therefore, our experiment should not be seen as a strict test of the model's predictions in the sense that we implement all the parametric assumptions of the model. Still the model provides a theoretical foundation and guide for the empirical relationships we will examine.

3.3 Experiment

The main challenge for the experimental design is to allow for buyer mistakes, where the rate of mistakes can be influenced by the sellers. We do this by providing the buyers with a decision problem which is relatively straightforward in itself (comparing two values of the form $\sum_{i=1}^{n} i * q_i - p$) but which may be difficult given the time limit we impose. Importantly, the sellers can affect the difficulty of the buyers' decision problem (by choosing the number of elements n in the summation).

Design

In the experiment, markets consist of two sellers and two buyers. The time-line of the experiment is the same as in the model above. The sellers learn the qualities of both goods. They simultaneously decide on the number of attributes of their good. The number of attributes does not affect the quality of the goods, but may make it more difficult for the buyer to evaluate the goods. Upon learning the number of attributes of the other seller, each seller simultaneously decides on the price of her good. Finally, each buyer decides whether to buy from Seller 1 or from Seller 2, given the price and (possibly) noisy quality information about the goods.

We explain the details of the experiment starting with the buyer's choice. The buyer can choose to buy one of the goods, or to refrain from buying. Each buyer has the following payoff function for the good she chooses:

$$Payoff = 5 * q_5 + 4 * q_4 + 3 * q_3 + 2 * q_2 + 1 * q_1 - p$$

where q_i is the quality level of the i'th attribute and p is the price of the good that is chosen. The information was presented to the buyer on screen as follows:

Product/Weight	5	4	3	2	1	Price
Good A	0	4	4	11	36	50
Good B	0	0	0	0	73	45

In this example, if the buyer chooses good A she earns a payoff equal to: $5 * 0 + 4 * 4 + 3 * 4 + 2 * 11 + 1 * 36 - 50 = 16 + 12 + 22 + 36 - 50 = 36$, whereas if she chooses good B she earns a payoff equal to $73 - 45 = 28$. The buyer has 15 seconds to make this choice and this time limit is binding. If the buyer does not make a choice within the time limit, she does not buy a good and earns a payoff of 0. Note that assessing the payoff of good A in this example is more difficult than assessing the payoff of good B. In particular, calculating the payoff is rather trivial if a good has only one attribute; it simply is the difference between the final two columns. The calculation becomes considerably more difficult when the number of attributes increases. As we will explain below, this level of difficulty is a decision variable of the respective sellers.

All the details of the buyer's decision problem are public information. In contrast, the buyers do not know all the details of the sellers' decision problem. They are informed that a seller makes decisions regarding the price and the attributes, and that a seller's payoff depends on the price of and the demand for her good, but buyers are not given information on the determination of the quality levels or the seller's incentives regarding the attributes.

The sellers first decide simultaneously on the number of attributes of their respective goods, given the quality levels of the two goods. The quality of each good is a value randomly, but not uniformly, drawn from the interval [60, 100] at the beginning of each period, where numbers close to 80 are more likely to be drawn. Buyers are not informed how the qualities are determined, only that the sellers make decisions regarding the attributes. The quality draws are i.i.d. across periods. Depending on the number of attributes that a seller chooses, the exogenous quality of the good is randomly allocated over the attributes such that the following is satisfied:

$$5 * q_5 + 4 * q_4 + 3 * q_3 + 2 * q_2 + 1 * q_1 = Quality$$

If the number of attributes chosen is 1 then $q_1 = Quality$ and $q_2 = q_3 = q_4 = q_5 = 0$. If the number of attributes chosen is 2 then the quality is randomly allocated over q_1 and q_2, such that $2 * q_2 + 1 * q_1 = Quality$ and $q_3 = q_4 = q_5 = 0$. And so on when the number of attributes chosen is 3, 4 or 5. In all cases, the algorithm makes sure that the quality levels of all attributes are integers. In one page of the instructions which was exclusively for the sellers, this procedure was explained to them. Moreover, it contained the following text: "Notice that the number of attributes you choose will not affect the payoff of the buyers since the Quality of your good is unaffected by it. However, the calculation of payoffs may get harder or easier depending on the number of attributes of your good."

After choosing the number of attributes the sellers decide on the price of their good given the quality and the number of attributes of each good. The sellers have zero cost and profits are equal to the price of a good times the number of sales (0, 1 or 2). Note that the number of attributes has no direct impact on sellers' profits.

Procedure

The experimental sessions were run in CentERLab of Tilburg University. The experiment was programmed and conducted with the software zTree (Fischbacher 2007). There were two treatments: one with markets consisting of 2 human buyers and 2 human sellers (main treatment), and one with 2 robot buyers and 2 human sellers (robot buyer treatment). Each treatment consisted of 2 sessions with 2 independent matching groups, where in each matching group there were 2 markets. In the main treatment the subjects were randomly assigned to the role of buyer or seller at the start of the experiment while in the robot buyer treatment all subjects were assigned to be sellers. The roles remained fixed throughout the experiment. In the robot buyer treatment sellers were informed that buyers' choices were made by the computer and that the buyers would always purchase from the seller with the highest difference between price and quality. Sellers had to choose the number of attributes in the robot buyer treatment just like in the main treatment. They were told that the number of attributes would not affect the computerized buyers' decisions. Markets were run for 30 periods and subjects knew this. Subjects remained in the same matching group throughout the 30 periods, but were randomly reassigned to one of the two markets in a matching group after each period. Subjects were told that all periods are identical except that the participants in a market will be changing from period to period. At the end of each period the participants got a feedback screen, which was different for the buyers and the sellers. The buyers could see the prices of the goods, their own choice and their own payoff. From this information they could deduce the quality of the good they bought, but this was not given explicitly. The sellers could see the price, quality, number of attributes, sales and profits of both sellers in their market. Both the buyers and the sellers also had a history table where they could observe the same feedback information from previous periods. Sellers' or buyers' identities from previous periods were not revealed. In total 48 student subjects participated in the experiment. They were recruited through e-mail lists of students interested in participating in experiments. Each session lasted about 75 minutes and average earnings were 13 Euros.

At the beginning of the experiment, the participants found their instructions on their tables. The experimenter read the instructions out loud, except for the details of the seller's task. The participants were then given some time to reread the instructions on their own pace. A short quiz was conducted to make sure that everyone understood the instructions. At the end of the experiment, subjects' accumulated earnings were privately paid in cash.

3.4 Results

In this section we present the results from the experiment. Unless otherwise indicated the statistics and tests are from the main treatment (with human buyers) and based on data from periods 6 until 30. In presenting the results we will refer to the theoretical model to guide the analysis. But, as noted above, the results should not be seen as a strict test of this model since experiment does not aim to implement all the parametric (behavioral) assumptions of the model.

Buyer confusion

One of the main goals of our experimental design was to create an environment in which buyers can potentially be induced to make decision errors. This is also an important element of the theoretical model, which assumes that buyer's evaluation of the goods is noisy and that this noise can lead to suboptimal decisions (mistakes). For the analysis we define a mistake as an instance in which a buyer purchases the good with the lower payoff (quality - price) or refrains from buying when a good with a positive payoff is available.[3] Moreover, we interpret the number of attributes of the goods as a source of noise.

Result 1. Buyers make a substantial amount of mistakes and the rate of mistakes is significantly higher when at least one seller chooses the number of attributes to be larger than 1.

Figure 3.1 displays how the fraction of buyers that make a mistake develops over the periods of the experiment. On average the buyers make a suboptimal choice in about 30% of the cases. Moreover, after the initial five periods there is only a weak sign of learning. The average payoff foregone due to these errors corresponds to about 6% of the optimal payoff.

[3]It would also be a mistake to buy a good with a negative payoff, but this never happened.

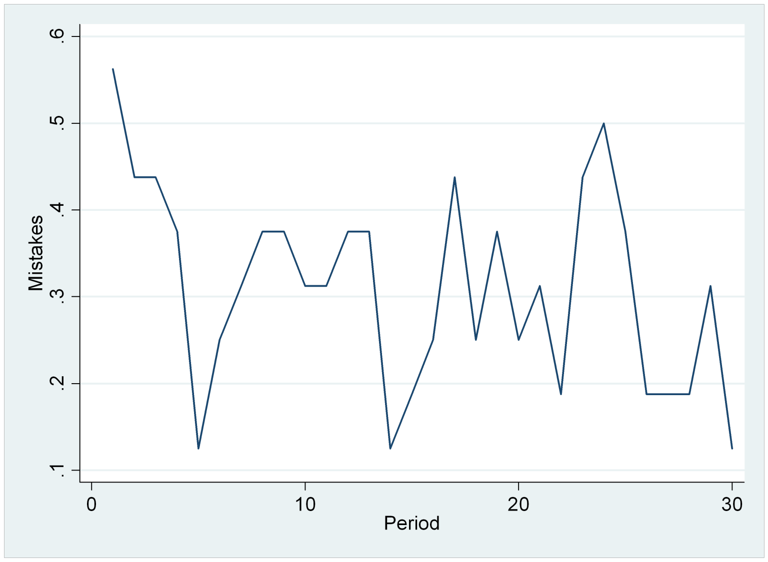
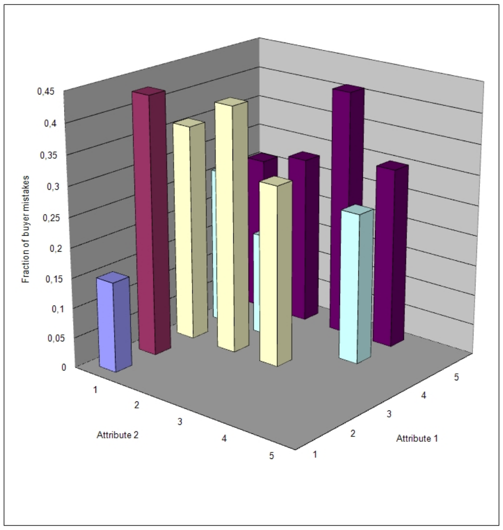
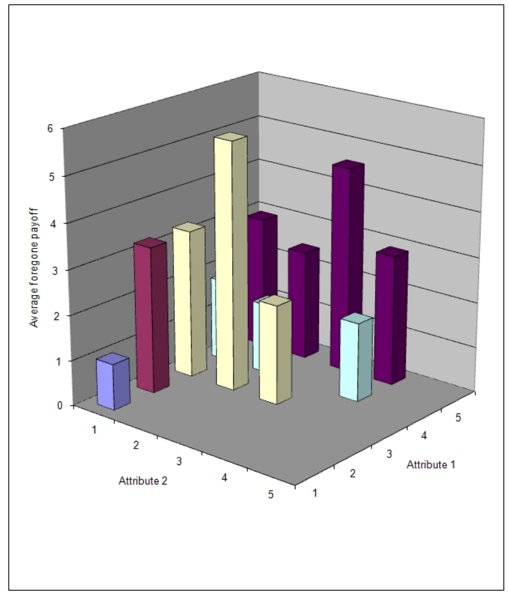


Figure 3.1: Fraction of buyer mistakes

Recall that the theoretical model assumes that the sellers' choices of complexity affect the buyers' propensity to make suboptimal choices. In the experiment, the numbers of attributes is hypothesized to affect the difficulty of calculating the payoff of a good. Buyers are expected to make more mistakes when the number of attributes of the goods is higher. Figure 3.2a relates the fraction of buyer mistakes to the number of attributes of the two goods, where the vertical axis displays the fraction of buyer mistakes and the horizontal axes represents the different combinations of the numbers of attributes chosen by the two sellers, respectively. It can be seen that the rate of buyer mistakes is lower when both sellers choose the number of attributes to be equal to 1. The relationship between the number of attributes of the two goods and the buyer errors is not monotonically increasing and is more like a step-function. The rate of mistakes increases as soon as the average number of attributes is larger than 1 but it doesn't increase further. A similar pattern can be observed in Figure 3.2b which shows the average payoffs that the buyers forego by making mistakes.



(a) Buyer mistakes by number of attributes



(b) Foregone payoff by number of attributes

Figure 3.2: Buyer mistakes and foregone payoff

note: The vertical axis in Figure 3.2a displays the proportion of times buyers purchased from the seller with lower payoff (price-quality). The vertical axis in Figure 3.2b gives the average foregone payoff of buyers. Horizontal axes give the attributes chosen by the sellers, with Attribute 1 and Attribute 2 being the highest and the lowest, respectively. Combinations of numbers of attributes that occur less than 10 times are omitted.

A logit regression with a binary variable indicating whether a buyer made a mistake or not as the dependent variable supports this conclusion (see Table 3.1). Column 1 indicates that the variable *Average number of attributes* has a positive but an insignificant effect on the probability that the buyer makes a mistake. The second column shows that the dummy variable *Obfuscated* indicating whether (1) or not (0) at least one seller chooses a number of attributes larger than 1, has a significantly positive coefficient. The marginal effect indicates that being obfuscated increases the probability of making a mistake by 35.1%. Moreover, the regression results indicate that buyers are less likely to make errors the larger is the payoff difference between the two goods, which is in line with the theoretical model. In the third column we add the variable *Attribute difference,* which is the difference between the number of attributes of the seller with the good that offers a higher payoff and the seller that offers the lower payoff. This variable has a positive coefficient, indicating that the buyer is less likely to buy the better good if this is relatively more complex. Though significant, the marginal effect of this variable is rather small. If the better seller chooses one more attribute the probability of making a mistake increases by 3.2%

Table 3.1: Buyer mistakes

	Model 1	Model 2	Model 3
Period	$-.014$ (.011) [.003]	$-.005$ (.016) [.001]	$-.010$ (.014) [.002]
Net payoff difference	$-.052$ (.029)* [$-.012$]	$-.056$ (.026)** [$-.012$]	$-.052$ (.023)** [$-.012$]
Average number of attributes	.078 (.141) [.018]		
Obfuscated		1.47 (.207)** [.351]	1.47 (.236)** [.351]
Attribute difference			0.140 (.073)* [.032]
# observations	386	386	386

notes: Logit model with subject fixed effects and standard errors clustered at the independent group level. The independent variable is *Buyer mistake* and takes the value 1 (0) if a buyer purchased from the seller with the lower payoff (quality-price) or refrained from buying; *Net payoff difference* is the payoff difference (quality-price) between the two sellers; *Obfuscated* takes the value 1 (0) if at least one of the sellers chose more than one attribute; *Attribute difference* is the difference between the number of attributes of the seller offering the higher payoff and the seller offering the lower payoff. * indicates statistical significance at %10, ** indicates statistical significance at %5; standard errors in parentheses; marginal effects in brackets. *Period*>5; observations with *Net payoff difference* equal to 0 are omitted.

Sellers' choice of the number of attributes

In the experiment the sellers have to choose the number of attributes for their goods, which according to Result 1 is positively affecting the buyers' propensity to make errors. Figure 3.3 displays the time pattern for the average number of attributes chosen by sellers over the periods of the experiment. The mean for the average number of attributes is 2.6 (with a standard deviation of 1.05), and there is a slight downward trend over time.

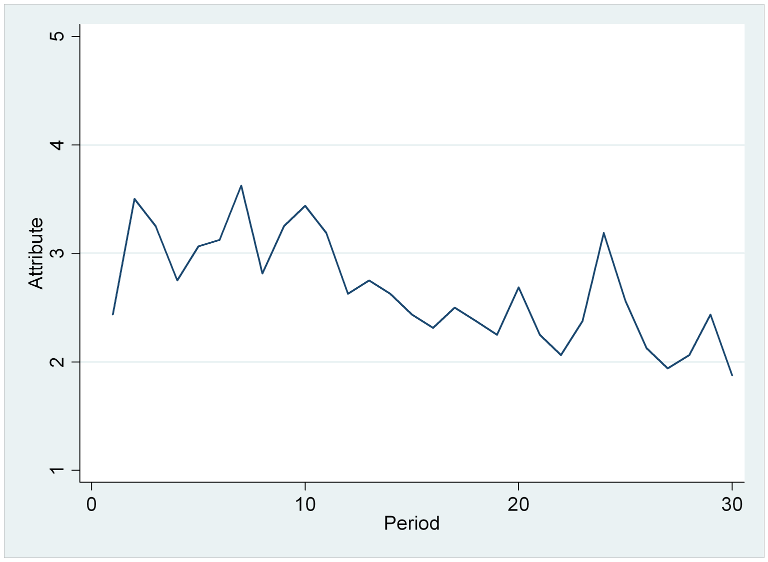


Figure 3.3: Average number of attributes over periods

Allowing for asymmetries in sellers' quality enables us to examine possibly different behavior for high and low quality sellers. The theoretical model suggests that the low and high quality seller will have the same incentives to obfuscate the buyers if the rate of noise that can be generated is so large that it is impossible for the high quality seller to secure the whole demand. If the latter condition holds, we are in the second regime with respect to Proposition 2. Experimental Result 1 indicates that if one seller chooses to obfuscate (i.e., choose a number of attributes larger than 1) this has a significant impact on the buyers' probability to make a mistake and choose the good with the lower payoff. It turns out that this holds even when the payoff (quality-price) difference between the two goods is relatively large. For example, if we restrict the regression of Table 1 to include only the cases in which the payoff differences is among the highest quartile (25%) of the distribution, then still the variable *Obfuscated* has a significantly positive coefficient. So, even when the payoff difference between the goods is large, the buyer is still affected by the noise generated by the sellers' choice of attributes.[4] This suggest that in terms of the theoretical model we are predominantly in the

[4] The same conclusion holds if we focus on the quality difference rather than payoff difference.

second regime of Proposition 2 in which both sellers have an incentive to obfuscate. This is partially supported by our second result.

Result 2. The high quality seller obfuscates somewhat less than the low quality seller, but this is not related to the size of the quality difference.

Table 3.2: Obfuscation

	Obfuscate		Number of attributes	
	Model 1	Model 2	Model 1	Model 2
Period	$-.102$ (.030)** [$-.001$]	$-.102$ (.033)** [$-.010$]	$-.038$ (.014)** [$-.014$]	$-.039$ (.015)** [$-.014$]
High quality seller	$-.618$ (.333)* [$-.059$]	$-.221$ (.582) [$-.022$]	$-.324$ (.182)* [$-.119$]	$-.070$ (.174) [$-.026$]
Quality difference		.005 (.030) [.001]		.014 (.014) [.005]
High q. seller * Q. diff.		$-.034$ (.064) [$-.003$]		$-.022$ (.026) [$-.008$]
# of Observations	375	375	400	400

notes: First two regression are logit models with subject fixed effects; last two regressions are ordered probits. Standard errors are clustered at the independent group level. *Obfuscate* is equal to 0 (1) when a seller chooses the number of attributes equal to 1 (larger than 1), one seller who always chose *Obfuscate* = 1 is dropped from the first two regressions; *High quality seller* is equal to 1 (0) when the seller's quality is strictly larger (smaller) than the other seller; *Quality difference* is the absolute value of the quality difference between the two sellers. Standard errors are clustered at the independent group level. * indicates statistical significance at %10, ** indicates statistical significance at %5. standard errors in parentheses; marginal effects, in brackets, relate to the probability that *Obfuscate* is 1 and the *Number of attributes* >2, respectively. *Period*>5.

The first two columns of Table 3.2 display a logit regression with the seller's choice of the number of attributes being larger than 1 (*Obfuscate*) as the dependent variable. In the first column, the explanatory variables are the period number and a dummy for being the high quality seller in that period. The variable *High quality seller* has a negative coefficient which is statistically significant at 10% level. This suggests that high quality seller is less likely to obfuscate than the low quality seller. The marginal effect indicates that being the high quality seller reduces the probability to obfuscate by 5.9%, which is not a big effect given that the overall rate of obfuscation is 65%. The regression in the second column adds the variable *Quality difference*, which is the absolute value of the quality difference between the two sellers, as well as an interaction term between *High quality seller* and

Quality difference. In this regression the coefficient for the interaction term *(High q. seller * Large q. diff.)* has a negative sign, but it is not statistically significant. The last two columns displays the results of ordered probit regressions with the *Number of attributes*, as the dependent variable. The results are qualitatively similar to the first two regressions. Being the high quality seller has a negative effect on the number of attributes of a seller, while this effect is not related to the quality difference between the sellers.

The results presented in this section show that the sellers often choose the number of attributes to be larger than 1, thereby making it more difficult for the buyers to assess and compare the quality and payoffs of the goods. We observe that the high quality seller uses a somewhat lower rate of obfuscation than the low quality seller.

Sellers' Prices

In this section we examine whether prices respond to the number of attributes chosen, which we believe is the most interesting question. After all, the issue is not so much how buyers actually are affected by the number of attributes, but whether and how sellers take them into account when setting their prices.

Result 3. Sellers' price offers and transaction prices increase with the average number of attributes of the goods offered in that market.

Table 3.3 presents the results from regressions of the sellers' price on the quality and the number of attributes in the market. In the first two columns the dependent variable is the posted price while in the last two columns the dependent variable is the transaction price. Transaction price is the posted price of a seller if she made at least one sale in that period. First note that in all four regressions, and in line with the theoretical model, the variable *Own quality* has a positive and statistically significant effect on price, whereas the quality level of the other seller (*Other's quality*) has a significant negative effect. Also, in all regressions in Table 3.3 we observe a negative time trend in prices which is often observed in posted offer market experiments with random matching (Bruttel, 2009).[5]

[5] It may be argued that including the period control in the regressions in Table 3 prevents

Table 3.3: Sellers' prices

	Price offer		Transaction price	
	Model 1	Model 2	Model 1	Model 2
Constant	25.9 (8.02)**	26.2 (8.56)**	19.8 (8.00)**	18.5 (8.08)**
Period	-0.87 (.30)*	-0.89 (.34)*	-0.80 (.23)**	-0.81 (.26)*
Own quality	0.36 (.07)**	0.36 (.07)**	0.42 (.06)**	0.42 (.05)**
Other's quality	-0.11 (.03)**	-0.11 (.02)**	-0.12 (.05)*	-0.12 (.05)*
Average number of attributes	1.88 (.43)**		1.62 (.60)*	
Obfuscated		5.78 (4.70)		6.60 (3.01)
# Observations	399	399	283	283

notes: Linear instrumental variables regression with subject fixed effects; standard errors clustered at the independent group level. *Average number of attributes* is instrumented by the number of attributes chosen of the other seller; *Obfuscated* takes the value 1 if at least one of the sellers chose a number of attributes >1 and 0 if both sellers chose attribute =1; *Obfuscated* is instrumented by obfuscation decision (0-1) by the other seller; * indicates statistical significance at %10, ** indicates statistical significance at 5%. Standard errors in parentheses. *Period*>5; one outlier *Price offer* of 120 excluded.

To examine the impact of the attributes on prices we use two alternative specifications. One employs the *Average number of attributes* across the two sellers; the other employs a dummy variable *Obfuscated* which is a dummy variable taking the value of 1 when at least one of the two sellers chooses the number of attributes to be larger than 1.[6] This is motivated by the result from Section 4.1, which shows that the rate of buyer mistakes is mainly affected by this variable. As can be seen from the regressions in column 1 and 3, *Average number of attributes* has a significantly positive impact on the price set by a seller as well as on the transaction price. Albeit positive, the coefficient for the variable *Obfuscated* is not statistically significant in either regression.

us from examining the effects of the other variables when subjects get more experienced. To check for this we have re-estimated the models in Table 3 omitting the period control. It turns out that the estimated coefficients do hardly change. We have also estimated all models using only the last half of the periods. Again results do not change; although for some coefficients significance levels are affected.

[6] As a referee pointed out, there may be an endogeneity problem here, in particular if a seller decides about attributes and price simultaneously. Therefore, we use the number of attributes of the other seller as an instrument for the *Average number of attributes* and the 0-1 obfuscation decision of the other seller as an instrument for *Obfuscated*.

Proposition 1 indicates that in case the quality difference between the two sellers is large relative to the noise ($b < Q/3$), the price of the high quality seller (Seller 1) is decreasing in the level of noise ($p_1^* = Q - b$), whereas the price of the low quality seller (Seller 2) is unaffected by the level of noise ($p_2^* = 0$). If this regime is relevant in some periods of the experiment, the effect of the level of noise on prices may be smaller for the high quality seller than for the low quality seller, and this should then in particular be the case in periods in which the quality difference (Q) is large. We find little evidence for this in the data, however. In Table 3.4 we add an interaction effect between the number of attributes and being the high quality seller to Model 1 of Table 3.3 . This interaction effect is negative but statistically insignificant. Also if we allow the interaction effect to vary with the quality difference between the two sellers the coefficient is negative and insignificant. This suggests that the second regime ($b \geq Q/3$) in Proposition 1, in which both sellers' prices are affected by the number of attributes in the same way, is the most relevant one.

Table 3.4: Sellers' prices

	Price offer	Price offer
Constant	25.7 (8.12)**	26.7 (8.31)**
Period	-0.86 (0.30)*	-0.87 (0.29)*
Own quality	0.39 (0.07)**	0.31 (0.10)**
Other's quality	-0.14 (0.04)**	-0.06 (0.02)*
Average number of attributes	2.01 (0.56)**	1.59 (0.56)*
High quality seller × Av.# attr.	-0.44 (0.27)	
High quality seller × Av.# attr. × Quality difference		0.04 (0.02)
# Observations	399	399

notes: Linear instrumental variables regression with subject fixed effects, standard errors clustered at the independent group level. *Average number of attributes* is instrumented by the number of attributes chosen of the other seller; *High quality seller* takes the value 1 (0) when the seller has a strictly larger (weakly smaller) quality than the other seller; *Quality Difference* is the absolute value of the quality difference between the two sellers. * indicates statistical significance at 10%, ** indicates statistical significance at 5%. Standard errors in parentheses. *Period*>5; one outlier *Price offer* of 120 excluded.

Sellers' Prices by Buyer Type

The results presented so far show that sellers' prices are positively affected by the number of attributes. The interpretation guided by the model is that prices increase when buyers are more confused, and that sellers use the number of attributes to encourage this confusion. However, two alternative interpretations cannot be ruled out. It could be that choosing a higher number of attributes distracted the sellers from choosing the right price, or that sellers used the number of attributes as a collusive device to coordinate on higher prices. To rule out these alternative explanations we ran a control treatment with the same design but one major difference. Instead of letting human buyers make purchases we let the computer purchase the goods from the seller that gives the highest payoff (quality minus price), irrespective of the number of attributes. In this treatment with robot buyers, sellers might still be distracted by the number of attributes or use it as a collusive device, just as in the treatment with human buyers, but we can rule out that prices are affected by buyer confusion. Therefore, this treatment allows for a clean comparison of prices in markets with boundedly rational buyers and prices in markets with perfectly rational buyers.

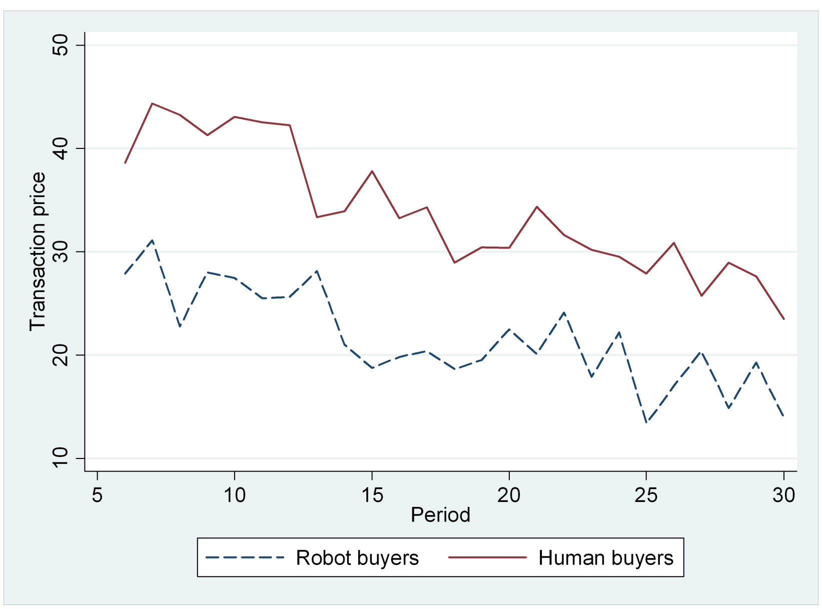


Figure 3.4: Average transaction price by buyer type

Result 4. Transaction prices are significantly higher with human buyers than with robot buyers. Moreover, in the treatment with robot buyers, prices are not affected by the number of attributes.

Figure 3.4 displays the development of average transaction prices over time for the treatments with human and robot buyers. Throughout the experiment average transaction prices are higher when the buyers are human subjects who occasionally make decision errors than when buyers are simulated by the computer to choose the optimal good. On average the sellers that interact with human buyers earn 12 points more in each period (3.69 euros throughout the experiment) than the sellers that interact with the robot buyers. The difference is statistically significant with a Mann-Whitney U test using the by-group means of the 8 independent matching groups as observations (p = 0.02).

Table 3.5: Sellers' prices and buyer type

	Price offer	Transaction price
Constant	20.1 (10.1)*	17.5 (7.45)*
Period	-0.66 (.16)**	-0.66 (.15)**
Own quality	0.35 (.05)**	0.45 (.05)**
Other's quality	-0.13 (.05)**	-0.25 (.05)**
Average number of attributes	-0.32 (1.21)	-0.36 (.92)
Human buyers	-0.16 (6.03)	1.52 (5.88)
Average number of attributes x Human buyers	4.01 (1.47)**	4.42 (1.57)**
# Observations	797	491

note: Linear instrumental variables regression, standard errors clustered at the independent group level; *Average number of attributes* is instrumented by the number of attributes chosen of the other seller; *Human buyers* takes the value 1 (0) for the treatment with human buyers (computerized buyers); * indicates statistical significance at 10%, ** indicates statistical significance at 5%. Standard errors in parentheses. *Period*>5; three outlier *Price offers* >120 excluded.

In the main experiment with human buyers we observe a positive impact of the average number of attributes on transaction prices (Result 3). To rule out that this impact is due to other reasons than buyer confusion, we examine whether the average number of attributes affects prices differently in the human treatment than in the robot treatment. We pool the data of the two treatments and run the same regression as we did in Table 3.3 but adding a treatment dummy for human buyers as well as an interaction between this treatment dummy and the average number of attributes. The results are presented in Table 3.5 for both price offers and for transaction prices. It turns out that *Human buyers* and *Average number of attributes* are not significant, but that the interaction between the two is. This indicates that the average number of attributes affects prices in the human treatment but not in the robot treatment[7]. Moreover, the fact that the treatment dummy for human buyers by itself is not significant whereas the interaction with the average number of attributes is significant suggests that prices are higher in this treatment because of buyer confusion and not because of some other reason.

3.5 Conclusion

In this paper we report experimental support for Scitovsky's (1950) argument that buyer confusion can be a source of market power. We find that sellers often make it overly complex for buyers to assess the quality of their goods. Doing so not only leads to more buyer mistakes but also induces the sellers to increase their prices. The comparison of the treatment with human buyers and the treatment with perfectly rational (robot) buyers reiterates these results; average prices are significantly higher when the buyers are human subjects who are prone to errors.

The behavioral and experimental economics literature has documented ample evidence that people are prone to make mistakes due to cognitive limitations. The present paper examines experimentally whether these limitations have an impact on marketing and pricing strategies. Theoretically one can show that sellers may have incentives to take advantage of the cognitive limitations of buyers by increasing the noise in buyers' evaluations and increase prices. That inexperienced

[7]The standard model with rational buyers would predict that the low quality seller should set price equal to marginal cost (which is zero) and the high quality seller should set price equal to the quality difference. We find that the prices of both the low and the high quality seller are much higher on average than these predictions, even in the final periods. This is reminiscent of experiments on Bertrand duopolies which find that prices do not converge to marginal costs (e.g., Dufwenberg Gneezy, 2000; Bruttel 2009). A prediction that finds considerable support though is that the price difference between the two sellers is equal to the quality difference.

experimental subjects in the role of sellers act on these incentives is quite remarkable we would argue. This also suggests that it is not heroic to assume that firms in "real" markets, given their experience and marketing knowledge, will act upon these incentives as well.

The findings in this paper suggest that bounded rationality of buyers can be costly for them in at least two levels. First, at the individual level by choosing inferior goods the buyer forgoes the benefits of the good with higher value. Second, at the market level by making occasional errors the buyers give incentives to sellers to charge higher prices. The first cost may be worth bearing for an individual buyer if the cost of decision making is higher than the foregone benefits. In the experiment the average foregone value by buyers is only about 6% of the value of the best available good, which may seem not to be high. However, this (possibly) individually rational ignorance is costly for the buyers as a whole since buyer errors lead to higher prices. Therefore, each buyer's ignorance poses an externality to other buyers.

Although in this paper we focus on complexity or noise regarding the quality aspect of a good the theoretical framework can also be applied to price complexity (Carlin, 2009). An interesting option for future research would be to examine the effects of price complexity on market power, for example by examining the use of hidden fees, surcharges or complicated multi-part tariffs on the market power of sellers.

Appendix

Proofs

Proof of Proposition 1

The proof follows the one sided information case of Anderson and Renault (2008). For $\Delta \in [-b, b]$ the expected demand for Seller 1 is $F(\Delta) = \dfrac{b+\Delta}{2b}$ where $\Delta = Q - p_1 + p_2$. Substituting into the first order conditions gives:

$$p_1 = \frac{1}{2}(p_2 + Q + b) \quad \text{and} \quad p_2 = \frac{1}{2}(p_1 - Q + b) \tag{4}$$

Solving for the equilibrium gives :

$$p_1^* = \frac{Q}{3} + b \quad \text{and} \quad p_2^* = b - \frac{Q}{3} \tag{5}$$

The non-negativity condition for Seller 2's price requires $b - \dfrac{Q}{3} > 0$, that is, $b > \dfrac{Q}{3}$. The equilibrium profit levels can be found by substituting (5) into the expected profits given by (2).

For $b \leq \dfrac{Q}{3}$, we have $p_2^* = 0$. Given Seller 2's price, the Seller 1 will charge the highest price that while allow her to retain the whole market, that is, $F(\Delta) = 1$. This requires $\Delta = b$ that is a price of $p_1^* = Q - b$. In this case, Seller 1's profit equals her price, $\pi_1^* = p_1^* = Q - b$ while Seller 2 makes zero profits. $\square$

Proof of Proposition 2

It follows from Proposition 1 that Seller 2 has a weakly dominant strategy to choose $b_2 = \bar{b}$ since for $b > \dfrac{Q}{3}$, we have $\dfrac{\partial \pi_2}{\partial b} = \dfrac{1}{18b^2}(9b^2 - Q^2) > 0$ while for $b \leq \dfrac{Q}{3}$ we have $\dfrac{\partial \pi_2}{\partial b} = 0$. Following this, and $b = b_1 + b_2$, gives $b_2^* = \bar{b}$.

For Seller 1, if $b > \dfrac{Q}{3}$ we have $\dfrac{\partial \pi_1}{\partial b} > 0$ whereas $b \leq \dfrac{Q}{3}$ implies $\dfrac{\partial \pi_1}{\partial b} < 0$. This implies that Seller 1 will set either $b_1^* = 0$ or $b_1^* = \bar{b}$ depending on the value of $\dfrac{Q}{3}$

relative to $\bar{b}$ and $2\bar{b}$. First, suppose $0 < \dfrac{Q}{3} < \bar{b}$. Since $b_2^* = \bar{b}$ implies $b > \dfrac{Q}{3}$, Seller 1 will set $b_1^* = \bar{b}$.Second, suppose $0 < \bar{b} \leq \dfrac{Q}{3} < 2\bar{b}$. If $b_1 = 0$ then $\pi_1 = Q - \bar{b}$. If $b_1 = \bar{b}$ then $\pi_1 = \frac{1}{2b}\left(b + \dfrac{Q}{3}\right)^2 = \frac{1}{36\bar{b}}\left(Q + 6\bar{b}\right)^2$. Seller 1 has to determine whether to retain the whole market or share the market with Seller 2. Seller 1 chooses $b_1^* = 0$ if $Q - \bar{b} > \frac{1}{36\bar{b}}\left(Q + 6\bar{b}\right)^2$ which is equivalent to $Q^2 - 24Qb + 72b^2 < 0$. This holds if $\bar{b} < \dfrac{\left(\sqrt{2}+2\right)}{12}Q$. Therefore $b_1^* = 0$ when $\bar{b} < \dfrac{\left(\sqrt{2}+2\right)}{12}Q$ and $b_1^* = \bar{b}$ when $\bar{b} \geq \dfrac{\left(\sqrt{2}+2\right)}{12}Q$. Lastly, for $0 < \bar{b} < 2\bar{b} \leq \dfrac{Q}{3}$ we have $b \leq \dfrac{Q}{3}$ and $\pi_1 = Q - b$. Since $\dfrac{\partial \pi_1}{\partial b} < 0$ Seller 1 will set $b_1^* = 0$. □

Instructions

General rules

This session is part of an experiment in the economics of decision making. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money. At the end of the session your earnings will be paid to you in cash and in private. The amount you earn will depend on your and other people's decisions.

There are sixteen people in this room who are participating in this session. It is important that you do not talk to any of the other people in the room until the session is over.

The session will consist of 30 periods, in each of which you can earn points. At the end of the experiment you will be paid an amount based on your total point earnings from all 30 periods. Points will be converted to cash using an exchange rate of **100 points = 1euro**. Notice that the more points you earn, the more cash you will receive at the end of the session.

Description of roles

Each person in the room has been designated as a seller or a buyer. Your identity as a seller or a buyer will stay fixed throughout the experiment. In each period, four markets consisting of 2 buyers and 2 sellers will be formed. One of the sellers will be selling Good A and the other will sell Good B.

You are a SELLER.[**You are a BUYER**.]

Buyer's decision

In each period a buyer makes a single decision. She can buy Good A, Good B or buy nothing. The payoff of the buyer from the choice of a good will depend on the quality of the chosen good and its price. A good is characterized by five so called attributes, each of which has a different weight: 5, 4, 3, 2, and 1, respectively. The overall quality of a good is determined by the quality level of each these five attributes. The payoff of a buyer when buying a good is calculated by the following formula:

$$Payoff = 5 * q_5 + 4 * q_4 + 3 * q_3 + 2 * q_2 + 1 * q_1 - p$$

In this formula q_5 is the quality level of the attribute with weight 5, q_4 is the quality level of the attribute with weight 4, q_3 is the quality level of the attribute with weight 3, q_2 is the quality level of the attribute with weight 2 and q_1 is the quality level of the attribute with weight 1. The price of the good is indicated by p.

In the **example** below, for Good A, q_5 is 0, q_4 is 4, q_3 is 4, q_2 is 11, q_1 is 36 and p is 50. For Good B, q_5 is 0, q_4 is 0, q_3 is 0, q_2 is 11, q_1 is 61 and p is 40.

Product / Weight	5	4	3	2	1	Price
Good A	0	4	4	11	36	50
Good B	0	0	0	11	61	40

If the buyer chooses **Good A** she gets:

$5*0+4*4+3*4+2*11+1*36-50 = 16+12+22+36-50 = 36$ **points**

If the buyer chooses **Good B** she gets:

$5*0+4*0+3*0+2*11+1*61-40 = 22+61-40 = 43$ **points**

If the buyer chooses **not to buy** anything she gets **0 (zero) points**.

Note that the buyer has **15 seconds** to make a decision at this stage. This **time limit is binding**, if the buyer doesn't make any choice in the time limit it will be assumed that she chose not to buy anything in that period.

Seller's decision

In each period a seller makes decisions regarding the attributes and the price of her good. The payoff of the seller will depend on the price of and the demand for his good, demand being the number of buyers that chose her good. Details for the Seller's decision are shown at the end of their instructions.

Differences between periods

All periods are identical except that the participants in a market will be changing from period to period. A market will not consist of the exact same four participants in any consecutive period. The sellers of the goods A and B may also change from period to period. Namely, a seller that is the seller of Good A in one period may be the seller of Good B in another period.

The procedure

In each period, first the sellers make decisions regarding the attributes and the price of their good. Then, the buyers will make their choices among the goods of the two sellers in their market. At the end of each period you will get feedback regarding your payoffs.

This is the end of the general instructions. Sellers have further instructions which is only for them to be read on their own. You have 5 minutes to read the instructions silently, at the end of which you will get a short quiz to test your understanding of the instructions. If you have any questions please raise your hand, a monitor will come to answer your question.

Details of the Seller's decision [only distributed to the sellers]

Remark: Please note that buyers do not have any more instructions than the part that was read out loud by the experimenter.

1. In the first stage of a round each seller gets a screen showing the *Quality* of her and the other seller's good. These qualities are drawn randomly between 60 and 100, where numbers close to 80 are more likely to be drawn. At this stage each seller has to decide on **the number of attributes** for her good. The number of attributes has to be between 1 and 5. Depending on the number of attributes you choose, the *Quality* value of your good will be randomly distributed among the attributes such that the following is satisfied:

$$Quality = 5 * q_5 + 4 * q_4 + 3 * q_3 + 2 * q_2 + 1 * q_1$$

In this formula q_5 is the quality level of the attribute with weight 5, q_4 is the quality level of the attribute with weight 4, q_3 is the quality level of the attribute with weight 3, q_2 is the quality level of the attribute with weight 2 and q_1 is the quality level of the attribute with weight 1.

If you choose your number of attributes to be 1, then your *Quality* will be assigned to the attribute with weight 1 such that $Quality = 1 * q_1$ and $q_2, q_3, q_{4,} q_5$ equals to zero.

If you choose your number of attributes to be 2, then your *Quality* will be distributed among the attributes with weight 1 and 2 such that $Quality = 1 * q_1 + 2 * q_2$ and $q_3, q_{4,} q_5$ equals to zero.

If you choose your number of attributes to be 3, then your *Quality* will be distributed among the attributes with weight 1,2 and 3 such that $Quality = 1 * q_1 + 2 * q_2 + 3 * q_3$ and $q_{4,} q_5$ equals to zero.

If you choose your number of attributes to be 4, then your *Quality* will be distributed among the attributes with weight 1,2,3 and 4 such that $Quality = 1 * q_1 + 2 * q_2 + 3 * q_3 + 4 * q_4$ and q_5 equals to zero.

If you choose your number of attributes to be 5, then your *Quality* will be distributed among all the attributes.

Example 1:

Suppose your *Quality* is equal to 72 and you choose your number of attributes to be 2. Then your *Quality* is distributed among the attributes with weight 1 and 2. As you can see $2 * 9 + 1 * 54$ is equal to 72, which is your *Quality*.

Product / Weight	5	4	3	2	1
Good A	0	0	0	9	54

Example 2:

Suppose your *Quality* is equal to 80 and you choose your number of attributes to be 5. Below is an example of how your good would look like in this case:

Product / Weight	5	4	3	2	1
Good A	6	2	2	16	4

You will have **30 seconds** to make your decision at this stage. This time limit is **binding**, if you don't enter anything your number of attributes will be 1 for this period.

Notice that the number of attributes you choose will not affect the payoff of the buyers since the *Quality* of your good is unaffected by it. However, the calculation of payoffs may get harder or easier depending on the number of attributes of your good.

2. After choosing the number of attributes you will advance to the second stage. In this stage you will learn the number of attributes that the other Seller has chosen for her good. At this stage each seller has to decide the **price** of her good.

Again, you have 30 seconds to make your decision at this stage. This time limit is binding, if you don't make your decision on time the price of your good will be 0 for this period.

3. After each seller makes their price decision the buyers will make their choices. You will see the same screen that the Buyers will see except the buttons to make choices among goods. You will have to wait until the buyers are finished.

4. After the buyers make their decisions you will get a feedback screen. Your point earnings from the period will be equal to **the price you charge times the number of buyers that chose your good**. Note that your *Quality* only effects the payoff of the buyers, not your profits.

Remember that the buyers do not know **how** the *Quality* or the number of attributes of any good is determined.

Quiz:

1. Answer the following arithmetic problems:

   a) $5 * 7 + 4 * 13$ = ☐

   b) $4 * 20$ = ☐

   c) $3 * 13 + 2 * 2 + 1 * 17 - 50$ = ☐

2. Consider the following goods:

Product / Weight	5	4	3	2	1	Price
Good A	0	1	15	4	14	80
Good B	1	7	7	13	17	60
Don't buy	0	0	0	0	0	0

   a) What is the payoff for the Buyer if she chooses Good A? : ☐

   b) What is the payoff for the Buyer if she chooses Good B? : ☐

   c) What is the payoff for the Buyer if she doesn't buy anything? : ☐

   [The following questions appear in the sellers' quiz only]

   d) If two Buyers choose Good A, what is the profit of its Seller? : ☐

   If only one Buyer chooses Good A and one Buyer chooses not to buy

   e) What is the profit of the Seller of Good A? : ☐

   f) What is the profit of the Seller of Good B? : ☐

   Please raise your hand when you are finished so that the experimenter can check your answers.

Chapter 4

Price Complexity and Buyer Confusion in Markets

4.1 Introduction

Is it worth the price? This is a question we often ask while considering to make a purchase. However, surprisingly we often need to ask another, more basic question: what is the price? Figuring out the price of a product or a service can be a daunting task. For example, in order to calculate the price of a single mobile phone call you need to consider; the time of the day, the day of the week, the country you are dialing to (and from, if you are abroad), number of minutes left in your bundled minutes package (and whether that call is included in your bundle), whether you are calling a mobile or a fixed phone, call duration rounding on the call (per minute, per second or per 10 seconds), call set-up fee, charge per minute, charge rounding and finally the duration of the call. After considering these you can check the associated costs for the tariff package you are subscribed to and calculate the actual cost. The prevalence of complex prices as well as other forms of complexity in markets raises the question whether it is reasonable to expect consumers to take the best deal in these complex markets.

There is an increasing amount of empirical evidence showing that consumers do not always make optimal decisions. Wilson and Waddams Price (2010) report that in the UK electricity market consumers who switch between suppliers reaped only a quarter to a half of the maximum gains available. Moreover, 20-30% of the consumers actually reduced their surplus as a result of switching. In similar vein, Chetty et al (2009) show that consumers underreact to taxes that are not salient, i.e. when the advertised price is not inclusive of taxes. Policy makers were already concerned about such issues and started taking action. For example, in July 2006, the European Commission passed a regulation on the European Single Market for Aviation to increase consumer protection against complicated pricing strategies of airlines. The regulation tells that "In order to help passengers compare fares, the proposed regulation imposes that fares should include all applicable taxes charges and fees".

Regulations concerning such practices of firms in competitive markets are not easily justified. After all, wouldn't firms that engage in obfuscation lose their customers to firms that don't? An emerging literature on behavioral industrial organization shows that this is not necessarily the case and that profit maximizing firms can exploit consumer biases (for an early review, see Ellison, 2006). From this literature one recent study that examines the use of price complexity as a method of obfuscation is Carlin (2009). Carlin presents a two-stage model. Firms, competing to sell a homogeneous product, set the price and the price complexity of their product in the first period. In the second period buyers make their purchases, while only a fraction of buyers (experts) purchase the good with the lowest price. The rest of the buyers (uninformed buyers) purchase randomly. The share of experts is determined inside the model and is an increasing function of each firm's price complexity choice. The model has interesting equilibrium predictions: the prices are dispersed and are higher than marginal cost, and higher complexity is associated with higher prices. In this paper, I use Carlin as the theoretical framework that guides the experimental setup and the hypothesis.

In the present paper, conducting a series of experimental studies I investigate two main questions derived from Carlin (2009). First, are high priced sellers more likely to obfuscate buyers? And second, are prices in markets higher when buyers are susceptible to obfuscation via price complexity? In my experimental posted-offer markets, each seller offers an identical good to buyers with homogeneous preferences. First, sellers simultaneously decide on the price and the tariff structure of their good, and then buyers make their choices among the goods.

Sellers can choose to have one, two or three-part tariffs for their good. The tariff structure affects neither the value nor the price of the good. However, having a higher number of tariffs makes it harder for buyers to calculate the price of the good. Main results show that high priced sellers choose high complexity more often than low priced sellers in case buyers are simulated in accordance with the bounded rationality model of Carlin (2009). However, the evidence for this effect is weaker in case the buyers are human subjects. Importantly, prices are higher when the sellers can confuse buyers using price complexity than when the sellers interact with perfectly rational robot buyers.

In investigating the usage of price complexity by sellers and the effects of this usage on market prices, I use laboratory experiments. Conducting this investigation in "real" markets is a problematic task. In real-world markets it is almost impossible to disentangle different motivations for the use of complex prices such as heterogeneous preferences on the buyer side (Pigou, 1920) and information costs (Salop, 1977). The laboratory environment provides the necessary control for this investigation by eliminating possible confounds.

This paper makes an empirical contribution to the emerging literature on behavioral industrial organization. This literature examines how markets respond to the bounded rationality of consumers. Bringing behavioral economics into the analysis of markets is important since after all, economics is more about markets than it is about individual decisions. Recent theories suggest that non-standard preferences or decision making at the individual level matter for market outcomes. Spiegler (2006) shows that if goods have multiple dimensions and consumers evaluate only some of these dimensions firms will have incentives to make it harder for consumers to compare the value of the goods. DellaVigna and Malmendier (2004) analyze the profit-maximizing contract design of firms if consumers have time-inconsistent preferences and are partially naive about it. They show that firms price investment goods below marginal cost while pricing leisure goods above marginal cost and at the same time firms introduce switching costs and charge back-loaded fees for both types of goods. Gabaix and Laibson (2006) show that firms charge above-marginal cost prices for add-ons when some consumers do not pay attention to these add-ons. In similar vein, Heidhues and Koszegi (2010) show in a model of a competitive credit market that present biased borrowers who are non-sophisticated end up overborrowing and paying high penalties for late payments and suffer large welfare losses.

The literature on behavioral industrial organization is mostly theoretical and there has been little empirical investigation. However, there is an increasing experimental interest. For example Sitzia and Zizzo (2009) report a posted-offer market experiment with a monopolist that offers either simple or complex lotteries. They find no evidence for the influence of complexity on prices; however the quantity demanded is higher for complex products. Kalaycı and Potters (2011) provide evidence for the use of complexity in the form of spurious product differentiation to gain market power in a duopolistic competition framework. In the present paper, I use a complexity mechanism similar to Kalaycı and Potters (2011) and provide a first experimental investigation of price complexity in markets.

The present paper is organized as follows: In section 2, I briefly describe the model of Carlin (2009), which is the theoretical framework that is used for the experimental setup. In the following two sections, I present the design and the results of two studies. Study 1, presented in section 3, examines the effects of price complexity using human subjects as buyers. Study 2, in section 4, provides tighter control on the buyers decisions by adding treatments with robot buyers that are simulated according to theory. In section 5, I conclude by discussing the implications of the results for economic theory and policy.

4.2 Theoretical background

Carlin (2009) proposes a simple two period game, where $n \geq 2$ firms offer a homogeneous good and compete for market share. The firms have zero marginal costs and have no capacity constraints. In the market there is a unit mass of consumers M, and each have unit demand for the homogeneous good. The utility of a consumer i is given by

$$U_i = v - p_i$$

where v is the value of the good and p_i is the price of the good that consumer i purchases. Consumers are risk neutral and maximize their expected utility. Since the goods in the market are homogeneous, maximizing utility for a consumer is equivalent to minimizing the price she pays. Consumers are divided into two groups: experts (fraction μ) and uninformed buyers (fraction $1 - \mu$). Experts are the consumers who are fully informed about the prices and purchase the good with the lowest price in the market. Uninformed consumers, however, purchase a good from a randomly chosen firm.

In the first period of the game, sellers choose a price and decide on the complexity of their price structure. Each firm j chooses a price $p_j \in [0, v]$ and complexity $k_j \in [\underline{k}, \bar{k}]$ for their good. k_j is a measure of how difficult it is to evaluate the actual price of the good. There is no cost involved in choosing different complexity levels. The firms decide on the price and the complexity simultaneously, therefore they choose a strategy $\sigma_j \in \Sigma_j$ where $\Sigma_j = [0, v] \times [\underline{\mathrm{k}}, \bar{k}]$.

The proportion of experts μ is determined by the complexity choices of the firms, $\mu : [\underline{\mathrm{k}}, \bar{k}]^n \to (0, 1)$ such that $\dfrac{\partial \mu}{\partial k_j} < 0$ for all j, and $\dfrac{\partial^2 \mu}{\partial k_j \partial k_l} = 0$ for all $j, l \neq j \in N$.

The condition $\dfrac{\partial \mu}{\partial k_j} < 0$ implies that by increasing its price complexity firm j makes the market less transparent, thereby decreasing the share of experts. The second condition $\dfrac{\partial^2 \mu}{\partial k_j \partial k_l} = 0$ implies that price complexity decisions are neither strategic complements nor substitutes.

In the second period, the consumers make their purchases. All the firms share $(1 - \mu)$ of the demand from uninformed buyers while the firm with the lowest price gets the share μ of the demand in addition.

The following proposition characterize the properties of a symmetric mixed-strategy Nash equilibrium of the game (see Carlin (2009) for the proof).

Proposition 1 *In the pricing complexity game, there exists a symmetric mixed-strategy Nash equilibrium $\sigma^* = \{F^*(p), k^*(p)\}$ in which firms choose prices according to the distribution $F^*(p)$ and choose complexity according to the map*

$$k^*(p) = \{ \begin{array}{ll} \underline{k} & \text{if } p < \hat{p} \\ \bar{k} & \text{if } p > \hat{p} \quad \text{where} \quad \hat{p} = F^{*-1}(1 - [\frac{1}{n}]^{1/(n-1)}) \\ k \in [\underline{k}\ , \bar{k}] & \text{if } p = \hat{p} \end{array}$$

In equilibrium, the distribution function $F^*(p)$ is continuous and strictly increasing in p.

The ex ante probability that each firm chooses high complexity $\bar{k}$ is uniquely *determined to be* $[\frac{1}{n}]^{1/(n-1)}$*. Additionally, the expected fraction of informed consumers* $E[\mu]$*is also uniquely determined in equilibrium.*

In addition to characterizing the equilibrium in proposition 1, Carlin (2009) shows that a symmetric equilibrium in pure strategies cannot exist and marginal cost pricing is a dominated strategy. Therefore, in this market a Bertrand paradox does not arise and prices are always above marginal cost.

For an experimental test of the model it is important to check whether the structural assumptions of the model hold. One of the most important assumptions in Carlin (2009) is the fact that the share of expert buyers decrease with each firm's price complexity ($\partial\mu/\partial k_j < 0$). This implies that by increasing it's price complexity a seller would lead more buyers to make suboptimal choices.

Assumption 1. Increasing the price complexity of a seller leads to an increase in buyer mistakes.

Another assumption regarding the price complexity mechanism is that the complexity of one firm's price does not affect the inherent difficulty in evaluating a competing firm's offer ($\partial^2\mu/\partial k_j \partial k_l = 0$).

Assumption 2. Price complexity decisions of sellers are neither strategic compliments nor substitutes.

The mixed strategy equilibrium is a common feature of models with buyer search that have a similar setup as Carlin (2009) employs. The equilibrium characterized above shows that firms have two conflicting goals and randomize between these two ends. On the one hand each firm desires to be the lowest priced seller and get the whole demand from expert buyers while minimizing the share of uninformed buyers by choosing low complexity. On the other hand, a seller can charge a much higher price and get the demand from uninformed buyers. In this case the firm chooses the highest complexity to maximize the share of uninformed buyers.

Hypothesis 1. Sellers that choose a higher price are more likely to choose the highest complexity ($\bar{k}$) than sellers that choose a lower price.

The basic setup of Carlin (2009) is inspired by models of search, where consumers are partitioned into two groups on the basis of their knowledge of prices (Baye et al., 2006). One of the common elements in these clearinghouse search models is that the share of experts μ is exogenously given, therefore it is possible to examine the price equilibrium for different values of μ. Since in Carlin (2009) μ is endogenously determined by the price complexity choices of the firms it is not possible to examine comparative statics based on exogenous changes in μ. However, if $\mu = 1$, then we are out of Carlin's model and back to the standard Bertrand world where in equilibrium prices equal to marginal cost. As equilibrium prices are strictly above marginal cost in Carlin's model, we would expect prices to be higher than when all the buyers are experts.

Hypothesis 2. Prices are higher when some buyers are uninformed $(0 < \mu < 1)$ compared to the case when all buyers are experts $(\mu = 1)$.

In the experimental studies that are presented in this paper, a two seller version of the theoretical model that is described above is employed. In the experiment, sellers can create price complexity by having multi-part tariffs where buyers have to find out the total price of a good by calculating the weighted sum of all tariffs under time pressure. Given the heterogeneity in cognitive ability of real buyers this way I aim to create a demand schedule similar to the one described in the theory above. However, the structural assumptions of the model described above are not guaranteed to hold with human buyers. In this regard, the treatments with human buyers should not be seen as a strict test of Carlin (2009).

4.3 Study 1

In this paper, I present results from two related studies. In Study 1, both buyers and sellers in the experiments are human subjects and the buyers' level of rationality is controlled by varying the decision time available to buyers. In Study 2, in addition to human buyers robot buyers are used. Using robot buyers allows to have a tighter control for the buyers' behavior and to focus on sellers' decisions.

In this section, I describe in detail the procedures used in the experimental sessions of Study 1. The main concern in designing the experiment is to create an environment, in which the structural assumptions of the underlying theoretical model could be implemented. This way the behavioral assumptions of the theory can be tested.

Design

In the experiment, subjects play a market game for real monetary rewards. The game is a two-stage posted offer market game where subjects play the roles of sellers and buyers. There are 2 sellers and 3 buyers in a market. In the first stage, sellers simultaneously post prices and choose the number of fees for their good. Choosing the number of fees reflects the price complexity mechanism described in the theoretical model of Carlin (2009). After sellers made their decisions, buyers decide whether and from which seller to buy a unit of good.

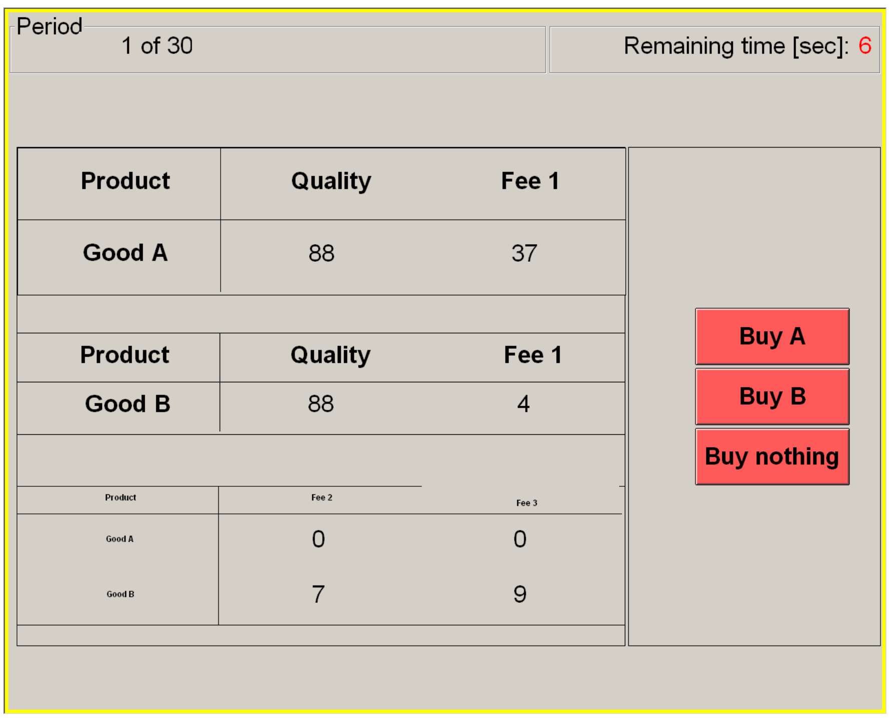


Figure 4.1: Buyer's Screen

In explaining the details of the game I will start with the buyers' decision. In the second stage, buyers make their purchasing decision. Each good offered in the market has a value for the buyers which is called the "quality" of the good. The qualities of the goods are identical, i.e. goods are homogeneous. The buyers observe the quality and Fee 1, Fee 2 and Fee 3 of each good as shown in the example screen in Figure 4.1. Each buyer has the option to buy good A or good B and also has the option to refrain from buying. The buyer's payoff when buying a particular good is the quality minus the weighted sum of the fees of that good,i.e. $Quality - (Fee\ 1 + 2 * Fee\ 2 + 3 * Fee\ 3)$. For making the purchasing decision the buyer has *10 seconds*. In case the buyer does not make a decision in *10 seconds* it is assumed that he chooses not to buy any of the goods.

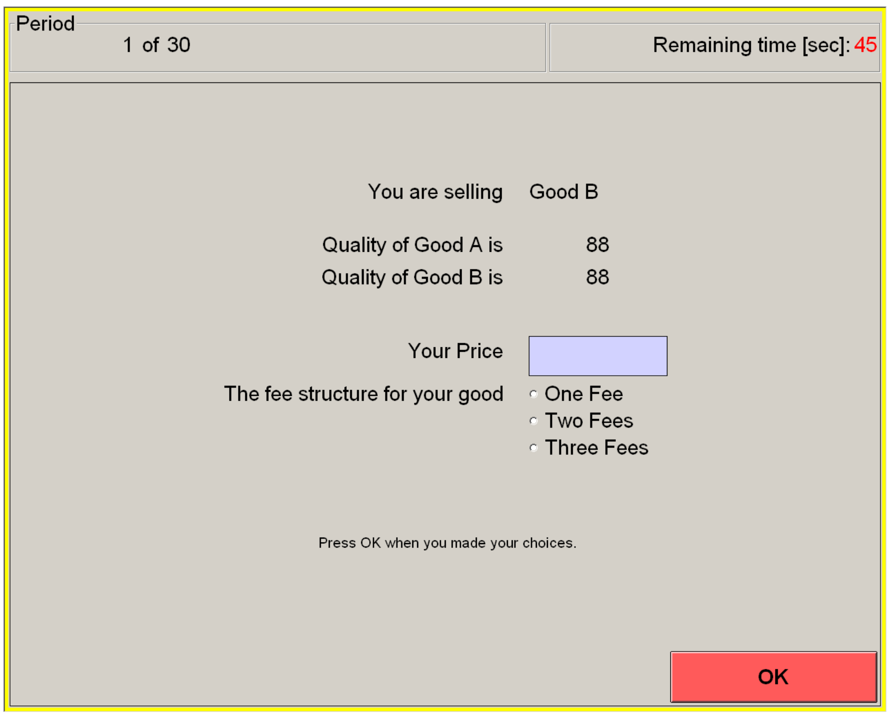


Figure 4.2: Seller's Screen

In the first stage, the sellers are informed about the quality of the goods in the market as shown in the sample screen in Figure 4.2 above. The quality level is a number between 60 and 100 and is determined by a random draw at the beginning of the game. After being informed about the quality the sellers make pricing decisions. They are asked to choose two things: the price and the number of fees for their good. The price a seller chooses has to be a non-negative integer.

For the number of fees the sellers have three options; One Fee, Two Fees or Three Fees. Depending on the number of fees they choose their price is randomly distributed among the fees such that $Fee\_1 + 2 * Fee\_2 + 3 * Fee\_3 = Price$. If a seller chooses One Fee then the price she chose equaled Fee_1. If she chooses Two Fees then the price is randomly distributed among Fee 1 and Fee 2 such that $Price = Fee\_1 + 2 * Fee\_2$ while Fee 3 equals to zero. If she chooses Three Fees, then her price is distributed among Fee 1, Fee 2 and Fee 3 such that $Price = Fee\_1 + 2 * Fee\_2 + 3 * Fee\_3$. The number of fees and the quality of a good do not affect the profit of the sellers directly. The profit of a seller is the price of her good times the number of buyers that chooses her good. The sellers have no costs and are able to serve all the buyers if the buyers chose their good.

After the buyer's decisions are finalized both sellers and buyers receive a feedback screen. Buyers and sellers receive different feedback. A buyer is only informed about which good he purchased, the quality of the good and his payoff from purchasing that good. He is not told what the price of the other good is nor what his payoff would have been had he chosen the other good. The sellers receive more detailed feedback. They are informed about the quality, price, the number of fees, sales and profits for both goods. The feedback screens also included a history table where the information from previous periods are displayed.

In this study there are 2 treatments. In the first treatment subjects play the game described above which I will call "*10 seconds*" as the buyers have 10 seconds to make a decision. In the second treatment called "*45 seconds*" the buyers have 45 seconds to make a decision. The purpose of giving the buyers a sufficient time to make a decision is to achieve a Bertrand like demand where the whole demand goes to the lowest priced seller. Comparing these two treatments allows to have a test for Hypothesis 2.

Procedure

The experiment was conducted at the Experimental Economics Laboratory at the University of Melbourne. The experiment was programmed and conducted with the software zTree (Fischbacher 2007).

At the beginning of a session subjects were randomly placed behind computer terminals where they could find the written instructions. The instructions including the buyers' decision were read out loud by the experimenter, while some details of the sellers' decision were left for them to be read on their own. The participants were told that "In each period a seller makes decisions regarding the price of her good." The motivation behind keeping the details of the seller's decision hidden from buyers was to minimize the role of intentions behind the choice of complexity that might have played a role. After the subjects finished studying the instructions a short computerized quiz was run to make sure the participants had understood the instructions. At the end of the experiment subjects were paid their accumulated earnings in cash and in private.

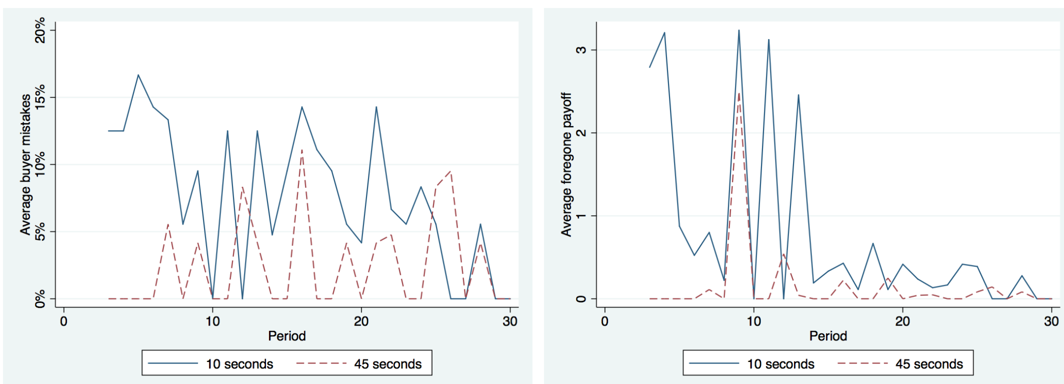
The game was played by subjects for 30 periods and subjects were informed about this. At the beginning of the experiment subjects were randomly assigned to be either a buyer or a seller and they retained this role for all periods. In addition, 4 matching groups each consisting of 4 sellers and 6 buyers were formed randomly. In each period, the subjects in a matching group were randomly allocated to two markets using a stranger matching protocol. The subjects' identities were kept anonymous, a seller couldn't know which of the other 3 sellers she was matched with or what were the decisions of any particular seller or buyer in previous periods. The purpose of this was to preserve the one-shot nature of the game.

The experimental sessions lasted about 90 minutes. 80 student subjects participated in the experiments. The subjects earned on average 33 Australian dollars, which was about 20 Euros at the time of the study.

Results of Study 1

Buyers' choices

The main purpose of the experimental setup was to create an environment where buyers could potentially make suboptimal choices, particularly in *10 seconds*. In the analysis concerning buyers' choices data from periods 3 to 30 are used. Figure 4.3a displays for each treatment the development of average rate of mistakes that buyers made over time. A mistake is defined as a buyer purchasing a good that does not have the highest payoff or refraining from buying while there is a good with a positive payoff. On average buyers make a mistake 8% of the time in *10* *seconds*, and 2% of the time in *45 seconds*. The rate of mistakes for *45 seconds* is significantly lower than for *10 seconds* with a Mann-Whitney U test using the independent matching group as the unit of observation (p-value=0.02). By making a mistake, a buyer foregoes a payoff equal to the difference between the payoff from the good he has chosen and the payoff from the cheapest good in the market. Figure 4.3b displays the development of foregone payoff over time for each treatment. Buyers on average lose 0.83 points (1% of the optimal payoff) in *10 seconds* and 0.15 points(0.2% of the optimal payoff) in *45 seconds*. The difference between average *foregone payoff* in the two treatments is significant (p-value=0.02)

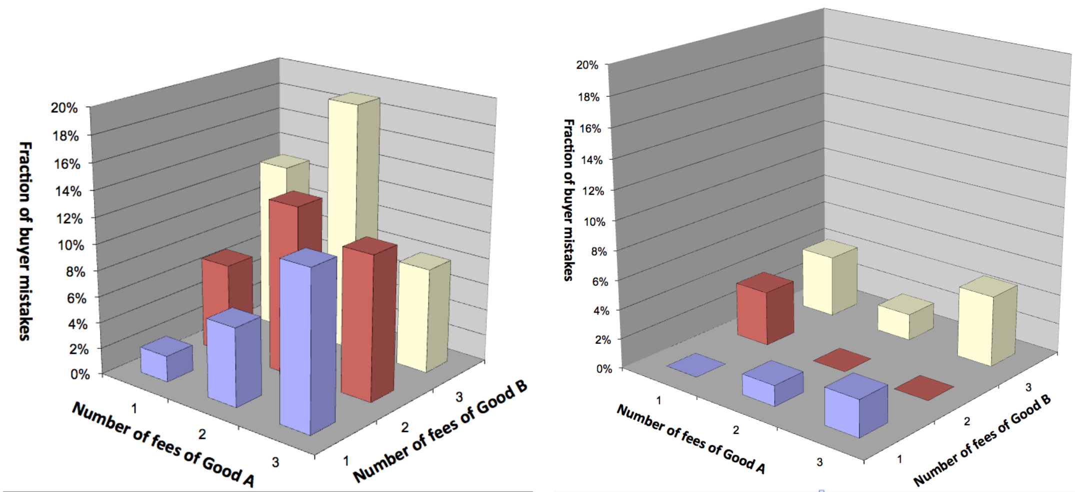


(a) Buyer mistakes

(b) Foregone payoff

Figure 4.3: Buyer mistakes and foregone payoff

According to Assumption 1 the number of buyer mistakes increase with the number of fees of each good in a market. Figures 4.4a and 4.4b below display the average rate of mistakes by the number of fees of each good in a market for *10 seconds* and *45 seconds* respectively. In Figure 4.4a it can be seen that the rate of mistakes is lowest when both goods have only one fee. Overall, there appears to be an increase in the rate of mistakes with the number of fees of each good but the relationship seems non-monotonic. The picture is less informative for *45 seconds* as seen in Figure 4.4b since there are very few mistakes. In order to have a direct test of Assumptions 1 and 2, I run a binary logit regression on the probability of making a mistake using the number of fees of each good in the market, interaction term for the number of fees of the two goods, the period number and the (absolute) price difference between the two goods as explanatory variables.



(a) 10 seconds

(b) 45 seconds

Figure 4.4: Buyers' mistakes by number of fees

Table 4.1 displays the results of this regression for each treatment. Column 1 and 2 show the regression results for *10 seconds* and columns 3 and 4 for *45 seconds* treatments. The dependent variable used in these regressions is a binary variable taking the value 0 if the buyer purchased the good with the highest payoff and value 1 if the buyer chose a good with a lower payoff or refrained from buying while there was a good with a positive payoff.

Table 4.1: Buyer mistakes

	10 seconds		45 seconds	
	Model 1	Model 2	Model 1	Model 2
Period	-0.06 (0.02) **	-0.09 (0.01) **	0.05 (0.03)	0.01 (0.03)
Good A's number of fees	2.20 (0.26) **	2.56 (0.39) **	1.39 (0.38)**	1.38 (0.35) **
Good B's number of fees	2.13 (0.48) **	2.28 (0.62) **	1.04 (0.95)	0.93 (0.81)
A's # of fees x B's # of fees	-0.91 (0.18) **	-1.03 (0.23) **	-0.29 (0.20)	-0.29 (0.15) *
Price difference	-	-0.12 (0.04) **	-	-0.25 (0.09) **
# of Observations	405	405	336	336

notes: Logit model with subject fixed effects and standard errors clustered at the independent group level; * indicates statistical significance at 10%, ** indicates statistical significance at 5%. standard errors in parentheses. Period >2; observations with Payoff difference equal to 0 and three outlier observations with Price offer equal to 1000 are omitted.

The regression results in Column 1 of Table 4.1 show that the number of fees of both goods have a positive effect on the probability of a buyer making a mistake[1]. This is in line with Assumption 1, which is a central assumption of Carlin (2009). The coefficient for the interaction term between *Good A's number of fees* and *Good B's number of fees* has a negative sign and is statistically significant. This implies that Assumption 2, which says that price complexity decisions of the two sellers are neither strategic substitutes nor complements, does not hold.

Although it is implicitly assumed in Carlin (2009) that the share of uninformed buyers is independent of the payoff variance, it is intuitive that buyers avoid errors when the errors are more costly[2]. The model displayed in Column 2 adds the variable *Price difference* to Model 1 to examine this. The coefficient for *Price difference* has negative sign and is statistically significant, indicating that the buyers make less mistakes when the price difference is larger.

[1] Note that being the seller of Good A or Good B is determined randomly at each period, therefore there is no systematic difference between the number of fees of Good A and Good B.

[2] See for example the Quantal Response Equilibrium concept of McKelvey and Palfrey (1995) and the experiment of Kalaycı and Potters (2010)

Despite the relatively low number of mistakes that has been made in the *45 seconds* treatment the number mistakes is somewhat affected by the number of fees of sellers. Last two columns in Table 4.1 shows that the coefficients for the number of fees of both Goods have positive sign, while only the coefficient of *Good A's number of fees* is statistically significant.

Price and complexity

Carlin (2009) makes a strong prediction on the relationship between the prices and the choice of complexity. According to the price-complexity equilibrium of Carlin (2009) when a seller chooses a relatively high price she is more likely to choose high price complexity than when she chooses a relatively low price. The corollary of this is summarized in Hypothesis 1; sellers that choose a high price are more likely to choose Three Fees than sellers that choose a low price. To test this hypothesis I look at the rate of choosing *Three Fees* for the sellers who has the highest price and the sellers who has the lowest price at a particular market at a given period. Figure 4.5 displays the development of average percentage of choosing *Three Fees* for high and low price sellers over time in both *10 seconds* and *45 seconds*.

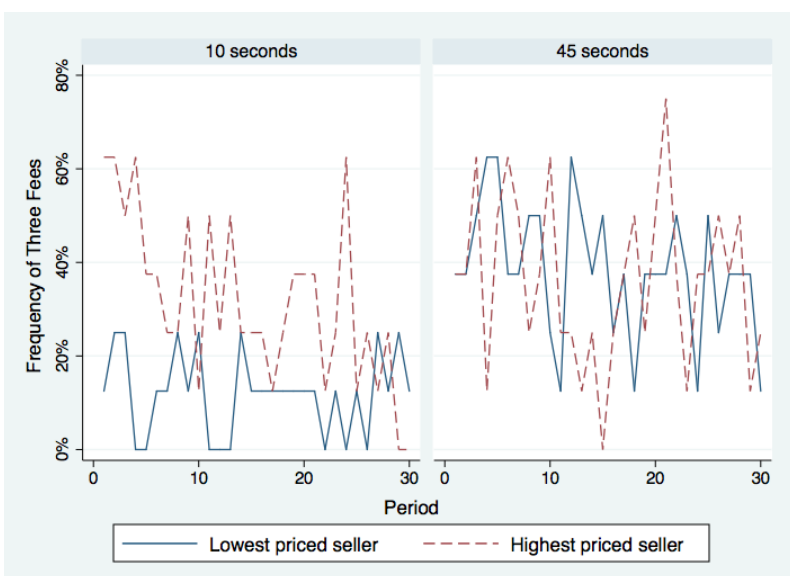


Figure 4.5: Frequency of high complexity

Result 1.1 In *10 seconds*, sellers that choose a higher price are more likely to choose *Three Fees* than sellers that choose a lower price. However, this effect is disappearing with experience. In *45 seconds* there is no relationship between choosing a higher price and choosing *Three Fees*.

The first graph in Figure 4.5 shows that there is clear difference between high and low price sellers in the frequency of choosing high complexity in *10 seconds*. On average high priced sellers choose *Three Fees* 32% of the time while low priced sellers choose *Three Fees* 12% of the time. To test whether this difference is significant average rate of choosing *Three Fees* for high and low price sellers is constructed and non-parametric Wilcoxon signed rank test is applied. The difference is significant (p-value=0.03, one-sided). If we look at the last 10 periods of the sessions, the difference narrows and is only significant at the 10% level (p-value=0.08, one-sided).

For completeness sake, I also present the relationship between price and high complexity for *45 seconds* treatment in the second graph in Figure 4.5 . On average high priced sellers choose Three Fees 36% of the time while low priced sellers choose Three Fees 38% of the time. The difference is not significant according to Wilcoxon signed rank test (p-value=0.577). Considering that *45 seconds* does not satisfy the structural assumptions of Carlin (2009), this result does not contradict Hypothesis 1.

Price levels

Hypothesis 2 tells that prices will be higher in *10 seconds* than in *45 seconds*, provided that the buyers sometimes make mistakes in *10 seconds* ($0 < \mu < 1$) while buyers always make optimal decisions in *45 seconds* ($\mu = 1$). The analysis of buyer's choice demonstrated that, though small (2%), the rate of buyer mistakes is still positive in *45 seconds* and that the sellers are able to influence the rate of these mistakes to some extent.

Result 1.2 There is no significant difference between the average prices in *10 seconds* and *45 seconds* treatments.

Figure 4.6 displays the development of average prices over time for both treatments. In both treatments a negative time trend in prices is observed. On average, sellers in *10 seconds* treatment charge a price of 22 points while sellers in *45 seconds* charge 22.7 points. A Mann-Whitney U test using the averages from the 8 independent matching groups shows that the difference is not significant. (p-value= 0.38).

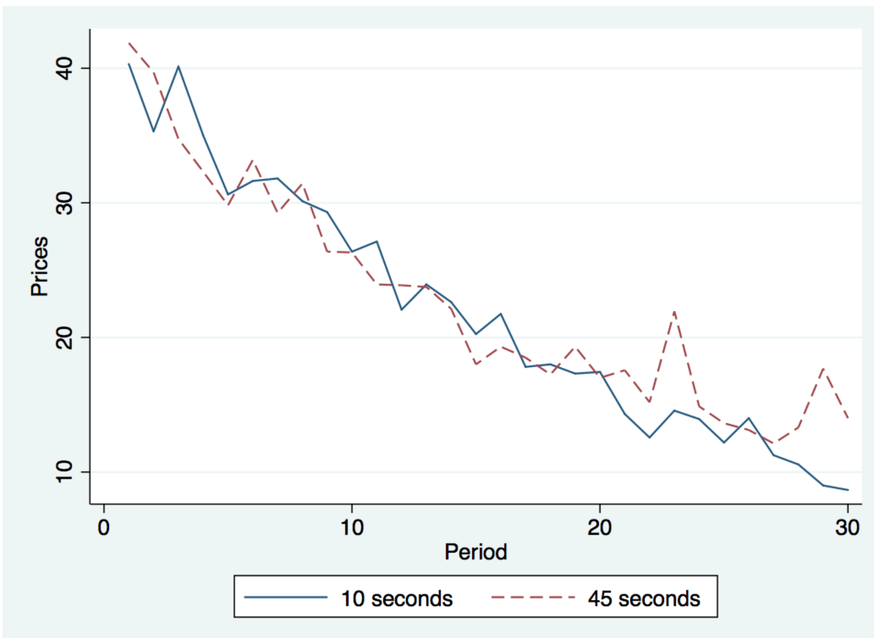


Figure 4.6: Average prices over time

Discussion

The results of Study 1 give limited support for the hypotheses. In the *10 seconds* treatment, sellers' use of high complexity is associated with higher prices, however this effect diminishes over time. Also, there is no evidence that prices are higher when buyers make more mistakes as shown by the comparison between *10 seconds* and *45 seconds*.

It was anticipated that the *45 seconds* treatment would operate like a Bertrand market. However, sellers with a higher price in this treatment still make positive profits since buyers make mistakes 2% of the time. Moreover, sellers are somewhat able to affect the rate of buyer errors, as can be seen in Table 4.1 . Given the data it is hard to judge whether the sellers perceive the buyers in the *45 seconds* treatment as rational or boundedly rational buyers. In addition, Assumption 2 of the model is not satisfied in *10 seconds*. Moreover, buyers' rate of errors were diminishing in the price difference of the goods. In this regard, in order to have a tighter control on buyers' behavior I ran another set of experiments where the demand side is simulated.

4.4 Study 2

Design and Procedure

Study 2 differs from Study 1 only with respect to the treatments that are run. There are 3 treatments. I run the *10 seconds* treatment of Study 1 again as a benchmark since Study 2 is conducted at Tilburg University. To prevent confusion, I call this treatment "*human*" treatment in this Study.

The second treatment is with simulated (robot) buyers, which are designed to purchase a good from the lowest priced seller. This would be the standard Bertrand case and enable a more accurate test of Hypothesis 2. I call this treatment the "*rational robot*" treatment.

The third treatment is also with robot buyers. However, this time the robot buyers are programmed to make mistakes as in the theory. The idea behind this treatment is to control for any discrepancy that could occur in human buyers' behavior and what the theory in Carlin (2009) assumes. This way it is possible to examine seller behavior in an environment in which buyer behavior is precisely controlled. In this "*boundedly rational robot*" treatment the sellers are instructed as follows:

" In this experiment the decisions of each buyer are simulated by the computer in accordance with the following rules. In principle the buyer will buy the good with the highest payoff. However, in each period the buyer may make an "error", that is, buy the good with the lower payoff. The probability that a buyer makes an error depends only on the total number of fees chosen by you and the other seller.

The probability that the buyer will make an error is indicated in the second column of the table below. In the first row you can see that if the total number of fees is 2 (which means that both you and the other seller chose **One Fee**), the probability of an error is **5%**. In the second row you can see that if the total number of fees is 3 (which means that you chose **One Fee** and the other seller chose **Two Fees** or you chose **Two Fees** and the other seller chose **One Fee**) the probability that each buyer makes an error is **10%**. Similarly the table gives the probabilities of a mistake when the total number of fees is 4,5 or 6. The 3rd and the 4th column of the table indicate how many sales you can expect to make, when you are the seller which offers the lowest or the highest payoff.

Total #	Each buyers' prob. of	Expected # of sales	
of Fees	making an error	For the lowest payoff seller	For the highest payoff seller
2	5 %	0,15	2,85
3	10 %	0,3	2,7
4	15 %	0,45	2,55
5	20 %	0,6	2,4
6	25 %	0,75	2,25

Total number of fees is the sum of the number of fees of Good A and the number of fees of Good B.

In case two goods in a market have the same (positive) payoff the computer will choose randomly between the two goods. Additionally if one of the goods have a negative payoff the buyers will only purchase the other good. If both goods have a negative payoff the buyers will buy nothing. "

The rest of the experimental procedure was the same as in Study 1, except that the experiments for Study 2 were conducted at the CentERLab in Tilburg University. 72 student subjects participated in the study. The game was played by subjects for 30 periods. Subjects in *human* were randomly assigned to be either a buyer or a seller and they retained this role for all periods. For *human*, 4 matching groups each consisting of 4 sellers and 6 buyers were formed randomly. For the robot buyer treatments matching groups consisted of 4 sellers. In each period, the subjects in a matching group were randomly allocated to two markets using a stranger matching protocol. The experiments lasted about 90 minutes and the subjects on average earned 15 Euros.

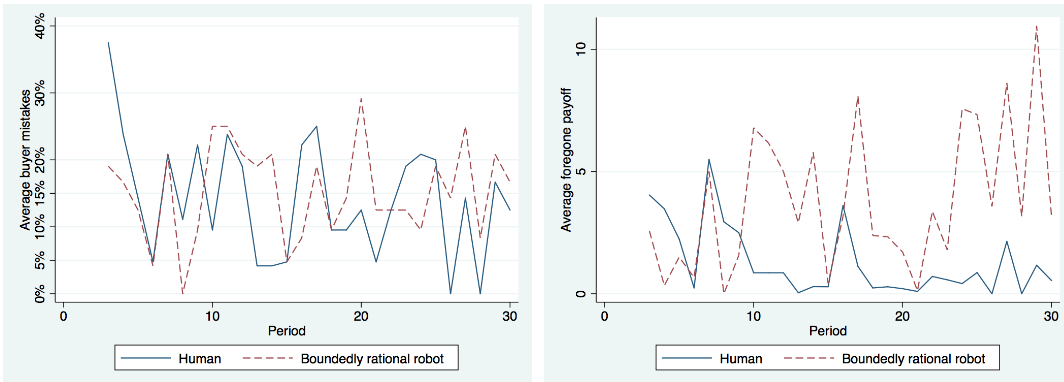
The mechanism at which the buyers made mistakes in *boundedly rational robot* ensures that both Assumption 1, that the rate of mistakes increase by each sellers complexity, and Assumption 2, that sellers price complexity decisions are neither strategic complements nor substitutes are satisfied. In addition, the implicit assumption that error rates are independent of the price differences also holds in *boundedly rational robot*.

For the *boundedly rational robot* and the *human* treatments, Hypothesis 1 implies that sellers that choose a higher price are more likely to choose *Three Fees* than sellers that choose a lower price. Since *rational robot* provides a true benchmark of Bertrand competition, we can test Hypothesis 2. According to this hypothesis, prices are expected to be lowest in *rational robot*.

Results of Study 2

Buyer's choices

Figure 4.7a displays the average mistake rates for the *boundedly rational robot* and the *human* treatments over time. On average the rate of mistakes for *boundedly rational robot* is 15% and for *human* it is 14%. The difference is not significant (p-value=0.39). Figure 4.7b displays the development of foregone payoff over time for each treatment. Buyers on average lose 3.8 points (7% of the optimal payoff) in *boundedly rational robot* and 1.3 points (2% of the optimal payoff) in *human*. The difference between average *foregone payoff* in the two treatments is significant (p-value=0.04). Although the rate of mistakes are similar in *human* and *boundedly rational robot*, the mistakes in *boundedly rational robot* are significantly more costly.



(a) Buyer mistakes

(b) Foregone payoff

Figure 4.7: Buyer mistakes and foregone payoff

The rate of mistakes in *boundedly rational robot* depends only on the number of fees of both sellers by design, while for *human* this is not necessarily the case. Table 4.2 displays regression results for a binary logit regression on the probability of making a mistake using the number of fees of each good in the market, and interaction term for the number of fees of the two goods, the period number and the (absolute) price difference between the two goods as explanatory variables.

Table 4.2: Buyer mistakes

	Human buyers	
	Model 1	Model 2
Period	-0.07 (0.02) **	-0.08 (0.02) **
Good A's number of fees	1.36 (0.59) **	1.68 (0.53) **
Good B's number of fees	1.51 (0.69) **	1.70 (0.66) **
A's # of fees x B's # of fees	-0.35 (0.20) *	-0.42 (0.19) **
Price difference	-	-0.15 (0.04)**
# of Observations	548	548

notes: Logit model with subject fixed effects and standard errors clustered at the independent group level; * indicates statistical significance at 10%, ** indicates statistical significance at 5%. standard errors in parentheses. Period >2; observations with Payoff difference equal to 0 are omitted.

Similar to the results in Study 1, the rate of buyer mistakes increase with the number of fees of the two goods in a market. This is in line with Assumption 1. The coefficient for the interaction term *# of fees Good A x # of fees Good B* has a negative sign and is statistically significant, which contradicts Assumption 2. It is also observed from the regression in column 2 that the price difference between the goods have a negative impact on the buyer mistakes. If a good has a much higher price than the other good, the chances are low that the buyers will mistakenly purchase that good.

Price and Complexity

Hypothesis 1 suggests that high prices should be associated with high complexity in *boundedly rational robot* and *human*. To analyze this we compare the rate of choosing *Three Fees* by the sellers with the highest price and the sellers with the lowest price in a particular market for a given period. Figure 4.8 displays the five period averages of percentage of choosing *Three Fees* for high and low price sellers in the *boundedly rational robot* and the *human* treatments.

Result 5. In *boundedly rational robot* , sellers that choose a higher price are more likely to choose *Three Fees* than sellers that choose a lower price. This is not the case for the treatment with human buyers.

The first graph in Figure 4.8 shows that in *boundedly rational robot* the rate of choosing *Three Fees* is higher on average for sellers who have a higher price. High priced sellers on average choose Three Fee's 49% of the time while low priced sellers choose *Three Fees* 25% of the time. Comparing the average percentage of high fees for high and low prices using the matching group averages as observations and applying the Wilcoxon signed-rank test shows that the difference is significant (p-value=0.03, one-sided). In *human* the association between the relative price and the choice of complexity disappears. On average low price sellers choose *Three Fees* 43% of the time, while high price sellers choose *Three Fees* 44% of the time and the difference is not significant (p-value=0.4).

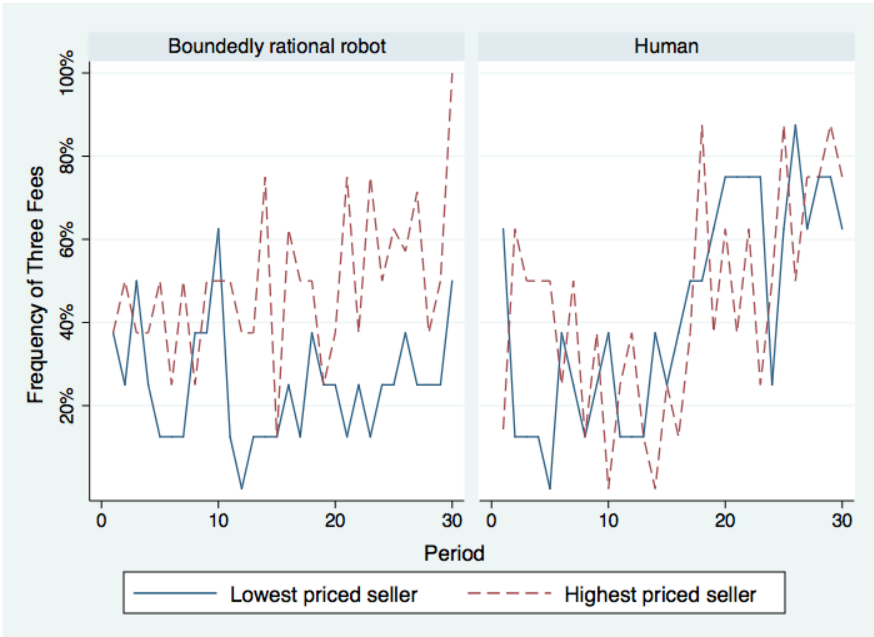


Figure 4.8: Frequency of high complexity

Price levels

Result 4. The prices are lowest in the *rational robot* treatment and highest in the *boundedly rational robot* treatment.

Figure 4.9 displays the development of average prices across 30 periods for all three treatments. The short-dashed line shows the average prices for *rational robot* , the solid line is the average prices for *human* and the long-dashed line is the average prices for *bounded rational robot.* The average price in *human* is mostly higher than the average price in *rational robot.* The difference between the two prices using the session averages for independent groups with a Mann-Whitney U test is significant (p-value=0.05, one-sided). Similar to the *10 seconds* and *45 seconds* treatments in Study 1, there is a downward trend in the average prices in *human* and *rational robot* treatments. However, the difference between the average prices in the two treatments persists also at the end of the session. If we look at the last 10 periods of play the average prices in the *human* treatment is 22.2 , while it is 12.7 points in the *rational robot* treatment (p-value=0.04, one-sided).

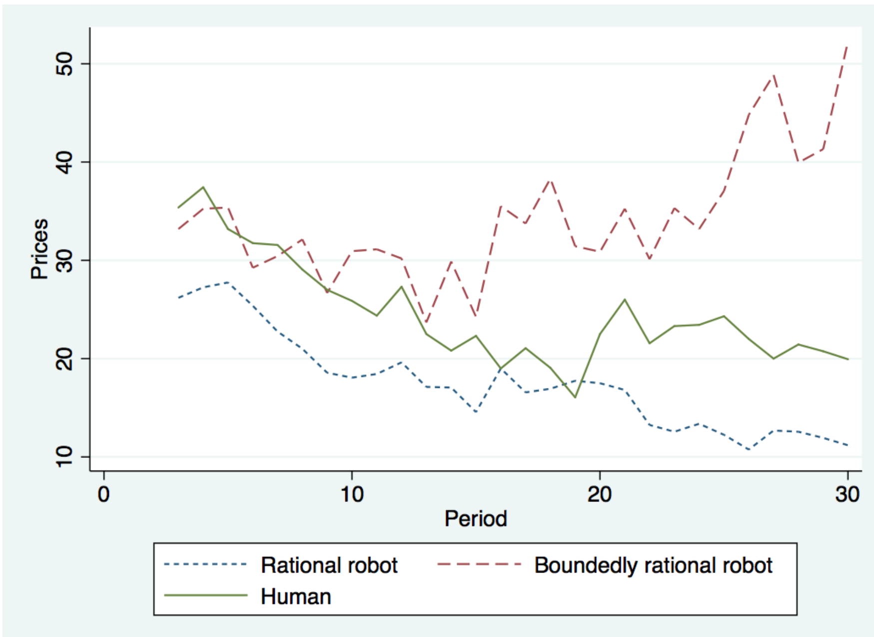


Figure 4.9: Average prices over time

The price pattern for the boundedly rational buyer treatment is remarkably different from the other two treatments. In the first 10 periods the average price offers in the *human* and the *boundedly rational robot* treatments are rather similar (p-value=0.772). However, around the middle of the game the average prices for *boundedly rational robot* treatment begins to increase and this trend continues till the end of the experiment. Average prices in *boundedly rational robot* is higher than in *human* (p-value=0.02, one-sided). The prices in *rational robot* buyer are lower than in *boundedly rational robot* (p-value=0.01, one-sided). The results confirm Hypothesis 2, that prices are lower in *rational robot* than in *human* and *boundedly rational robot* treatments.

Discussion

The results of Study 2 from *boundedly rational robot* provides support for Hypothesis 1. In *boundedly rational robot* high priced sellers choose high complexity more often than low priced sellers. The support for Hypothesis 1 found in Study 1 turns out not to be robust to replication in Study 2. In *human*, there is no relationship between being a high priced seller and choosing high complexity. There are at least two possible explanations for this. One is due to the violation of Assumption 2 in *human*. Price complexity is a strategic substitute, if an increase in the other seller's complexity is decreasing the effect of my price complexity. The second explanation is related to the finding that buyers mistakes are negatively related to the price difference in *human* while this is not the case in *boundedly rational robot*. This second finding may also explain why average prices are higher in *boundedly rational robot* than *human*, despite similar rates of buyer mistakes in these two treatments. In *boundedly rational robot* sellers can charge a very high price and still make a sale with positive probability, while this is less likely to happen with human buyers.

The results support Hypothesis 2, that prices are lower when buyers are perfectly rational robots who always buy from the cheapest sellers rather than being prone to making errors. This finding shows the importance of incorporating bounded rationality in the study of markets. When buyers are boundedly rational, sellers can use obfuscation methods such as price complexity which leads to higher market prices.

4.5 Conclusion

Conducting a series of experimental studies I investigate the effects of price complexity on market prices. Using Carlin (2009) as the guiding model, I examine two main questions. First, are sellers that charge higher prices in the market more likely to choose high complexity? And second, are prices in markets higher when buyers are prone to making errors?

The main finding is that high priced sellers choose high complexity more often when demand is simulated in accordance with the model of Carlin (2009). However, the results are inconclusive when the buyers are human subjects. In Study 1, sellers that have a higher price choose high complexity more often, though with experience the relationship weakens. In Study 2, there is no relationship between high prices and high complexity when buyers are human subjects. Importantly, market prices are higher when sellers can confuse buyers using price complexity than when they interact with perfectly rational robot buyers that always purchase the lowest priced good. This price effect is in line with a previous study by Kalaycı and Potters (2011), who find that in a posted offer market with asymmetric sellers, sellers are able to charge higher prices by using product complexity to obscure the quality of their good.

In this paper, having treatments with both real and simulated buyers enables us to focus both on the sellers' and the buyers' behavior. According to Carlin (2009), the share of experts (or the accuracy of buyers' choices) is affected only by the price complexity in the market. However, the results from human buyer treatment suggest that price differences also matter. Human buyers can be only fooled by the sellers if the value of the goods in the market are not too different.

The standard skepticism towards behavioral economics has been due to the belief that competitive markets would eliminate behavioral biases. This paper provides evidence against this belief. Cognitive limitations of buyers can and will be exploited by sellers even in a competitive market, leading to a lower consumer surplus.

The results in this paper have important policy implications, especially for consumer protection. Policy makers mostly focus on the supply side of the market in evaluating the efficiency of markets. However, in order to improve the efficiency of markets and increase consumer surplus policy makers should pay more attention to the demand side. It is evident that demand side imperfections due to bounded rationality can have important effects on market outcomes. In this respect, a natural extension of this paper would be to examine possible policy interventions and market design issues that would minimize the vulnerability of consumers to obfuscation strategies of firms.

Appendix

Instructions

General rules

This session is part of an experiment in the economics of decision making. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money. At the end of the session your earnings will be paid to you in cash and in private. The amount you earn will depend on your and other people's decisions.

There are 20 people in this room who are participating in this session. It is important that you do not talk to any of the other people in the room until the session is over.

The session will consist of 30 periods, in each of which you can earn points. At the end of the experiment you will be paid an amount based on your total point earnings from all 30 periods. Points will be converted to cash using an exchange rate of **100 points = 1 Euros**. Notice that the more points each individual earns, the more cash they will receive at the end of the session.

Description of roles

Each person in the room has been assigned the role of a seller or a buyer. Your role as a seller or a buyer will stay fixed throughout the experiment. Sellers and buyers interact in markets. In each period four markets each consisting of 3 buyers and 2 sellers will be formed. Therefore, if you are a seller, in each period you will be placed in a market with one more seller and 3 buyers. If you are a buyer you will be placed in a market with 2 other buyers and 2 sellers. One of the sellers will be selling Good A and the other will sell Good B.

You are a SELLER.

Buyer's decision

In each period a buyer makes a single decision. She can buy Good A, Good B or buy nothing. The payoff of the buyer from the choice of a good will depend on the quality of the chosen good and its price. The overall price of a good is characterized by three fees. The payoff of a buyer when buying a good is calculated by the following formula:

$$Payoff = Quality - (Fee\_1 + 2 * Fee\_2 + 3 * Fee\_3)$$

In the **example** below, for Good A, the **Quality** is 80, **Fee 1** is 43, **Fee 2** and **Fee 3** are 0. For Good B, the **Quality** is 80, **Fee 1** is 24, **Fee 2** is 5 and **Fee 3** is 2.

Product	Quality	Fee 1
Good A	80	43

Product	Quality	Fee 1
Good B	80	24

Product	Fee 2	Fee 3
Good A	0	0
Good B	5	2

Figure 4.10: Buyer's Screen

If the buyer chooses **Good A** she gets: $80 - 43 = 37$ **points**

If the buyer chooses **Good B** she gets: $80-(24+2*5+3*2)=80-40=40$ **points**

If the buyer chooses **not to buy** anything she gets **0 (zero) points**.

The buyer has ***10 seconds*** to make a decision at this stage. This **time limit is binding**, if the buyer doesn't make a choice in the time limit it will be assumed that she chose not to buy anything in that period.

Seller's decision

In each period a seller makes decisions regarding the price of her good. The quality of her good will be determined by the computer. The qualities of Good A and Good B in a market will be equal to each other at a given period. The payoff of the seller will depend on the price of and the demand for his good, demand being the number of buyers that chose her good. Details for the Seller's decision are shown at the end of their instruction

Differences between periods

The rules of all periods are identical. However, the participants in a market will be changing from period to period. The allocation of participants to markets will be randomly determined. A market will not consist of the exact same five participants in any consecutive period. The sellers of the goods A and B may also change from period to period. Namely, a seller that is the seller of Good A in one period may be the seller of Good B in another period. The quality of the goods in a market may also change between periods.

The procedure

In each period, first the sellers are informed about the quality of their good and then must make their decisions regarding the price of their good. Then, the buyers will choose among the two goods in their market. At the end of each period you will get feedback regarding your payoffs.

This is the end of the general instructions. Sellers have further instructions which are only for them to be read on their own. You have 5 minutes to read the instructions silently, at the end of which you will get a short quiz to test your understanding of the instructions. If you have any questions please raise your hand, a monitor will come to answer your question.

Details of the Seller's decision

Please note that buyers do not have any more instructions than the part that was read out loud by the experimenter.

1. In the first stage of a period each seller gets a screen showing the *Quality* of her and the other seller's good. The *Quality* levels of each seller will be equal to each other in a given period. The quality levels will be randomly drawn from the interval [60, 100] before each period starts. Below is an example screen for this stage;

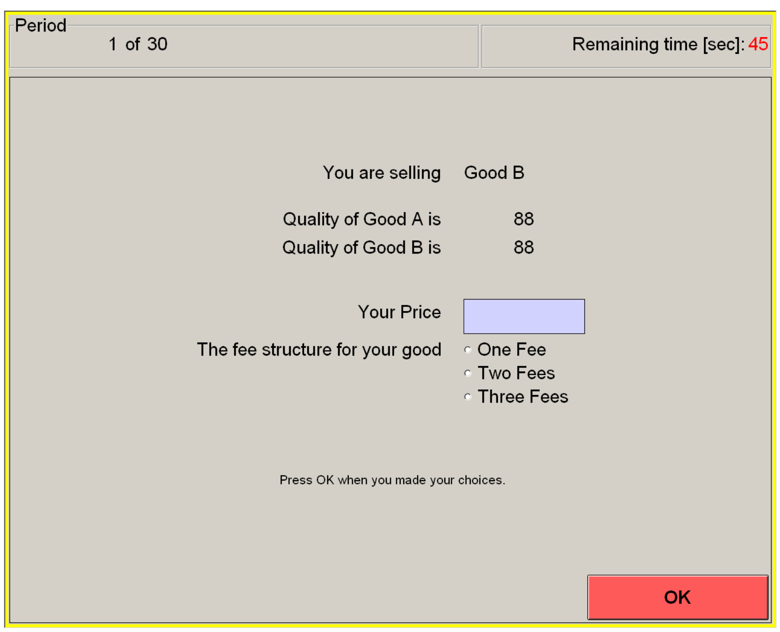


Figure 4.11: Buyer's Screen

At this stage each seller has to decide on **the price** and **the fee structure** for her good. The number of fees can be either 1, 2 or 3. Depending on the fee structure you choose, the *Price* that you choose for your good will be randomly distributed among the three fees such that the following is satisfied:

$$Price = Fee\_1 + 2 * Fee\_2 + 3 * Fee\_3$$

If you choose your fee structure to consist of One Fee, then your $Price$ will be assigned only to **Fee 1** such that $Price = Fee\_1$ while Fee_2 and Fee_3 equals to zero.

If you choose your fee structure to consist of Two Fees, then your $Price$ will be distributed among **Fee 1** and **Fee 2** such that $Price = Fee\_1 + 2 * Fee\_2$ while Fee_3 equals to zero.

If you choose your fee structure to consist of Three Fees, then your $Price$ will be distributed among **Fee 1**, **Fee 2** and **Fee 3** such that $Price = Fee\_1 + 2 * Fee\_2 + 3 * Fee\_3$.

Example:

Suppose you choose your $Price$ to be equal to **42** and choose the fee structure with Three Fees. Then your $Price$ will be randomly distributed among Fee 1,Fee 2 and Fee 3. As you can see in the example below; the total price $7 + 2 * 4 + 3 * 9$ equals to 42, which was the $Price$ you chose.

Product	Quality	Fee 1	Fee 2	Fee 3
Good A	80	7	4	9

Figure 4.12: Buyer's Screen

You will have ***45 seconds*** to make your decision at this stage. This time limit is **binding**. This means that if you don't enter anything for your *Price* it will be 0 and if you don't choose any of the fees your fee structure will be 1 for that period.

Notice that the fee structure you choose will not affect the payoff of the buyers since the *Price* of your good is unaffected by it. However, the calculation of payoffs may get harder or easier depending on the fee structure of your good.

2. After both sellers choose their prices and fee structures the buyers will choose from which seller to buy. You will see the same screen that the buyers will see except the buttons to make choices among goods. You will have to wait until the buyers finish making their decisions.

3. After the buyers make their decisions you will get a feedback screen. Your point earnings from the period will be equal to **the price you charge multiplied by the number of buyers that chose your good**. You have no costs and able to sell to all buyers, if they wish to buy your good. Your *Quality* only effects the payoff of the buyers, not your profits. The fee structure also has no direct effect on your profits.

Remember that the buyers do not know exactly **how** the *Price* or the fee structure of any good is determined. They are only told that "In each period a seller makes decisions regarding the price of her good."

Chapter 5

Confusopoly: Competition and Obfuscation in Markets

5.1 Introduction

Competition has been widely regarded as the best protector of consumer interests. This view has led governments to liberalize markets that used to be state monopolies and encourage entry of more firms, sometimes even at the expense of duplicate infrastructure investments (Armstrong, 2008). Recently however, governments have raised concerns regarding the consumers ability to reap full benefits of competition due to complexity and intransparency of certain markets. In a Common Position document regarding electronic communications networks and services the European Commission (2009) states that ”In order to take full advantage of the competitive environment, consumers should be able to make informed choices and to change providers when it is in their interests. It is essential to ensure that they can do so without being hindered by legal, technical or practical obstacles, including contractual conditions, procedures, charges and so on.” Similar concerns has been an important motivation in the Obama Administration's Health Care Reform[1] and Credit Card Act[2].

Recent literature in behavioral economics give support for such concerns. For

[1]http://www.whitehouse.gov/assets/documents/CEA_Health_Care_Report.pdf

[2]http://www.whitehouse.gov/the_press_office/Fact-Sheet-Reforms-to-Protect-American-Credit-Card-Holders/

example, Choi et al. (2010) show in an experiment that investors fail to minimize on mutual fund fees. Brown et al. (2010) show in a field experiment that buyers underestimate the shipping costs on eBay auctions. This literature also suggests that when some consumers are boundedly rational, firms in a competitive market might have an incentive to take advantage of this bounded rationality (Gabaix and Laibson, 2006, Carlin, 2009). Kalaycı and Potters (2011) and Kalaycı (2011) demonstrate experimentally that sellers in a duopoly market use product and price complexity to confuse buyers, and that market prices are higher in markets where buyers are susceptible to confusion than in markets with perfectly rational (robot) buyers.

A striking theoretical result in this literature is that increased competition may be detrimental for consumers when firms can confuse buyers (Gabaix and Laibson, 2004 and Carlin, 2009). The intuition, according to Carlin (2009) is as follows: If the consumer base is divided between expert buyers who always buy from the cheapest seller and uninformed buyers who just shop randomly there will be only one (low-priced) seller who will be serving the experts while the other (high-priced) sellers will share the demand from uninformed buyers. Therefore, if the number of sellers in a market increases the portion of informed buyers per seller will fall and this will increase the sellers' incentives to create more confusion to raise the share of uninformed buyers in the market. Therefore, increased competition will lead to more complexity and more confused buyers.

In this vein, the goal of this paper is to examine empirically how increasing the number of sellers affects market outcomes when sellers can confuse buyers. Specifically, I look at how increased competition affects the amount of complexity generated by sellers and the consequences for buyer surplus. In principle, one would expect that increased competition would lead to a fiercer price competition. This would result in lower prices and higher buyer surplus. However, if the sellers make their goods more complex in response to increased competition the buyers may not be able to identify the best deal in an increasingly complex market. If increased competition leads to more complexity and consumer confusion sellers may not compete in prices fiercely. As a result market prices may not fall.

I examine two questions regarding the effects of increasing the number of sellers in a market. First, does increased competition lead to more obfuscation by sellers?

And second, how is the buyer surplus affected by increasing the number of sellers in a market? To answer these questions, I use laboratory experiments, designing a setup in which sellers can confuse buyers using product or price complexity. The market institution employed in the experiment is a posted-offer market where the sellers are setting prices and complexity level for their goods and then the buyers make their purchasing decisions. I conduct two studies: A quality complexity study based on Kalaycı and Potters (2011) and a price complexity study based on Kalaycı (2011). In the quality complexity study the sellers have vertically differentiated goods with different quality levels. Each seller first chooses the number of attributes for her good which affects the complexity of buyers' evaluation of the good . Then the sellers decide on prices and after that the buyers make purchases given the complexity and price choices of the sellers. In the price complexity study the sellers are offering an identical good and they decide on the price and the number of fees for their good, where a higher number of fees potentially makes it harder for the buyer to calculate the price of the good. In both studies, the treatment variable is the number of sellers; there are treatments with two and three sellers in each study.

In both quality complexity and price complexity studies I find that sellers use complexity and this leads buyers to make suboptimal choices. I find that increased competition has no effect on the number of attributes or the number of fees chosen by the sellers, suggesting the incentives to confuse are not affected by the number of sellers. Moreover, I find that buyer surplus in the treatments with three sellers is significantly higher than buyer surplus in treatments with two sellers. The results indicate that, although buyer confusion induced by sellers might be a concern, increased competition does not exacerbate such concerns and still benefits buyers through lower prices and higher buyer surplus.

This paper also contributes to the literature on the number effects in experimental oligopolies. Dufwenberg and Gneezy (2000) find in markets with Bertrand competition that prices are lower when there are four rather than two sellers in a market. Huck et al. (2004) examine the effect of number of sellers on collusion in Cournout oligopolies. They find some collusion with two firms, while there is no evidence of collision in markets with three, four and five firms. Orzen (2008) examines the effect of competition on prices in markets where a large portion of the buyers (convenience shoppers) are simulated to purchase randomly. He finds that transaction prices are lower in markets with four sellers than with two sellers under a fixed matching protocol but no difference is observed when random matching is used. Abbink and Brandts (2007) find that prices decrease with the number firms in Bertrand competition with decreasing returns. Papers in this literature use simulated demand schedules. The main methodological difference of my paper however is that human buyers are used, which can potentially be confused by sellers.

5.2 The Experiment

The experiment is a posted offer market experiment with human buyers and sellers as participants. Each seller is offering a good the quality of which is exogenously determined and is common knowledge to sellers. Sellers decide on the price and the complexity of their good, details of which I will explain below. Then, given the goods offered by sellers the buyers make their choice among the goods in the market under a strict time limit. Each buyer can purchase one good and his surplus equals the quality minus the price of the good he chooses.

In the experiment I endogenize complexity using two different methods. In the quality complexity (QC) study each seller can make her good more complex by choosing the number of attributes of her good, which can potentially affect the buyers' evaluation of the quality of the good. In the price complexity (PC) study each seller chooses the number of tariffs for the price of her good, which can potentially hinder the buyer's evaluation of the price of the good.

Although the basic design of the two studies are quite similar, there are a number of differences as well. I will explain first the QC study then the PC study. You can find a summary of the treatment differences in Table 5.1.

Table 5.1: Main properties of the treatments

	Quality complexity		Price complexity	
	QC2	QC3	PC2	PC3
Number of sellers	2	3	2	3
Number of buyers	2	2	3	3
Quality of goods in a market	Heterogeneous	Heterogeneous	Identical	Identical
Decision time for buyers	15 seconds	15 seconds	10 seconds	10 seconds
Complexity & price choice	Sequential	Sequential	Simultaneous	Simultaneous
Size of a matching group	4 sellers and 4 buyers	6 sellers and 4 buyers	4 sellers and 6 buyers	6 sellers and 6 buyers
Number of matching groups	4	4	4	4
Number of periods	30	30	30	30
Total number of subjects	32	40	40	48

Quality complexity (QC) study

I first describe the buyers' decision problem. There are two buyers in a market. Each buyer can choose to buy one of the goods in his market, or to refrain from buying. Each buyer's surplus is equal to the quality minus the price of the good he chooses. However, the buyer doesn't directly observe the quality. Each good in the market has five so-called attributes and each attribute has a different weight. The buyer's surplus from buying a particular good is:

$$Surplus = 5 * q_5 + 4 * q_4 + 3 * q_3 + 2 * q_2 + 1 * q_1 - Price$$

where q_i is the quality level of the i'th attribute of the good that is chosen. The information is presented to the buyer on screen as follows:

Product / Weight	5	4	3	2	1	Price
Good A	0	4	4	11	36	50
Good B	0	0	0	0	73	45

Figure 5.1: Example quality complexity

In this example, if the buyer chooses good A his surplus equals to: $5*0+4*4+3*4+2*11+1*36-50 = 16+12+22+36-50 = 36$, whereas if he chooses good B his surplus equals to $73-45 = 28$. The buyer has 15 seconds to make his choice and this time limit is binding. If the buyer does not make a choice within the time limit, he does not buy a good and earns a surplus of 0.

As you may notice, evaluating the surplus from a good that has fewer attributes is easier given the time limits. As I will explain below the number of attributes is a decision variable for sellers in the experiment.

In the first stage, sellers are informed about the quality of each others' goods, which is a number between 60 and 100. The quality level of each good is determined by a random draw at the beginning of the game. There is a separate and independent draw for each seller, therefore the sellers quality levels are (potentially) different.

After being informed about the quality levels the sellers make decisions about the number of attributes and the price for their good. In this study, these decisions are made sequentially. Each seller first decides on the number of attributes for her good. Upon being informed about each others' number of attributes each seller chooses a price for her good.

The sellers can choose a number of attributes from 1 up to 5. Depending on the number of attributes that a seller chooses, the exogenous quality of the good is randomly allocated over the attributes such that the following is satisfied:

$$5 * +4 * q_4 + 3 * q_3 + 2 * q_2 + 1 * q_1 = Quality$$

If the number of attributes chosen is 1 then $q_1 = Quality$ and $q_2 = q_3 = q_4 = q_5 = 0$. If the number of attributes chosen is 2 then the quality is randomly allocated over q_1 and q_2, such that $2 * q_2 + 1 * q_1 = Quality$ and $q_3 = q_4 = q_5 = 0$. And so on when the number of attributes chosen is 3, 4 or 5. In all cases, the algorithm makes sure that the quality levels of all attributes are integers. In one page of the instructions which is exclusively for the sellers, this procedure is explained. Moreover, it contains the following text: "Notice that the number of attributes you choose will not affect the surplus of the buyers since the quality of your good is unaffected by it. However, the calculation of surpluses may get harder or easier depending on the number of attributes of your good." After choosing the number of attributes the sellers decide on the price of their good given the quality and the number of attributes of each good. The sellers have zero cost and profits are equal to the price of a good times the number of sales (0, 1 or 2). Note that the number of attributes has no direct impact on sellers' profits.

There are two treatments in this study; one with two sellers (QC2) and one with three sellers (QC3).

Price complexity (PC) study

There are three buyers in a market in the PC study. The buyer directly observes the quality but not the price of the goods. Instead the price is presented in the form of multiple fees. Each goods price has three so-called fees and each fee has a different weight. The buyer's surplus from buying a particular good is:

$$Surplus = Quality - (Fee1 + 2 * Fee2 + 3 * Fee3)$$

The information was presented to the buyer on screen as follows:

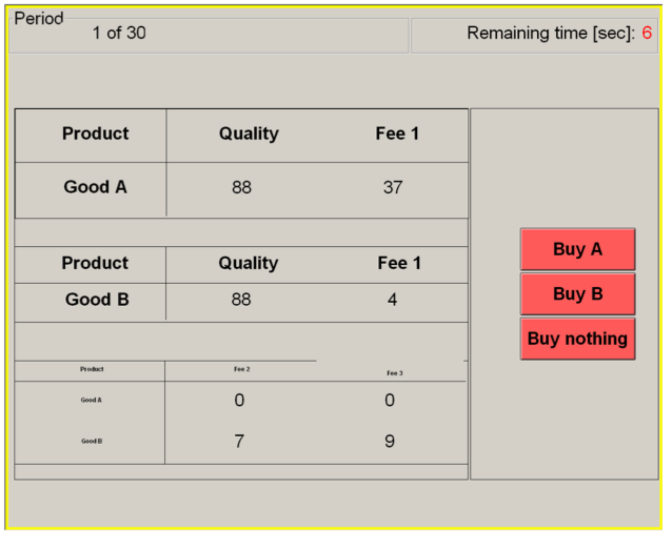


Figure 5.2: Example price complexity

In this example, if the buyer chooses good A her surplus equals: $88 - 37 = 51$, whereas if she chooses good B her surplus equals to $88 - (1*4+2*7+3*9) = 43$. The buyer has 10 seconds to make this choice and this time limit is binding. If the buyer does not make a choice within the time limit, she does not buy a good and earns a surplus of 0.

In contrast to the QC study, in this study there is only one quality draw, therefore the sellers are offering an identical good. Also, the sellers choose the number of fees and the price of their good simultaneously.

Each seller has to decide on the price, which has to be a non-negative integer and the number of fees. For the number of fees the sellers have three options; One Fee, Two Fees or Three Fees. Depending on the number of fees they choose their price is randomly distributed among the fees such that $Fee\_1 + 2 * Fee\_2 + 3 * Fee\_3 = Price$. If a seller chooses One Fee then the price she chose equals Fee_1. If she chooses Two Fees then the Price is randomly distributed among Fee 1 and Fee 2 such that $Price = Fee\_1 + 2 * Fee\_2$ while Fee 3 equals zero. If she chooses Three Fees, then her price is distributed among Fee 1, Fee 2 and Fee 3 such that $Price = Fee\_1 + 2 * Fee\_2 + 3 * Fee\_3$. Similar to the QC study the number of fees and the quality of a good do not effect the profit of the sellers directly. The profit of a seller is the price of her good times the number of buyers (0, 1, 2 or 3) that choose her good. The sellers have no costs and are able to serve all the buyers if the buyers choose their good.

As in QC study, there are two treatments; one with two sellers (PC2) and one with three sellers (PC3).

Procedure

The QC studies were conducted at CentERLab of Tilburg University and the PC studies were run at the Experimental Economics Laboratory at the University of Melbourne. The experiment was programmed and conducted with the software zTree (Fischbacher 2007).

At the beginning of a session subjects were placed behind computer terminals where they could find the written instructions. The instructions including the buyers' decision were read out loud by the experimenter, while some details about the sellers' decision were left for them to be read on their own. After the subjects finished reading the instructions a short quiz was run to make sure the participants understood the instructions. At the end of the experiment subjects were paid their accumulated earnings in cash and in private.

The game was played by subjects for 30 periods and subjects were informed about this. At the beginning of the experiment subjects were randomly assigned to be either a buyer or a seller and they retained this role for all periods. In addition, matching groups consisting of 4 (6) sellers and 4 (6) buyers were formed randomly. In each period, the subjects in a matching group were allocated to two markets using a stranger matching protocol. The subjects' identities were kept anonymous, a seller could not know which of the other sellers she was matched with or what the decisions of any particular seller or buyer were in previous periods.

The experimental sessions lasted about 90 minutes. 160 student subjects participated in the experiments. The subjects in the QC study earned 12 Euros and the subjects in the PC study earned on average 32 Australian dollars, which was about 20 Euros at the time of the study.

Research questions

The main research question in this paper is the effects of increased competition on the amount of obfuscation created by the sellers.

In addition I am interested in what happens to the buyer surplus. This a more intriguing question since it is determined by both the prices that sellers post and the accuracy of decisions that buyers make. It is possible that increased competition does not affect the prices but lead to more decision errors or lower the prices without affecting the decision errors. In this regard the following questions guide the analysis of the results that are presented in section 3:

1. How will increased competition affect the number of attributes and fees chosen by sellers?

2. How will the number of sellers affect market prices?

3. Will the buyers make more or less errors when the number of sellers is three instead of two?

4. And finally how will the buyer surplus be affected by the number of sellers?

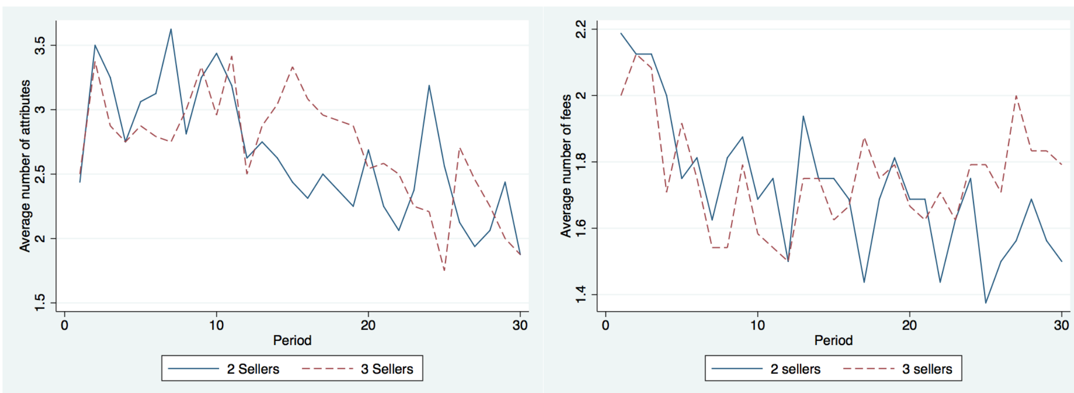
These questions will guide the analysis and lead to the results presented in the following section.

5.3 Results

In this section, I present the results from both of the studies. All the analysis are based on data from period 3 until 30. Treatment effects are examined with a Wilcoxon-matched pairs signed rank test using the averages of a matching group as the unit of observation. Reported p-values in parenthesis are two sided. First, I examine the effects of increased competition on the level of complexity the sellers choose and then the transaction prices. Then, I look at the rate of mistakes and foregone surplus due to the mistakes. Lastly, I examine the net effect of increased competition on buyer surplus.

Obfuscation

I start with examining the effect of increased competition on the average complexity in a market, which is the main research question in this paper. Figure5.3a shows the *average number of attributes* in QC and Figure 5.3b shows the *average number of fees* in the PC treatments.



(a) Quality complexity (b) Price complexity

Figure 5.3: Obfuscation

Result 1. Average complexity in a market is not affected by the number of sellers in the market.

The sellers in the QC2 treatment choose 2.6 attributes on average, whereas in QC3 treatment the average number of attributes is 2.7. The difference between the average number of attributes in QC2 and QC3 is not significant (p-value= 0.77). In the PC2 treatment the sellers on average choose 1.7 fees while in the PC3 treatment average number of fees chosen by the sellers is also 1.7. The difference is statistically not significant (p-value= 0.39).

Table 5.2 displays results from an ordered probit regression for QC and PC studies. The dependent variables are the number of attributes and the number of fees chosen by a seller in QC and PC studies, respectively. The dummy variable *Three sellers* takes value 1 if the treatment is with three sellers and 0 otherwise. *Three sellers* has no significant effect on the number of attributes as can be seen in column 1 of Table 5.2 . Similarly, in PC the coefficient for *Three sellers* is not significantly different from zero as seen in column 2. Figure 3 suggests that both the average number of treatments in QC and the average number of fees in PC are declining over time. The regression results displayed in Table 5.2 confirm this. The *Period* number is negatively related with the number of attributes chosen in QC and the number of fees chosen in PC . The *Quality difference* between the seller with the highest quality and the seller with the second highest quality has no effect on the number of attributes. The Quality of the goods in a market has a slightly positive effect on the number of fees chosen in PC. The interaction variables that interact *Three sellers* with *Period* and *Quality difference* in QC, and with *Period* and *Quality* in PC are not significant, suggesting no differential effect of increased competition on complexity choice.

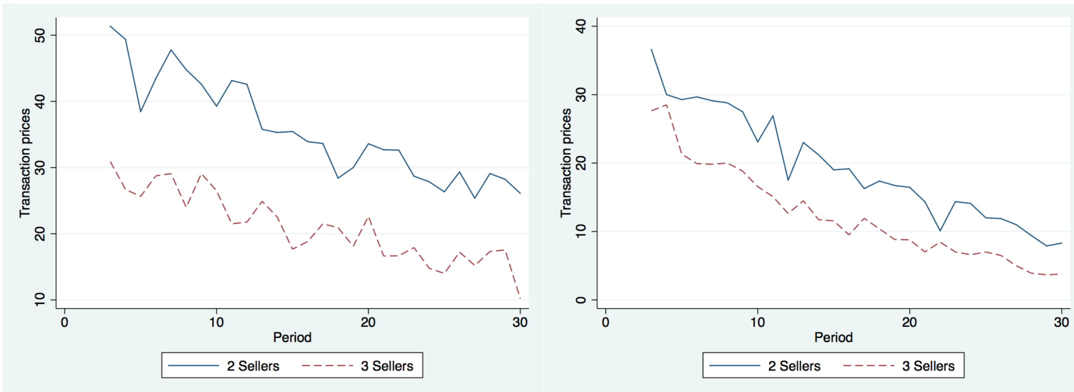
Table 5.2: Obfuscation

	Number of attributes	Number of fees
Period	-0.03 (0.01) **	-0.02 (0.01) *
Three sellers	-0.02 (0.37)	-0.01 (0.75)
Quality difference	0. 00 (0.01)	-
Quality	-	0.01 (0.00) *
Period x Three sellers	0.00 (0.01)	0.02 (0.01)
Quality diff. x Three sellers	-0.00 (0.01)	-
Quality x Three sellers	-	-0.00 (0.01)
# of Observations	1120	1120

notes: Ordered probit model; standard errors clustered at the independent group level; * indicates statistical significance at 10%, ** indicates statistical significance at 5%. standard errors in parentheses. Period >2.

Prices

Figure 5.4a and Figure 5.5b displays average transaction prices for QC and PC treatments, respectively. The straight lines in Figure 5.4 shows the average transaction prices for treatments with two sellers and the dashed line shows the average transaction prices for treatments with three sellers. The prices in all treatments display a negative time trend, which is common in posted offer markets with random matching (Bruttel, 2009).



(a) Quality complexity

(b) Price complexity

Figure 5.4: Transaction prices

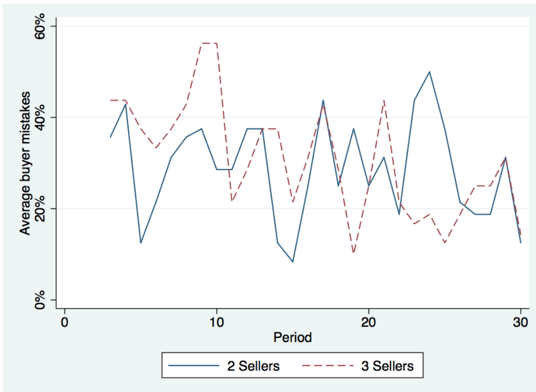
Result 2. Average prices in a market is lower when the number of sellers in a market is three than when the number of sellers is two.

On average the transaction prices are 37.2 points in QC2 and 23.7 points in QC3. The difference between the average transaction prices is significant (p-value=0.02). Similarly, the average transaction prices are significantly higher in PC2, 23.1 points, than in PC3 treatment, 16.8 points (p-value=0.02).

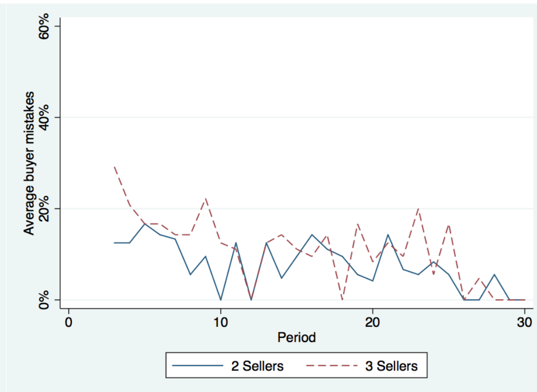
Buyer mistakes

One of the key aspects of the experiment was to create an environment where the buyers can potentially make mistakes and the sellers can affect the amount of mistakes using the complexity mechanism. Figures 5.5a and 5.5b display the development of average buyer mistakes over time for each treatment. A mistake is defined as the buyer purchasing a good that offers a surplus lower than one of the other goods in the market or refrains from buying while there is a good with a positive surplus.

Result 3. Average buyer mistakes in a market is not affected by the number of sellers in the market.



(a) Quality Complexity



(b) Price Complexity

Figure 5.5: Buyer mistakes

In QC2 the buyers make a mistake around 29% of the time while in QC3 they make a mistake 31% of the time. The difference between the average buyer mistakes in these two treatments is not significant (p-value = 0.77). In PC study the buyers also make a significant amount of mistakes. In PC2 the buyers make a mistake around 8% of the time while in PC3 they make a mistake in 12% of the time, while the difference is not statistically significant (p-value = 0.25).

Table 5.3 displays regression results for the relationship between the number of mistakes and the complexity choices of the sellers. The dependent variable in all the regressions in Table 5.3 is a binary variable that takes value 0 if the buyer purchases the good that offers the highest surplus and value 1 if the buyer chooses a good with lower surplus or refrains from buying while there is a good with a positive surplus.

Column 1 shows regression results for the QC study. The variable *Period* has a negative coefficient, indicating some learning throughout the sessions. *Three sellers* has no significant effect on the mistakes the buyers make. Increasing the *Average number of attributes* leads to more mistakes only in QC3. Buyer mistakes are negatively related with the variable *Surplus Difference*, the surplus difference between the best two goods in a market.

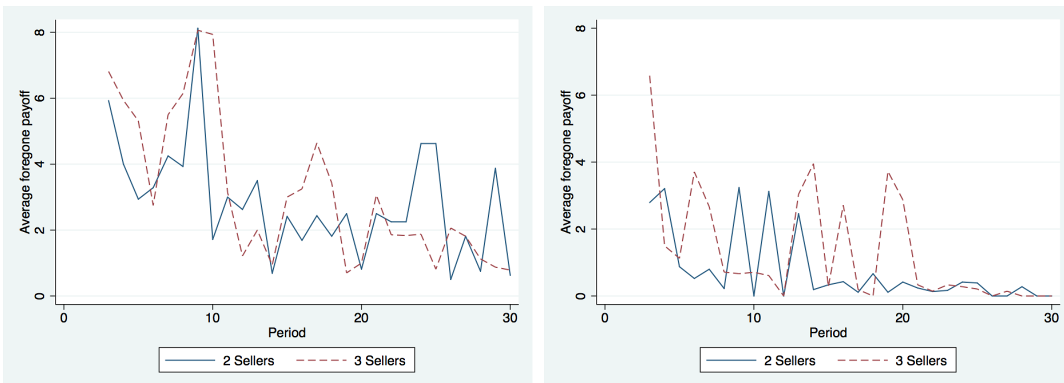
Table 5.3: Buyer mistakes

	Quality complexity	Price complexity
Constant	-0.41 (.21) *	-2.96 (.50) **
Period	-0.02 (.01) **	- 0.06 (.00) **
Three sellers	-0.02 (.50)	- 0.33 (.59)
Surplus difference	- 0. 04 (.01) **	-0.08 (.04) **
Average number of attributes	0.06 (.09)	-
Average number of fees	-	0.94 (.21) **
Period x Three sellers	-0.03(.04)	-0.03 (0.01) **
Surplus diff. x Three sellers	- 0.03 (.03)	-0.08 (.05)
Av. # of attributes x Three sellers	.027 (.12) **	-
Av. # of fees x Three sellers	-	0.79 (.28) **
# of Observations	848	1152

notes: Logit model with random effects and standard errors clustered at the independent group level; * indicates statistical significance at 10%, ** indicates statistical significance at 5%. standard errors in parentheses. Period >2; observations with Surplus difference equal to 0 are omitted.

Column 2 shows regression results for the PC study. Buyer mistakes are negatively related with *Period*, while this effect is more pronounced in PC3 since the interaction variable *Period* x *Three sellers* has a negative coefficient. As in QC, buyer mistakes are not affected by *Three sellers*; increasing the number of sellers in a market doesn't affect the rate of mistakes buyers make. As in regressions for QC study the variable *Surplus Difference* is negatively related with the buyer mistakes, suggesting that buyers make fewer mistakes when the mistakes are more costly. The buyer mistakes are positively related with the *Average number of fees* in a market, while average number of fees have a significantly larger effect in PC3 relative to PC2.

Figure 5.6a and Figure 5.6b illustrate the direct cost of making mistakes in QC and PC studies, respectively. In QC2 buyers lose on average 2.83 points by making a suboptimal choice, which is about 6% of the optimal surplus. In QC3 buyers for ego on average a surplus of 3.2 points, which is about 5% of the optimal surplus in that treatment. The difference between average *foregone surplus* in QC2 and QC3 is not significant (p-value =1). In the price complexity study, buyers on average lose .83 points (1% of the optimal surplus) in PC2 and 1.4 points(2% of the optimal surplus) in PC3. The difference between average *foregone surplus* in PC2 and PC3 is significant (p-value=0.04)[3].



(a) Quality complexity

(b) Price complexity

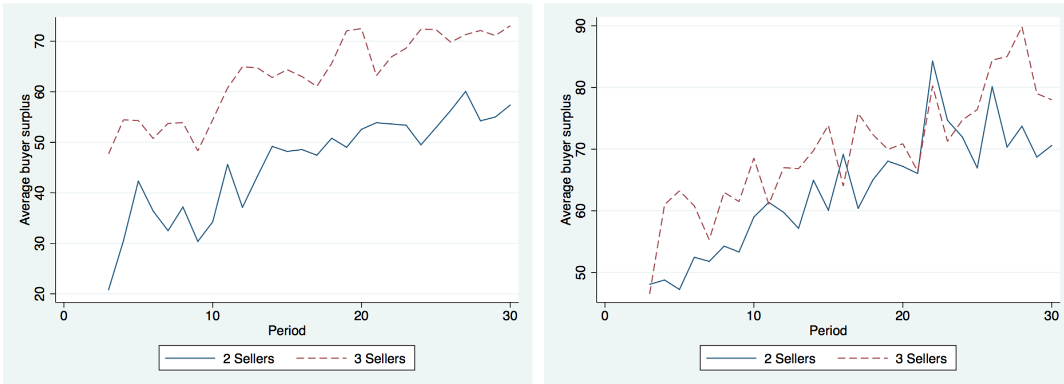
Figure 5.6: Foregone surplus

Buyer surplus

Lastly, I examine the effects of increased competition on buyer surplus. So far, we have observed that transaction prices are lower and buyers make similar amount of mistakes in treatments with three sellers compared to treatments with two sellers. Figure 5.7 shows that the net effect of increased competition is advantageous for buyers.

Result 4. Buyer surplus is higher when the number of sellers in a market is three than when the number of sellers is two.

[3]However, there is no significant difference when the average percentage loss is used (p-value =0.24)



(a) Quality complexity (b) Price complexity

Figure 5.7: Buyer surplus

Figure 5.7a and Figure 5.7b displays the development of average buyer surplus over time for QC and PC studies, respectively. The straight lines show the average buyer surplus for treatments with two sellers and the red line shows the average buyer surplus for treatments with three sellers. On average the buyer surplus is 45.8 points in QC2 and 62.22 points in QC3. The difference between the average buyer surpluses is significant (p-value=0.04). Similarly, the average buyer surplus is significantly lower in PC2, 63.83 points, than in PC3 treatment, 69.47 points (p-value=0.02).

Table 5.4 reports regression results for the relationship between buyer surplus and the complexity choices of the sellers. Column 1 shows that in QC, buyer surplus increases with increasing the number of sellers from two to three. Also, we observe a positive time trend in buyer surplus. *Average number of attributes* has a negative impact on the buyer surplus in QC. Column 2 displays regression results for the PC study. Similar to QC study, increasing competition increases the average buyer surplus. Buyer surplus increases over time while *average number of fees* has no effect on the buyer surplus.

Table 5.4: Buyer surplus

	Quality complexity	Price complexity
Constant	36.36 (5.34) **	46.25 (4.07) **
Period	0.97 (.15) **	1.00 (0.07) **
Three sellers	14.41 (7.29) **	10.82 (6.48) *
Average number of attributes	-2.49 (.85) **	-
Average number of fees	-	0.06 (1.67)
Period x Three sellers	-0.10(.20)	-0.04 (0.17)
Av. # of attributes x Three sellers	1.79 (1.55)	-
Av. # of fees x Three sellers	-	-2.03 (2.53)
# of Observations	896	1344

notes: Logit model with random effects and standard errors clustered at the independent group level; * indicates statistical significance at 10%, ** indicates statistical significance at 5%. standard errors in parentheses. Period >2.

5.4 Conclusion

I show that increased competition in the form of increasing the number of sellers has no effect on the sellers' propensity to confuse buyers. In addition, prices are lower and buyer surplus is higher when the number of sellers in a market is larger. These results suggest that sellers' ability to confuse buyers is not by itself a concern against increasing competition in markets.

The results clearly contradict the theoretical results in Gabaix and Laibson (2004) and Carlin (2009), who suggest that increasing the number of sellers will lead to more obfuscation. Pinning down exactly where these models depart from the actual behavior of buyers and/sellers require further research. One key issue seems to be in the specifications of the behavior of confused buyers. Even though buyers get confused due to complexity in my experiments they avoid making very costly mistakes. This probably puts a bound on how much sellers can abuse the ability to confuse by charging high prices.

Naturally, these findings are limited to the comparative statics in duopoly and triopoly markets. It is possible that competition has a non-monotonic or maybe a

U shaped affect on confusion and prices in markets. This may especially be true in markets with very large number of competitors since the amount of confusion is likely to be much larger in those environments. For example in financial markets, Hortacsu and Syverson (2004) find that entry into the S&P index fund industry in 1995–1999 was associated with a rightward shift in the distribution of prices. However, it remains an open empirical question whether this shift is related to consumer confusion and price complexity in these markets.

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