Paying for a Chance to Save Money:

Buyer Behavior in Name-Your-Own-Price Markets with Bidding Fees

July 5, 2016

Robert Zeithammer, Lucas Stich, Martin Spann, and Gerald Häubl

Abstract

According to a recently introduced theory (Spann, Zeithammer and Häubl 2010), a name-your-own-price retailer should benefit from charging prospective buyers a non-refundable bidding fee rather than providing the bidding opportunity free of charge. We use an incentive-compatible experiment to provides the first empirical test of the profitability of bidding fees. Confirming the theory's qualitative prediction, our results reveal that retailers charging moderate bidding fees make more profits than retailers charging no fees. However, the empirically optimal fee level is lower than predicted, and both entry and bidding behavior systematically deviate from the theoretical predictions. To account for these deviations, we propose and estimate a structural model of entry and bidding based on cumulative prospect theory. It incorporates two behavioral enrichments of a standard prospect-theoretic model: (1) a "joy of playing" component that captures the entertainment value of participating in bidding and (2) partial myopia whereby bidders do not fully account for the outside option of buying in the posted-price market. The proposed model adequately characterizes the observed entry and bidding behavior. Counterfactual simulations based on the estimated model reveal that both optimal bidding fees and optimal minimum bids can increase retailer profits by more than 40% compared to the no-fee alternative.

Keywords: Pricing, Auctions, Behavioral Economics, Induced-values Laboratory Experiment

Contact: Robert Zeithammer, rzeitham@ucla.edu

INTRODUCTION

Name-your-own-price (NYOP) is a buyer-driven pricing mechanism pioneered by Priceline in 1998 to sell travel products, and adopted by a wide variety of retailers since then to sell other products and services (e.g., restaurant vouchers at chiching.com, event tickets at scorebig.com, electronics at meanbuy.com or greentoe.com, and a variety of products on eBay.com via its "Best Offer" option). A NYOP buyer bids a binding price-offer to the retailer, and the retailer decides whether to accept the bid or not. When the retailer accepts a buyer's bid, the buyer pays the bid as his purchase price, and the retailer generally keeps the difference between the bid and its procurement cost. Although the retailer firm thus cannot lose money as long as its acceptance threshold exceeds its procurement cost, simply accepting all bids above cost is not optimal for the retailer because such a policy does not exercise the retailer's market power (Zeithammer 2015). One way the retailer can increase profits is to charge an upfront non-refundable bidding fee akin to an entry fee into the retailer's store. Spann et al. (2010 & 2015, hereafter "SZH") show analytically that such bidding fees can increase the NYOP retailer's profit compared to providing the bidding opportunity free of charge. In this paper, we test SZH's prediction in an incentive-compatible laboratory experiment that implements their model of the retailer's behavior, but does not enforce any aspect of buyer preferences beyond manipulating their private valuations.

Bidding fees are a realistic possibility for NYOP retailers in that they constitute a significant source of revenue in several participative pricing mechanisms similar to NYOP, such as price-reveal auctions (e.g., zoograb.com), lowest-unique-bid auctions (e.g., vipauction.com), and pay-to-bid auctions (Platt, Price and Tappen 2013). Should NYOP retailers follow suit and introduce bidding fees as these similar mechanisms suggest and as SZH recommend? One possible reason against using bidding fees is that human buyers might behave sufficiently differently from the rational forward-looking risk-neutral buyers SZH assume. For example, real humans may exhibit "fee aversion" and use a decision rule to never pay for anything other than the product itself (Amir and Ariely 2007). Another possible difference is risk aversion or loss-aversion, which obviously reduce the fees' potential profitability. We find support for the main theoretical prediction of SZH: the NYOP retailer we simulate can increase profits by charging a

positive bidding fee. We do not find evidence of fee aversion: Very small fees are significantly and substantially more profitable than zero fees. Loss-aversion also does not seem to play a large role in the buyer behavior we observe: Buyers do not bid more aggressively in situations where getting their bid accepted is the only chance to avoid an overall loss compared to when they can still realize a gain by buying the product on the outside posted-price market should their bid be rejected. Finally, we find that the optimal fee a NYOP retailer should charge is lower than that predicted by SZH, and the buyers' entry and bidding behaviors systematically deviate from SZH's model predictions.

To capture the observed entry and bidding behavior and conduct counterfactual simulations, we develop and estimate a structural model of entry and bidding behavior that is based on cumulative prospect theory. Our proposed model incorporates two behavioral enrichments of a standard prospect-theoretic model: (1) a "joy of playing" component that captures the entertainment value of participating in NYOP bidding and (2) partial myopia whereby some bidders do not fully account for the outside option of buying in the posted-price market. We estimate our proposed model at the individual level using maximum-likelihood techniques, and find it fits the observed behavior well. Using the estimated model, we can answer the following counter-factual questions: First, what is the optimal fee a NYOP retailer should charge, and how much does it improve profits relative to zero fee? In other words, how should we interpolate between the few discrete fee- and buyer-valuation levels used in our experiment? Second, what is the optimal minimum bid – a strategy proposed by Zeithammer (2015) – a NYOP retailer should set, and how much does it improve profits relative to no minimum bid? Finally, how do the answers to the first two questions depend on our behavioral enrichments? Put differently, how would our managerial recommendations change in alternative settings with buyers who do not exhibit joy of playing and/or partial myopia?

We find that optimal bidding fees can increase retailer profit by 44 percent relative to no fees. The percentage incremental profit from using the optimal bidding fee (relative to no fee) is sensitive to the behavioral enrichments, but remains above 20 percent under all possible model restrictions. The presence of joy of playing obviously increases the fee a NYOP retailer should charge, and the incremental profits

he can get. Less obviously, the presence of partial myopia decreases the fee a NYOP retailer should charge and the profits he can get because myopic high-valuation buyers find the NYOP value proposition less lucrative. In our second counter-factual simulation, we compare the maximum profit achievable with a minimum-bid strategy to the profit achievable with bidding fees. We find that the two selling strategies are roughly comparable in achievable profit, but the minimum-bid strategy is more robust in that the impact of behavioral enrichments on profitability is smaller.

The remainder of this paper is structured as follows. In the next section, we discuss our contribution to the literature. We then outline the SZH model for NYOP selling and bidding, as well as our method and experimental design. A subsequent section depicts the model-free analysis of our test of SZH's predictions regarding retailer profits as well as observed entry and bidding behavior. The test reveals several systematic deviations of the observed behavior from the predictions, and so we then develop our structural model based on the idea of cumulative prospect theory, outline the econometric specification, and discuss identification. Two subsequent sections report the estimation results and the counterfactual simulations, respectively. Finally, we discuss practical implications, limitations, and future research.

LITERATURE REVIEW

This paper is related to three strands of literature: (1) the literature on NYOP selling, (2) the experimental auction literature, and (3) the literature on prospect-theoretic preferences, including risk aversion. We discuss our contribution to the three strands in turn.

The majority of prior research on NYOP pricing is analytical and focuses on retailers' design decisions such as responding to repeat bidding (Fay 2004), facilitating joint bidding for multiple items (Amaldoss and Jain 2008), charging bidding fees or committing to minimum markups (SZH), or committing to the optimal bid-acceptance schedule (Zeithammer 2015). Another stream of research gives reasons for the emergence of the NYOP channel, including its ability to soften competition (Fay 2009), exploit buyer risk aversion (Shapiro 2011), achieve price discrimination based on haggling friction costs (Terwiesch, Savin and Hann 2005), and adapt to uncertain demand (Wang, Gal-Or and Chatterjee 2009).

All but one of the papers mentioned above rely on the assumption of risk neutrality. The one exception is Shapiro (2011), who assumed risk-averse buyers. We contribute to the theoretical literature by directly testing the predictions of SZH, and by developing and empirically validating a more realistic prospect-theoretic model of bidding in NYOP settings. We also contribute to the relatively smaller literature on laboratory tests of analytical model predictions regarding particular NYOP retailer strategies, such as different threshold-setting strategies (Hinz, Hann and Spann 2011), different modes of information diffusion about retailers' threshold level (Hinz and Spann 2008), or the opacity of the NYOP offering (Shapiro and Zillante 2009). The most related paper in this literature is the work by Bernhardt and Spann (2010), who study the effects of bidding fees on buyer behavior. In contrast to our setting, Bernhardt and Spann (2010) analyze bidding fees that accrue only in the event of a successful bid, and they do not consider the NYOP retailer's competition with the outside posted-price market. They find bidding fees can increase retailer profit, because consumers bid by higher increments in the presence of bidding fees.

By proposing a behaviorally realistic structural model, we bridge the gap between the analytical literature rooted in economics and the behavioral literature rooted in psychology, that considers the impact on buyer behavior of emotions (Ding et al. 2005), menus of possible bids (Chernev 2003; Spann et al. 2012), and expectations about changes in retailers' threshold level (Fay and Laran 2009; Fay and Lee 2015). Relatedly, our proposed model also contributes to the literature that uses NYOP selling as a convenient measurement tool of consumer characteristics such as risk aversion (Abbas and Hann 2010), frictional costs of online transactions (Hann and Terwiesch 2003), willingness to pay (Spann, Skiera and Schäfers 2004), and buyer haggling costs (Terwiesch, Savin and Hann 2005).

Second, our paper is related to the large literature in experimental economics on consumer behavior in first-price sealed-bid (1PSB) auctions. The decision of a NYOP bidder is simpler than that of a 1PSB bidder because a NYOP bidder does not compete with other potential buyers. Therefore, NYOP bidding provides a clearer empirical setting for studying the impact of preferences on bidding behavior by avoiding the need for both subjects and the analyst to understand the equilibrium of the bidding game. Nevertheless, our results are consistent with two major findings of the empirical literature on 1PSB bidding: overbidding

and over-entry relative to a risk-neutral model. Overbidding is one of the consistent findings in this literature, and thus a large body of work has focused on explaining that phenomenon (Cox, Roberson and Smith 1982; Cox, Smith and Walker 1988). The most common explanation that has been put forward is risk aversion (Cox, Smith and Walker 1988; Filiz-Ozbay and Ozbay 2007). However, other factors that have been considered include the misperception of winning probabilities (Dorsey and Razzolini 2003), anticipated regret (Filiz-Ozbay and Ozbay 2007), and the joy of winning (Ertaç, Hortaçsu and Roberts 2011). We show how overbidding can occur in the absence of equilibrium considerations, and how it arises in a prospect-theoretic model from the curvature of the value function.

Another consistent finding in 1PSB auctions is over-entry. For instance, Palfrey and Pevnitskaya (2008) find evidence for excess entry and provide a review of similar findings in other games with endogenous entry. They propose an entertainment value of bidding in an auction as an explanation of the over-entry phenomenon. Ertaç et al. (2011) propose a model that combines risk aversion and the joy of winning to explain both bidding behavior and endogenous entry behavior. They show that a model incorporating joy of winning together with risk aversion better matches the observed entry behavior than a model lacking that component. We do not find evidence of joy of winning (recall that "winning" NYOP bidding merely arises from the seller accepting the bid; there are no other buyers to beat), but our results are consistent with the existence of the entertainment value, which we call "joy of playing".

The third strand of the literature our paper is related to is work in marketing and economics on risk aversion (e.g., Charness, Gneezy and Imas 2013, Dohmen et al. 2012, DellaVigna 2009; Kőszegi and Rabin 2007) and loss aversion (e.g., Kahneman and Tversky 1979; Tversky and Kahneman 1991, Andersson et al. 2014). We contribute to this literature by proposing and estimating a model that backs out parameters of cumulative prospect theory from bidding data at the individual level. As far as we can tell, we are the first to estimate a prospect-theoretic model of bidding. By estimating at the individual level, we can shed light on the population distribution of the model parameters, documenting both their heterogeneity and their mutual correlations. We find substantial and heterogeneous curvatures of the value function and the probability weighting function. Consistent with cumulative prospect theory, most of our

subjects thus exhibit risk-averse preferences when their valuations are relatively large and risk-seeking preferences when their valuations are relatively low. Interestingly, we do not find evidence of loss aversion.

SZH'S MODEL OF NYOP SELLING AND BIDDING

Suppose a buyer is interested in buying one particular indivisible object, and submits a binding price offer (i.e., a "bid") to a NYOP retailer. In our laboratory paradigm, we implement the following SZH model of a NYOP retailer competing with an outside posted-price market:

Supply-Side Model: NYOP Retailer with a Non-Strategic Posted-Price Competitor

The object is readily available from an outside posted-price market for a commonly known price $p \leq M$. A NYOP retailer can procure the object for a privately known procurement cost w (for "wholesale cost"), and accepts all buyer bids above his cost. It is common knowledge that the retailer's cost w is ex-ante uncertain and distributed uniformly on $[0, p]$.[1] Realistically, the outside posted price is thus a public upper bound on the NYOP retailer's procurement cost. A lower p is both bad news (tougher competition) and good news (lower expected cost) for the NYOP retailer. The NYOP retailer keeps the difference between w and an accepted price as his profit, and he can also charge a non-refundable bidding fee f.

Demand-Side Model: A Risk-Neutral Forward-Looking Buyer

SZH consider a risk-neutral forward-looking buyer who privately values the object v, where the buyer's valuation is drawn from a uniform distribution on the interval $[0,M]$. When the buyer does not buy the object from either retailer, his payoff is zero. SZH then solve for the optimal bidding fee $f^*(p)$ the above retailer should charge when M=1. It is straightforward to extend their results to an arbitrary M. The

[1] Both in the travel industry (e.g., Priceline.com) and the restaurant industry (e.g., Chiching.com), the wholesale cost uncertainty arises from the producers' opportunity cost of not filling their full capacity using standard posted pricing (Belobaba 1989). Such an opportunity cost varies over time, and is specific to details of the product such as date, time, quantity requested, etc.

extension of SZH's Proposition 2 implies f^* is $f^*(p) = {4M^2}/{49p}$ as long as $p > {4M}/{7}$ – a technical assumption we make throughout this paper. The lower bound on p ensures that at least some buyers with $v<p$ enter the NYOP store and bid when the bidding fee is set optimally.

We now briefly summarize the predicted behavior of a risk-neutral buyer facing a bidding fee f (please see SZH for details). For any $f < \frac{p}{4}$, buyers with $v > 2\sqrt{pf}$ pay the bidding fee and submit a bid to the NYOP retailer. To derive their optimal bid level, consider the bidding problem implied by the uniform distribution of retailer cost w:

$$\max_b \quad \underbrace{\left(\frac{b}{p}\right)}_{\substack{\text{probability}\\ \text{NYOP store}\\ \text{accepts bid}}} \underbrace{(v-b)}_{\substack{\text{surplus when}\\ \text{bid } b \text{ is accepted}}} + \underbrace{\left(1-\frac{b}{p}\right)}_{\substack{\text{probability}\\ \text{NYOP store}\\ \text{rejects bid}}} \underbrace{\max(0, v-p)}_{\substack{\text{utility of buying}\\ \text{from the posted}\\ \text{price store if}\\ \text{bid } b \text{ is rejected}}} = \begin{cases} v \le p : \max_b \left(\frac{b}{p}\right)(v-b) \\ v > p : \max_b \left(\frac{b}{p}\right)(p-b) + (v-p) \end{cases} \tag{1}$$

Two types of bidders thus emerge: "low" bidders with $v < p$ who cannot afford the outside option bid $b(v) = \frac{v}{2}$, and "high" bidders with $v \ge p$ who mimic the bidder with $v = p$ and bid $\frac{p}{2}$ because they have a real option of buying in the outside market should their NYOP bid not be successful. We now describe our experimental design to test the model described in this section.

TEST OF SZH'S PREDICTIONS: METHOD

The two main goals of our empirical study are to test the profitability of bidding fees, and to assess how well the risk-neutral model of SZH fits the actual behavior. We employ a laboratory experiment to achieve our goals. The products are virtual tokens with induced value, allowing us to abstract away from specific product categories and vary and control buyer valuation (Smith 1976). Subjects are assigned the role of buyers and bid against computerized retailers called "stores" in a session involving multiple rounds. Every round represents an independent market with one buyer and two stores: store A, which uses the name-your-own-price (NYOP) mechanism, store B, which sells the same product using posted pricing, and a

"Don't Buy In This Period"-option (please see Figure A1 in the Appendix for the screen layout, and see the Web Appendix for our complete instructions and procedures).

Design: Within-subject manipulation of valuations and fees

We begin our design development by setting the range of valuations to M=100, and considering an outside price p=70, which exceeds $4M/7$ as needed for the theoretical predictions to hold. To test the behavioral consequences of bidding fees, we vary the fee from 0 to 18, and include three intermediate levels: 1 to capture a very small fee that some "fee-averse" subjects may still reject, 12 to test a level optimal under risk neutrality $\left(f^*(70) \approx 11.7\right)$, and 6 as an intermediate, non-negligible value below the level optimal under risk neutrality. To allow for subsequent pooling of the data at different valuation levels while approximating the Uniform[0,100] distribution, we draw the individual valuations from the following equispaced discrete points: {5, 20, 35, 50, 65, 80, 95}. Each subject experiences all possible combinations of valuations and fees (in random order), so our design is a 5(f)x7(v) within-subject design, resulting in 35 conditions per subject. All conditions are collected in a single session, and the condition order is fully randomized across subjects.

Experimental Procedure

Each round has the following experimental procedure: The buyer is informed about his private valuation, the bidding fee at store A, and the posted price at store B. The buyer then has to decide whether to bid in store A, buy from store B, or skip the round. If the subject chooses to bid, he enters the bid amount into a box and presses "Submit Bid," automatically deducting the bidding fee (please see Figure A1 in the Appendix for the screen layout). If a bid is rejected, the buyer is given one more chance to buy from the posted-price store. To decide whether a bid is accepted, we draw the secret threshold price w from a uniform distribution on [0, p], and we make sure the subjects understand this threshold distribution. Note that for measurement of buyer behavior, it is sufficient for subjects to believe the threshold distribution – they do not need to believe the relationship between the threshold and the retailer's wholesale cost.

If the buyer decides to not buy in a round, he receives a payment of 0 points and the round ends. The income of a buyer in a round in which he purchased the product from the posted-price store is his valuation minus the posted price. If the NYOP store accepts a buyer's bid, the buyer's payoff on this round is his valuation minus the bid submitted and minus the bidding fee. Instead, if the store rejects a buyer's bid, the buyer's tentative payoff on this round is 0 minus the fee. The final payoff, however, is contingent on his subsequent decisions. If he decides not to use his additional chance to buy from the posted-price store, his final payoff from this round is 0 minus the fee. On the other hand, if the buyer wants to make use of the additional chance, his final payoff is his valuation minus the posted price and minus the fee. Subjects are shown their profit after each round but not their total profit to limit potential wealth effects.

After completing the experiments, subjects were asked to answer an exit survey for additional credit. The exit survey focused primarily on measures of individual differences that we hypothesized to be related to entry and bidding behavior: number of "safe" choices in the paired lottery choice task by Holt and Laury (2002); number of rejected risky lotteries in the lottery choice task by Gächter et al. (2010); subjective risk-taker scale by Dohmen et al. (2012): "How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" (1=*completely unwilling to take risks* to 7=*completely willing to take risks*); a question about attitude towards bidding fees, "I want to pay for the actual product only, I refuse a bidding fee in general" (1=*strongly disagree* to 7=*strongly agree*); a question about mood, "How would you rate your general mood today?" (1=*very bad* to 5=*very good*); and frequency of participation in lab experiments to date. All scales were administered as hypotheticals, not separately incentivized.

Data Collection

We conducted four sessions of the experiment at the Munich Experimental Laboratory for Economic and Social Sciences (MELESSA) of the University of Munich in 2015. With 24 subjects per session, a total of 96 subjects participated in the experiments. Subjects were mainly undergraduate students from the University of Munich and the Technical University of Munich studying a wide range of majors. We used the software z-Tree (Fischbacher 2007) and ORSEE (Greiner 2015) to program and conduct the

experiments. Subjects took about 45 minutes to complete the main part of the study – a little over a minute per task. Subjects earned on average about 16.90 EUR (USD 21.70 at the time of the experiments), which included a show-up fee of 4 EUR (USD 5.10) and another 4 EUR for taking the exit survey.

Training and Elimination of Seemingly Irrational Subjects

A pilot study found some subjects use the first few rounds to explore actual consequences of seemingly irrational behavior, such as bidding above one's valuation. Once they incur an avoidable loss, most subjects refrain from such behavior in later rounds. To give the subjects an opportunity for such an exploration without compromising our experimental design, we included five "training" rounds in the beginning of the session. The rounds were not marked in any way to the subjects, who simply experienced them as the first five rounds of the experiment, and we discarded the data. To encourage bidding, we kept the fees low during the training rounds. To expose the subjects to the second chance should their bid be not accepted, we also included a valuation above p. Specifically, the five rounds exposed the subjects to the following (*fee, valuation*) pairs: (1, 65), (0, 5), (6, 80), (6, 5), (0, 50).

We found the following evidence of learning during the training rounds: 15 subjects bid over their valuation at least once during the five training rounds, but only five subjects did so in the subsequent 35 rounds. The per-round incidence of such seemingly irrational behavior was thus sharply reduced but not entirely eliminated in the subsequent rounds. We exclude the 5 subjects who continued bidding over valuation from our analysis, because we fear they did not understand the experimental procedure. Everything that follows is based on the 91 remaining subjects. Note, however, that the 5 seemingly irrational subjects provide an upper bound on the prevalence of additive "joy of winning" proposed by Ertaç et al. (2011): in our design, additive joy of winning of more than two units of experimental currency would manifest as bids exceeding valuations when v=5. Since very few subjects' bids exceed valuations, joy of winning is either negligibly small or rare in our population, or both.

TEST OF SZH'S PREDICTIONS: RESULTS

Results: Retailer Profits

We begin with an analysis of the key managerially relevant statistic, namely, the expected NYOP retailer profit conditional on the observed bids. To compute the expected retailer profit from each observed bid, denoted $\pi(bid)$, we average over the retailer's uniform cost realizations as follows:

$$\pi(bid) \equiv \int_0^{bid} (bid - w)\left(\frac{1}{p}\right) dw = \frac{bid^2}{2p} \tag{2}$$

Let $bid_{i,f}$ submitted by subject *i* when the bidding fee is *f*, and let $bid_{i,f} = 0$ when the subject does not enter when fee is *f*. Then, we calculate the expected NYOP retailer profit when the fee is *f* as the average over *i* of $\pi(bid_{i,f})$, generating an estimate of $E_i\left[\pi(bid_{i,f})\right]$. This calculation allows us to abstract from the specific threshold realizations that arose in the experiment. Figure 1 plots the expected retailer profit, and compares it to the profit expected under risk-neutral buyer preferences.

We start our discussion of Figure 1 by focusing on the two lowest levels of the bidding fee. The higher profit under a small fee (f=1) than under no fee (f=0) suggests our subjects did not exhibit fee aversion as defined in the introduction: fee aversion would imply a drop in profits as the fee increases from zero to one. Instead, the expected profit rises significantly from 7.2 to 8.4 (p=0.002 in a two-sample t-test with one observation defined as the expected profit from one subject resulting in N=91, p<0.0001 in a t-test comparing the 91 within-subject differences in expected profit to zero)[2].

Given that buyer entry into the NYOP store decreases from 95% to 84%, the rise in expected profit by *more* than the unit increase in fee is interesting. If, as the risk-neutral model suggests, the fees did not affect entrants' bids, we would expect the profit to have a slope of less than unity at zero. Instead, profits rise because bids conditional on entry rise as the fee increases from 0 to 1. We summarize all this as:

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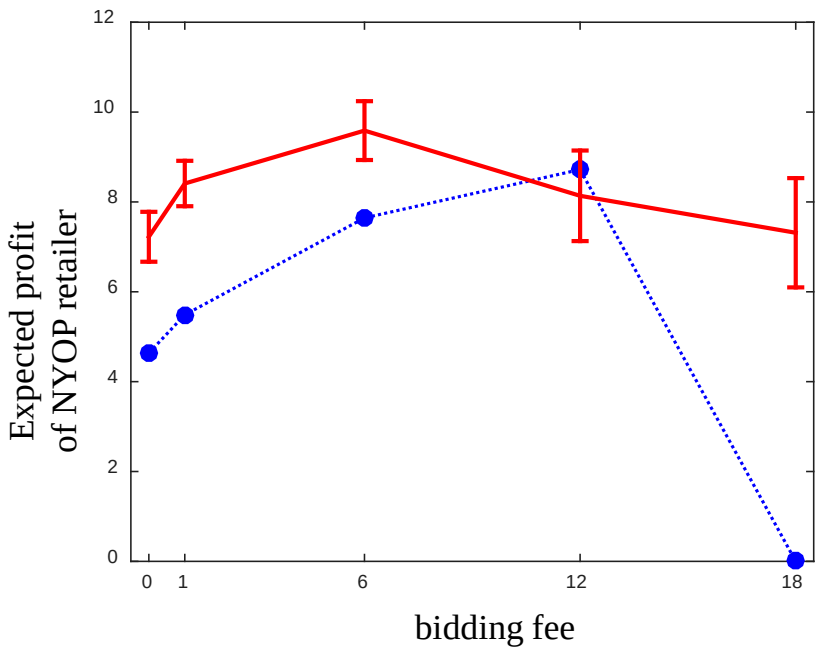
[2] The test using within-subject differences is definitive because fees vary within subject in our design. The two-sample test incorrectly assumes independence between the two samples, but facilitates visualization using error bars (e.g., in Figure 5) and ends up being more conservative because the bids are positively correlated within subject.

Result 1: *We find no evidence of fee aversion. A small increase of the bidding fee from zero results in a significantly higher expected NYOP retailer profit. The profit increase arises from a combination of less entry and higher bid levels.*

Figure 1: NYOP retailer profits



Note to Figure: The solid (red) line connects the observed expected profits, displayed as error bars. Each error bar represents the 95% confidence interval with one observation defined as the expected profit from one subject, so N=91. The dotted (blue) line connects the expected profits predicted by risk-neutral buyers.

Having ruled out fee aversion, we now consider the main prediction of SZH, namely, that non-trivial, positive bidding fees generate higher profits than zero fees. Figure 1 shows the bidding fee of 6 generates 2.3 units more expected profit than no fee — an increase of 33% (p<0.001 regardless of how the t-test is set up[2]). The expected profit with f=6 is also significantly greater than the adjacent fee levels in our design: 18% larger than with f=12 (p=0.02 in a two-sample test, p=0.006 in a single sample of 91 differences[2]) and 14% larger than with f=1 (p=0.006 in a two-sample test, p=0.001 in a sample of 91 differences[2]). Thus, the optimal fee to charge from the set {0, 1, 6, 12, 18} is f=6, which is positive but smaller than f=12 suggested by the model with risk-neutral buyers. Moreover, observed profit exceeds the predicted profit for all fee levels other than 12. We summarize these findings in our second result:

Result 2: *The optimal fee to charge is positive but smaller than that suggested by the model with risk-neutral buyers, which tends to under-predict the profitability of NYOP selling.*

Results: Entry and Bidding

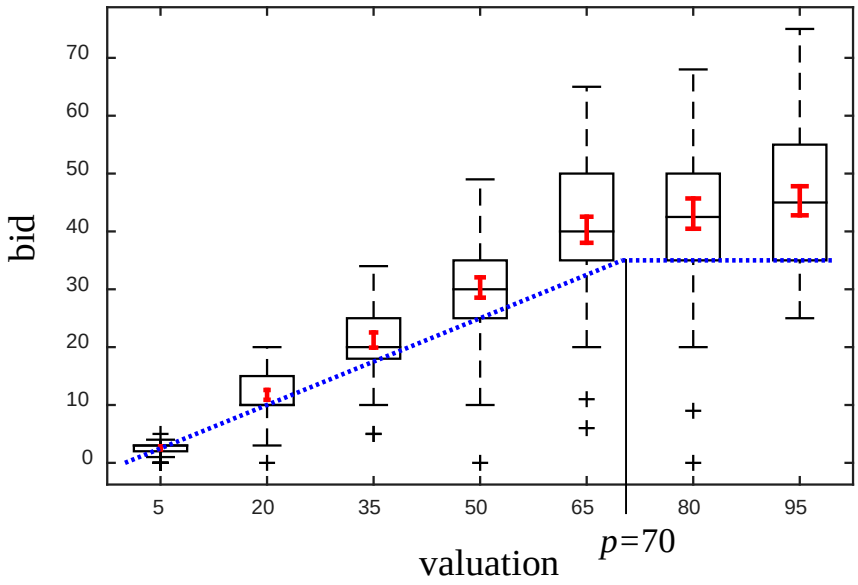
To understand why the risk-neutral model tends to under-predict profits, we decompose the profits into entry and bidding. Table 1 lists the percentage of subjects who enter under the different valuation-fee conditions. The shaded cells delineate the conditions under which risk-neutral buyers should not enter. Clearly, one of the reasons the risk-neutral model tends to under-predict profits is that it under-predicts entry by high-valuation buyers facing relatively high bidding fees. In addition to excess entry, Table 1 includes another pattern that is not consistent with risk neutrality. Risk neutrality predicts entry probabilities should be non-decreasing in valuation. By contrast, for several fee levels, entry probabilities seem to decrease after peaking at v=65.

Table 1: Probability of entry

	bidding fee				
valuation	0	1	6	12	18
5	91%	31%	0%	0%	0%
20	96%	84%	16%	5%	4%
35	97%	97%	53%	19%	14%
50	100%	98%	84%	43%	25%
65	99%	100%	96%	66%	48%
80	95%	95%	84%	63%	45%
95	85%	85%	75%	58%	48%

Figure 2 plots the submitted bids when the fee is zero whence almost all buyers enter the NYOP store (and hence we are the least concerned about selection into the observed sample). It is immediate that at all valuation levels other than the lowest one, bids exceed the risk-neutral prediction. The difference is not only significant, but also large in that the entire inter-quartile range lies above the predicted level.

Figure 2: Observed bids when bidding fee is zero



Note to figure: The boxplots illustrate the distribution of bids at each valuation level. The thicker (red) error bars represent 95% confidence intervals with one observation defined as the expected profit from one subject, so N=91. The dotted (blue) line shows the optimal bidding function by risk-neutral buyers. The case of v=5 is difficult to discern from the figure ─ the risk-neutral prediction is 2.5, and the 95% confidence interval is [2.35, 2.85].

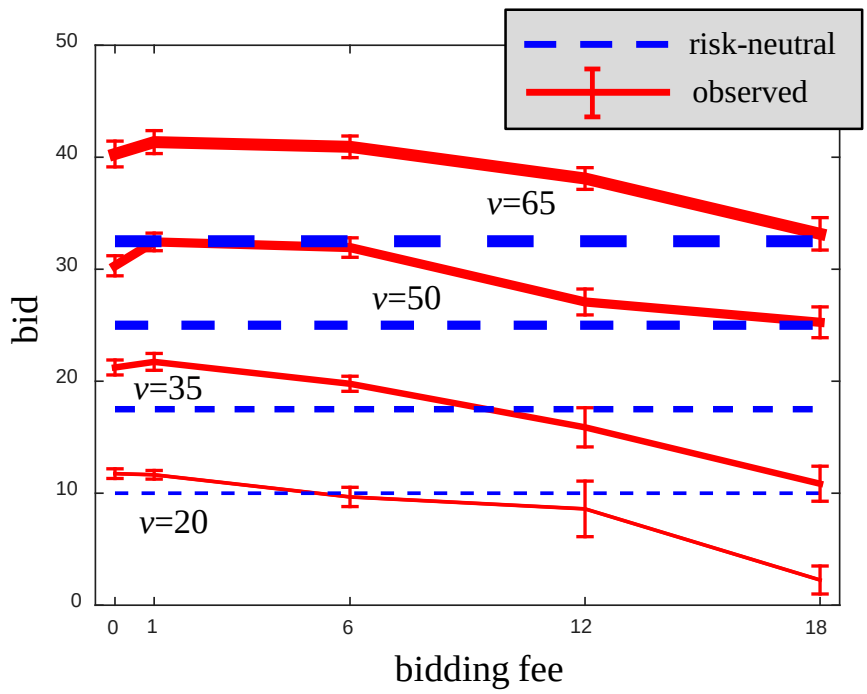
Another qualitative prediction of the risk-neutral model of buyer preferences that can be tested with our data is that the fee paid should not influence bidding, because it is effectively sunk. To see why the fee is sunk in the risk-neutral model, consider solving the overall entry-and-bid problem risk-neutral buyers face: Since the fee enters their surplus additively, considering the bidding problem as "pay fee, and then figure out how much to bid" is identical to "figure out how much to bid given that an extra fee is subtracted from the payoff when I win, and the same fee is also subtracted when I lose." Figure 3 plots the observed bids at four middle valuation levels. Because the error bars represent confidence intervals, it is immediate that observed bids are *not* constant in fee. They are not even monotonic: for intermediate valuation levels, bids first rise as the fee increases from zero to one, and then gradually fall.

The finding of bids changing as a function of the fee level rules out not only risk-neutrality, but also other models that assume fees to be sunk. For example, Smith and Levin (1996) propose a model with risk-averse preferences that additively separates the fee f from the bidding surplus S in the buyer's utility

function: $U(f,S) = S^r - f^r$. The pattern in Figure 3 is not consistent with such a model. Instead, the buyers seem to consider the fee in formulating their bidding strategy. We summarize our comparisons of the observed entry decisions and bids with the risk-neutral prediction in our next result:

Result 3: *Buyers enter more often and submit higher bids upon entry than the risk-neutral model predicts. Also contrary to risk-neutral predictions, submitted bids are concave in fee paid instead of being constant.*

Figure 3: Observed bids are not constant in bidding fee paid



Note to figure: Bidding curves for higher valuations are denoted with thicker lines. The (red) error bars represent 95% confidence intervals with the number of observations equal to the number of observed bids. The dashed (blue) lines show the optimal bidding function by risk-neutral buyers.

The higher-than-predicted profits summarized in Result 2 are thus not merely an outcome of excessive entry, because observed bids also deviate from predictions in important ways. In the next section, we introduce a behaviorally enriched model that better matches both the entry behavior and the bids we observe.

Before analyzing the data through the lens of a parametric model, considering model-free evidence regarding the effect of individual differences is interesting. Table A1 (in the Appendix) shows that lower

bids are correlated with better mood and subjective willingness to take risk. Entry declines slightly as the experiment proceeds and with age, and it increases with the frequency of visits to the experimental lab. In terms of the various risk-attitude scales, entry increases with subjective willingness to take risk, and decreases with the number of rejected risky lotteries in the in the Gächter et al. (2010) task. Another take-away from Table A1 is that the non-monotonic relationship between bids and fees survives all of the included controls: the significant interactions are mostly positive, and they involve intermediate fee levels.

PROPOSED MODEL OF NYOP BIDDING:

BEHAVIORALLY ENRICHED CUMULATIVE PROSPECT THEORY

Participating in NYOP bidding is risky for buyers because they may not win anything. We propose to model the behavior of human bidders using cumulative prospect theory (Tversky and Kahneman 1992, hereafter CPT). CPT evaluates uncertain outcomes as gains or losses relative to a reference point. In our NYOP setting, it is natural to let the income state in the beginning of the game be the reference point: if the buyer does not pay any bidding fees and does not win or buy any products, he remains at this reference point. When he buys a product and his valuation exceeds the total price paid (potentially including the bidding fee), he experiences a gain. Otherwise, the outcome is a loss for the buyer.

We begin our model development with an example of the CPT model of the bidding problem when bidders perfectly anticipate the outside option of buying in the posted-price market should their bid be rejected. Let $U_{bid}(v)$ be the value of the prospect of entering the NYOP store and bidding. CPT relies on a value function V and a probability-weighting function W to characterize $U_{bid}(v)$ in equation 3. Compared to equation 1's two bidder types, equation 3 involves three types. The first type maps exactly onto its counterpart in equation 1, delineating buyers who cannot afford the outside option ($v>p$). The second and third type effectively split the rest of the buyers (i.e., the "high" buyers in equation 1) depending on whether they experience a gain or a loss when they buy from the outside market *after* also paying the bidding fee to the NYOP store.

$$U_{bid}(v)=\begin{cases} f<v<p: & \max\limits_{b<v-f} \underbrace{W\left(\frac{b}{p}\right)V(v-f-b)}_{\text{gain } v-f-b} - \underbrace{W\left(1-\frac{b}{p}\right)V(f)}_{\text{lose } f} \\ p<v<p+f: & \max\limits_{b<v-f} \underbrace{W\left(\frac{b}{p}\right)V(v-f-b)}_{\text{gain } v-f-b} - \underbrace{W\left(1-\frac{b}{p}\right)V(p+f-v)}_{\text{lose } |v-p-f|=p+f-v} \\ p+f<v: & \underbrace{V(v-f-p)}_{\substack{\text{gain } v-f-p \text{ for sure} \\ (\text{recall } W(1)=1)}} + \max\limits_{b<v-f} \underbrace{W\left(\frac{b}{p}\right)\left[V(v-f-b)-V(v-f-p)\right]}_{\text{gain the difference when you win}} \end{cases} \tag{3}$$

The prospect of buying immediately from the outside posted-price market is evaluated as $U_{PP}(v)=V(v-p)$ whenever $v>p$, and zero otherwise.

It is important to point out which part of equation (3) relies on the key insights of CPT relative to its better-known prospect theory predecessor. Because the first two buyer types ($v < p+f$) involve mixed binary prospects (gain if you win, loss if you lose), CPT analysis of bidding by those buyers does not qualitatively differ from the original prospect theory that weights event probabilities (Kahneman and Tversky 1979). However, the last case involves a binary gamble with both outcomes on the gain side of the reference point, which CPT intuitively evaluates as the smaller gain for sure plus a weighted chance of also getting the difference between the two gains. Because $1-W(z)\neq W(1-z)$, CPT deviates from standard prospect theory for this third type of buyer.

Note that compared to the fully general model of Tversky and Kahneman (1992), equation 3 assumes the probability weighting function is the same for gains and losses in order to reduce the number of parameters required. In addition, we do not allow loss aversion to magnify the negative value of a loss compared to the same amount of a gain, because empirically identifying loss aversion in our data is difficult. Moreover, the following model-free evidence suggests loss aversion does not play a large systematic role: consider the bids of a buyer with valuation 80. When the fee is 6, the buyer is in the loss-free case of equation 3, whereas a fee of 12 switches the buyer to the middle case, facing a loss should his bid not be accepted. Loss aversion predicts the buyer should thus bid more when the fee is 12 than when

it is only 6. The average observed bids in the two situations are 43.6 and 43.1, respectively ─ not a significant difference. Therefore, loss aversion is likely not needed to capture bidding in our data.

To take the CPT model to data, we need to parametrize the probability weighting and value functions. We follow Prelec (1998) in both choices:

$$W(z) = \exp\left[-\left(-\ln(z)\right)^{\alpha}\right] \text{ and } V(x) = x^{r} \tag{4}$$

where z is a probability and $0 < \alpha \leq 1$ controls the curvature of the function, increasing the extent to which it over-weighs small probabilities and under-weighs large ones. The power-function form of the value function is a convenient partner to this weighting function because one can derive the boundary between risk-seeking and risk-averse preferences in closed form. Specifically, buyers are risk seeking in the gain domain for probabilities that satisfy $\exp\left[-(1/r)\left(-\ln(z)\right)^{\alpha}\right] > z$, that is, whenever a modified weighting function over-weighs probabilities (Prelec 1998). Therefore, this pair of a probability-weighting function and a value function may capture the excessive entry by low-valuation bidders who inherently face a small probability of having their bid accepted. On the other hand, it cannot explain excessive entry by large-valuation buyers whose bids are accepted relatively more often.

To understand the model's predictions, first considering the special case without probability weighting (α=1) is useful. Then, buyers are risk-averse in the entire gain domain, and 1-r is the coefficient of relative risk aversion: $-x\frac{\partial^2 V}{\partial x^2}\Big/\frac{\partial V}{\partial x} = 1 - r$. In other words, lower r implies greater risk aversion. We now briefly summarize the effect of concave value functions (r<1) on bidding, with a special focus on the reason why such concavity makes optimal bids depend on bidding fees in our setting. In standard expected utility models, it is well known that risk aversion increases bids in first-price sealed-bid auctions, both in theory (Riley and Samuelson 1981) and in the laboratory (Cox, Smith and Walker 1988). Concavity of the value function in our CPT model leads to the same result. Figure 4 shows bidding functions for different levels of bidding fee when α=1 and r=0.6, where the level of r is selected to roughly rationalize the average observed bid levels. Before discussing the impact of bidding fees on bidding, we first focus

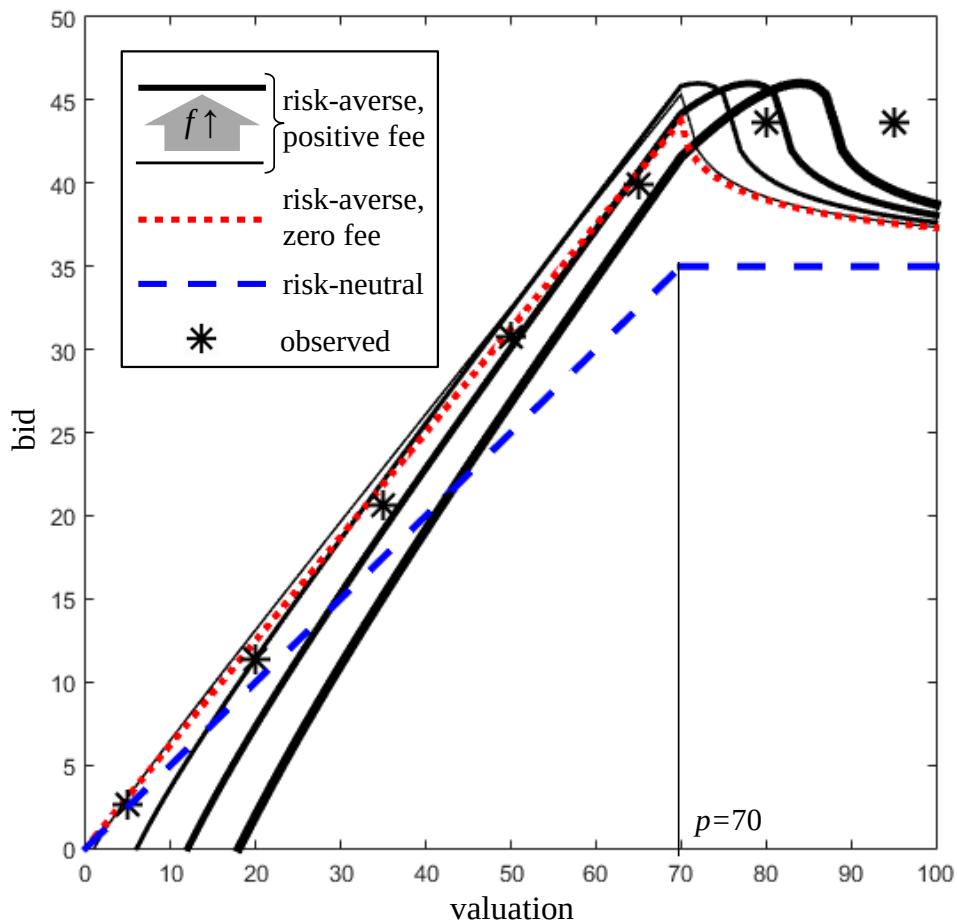
on the general impact of concavity of the value function (r<1) on the optimal bidding strategy. For low-valuation bidders (v<p), the impact of concavity of the value function on bidding follows standard intuition of Riley and Samuelson 1981): bidders bid more because they experience diminishing marginal utility in surplus; therefore (compared to risk-neutral bidders), they prefer increased chances of winning associated with higher bids. For high-valuation bidders (v>p+f), the implication of concavity of the value function is less obvious because optimal bids *de*crease in valuation when valuations are high enough. Among buyers who can afford the outside option, the bidding function is decreasing in valuations because the *net* benefit of having a NYOP bid accepted is decreasing in one's valuation. Because the option of buying for the outside price p is riskless and worth $(v-p-f)^r$ in utility terms, a winning bid b delivers a benefit valued at utility of $(v-b-f)^r$ at the cost of not getting utility $(v-p-f)^r$. Since the utility function is concave (r<1), an increase in v brings the benefit relatively closer to the cost. In summary, concavity of the value function increases bids relative to risk-neutral levels, and predicts a bidding function that is increasing in valuation up to about p, and decreasing in valuation for v>p+f.

We now turn to the impact of fees on the optimal bids. From Figure 4, we can see risk aversion produces the observed bidding pattern shown in Figure 3 in that the bidding function for f=6 crosses that for f=0 for intermediate valuations. In other words, bids first rise in fee and eventually start falling as the fee increases. The reason behind the non-monotonic pattern is that the marginal disutility of losing the fee (if one's bid is not accepted) is diminishing in the fee magnitude. With r=0.6, the disutility of losing a fee of 12 is only about 4.4 times greater than losing the fee of 1. At the same time, the impact of a small fee on the utility of winning is miniscule. Therefore, small fees make the loss of the fee relatively more important, causing bids to rise.

After looking at the relatively good fit of the average bids to predictions in Figure 4, one is tempted to conclude a simple CPT model with α=1 and r=0.6 may capture the data sufficiently well. However, two large discrepancies still remain: over-entry into the NYOP store (Table 1) and overbidding by high-valuation bidders (v=95, Figure 4). We will address each discrepancy in turn by enriching the basic CPT

model in equation 3 to better match the data. In addition, we will explore how the enriched model fits the behavior of each subject in isolation, and we will show a substantial amount of heterogeneity masked by averaging in Figure 4 but clearly evident in Figure 2.

Figure 4: Optimal bidding by risk-averse bidders as a function of valuation



Note to figure: The dashed (blue) line shows the optimal bidding strategy of a risk-neutral bidder. All other bidding strategies assume constant risk aversion of ½. The dotted (red) line shows the case when the fee is zero. The solid (black) lines show the cases of positive fees, with thicker lines denoting higher fees, and each strategy intersecting the valuation axis at the fee level. The stars show the mean observed bids at the experimental valuation levels.

First Behavioral Enrichment

Recall that Table 1 documents over-entry relative to the risk-neutral predictions. Although a "risk-averse" model with a concave value function fits the bidding data better than a risk-neutral one, the concavity exacerbates the over-entry discrepancy: intuitively, risk-averse bidders enter the NYOP store less often that risk-neutral ones because bidding is risky. In other words, a model that fits bidding data better fits the entry behavior worse. Finding excessive entry in an entry game involving bidding is not unexpected. Palfrey and Pevnitskaya (2008) find it in 1PSB auctions with entry fees, and provide a review of similar findings in other games with endogenous entry. They argue that "entering the auction provides some entertainment value" (Palfrey and Pevnitskaya 2008, p. 741). The entertainment value of bidding likely generalizes to real-world NYOP settings outside of the laboratory as evidenced by numerous online customer reports (e.g., on Twitter) or "excitement" during the Priceline bidding process. One blogger even concludes that bidding on Priceline is "like gambling for travel enthusiasts" (Sommer 2014). We call the entertainment value of participating in NYOP bidding "joy of playing," and model it as a positive intercept of the expected value of the NYOP prospect.

Why some of our subjects experience the joy of playing is not clear, but we can rule out one underlying reason – an anticipated additive joy of winning. If buying from the NYOP store delivered the value V of the good plus some additional joy from winning the good (as opposed to just purchasing it in a store), the empirical bidding function should have a positive intercept corresponding to this joy of winning. Instead, we find the intercept of the average bid to be approximately zero (see Figure 2). We have also looked for positive intercepts in individual-specific OLS regressions of bids on valuations (restricting attention to $v<p$), and we did not find a systematic trend to positive intercepts at the population level (details available from the authors). We conclude that the observed entry behavior is not easily explained by anticipated additive joy of winning heterogeneous across the subjects.

The model-free regression in Table A1 (Appendix) suggests that the overall tendency to enter the NYOP store is reduced in later rounds of our experiment. A fraction of the entertainment value might thus arise from novelty of the stimuli. We will explore the strength of this explanation by discarding some of

the early periods and measuring the implied reduction in the estimated joy of playing in an extension.

Second Behavioral Enrichment

The second discrepancy between the simple (α=1 and r=0.6) CPT model and observed behavior we need to account for can most easily be seen in Figure 4: the observed bids for the largest valuation (95) are clearly above the predicted levels. Thus, the empirical average bidding function is not decreasing for high valuations as predicted. To account for this behavior, we enrich the model in equation 3 by allowing the bidders to be partially myopic, incorporating only a part of the option value into solving the bidding problem. Specifically, we let the buyers behave *as if* they believed, should their bid be rejected, the outside posted-price option will only be available with a probability δ. Note that there is nothing in our instructions that would lead subjects to believe that the outside option may actually disappear should their bid be rejected. Therefore, we are using the probability of disappearance as a modeling device that captures subjects' tendency to forget about the outside option in the heat of the moment.

The two behavioral enrichments of the model result in the following value of the prospect of bidding in the NYOP store:

$$
\begin{aligned}
f < v < p : U_{bid}(v, f) &= J + \max_{b<v-f} \underbrace{W\left(\frac{b}{p}\right)V(v-f-b)}_{\text{gain } v-f-b} - \underbrace{W\left(1-\frac{b}{p}\right)V(f)}_{\text{lose } f} \\
p < v < p+f : U_{bid}(v, f) &= J + \max_{b<v-f} \underbrace{W\left(\frac{b}{p}\right)V(v-f-b)}_{\text{gain } v-f-b} - \underbrace{W\left(1-\frac{b}{p}\right)V(p+f-v)}_{\text{lose } |v-p-f| = p+f-v} \\
&\quad - \underbrace{W\left[(1-\delta)\left(1-\frac{b}{p}\right)\right]\left[V(f)-V(p+f-v)\right]}_{\text{when bid rejected \& option unavailable, also lose } f > p+f-v} \\
p+f < v : U_{bid}(v, f) &= J + \underbrace{V(v-f-p)}_{\substack{\text{gain } v-f-p \text{ for sure} \\ \text{(recall } W(1)=1)}} + \max_{b<v-f} \underbrace{W\left(\frac{b}{p}\right)\left[V(v-f-b)-V(v-f-p)\right]}_{\text{gain the difference when you win}} \\
&\quad - \underbrace{W\left[(1-\delta)\left(1-\frac{b}{p}\right)\right]V(f)}_{\text{when bid rejected \& option unavailable, lose } f}
\end{aligned}
\tag{5}
$$

where J is the joy of playing discussed above. Compared to equation 3, the "low" bidder type is obviously unaffected by partial myopia, but both of the higher types now face the possibility of a large loss of f. Both of the higher types thus face trinary mixed prospects thanks to partial myopia. Before taking the model to the data, we need to specify the econometric error terms, and explain how the parameters of the model are empirically identified. We turn to the econometric model first before discussing identification.

Econometric specification

Let the bidding function arising from the optimization in equation 5 be $b\left(v, f \middle| \theta\right)$, where $\theta = \{\alpha, \delta, r\}$ are the parameters that influence bidding. Suppose we observe bids that do not exactly match these theoretical predictions. We model the deviation between the buyer's n-th bid bid_n and the theoretical prediction using a truncated lognormal distribution. Specifically, we introduce a positive multiple $\exp\left(\varepsilon_n\right)$ to ensure the observed bids are positive, and we restrict the observed bid to be below both valuation and posted price (as implied by our definition basic rationality in cleaning the data):

$$\text{bid}_n = b\left(v_n, f_n \mid \theta\right)\exp\left(\varepsilon_n\right) \tag{6}$$

where ε_n is normally distributed with a mean of 0 and variance σ^2 truncated such that $\text{bid}_n < \min\left(v_n, p\right) \Leftrightarrow \varepsilon_n < \log\left(\min\left(v_n, p\right)\right) - \log\left(b\left(v_n, f_n \mid \theta\right)\right)$. As long as σ^2 is small enough, the truncation will not matter much compared to an unconstrained lognormal distribution. Either way, we do need to account for it in the likelihood of a bid observation, which we present in the Appendix.

To model the entry decision, let $U_{bid}\left(v_n, f_n \middle| \theta, J\right)$ be the utility function in equation 5. Recalling that the prospect of buying immediately from the outside posted-price market is evaluated as $V\left(\min\left(0, v - p\right)\right)$, we model the deviation between a subject's n-th entry choice and the predicted behavior using an additive error term:

$$\Pr_{enter}\left(v_n, f_n \middle| \theta, J, \tau\right) = \Pr\left[U_{bid}\left(v_n, f_n \middle| \theta, J\right) > V\left(\min\left(0, v_n - p\right) \middle| r\right) + \eta_n\right] =$$
$$= \Phi\left(\frac{U_{bid}\left(v_n, f_n \middle| \theta, J\right) - V\left(\min\left(0, v_n - p\right) \middle| r\right)}{\tau}\right) \tag{7}$$

where η_n is Normal with mean zero, variance τ^2. For simplicity, we assume η_n is independent of ε_n.

The entry and bidding behavior of each experiment participant is thus captured by six parameters: $\{\theta, J, \sigma, \tau\} = \{\alpha, \delta, r, J, \sigma, \tau\}$. We use all 35 post-learning observations of each participant to maximize the likelihood detailed in the Appendix. The computation is straightforward except for the need to solve the bidding problem in equation 5 at every step, which we accomplish by searching for the optimal bid on a grid given a candidate θ. We conduct a constrained search for the maximum-likelihood estimates, with J unconstrained, σ and τ positive, and the constraints on the remaining parameters set as follows: $\delta \in [0.1,1]$ to restrict attention to myopia (as opposed to hyperopia), $r \in [0.2,1.5]$ to allow both extreme risk-aversion and moderate risk-seeking preferences, and $\alpha \in [0.1,1]$ to enforce overestimation of small probabilities and underestimation of large ones.

Identification

The bidding data in isolation identify several of the parameters. The curvature parameter r is identified by the magnitude of bids given valuations: larger bids imply smaller r. The partial myopia parameter δ is identified by bids at the largest valuation 95, for which predictions from different r parameters concentrate to a narrow interval between 35 and about 40 (see Figure 4 for an illustration): any observed bids exceeding 40 cannot be rationalized by even the smallest reasonable r, even with probability weighting (α<1). The probability-weighting parameter α is identified from curvature of the bidding function for v<p. The bidding function under α=1 is either a straight line (when f=0) or a slightly concave curve (when f>0), whereas the bidding function is convex for low valuations when α<1. In addition, probability weighting reduces the level of the optimal bid. Intuitively, overestimation of the probability of winning reduces the optimal bids for small valuations because small valuations imply small bids.

Given the identification from bidding data alone described above, consider the added information from the entry data. First, entry data clearly identify the joy-of-playing parameter J through a systematic difference between observed entry and the entry-pattern bids by the same person would predict. Second, entry data also add information to the identification of the other parameters already identified by bidding data alone: entry data help identifying r in that more risk-averse buyers (lower r) should enter less often, ceteris paribus. Also, recall from Table 1 that, in contrast to risk-neutrality's prediction, entry probabilities seem to decrease after peaking at v=65 for several fee levels. This pattern is consistent with r<1 as explained in the discussion of Figure 4, and it is also consistent with δ <1 because the partial removal of the outside-market option value reduces the perceived value of bidding by large-valuation buyers, decreasing their chance of entry. Finally, the two error standard deviations σ and τ are obviously identified by departures of the observed data from predictions.

PROPOSED MODEL: PARAMETER ESTIMATES AND MODEL SELECTION

We estimated four specifications of the model using a 2x2 design with either probability weighting and/or joy of playing allowed in the model. Table 2 gives the population average and standard deviation of the MLE of each parameter in each specification. The interpretation of the δ parameter that captures partial myopia is straightforward: it is a probability the outside option is available should one's bid get rejected. To aid in the interpretation of the J parameter that captures joy of playing, one can use the $sign(J)|J|^{(1/r)}$ transformation to joy of playing in the units of experimental currency (by assuming joy-exhibit the same pattern of diminishing marginal returns). At the population average for the full model shown in Table 2, this transformation yields an estimate of about 1.46 monetary units – a modest amount. However, the population does include three subjects with monetary joy of playing over 10 units. In fact, all parameters exhibit a lot of heterogeneity in the population; see Figure A2 in the Appendix for histograms of parameters under the full model.

Table 2: Population averages and standard deviations of parameter estimates

specification	J=0, α=1		J=0		α=1		full model	
population:	mean	stdev	mean	stdev	mean	stdev	mean	stdev
δ	0.62	0.34	0.71	0.29	0.55	0.34	0.69	0.30
r	0.67	0.27	0.61	0.24	0.64	0.26	0.55	0.22
σ	0.25	0.17	0.23	0.14	0.26	0.19	0.23	0.16
τ	2.85	2.42	2.45	2.20	1.86	2.05	1.30	1.39
J	0	0	0	0	1.80	2.90	1.37	1.90
α	1	0	0.83	0.17	1	0	0.80	0.18
Log likelihood	1063.5		1140.3		1429.7		1539.9	

Before selecting a model for counterfactual simulations, interpreting the parameters in Table 2 is useful for understanding their interplay and empirical identification. Restricting the full model to a model without probability weighting (α=1) reduces the fit of both the bidding and entry parts of the model as evidenced by greater error standard deviations σ and τ. The increase is large for the entry part of the model, suggesting that probability weighting is mostly identified by the observed entry patterns. Since the model with a free α involves a smaller average utility from joy of playing, probability weighting explains a part of the observed over-entry as originally hypothesized. The added non-linearity arising from an unrestricted α seems to be a complement to the non-linearity arising from the curvature of the value function in that the full model involves greater average curvature (smaller r). Restricting the full model to a model without joy of playing (J=0) also reduces the curvature of the value function, but mostly dramatically reduces the fit of the entry model: the average τ nearly doubles. The J=0 restriction does not affect the fit of the bidding model because J is only identified by entry data. Finally, the joint restriction (J=0, α=1) influences the model fit and parameters similarly to the (α=1) restriction, with the entry model fitting even worse.

Our 2x2 design involves nested models, so we can perform five likelihood ratio tests to select the best model for use in counterfactual simulations. Because we estimate separate parameters for each of the 91 subjects, a population-wide restriction of one of the parameters to a constant (e.g., J=0) can be tested with a likelihood ratio test with 91 degrees of freedom such that $2*\left(LL_{unrestricted} - LL_{restricted}\right) \sim \chi^2_{91}$. A population-wide restriction of two parameters can be tested with an analogous likelihood ratio test with

182 degrees of freedom. Table 3 lists the relevant log likelihoods along with the test results. All five of the feasible likelihood ratio tests are highly significant (p<0.001). Therefore, we select the full model for our counterfactual simulations.

Table 3: Model selection using the likelihood ratio test, all possible comparisons imply *p*<0.001

Log likelihoods	*J* restricted to 0	*J* unrestricted	2*difference in row ~ χ^2_{91}
α restricted to 1	1063.5	1429.7	732.4
α unrestricted	1140.3	1539.9	799.2
2*difference in column ~ χ^2_{91}	153.6	220.4	2* diagonal difference ~ χ^2_{182} : 952.8

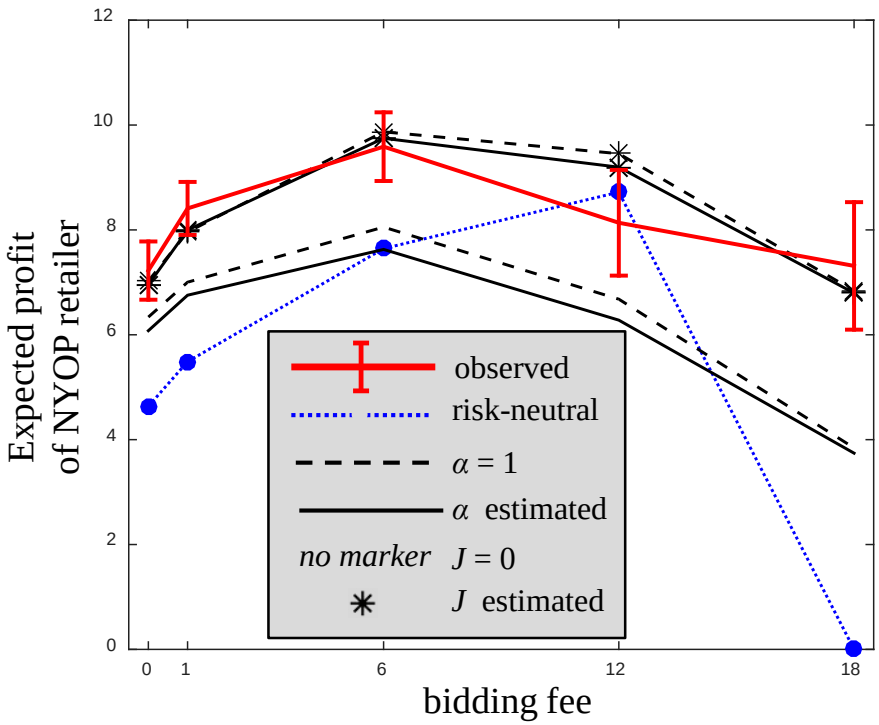
Note: The exact critical values of χ^2_{91} are: p=0.01 when statistic=125.3, p=0.001 when statistic= 138.4. The exact critical values of χ^2_{182} are: p=0.01 when statistic=229.3, p=0.001 when statistic= 246.7.

Several interesting correlates of demographic and psychographic variables emerge (correlations not reported in detail). Females are more myopic (average δ=0.60 among females vs. 0.80 for males), subjects who choose fewer risky lotteries in the Holt-Laury and Gächter et al. tasks appear more risk-averse by virtue of having a more curved value function (lower average r), and subjects who consider themselves to be risk-takers according to the Dohmen et al. scale are less myopic and have a higher joy-of-playing average parameter. Interestingly, the subjective risk-taker scale does not correlate with curvature of the value function, and the lottery-choice tasks do not correlate with joy of playing. Finally, a negative attitude towards bidding fees and frequency of participation in experiments do not correlate with any parameters.

Figure 5 shows the main construct of interest, namely, the expected profit of the NYOP retailer implied by equation 2, under all specifications we considered. Note that the models were estimated using entry and bidding data, so we do not expect them to fit observed profit patterns perfectly. The main takeaway from Figure 5 is that all models produce a very similar concave shape of the profit, which matches the observed shape quite well. As discussed above, this concave shape arises thanks to the concavity of the value function (r<1). Between the joy of playing and the curvature of the probability weighting function, the former has a much greater impact on the quality of profit fit, essentially raising the intercept of the profit function to the observed level. Even for the full model selected by our likelihood

ratio tests, there remains a relatively large discrepancy when fee=12. Drilling down into the data, we find that the discrepancy is caused by under-entry when valuation=65. Here, the model predicts 90% of buyers should enter, but only 66% of them do. We hope to reconcile this difference in future work.

Figure 5: NYOP retailer profits predicted by all different model specifications



Note to Figure: The observed and risk-neutral lines are same as in Figure 1. A solid line indicates the presence of probability weighting, and a star marker indicates the presence of joy of playing.

The joy of playing clearly plays a big role in model fit. To investigate the possible antecedents of this additional utility provided by the NYOP store, we repeated the estimation procedure using only the last 25 periods of the data. This restriction reduces the impact of novelty as a reason behind joy of playing by effectively starting the measurement only on the 16th round each subject experienced – after at least some of NYOP's novelty has worn off. Table A2 in the Appendix documents the results using the same format as Table 2. We find that the curvature and myopia parameters (r and δ) are robust to this restriction: their population averages barely budge. However, the average joy of playing parameter (J) declines by about 20 percent. We conclude that some but not most of the joy of playing can be explained by novelty.

Another explanation that is not consistent with the data is optimism bias, i.e. the mistaken belief that one's bids will somehow get accepted more often than the experiment states. Such an optimism bias would predict not only excess entry, but also lower bids. Instead, we find that bids are high relative to the risk-neutral benchmark (Figure 2) and the individual bidding strategies are well captured by our model that does not account for optimism bias.

PROPOSED MODEL: COUNTERFACTUAL SIMULATIONS

We conduct counterfactual simulations to answer the following questions:

1) What is the optimal fee a NYOP retailer facing uniformly distributed buyers should charge and how much does the optimal fee improve profits relative to charging no fee?
2) What is the optimal minimum bid a NYOP retailer facing uniformly distributed buyers should set and how much does the optimal minimum bid improve profits relative to setting the minimum at zero?
3) How do the answers to 1) and 2) depend on the two behavioral enrichments we introduce and how do the two selling strategies (fees and minimum bids) compare in profitability?

Simulation 1: Profitability of Bidding Fees

Model-free evidence suggests a bidding fee can increase profits by 33% when buyer valuations are distributed uniformly on a small discrete set $\{5, 20, 35, 50, 65, 80, 95\}$. We can use the calibrated structural model to predict profitability of all other fee levels between 0 and 18 while also allowing the distribution of buyer valuations to be uniform on a larger set to better approximate a continuous uniform distribution on [0,100]. To estimate the profitability of every combination of valuation and fee for every subject, we simulate 1,000 draws of the bidding error ε (taking care to truncate its distribution as specified in our econometric specification), generate the corresponding draws of bids using equation 6, apply equation 2 to average over the possible retailer acceptance thresholds, and average over the draws. Given the resulting estimate of the expected profitability of the focal buyer entering the NYOP store, we then calculate the overall expected profitability of the buyer by calculating the probability of entry given that buyer's

estimated J and τ. In simulation jargon, we thus generate a plug-in estimate of the expected NYOP profit at the MLE parameter estimates.

The line marked with stars in the left panel of Figure 6 plots the expected profit from the full model. One way to think about this line is as a model-driven interpolation of profit between the fee levels that actually appeared in the experiment. It is evident that the optimal fee is 8, and it raises the expected profit by 44% relative to no fee. We conclude that bidding fees can be quite profitable for NYOP retailers. One may wonder how this result depends on the model specification. Table A3 in the Appendix conducts the counterfactual analysis for all the specifications in Table 2, and documents the importance of accounting for behavioral enrichments. For example, an analyst who did not account for the joy of playing would conclude a fee of 5 was optimal and he would expect it to increase profits only about 20%.

In our third simulation, we will return to the related question about how our behavioral enrichments influence the estimated profitability of bidding fees. Comparing the possible profit lift with that predicted by SZH, whose results predict it to be 83% under risk neutrality and without any of our behavioral enrichments or econometric error-terms, is also interesting. All of these factors together obviously combine to reduce the relative profitability of bidding fees, but it remains very substantial with them.

Simulation 2: Profitability of Minimum Bids

In a recent paper, Zeithammer (2015) argues an NYOP retailer analogous to the one modeled here can profit from setting a minimum bid (equivalent to a public reserve price in an auction). Under the assumption of buyer risk neutrality, Zeithammer (2015) also shows the minimum-bid strategy approximates the optimal mechanism, and it is more profitable than the entry-fee strategy for a wide variety of distributions of buyer valuations and retailer wholesale costs.

Given these predictions, simulating how our bidders with behaviorally enriched prospect-theoretic preferences would react to a minimum bid is interesting. To simulate their behavior under such circumstances, we assume bidders with valuations below the minimum bid do not enter, and bidders with valuations above the minimum bid submit either the minimum bid or their optimal bid suggested by equation 6, whichever is greater. Specifically, we simulate the econometric error terms from the truncated

lognormal distribution as described above, and censor the draws below at the minimum bid.

After trying all possible minimum bids between 0 and 70, we find the optimal minimum bid is 59, and it increases profits relative to no-minimum bid by 42%. As in the first simulation, one may wonder how the minimum-bid result depends on the model specification and Table A2 again provides the answer: in this case, not much – the optimal bid is between 56 and 59 under all model specifications. Under the specific distributional assumptions we make, the optimal minimum bid under buyer risk-neutrality and without any of our behavioral enrichments or econometric error-terms is $\frac{2}{3}M \approx 66.6$ and this optimal minimum bid more than doubles profits relative to the passive retailer strategy of no minimum bids and no bidding fees. Therefore, as in the case of bidding fees, the proposed model of buyer behavior reduces the relative profitability of minimum bids.

Simulation 3: Impact of Behavioral Enrichments on Optimal Selling Strategies

This simulation investigates the profitability impact of the two behavioral enrichments we propose in this paper. Starting with the full model, we can restrict one or both enrichment parameters to their default ("non-enriched") values of J=0 and δ=1, and re-do both simulations 1 and 2. Figure 6 and Table 4 provide the results of this exercise. We discuss bidding fees and minimum bids in turn.

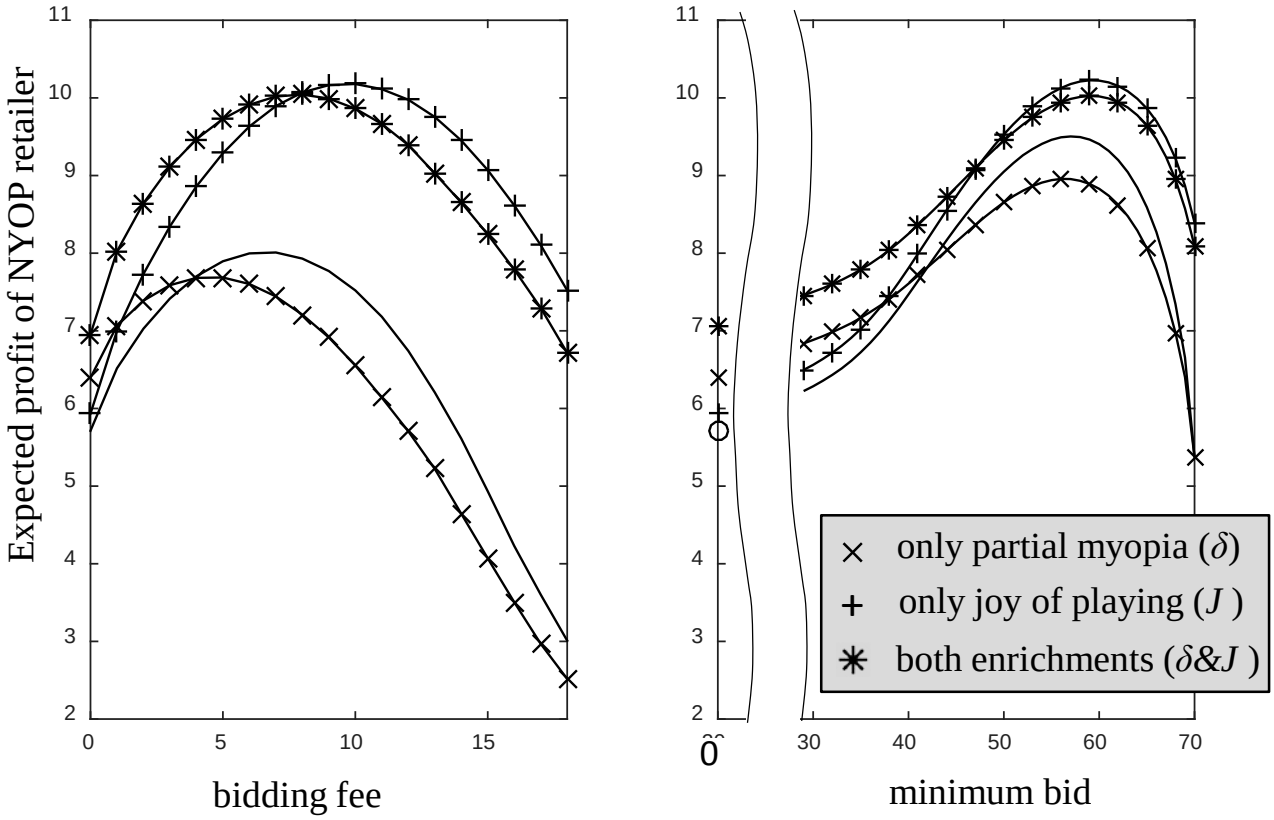
Table 4: Impact of behavioral enrichments on optimal selling strategies

Model restriction:	optimal bidding fee	% profit lift vs. no fee	optimal minimum bid	% profit lift vs. no min. bid
full model	8	44%	59	42%
δ=1	10	72%	59	72%
J=0	5	20%	56	40%
δ=1 & J=0	7	40%	57	66%

We find that joy of playing increases the optimal fees the NYOP retailer should charge, as well as the maximal profitability of NYOP selling. Relative to a model without joy of playing (comparing "✳" to "X," and "+" to "no marker" in Figure 6), absolute achievable profits rise about 30%. The percentage profit lift relative to no fee rises from 20% to 44%, suggesting that joy of playing makes fee optimization

more important for the retailer. The reason underlying all three effects is that joy of playing increases the utility of the NYOP store, so buyers are willing to pay more to enter it, in turn increasing the retailer's profit.

Figure 6: Impact of behavioral enrichments on the profitability of bidding fees and minimum bids



Note to Figure: The circle at the minimum-bid level of zero indicates the profitability prediction of the model without partial myopia and without the joy of playing.

In contrast to the joy of playing, partial myopia decreases the fee a NYOP retailer should charge (by about 2 units) and the profits he can get. Without the option value of returning to the posted-price store, entering the NYOP store is less desirable. Relative to the effect of the joy of playing, eliminating partial myopia (comparing "+" to "✳," and "no marker" to "X" in Figure 6) increases the achievable profit only minimally (between 1% and 4%). This smaller effect size stems from the fact that forward-looking bidders not only enter more often, but also bid less, and thus capture more of the value created by the NYOP opportunity. We now turn to the minimum-bid strategy.

The impact of behavioral enrichments on the magnitude of the optimal bid is less pronounced than that on the magnitude of the optimal bidding fee (see Table 4). Although the joy of playing continues to increase the absolute achievable profitability, the effect (comparing "✳" to "X," and "+" to "no marker" in Figure 6) is smaller than that for bidding fees: absolute achievable profits rise only about 10%. The reason is that the minimum-bid strategy does not capture the added value from the joy of playing as well as the entry-fee strategy that effectively charges a monopoly price for it. The impact of partial myopia on both the absolute and the relative profitability is analogous to that in the case of bidding fees.

Comparing the maximal achievable profitability of the two selling strategies is straightforward because both panels in Figure 6 have the same scale of the *y*-axis. We note that, contrary to the risk-neutral predictions of Zeithammer (2015), the minimum-bid strategy does not outperform the entry-fee strategy. Instead, the entry-fee strategy results in a slightly higher lift relative to the common status-quo baseline. However, this superiority of bidding fees is fragile in that it depends on the joy of playing being active: the minimum-bid strategy dominates without it. In this sense, the minimum-bid strategy is more robust.

GENERAL DISCUSSION

We make two contributions: First, we empirically test the predictions by Spann et al. (2010 & 2015) that a NYOP retailer can benefit from charging non-refundable bidding fees ─ a two-part tariff adapted to the NYOP setting. Second, we propose and estimate a structural model of the observed entry and bidding behavior. The model can be used to assess and compare the profitability of counterfactual levels of bidding fees, and compare it to the profitability of alternative selling strategies. We summarize the contributions in turn, starting with the empirical test.

The theory that advocates charging bidding fees is based on buyer risk neutrality and ambivalence to the very concept of a bidding fee. By contrast, real buyers are likely to be risk averse and may have an a priori negative reaction to paying a fee ─ an attitude we call "fee aversion." We find bidding fees can be profitable, but the optimal fee to charge is smaller than that suggested by the model with risk-neutral buyers. Moreover, the model based on risk neutrality tends to under-predict the profitability of NYOP

selling. We find no evidence of fee aversion. Contrary to such an aversion's implication a small increase of the bidding fee from zero results in a significantly higher expected NYOP retailer profit.

A closer look at the observed entry and bidding behavior reveals two patterns incompatible with risk neutrality: (1) for intermediate fee levels, entry probabilities have an inverse-U shape in terms of valuations (instead of being non-decreasing), and (2) bids tend to exceed the risk-neutral predictions. Both of these phenomena are consistent with risk aversion. However, risk aversion cannot explain the excessive levels of entry we observe.

To explain the observed entry and bidding behavior, we propose a structural model based on cumulative prospect theory (CPT). Relative to a standard application of CPT, we enrich the model with two behavioral modifications motivated by the data patterns. First, we explain the excessive entry by proposing that participating in NYOP has an entertainment value to the buyer. We call this value the "joy of playing". Second, we explain excessive bids by high-valuation bidders as partial ignorance of the outside option during the bid-optimization decision. We model this ignorance as a probability that the outside option is in fact available should the bid be rejected and call it "partial myopia." The behavioral enrichments we have introduced have a substantial and systematic impact on the profitability of the NYOP retailer. Our counterfactual simulations show that both optimal bidding fees and optimal minimum bids can increase retailer profits by more than 40%. The maximal achievable profit benefits more from the presence of the joy of bidding than from eliminating myopia. The minimum-bid strategy is more robust in the sense that the impact of the behavioral enrichments on profitability is smaller.

The findings of the present research have important practical implications. First, they confirm that retailers using NYOP can substantially increase their profits by charging non-refundable bidding fees. Thus, if companies employing NYOP to date were afraid buyers would react negatively to bidding fees, our results provide empirical evidence that such a thing as "fee aversion" does not prevail. We therefore encourage NYOP retailers to experiment with the introduction of this additional source of revenue. For retailers contemplating the use of NYOP, this finding has important implications on how to design their NYOP mechanism.

Second, our behaviorally enriched model, based on a theory (i.e., CPT) that is widely accepted and useful in a variety of situations, provides managers with a tool to derive the optimal bidding fee they should charge based on an experiment with only a few fee levels. The model allows an analyst to interpolate a fundamentally concave profit function between only a few experimental fee levels. Technically, it should be possible to perform such a counterfactual analysis based on a field experiment with just a single positive fee-level, which is likely a realistic restriction for real-world NYOP retailers who do not want to confuse or upset their customers.

Third, the finding that the "joy of playing" is a relevant factor in explaining consumer behavior in NYOP settings has implications for which type of products a NYOP strategy with bidding fees is more suitable. For example, hedonic products may be more congruent with the joy involved in the bidding process. Likewise, the "joy-of-playing" factor has implications for how NYOP retailers should advertise and label their offerings. The more joy of playing buyers perceive in a NYOP offering, the higher the utility of the NYOP store, and the higher their willingness to pay more to enter it, which in turn increases the retailer's profit. Stimulation of the joy of playing among consumers could be achieved by communicating the entertainment value of the NYOP model and the fun involved, thus making the joy of participating more salient to buyers.

We have to acknowledge several limitations that provide avenues for future research. First, of course, a laboratory setting in which subjects trade virtual tokens and real-world markets differ in many respects. We therefore have to be cautious in generalizing the current findings to the wild. Future research may conduct randomized field experiments to externally validate our findings. Second, in our experiment, the NYOP store faces competition from a posted-price retailer that is "passive" in that it does not react to fluctuations in demand by changing its price. Endogenizing the posted-price competition offers another avenue for future research. For instance, the role of the posted-price retailer could be assigned to subjects with different pricing strategies at their disposal. Finally, more work is needed to understand the antecedents of the behavioral enrichments we propose.

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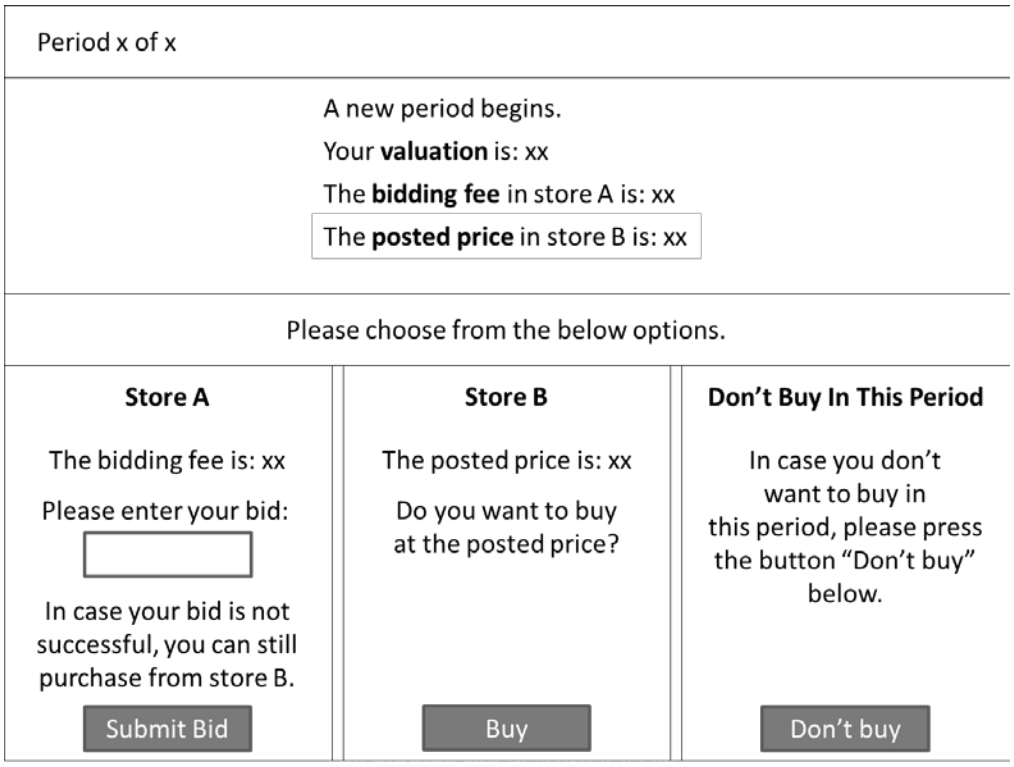
APPENDIX

Figure A1: Experimental interface



Log-likelihood specification

We first derive the likelihood of a bid observation. Taking logs of both sides of equation 4 yields a truncated Normal log-likelihood of the logarithm of observed bid data:

$$\begin{aligned}\log L_{n,bid}\left(\theta,\sigma \middle| v_n, f_n\right) = & -\log(\sigma) - \frac{\left(\log \text{bid}_n - \log b\left(v_n, f_n \mid \theta\right)\right)^2}{2\sigma^2} \\ & -\log\left[\Phi\left(\frac{\log\left(\min\left(v_n, p\right)\right) - \log\left(b\left(v_n, f_n \mid \theta\right)\right)}{\sigma}\right)\right]\end{aligned} \tag{A1}$$

where the last term accounts for the truncation. Overall, the likelihood of the data combines the entry information with the observed bid information as follows:

$$\begin{aligned}\log L\left(\theta, J, \sigma, \tau\right) = & \sum_{n \text{ where } entry} \log\left[\Pr_{enter}\left(v_n, f_n \middle| \theta, J, \tau\right)\right] + \log L_{n,bid}\left(\theta,\sigma \middle| v_n, f_n\right) \\ & + \sum_{n \text{ where } no\ entry} \log\left[1 - \Pr_{enter}\left(v_n, f_n \middle| \theta, J, \tau\right)\right]\end{aligned} \tag{A2}$$

Figure A2: Population heterogeneity in the selected full-model specification

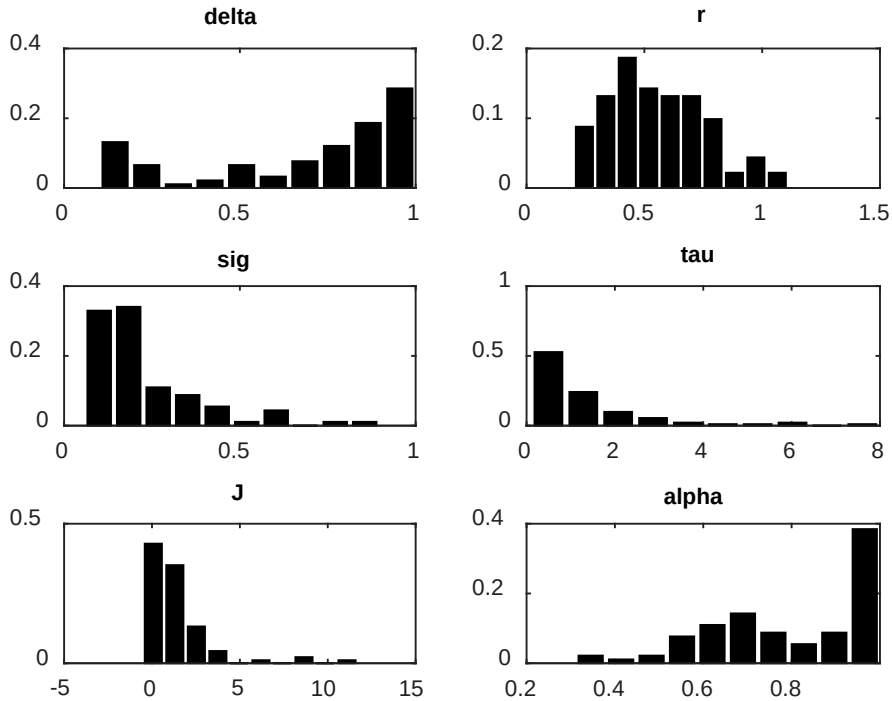


Table A2: Population averages and standard deviations of parameter estimates, periods 15-40

specification	J=0, α=1		J=0		α=1		full model	
population:	mean	stdev	mean	stdev	mean	stdev	mean	stdev
δ	0.61	0.34	0.71	0.27	0.56	0.34	0.69	0.29
r	0.66	0.28	0.60	0.27	0.64	0.28	0.56	0.24
σ	0.23	0.19	0.20	0.14	0.23	0.20	0.20	0.16
τ	2.43	2.37	2.15	2.25	1.50	1.89	1.16	1.52
J	0	0	0	0	1.45	2.58	1.07	1.41
α	1	0	0.82	0.21	1	0	0.80	0.21
Log likelihood	958.4		1020.0		1215.1		1298.7	

Table A3: Optimal fees and minimum bids under different model specifications

Data / specification	Optimal fee	% lift	Optimal minimum bid	% lift
bids & entry / J=0, α=1	6	28%	56	42%
bids & entry /J=0	6	26%	56	43%
bids & entry / α=1	8	45%	59	42%
bids & entry / full model	8	44%	59	43%

Table A1: Reduced-form analysis of bidding and entry behavior

Dependent variable	Observed bid		Entry	
Model	OLS with clustered std. errors		Logistic regression	
Number of observations	1907 (91 clusters)		3185	
Model fit (R-squared)	0.73		0.54	
	Estimate	t-statistic	Estimate	t-statistic
Percent of periods completed (0 to 1)	0.11	0.13	-0.74	-3.89
Age (years)	0.06	0.89	-0.04	-4.77
Female (1=female, 0=male)	0.70	0.65	-0.20	-1.64
Frequent subject (standardized)	-0.55	-1.07	0.19	3.35
Holt-Laury # safe choices (standardized)	0.10	0.18	-0.11	-1.74
Gächter et al. # rejected lotteries (standardized)	0.93	1.62	-0.16	-2.55
Dohmen et al. risk taker scale (standardized)	-0.78	-1.47	0.24	4.11
Refuse to pay fee (standardized)	0.11	0.21	-0.06	-1.03
Mood (standardized)	-1.47	-2.74	-0.12	-2.04
Constant	0.74	0.42	3.32	8.88
Valuation = 20	9.11	21.56	2.23	4.10
Valuation = 35	18.06	26.59	2.47	3.88
Valuation = 50	28.06	32.06	3.41	5.16
Valuation = 65	37.60	32.52	5.56	5.39
Valuation = 80	40.55	30.14	1.06	1.93
Valuation = 95	42.75	33.78	-0.14	-0.33
Fee = 1	-0.26	-0.72	-2.69	-7.24
Fee = 6	-2.67	-2.41	-5.96	-10.56
Fee = 12	-3.59	-1.50	-7.11	-10.42
Fee = 18	-7.23	-6.27	-6.45	-10.48
Significant interactions*:				
v35_fee1	1.28	1.53	1.88	2.08
v35_fee6	1.79	1.39	1.78	2.11
v50_fee1	1.98	2.15	1.36	1.36
v50_fee6	3.97	2.75	2.40	2.72
v65_fee6	3.45	2.33	1.72	1.35
v80_fee1	2.99	1.99	2.70	3.57
v80_fee6	2.93	1.58	4.74	6.03
v80_fee12	4.43	1.59	4.68	5.48
v80_fee18	7.29	3.89	3.32	4.15
v95_fee1	-0.24	-0.17	2.75	4.92
v95_fee6	2.37	1.59	5.40	7.89
v95_fee12	0.61	0.22	5.68	7.34
v95_fee18	3.50	2.03	4.64	6.47

*: the following interactions were identified by the data and included, but turned out insignificant: v20_fee1, v20_fee18, v35_fee12, v50_fee12, v65_fee1, v65_fee12, and v65_fee18.