



Price complexity and buyer confusion in markets[☆]



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ABSTRACT

This paper reports a duopoly market 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. 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 but influences buyers' ability to calculate the good's price. The main results show that high-price sellers choose high complexity more often than low-price sellers if buyers are simulated in accordance with the bounded rationality model of Carlin (2009). However, the evidence for this effect is weaker if the buyers are human subjects. Importantly, prices are higher when the sellers can confuse buyers using price complexity than when sellers interact with perfectly rational robot buyers.

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1. Introduction

Is it worth the price? This is a question we often ask when considering a purchase. 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 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 land line, 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

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actual cost. The prevalence of complex pricing as well as other forms of complexity in markets raises the question whether it is reasonable to expect consumers to obtain 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 from switching. Moreover, 20–30% of the consumers actually reduced their surplus as a result of switching. [Kling et al. \(2012\)](#) demonstrate a lack of switching in the Medicare Part D prescription drug plans in the United States and show that many consumers are unable to take advantage of the free and widely advertised information. In a similar vein, [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. 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 states: “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](#); for a graduate level textbook, see [Spiegler, 2011](#)). 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, with only a fraction of buyers (experts) purchasing the good with the lowest price. The rest of the buyers (uninformed buyers) purchase randomly. The share of experts is determined endogenously and is a decreasing 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 the present paper, I use [Carlin \(2009\)](#) as the theoretical framework that guides the experimental setup and the hypotheses.

In the present paper, by conducting a series of experimental studies, I investigate two main questions derived from [Carlin \(2009\)](#). First, are high-price sellers more likely to obfuscate buyers than low-price sellers? And second, are prices in markets higher when buyers are susceptible to obfuscation via price complexity? I conduct a duopoly posted-offer market experiment where sellers offer identical goods to buyers with homogeneous preferences. Sellers simultaneously choose the price and the number of components of their price and then buyers make their choice between the two goods. Each price can have up to three components where the number of price components does not affect the value or the price of a good. However, a higher number of components can make it more difficult for the buyer to calculate the price of a good. The results show that high-price sellers are more likely to choose a higher number of price components if the buyers are simulated in accordance with the bounded rationality model of [Carlin \(2009\)](#). However, this relationship is weaker when subjects are human buyers. Market prices are higher when the sellers can obfuscate buyers using price complexity than when perfectly rational robot buyers are used. Additionally, in a follow-up individual choice experiment, buyers make more mistakes when price differences between the two goods are small, even when such mistakes are as costly as when price differences are large.

In investigating the usage of price complexity by sellers and its effects 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's 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 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, when consumers have time-inconsistent preferences and are partially naive about this. They show that firms price investment goods below marginal cost while pricing leisure goods above marginal cost; 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 over-borrowing and paying high penalties for late payments.

The theoretical papers in this literature most related to [Carlin \(2009\)](#) are [Piccione and Spiegler \(2012\)](#) and [Chioveanu and Zhou \(2013\)](#). The novelty of [Chioveanu and Zhou \(2013\)](#) compared to [Carlin \(2009\)](#) is that they distinguish between price frame differentiation and price frame complexity. The model of [Piccione and Spiegler \(2012\)](#) on the other hand, is a more general version of the duopoly version of [Chioveanu and Zhou \(2013\)](#) and also introduces default effects.

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 \(2011\)](#) 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. There is related experimental literature that follows the [Varian \(1980\)](#) search framework and examines seller behavior under different market conditions (unlike the present paper, these papers use simulated buyers). For example, [Cason and Friedman \(2003\)](#) show that price dispersion can arise when buyers have search costs. [Morgan et al. \(2006\)](#) find evidence for price dispersion when some buyers are captive (i.e. uninformed about the price).

The present paper is most closely related to [Kalaycı and Potters \(2011\)](#). While, [Kalaycı and Potters \(2011\)](#) duopoly market experiment examines complexity on the quality dimension of goods, the present paper looks at the effects of complexity on the price dimension. Price complexity is different from quality complexity as, while quality is exogenously given to sellers in these experiments, price is a choice variable. This makes the interaction between price and complexity choice more interesting. Additionally, unlike [Kalaycı and Potters \(2011\)](#), the present paper provides insights by providing tighter control on the behavior of agents on both sides of the market by experimentally simulating buyer behavior in Study 2 and simulating seller behavior in Study 3.

The present paper is organized as follows: In Section 2, I briefly describe the model of [Carlin \(2009\)](#), which is the theoretical framework used for the experimental setup. In Sections 3 and 4, I present the design and the results of three studies. Study 1, presented in Section 3, examines the effects of price complexity using human subjects as buyers. Study 2, also in Section 3, provides tighter control on the buyers decisions by adding treatments with robot buyers that are simulated according to theory. In Section 4, I conduct an additional study (Study 3) to identify how complexity and price differences affect buyers' decisions. In Section 5, I conclude by discussing the implications of the results for economic theory and policy.

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 has a 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 its 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 $\sigma_j \in [0, v] \times [\underline{k}, \bar{k}]$.

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

The condition $\partial\mu/\partial k_j < 0$ implies that by increasing its price complexity firm j makes the market less transparent, thereby decreasing the share of experts. The second condition $\partial^2\mu/\partial k_j \partial k_l = 0$ 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 a continuous and strictly increasing distribution function $F^*(p)$ and choose complexity according to the map*

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

Although the uniqueness of a specific $F^(p)$ cannot be proven, the ex ante probability that each firm chooses high complexity \bar{k} is uniquely determined to be $[1/n]^{1/(n-1)}$. 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 the 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 decreases with each firm's price complexity ($\partial\mu/\partial k_j < 0$). This implies that, by increasing its price complexity, a seller would lead more buyers to make sub-optimal 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 relationship between the inherent difficulty in evaluating a competing firm's offer and the share of experts ($\partial^2\mu/\partial k_j\partial k_l = 0$).

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

The mixed strategy equilibrium is a common feature of models with buyer search that have a similar setup to that [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 are 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 where 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 tariff components 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 \(2009\)](#).

3. Study 1 and 2

In this section, I describe in detail the procedures used in the experimental sessions of Study 1 and 2. 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 tighter control of the buyers' behavior and to focus on sellers' decisions. 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, so that the behavioral assumptions of the theory can be tested.

3.1. 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 two sellers and three 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 make their decisions, buyers decide whether and from which seller to buy a unit of good.

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 [Fig. 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

Period		1 of 30		Remaining time [sec]: 6	
Product	Quality	Fee 1		<input type="button" value="Buy A"/> <input type="button" value="Buy B"/> <input type="button" value="Buy nothing"/>	
Good A	88	37			
Product	Quality	Fee 1			
Good B	88	4			
Product	Fee 2	Fee 3			
Good B	0	0			
Good B	7	9			

Fig. 1. Buyer's screen.

Period		1 of 30		Remaining time [sec]: 45	
You are selling		Good B			
Quality of Good A is		88			
Quality of Good B is		88			
Your Price		<input type="text"/>			
The fee structure for your good		<input type="radio"/> One Fee <input type="radio"/> Two Fees <input type="radio"/> Three Fees			
Press OK when you made your choices.					
					<input type="button" value="OK"/>

Fig. 2. Seller's screen.

that good; i.e. $Quality - (Fee_1 + 2 * Fee_2 + 3 * Fee_3)$. For making the purchasing decision the buyer has *10 seconds*. If the buyer does not make a decision in *10 seconds* it is assumed that he chooses not to buy any of the goods.

In the first stage, the sellers are informed about the quality of the goods in the market as shown in the sample screen in Fig. 2. 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 between the fees such that $Fee_1 + 2 * Fee_2 + 3 * Fee_3 = Price$. If a seller chooses One Fee then Fee_1 equals her price. 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 $Price = Fee_1 + 2 * Fee_2 + 3 * Fee_3$. 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 choose their good.

After the buyer's decisions are finalized both sellers and buyers view 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, number of fees, sales and profits for both goods. The feedback screens also included a history table where the information from previous periods is displayed.

Table 1
Probability of an error and expected sales.

Total # of fees	Each buyers' prob. of making an error	Expected # of sales	
		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

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

In Study 1 there are two 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 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 provides a test for [Hypothesis 2](#).

Study 2 differs from Study 1 only with respect to the treatments that are run. There are three treatments. I run the 10 seconds treatment of Study 1 again as a benchmark since Study 2 is conducted at a different location. To prevent confusion, I call this treatment “human” treatment in this study. The second treatment in Study 2 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 in Study 2 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 that the buyer will, in principle, buy the goods with the highest payoff but that the buyer may make an “error”, that is, buy the good with the lower payoff. The probability that the buyer makes an error increases with the total number of fees chosen by the two sellers. The probability that a buyer makes a mistake is 5% when both sellers choose to have *One Fee*, and the error rate increases by 5% with every additional fee. [Table 1](#) displays the specific relationship between the total number of fees, the probability of a buyer error and the expected number of sales.

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

This mechanism underlying the buyers' mistakes in *boundedly rational robot* ensures that both [Assumption 1](#), the rate of mistakes increases with each seller's increasing complexity, and [Assumption 2](#), 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 who choose a higher price are more likely to choose *Three Fees* than sellers who 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*.

3.2. Procedure

The experiments for Study 1 were conducted at the Experimental Economics Laboratory at the University of Melbourne, while the experiments for Study 2 were conducted at the CentERLab at Tilburg University. The experiments were 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 (see the online Appendix for the instructions). The instructions, including the buyer's decision, were read out loud by the experimenter, while some details of the seller's decision were left for the sellers to read on their own. The participants were told: “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 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, four matching groups each consisting of four sellers and six buyers were formed randomly. For the robot buyer treatments, matching groups consisted of four sellers. 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 could not know which of

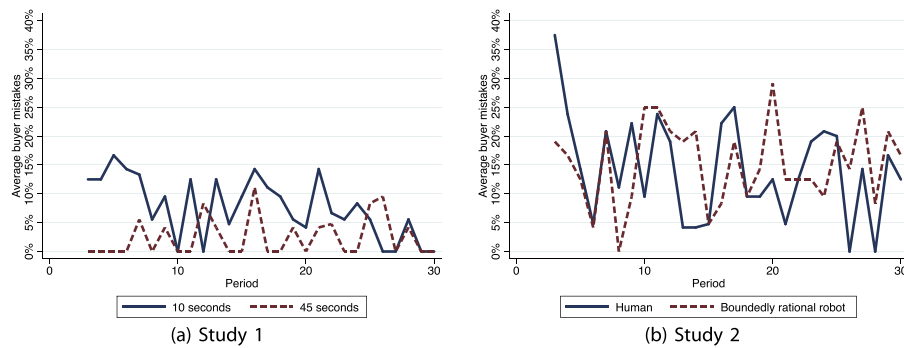


Fig. 3. Buyer mistakes.

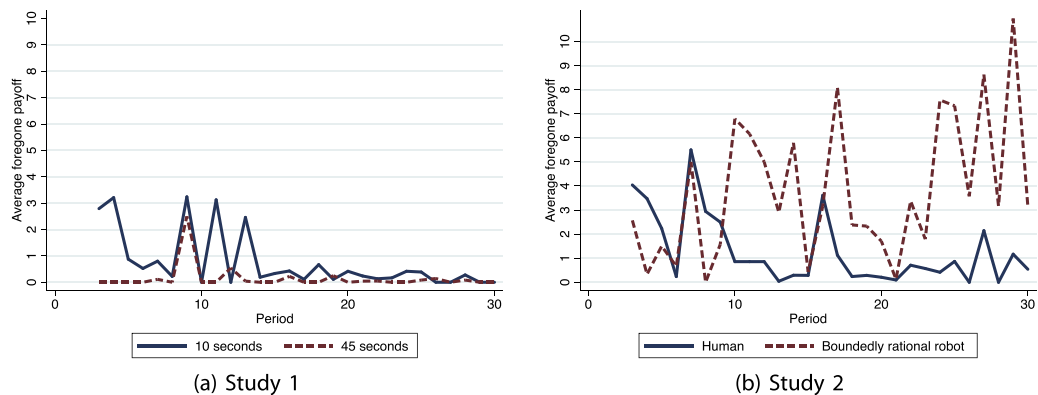


Fig. 4. Foregone payoff.

the other three sellers she was matched with or what decisions any particular seller or buyer had made in previous periods. The purpose of this was to preserve the one-shot nature of the game.

The experimental sessions lasted about 90 min. Eighty student subjects participated in Study 1 and 72 subjects participated in Study 2. The number of matching groups was four in each treatment. Earnings were denoted in points and transferred to cash at a rate of 100 points = 1 EUR in Tilburg and 60 points = 1 AUD in Melbourne. The subjects earned on average 33 Australian dollars in Study 1, which was about 20 Euros at the time of the study. Subjects in Study 2 earned 15 Euros on average.

3.3. Results of Study 1 and 2

3.3.1. Buyers' choices

The main purpose of the experimental setup was to create an environment where buyers could potentially make sub-optimal choices, particularly in *10 seconds* and *human*. In the analyses concerning buyers' choices data from periods 3 to 30 are used. Fig. 3 displays for each treatment the development over time of the 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.¹ 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). The rate of mistakes for *boundedly rational robot* is 15% and for *human* it is 14%. (p -value = 0.39).²

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. Fig. 4 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

¹ Refraining from buying is extremely rare (less than 1%) in all treatments; it happens only in the first five periods and is almost always due to subjects running out of decision time.

² Although *human* is a replication of *10 seconds*, there are significant differences between these two treatments, especially in error rates and complexity choices. These discrepancies are likely due to subject pool differences in culture and background. While both subject groups are drawn from a pool of undergraduate students, the majority of subjects in Tilburg are Business/Economics students while most subjects in Melbourne study Science/Engineering.

Table 2
Buyer mistakes.

	10 seconds		45 seconds		Human	
	Model 1	Model 2	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)	−0.07 (0.02)**	−0.08 (0.02)**
Total number of fees	2.20 (0.26)**	2.49 (0.41)**	1.36 (0.30)**	1.29 (0.29)**	1.43 (0.64)**	1.69 (0.58)**
A's # of fees × B's # of fees	−0.92 (0.18)**	−1.06 (0.18)**	−0.36 (0.13)**	−0.34 (0.14)**	−0.34 (0.20) [†]	−0.42 (0.19)**
Price difference	–	−0.11 (0.05)**	–	−0.24 (0.09)**	–	−0.15 (0.04)**
# of observations	405	405	336	336	548	548

Notes. Logit model with subject fixed effects and standard errors clustered at the independent group level.

[†] Statistical significance at 10%.

** 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.

= 0.02). 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.

According to [Assumption 1](#), the number of buyer mistakes increases with the number of fees of each good in a market. 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 total number of fees of the two goods 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.

[Table 2](#) displays the results of this regression for each treatment. Columns 1 and 2 show the regression results for 10 seconds, columns 3 and 4 for 45 seconds, and columns 5 and 6 for *human* 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.

The regression results displayed in [Table 2](#) show that the total number of fees of the two goods have a positive effect on the probability of a buyer making a mistake in all three treatments. This is in line with [Assumption 1](#). 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 in all three treatments. 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. Model 2 adds the variable *Price difference* to Model 1 to examine this. In all three treatments, the coefficient for *Price difference* has negative sign and is statistically significant, indicating that the buyers make fewer mistakes when the price difference is larger.

In the regression results the only qualitative difference between the treatments with human subjects is the time trend. While subjects are found to make fewer errors over time in 10 seconds and *human*, learning is nonexistent (Model 2) in 45 seconds.

3.3.2. 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 seller who has the highest price and the seller who has the lowest price in a particular market at a given period. [Fig. 5a](#) 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.

Result 1.1. In 10 seconds, sellers that choose a higher price are more likely to choose *Three Fees* than sellers who 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 [Fig. 5a](#) 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-price sellers choose *Three Fees* 32% of the time while low-price 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 a 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). The relationship between price and high complexity for the 45 seconds treatment is presented in the second graph in [Fig. 5a](#). On average high-price sellers choose *Three Fees* 36% of the time while low-price sellers choose *Three Fees* 38% of the time. The difference is not significant (p -value = 0.577). Considering that 45 seconds does not satisfy the structural assumptions of [Carlin \(2009\)](#), this result does not contradict [hypothesis 1](#).

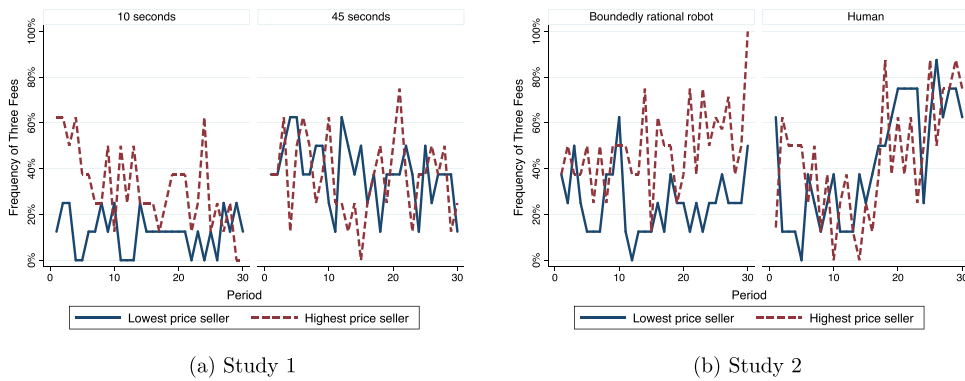


Fig. 5. Frequency of high complexity.

Table 3

Frequency of fee choices and price correlations.

Treatment	Number of fees			Correlation with prices
	One fee	Two fees	Three fees	Spearman's rho
10 seconds	50%	28%	22%	0.30**
45 seconds	38%	24%	37%	0.01
Rational robot	47%	28%	25%	0.19**
Boundedly rational robot	51%	12%	37%	0.61**
Human	32%	24%	44%	-0.02
All Treatments	44%	23%	33%	0.21**

** Statistical significance at 5%.

Fig. 5b displays the average percentage of choosing *Three Fees* for high- and low-price sellers in the *boundedly rational robot* and the *human* treatments.

Result 1.2. 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 Fig. 5b shows that in *boundedly rational robot* the rate of choosing *Three Fees* is higher on average for sellers who have a higher price. High-price sellers on average choose *Three Fees* 49% of the time while low-price 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). Another way to examine the relationship between prices and the number of fees is to look at the correlation between the price choice of a seller and her fee choice. The last column in Table 3 displays Spearman correlations between *price* and *number of fees* for all treatments. The correlation is positive and highest in *boundedly rational robot* (p -value < 0.01) but non-existent in *45 seconds* (p -value = 0.79) and in *human* (p -value = 0.56).

Although, at the theoretical equilibrium, sellers should never choose moderate complexity of *Two Fees*, a substantial proportion of them still do. Table 3 displays the frequency of different fee choices across treatments. Frequency of *Two Fees* is similar in all treatments except it is significantly lower in *boundedly rational robot* than in *rational robot* (p -value = 0.04).

3.3.3. Price levels

Hypothesis 2 suggests 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, although 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 2.1. There is no significant difference between the average prices in *10 seconds* and *45 seconds* treatments.

Fig. 6a displays the development of average prices over time for both treatments in Study 1. In both treatments, a negative time trend in prices is observed. On average, sellers in *10 seconds* charge a price of 22 points while sellers in *45 seconds* charge 22.7 points. The difference is not significant (p -value = 0.38).

Result 4. In Study 2, the prices are lowest in the *rational robot* treatment and highest in the *boundedly rational robot* treatment.

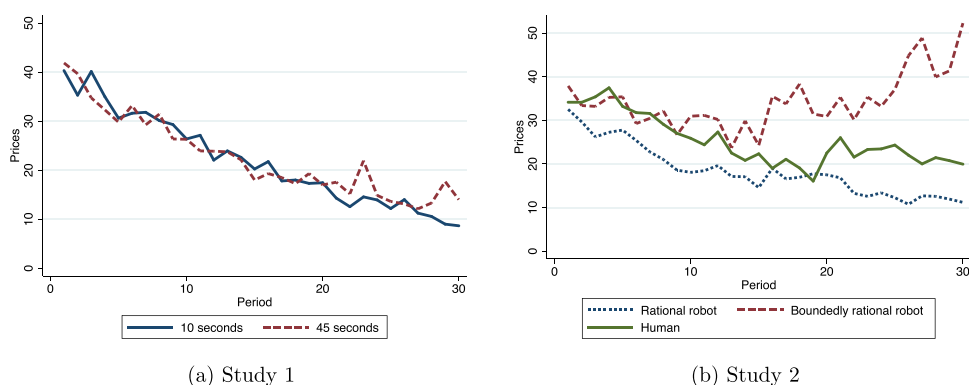


Fig. 6. Average prices over time.

Fig. 6b displays the development of average prices across 30 periods for all three treatments in Study 2. 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 *boundedly rational robot*. The average price in *human* is higher than the average price in *rational robot* (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 also persists at the end of the session. If we look at the last 10 periods of play the average prices in *human* is 22.2, while it is 12.7 points in *rational robot* (p -value = 0.04, one-sided).

The price pattern for *boundedly rational robot* 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* begin to increase and this trend continues till the end of the experiment. Average prices in *boundedly rational robot* are higher than *inhuman* (p -value = 0.02, one-sided). The prices in *rational robot* buyer are lower than *inboundedly 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.

3.4. 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 2](#). 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, the buyers' rate of errors was 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.

In the robot buyer treatments in Study 2, the demand side is simulated which provides tighter control on buyers' behavior. The results of Study 2 from *boundedly rational robot* provides support for [Hypothesis 1](#). In *boundedly rational robot* high-price sellers choose high complexity more often than low-price 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-price 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; 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 in *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.³

³ Many sellers learn, over time, how to optimally exploit the robot buyers and start charging the maximum price (combined with high complexity). For example, out of 53 instances where a seller charges a price close to (within five points of) its quality level, 48 of them are in *boundedly rational robot*. The effects of this pricing behavior is also reflected in the higher cost of errors for buyers in *boundedly rational robot* in the second half of the experiment ([Fig. 4b](#)). In the treatment with human buyers, sellers rarely try offering a high price as human buyers are not as susceptible to exploitation as the robot buyers.

The results from Study 2 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. Study 3

4.1. Motivation

Results from Study 1 and Study 2 suggest that the theory performs reasonably well when the buyers in the experiment are simulated according to the theoretical assumptions in [Carlin \(2009\)](#), but performs poorly when the buyers are human subjects. This suggests that the assumptions of the model regarding the buyers' behavior are imperfect. A particular finding with regards to buyer behavior is that buyers' mistakes are negatively related to the price difference in *human*, while this is not the case in *boundedly rational robot*.⁴ In Study 3, I further examine the robustness of this finding by focusing on the buyers' behavior in an individual choice experiment. In this study, I vary the price and complexity levels in a within-subject treatment variation, and the buyers' incentive to make an accurate decision with a between-subjects variation.

4.2. Design and procedure

Study 3 is an individual decision-making experiment where subjects play the role of buyers. The task of the buyers in Study 3 is identical to the task of buyers in *10 seconds* of Study 1. The difference is that the prices and complexity level of the goods participants face are computer generated instead of being determined by human sellers. This enables the generation of prices that are widely dispersed and with complexity levels that are independent of the price levels of each seller.

The specifics of the price- and complexity-generating process for the two goods in the "market" are as follows. The complexity level is varied such that a third of the time both Good A and Good B had only one fee, a third of the time both goods had three fees, and the remaining third of the time Good A had one fee and Good B had three fees. The price and quality levels are varied in a way that half of the time the quality level of both goods are randomly drawn from the range [60,100] points and the prices are drawn from the range [20,60] points (*Low Price Level* treatment). In the other half of the periods the quality level of both goods are randomly drawn from the range [600,1000] points and the prices are drawn from the range [200,600] points (*High Price Level* treatment). To generate different levels of price differences in half of the periods the prices of the two goods were bound to be within five points of each other in *Low Price Level* and within 50 points in *High Price Level* (*Low Price Difference* treatment). In the other half of the periods no restrictions have been imposed on price differences (*High Price Difference* treatment). These variations create 12 treatments which are quasi-randomly allocated to 12 periods and the ordering of these 12 periods is repeated five times leading to 60 decision periods.

Buyers' decision process at a given period – including the decision screens, the time allowed to make a decision and the type of feedback – was identical to that of the buyers in *10 seconds*. However, as mentioned above, buyers in Study 3 played the game for 60 periods instead of 30 in order to generate more data points for each individual. In addition to the game described above (which will be called *VariablePay* treatment from here on), there is another treatment (to be called *FixedPay* treatment) where the buyers' payoff is determined differently. In *FixedPay*, buyers received a fixed payoff of 300 points for each correct choice and 0 for a mistake; i.e., choosing the good that offers a strictly lower payoff than the other good or failing to make a decision on time.

The rest of the experimental procedure was the same as in the first two studies, except that the experiments for Study 3 were conducted at the economics laboratory at the University of Queensland in late 2013. Thirty subjects participated in *VariablePay* session and 23 participated in the *FixedPay* session. The game was played by subjects for 60 periods and the exchange rate was 1000 points = 1 AUD. The sessions lasted about 60 min and the subjects on average earned 27 AUDs.

4.3. Hypotheses

The main goal of Study 3 is to test the implicit assumption in [Carlin \(2009\)](#) that buyers' mistakes are independent of the payoff differences between the goods in a market. The following hypothesis is formulated to test this assumption:

Hypothesis 3.1. Price differences have no effect on buyers' mistake rate.

Results from Study 1 and 2 suggest that human subjects make fewer mistakes over time but it is hard to attribute this result to learning as the price levels also go down throughout the experiments. It is possible that subjects are more confused when the price levels are higher, for example due to increased cognitive load in working memory ([de Fockert et al., 2001](#)).

⁴ This relationship between price differences and buyer mistakes can potentially explain the lack of correlation between high prices and higher complexity in *human*. For example [Basov and Danilkina \(2015\)](#) present a model based on the probabilistic choice model of [Luce \(1959\)](#), where the probability of choosing a good depends on the utilities offered by the goods in the market and the level of aggregate obfuscation. They show that equilibrium prices depend on the aggregate obfuscation level but not on a particular firm's obfuscation investment.

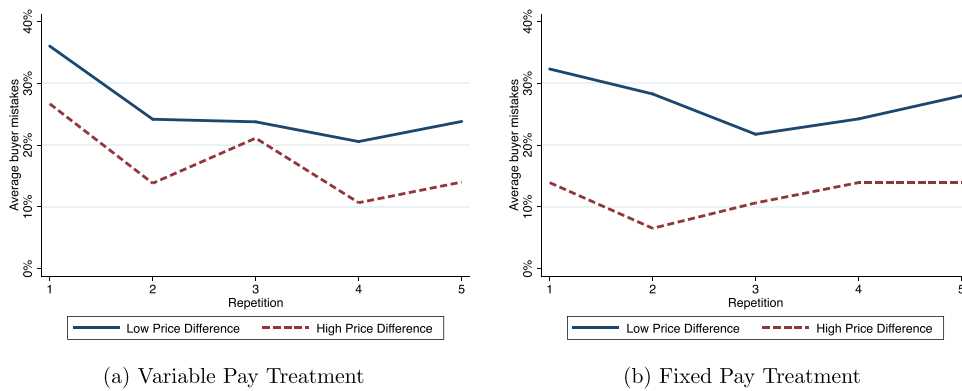


Fig. 7. Buyer mistakes and price differences.

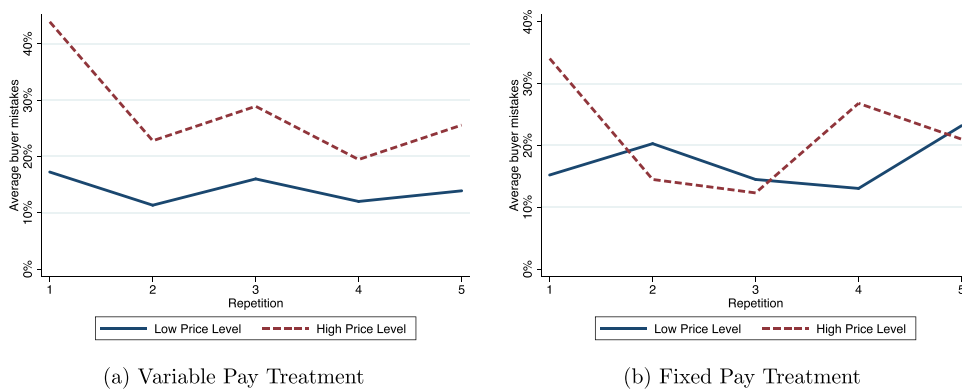


Fig. 8. Buyer mistakes and price levels.

Hypothesis 3.2. The rate of buyer mistakes is higher at higher price levels.

The next hypothesis is based on Assumption 2 of Carlin (2009), which suggests that increasing the price complexity of a seller leads to an increase in buyer mistakes.

Hypothesis 3.3. The buyers' mistake rate increases with the level of price complexity in the market.

The finding in Study 1 and 2 that buyer mistakes decrease with price differences can be attributed to “rational inattention”; i.e., as the cost of making a mistake is lower when the payoffs of the two goods are similar, buyers have lower incentives to pay attention to the prices of the goods. By comparing *VariablePay* and *FixedPay*, we can test whether the cost of making a mistake plays a role in the accuracy of buyer decisions.

Hypothesis 3.4. There is no difference in error rates between *VariablePay* and *FixedPay*.

4.4. Results of Study 3

Fig. 7a displays the average mistake rates for the *VariablePay* treatment across small and large price difference trials over time. In *VariablePay*, the average rate of mistakes when price differences are small is 23%, while it is 17% when price differences are large. The difference is significant (p -value = 0.01). Fig. 7b displays the development of mistakes over time in *FixedPay* for small and large price differences. Buyers on average make a mistake 28% of the time when price differences are small, and 11% of the time when price differences are large. The difference is significant (p -value < 0.01). These results are contrary to Hypothesis 3.1 and the assumption of Carlin (2009) that price differences have no effect on error rates.

Result 3.1. Buyers make significantly more mistakes when price differences between the two goods are small than when they are large. This is true in both *VariablePay* and in *FixedPay*.

Fig. 8 displays the average mistake rates across low and high price level trials over time. In *VariablePay* (Fig. 8a) the rate of mistakes when price levels are low (13%) is 15% smaller than when the price levels are high (28%) (p -value = 0.01, one-sided). The difference between low and high price level trials is smaller (5%) in *FixedPay* but it is still significant (p -value = 0.02, one-sided). Hence we support Hypothesis 3.2, that the rate of buyer mistakes is higher at higher price levels.

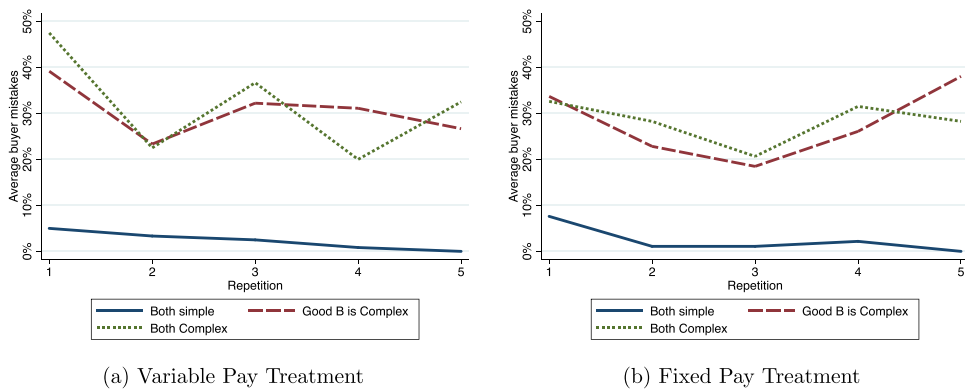


Fig. 9. Buyer mistakes and price complexity.

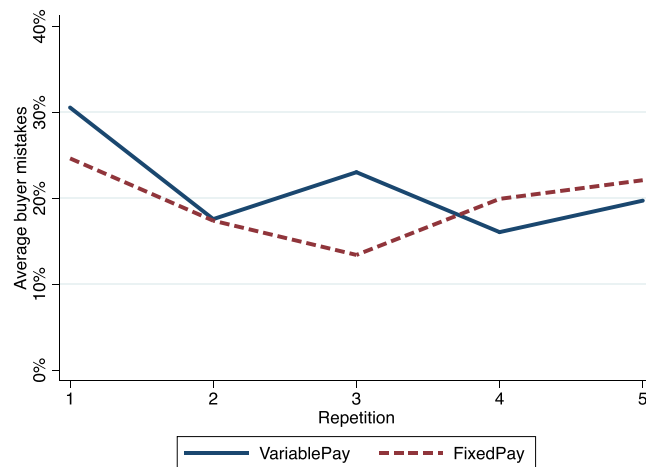


Fig. 10. Percentage of buyer mistakes across payment schemes.

Result 3.2. The buyers' mistake rate is higher when price levels are high than when they are low. The price level effect is larger in *VariablePay* than it is in *FixedPay*.

The first graph in Fig. 9 shows the average rate of mistakes in *VariablePay* for the three complexity levels present in the choice task. In *VariablePay*, buyers on average make a mistake 2% of the time when both goods have simple fees, 30% of the time when only Good B has complex fees and 32% of the time when both goods have complex fees. The last difference is not significant (p -value = 0.38, one-sided). Similarly, in *FixedPay*, buyers make the lowest number of mistakes when both goods are simple (2%, p -values < 0.01), and there is no difference between the rate of mistakes when only Good B has complex fees (28%) and when both goods have complex fees (28%) (p -value = 0.4, one-sided).

Result 3.3. Buyers make the least number of mistakes when both goods have simple fees. Mistake rates are not different when both goods have complex fees than when only one good has complex fees.

Buyers on average make a mistake 22% of the time in *VariablePay* (Fig. 10) and 19% of the time in *FixedPay*. The difference is not significant (p -value = 0.4).

Result 3.4. There is no significant difference in buyers' mistake rates between *VariablePay* and *FixedPay*.

In order to further examine the effects of price differences, price levels and price complexity on error rates, I run a binary logit regression on the probability of making a mistake using the total number of fees of the two goods in the market, interaction term for the number of fees of the two goods, the period number, the (absolute) price difference between the two goods and a dummy variable for when price level is high as explanatory variables.

The first column in Table 4 displays the regression results for *VariablePay* and the second column displays the results for *FixedPay*. The coefficient estimates of all variables are qualitatively similar for both treatments. The regression results in Table 4 show that the total number of fees of the two goods has a positive effect on the probability of a buyer making a mistake. This is in line with Assumption 1 and the regression results of 10 seconds and human. 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 again goes against Assumption 2, which says that price complexity decisions of the two sellers are neither strategic substitutes nor

Table 4
Buyer mistakes.

	Human buyers					
	Variable pay			Fixed pay		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Period	–0.01 (0.00)**	–0.01 (0.00)**	–0.01 (0.00)**	–0.00 (0.00)	–0.00 (0.00)	–0.00 (0.00)
Total number of fees	2.29 (0.43)**	2.30 (0.42)**	2.31 (0.43)**	2.18 (0.26)**	1.97 (0.25)**	1.99 (0.26)**
A's # of fees × B's # of fees	–0.73 (0.15)**	–0.74 (0.15)**	–0.75 (0.15)**	–0.74 (0.10)**	–0.63 (0.10)**	–0.63 (0.10)**
Price difference	–0.01 (0.00)**	–	–	–0.01 (0.00)**	–	–
Price difference is low	–	0.81 (0.14)**	0.81 (0.15)**	–	1.10 (0.13)**	1.13 (0.13)**
Price level is high	1.36 (0.19)**	1.00 (0.16)**	1.00 (0.17)**	1.00 (0.20)**	0.28 (0.18)	0.32 (0.19)
Fee difference	–	–	–0.01 (0.09)	–	–	0.16 (0.06)**
# of observations	1710	1710	1710	1380	1380	1380

Notes. Logit model with subject fixed effects and standard errors clustered at the individual level.

* Statistical significance at 10%.

** Statistical significance at 5%.

Standard errors in parentheses. Observations with payoff difference equal to 0 are omitted.

complements. The coefficient for *Price difference* has a negative sign and is statistically significant, indicating that the buyers make fewer mistakes when the price difference is larger. The coefficient for *Price level is high* is positive and significant in most model specifications. Finally, I add a variable *Fee Difference*, which measures the difference between the number of fees of the good that offers the higher payoff and the good that offers the lower payoff. The coefficient for *Fee Difference* is significant in *FixedPay*, indicating that having a more complex fee hurts the seller with lower price in this treatment.

4.5. Discussion

The results from Study 3 provide additional insights regarding buyers' behavior that is helpful in understanding where the theory falls short. In line with the results from *10 seconds* and *human* treatments, I find that buyers make more errors when the prices of the two goods are similar. Potentially, this effect can be due to two mechanisms. First, detecting small differences might be cognitively more difficult. Second, buyers might display “rational inattention”; i.e., make mistakes when mistakes are financially less costly. The fact that *Price difference* has a negative effect on errors in *FixedPay* supports the first mechanism, as the financial cost of making a mistake does not depend on price differences in that treatment.

Lastly, I find that buyers make more mistakes when they are dealing with high price (and quality) levels. This is surprising as the financial loss from making mistakes at high-price levels is likely to be higher as well. Again, the fact that the price level effect is also present in *FixedPay* calls for alternative explanations. One possible explanation is that dealing with larger numbers is cognitively more demanding for buyers (de Fockert et al., 2001).

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? Second, are prices in markets higher when buyers are prone to making errors?

The main finding is that high-price 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 who 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 by 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 Kalayci and Potters (2011), who find that in a posted offer market experiment, 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 buyers' choice accuracy) is affected only by the price complexity in the market.⁵ However, the results from *human* treatment suggest that price differences also matter. Human buyers can only be fooled by the sellers if the value of the goods in the market are not too different. By focusing only on the buyers' decision, Study 3 confirms that price differences and price levels have an effect on buyers' susceptibility to make sub-optimal choices.

⁵ The assumption that the level of buyer confusion is independent of the value difference of the goods in the market is not exclusive to Carlin (2009). For example, Piccione and Spiegler (2012) assume that the probability that a consumer will switch from the default firm depends only on price formats, not on the actual prices. Chioveanu and Zhou (2013) discuss the possibility of modeling price complexity by allowing “noisy price comparisons” but do not report any results.

The standard skepticism toward 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 A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.jebo.2015.01.001>.

References

- Basov, S., Danilkina, S., 2015. *Bertrand oligopoly with boundedly rational consumers*. *B.E. J. Theor. Econ.* 15, 107–123.
- Baye, M., Morgan, J., Scholten, P., 2006. *Information, search, and price dispersion*. In: Hendershott, T. (Ed.), *Handbook on Economics and Information Systems*. Elsevier Science, Amsterdam, pp. 323–371.
- Carlin, B.I., 2009. *Strategic price complexity in retail financial markets*. *J. Financ. Econ.* 91, 278–287.
- Cason, T., Friedman, D., 2003. *Buyer search and price dispersion: a laboratory study*. *J. Econ. Theory* 112, 232–260.
- Chetty, R., Looney, A., Kroft, K., 2009. *Saliency and taxation: theory and evidence*. *Am. Econ. Rev.* 99, 1145–1177.
- Chioveanu, I., Zhou, J., 2013. *Price competition with consumer confusion*. *Manage. Sci.* 59 (11), 2450–2469.
- DellaVigna, S., Malmendier, U., 2004. *Contract design and self-control: theory and evidence*. *Q. J. Econ.* 119 (2), 353–402.
- Ellison, G., 2006. *Bounded rationality in industrial organization*. In: Blundell, R., Newey, W.K., Persson, T. (Eds.), *Advances in Economics and Econometrics: Theory and Applications, Ninth World Congress*, vol. 2. Cambridge University Press, Cambridge/New York, pp. 142–174.
- Fischbacher, U., 2007. *z-Tree: Zurich toolbox for ready-made economic experiments*. *Exp. Econ.* 10, 171–178.
- de Fockert, J.W., Rees, G., Frith, C.D., Lavie, N., 2001. *The role of working memory in visual selective attention*. *Science* 291 (5509), 1803–1806.
- Gabaix, X., Laibson, D., 2006. *Shrouded attributes, consumer myopia, and information suppression in competitive markets*. *Q. J. Econ.* 121 (2), 505–540.
- Heidhues, P., Koszegi, B., 2010. *Exploiting naivete about self-control in the credit market*. *Am. Econ. Rev.* 100, 2279–2303.
- Kalaycı, K., Potters, J., 2011. *Buyer confusion and market prices*. *Int. J. Ind. Org.* 29 (1), 14–22.
- Kling, J., Mullainathan, S., Shafir, E., Vermeulen, L., Wrobel, M.V., 2012. *Comparison friction: experimental evidence from medicare drug plans*. *Q. J. Econ.* 127 (1), 199–235.
- Luce, R.D., 1959. *Individual Choice Behavior: A Theoretical Analysis*. Wiley, New York.
- Morgan, J., Orzen, H., Sefton, M., 2006. *An experimental study of price dispersion*. *Games Econ. Behav.* 54 (1), 134–158.
- Piccione, M., Spiegler, R., 2012. *Price competition under limited comparability*. *Q. J. Econ.* 127 (1), 97–135.
- Pigou, A.C., 1920. *The Economics of Welfare*. Macmillan, London.
- Salop, S., 1977. *The noisy monopolist: imperfect information, price dispersion and price discrimination*. *Rev. Econ. Stud.* 44, 393–406.
- Sitzia, S., Zizzo, D.J., 2011. *Does product complexity matter for competition in experimental retail markets? Theory Decis.* 70 (1), 65–82.
- Spiegler, R., 2006. *Competition over agents with boundedly rational expectations*. *Theor. Econ.* 4, 207–231.
- Spiegler, R., 2011. *Bounded Rationality and Industrial Organization*. Oxford University Press.
- Varian, H.R., 1980. *A model of sales*. *Am. Econ. Rev.* 70, 651–659.
- Wilson, C.M., Waddams Price, C., 2010. *Do consumers switch to the best supplier? Oxf. Econ. Pap.* 62 (4), 647–668.