An Empirical Analysis of Bidding Fees in Name-Your-Own-Price Auctions

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Abstract

Interactive pricing mechanisms integrate customers into the price-setting process by letting them submit bids. Name-your-own-price auctions are such an interactive pricing mechanism, where buyers' bids denote the final price of a product or service in case they surpass a secret threshold price set by the seller. If buyers are given the flexibility to bid repeatedly, they might try to incrementally bid up to the threshold. In this case, charging fees for the option to place additional bids could generate extra revenue and reduce incremental bidding behavior. Based on an economic model of consumer bidding behavior in name-your-own-price auctions and two empirical studies, we analytically and empirically investigate the effects bidding fees have on buyers' bidding behavior. Moreover, we analyze the impact of bidding fees on seller revenue and profit based on our empirical results.

Keywords: Interactive Pricing, Bidding Fees, Laboratory Experiment, Field Experiment

Introduction

Interactive pricing mechanisms that integrate customers into the price-setting process are an essential part of the Web economy and electronic commerce (Bapna et al. 2003; Jap and Naik 2004; Pan et al. 2004; Ratchford 2009). Online marketplaces apply a broad variety of interactive pricing mechanisms, such as ascending bid auctions (e.g., eBay), reverse auctions (e.g., My-Hammer), or name-your-own-price auctions (e.g., Priceline). As opposed to posted prices set by the seller or the retailer, buyers can interactively influence the final price of a product through the submission of bids or the exchange of messages with a seller through the auction interface.

Given certain consumer and market characteristics, the specific design of interactive pricing mechanisms determines consumers' bidding behavior and thus seller revenue and profit. Previous research (for an overview see Bajari and Hortaçsu 2004 or Jap 2007) derives design recommendations for standard online auction mechanisms. However, the Internet has also given rise to new interactive pricing mechanisms such as name-your-own-price auctions, which have generated considerable research interest (e.g., Hann and Terwiesch 2003; Fay 2004; Spann et al. 2004; Wang et al. 2009; Wolk and Spann 2008). Name-your-own-price auctions were pioneered by Priceline, which sells travel services such as airline tickets, hotel rooms or car rentals on its electronic platform. Broadening Priceline's concept, where many firms vie to make a sale to a particular consumer (Pinker et al. 2003), other companies use name-your-own-price auctions to sell products or services in B2C-markets (e.g., low-cost airlines (www.germanwings.com) or software sellers (www.ashampoo.com)). eBay's "Best Offer"-feature is yet another example of this mechanism.

At the outset of a name-your-own-price auction, a seller sets a secret threshold price indicating her minimum acceptable price. A buyer's bid then determines the price of the product if it at least equals the seller's threshold price. Hence, buyers in name-your-own-price auctions always pay the price denoted by their bid. Moreover, information about the seller's threshold price or other buyers' bids is never published. Name-your-own-price auctions differ from standard auctions in that bidders do not compete with each other based on their bid amount but only have to surpass the secret threshold price set by the seller in order for a transaction to occur.

As buyers at Priceline are typically allowed to place one bid for a specific product (e.g., airline tickets) within 24 hours, Priceline's implementation of a name-your-own-price auction has been referred to as a single-bid policy (Hann and Terwiesch 2003). Despite this restriction to a single bid, bidders may place multiple bids, for example, by the illegitimate but practicable use of multiple credit cards (Fay 2004). Thus, perfect enforcement of the single-bid policy may not be feasible. This is part of the reason why some name-your-own-price sellers – including Priceline for some product categories such as calling capacity – have used a multiple-bidding policy to allow their customers to engage in "online haggling" (Hann and Terwiesch 2003) and raise their bids if an initial bid did not surpass the secret threshold price. Given this flexibility to place additional bids, buyers generate a higher expected consumer surplus due to the possibility of transacting at lower prices when they start bidding sequences at lower values. Further, buyers might bid closer to their reservation price with a multiple-bidding policy (Spann et al. 2004). This, in turn, could lead to a higher number of successful bids and increase seller profit.

Nevertheless, buyers could exploit their ability to place multiple bids and – starting at the lowest price – increase their bids with minimum increments. Using such an "epsilon strategy" (Hann and Terwiesch 2003), bidders could ensure that they purchase the product for the minimum price accepted by the seller (i.e., the seller's threshold price). Simultaneously, sellers can employ a number of constraints to avoid such minimum increment bidding behavior. For example, sellers could ask buyers to pay a small monetary fee per bid and thus charge buyers for the additional flexibility they gain over the single-bid format. Given such bidding fees are solely imposed upon the rejection of an initial bid free of charge, they constitute a form of a name-your-own-price auction in-between the single-bid format (i.e., virtually “infinite” bidding fees following the initial bid) and a multiple-bidding policy with no bidding fees.

We distinguish bidding fees from both costs of entry (Samuelson 1985; McAfee and McMillan 1987) and frictional costs (also “search costs” or “bid evaluation costs”) such as the opportunity cost of time necessary to log on the bidding site and to place the bid and the cost of the mental effort to determine optimal bid values (Bakos 1997; Carr 2003; Hann and Terwiesch 2003; Shugan 1980; Snir and Hitt 2003; Stigler 1961). Yet, unlike these frictional costs, bidding fees are explicitly charged by the seller and have to be paid by the buyer on top of her successful bid. Therefore, sellers could use bidding fees to increase profits in name-your-own-price auctions with a multiple-bidding policy. In this case, the profit-increasing effect of bidding fees for a seller depends on the additional profit from these fees and their effect on bidding behavior. Moreover, the use of bidding fees has recently gained momentum with the rise of entertainment shopping platforms such as Swoopo (www.swoopo.com) and DubLi (www.dubli.com).

Factors potentially influencing bidding behavior suggest ambiguous implications for seller revenue and profit. Since bidding fees reduce expected consumer surplus, fewer buyers will have an incentive to engage in a name-your-own-price auction. Moreover, bidding fees could diminish maximum bid values if bidders account for the decreasing consumer surplus, thus reducing the likelihood that bids surpass the seller‘s threshold price. Both effects could reduce the number of products sold and seller revenue. However, bidding fees could encourage bidders to increase consecutive bid values by higher amounts if they want to enhance the likelihood of success with a lower number of bids. This, in turn, could result in a higher degree of price discrimination when some buyers "overbid" the seller's uniform threshold price by a larger amount than other buyers would in a multiple-bidding scenario. Apart from the monetary amount of the bidding fees, employing this strategy could generate higher profit margins and thus increase seller profit.

As a result of this potential benefit, bidding fees as a design option in a name-your-own-price auction require a thorough study of their effect on bidding behavior, revenue and seller profit. Therefore, the aim of this study is to analytically and empirically investigate the effects that bidding fees have on buyers' bidding behavior. The contribution of our paper is fourfold. First, we develop an economic model of bidding behavior to derive theoretical explanations for the effects of bidding fees on bidding behavior in a name-your-own-price auction. Second, we empirically compare multiple-bidding with single-bid policies. Third, we analyze the effects of bidding fees on bidding behavior in two empirical studies: a laboratory experiment with induced valuations and a field study with real-world transactions over the Internet. Fourth, we derive revenue and profit implications from the use of bidding fees based on the data gathered in the field study.

Our paper is structured as follows. In Section 2, we develop an economic model of bidding behavior in a name-your-own-price auction with bidding fees charged by a seller. Building on this model, we provide theoretical hypotheses for bidding behavior in such name-your-own-price auctions. In Section 3, we test our hypotheses in two empirical studies: a laboratory experiment and a field experiment. Further, we use the results of the field experiment to draw revenue and profit implications on the usage of bidding fees for name-your-own-price sellers. Section 4 concludes the paper with final implications and directions for future research.

Analytical Model of Bidding Behavior with Bidding Fees

Bidding can be costly for consumers engaging in online transactions, such as placing a bid in a name-your-own-price auction. First of all, bidders face frictional costs (Hann and Terwiesch 2003; Stigler 1961; Shugan 1980). Additionally, sellers could charge a monetary fee for the option to place a bid and thus manipulate the cost incurred for bidders when placing bids. Extending economic models of consumer bidding behavior in name-your-own-price auctions (e.g., Hann and Terwiesch 2003; Spann et al. 2004), we include monetary fees for the option to place additional bids into our model. Based on the economic rationale of our model, we derive hypotheses for the effect of bidding fees on consumer bidding behavior in a name-your-own-price auction.

Economic Model of Bidding Behavior

In our model of bidding behavior, a consumer only participates in a name-your-own-price auction if she expects a non-negative consumer surplus from submitting a bid (Hann and Terwiesch 2003). Each consumer j has an externally given reservation price r_j. Consumer surplus for the i^{th} bid is given by the difference between a consumer's reservation price and the price she has to pay for the product, less any frictional costs $c_{j,i}$ she would incur. Upon bidding, consumer j chooses the strategy (i.e., the maximum number of bids she submits n_j and respective bid values $b_{j,n_j,i}$) that maximizes her expected consumer surplus ($ECS_{j,n_j,i}$). Bidding fees in our model are contingent on bidding success. That is, bidding fees and the bid amount only have to be paid if the bid is successful, i.e., equal to or above the seller's secret threshold price tp. Thus, the price paid equals the bid value of the successful bid $b_{j,n_j,i}$ plus the sum of all bidding fees f_t for the total number of bids submitted.

The uncertainty about the outcome of a bid is represented in the expected consumer surplus by incorporating the probability that the i^{th} bid is at least equal to the seller's threshold price tp. Further, the expected consumer surplus of the i^{th} bid includes the expected consumer surplus of additional bids because consumers have the option to place such an additional bid in case the i^{th} bid is rejected. Equation (1) gives the expected consumer surplus of the i^{th} bid:

$$(1)\qquad ECS_{j,n_j,i} = \Pr\left(b_{j,n_j,i} \geq tp\right) \cdot \left[r_j - \left(b_{j,n_j,i} + \sum_{t=1}^{i} f_t \right) \right] + \left[1 - \Pr\left(b_{j,n_j,i} \geq tp\right) \right] \cdot ECS_{j,n_j,i+1} - c_{j,i}$$

The expected consumer surplus for the initial bid recursively includes the potential expected consumer surplus of all subsequent bids that consumer j would place (equation (1)). Hence, consumers maximize the expected consumer surplus of the initial bid (i = 1) by choosing the maximum number of bids and respective bid values optimal for them. Assuming a consumer's belief in a uniformly distributed threshold price on $\left[\underline{tp};\overline{tp}\right]$, we can derive closed-form solutions for the optimal bid values of a surplus-maximizing consumer (see Appendix):

$$(2)\qquad b_{j,n_j,i} = \frac{i \cdot \left(r_j - \sum_{t=1}^{n_j} f_t + \sum_{t=i+1}^{n_j} \left(n_j - t + 2\right) \cdot \left(f_t + c_{j,t}\right) \right) + \left(n_j - i + 1\right) \cdot \left(\underline{tp} + \sum_{t=2}^{i} (t-1) \cdot \left(f_t + c_{j,t}\right) \right)}{n_j + 1}$$

Numerical Example

Consider a consumer with a reservation price r_j = 50 €, a belief in a uniformly distributed threshold price on [20 €, 70 €] and frictional costs $c_{j,i}$ = 0.40 €. If the seller charges a bidding fee f = 0.40 € per bid, the consumer will choose the bidding strategy depicted in Figure 1 according to our model of bidding behavior. Thus, our model predicts that the consumer starts with an initial bid $b_{j,n_j=5,i=1}$ = 26.60 € and will submit a maximum number of n_j = 5 bids with a final bid $b_{j,n_j=5,i=5}$ = 45.00 €. If the secret threshold price is at tp = 40.00 €, the consumer will surpass this threshold with her fourth bid $b_{j,n_j=5,i=4} = 41.60$ €, making this fourth bid the actual maximum, successful bid that terminates the consumer's bidding sequence.

== Please insert Figure 1 about here ==

Hypotheses for Bidding Behavior

Based on the economic rationale of our model for bidding behavior in name-your-own-price auctions, we develop hypotheses for the effects of multiple bidding versus a single bid as well as the effects of bidding fees on bidding behavior.

Single versus multiple bidding. Previous research on the two-bid case demonstrated that consumers raise their final bid values in a multiple-bidding format compared to the single-bid case (Spann et al. 2004). It follows from our model of bidding behavior that the final bid values are increasing in the optimal number of bids to be placed (see Appendix). If placing multiple bids is possible and optimal ($n_j > 1$), final bid values will surpass those of the single-bid case ($n_j = 1$) regardless of bidding fees:

Hypothesis 1: Consumers' final bid values are higher in multiple-bidding cases as compared to the single-bid case.

Multiple bidding: Effect of bidding fees. Assuming constant bidding fees f for all bids but the initial one, we can derive the effect of bidding fees on the maximum number of bids consumers place from our economic model of bidding behavior. The expected consumer surplus is decreasing in f as long as consumers increase consecutive bid values (see Appendix). Therefore, an increase in bidding fees reduces the expected consumer surplus for a given number of bids (Spann and Tellis 2006). Consumers only place an additional bid if they expect a non-negative consumer surplus from this bid. An increase in bidding fees will thus have a negative effect on the maximum number of bids n_j if the expected consumer surplus of a consumer's consecutive bid turns negative. This yields our second hypothesis:

Hypothesis 2: Consumers will place fewer bids when bidding fees are present.

A negative effect of bidding fees on entry is consistent with auction theory and is generally attributed to two possible effects. First, a cost effect might lead to a lower number of bids. When bidding is costly, it might be economically rational for consumers to move away from "ratchet bidding" (Easley and Tenorio 2004) and increment bids by larger amounts than the minimum necessary to avoid these costs. Second, in order to reduce the number of potential competitors, consumers engaging in an auction might place fewer bids due to a signaling effect (Daniel and Hirshleifer 1998), often leading to the phenomenon of jump bidding (Avery 1998; Easley and Tenorio 2004). Since no information about the current highest bid is available to competitive bidders in name-your-own-price auctions, this signaling effect should not be observable. However, the intuition of the cost effect does apply to economically rational bidding behavior in name-your-own-price auctions.

One major driver of seller profit when considering the usage of bidding fees in name-your-own-price auctions is the effect bidding fees have on consumers' actual bid values. From our model, we can derive that the effect of bidding fees on actual bid values is positive for all but the final bid (see Appendix). Further, bidding fees reduce the final bid value for all but the single-bid case (since no fees are charged for the initial bid; see Appendix). This leads to our final hypotheses:

Hypothesis 3a: In case of multiple bidding, bidding fees increase the value of consumers' initial bids when compared to a scenario with no bidding fees.

Hypothesis 3b: In case of multiple bidding, bidding fees decrease the value of consumers' final bids when compared to a scenario with no bidding fees.

The economic intuition behind these final hypotheses is driven by two effects. First, consumers want to minimize the total amount of bidding fees and thus reduce the total number of bids. In order to reduce the number of bids needed, consumers increase the value of their bids, enhancing the probability of a successful bid. We capture this effect in Hypothesis 3a. Second, following our argument for Hypothesis 1, consumers' final bids are increasing in the maximum number of bids they place. Conversely, if consumers reduce the maximum number of bids, they will simultaneously reduce the value of their final bid. Hypothesis 3b captures this effect.

Empirical Studies of Bidding Behavior with Bidding Fees

We conducted two empirical studies designed to enhance our understanding of the effects of bidding fees on bidding behavior in name-your-own-price auctions with multiple bidding. In both studies, we systematically varied the level of bidding fees while controlling for other potential influences. Moreover, bidders' decisions had economic consequences for them.

The first study is a laboratory experiment in which we controlled for consumers' valuations of the offered hypothetical products by using the induced values paradigm (Smith 1976). In this experiment, we designed the bidding process to minimize the influence of consumers' frictional costs and subjective product valuations to provide high internal validity.

The second study is a field experiment involving actual sales of bundles of movie DVDs at a commercial name-your-own-price Web site that we specifically set up for this study. Since our observations are real economic transactions in a public marketplace unobtrusively manipulated to implement our experimental conditions, this experiment possesses high external validity.

Laboratory Experiment

We first conducted a laboratory experiment in which we controlled for consumers' valuations, the entry decision and information sharing. We designed our laboratory experiment such that frictional costs are minimized by the absence of waiting time between consecutive bids and the use of known, induced valuations for hypothetical products. The results from the laboratory experiment are intended as a controlled test of the effect of monetary bidding fees on bidding behavior in a name-your-own-price auction.

Method

We set up an online laboratory experiment where we investigate bidding behavior under different levels of bidding fees and provide for known (i.e., "induced") valuations (Smith 1976). Further, we controlled for entry by inducing all consumers to place a bid. Subjects could submit bids for six hypothetical products over a Web interface specifically implemented for this experiment. We tested the following treatment conditions: (1) *no fee*, (2) *low fee* corresponding to 0.6 % of the induced valuation for a given product and (3) *high fee* corresponding to 1.2 % of induced valuation for a given product. These levels of bidding fees as a percentage of product values are in the range found at Web sites asking fees for bids (e.g., www.swoopo.com, www.dubli.com).

While subjects could freely enter as many bids as they wanted for all of the six hypothetical products (a laptop, a raclette grill, a washing machine, a DVD-recorder, opera tickets and a bicycle) in an unconstrained format, each treatment condition comprised two products. Therefore, in our within-subjects design, each subject could submit a bid for the same six hypothetical products and was presented with three different levels of bidding fees. To avoid order effects, we systematically varied the order of bidding fees (e.g., high fee, no fee, low fee), ensuring that bidding data are available for every combination of product and bidding fee level. Irrespective of the level of bidding fees, subjects' initial bids on all six products were always free. Thus, bidding fees served as a means to increase consumers' total cost for placing additional bids following the initial bid.

In order to eliminate possible collusion, we separated subjects by boxes such that they were unable to talk to each other or look at each other's screens. In addition, we varied the secret threshold price of each product across subjects using six different levels of threshold prices for every product. These threshold prices were generated by multiplying a base threshold specific to each product with six multipliers common to all products. Moreover, the a priori specification of the secret threshold prices in the online laboratory experiment was required as subjects had to be notified immediately about the outcome of their bids. Upon notification, they could then decide about placing additional bids.

Our design consisted of three different alignments of products and levels of bidding fees. Along with the use of six different relative threshold price levels (resulting in six different threshold prices for each product) across different subjects, this systematically generated 18 different scenarios (see Table 1). A scenario consisted of a specific alignment of products and level of bidding fees (e.g., 'A', 'B' or 'C' in Table 1) combined with a specific set of threshold price levels TP (from TP1 (lowest) to TP6 (highest) aligned with the different products (e.g., 'I' to 'VI' in Table 1)). For example, one scenario was the combination of 'A' (where products P1 and P2 were aligned with no fee, P3 and P4 aligned with a low fee and P5 and P6 aligned with a high fee) with 'II' (where product P1 was aligned with threshold price level TP2, P2 aligned with TP3, P3 aligned with TP4, P4 aligned with TP5, P5 aligned with TP6 and P6 aligned with TP1).

Subjects were then randomly assigned to one of the 18 scenarios, balancing the number of subjects in each group.

== Please insert Table 1 about here ==

We controlled subjects' valuations by inducing valuations for the hypothetical products and remunerating participants according to their surplus generated in the experiment. Participants were told that they could resell each product to a friend for the price given on a "valuation card" handed out to subjects (see appendix for experimental instructions). This design also controlled for consumers' entry because consumers could only generate consumer surplus through the submission of successful bids. Consequently, we did not have to account for non-bidders in the laboratory experiment.

If a bid was successful (i.e., at least equal to the secret threshold price corresponding to the scenario in which a subject was placed in), the difference between the induced valuation and the bid (i.e., their consumer surplus) was converted to a Euro-denominated amount. The monetary amounts of all six possible transactions (i.e., products) were then summed up in a "winning-account" for each subject and paid out after the end of the experiments. The average payment to the subjects was 9 €.

Results and Discussion

We collected bids on the six hypothetical products in the three treatment conditions from 180 participants in our experiment (undergraduate students from a large Western European university). Our dataset thus consists of 1,080 bidding sequences (180 consumers × 6 products, with 360 sequences for each treatment condition) and 6,012 individual bids.

We examine the hypotheses formulated above for consumers' bidding behavior by analyzing differences between the three treatment conditions. We analyze the effect of different experimental treatments of bidding fees on bid *values* (i.e., bid amounts excluding possible bidding fees), which were calculated relative to induced valuations to account for different induced values for different products.

Table 2 displays the effect of different levels of bidding fees on consumers' bidding behavior. Consumers submitted an average number of 10.9 bids per bidding sequence if bidding fees were zero. Positive bidding fees significantly reduced the number of bids per sequence to 3.1 in the low fee case and 2.7 in the high fee case, which is consistent with Hypothesis 2 ($F_{2,1077}$=95.13, $p < .01$). Moreover, we also obtained significant differences between the two fee-based treatment conditions ($F_{1,718}$=4.92, $p < .1$).

We further find that consumers submitted significantly higher initial bids if they have to bear bidding fees. Thus, given bidding fees, consumers' bidding strategy was to submit fewer bids and start bidding at a higher level. We do not find a significant influence of bidding fees on consumers' observed maximum bid values for all bidding sequences but find such an effect for bidding sequences not terminated by a successful bid ($F_{2,225}$=21.12, $p < .01$). While our results are consistent with Hypothesis 3a (for initial bid values), the effect of bidding fees on observed maximum bid values is only significant and consistent with Hypothesis 3b for unsuccessful bidding sequences. This might be explained by the higher increments, which allows consumers to overbid the threshold price by higher amounts, leading to higher average observed maximum bid values when bidding fees are present.

== Please insert Table 2 about here ==

Thus, we observe that consumers reacted by submitting fewer bids but within a smaller interval between initial and maximum bid value when bidding fees were present. This implies two opposite effects on bid increments (fewer bids increase increments but a smaller interval reduces increments). The effect of fewer bids dominates the effect of a smaller interval because we find a significant increase in bid increments in the case of positive bidding fees. The difference between the two fee-based treatment conditions for average increments is not significant ($F_{1,501}$=2.26, $p > .1$).

The within-subject design we used in this experiment allows us to control for order effects and to account for them explicitly in the analyses above. We observed that within each treatment block, the initial bid tended to be higher for the first product in a specific treatment than for the second product (repeated-measures ANOVA: $F_{1,178}$=9.78, $p < .05$). This was the case consistently across the three treatment conditions. We did not find order effects for the maximum bid, the number of bids or the average increment.

Thus, we found an asymmetric effect of bidding fees on bidding behavior. Apparently, the existence rather than the actual level of bidding fees seemed to matter to consumers. For instance, the difference between values for average increments in the high fee and the low fee treatment was less than a forth of the difference between the no fee and the low fee treatment. For the number of bids placed and the bid values for the initial bid, the difference is even less (see Table 2). This may be explained by previous behavioral research. For example, Amir and Ariely (2007) find that consumers may not be willing to pay for anything other than the product itself.

Field Experiment

Method

The goal of the field experiment was to test our hypotheses in an unobtrusively implemented field setting conducted on a commercial Web site for DVD sales. Further, we wanted to compare the effects of treatments with multiple bidding to a setting with a single bid restriction.

We attracted traffic to this Web site by means of a promotional campaign mainly involving press releases, mailing lists and postings in online forums. Participation in the experiment was possible during a time period lasting 10 hours from 8 a.m. to 6 p.m. on a single day. During this time, a total number of 480 consumers registered on the Web site. To register, consumers had to fill out a Web form with their complete name, a shipping address and a valid e-mail address. Immediately thereafter, we sent a password to all registered consumers that they could then use to log on to the commercial Web site and participate in the experiment (see Figure 2).

== Please insert Figure 2 about here ==

Participants could place bids on a set of three movie DVDs, which they could freely select from a list of 100 titles. The sum of average retail prices for a bundle of three DVDs was about 60 €. Upon bidding, participants were instantly notified about the success of their bid (i.e., if a bid surpassed the secret threshold price), and a Web site indicating the success was displayed. Simultaneously, successful bidders received an e-mail including online money transfer instructions needed to receive the chosen DVDs. As soon as the money transfer was completed, the respective DVDs were sent to successful bidders by a large cooperating DVD retailer. If a bid was not successful, participants could – depending on their experimental design – bid repeatedly and increase their bid value immediately. The secret threshold price was calculated depending on the selected DVDs, creating different threshold prices across different DVD bundles and consumers. This was done to reflect the different wholesale prices for the underlying DVDs as well as to reduce potential information diffusion via communities over the Internet. In order to calculate threshold prices, we used the wholesale prices of the underlying DVD bundles, which averaged 40.55 €.

When logging on to the commercial Web site, each participant was randomly assigned to one of the following four treatment conditions (see Figure 2): (1) *no fee*, where consumers could place an unlimited number of bids at no fee, (2) *low fee*, where consumers could place one free bid and an unlimited number of additional bids at a fee of 0.20 € per additional bid (representing approximately 0.63 % of average final bid values), (3) *high fee*, where consumers could place one free bid and an unlimited number of additional bids at a fee of 0.40 € per additional bid (representing approximately 1.27 % of average final bid values), and (4) *single bid*, where consumers could place only one bid. Each bid could be placed in an unconstrained format by simply typing any positive Euro and Cent value in a suitable textbox. Using this between-subjects experimental design allowed us to examine the effects of different levels of bidding fees on consumer bidding behavior. The initial bid was always free of charge to encourage consumers' participation in the experiment. Moreover, consumers only had to pay bidding fees in cases where their bid was successful.

Along with their notification via e-mail, participants received a link to a web-based follow-up survey designed to measure their estimate of the retail value of the bundle and their acceptance of bidding fees (if applicable). Participants who had not placed a successful bid were also asked via e-mail to fill out a corresponding survey shortly after their participation. Participation in the survey was encouraged by a lottery of three 25 € gift certificates. We received 285 completed surveys (59.4 % response rate).

Results and Discussion

Out of the 480 registered consumers, 474 participated in the experiment and placed a total number of 1,261 bids. Thus, 98.75 % of registered consumers chose to submit at least one bid with no significant differences across the different treatment conditions. We attribute this almost complete entry into the bidding process to the fact that (1) consumers could bid any positive amount without further restrictions and (2) that no fees were charged for the initial bid in all four treatment conditions. In aggregate, 109 (23.0 %) of the 474 different bidding sequences were successful (i.e., the maximum bid in these sequences was sufficient to surpass the secret threshold price calculated for the respective bundles). However, the success rate significantly differed between treatments (χ^2: $p < .01$); only 8.6 % of single bids were successful compared to 35.3 % (25.2 % / 22.5 %) of multiple-bidding sequences in the no fee (low fee / high fee) treatment condition, respectively.

In order to examine the hypotheses formulated above, we first analyze differences for consumers' bidding behavior for the four different treatment conditions. As we did in the laboratory experiment, we compare consumers' bid *values* (i.e., the amount of their bid excluding possible bidding fees).

Table 3 provides information on the bidding data. Comparing consumers' final bid values across the different treatment conditions, we find results consistent with Hypothesis 1: consumers bid up to significantly higher levels when they were allowed to bid repeatedly. While the maximum bid value of 33.91 € in the no fee treatment is 5.31 € (18.6 %) higher compared to the single-bid treatment ($F_{1,233}$=13.20, $p < .01$), we find a similar result for the fee-based treatments: the average maximum bid value of 31.92 € (31.59 €) in the low fee (high fee) treatment is 3.32 € (2.99 €) higher than the respective value of 28.60 € in the single-bid treatment ($F_{1,233}$=4.86 ($F_{1,234}$=3.93), $p < .05$). An additional explanation for this result is that an escalation of commitment may arise in multiple bidding (Shubik 1971) because past bids result in sunk costs with respect to frictional costs associated with bidding. Such an effect would be amplified if bidding fees had to be paid for every bid irrespective of bidding success.

In line with Hypothesis 2, consumers placed significantly less bids when bidding fees were present (χ^2: $p < .01$). Consumers bid on average 4.56 times when they did not have to bear additional fees for the option to bid repeatedly. However, the difference between the two fee-based treatment conditions is not significant with consumers in the high fee treatment even placing slightly more bids (2.60) than those in the low fee treatment (2.59, χ^2: $p > .9$). Thus, the effect of bidding fees is consistent with the results of our laboratory experiment.

== Please insert Table 3 about here ==

According to our economic model of consumer bidding behavior, consumers started their bidding sequences at higher but end at lower bid values relative to the no fee auction when bidding fees are present. Comparing consumers' initial bids across treatments, we find initial bid values of 27.64 € (low fee) and 27.30 € (high fee), respectively, which is slightly higher than the 26.98 € in the no fee treatment but lower than the 28.60 € consumers placed on average in the single-bid treatment condition. Although the direction of these differences is consistent with Hypothesis 3a, the magnitude is not significant. This may be due to frictional costs mitigating the effect of bidding fees (Hann and Terwiesch 2003). Following the rationale of our economic model, both frictional costs and bidding fees affect consumers' bidding behavior in a similar way. However, frictional costs should be prevailing independent of treatment conditions. Therefore, their presence should not influence the direction of our results.

Consistent with Hypothesis 3b, consumers' observed maximum bid values are significantly higher when no bidding fees were present ($F_{2,471}=4.61$, $p < .01$). The average observed maximum bid value of 33.91 € clearly dominates the average observed maximum bid values for the low and high fee treatment by 1.99 € (6.2 %) and 2.32 € (7.3 %), respectively. For unsuccessful sequences only, the direction of the differences is consistent but not significant. Again, the existence rather than the actual value of bidding fees seemed to matter more to consumers with only slight and insignificant ($F_{1,180}$=.03, $p > .8$) differences between the fee-based treatments. This result confirms our previous result from the laboratory experiment of an asymmetric effect of the levels of bidding fees on bidding behavior, which may be explained by consumers' unwillingness to pay for anything other than the product itself.

In the follow-up survey, we asked consumers in fee-based treatment conditions to rate the following statements: "The bidding fee was too expensive," "Due to the bidding fee I bid less often," "Due to the bidding fee I raised my increments to avoid a large number of bids" and "Due to the bidding fee I raised my first bid." The survey permitted responses on a scale from 1 ("do not agree") to 5 ("completely agree"). Although we find a significantly higher level of agreement from consumers in the high fee treatment (3.61) than in the low fee treatment (2.78) that bidding fees were too expensive ($F_{1,93}$=8.94, $p < .01$), we cannot find a significant difference between these two groups for the statements concerning their bidding behavior. Thus, even though consumers perceived the differences in the levels of bidding fees, they did not respond differently, which is consistent with the bidding behavior observed in our experiment. We believe these insignificant differences are a result of the behavioral aspects discussed above. Further, we use the fact that no fee was charged for initial bids as an explanation for insignificant differences about higher initial bid values in the survey.

Thus, we have found that consumers bid up to higher values when they are allowed to bid repeatedly (see Hypothesis 1) and that the introduction of bidding fees leads to fewer bids (see Hypothesis 2) and a narrower price range with higher initial but lower final bid values (see Hypotheses 3a and 3b). An analysis of the net effect of bidding fees on consumers' increments depends largely on the trade-off between the latter two conflicting factors. Table 3 suggests that the lower number of bids dominates this trade-off, indicating that if bidding fees were present, consumers bid by higher average increments of 3.35 € (3.50 €) in the low (high) fee treatment. This represents an increase of 22.3 % (27.7 %) over the 2.74 € in the case where there were no bidding fees ($F_{1,176}$=2.82, $p < .1$ for low fee and $F_{1,177}$=4.30, $p < .05$ for high fee).

Impact of Bidding Fees on Seller Profit and Revenue

Due to their effect on bidding behavior, bidding fees can have crucial implications for seller profit and revenue in name-your-own-price auctions. Particularly, changes in the number of units sold and the profit margin per unit sold will affect seller revenue and profit when bidding fees are present. Though organizers of a name-your-own-price auction may have different objectives, a profit maximization objective usually applies for sellers who organize the auction. Priceline, which sells online travel services, aims at maximizing the information rent (i.e., the difference between the price of a successful bid and the threshold price (Hann and Terwiesch 2003)) that it receives from a successful transaction (Anderson 2009). However, a name-your-own-price auction platform may alternatively receive a fixed commission (e.g., 5 %) from each successful transaction. In this case, such a platform's objective would be the maximization of transaction revenue. Next, we analyze the profit and revenue implications for the bidding data collected in the field experiment.

Results from the field experiment indicate that, on average, bidding fees lead to lower maximum bid values but simultaneously encourage consumers to use higher increments. This will potentially lead to fewer units sold but, at the same time, leave more information rent and improve the seller's profit margin (since consumers are more likely to overbid the threshold price by a larger amount). Therefore, the net effect on seller profit depends on the magnitude of these two opposing factors. While the number of products sold depends solely on bid values, an examination of *bid prices* (i.e., the bid value *plus* bidding fees accrued by consumers) is required to capture the effect of bidding fees on seller profit.

From Table 3 we see that bid values per sequence are highest for multiple bidding with no bidding fees and lowest for the single-bid treatment. In line with these results, Table 4 depicts that most successful bids are placed in the no fee, multiple-bidding treatment with a total of 42 DVD bundles sold compared to 30 (27) for the low fee (high fee) treatment and only 10 bundles sold in the single-bid treatment condition (χ^2: $p < .01$).

For successful consumers, the single-bid treatment condition yields the highest average price across different treatment conditions. However, this is partly due to the fact that the threshold prices of successful consumers differ significantly across different treatment conditions ($F_{3,105}$=2.39, $p < .1$), reflecting different wholesale prices of the underlying DVDs. Therefore, in order to draw profit implications for sellers, we analyze average profit margins taking into account different threshold prices.

Successful bids in the no fee treatment condition only generate a 4.74 % average profit margin and a profit from the information rent of 76.45 € for the seller. While bidders in the low fee treatment (margin of 6.09 %, profit of 75.74 €) yield no significantly different average profit margin ($p > .2$) for the seller, both the single-bid treatment (margin of 8.57 %, $p < .05$; profit of 38.28 €) and the high fee treatment (margin of 11.20 %, $p < .05$, profit of 109.04 €) allow the seller to significantly increase the average profit margin compared to the no fee treatment. The high fee treatment even generates a significantly higher average profit margin than the low fee treatment ($p < .1$). Conversely, we observed no significant difference in profit margins between the high fee (low fee) treatment and the single-bid treatment ($p > .5$ for high fee, $p > .15$ for low fee). Moreover, profit margins differ significantly with respect to their variance

($p < .01$). Indicating an increase in price discrimination, standard deviation in the high fee treatment of 13.43 % is above respective values for low fee (no fee) treatment at 4.66 % (4.48 %) and the single-bid treatment at 6.19 %.

If we look at revenue, however, multiple bidding with no fees yields the highest total revenue (1,758 €), followed by the low-fee treatment (1,344 €) and the high-fee treatment (1,204 €). Revenue is lowest in the single-bid treatment (481 €). Thus, a name-your-own-price auction platform that receives a fixed commission from each successful transaction and has a revenue maximizing objective would be better off with multiple bidding and no bidding fees.

== Please insert Table 4 about here ==

Figure 3 compares the total seller profit in Euros (on the vertical axis) for varying levels in threshold price relative to the cost of the DVD bundles (on the horizontal axis) with costs set at the wholesale prices of the respective DVD bundles. In our field experiment, we observed the first bid that met or surpassed the threshold price per consumer as a basis for our profit implications. Therefore, we need to account for the fact that bidding sequences were terminated when bidders were successful – i.e., they could have further raised their bids according to their bidding strategy (maximum number of bids) if they had not been successful. Such terminated bidding sequences may bias our results of profit differences across treatments. However, the fact that threshold prices of the chosen DVD bundles were not significantly different across different treatment conditions for *all* consumers should ensure that the direction of our results is stable.

== Please insert Figure 3 about here ==

As can be seen from Figure 3, the high fee treatment yields the highest profit for sellers for all levels of the threshold price. The maximum profit of 116 € occurs at a threshold price relative to 98 % of seller's costs. This is because that although bid values determine the acceptance of a bid, the final price contains the bidding fees, which – when added to the final bid value – let the bid become profitable for a seller even though the bid value maybe below the cost. Both the no fee and the low fee treatment provide maximum seller profits of about 76 € and 80 € with similarly shaped profit curves. Again, the single-bid treatment provides the least favorable outcome for a seller with only about 38 € of maximum profit.

These results reflect the trade-off between the number of products sold and the profit margin sellers realize in a certain treatment. Seller profit is highest using the high fee treatment because consumers significantly overbid secret threshold prices compared to the other treatment conditions. In the high fee treatment, the average profit margin is almost 122 % above the corresponding value for the no fee treatment and, as a result, overcompensates for the lower number of units sold. Yet, in the single-bid treatment, the fact that only 10 units were sold obviously reduces seller's total Euros of profit compared to other treatment conditions, despite an average profit margin of 8.57 % for each unit sold.

Thus, our results indicate that sellers are able to increase profits in the field study by allowing consumers to bid repeatedly compared to a single-bid policy. If the seller's objective is to maximize profits from the information rent, charging a fee further increases profits in the case of multiple bidding. If, however, the seller's objective is to maximize transaction revenue, she is better off with a multiple bidding policy and no fees.

Conclusions

We analyze the effects of bidding fees on bidding behavior in name-your-own-price auctions, where the payment of the bidding fees is contingent on a successful bid. We base our analyses on an economic model of bidding behavior and two distinct data sets: a laboratory experiment with induced valuations and a field experiment involving real-world transactions.

Despite some name-your-own-price sellers' current enforcement of a single-bid policy, our results indicate that consumers bid up to higher values if they are given the flexibility to bid repeatedly. Furthermore, our analytical predictions and our empirical data both indicate the strong influence bidding fees have on bidding behavior in name-your-own-price auctions. The use of bidding fees leads to a lower number of bids and higher bidding increments. Especially when we control for consumers' valuations and minimize confounding effects in the laboratory, bidding fees result in consumers starting their bidding sequences at much higher values. Interestingly, we find an asymmetric effect of bidding fees on bidding behavior, indicating that consumers' perceived impact of bidding fees is dominated by their existence rather than their actual level.

We find in our empirical studies that bidding fees increase seller profit because consumers bid by higher increments when bidding fees are present. Thereby, bidding fees provide additional profit when consumers overbid the unknown threshold price by a higher amount than they would without bidding fees. This allows sellers to more effectively price-discriminate. Moreover, we find no significant effect of bidding fees on consumers' entry decision in the field experiment, suggesting consumer acceptance is not a crucial factor for the chosen levels of bidding fees and the chosen design when the initial bid always free. Additionally, we control for entry in our laboratory experiment and generate results consistent with the field experiment. However, we find that fewer units are sold when bidding fees exist because consumers submit fewer bids compared to a situation with multiple bidding and no bidding fees. Therefore, sellers who are interested in maximizing transaction revenue – perhaps because they receive a fixed commission from this revenue – are better off applying a multiple bidding policy without bidding fees.

Consequently, the heretofore neglected use of bidding fees in name-your-own-price auctions can be beneficial for sellers. However, it depends on the seller's business model whether bidding fees are beneficial. Our results on the impact of bidding fees on average increments, the number of bids placed, the percentage of successful bidding sequences and selling prices support sellers in their decision on whether to use bidding fees in name-your-own-price auctions. Further, our empirical results could be used to augment analytical models of optimal pricing mechanism design (Spann et al. 2010).

Further, our economic model of bidding behavior in name-your-own-price auctions with bidding fees can be used to simulate seller revenue and profit as well as the optimal threshold price and bidding fee levels for different demand conditions (i.e., distributions of consumers' willingness-to-pay, frictional costs and beliefs) and supply conditions (e.g., capacity and costs). Such a simulation analysis can be the basis of a decision support system for sellers on the use of bidding fees and related threshold price levels.

We have to acknowledge several limitations, which provide avenues for future research. First, our profit and revenue results are limited to the specific values of bidding fees applied in our field study and to the chosen values of the threshold prices.

Second, we cannot analyze the long-term effects of multiple bidding and bidding fees on seller revenue and profit. Although we find in our analysis that allowing multiple bidding is advantageous with and without bidding fees, this cannot be generalized to all competitive situations. Fay (2009) shows that multiple bidding may be disadvantageous if a posted-price rival reacts and chooses a lower price than the single-bid policy of the name-your-own-price seller. Therefore, the long-term viability of a multiple-bidding policy may require that the name-your-own-price seller is small compared to the posted price rival. Further, fewer successful transactions when bidding fees exist can have adverse effects on repeat purchases, word-of-mouth and the consumer acceptance of a name-your-own-price seller.

Third, factors such as seller ratings (Bruce et al. 2004), collusion and information sharing on the Internet could alter average profit margins over time. Consumers may learn about the threshold prices from other consumers' bidding success via information diffusion (Hinz and Spann 2008), which can influence optimal threshold price levels and may require additional differentiation of products to make them and their threshold prices less comparable.

Fourth, an interesting challenge for future research will be to better understand the mental processes that drive consumers' reactions to bidding fees.

Appendix

Calculation of optimal bid values

Assuming a uniform distribution of a consumer's belief about the threshold price tp in the interval $\left[\underline{tp};\overline{tp}\right]$, we obtain a closed-form solution of equation (1) as given by equation (A1):

$$\text{(A1)}\quad ECS_{j,n_j,1} = \left(\frac{1}{\overline{tp}-\underline{tp}}\right)\cdot\sum_{i=1}^{n_j}\left[\left(b_{j,n_j,i}-b_{j,n_j,i-1}\right)\cdot\left(r_j-b_{j,n_j,i}-\sum_{t=1}^{i}f_t\cdot\right)-\left(\overline{tp}-b_{j,n_j,i-1}\right)\cdot c_{j,i+1}\right]$$

$$\text{with } b_{j,n_j,0}=\underline{tp}\text{, and } b_{j,n_j,i}\in\left[\underline{tp};\min\left(\overline{tp},r_j\right)\right]\quad\forall\quad i\in I_j=\left\{1,\ldots,n_j\right\}$$

In order to maximize the total expected consumer surplus for placing n_j bids, we differentiate equation (A1) with respect to $b_{j,n_j,i}$ for $i < n_j$ and set equation (A2) equal to zero (the second derivative is always negative).

$$\text{(A2)}\quad \frac{\partial ECS_{j,n_j,1}}{\partial b_{j,n_j,i}} = \frac{1}{\overline{tp}-\underline{tp}}\cdot\left[\left(r_j-b_{j,n_j,i}-\sum_{t=1}^{i}f_t\right)-\left(b_{j,n_j,i}-b_{j,n_j,i-1}\right)-\left(r_j-b_{j,n_j,i+1}-\sum_{t=1}^{i+1}f_t\right)+c_{j,i+1}\right]$$

$$=\frac{1}{\overline{tp}-\underline{tp}}\cdot\left[-2\cdot b_{j,n_j,i}+b_{j,n_j,i-1}+b_{j,n_j,i+1}+f_{i+1}+c_{j,i+1}\right]=0$$

Equation (A2) is true for $b_{j,n_j,i}$ as given by equation (A3) for $i < n_j$. Moreover, equation (A4) denotes the respective solution for the final bid value ($i = n_j$).

$$\text{(A3)}\quad b_{j,n_j,i}=\frac{\left(b_{j,n_j,i-1}+b_{j,n_j,i+1}+f_{i+1}+c_{j,i+1}\right)}{2}\quad\text{for all}\quad i\in\left\{1,\ldots,n_j-1\right\}$$

$$\text{with } b_{j,n_j,0}=\underline{tp}$$

$$\text{(A4)}\quad b_{j,n_j,i}=\frac{b_{j,n_j,i=n_j-1}+r_j-\sum_{t=1}^{n_j}f_t}{2}\quad\text{for}\quad i=n_j$$

As can be seen, optimal bid values $b_{j,n_j,i}$ depend on both preceding and succeeding bid values $b_{j,n_j,i-1}$ and $b_{j,n_j,i+1}$ as long as $i < n_j$, while the optimal final bid value b_{j,n_j,n_j} only depends on the preceding bid value b_{j,n_j,n_j-1}. Insertion of equation (A4) into the respective formula for preceding bid values descending in i from $i = n_j - 1$ to $i = 1$ reduces the dependency to preceding bid values as can be seen in equation (A5).

$$\text{(A5)} \quad b_{j,n_j,i} = \frac{\left(n_j - i + 1\right)\cdot b_{j,n_j,i-1} + r_j - \sum_{t=1}^{n_j} f_t + \sum_{t=i+1}^{n_j}\left(n_j - t + 2\right)\cdot\left(f_t + c_{j,t}\right)}{n_j - i + 2} \quad \text{for all } i = 2 \ldots n_j$$

Using equation (A3) for $i = 1$, we can then calculate the initial bid value $b_{j,n_j,1}$ by the insertion of equation (A5) for $i = 2$. Equation (A6) denotes the result of this calculation.

$$\text{(A6)} \quad b_{j,n_j,1} = \frac{n_j \cdot \underline{tp} + r_j - \sum_{t=1}^{n_j} f_t + \sum_{t=3}^{n_j}\left(n_j - t + 2\right)\cdot\left(f_t + c_{j,t}\right) + n_j \cdot\left(f_2 + c_{j,2}\right)}{\left(n_j + 1\right)} \quad \text{for } i = 1$$

Finally, insertion of equation (A6) into equation (A5) and then mutually inserting equation (A5) for ascending i allows us to calculate optimal bid values $b_{j,n_j,i}$ for all $i = 1 \ldots n_j$. Equation (A7) displays the outcome of these insertions: a closed-form solution for optimal bid values $b_{j,n_j,i}$ for the j^{th} consumer, who places a maximum number of n_j bids to maximize her expected consumer surplus $ECS_{j,n_j,1}$.

$$\text{(A7)} \quad b_{j,n_j,i} = \frac{i \cdot\left(r_j - \sum_{t=1}^{n_j} f_t + \sum_{t=i+1}^{n_j}\left(n_j - t + 2\right)\cdot\left(f_t + c_{j,t}\right)\right) + \left(n_j - i + 1\right)\cdot\left(\underline{tp} + \sum_{t=2}^{i}\left(t-1\right)\cdot\left(f_t + c_{j,t}\right)\right)}{n_j + 1}$$

Final bid values increasing in n_j

Based on the calculation of optimal bid values in equation (2), the final bid ($i = n_j$) of consumer j can be calculated as given by equation (A8).

$$\text{(A8)} \quad b_{j,n_j,i} = \frac{n_j \cdot\left(r_j - \sum_{t=1}^{n_j} f_t\right) + \underline{tp} + \sum_{t=2}^{n_j}\left(t-1\right)\left(f_t + c_{j,t}\right)}{n_j + 1} \quad \text{for } i = n_j$$

Assuming constant frictional costs c_j for consumer j and constant bidding fees f with no bidding fees charged for the initial bid, we can rewrite equation (A8) in equation (A9).

(A9) $$b_{j,n_j,i} = \frac{n_j \cdot \left(r_j - \left(n_j - 1\right) \cdot f\right) + \underline{tp} + \frac{n_j\left(n_j - 1\right)}{2}\left(f + c_j\right)}{n_j + 1} \text{ for } i = n_j$$

Subtracting the initial bid value $b_{j,n_j=1,1}$ off the calculated final bid for cases where $n_j > 1$ leads to equation (A10).

(A10) $$\begin{aligned}\Delta b_j = b_{j,n_j,n_j} - b_{j,n_j=1,1} &= \frac{n_j \cdot \left(r_j - \left(n_j - 1\right) \cdot f\right) + \underline{tp} + \frac{n_j\left(n_j - 1\right)}{2}\left(f + c_j\right)}{n_j + 1} - \frac{r_j + \underline{tp}}{2} \\ &= \frac{\left(n_j - 1\right)\left(r_j - \underline{tp}\right) + \left(n_j^2 - n_j\right)\left(c_j - f\right)}{2\left(n_j + 1\right)}\end{aligned}$$

Since $n_j > 1$, $r_j \geq \underline{tp}$ (in both cases consumer j would place at most one bid) and $n_j^2 > n_j$ for all $n_j > 1$ we can immediately infer $\Delta b_j > 0$ for all cases where frictional costs c_j surpass bidding fees f, i.e., $c_j > f$. In order to investigate cases where $c_j \leq f$, we consider the condition for Δb_j not to be positive in equation (A11).

(A11) $$\Delta b_j \leq 0 \Leftrightarrow \left(n_j - 1\right)\left(r_j - \underline{tp}\right) - \left(n_j^2 - n_j\right)\left(f - c_j\right) \leq 0 \Leftrightarrow f \geq \frac{\left(r_j - \underline{tp}\right)}{n_j} + c_j$$

As can be seen from equation (A11), bidding fees f need to surpass frictional costs c_j by at least $\left(r_j - \underline{tp}\right)/n_j$ for Δb_j not to be positive. However, consumer j only places the final bid ($i = n_j$) in case equation (A12) holds.

(A12) $$\begin{aligned}ECS_{j,n_j,n_j} \geq 0 &\Leftrightarrow \underbrace{\left(\frac{b_{j,n_j,n_j} - b_{j,n_j,n_j-1}}{\overline{\underline{tp}} - b_{j,n_j,n_j-1}}\right)}_{\geq 0} \cdot \left(r_j - b_{j,n_j,n_j} - \left(n_j - 1\right)f\right) - \underbrace{c_j}_{\geq 0} \geq 0 \\ &\Leftrightarrow r_j - b_{j,n_j,n_j} - \left(n_j - 1\right)f \geq 0 \qquad \Big| \; n_j > 1 \\ &\Leftrightarrow f \leq \frac{r_j - b_{j,n_j,n_j}}{n_j - 1}\end{aligned}$$

Extending both the latter condition and the requirement for Δb_j to be non-positive in equations (A13) and (A14), we prove that if f takes values as required by equation (A11), it will not be optimal for consumer j to place n_j bids and that this consequently violates the requirement in equation (A12). $\Delta b_j > 0$ thus holds for all values of f, q. e. d.

(A13) $$f \le \underbrace{\frac{r_j - b_{j,n_j,n_j}}{n_j - 1}}_{b_{j,n_j,n_j} \ge \underline{tp}} \le \frac{r_j - \underline{tp}}{n_j - 1}$$

(A14) $$f \ge \frac{r_j - \underline{tp}}{n_j} + c \ge \frac{r_j - \underline{tp}}{n_j} \overset{n_j > 1}{\overset{!}{>}} \frac{r_j - \underline{tp}}{n_j - 1}$$

Thus, consumers raise their final bid values if it is optimal for them to place multiple bids as compared to a single-bid scenario. Moreover, this is true irrespective of either an external restriction to $n_j = 1$ (i.e., the single-bid constraint is imposed by the seller), or the determination of $n_j = 1$ internally through the maximization of $ECS_{j,n_j,1}$ following our model.

Expected consumer surplus is decreasing in *f*

ECS is decreasing in f is negative as long as consumers increase consecutive bid values:

(A15) $$\frac{\partial ECS_{j,n_j,1}}{\partial f} = -\underbrace{\frac{1}{\overline{tp} - \underline{tp}}}_{>0} \cdot \underbrace{\sum_{i=1}^{n_j} \left(b_{j,n_j,i} - b_{j,n_j,i-1}\right)}_{>0} \cdot i < 0 \quad \text{with } b_{j,n_j,0} = \underline{tp}$$

Effect of bidding fees *f* on bid values

Using the first order derivative of optimal bid values with respect to bidding fees, we can analytically examine this effect:

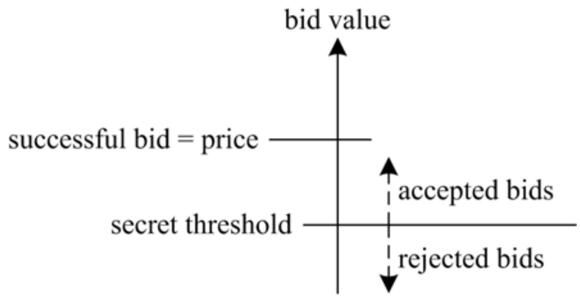
(A16) $$\frac{\partial b_{j,n_j,i}}{\partial f} = \frac{i \cdot \left(n_j^2 - i \cdot \left(1 + n_j\right) + 1\right)}{2 \cdot n_j + 2} > 0 \Leftrightarrow n_j^2 - i \cdot \left(1 + n_j\right) + 1 > 0 \Leftrightarrow i < \frac{1 + n_j^2}{1 + n_j} \qquad \text{(for } i < n_j\text{)}$$

(A17) $$\frac{\partial b_{j,n_j,n_j}}{\partial f} = \frac{n_j - n_j^2}{2 \cdot n_j + 2} < 0 \ \forall\ n_j > 1 \qquad \text{(for } i = n_j\text{)}$$

Instructions in the laboratory experiment

General procedure of the experiment. The experiment started with an oral introduction to the reverse pricing mechanism and the remuneration according to the induced valuations. We put special focus on the explanation of the multiple-bidding policy with potentially costly bidding. Then, subjects had to draw a valuation card which contained the induced valuations for the six products as well as a login and a password they needed to participate in the online experiment. After the initial login, subjects could get acquainted to the reverse pricing mechanism with bidding fees in a trial round. Following this trial round, subjects placed their bids on the six products with different levels of bidding fees. Finally, subjects were directed to an online-questionnaire which they had to fill in.

Explanation of the reverse pricing mechanism. We explained the reverse pricing mechanism to subjects as follows: "In reverse pricing mechanisms, potential buyers can submit bids on a product. Prior to the bidding, the seller of the product set a threshold price secret to all potential buyers. If a buyer's bid is equal to or above the seller's threshold price, the transaction is initiated and the buyer will receive the product for the price denoted by her bid. If a buyer's bid is below the seller's threshold price, the buyer's bid will be rejected and the transaction will not take place. Contrary to auctions such as eBay, not only the highest bid but all bids equal to or above the seller's threshold price will result in a transaction. Thus, there is no competition among bidders." To illustrate the mechanism, we presented the following figure to subjects:



Next, we described the specific design of the reverse pricing mechanism with multiple-bidding to subjects: “In the course of the experiment, it is possible to place multiple bids on one and the same product. If a bid equals or surpasses the secret threshold price, the transaction will be initiated. If the bid is below the secret threshold price, additional bids are possible. The number of bids you can place on one product is not limited in the experiment. You can place additional bids on the products until you either surpass the seller’s secret threshold price or until you indicate you do not want to place additional bids by clicking a cancel-button. You will then continue bidding with the next product.”

Remuneration of participants. We communicated remuneration in the experiment as follows to the subjects before the experiment: “The payment you can receive in this experiment depends on your bidding behavior. You will be able to sell each product you have successfully placed a bid on for a value given to you on a valuation card. Your payment is calculated by adding the differences between the value on your valuation card and your bid value for all products that you have successfully placed a bid on (bid value is equal to or above the seller’s threshold price).”

Incorporation of bidding fees. Finally, we instructed subjects about the possibility that bidding fees could be charged in the experiment: “Further, it is possible that – beginning with the second bid for one and the same product – bidding will be costly. This means, you will be given the opportunity to place an additional bid for this product for the payment of a monetary fee. However, you will only have to pay the fee in case you place a successful bid on this product. If bidding is costly in the experiment, the difference between the value on your valuation card and the value of your bid will be diminished by the fees accumulated by your bidding behavior. These accumulated fees result from (number of your bids – 1) · fees. The seller's secret threshold price is independent from these fees and remains constant during one bidding process."

For illustration purposes, subjects were shown the following figure:

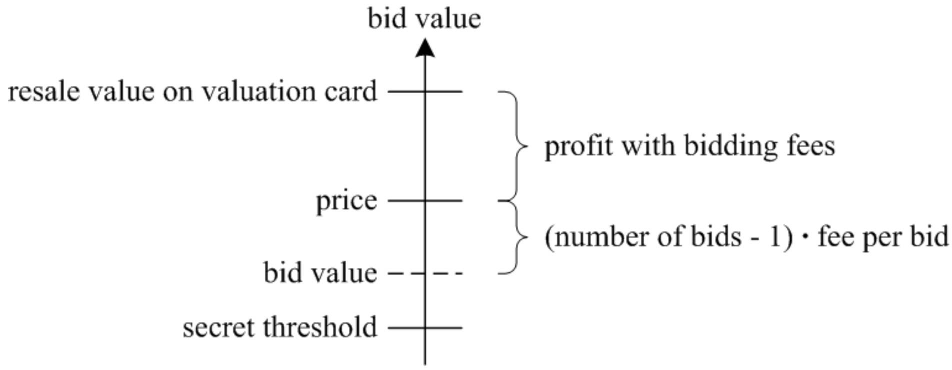


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Table 1: Design of Laboratory Experiment: Scenarios

Product-bidding fee combinations					
A		B		C	
P1	no fee	P3	high fee	P5	low fee
P2		P4		P6	
P3	low fee	P5	no fee	P1	high fee
P4		P6		P2	
P5	high fee	P1	low fee	P3	no fee
P6		P2		P4	

×

Relative threshold price level combinations					
I	II	III	IV	V	VI
TP1	TP2	TP3	TP4	TP5	TP6
TP2	TP3	TP4	TP5	TP6	TP1
TP3	TP4	TP5	TP6	TP1	TP2
TP4	TP5	TP6	TP1	TP2	TP3
TP5	TP6	TP1	TP2	TP3	TP4
TP6	TP1	TP2	TP3	TP4	TP5

Note: P1-P6: hypothetical products; TP1-TP6: relative threshold price levels

Table 2: Laboratory Experiment: Effect of Bidding Fees on Bidding Behavior

Treatment	Average Number of Bids per Sequence[a)]	Average Initial Bid per Sequence[a,b)]	Average Maximum Bid[b,c)]		Average Increment[e)]
			All Sequences[a)]	Unsuccessful Sequences[d)]	
No Fee	10.87	69.98 %	90.99 %	98.63 %	4.28 %
Low Fee	3.07	79.19 %	92.04 %	94.77 %	7.91 %
High Fee	2.73	79.82 %	91.93 %	93.72 %	8.66 %
Test[f)]	F=95.13, df=2, p=.000	F=71.47, df=2, p=.000	F=1.46, df=2, p=.233	F=21.12, df=2, p=.000	F=14.95, df=2, p=.000
No. of Sequences	1,080	1,080	1,080	228	799

a) Data comprise two bidding sequences per consumer and treatment condition (due to the within-subject design).
b) Consumer's bid value relative to the induced value for specific product.
c) We use the expression *maximum* bid value to capture the fact that bidding sequences could be terminated by success in our data. However, *final* bid values specify theoretical values we expect from our economic model.
d) Sequences not terminated by successful bids (due to high relative threshold price levels).
e) Increment: relative bid value of $(i+1)^{th}$ bid – relative bid value of i^{th} bid. We only use sequences where we observe at least two bids for this analysis.
f) ANOVA; Factor: fee treatment.

Table 3: Field Experiment: Effect of Bidding Fees on Bidding Behavior

Treatment	Number of Consumers	Number of Bids per Consumer	Average Initial Bid	Average Maximum Bid[a)]		Aver. Increment per Bidding Sequence[c)]
				All Sequences	Unsuccessful Sequences[b)]	
No Fee	119	4.56	26.98 €	33.91 €	29.58 €	2.74 €
Low Fee	119	2.59	27.64 €	31.92 €	27.74 €	3.35 €
High Fee	120	2.60	27.30 €	31.59 €	27.96 €	3.50 €
Single Bid	116	1.00	28.60 €	28.60 €	26.76 €	n. a.
Test		χ^2=27.21[d)], df=2, p=.000	F=0.46[e)], df=3, p=.708	F=4.61[e)], df=3, p=.003	F=1.23[e)], df=3, p=.299	χ^2=4.02[d)], df=2, p=.134
N	474	474	474	474	365	257

a) We use the expression *maximum* bid value to capture the fact that bidding sequences could be terminated by success in our data. However, *final* bid values specify theoretical values we expect from our economic model.
b) Sequences not terminated by successful bids.
c) Increment = (bid value of final bid – value of initial bid) / (number of bids in sequence – 1). We only use sequences where we observe at least two bids for this analysis.
d) χ^2 of Kruskal-Wallis-Test for parameter differences between groups with heterogeneous variances (for treatment conditions 1 to 3 only).
e) ANOVA; Factor: fee treatment.

Table 4: Field Experiment: Effect of Bidding Fees on Seller Profit

Treatment	Number of Successful Bids[a)]	Average Threshold Price[b)]	Average Successful Price[c)]	Average Profit Margin[d)]	Profit (Sum)[e)]	Revenue (Sum)
No Fee	42 (= 35.29 %)	40.05 €	41.87 €	4.74 %	76.45 €	1,758.43 €
Low Fee	30 (= 25.21 %)	42.28 €	44.80 €	6.09 %	75.74 €	1,344.01 €
High Fee	27 (= 22.50 %)	40.58 €	44.62 €	11.20 %	109.04 €	1,204.70 €
Single Bid	10 (= 8.62 %)	44.29 €	48.12 €	8.57 %	38.28 €	481.15 €
Test	χ^2=24.05[f)], df=3, p=.000	F=2.39[g)], df=3, p=.073	F=5.08[g)], df=3, p=.003	χ^2=10.31[h)], df=3, p=.016	n.a.	n.a.

a) Number of bids equal to or above threshold price, i.e., number of transactions (success rate). N=109.
b) Differences in threshold prices reflect different wholesale prices of the underlying DVDs.
c) Consumers' final bid value plus bidding fees for the bundle of three selected DVDs.
d) Relative information rent: Bid value plus bidding fees minus threshold price divided by threshold price.
e) Sum of successful bid values plus bidding fees minus threshold prices.
f) χ^2 test of independence between success and treatment.
g) ANOVA; Factor: fee treatment.
h) χ^2 of Kruskal-Wallis-Test for parameter differences between groups with heterogeneous variances.

Figure 1: Model of Bidding Behavior – Numerical Example

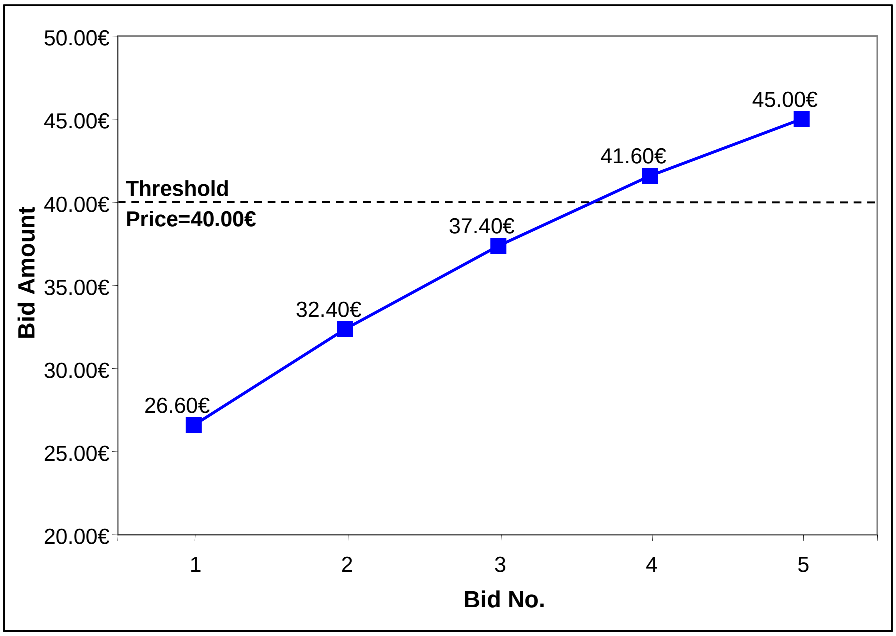

Figure 2: Design of Field Experiment

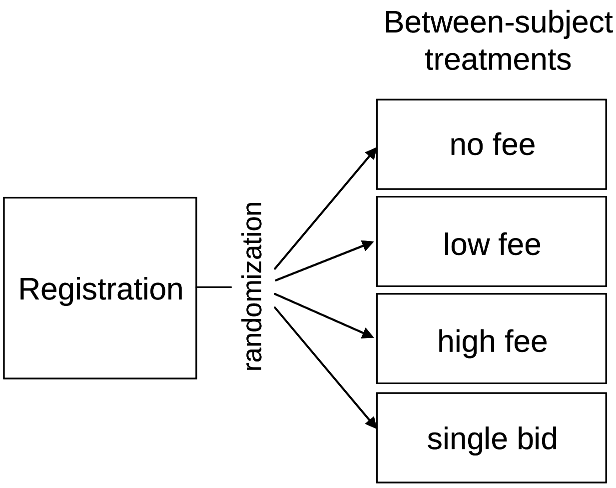

Figure 3: Seller Profit for Varying Levels of Threshold Prices