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Buyer confusion and market prices

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ABSTRACT

We 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.

1. Introduction

"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).

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, bluetooth, 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?

The main reason for product complexity is product differentiation. Different people have different preferences so firms provide differentiated products. The more heterogenous 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

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decisions of the sellers. What is not possible in the lab – or 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.[1] 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 (2007) 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 20–30% 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 (Besedes et al., 2009; Payne, Bettman, Johnson, 1993). 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 (Carlin, 2009; Gabaix and Laibson, 2004; Spiegler, 2006). 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.

2. The model

In this section we develop a duopoly model with vertically differentiated products and boundedly rational buyers with homogenous 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.

2.1. Demand and profit functions

The buyers have homogenous 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

[1] 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.

the difference between the utilities u_1 and u_2 only with some noise ε. This noise is a random variable with support $[-b,b]$, density function $f(x)$ and distribution $F(x)$. The variable b is determined by the sellers' product complexity decisions (see below). For simplicity we assume that $F(x)$ is uniform continuous. 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:

$$\begin{aligned}\pi_1(p_1,p_2) &= p_1F(\Delta)\\ \pi_2(p_1,p_2) &= p_2F(-\Delta)\end{aligned} \tag{2}$$

2.2. 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:

$$\begin{aligned}F(\Delta)-p_1f(\Delta) &= 0\\ F(-\Delta)+p_2f(-\Delta) &= 0\end{aligned} \tag{3}$$

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 $b\le\frac{Q}{3}$, 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 $\pi_1^*=\frac{1}{2b}\left(b+\frac{Q}{3}\right)^2$ and $\pi_2^*=\frac{1}{2b}\left(b-\frac{Q}{3}\right)^2$.

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 ($b\le Q/3$), 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. $b>\Delta=Q-\left(p_1^*-p_2^*\right)=\frac{Q}{3}$. Importantly, in this regime the prices of both sellers are increasing in the buyer's rate of confusion (characterized by b).

2.3. 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 $b_i\in\left[0,\overline{b}\right]$ 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 $b_2^*=\overline{b}$. Seller 1's choice of complexity depends on the value of Q relative to $\overline{b}$. If $\overline{b}\le\frac{Q}{\mu}$, Seller 1 chooses $b_1^*=0$; if $\overline{b}>\frac{Q}{\mu}$, Seller 1 chooses $b_1^*=\overline{b}$ (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 $\left(\overline{b}<Q/\mu\right)$, Seller 1 prefers not to add to the noise ($b_1^*=0$). In this case the noise distribution $\left(b=b_1^*+b_2^*=\overline{b}\right)$ ensures that the pricing stage of the game will be in the first regime of Proposition 1 $\left(\text{since } \overline{b}<Q/\mu<Q/3\right)$ where Seller 1 captures the whole market. However, if the level of noise that Seller 2 can bestow on the buyer is sufficiently large $\left(b_2^*=\overline{b}>Q/\mu\right)$, it is in Seller 1's interest to choose the maximum level of noise as well ($b_1^*=\overline{b}$). In this case the noise distribution ($b=b_1^*+b_2^*=2\overline{b}$) ensures that the pricing stage of the game will be in the second regime of Proposition 1 (since $2\overline{b}>2Q/\mu>Q/3$) where both sellers' prices (and profits) are increasing in the noise variance (characterized by b).

2.4. 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. 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).

3.1. 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.

3.2. 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.

At the beginning of the experiment, the participants found their instructions on their tables (See Appendix B for the instructions). 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.

4. Results

In this section we present the results from the experiment. Unless otherwise indicated the statistics and tests are from the main

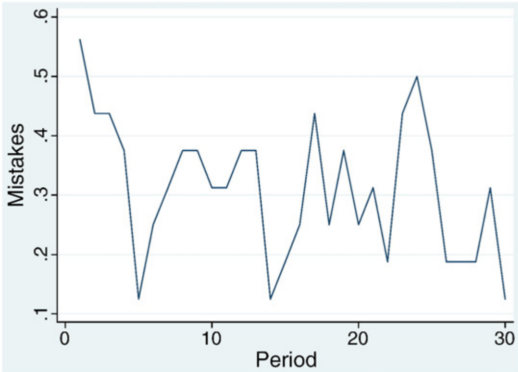

Fig. 1. Fraction of buyer mistakes.

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.

4.1. 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.[2] 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.*

Fig. 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.

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. Fig. 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 Fig. 2b which shows the average payoffs that the buyers forego by making mistakes.

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

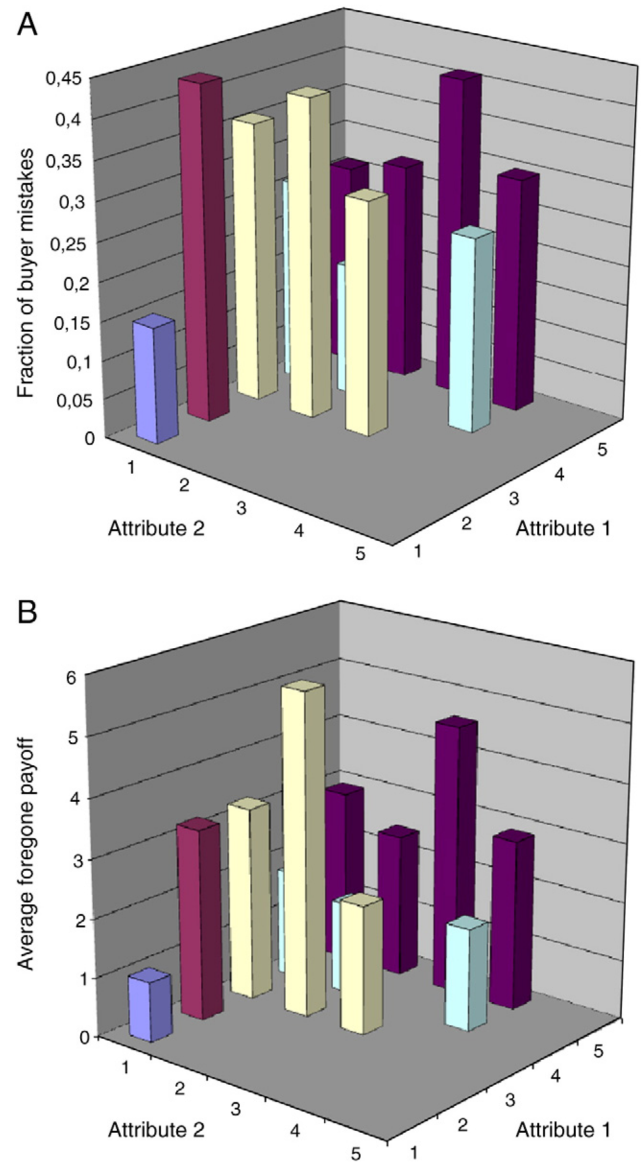

Fig. 2. a. Buyer mistakes by number of attributes. b. Foregone payoff and number of attributes. Note: The vertical axis in Fig. 2a displays the proportion of times buyers purchased from the seller with lower payoff (price–quality). The vertical axis in Fig. 2b gives the average foregone payoff by buyers. 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 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

Table 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.

Table 2

	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 Obs.	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.

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%.

4.2. 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. Fig. 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.

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.[3] This suggest that in terms of the theoretical model we are predominantly in the second regime of Proposition 2 in which both sellers have an incentive to obfuscate. This is partially supported by our second result.

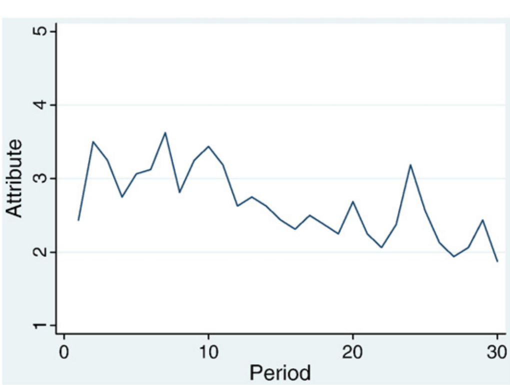

Fig. 3. Average number of attributes over periods.

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.*

The first two columns of Table 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.

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

Table 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.

4.3. 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 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 2 we observe a negative time trend in prices which is often observed in posted offer market experiments with random matching (Bruttel, 2009).[4]

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.[5] 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.

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

[5] 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 4 we add an interaction effect between the number of attributes and being the high quality seller to Model 1 of Table 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.

4.4. 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.

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.*

Fig. 4 displays the development of average transaction prices over time for the treatments with human and robot buyers. Throughout

Table 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 by the other seller; *High quality seller* takes the value of 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.

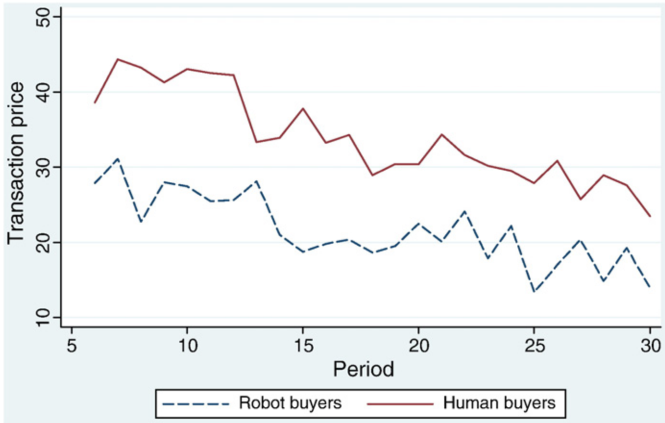

Fig. 4. Average transaction price by buyer type.

Table 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 × 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.

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 ($p = 0.02$).

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 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 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.[6] 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.

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 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.

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Appendix A. Proofs

Proof of Proposition 1. The proof follows the one sided information case of Anderson and Renault (2009). For $\Delta \in [-b, b]$ the expected

[6] 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 and 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.

demand for Seller 1 is $F(\Delta) = \frac{b+\Delta}{2b}$ where $\Delta = Q - p_1 + p_2$. Substituting into the first order conditions gives:

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

Solving for the equilibrium gives:

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

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

For $b \le \frac{Q}{3}$, 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. □

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 $b > \frac{Q}{3}$, we have $\frac{\partial \pi_2}{\partial b} = \frac{1}{18b^2}(9b^2 - Q^2) > 0$ while for $b \le \frac{Q}{3}$ we have $\frac{\partial \pi_2}{\partial b} = 0$. Following this, and $b = b_1 + b_2$, gives $b_2^* = \bar{b}$.

For Seller 1, if $b > \frac{Q}{3}$ we have $\frac{\partial \pi_1}{\partial b} > 0$ whereas $b \le \frac{Q}{3}$ implies $\frac{\partial \pi_1}{\partial b} < 0$. This implies that Seller 1 will set either $b_1^* = 0$ or $b_1^* = \bar{b}$ depending on the value of $\frac{Q}{3}$ relative to $\bar{b}$ and $2\bar{b}$. First, suppose $0 < \frac{Q}{3} < \bar{b}$. Since $b_2^* = \bar{b}$ implies $b > \frac{Q}{3}$, Seller 1 will set $b_1^* = \bar{b}$.Second, suppose $0 < \bar{b} \le \frac{Q}{3} < 2\bar{b}$. If $b_1 = 0$ then $\pi_1 = Q - \bar{b}$. If $b_1 = \bar{b}$ then $\pi_1 = \frac{1}{2b}\left(b + \frac{Q}{3}\right)^2 = \frac{1}{36\bar{b}}\left(Q + 6\bar{b}\right)^2$. 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 $\bar{b} < \frac{\left(\sqrt{2}+2\right)}{12}Q$. Therefore $b_1^* = 0$ when $\bar{b} < \frac{\left(\sqrt{2}+2\right)}{12}Q$ and $b_1^* = \bar{b}$ when $\bar{b} \ge \frac{\left(\sqrt{2}+2\right)}{12}Q$. Lastly, for $0 < \bar{b} < 2\bar{b} \le \frac{Q}{3}$ we have $b \le \frac{Q}{3}$ and $\pi_1 = Q - b$. Since $\frac{\partial \pi_1}{\partial b} < 0$ Seller 1 will set $b_1^* = 0$. □

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi: 10.1016/j.ijindorg.2010.06.004.

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