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Decision Support

How auctioneers set reserve prices in procurement auctions

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ABSTRACT

We introduce a behavioral model that effectively predicts auctioneers' reserve choice patterns in English clock auctions across varying reserve price formats (whether reserve prices are set ex-ante or ex-post auction events), number of bidders and the distribution of suppliers' costs. In a two-parameter model, which we call Subjective Conditional Probability (SCP), auctioneers have subjective judgement of conditional probabilities. We theoretically show that the SCP explains two intuitive, but sub-optimal, reserve price setting patterns. It predicts and provides rationalizations for ex-ante reserve prices that decrease in the number of bidders and ex-post reserve prices that increase in the realized auction price. We conduct two experiments; one with a uniform cost distribution and another with a left-skewed cost distribution. We validate the SCP model internally and externally by comparing it to a wide range of models, including reduced form linear regression, risk aversion, anticipated regret model, and subjective probability judgement via in-sample and out-of-sample predictions. We conclude that the SCP has strong external validity across a variety of procurement environments.

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1. Introduction

Auctions with reserve prices are commonly used in procurement. A strategic buyer sets a reserve price, a maximum acceptable price in the procurement setting, to increase the expected surplus of a purchase.¹ We introduce a behavioural model for setting reserve prices in which auctioneers have subjective judgement of conditional probabilities. Using controlled laboratory experiments, we establish its robustness vis-a-vis rational and other common behavioural models with respect to ex-ante and ex-post reserve price formats, number of bidders, and distribution of suppliers' costs.

In procurement practice, two reserve prices formats are commonly used. In one format the procurer sets an ex-ante reserve price. For example, Kawai & Nakabayashi (2014) report that between 2003 and 2006 Japanese public construction projects spent more than 42 billion US dollars via this format. Ex-ante reserve

prices are also commonly found in e-auctions, such as auctions on eBay, auctions for online advertisements (Kanoria & Nazerzadeh, 2021), and public procurement auctions in the United Kingdom and Australia.² In the other format, the procurer retains an option to negotiate with the auction winner. Ex-post negotiations can happen after the auction winner is determined for ex-post cooperation (Xu, Feng, & He, 2017), ex-post split-award (Kokott, Bichler, & Paulsen, 2019; Paulsen, Bichler, & Kokott, 2021), and also for price concession. For example, Muttitt (2011) reports after an auction for the Rumaila oilfield in southern Iraq in 2009, the Iraqi government privately renegotiated with the winning BP/CNPC consortium. Shachat & Tan (2015) report that in 2012, the Hunan Province (China) Procurement Center made over 9000 orthopedic related purchases also using this format. While there are inevitably many ways in which ex-post auction negotiations are conducted, we proceed assuming that the auctioneers in all cases have a limit price, potentially implicit, beyond which they walk away from the po-

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¹ There are other strategic and non-strategic reasons for adopting reserve prices. Reserve prices can play an important strategic role when the numbers of bidders is endogenously determined (Menezes & Monteiro, 2000). Procurers may also non-strategically adopt reserve prices to reflect budgetary constraints.

² eBay's link: <https://www.ebay.com/help/selling/listings/selling-auctions/reserve-prices?id=4143>; UK cabinet office: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/850566/PPN_for_New_Thresholds_2020_pdf.pdf; Australia: <https://www.buyingfor.vic.gov.au/procurement-auctions-goods-and-services-procurement-guide>.

tential transaction. We focus on this limit price and refer to as the ex-post reserve price.

Choosing the optimal strategic reserve price is a cognitively challenging decision problem.³ Two counter-intuitive prescriptions of the optimal reserve price exemplify these difficulties. First, optimal ex-ante reserve prices in English auctions with symmetric and independently distributed private values or costs do not vary with the number of bidders. Davis, Katok, & Kwasnica (2011) experimentally tested whether subjects follow this prescription in forward auctions, those for selling an object. Subjects' ex-ante reserve prices were increasing, not constant, in the number of bidders. Second, in English procurement auctions with ex-post bargaining the auctioneer's optimal strategy is to make the winner a take-it-or-leave-it (TIOLI) offer if the auction price is too high. This optimal offer, the ex-post reserve price, is counter-intuitively invariant to the auction price (Bulow & Klemperer, 1996). Shachat & Tan (2015) report laboratory experiments on this setting and find subjects on average correctly choose when to bargain, but their ex-post reserve prices are increasing, not constant, in auction prices.

These systematic deficiencies of the standard theory to predict actual reserve price choices led the documenting researchers to identify more empirically accurate behavioral models. Davis et al. (2011) and Shachat & Tan (2015) use different behavioral approaches to rationalize their participants' choices. The former incorporates anticipated regret into the auctioneer's expected utility function. The auctioneer's regret in this case reflects potential ex-post gains that an ex-ante reserve price does not capture. The latter model takes into account the auctioneer's subjective distortion of the Bayesian posterior of the auction winner's cost. Both behavioural models are parsimonious as each is characterized by just two parameters. However, the need to specify distinct models for the two formats raises questions of external validity. Specifically, the anticipated regret model performs poorly in the ex-post reserve price case and the distorted Bayesian posterior performs poorly in the ex-ante reserve price case.

In this paper we propose a robust behavioural model, referring to as the subjective conditional probability (SCP hereafter) model, to predict auctioneers' reserve price choice patterns in ex-ante and ex-post formats. Support theory (Tversky & Koehler, 1994) provides an intuition for the SCP model. In support theory, a decision maker discriminates among uncertain outcomes by their saliency, either by framing or focalness within context, and distorts their likelihood in accordance. In the SCP, the events in which the reserve price either sets the auction price or results in no purchase are more salient than the auction outcome in which the reserve price is not binding. Theoretically the SCP model predicts, under a wide range of parameter values, decreasing ex-ante reserve prices in English procurement auctions as the number of bidders increases. And it is equivalent to Shachat & Tan's subjective posterior probability model in the ex-post reserve price format; preserving the predicted positive relationship between auction and ex-post reserve prices.

Our goal is to formulate a parsimonious behavioral model that predicts reserve prices across settings with varying English auction formats, number of bidders, and distributions of sellers' private costs. We empirically evaluate the SCP model by blending the control of factors afforded by laboratory experiments and the model validation principles of structural econometrics. Our empirical strategy starts by collecting a pair of data sets from two experiments of English procurement auctions. Our two experiments incorporate three treatment variables: the auction format, the number of bidders, and the distribution of sellers' costs. The first treat-

ment variable, auction format, follows a between-subject design. We call the ex-ante format the EA format treatment and the ex-post format the EP format treatment. The second treatment variable, number of bidders, follows a within-subject design. Each subject participates in auctions with one, two, and three bidders. The third treatment variable, cost distribution, delineates our two experiments. In the first experiment the distribution of sellers' private costs follows a uniform distribution, the *U* cost treatment. In the second experiment, these costs follow a heavily left-skewed distribution, the *S* cost treatment.

We conduct two types of model validation: classical specification tests or likelihood value comparisons, and forecasting accuracy. First, we present structural maximum likelihood estimates for both the SCP and anticipated regret models using the data from Experiment 1. For the EA-*U* data, the two structural models' performances are on par with each other as they have similar likelihood values and their respective parameter values are in line with previous studies. For the EP-*U* data, consistent with Shachat & Tan (2015), the SCP model validates well but the estimated anticipate regret parameters reflect nonsensical positive utility for ex-post losses. Later, using the data from Experiment 2, we re-estimate the SCP model parameters and find they generate a similar pattern of subjective conditional probability distortions. However, the parameter estimates statistically differ between the uniform and left-skewed distributions of costs environments.⁴

A key benefit of an appropriate structural model is its use in counterfactual analysis such as ex ante policy modeling or prediction in a managerial setting. Keane (2010) suggests the proper validation exercises to establish a relative ranking of models are in-sample and out-of-sample forecast evaluations for internal and external validity respectively. The in-sample forecasts are formed by using the estimates of a linear reduced form model, the anticipated regret model and the SCP model from the Experiment 1 data to forecast the subject choices included in that same data. The ranking of the mean squared error scores of these forecasts from lowest to highest are linear, SCP and anticipated regret. The linear model's strong performance is driven by its specification that allows for maximum flexibility to adjust intercept and slope terms for the number of bidders and a time adjusting component. This over-fitting is revealed by the out-of-sample exercise.

Out-of-sample forecasts always use the data from Experiment 1 for model estimation and use these estimated models to predict reserve price decisions for Experiment 2. The external validity of our structural models is demonstrated by a strikingly low accuracy of the linear model predictions. Between the two structural models, we find that the SCP is superior as it exhibits a lower mean squared error score for prediction accuracy than the anticipated regret model in the ex-ante auction frame.

In the penultimate section of the paper we explore the relative merit under the same criteria of the SCP model in comparison to a simple model of risk aversion, a SCP model that allows for risk aversion, and a subjective probability (SP) model that allows for subjective judgements that transform both conditional and unconditional probabilities. Estimates of the simple risk aversion model reflect moderate risk aversion. However, when incorporated into the SCP the resulting estimates reflect nearly perfect risk neutrality. Estimates of the SP model, reflect transformations of unconditional probabilities that are strictly convex while unconditional probabilities still maintain their S-shaped transformations. This suggests the ability of the SCP to track the comparative statics

³ Note that we do not focus on repeated auctions in which the auctioneer can dynamically update a common reserve price based on the bidding history (Kanoria & Nazerzadeh, 2021).

⁴ Parameter recovery in alternative contexts, sometimes referred to as sensitivity in the structural econometrics literature (DellaVigna, 2018), is a lofty standard seldom satisfied empirically. For example, estimates of risk aversion vary greatly for individuals across choice tasks (Isaac & James, 2000), as do the parameters of Delta-Beta time preferences (Laibson, Maxted, Repetto, & Tobacman, 2017).

on the number of bidders and auction price derive solely from the transformation of conditional probabilities. In out-of-sample forecast validations, we find the vast majority in predictive effectiveness derives from the simple SCP model.

The contribution of the SCP model is twofold. On one hand, the SCP model effectively captures auctioneers' behaviour regardless of English auction frames, revealing judgement biases are deeply embedded. On the other hand, the SCP model efficiently predicts reserve prices across cost distributions. Analysts who intend to forecast reserve prices, can easily estimate this two-parameters model with one data set to build a tool capable of accurately forecasting reserve prices across a variety of procurement auction settings.

2. Theoretical models of reserve prices

2.1. The standard case

We review the standard theoretical results for optimal ex-ante and ex-post reserve prices. Consider an auctioneer desiring an indivisible object. Her valuation of the object, denoted v , is a random variable with the absolutely continuous distribution H and associated density h whose supports are the interval $[v, \bar{v}]$. There are n potential sellers, indexed by i , each of whom can provide the object at a cost of c_i . Each seller's cost is an independent draw from the interval $[0, \bar{c}]$, with $\bar{c} < \bar{v}$, according to the distribution function F . The density function for F is denoted f . We order realized sellers' cost by ascending value; i.e. c_1 is the lowest realized cost, c_2 is the second lowest realized costs, *et cetera*. We denote the distribution and density functions of the i^{th} lowest cost by $F_{(i)}$ and $f_{(i)}$ respectively. We further assume $c_i + \frac{F(c_i)}{f(c_i)}$ is strictly increasing on the support of F . The auctioneer's value and sellers' costs are all private information. Each individual knows their own realized value or cost, and the distributions of others' private information. This information structure is known by all parties.

2.1.1. Ex-post reserve prices

In an ex-post format, the process begins with an auction with a price clock starting at $\bar{c}$ and all sellers in the auction. As the price clock ticks down sellers can exit. The auction closes once $n - 1$ sellers have exited, or the clock reaches zero. The remaining seller is the auction winner.⁵ The auction price is the last tick of the price clock. The auctioneer then has the option to either accept the auction outcome, or to issue the auction winner a lower take-it-or-leave-it offer, which we call the ex-post reserve price $r_p \in [0, \min\{v, c_2\}]$.⁶ If the auctioneer accepts the auction outcome her payoff is her value less the auction price, the auction winner's payoff is the auction price less her realized cost, and all other sellers' payoffs are zero. If the auctioneer chooses the ultimatum bargaining option and the seller accepts, the auctioneer's payoff is her value less r_p , the auction winner's payoff is r_p less his realized cost, and all other sellers' payoffs are zero. If the counter offer of r_p is rejected, there is no trade and all parties' payoffs are zero.

In this format a seller has a weakly dominant strategy to exit the auction at the price equal to her cost, and to accept any take-it-or-leave-it offer that does not generate a loss. Accordingly the seller holding c_1 will win the auction and the auction price will be c_2 . The auctioneer's strategy is a function that maps from possible value-auction price pairs to possible counter offers joint with accepting the auction outcome. The auctioneer's payoff function, when sellers follow their weakly dominant strategy, is

$$E[\pi(r_p; v, c_2)] = \max\{v - c_2, (v - r_p)D(r_p|c_2)\}. \quad (1)$$

⁵ If there are multiple winners one is selected at random.

⁶ For simplicity in upcoming arguments, we rule out reserve prices in which the auctioneer exposes themselves to negative payoff outcomes.

The conditional probability of purchasing at r_p is $D(r_p|c_2) = \Pr\{c_1 \leq r_p | c_1 < c_2\} = F(r_p)/F(c_2)$ via Bayes Rule. The first order condition for an interior maximum of the second argument of (1) implies,

$$r_p^* = v - \frac{F(r_p^*)}{f(r_p^*)}. \quad (2)$$

Bulow & Klemperer (1996) show the maximized value of the first argument exceeds the second when $c_2 \leq r_p^*$. In other words, the auctioneer should accept the auction outcome when the auction price is less than the optimal ex-post reserve price; otherwise make the auction winner a take-it-or-leave-it offer at the optimal ex-post reserve price.

2.1.2. Ex-ante reserve prices

In the ex-ante format, the auctioneer chooses a reserve price $r_a \in [0, \min\{v, \bar{c}\}]$. This pre-committed maximum price is announced to all sellers. Each seller then decides whether or not to participate in the auction. The auctioneer conducts an English auction with a price clock starting at r_a . The only action that an auction participating seller can take is to exit as the clock ticks down. The auction closes once $n - 1$ sellers have exited. The auction price is the last tick and the remaining seller is the winner.⁷ A seller has a weakly dominant strategy to enter the auction when her cost is no more than r_a and to exit when the clock price equals her cost (Vickrey, 1961). Accordingly the auction price is the minimum of either the second lowest realized cost c_2 or the r_a . When no seller's cost is less than r_a there is no auction and all parties receive a payoff of zero. When there is an auction the auctioneer's payoff is v less the auction price, the winning seller's payoff is the auction price minus her cost, and all other sellers' payoffs are zero.

When sellers follow their weakly dominant strategy, the auctioneer's ex ante expected payoff, as a function of r_a , is

$$E[\pi_a(r_a; v)] = (v - r_a)B(r_a) + \int_0^{r_a} (v - y)f_{(2)}(y)dy. \quad (3)$$

The reserve price r_a is the purchase price when it lies between the second lowest and lowest realized costs. The probability of this event is $B(r_a) = \Pr\{c_1 \leq r_a < c_2\} = nF(r_a)(1 - F(r_a))^{n-1}$. The second lowest realized cost is the purchase price when it is exceeded by the reserve price, $r_a > c_2$. This occurs with probability, $F_{(2)}(r_a) = 1 - nF(r_a)(1 - F(r_a))^{n-1} - (1 - F(r_a))^n$. Note, the density function of the second lowest realized cost is $f_{(2)}(y) = n(n - 1)F(y)f(y)[1 - F(y)]^{n-2}$. The auctioneer's optimal ex-ante reserve price r_a^* , derived from the first order condition of Eq. (3), is

$$r_a^* = v - \frac{F(r_a^*)}{f(r_a^*)}. \quad (4)$$

We highlight three counter-intuitive properties of the optimal reserve prices. First, inspection of Eqs. (4) and (2) reveals that the optimal ex-ante and ex-post reserve prices are the same. Despite the ex-post format clearly providing the auctioneer more information this does not change the optimal action; rather just the valuation of the maximized expectation changes for different realized values of c_2 . Second, both the optimal ex-ante and ex-post reserve prices are invariant to the number of bidders. Third, the optimal ex-post reserve price is independent of the observable auction price.

2.2. Optimal reserve prices with subjective conditional probabilities

There are three key mutual exclusive events as the consequence of setting a reserve price: (1) a reserve price sets the purchase

⁷ Again, in the case of multiple winners, one is chosen randomly. All winners have the same probability of being selected.

price; (2) there is no purchases due to a low reserve price; and (3) the auction price sets the purchase price. According to support theory developed by [Tversky & Koehler \(1994\)](#), probability judgements are influenced by the focalness or framing of events. A reserve price's functionality enhances its salience, and the support, of the first two outcomes given above. Explicitly, when auctioneers consider a reserve price, they judge the probability it sets the purchase price or it is low enough that it results in a failure to purchase. With this perception, the relevant probability judgements most likely are distorted. What are the relevant probability judgements about? Notice the first two events occurs only occur when the reserve price is lower than the realized second lowest supplier cost.

[Shachat & Tan \(2015\)](#) find that auctioneers do distort conditional probability when the reserve price is ex-post, and model this distortion with a two-parameter function. In this study, we employ a similar two-parameter function, as [Eq. \(5\)](#) shows,

$$\psi(K) = e^{-\mu(-\ln(K))^\lambda}, \mu > 0, \lambda > 0, K \in [0, 1], \quad (5)$$

to capture the auctioneers' distortion on a conditional probability of K in both ex-ante and ex-post formats. This equation has five potential shapes based on the values of μ and λ . In particular, when $\mu = \lambda = 1$ the equation reduces to the identity function $\psi(K) = K$.⁸ In this case, the auctioneer's subjective conditional probability judgement is not distorted.

Based on [Shachat & Tan \(2015\)](#)'s finding, the transformation function takes on an S-shape. Unlike a probability weighting function, the SCP considers the probability of an event which is conditional on another event, e.g. in the auction context, the event of auctioneer's reserve price setting the purchase price is conditional on the auction price exceeding the reserve price. The behavioural implication of the S-shaped transformation function is that, the auctioneer is overconfident that her reserve price will set the purchase price when she sets it slightly below the auction price, and is overly pessimistic of not purchasing when she sets her reserve price far below the auction price.

2.2.1. Ex-post reserve prices

We first consider how subjective conditional probabilities impact optimal reserve prices in the ex-post auction format and how optimal reserve prices respond to changes in the auction price. The auctioneer's subjective expected utility from making the take-it-or-leave-it offer r_p is

$$E[\pi_p(r_p; v, c_2)] = \max \{v - c_2, (v - r_p)\psi(D(r_p|c_2))\}. \quad (6)$$

The auctioneer's optimal strategy ([Shachat & Tan, 2015](#)) is,

Proposition 1.

- (i) The optimal ultimatum offer is $r_p^* = v - \frac{\Phi(r_p^*)}{\Phi'(r_p^*)}$, where $\Phi(r_p^*) = \psi\left(\frac{F(r_p^*)}{F(c_2)}\right)$, and
- (ii) Accept the auction outcome if $r_p^* \geq c_2$.

Subjective conditional probabilities result in optimal ex-post reserve prices which generally vary with respect to the realized auction price. The following proposition, for proof see [Proposition 2](#) of [Shachat & Tan \(2015\)](#), conveys the relevant comparative static result.

Proposition 2. If $\lambda > 1$, then $\frac{\partial r_p^*}{\partial c_2} > 0$.

⁸ [Prelec \(1998\)](#) introduced this functional form for the probability weighting function, with an inverted S-shape, component of Prospect Theory ([Kahneman & Tversky, 1979](#)). However, probability weighting is mathematically and behaviourally distinct from the conditional probability distortions we study.

The condition of $\lambda > 1$ guarantees an S-shaped transformation function ψ . This shape implies that, the auctioneer over-weighs the probability of her reserve price setting the purchase price when the reserve price is slightly below the auction price c_2 , whereas she under-weighs this probability when a reserve price is far below the auction price. Therefore, a lower auction price encourages auctioneers setting a lower reserve price, and vice versa.

2.2.2. Ex-ante reserve price format

In the ex-ante format the auctioneer receives no information regarding the lowest realized cost. Consequently, the lens of [Shachat & Tan \(2015\)](#) yields the same optimal reserve price as the standard model. We extend the transformed judgement notion from Bayesian updating to the more general case of conditional probability. The auctioneer's key conditional judgement is the likelihood of a reserve price exceeding the lowest cost conditional on not exceeding the second lowest cost. Restating the probability of a reserve price setting the purchase price highlights this:

$$B(r_a) = \Pr\{c_1 \leq r_a < c_2\} = \Pr\{c_1 \leq r_a | c_2 > r_a\} \Pr\{c_2 > r_a\}.$$

For convenience let $G(r_a) = \Pr\{c_1 \leq r_a | c_2 > r_a\}$, or more explicitly, $G(r_a) = \frac{nF(r_a)}{(n-1)F(r_a)+1}$. If the auctioneer transforms the conditional probability of the auction price setting the purchase price by [Eq. \(5\)](#), then the objective probability of $B(r_a)$ becomes to the subjective probability of

$$Z(r_a) = \psi(G(r_a))(1 - F_{(2)}(r_a)).$$

We note that the auctioneer may have a subjective probability judgement on the probabilities of $\Pr\{c_2 > r_a\}$ and $1 - \Pr\{c_2 > r_a\}$. This possibility is examined in [Section 6](#).

Corresponding under the SCP model, the auctioneer's expected utility from choosing r_a is

$$E[\pi_a(r_a; v)] = (v - r_a)Z(r_a) + \int_0^{r_a} (v - y)f_{(2)}(y)dy. \quad (7)$$

The optimal ex-ante reserve price r_a^* derived from the first order condition needs to satisfied the condition $Z'(r_a^*)\tilde{Z}(r_a^*) - Z(r_a^*)\tilde{Z}'(r_a^*) + \tilde{Z}(r_a^*)^2 > 0$ that guarantees an interior maximum. [Proposition 3](#) characterizes the auctioneer's optimal ex-ante reserve price.

Proposition 3. The optimal ex-ante reserve price for auctioneers with subjective conditional probability judgement is

$$r_a^* = v - \frac{Z(r_a^*)}{\tilde{Z}(r_a^*)}, \quad (8)$$

where $\tilde{Z}(r_a) = Z'(r_a) + f_{(2)}(r_a)$.

Proof: Provided in the appendix.

How do subjective conditional probabilities impact optimal reserve prices as the number of bidders varies? Under subjective conditional probabilities, the optimal ex-ante reserve price is no longer invariant to the number of bidders. Note that $\tilde{Z}(r_a)$ and $Z(r_a)$ are functions of the number of bidders n . When the conditional probability is not distorted it has $\frac{Z(r_a)}{Z(r_a)} = \frac{F(r_a)}{f(r_a)}$ and the standard model is recovered. At the optimal ex-ante reserve price of r^* , we assume the condition $Z'(r_a^*)\tilde{Z}(r_a^*) - Z(r_a^*)\tilde{Z}'(r_a^*) + \tilde{Z}(r_a^*)^2 > 0$ holds. [Proposition 4](#) characterizes the comparative static on how the optimal ex-ante reserve price relates to the number of bidders. We will relate this proposition to the parameters λ and μ when we discuss hypotheses in the next section.

Proposition 4.

- (i) If $\frac{\partial \tilde{Z}(r_a^*)}{\partial n} Z(r_a^*) = \frac{\partial Z(r_a^*)}{\partial n} \tilde{Z}(r_a^*)$, then $\frac{\partial r_a^*}{\partial n} = 0$. This occurs when the auctioneer does not distort the conditional probability of $G(r_a)$.
- (ii) If $\frac{\partial \tilde{Z}(r_a^*)}{\partial n} Z(r_a^*) < \frac{\partial Z(r_a^*)}{\partial n} \tilde{Z}(r_a^*)$, then $\frac{\partial r_a^*}{\partial n} < 0$.
- (iii) If $\frac{\partial \tilde{Z}(r_a^*)}{\partial n} Z(r_a^*) > \frac{\partial Z(r_a^*)}{\partial n} \tilde{Z}(r_a^*)$, then $\frac{\partial r_a^*}{\partial n} > 0$.

Proof. Provided in the appendix. There is some intuition for this proposition. For auctioneers whose $\frac{Z(r_a)}{\tilde{Z}(r_a)}$ is increased by n , they perceive a low reserve price has a higher chance of setting the purchase price when the number of bidders increases. This leads to a lower reserve price when n increases. $\square$

2.3. Optimal reserve prices when an auctioneer has anticipated regret

When an auctioneer experiences disutility of inefficient ex-post outcomes resulted by her ex-ante decisions, she incorporates these potential disutilities into her ex-ante calculations of expected utility. These disutilities are referred to as win regrets and lose regrets according to the auction outcomes (Davis et al., 2011). An auctioneer experiences *win regret* after a purchase and realizes a lower reserve price would have increased her ex-post payoff. Note in the ex-post format, when an auctioneer accepts the auction outcome no further uncertainties resolve and her win regret is zero. We assume that an expected amount of win regret x_w generates a proportional disutility, $w(x_w) = \delta_w \cdot x_w$, with $\delta_w \geq 0$. We measure x_w as the auctioneer's purchase price less the revised expectation of the winner's cost, c_1 , whose distribution function is $\frac{F(x_w)}{F(\min\{c_2, r\})}$. Explicitly,

$$x_w = \begin{cases} r - k(r), & \text{for } r \leq c_2 \text{ and } r \geq c_1, \\ c_2 - k(c_2), & \text{for } r > c_2 \end{cases}, \text{ where } k(y) = \int_0^y v \frac{f(v)}{F(y)} dv.$$

An auctioneer experiences *loss regret* when he fails to purchase the object which he could have done so profitably given the realized auction outcome. We assume that an expected amount of loss regret x_l generates a proportional ex-ante disutility, $l(x_l) = \delta_l \cdot x_l$, with $\delta_l \geq 0$. The auctioneer experiences loss regret in the ex-post format when setting aside an auction outcome yielding a certain positive payoff, and then her ultimatum offer is rejected. The loss regret is calculated,

$$x_l = \begin{cases} 0, & \text{for } v - c_2 \leq 0 \text{ and } r_p \leq c_1 \\ v - c_2, & \text{for } v - c_2 > 0 \text{ and } r_p \leq c_1 \end{cases}.$$

When the auctioneer experiences a loss regret in the ex-ante auction format, we assume it is proportional to the difference between her value and reserve price. In this case the loss regret is calculated as $x_l = v - r_a$.⁹

2.3.1. Ex-post reserve prices

We first examine the impact of anticipated regret on the optimal reserve price and its response to varying auction prices in the ex-post format. The auctioneer's expected utility function is

$$E[\pi_p(r_p; v, c_2)] = \max\{v - c_2, -l(v - c_2) \mathbb{1}_{\{v - c_2 > 0\}} (1 - D(r_p|c_2)) + (v - r_p - w(r_p - k(r_p)))D(r_p|c_2)\}.$$

The optimal ex-post reserve price is characterized by the following proposition.

Proposition 5. The optimal ex-post reserve price for an anticipated regret auctioneer is

$$r_p^* = \frac{1}{1 + \delta_w} (V(r_p^*) + \delta_l \max\{0, v - c_2\} + \delta_w M(r_p^*)). \quad (9)$$

⁹ We are following specification of loss regret provided by Davis et al. (2011), although we recognize an alternative valid calculation is to let $x_l = v - E[c_1|c_1 \geq r_a]$.

where $\delta_l \geq 0$ and $\delta_w \geq 0$, $V(r_p^*) = v - \frac{F(r_p^*)}{f(r_p^*)}$ and $M(r_p^*) = k(r_p^*) - \frac{F(r_p^*)}{f(r_p^*)} (1 - k'(r_p^*))$.

Proof. Provided in the appendix. $\square$

With respect to varying auction prices c_2 , we find that optimal ex-post reserve price r_p^* depends only upon the coefficient of loss regret. Further, we find there is a negative relationship between the auction price and the auctioneer's optimal ex-post reserve.

Proposition 6. If $\delta_l > 0$ and $v - c_2 > 0$, then $\frac{\partial r_p^*}{\partial c_2} < 0$.

Proof. Provided in the appendix. $\square$

There is some intuition for this comparative static result. At higher auction prices the potential loss regret from setting aside the auction outcome is smaller. This leads to more aggressive ex-post auction bargaining.

2.3.2. Ex-ante reserve prices

We revisit the analysis of Davis et al. (2011), allowing for v to be a random variable, regarding the optimal ex-ante reserve price for an auctioneer with anticipated regret, and the comparative static of this reserve price with respect to the number of bidders. The auctioneer's expected utility for reserve price r_a is,

$$E[\pi_a(r_a; v)] = -l(v - r_a)(1 - F_{(2)}(r_a) - B(r_a)) + (v - r_a - w(r_a - k(r_a)))B(r_a) + \int_0^{r_a} (v - y - w(y - k(y)))f_{(2)}(y)dy.$$

The auctioneer's optimal action in this case is given in the following proposition.

Proposition 7. The optimal ex-ante reserve price for an auctioneer with anticipated regrets is

$$r_a^* = \frac{1}{1 + \delta_l + \delta_w} (V(r_a^*) + \delta_l L(r_a^*, n) + \delta_w M(r_a^*)),$$

where $\delta_l \geq 0$, $\delta_w \geq 0$, $V(r_a^*) = v - \frac{F(r_a^*)}{f(r_a^*)}$, $L(r_a^*, n) = v + \frac{1 - F(r_a^*)}{f(r_a^*)} \frac{1}{n}$ and $M(r_a^*) = k(r_a^*) - \frac{F(r_a^*)}{f(r_a^*)} (1 - k'(r_a^*))$.

Proof. Provided in the appendix. $\square$

The impact of varying the number of bidders on the optimal ex-ante reserve price is given in the following proposition.

Proposition 8. If $\delta_l > 0$, then $\frac{\partial r_a^*}{\partial n} < 0$.

Proof. Provided in the appendix. The intuition is that auctioneers with loss regret tend to set lower reserve prices when failing to purchase is less likely happen, as is the case when the number of bidders is larger. $\square$

3. Experimental design and hypotheses**3.1. Experimental design**

Our experimental treatment design had two factors. The first factor was the English auction format, which we implemented between-subjects. The second factor was the number of bidders, which we implemented within-subject. All subjects assumed the role of the auctioneer. An auctioneer took part in a sequence of 90 procurement auctions without any practice. In each auction, the auctioneer's value v was an independent random draw from a Uniform distribution between 50 to 150. An auctioneer knew

that (1) the bidders were computerized and programmed to follow their respective weakly dominant strategy in each format¹⁰ Further, Shachat & Tan (2015) used human sellers in their ex-post format study and found human subjects overwhelmingly exit the auction at cost and almost always accept any ultimatum offer that does not generate a loss, and (2) each seller's cost was an independent draw from a Uniform distribution over the range 0 to 100. Note, we created paired sequences of values and costs by randomly drawing the value and costs for the 90 auctions for one subject participating in the ex-post format, and then using the same sequence for a subject participating in the ex-ante format.

All auctioneers faced a varying number of bidders across auctions. The number of bidders in an auction was either 1, 2, or 3. An auctioneer's sequence of auctions was broken into three blocks of 30 auctions each; one block for each of the three levels of bidders. As we will discuss shortly, we conducted four sessions for each auction format, and each session's block sequence of n uniquely followed one of four orders: $\{1, 2, 3\}$, $\{2, 1, 3\}$, $\{2, 3, 1\}$ and $\{3, 2, 1\}$. This was done to control for order effects. You may notice the one bidder case auction closely more resembles one-to-one negotiations starting from the price of 100 rather than a conventional auction. However, this is a meaningful baseline in which auctioneers are given exact the same information (auction price constantly equals to 100) across formats while making reserve price decisions. Thus, this baseline controls for the pure framing effect generated by the two reserve price formats.

The two experimental English auction format treatments were Ex-post reserve price (EP-U) and Ex-ante reserve price (EA-U). In an auction, the computer software¹¹ first informed a subject of her current value and the number of bidders. In the EP-U treatment, the software presented n cards, one for each bidder, sorted left-to-right by descending cost. When $n = 2$ or 3, the left most $n - 1$ cards displayed the corresponding seller's bid, and the right most card displayed "W" to indicate the auction winner. The auctioneer was informed of the auction price, which matched the number on the second farthest right card. In the case of $n = 1$, the auctioneer saw a single card with a "W" and was informed the auction price was 100. Next the auctioneer decided to either accept the auction price or make a take-it-or-leave-it offer, r_p , to the winning seller. The winning seller accepted r_p if it exceeded his cost, otherwise he rejected it and there was no purchase.¹²

In the EA-U treatment, an auction started with the auctioneer learning her value and the number of bidders. Then she was prompted to select a reserve price, r_a . Next the software presented n -cards in similar fashion to the EP-U treatment. However, if a seller's cost exceeded r_a , her card displayed "D". If all cards displayed "D," there was no purchase. Otherwise the auctioneer purchased at price equal to the lower of r_a and c_2 .

We recruited 16 subjects for each session, conducted four sessions for both formats, giving us a total of 128 subjects. The subjects were undergraduate and graduate students at a large prestigious university in Southern China and recruited via the subject pool management software ORSEE (Greiner, 2004). Subjects could only participate in one session. An experimental session lasted no more than two hours. We paid subjects their accumulated earnings from their 90 auctions, with an exchange rate of 60 experimental currency units to 1 Chinese RMB. We also paid subjects a 5 RMB

show-up fee. Overall subjects earned approximately 60 RMB on average from their participation.

3.2. Hypotheses

Our hypotheses are developed around three alternative models of auctioneer expected utility: risk neutrality, SCP, and anticipated regret. Our hypotheses concern the equality of reserve prices across auction formats, the comparative statics of reserve prices with respect to the number of bidders in the ex-ante format and with respect to the level of realized auction prices in the ex-post format. We develop the specific nature of the hypotheses by using the value and cost respectively adopted Uniform distributions.

In the standard model, optimal ex-ante and ex-post reserve prices are the same. Thus for any realized value and set of costs, the same allocation and price results in the two formats. With the adopted distributions for value and costs, the optimal reserve price in both formats, according to Eqs. (4) and (2), respectively, is $r^*(v) = v - F(r^*(v))/f(r^*(v)) = v/2$.¹³ Hypothesis 1 summarizes these predictions.

Hypothesis 1 Risk neutral benchmark. (a) Selected reserve prices are invariant to the English auction format. (b) Reserve prices are invariant to the number of bidders in both formats. (c) Reserve prices are invariant to the realized auction price in the ex-post format.

In the SCP model the two comparative statics results of interest depend upon the specific distributions of value and costs, and the value of the SCP transformation parameters λ and μ . Shachat & Tan (2015) find the estimated values of λ for most subjects exceeds 1. This implies an S-shaped transformation function of ψ , which redistributes probability density away from the ends of the support towards the interior.¹⁴ For the ex-post format, Proposition 2 shows when $\lambda > 1$ that ex-post reserve prices increase with auction prices.

For the ex-ante format, Proposition 4 gives a condition in which optimal reserve prices are decreasing in n . Under our uniform distributions for value and costs the sign of the $\partial r_a^*(v)/\partial n$ is ambiguous with respect to absolute bounds on λ and μ . We develop a numerical characterization of the (μ, λ) pairs for which $\partial r_a^*(v)/\partial n < 0$.

We consider the sign of the $\partial r_a^*/\partial n$ for the range of $(\mu, \lambda) = [0.9, 2] \times [1.05, 1.3]$ with a grid size of 0.05. For each grid point, we evaluate the sign of $\partial r_a^*/\partial n$ for each integer value of $v = 50, 51, \dots, 150$ and for each number of bidders of $n = 1, 2, \dots, 10$. We then calculate the percentage of cases in which this sign is negative. We report these percentages in the heat map of Fig. 1. The figure reveals that as long as μ does not greatly exceed λ , then the relationship between the optimal ex-ante reserve prices and the number of bidders is certainly negative.

Hence, when the parameter of λ is sufficient larger than 1 and additionally μ does not greatly exceed λ , we can obtain Hypothesis 2 based on the subjective conditional probability model.

Hypothesis 2 Subjective conditional probability. (a) Ex-post reserve prices are positively related to realized auction prices. (b) Ex-ante reserve prices are negatively related to the number of bidders.

We notice as μ increasingly exceeds λ , the SCP converges to a convex function. This convergence is depicted by Fig. 2, particu-

¹⁰ We are assuming that individuals would also strongly adhere to the weakly dominant strategy to exit at cost and that individuals in the auctioneer role will not hold consequential social preferences for human bidders' welfare. These assumptions are also implicit to Davis et al. (2011) who adopted computerized sellers.

¹¹ All experiments were computerized with a program developed using zTree (Fischbacher, 2007).

¹² We provide full instructions for both treatments in an appendix.

¹³ Note that if the auctioneer is risk averse that both the optimal ex-ante reserve price (Hu, 2011) and ex-post Shachat & Tan (2015) are increasing in the degree of risk aversion, but invariance to the number of bidders and realized auction price remain.

¹⁴ While the value of λ exceeding 1 determines the function of ψ is S-shaped, the value of μ decides the crossing point of the function of ψ and the 45° line.

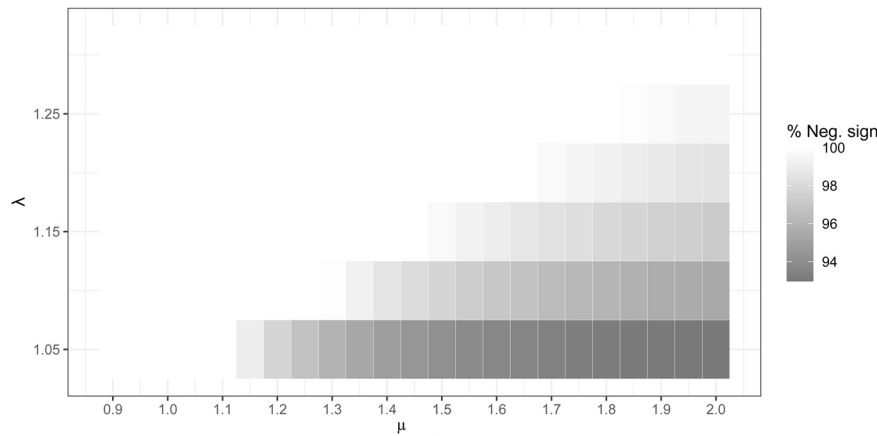


Fig. 1. The percentage of cases that $\partial r_a^*(v)/\partial n < 0$ for alternative (μ, λ) pairs.

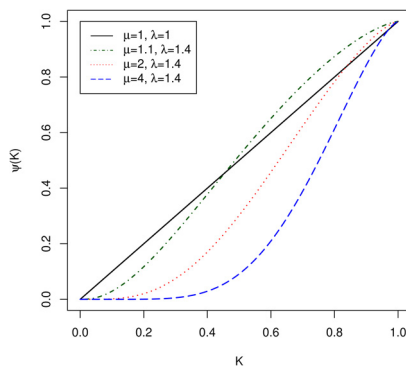


Fig. 2. S-shaped $\psi(K)$ when μ differs.

larly in the case where $(\mu = 4, \lambda = 1.4)$. In this case, the auctioneer only over-weights conditional probabilities that are nearly one while under-weighting all other probabilities. With this SCP, she will behave like a risk averse auctioneer, and the number of bidders is unlikely to impact her ex-ante reserve price.

In the anticipated regret model, Proposition 5 shows that the optimal ex-post reserve prices are $r_p^*(v) = \frac{v + \delta_l \max\{0, v - c_2\}}{2 + \delta_w}$, and Proposition 6 demonstrates that when $\delta_l > 0$ and $v - c_2 > 0$, $\frac{\partial r_p^*}{\partial c_2} < 0$. Proposition 7 indicates when auctioneers have anticipated regret their ex-ante reserve prices vary with the number of bidders. In the uniform-distributed cost environment, winning regret reduces to $w(r) = \frac{\delta_w r}{2}$ and losing regret to $l(v - r) = \delta_l(v - r)$. The optimal ex-ante reserve price is $r_a^*(v) = \frac{100 \frac{\delta_l}{n} + (\delta_l + 1)v}{\frac{\delta_l}{n} + \delta_l + (2 + \delta_w)}$. This implies the optimal ex-ante reserve price r_a^* is decreasing in n , when $1 + 2\delta_w > \delta_l > 0$.

Hypothesis 3 Anticipated regret. : (a) The auctioneers' ex-post reserve prices are negatively related to the auction price, and (b) their ex-ante reserve prices are negatively related to the number of bidders.

To summarize, the SCP and anticipated regret models predict specific deviations from the standard model in terms of the counter intuitive predictions of reserve prices that are invariant to the number of bidders and, in the ex-post format, the realized auction prices. The SCP and anticipated regret models disagree on the direction by which ex-post reserve prices vary with respect to re-

Table 1

Reserve prices and auction outcome rejection rates.

	$n = 1$	$n = 2$	$n = 3$	Pooled
Ex-ante reserve price				
EA-U	59.07*** (8.44)	55.25*** (10.66)	52.29 (15.18)	55.54*** (9.45)
Risk neutral benchmark	49.71 (2.22)	50.08 (2.27)	50.26 (2.14)	50.02 (0.38)
Ex-post reserve price				
EP-U	57.41*** (7.64)	48.31 (6.67)	42.06*** (6.97)	50.46*** (5.81)
Risk neutral benchmark	49.71 (2.22)	47.03 (3.00)	44.15 (3.31)	47.61 (0.80)
Auction price rejected rate				
EP-U	0.97*** (0.06)	0.80*** (0.18)	0.61** (0.28)	0.80*** (0.15)
Risk neutral benchmark	1.00 (0.00)	0.74 (0.08)	0.49 (0.09)	0.74 (0.03)

Note, standard deviations are in parentheses and each subject is an independent observation. *** Observed data is significantly different from the risk neutral benchmark at the 1% level, ** 5% and * 10% based on Wilcoxon rank sum test.

alized auction prices, but agree on direction by which ex-ante reserve price vary with number of bidders.

4. Experimental results

4.1. Descriptive statistics on reserve prices

We start with a visual examination of the auctioneers' reserve prices. Fig. 3 displays scatter plots of ex-post and ex-ante reserve prices versus value, overlaid with a line for the optimal reserve price of the risk neutral benchmark, $r^* = v/2$, and a regression fitted line. The first row of Fig. 3 presents the scatter plots for the EP-U treatment. Recall that ex-post reserve prices are right-censored at realized auction prices. We observe ex-post reserve prices when auction outcomes are rejected, i.e. auction outcome rejection rates of 0.97, 0.80, and 0.61 for $n = 1, 2$, and 3 respectively (reported in the third panel of Table 1). The fitted lines for the EP-U treatment are derived from linear regressions of observable ex-post reserve prices (shown by grey triangles) on values.¹⁵ The differences between the observable ex-post reserve prices and the optimal risk neutral reserve prices reported in the second panel of Table 1 are significant at the levels of $n = 1$ and $n = 3$ (p -values are < 0.01 , $= 0.15$ and < 0.01 when $n = 1, 2$ and 3, respectively.)

¹⁵ We report more appropriate Tobit regressions below.

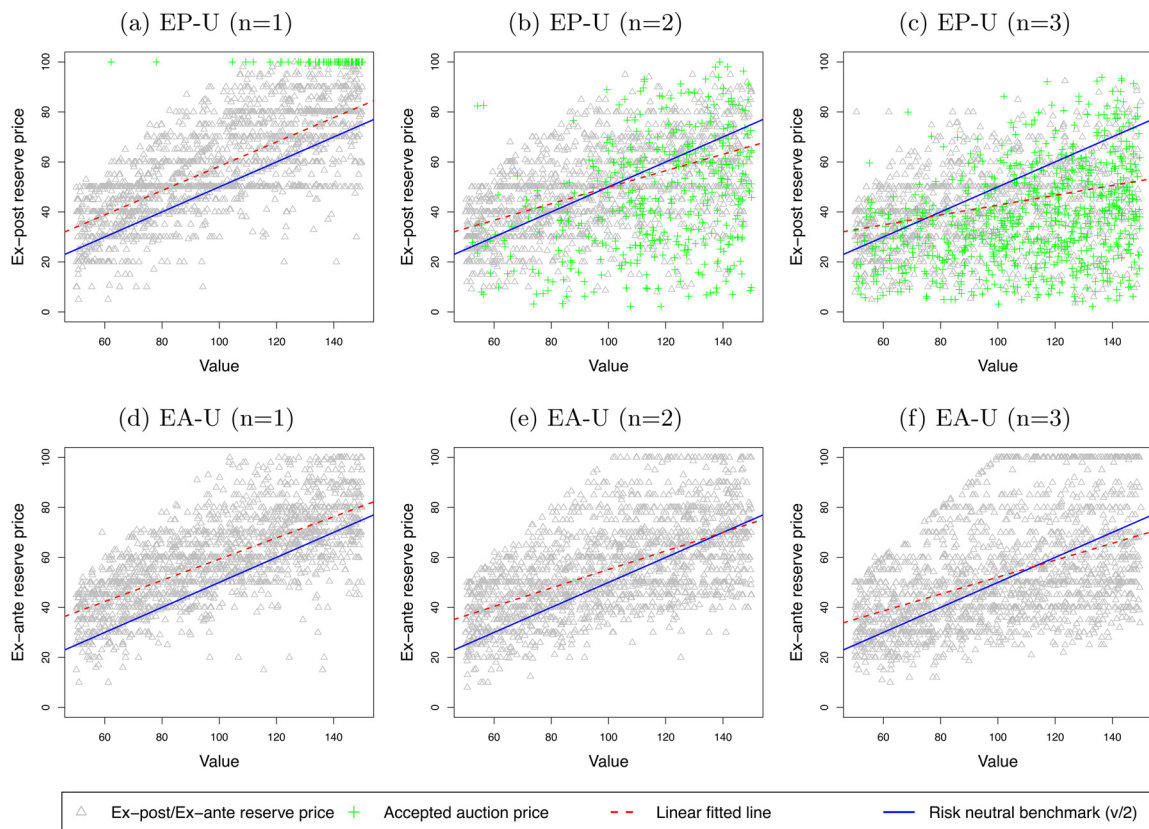


Fig. 3. Reserve prices in treatments.

The second row of Fig. 3 presents the scatter plots for the EA-U treatment. The ex-ante reserve prices do not align with the risk neutral benchmark, but the differences between the fitted line and the risk neutral benchmark grow less stark as the number of bidders increases. By Wilcoxon rank sum tests, the ex-ante reserve prices and risk neutral optimal reserve prices are significantly different at the levels of $n = 1$ and $n = 2$ (p -values are <0.01 , <0.01 and $= 0.40$ when $n = 1, 2$ and 3 , respectively), as shown in the first panel of Table 1.

In the two treatments, the values and costs are fully paired, allowing us to compare the non-censored ex-post reserve prices with matched ex-ante reserve prices. The p -values derived from Wilcoxon signed rank test are 0.02 , <0.01 and <0.01 for $n = 1, 2$, and 3 respectively. Thus the difference between ex-ante and ex-post reserve prices is significant at the level of 5%. Disaggregating by the number of bidders, we find the average observed ex-post reserve prices of 57.47 , 48.59 and 41.42 are lower than average of their respectively matched ex-ante reserve prices are 58.48 , 52.78 and 48.93 for $n = 1, 2$, and 3 .

Based on these results above, we reject the first two parts and confirm the last part of Hypothesis 1(a) to obtain Result 1.

Result 1. Ex-ante reserve prices significantly differ from ex-post reserve prices, and both deviate significantly from the optimal reserve price.

4.2. Do auctioneers' values solely determine the reserve prices?

We next evaluate, via reduced form regressions, the hypotheses regarding the relationship between reserve prices and other factors, such as, value, the number of bidders, and realized auction prices. Table 2 shows that linear model estimates for reserve prices in the two treatments. Relevant standard errors are clustered by

subject. Models (1) - (3) are Tobit regression models for the EP-U treatment, accommodating the right-censoring of ex-post reserve prices by realized auction prices. Model (1) only includes a constant and the factors value, v , and auction price. The risk neutral benchmark predicts that the constant and auction price coefficients are 0 and the coefficient for v is 0.5. However, estimated constant is significantly positive, the estimated price coefficient is 0.30, and the estimated value coefficient is 0.39.¹⁶ The significant and positive price coefficient is evidence in favor of the SCP model over the risk neutral and anticipated regret models.

Model (2) takes into account the number of bidders in terms of constant and interaction terms with value and realized auction price. Note there is no estimate for the auction price coefficient in 1-bidder auctions, because the auction price is always 100 in these cases. We reject the Model (1) in favor of Model (2) by a Likelihood Ratio test with a p -value < 0.01 . As n increases, the auctioneers' ex-post reserve prices grow more sensitive to realized auction prices and less sensitive to values. These countervailing effects do not allow us to sign the direction of change in r_p in response to changes in n .

Model (3) allows evaluation of the impact of experience on the constant term. We reject the Model (2) in favor of Model (3) (p -value < 0.01). This suggests auctioneers' ex-post reserve price increase as they experience more periods. By the last period the ex-post reserve price increases by 4.5 on average.

For the EA-U treatment, Models (4) and (5) presents OLS estimations for ex-ante reserve prices. Model (4) only considers the intercept and value, while Model (5) additionally takes into account the number of bidders. An F -test rejects the Model (4) in

¹⁶ A Chi-squared test rejects the restricted model where intercept is 0 and value coefficient is 0.5 imposed by the risk neutral model, at the 1% significant level.

Table 2
Estimates of linear models in EP-U and EA-U treatments.

Variable	EP-U treatment			EA-U treatment		
	Model(1)	Model(2) ^a	Model(3)	Model(4)	Model(5) ^a	Model(6)
Intercept	-9.25*** (1.58)	7.17*** (2.20)	4.82*** (2.31)	17.94*** (1.74)	16.89*** (2.04)	12.41*** (2.40)
$\mathbb{1}_{\{n=2\}}$	-	-15.45*** (2.36)	-14.65*** (2.31)	-	1.25 (1.68)	2.92* (1.71)
$\mathbb{1}_{\{n=3\}}$	-	-11.11*** (2.65)	-11.29*** (2.66)	-	1.40 (2.20)	1.22 (2.30)
Value	0.39*** (0.02)	0.52*** (0.02)	0.52*** (0.02)	0.38*** (0.02)	0.42*** (0.02)	0.42*** (0.02)
Value · $\mathbb{1}_{\{n=2\}}$	-	-0.17*** (0.02)	-0.16*** (0.02)	-	-0.05*** (0.02)	-0.05*** (0.02)
Value · $\mathbb{1}_{\{n=3\}}$	-	-0.25*** (0.03)	-0.25*** (0.03)	-	-0.09*** (0.03)	-0.08*** (0.03)
Period	-	-	0.05*** (0.02)	-	-	0.09*** (0.03)
Auction price	0.30*** (0.03)	-	-	-	-	-
Auction price · $\mathbb{1}_{\{n=2\}}$	-	0.35*** (0.03)	0.35*** (0.03)	-	-	-
Auction price · $\mathbb{1}_{\{n=3\}}$	-	0.45*** (0.03)	0.45*** (0.03)	-	-	-
Log(scale)	2.63*** (0.03)	2.58*** (0.04)	2.58*** (0.04)	-	-	-
R^2	-	-	-	0.33	0.35	0.36
F test (p -value)	-	-	-	-	<.001	<.001
$\ln(\text{Likelihood})$	-19216	-19040	-19023	-24014 ^b	-23897 ^b	-23845 ^b
LR test (p -value)	-	<.001	<.001	-	-	-
Number of observations	5760	5760	5760	5760	5760	5760

Standard deviations clustered by subject are in parentheses. ** Coefficient is significant at the 5% level. *** Coefficient is significant at the 1% level. ^a We also consider models for which the number of bidders only impacts the intercept. We report estimations of these models in Table A.12, found in the Appendix. When we compare the differences between the $\text{Log}(L)$ values of Model (24) and Model (2), and the R^2 values of Model (25) and Model (5), the Likelihood Ratio test and F -test reject Model (24) and Model (25) in favor of Model (2) and Model (5), respectively (p -values < 0.01). These results validate the interaction effect of the number of bidders and value as the appropriate channel of the number of bidders impact. ^b Log-likelihood is extracted from OLS estimations.

favor of Model (5). Strong evidence that the number of bidders influences ex-ante reserve prices, and the negative values of the estimated coefficients for the interaction of the number of bidders and value are indicative of auctioneers who more aggressively set reserve prices based when there are more bidders. This is consistent with both the SCP and anticipated regret models, but contradicts the risk neutral benchmark. Another F -test rejecting Model (5) in favor of (6) indicates the similar experience effect as in EP-U treatment. In addition, the amount of ex-ante reserve prices increased by experiencing 90 periods is about 8.1 on average, which is higher than in EP-U treatment. We summarize the conclusions of these reduced form analyses.

Result 2. Reserve prices do not solely depend on auctioneers' values. When the number of bidders increases, ex-ante reserve prices decrease. Ex-post reserve prices are not independent from realized auction prices or the number of bidders. Hence we reject Hypotheses 1(b) and (c).

We also note the impact of the number of bidders on reserve prices might not be linear and thus the linear models estimated above would encounter a difficulty of capturing the actual relationship between them. The alternative relationship will be discussed in the next subsection.

4.3. Structural estimates of the SCP and anticipated regret models

Table 3 presents the maximum likelihood estimates of the SCP model parameters for each auction format and then pooled. We first note that for all models, the estimated values of μ and λ are all greater than 1, suggesting that S-shaped transformation func-

tions, $\psi(p)$ prevails in both EP-U and EA-U treatments. With respect to EP-U treatment, Model (7) is an estimate of our base SCP formulation. Model (8) extends by allowing the parameters of ψ to depend on the number of bidder in the most general way by letting $\mu_n = \mu + \mu \cdot \mathbb{1}_{\{n=2\}} + \mu \cdot \mathbb{1}_{\{n=3\}}$ and $\lambda_n = \lambda + \lambda \cdot \mathbb{1}_{\{n=2\}} + \lambda \cdot \mathbb{1}_{\{n=3\}}$. A Likelihood Ratio test rejects Model (8) in favor of Model (7) (p -value=0.63). This is strong evidence in favor of the SCP model as it demonstrates an ability to explain the comparative statics of the $\partial r_p^* / \partial n$ without having λ and μ depend on n . Furthermore, recall that in our reduced form regression Model (2) we found n significantly impacts the marginal effects of value and realized auction prices on ex-post reserve prices.

We consider the same specifications for the EA-U treatment in Models (9) and (10). The estimated values of μ are similar for EP-U and EA-U; However, the estimated values of λ are larger for EA-U. Further in this case, we can't conclude that λ and μ are jointly unaffected by the number of bidders. A Likelihood Ratio test rejects Model (9) in favor of Model (10). The estimates of Model (10) suggests these differences arise from large differences in the estimations of μ for each of the level of bidders; however the estimated values are not monotonic in n and thus difficult to interpret.¹⁷ We summarize these findings in our next result.

¹⁷ In the linear regression model we found reserve prices evolve with experience, and one might wonder if the SCP model parameters adjust in a meaningful way. In Table A.16 of Appendix A.3, we report SCP parameter estimates for both the first and second half sub-samples. The estimated parameter values change from the first half to the second half with increasing μ and decreasing λ . While the curvature of the estimated transformation function decreases, it retains its critical S-shape.

Table 3
Maximum Likelihood estimates of the SCP model for Experiment 1.

Variable	EP-U treatment		EA-U treatment		Pooled
	Model(7) ^h	Model(8)	Model(9) ^h	Model(10)	Model(11)
μ	1.45*** ($<.001$)	1.45*** (0.02)	1.57*** ($<.001$)	1.47*** ($<.001$)	1.50*** ($<.001$)
λ	1.25*** ($<.001$)	1.23*** (0.03)	1.42*** ($<.001$)	1.55*** ($<.001$)	1.35*** ($<.001$)
$\mu \cdot \mathbb{1}_{\{n=2\}}$	-	-0.07** (0.03)	-	0.35*** ($<.001$)	-
$\mu \cdot \mathbb{1}_{\{n=3\}}$	-	0.10*** (0.03)	-	0.17*** ($<.001$)	-
$\lambda \cdot \mathbb{1}_{\{n=2\}}$	-	0.02 (0.03)	-	0.03*** ($<.001$)	-
$\lambda \cdot \mathbb{1}_{\{n=3\}}$	-	0.02*** ($<.001$)	-	0.01*** ($<.001$)	-
Log(scale)	12.71*** (0.15)	12.32*** (0.12)	15.33*** (0.15)	15.27*** (0.15)	14.27*** (0.10)
ln(Likelihood)	-19063.6	-19062.3	-23898.8	-23874.9	-43067.9
LR-test(p-value)	-	0.63	-	$<.001$	$<.001$
Number of observations	5760	5760	5760	5760	11520

Standard deviations are in parentheses. * Coefficient is significant at the 10% level, ** 5% level and *** 1% level. ^h In addition to estimating parameters from the aggregate data, we estimate the parameters of (μ, λ) for each subject. We find 76.6% of subjects in EP-U and 87.5% subjects in EA-U have estimated λ greater than 1, i.e. S-shaped transformation functions. We report the individual estimates of λ for the EP-U and EA-U treatments in Fig. A.4(a) of Appendix A.2.

Table 4
The estimates of anticipated regret model.

Variable	EP-U treatment	EA-U treatment
Lossing regret (δ_l)	-0.59*** (0.01)	2.25*** (0.56)
Winning regret (δ_w)	-0.46*** (0.01)	2.70*** (0.70)
Log(scale)	13.23*** (0.14)	15.46*** (0.16)
ln(Likelihood)	-19043.1	-23946.3
Number of observations	5760	5760

Standard deviations are in parentheses. *** Coefficient is significant at the 1% level.

Result 3. In EA-U treatment, ex-ante reserve prices are negatively correlated to the number of bidders, and, in EP-U treatment, ex-post reserve prices are positively correlated to the auction price. These two correlations are consistent with the subjective conditional probability model in which auctioneers have an S-shaped transformed function.

We next consider the structural estimates of the anticipated regret model. Table 4 presents the results of maximum likelihood estimates of the anticipated regret model parameters for each auction format. For the EP-U treatment, the estimates of δ_l and δ_w are both negative, as Shachat & Tan (2015) also found, indicating that regret generates utility rather than disutility. This is largely driven, at least with respect to loss regret, by auctioneers selection of ex-post reserve prices that are increasing in realized auction prices rather than decreasing. Thus, we confirm that the anticipated regret model is an inappropriate behavioral model for the ex-post format.

However, the anticipated regret performs well for the EA-U treatment. In EA-U treatment, the estimates of δ_l and δ_w are 2.25 and 2.7 respectively. This suggests that the anticipated regret model has some degree of robustness for explaining ex-ante reserve price setting. Our estimates are similar to those of Davis et al. (2011) in a quite different environment. For example, in our experiment the auctioneers' values vary across the range 50 to 150 while in Davis et al.'s study the auctioneers' values are constant. Overall, the first half of Hypothesis 3 is confirmed but the second half has to be rejected, which gives us Result 4.

Result 4. Anticipated regret model predicts the right direction for EA-U treatment in which auctioneers' ex-ante reserve prices are decreased by the number of bidders. But it predicts an opposite direction for EP-U treatment in which auctioneers' ex-post reserve prices positively correlate to auction prices.

4.4. Model validation by in-sample prediction

We conduct an in-sample prediction exercise using the estimated linear, anticipated regret and SCP models to predict auctioneers' reserve prices and ex-post auction outcome rejection and acceptance consistency¹⁸ for Experiment 1. The parameters used for linear model predictions are based on the estimates in Model (3) and (6) for ex-post and ex-ante formats, respectively. The parameters for SCP are derived from Model (7) and (9) where $\mu = 1.45$ and $\lambda = 1.25$ for ex-post format, and $\mu = 1.57$ and $\lambda = 1.42$ for ex-ante format. For each model we report the mean squared errors (MSE) for each prediction type.

Table 5 reports the MSE at different levels of n as well as the pooled data. The risk neutral model yields high MSE relative to the other models. The linear model actually provides the smallest MSE of predict reserve prices, although the SCP provides lower MSE for predictions of reserve prices when $n = 1$. However, the linear model is reduced form and we will observe this model has poor external validity and fails rather miserably at out-of-sample forecasting. With respect to the two structural models, the SCP performs slightly better than anticipated regret model in the ex-ante format.

5. Experiment 2: Left-skewed cost distribution

We conduct a second experiment to evaluate the hypothesis auctioneers use the SCP model to set both ex-post and ex-ante reserve prices, versus the alternative hypothesis auctioneers use distinct models to set these reserve prices. The alternative hypothesis more specifically stated: auctioneers set ex-post reserve prices

¹⁸ The ex-post auction outcome rejection and acceptance consistency measure report the frequency at which a model accurately predicts whether a subject rejects or accepts the auction outcome in the EP treatment.

Table 5
In-sample prediction performance of different models.

	$n = 1$	$n = 2$	$n = 3$	Pooled
MSE of predicted ex-ante reserve price				
Risk neutral model	240.51	254.01	370.01	288.18
Linear model	159.96	208.39	324.38	230.91
Anticipated regret	152.55	215.05	349.66	239.09
SCP	149.43	212.59	343.50	235.17
MSE of predicted ex-post reserve price^a				
Risk neutral model	244.83	156.43	125.28	184.40
Linear model	178.15	125.45	99.64	140.26
SCP	175.36	129.74	108.57	142.86
Ex-post auction outcome rejection and acceptance consistency				
Risk neutral model	0.97	0.81	0.73	0.84
Linear model	0.97	0.83	0.75	0.85
SCP	0.97	0.79	0.70	0.82

^a Reserve price conditional upon auction price rejects. Note, the MSE is computed by the formula of $\frac{1}{5760} \sum_{i=1}^{5760} (r_i - \hat{r}_i)^2$, for 5760 observations, where r_i is the actual reserve price in observation i and $\hat{r}_i$ is the corresponding model prediction on reserve price for observation i .

using the SCP model and set ex-ante reserve prices using the anticipated regret model. Further, we use this new data to assess the robustness of structural SCP parameter estimates. This experiment uses identical procedures and sampling as the first, except it substitutes the Uniform distribution of cost for a left-skewed one.

In the second experiment, bidders' costs are drawn from a left-skewed cumulative distribution $F(c) = (c/100)^4$. We call the two treatments in this experiment EA-S and EP-S. Left-skewed distributions are commonly used in various auction environments to capture the features of specific markets, such as, markets with bid rigging (Imhof, 2017), and stock markets (Jovanovic & Menkveld, 2017). Left-skewed distributions are also in a variety of settings such as analyzing the costs of orthotopic liver transplantation (Kraus et al., 2005), modeling life expectancies in developed countries (Nations, 2017), portfolio payoffs (Krawczyk, 2015), *et cetera*. An additional benefit of using left-skewed cost distribution in this study is that more ex-post reserve prices should be observed due to a high auction outcome rejection rate.

We start by generating, for 64 auctioneers each, a 90-element sequence of values and costs as we did in the first experiment, but this time drawing costs from its new distribution. Second, we predict the auctioneers' ex-ante reserve prices, by using the parameter values of $\delta_w = 2.7$ and $\delta_l = 2.25$, as well as the parameters of $\mu = 1.57$ and $\lambda = 1.42$, the structural parameter estimates reported in Tables 3 and 4.

Our empirical strategy is threefold. We first focus on the ex-ante reserve prices. Using these parameters to predict ex-ante reserve prices in the second experiment. Second, we generate out of sample predictions of ex-ante and ex-post reserve prices by using different models and evaluate their prediction performances via MSE. Third, we re-estimate the SCP parameters using the new data to evaluate parameter recovery when the cost environment differs.

Table 6 reports the predicted average ex-ante reserve prices under the anticipated regret and SCP models and formats. The anticipated regret model predicts higher reserve prices, for each level of n , relative to the SCP model (all p -values ≥ 0.01). These predictions facilitate a horse race between the SCP and anticipated regret models on predicting ex-ante reserve prices. If we observe the SCP model offers a closer prediction, relative to the observed data, this favors the conjecture of the auctioneers following the SCP model in both formats. However, if we observe the anticipated regret model provides a better prediction, this favors the format-specific model where the anticipated regret for ex-ante format and SCP model for ex-post format, respectively. Hypothesis 4 summarizes this.

Table 6
Predicted and observed ex-ante reserve prices under left-skewed cost distribution.

	$n = 1$	$n = 2$	$n = 3$	Pooled
Predictions				
SCP	81.66 (2.51)	80.26 (2.43)	79.13 (2.19)	80.35 (0.45)
Anticipated regret	83.83 (2.21)	82.54 (2.36)	81.80 (2.21)	82.72 (0.43)
Experimental results				
EA-S	80.33 (4.09)	78.18 (6.12)	77.18 (5.72)	78.56 (3.83)
Differences between observed and predicted ex-ante reserve prices				
SCP - EA-S	1.33**	3.48***	4.48***	1.79***
Anticipated regret - EA-S	3.50***	5.65***	6.65***	4.16***

Note, standard deviations are in parentheses and each subject is an independent observation. The ex-post reserve prices predicted by regret model are significantly higher than those predicted by SCP model, for all levels of n (all p -values ≤ 0.01). *** Difference is significantly different from zero at the 1% level, ** 5% and * 10%.

Table 7
Out of sample prediction performance by different models.

	$n = 1$	$n = 2$	$n = 3$	Pooled
MSE of predicted ex-ante reserve price				
Risk neutral model	90.87	111.68	133.87	112.14
Linear model	536.99	640.69	712.71	630.13
Anticipated regret	62.35	102.78	118.75	94.63
SCP	49.48	81.47	89.35	73.50
MSE of predicted ex-post reserve price^a				
Risk neutral model	90.93	76.27	68.48	79.40
Linear model	470.38	321.75	203.56	341.95
SCP	78.34	63.57	50.60	65.22
Ex-post auction outcome rejection and acceptance consistency				
Risk neutral model	0.84	0.79	0.75	0.79
Linear model	0.85	0.78	0.69	0.77
SCP	0.85	0.80	0.74	0.80

^a Reserve price conditional on auction outcome rejection. Note, the MSE is computed by the formula of $\frac{1}{5760} \sum_{i=1}^{5760} (r_i - \hat{r}_i)^2$, for 5760 observations, where r_i is the actual reserve price in observation i and $\hat{r}_i$ is the corresponding model prediction on reserve price for observation i .

Hypothesis 4. In the left-skewed cost environment, the format-specific models hypothesis predicts that auctioneers select ex-ante reserve prices are closer to the anticipated regret model predictions. The SCP model hypothesis predicts auctioneers select ex-ante reserve prices are closer to those predicted by the SCP model.

Table 6 summarizes the observed ex-ante reserve prices in the new experiment. The SCP model makes more accurate predictions than the anticipated regret model does at all levels of n . However, for both models the predicted prices are demonstrably higher than the observed prices (all p -values < 0.01 except for SCP- EA-S at the level of $n = 1$ which p -value = 0.02). We view these as evidence in favour of the SCP model for both formats hypothesis.

Next, we conduct an out-of-sample prediction to evaluate the prediction performance of the risk neutral, linear, and SCP models in the ex-post format, and these model together with anticipated regret model in ex-ante format. As the same as we have done in Section 4.4, the performance is measured by MSE. Note, the parameters used to generate predictions are the same as we used in Table 5 for the in-sample predictions.

Table 7 reports the prediction results. Unlike what we found in the in-sample prediction, the linear model exhibits the worst performance among these models. It is not surprising that the linear regression model forecasts well in-sample but poorly out-of-sample, as it is a reduced form regression, particularly when the cost environment changes. In the ex-ante format, the anticipated regret model generates higher MSE than the SCP for all levels of n . Overall, the SCP model more accurately predicts the auctioneers' behaviour than both the linear and risk neutral models, as well as

Table 8
The estimates of the SCP model - left-skewed cost distribution.

Variable	EP-S treatment		EA-S treatment		Pooled ^c
	Model(12) ^{a,h}	Model(13)	Model(14) ^{b,h}	Model(15)	Model(16)
μ	1.31*** (<0.01)	1.22*** (0.03)	1.41*** (<0.01)	1.55*** (<0.01)	1.20*** (<0.01)
λ	1.15*** (<0.01)	1.21*** (<0.01)	1.65*** (<0.01)	1.84*** (<0.01)	1.35*** (<0.01)
$\mu \times \mathbb{1}_{\{n=2\}}$	-	0.08** (0.03)	-	-0.26*** (<0.01)	-
$\mu \times \mathbb{1}_{\{n=3\}}$	-	0.54*** (<0.01)	-	0.28*** (<0.01)	-
$\lambda \times \mathbb{1}_{\{n=2\}}$	-	-0.05*** (<0.01)	-	-0.26*** (<0.01)	-
$\lambda \times \mathbb{1}_{\{n=3\}}$	-	-0.16*** (<0.01)	-	0.14*** (<0.01)	-
Log(scale)	8.58*** (0.10)	8.55*** (0.09)	8.27*** (0.08)	8.34*** (0.08)	8.64*** (0.06)
ln(Likelihood)	-16742.75	-16721.53	-20345.07	-20341.22	-37437.53
LR test(p-value)	-	<0.01	-	$=0.10$	<0.01
Number of observations	5760	5760	5760	5760	11,520

Standard deviations are in parentheses. ^a Log(L) of pooled model (EP-U & EP-S) is -36173.55 and estimated (μ, λ) is (1.35, 1.15). ^b Log(L) of pooled model (EA-U & EA-S) is -45347.69 and estimated (μ, λ) is (1.61, 1.51). ^c EP-S and EA-S treatments. * Coefficient is significant at the 10% level, ** 5% level and *** 1% level. ^d 60.9% of subjects in EP-S and 95.3% of subjects in EA-S have estimated λ greater than 1. The estimated λ over all subjects are plotted in Fig. A.4(b) of Appendix A.2.

the anticipated regret model. We view this as evidence in favour of the SCP model for both format hypotheses.

Result 5. The SCP model provides more accurate predictions on ex-ante reserve prices than the anticipated regret model does in left-skewed cost distribution environment.

We next take the opportunity to evaluate the models according to the high-bar of parameter consistency. We re-estimate the parameter values of μ and λ for the left-skewed cost treatments and report them in Table 8. First, we note the estimated parameters of (μ, λ) for the EP-U treatment move from (1.45, 1.25) to (1.31, 1.15) in the EP-S treatment; and, the estimated parameters for the EA-U treatment move from (1.57, 1.42) to (1.41, 1.65) in the EA-S treatment. Likelihood ratio tests reject that these parameters values within format are the same. Second, we reject that the parameters values of (μ, λ) are the same for the EP-S and EA-S treatments. This is evidenced by the Likelihood ratio test reported for model (16) - the last column of Table 8. Finally we reject, via a Likelihood ratio test, that our estimates of (μ, λ) are invariant to the number of bidders in the EP-S treatment; but we only weakly reject parameter invariance with respect to the number of bidders in the EA-S treatment. While these hypothesis test do not favor parameter recovery, we are encouraged that estimates of (μ, λ) uniformly reflect the S-shaped character of the conditional probability transformation function.

6. Examination of alternative models

After establishing that the SCP model outperforms both the anticipated regret and linear regression models in out-of-sample prediction, we examine the SCP model's out-of-sample prediction performance relative to a wider set of alternative models. The first type of alternative models incorporate risk aversion. There are two variants: a risk averse model with standard conditional probability judgements and a SCP model with risk aversion. The second type of alternative models consider transformations of unconditional probabilities in the ex-ante format. In this section, we first present these alternative model and relevant estimate results by using the data of Experiment 1, and then we use these parameter values to calculate out-of-sample predictions of the individual choices of Experiment 2.

6.1. Risk averse model and SCP model with risk aversion

We utilize the constant relative risk averse utility function $U(x) = x^\gamma$, where $\gamma > 0$, to capture the risk attitude of the auctioneers. Note auctioneers are risk neutral when $\gamma = 1$, risk averse when $\gamma < 1$ and risk loving when $\gamma > 1$. The risk averse model's reserve price setting rule for Experiment 1 is,¹⁹

$$\hat{r}_a = \hat{r}_p = \frac{4}{4 + \gamma} v.$$

These risk-averse reserve prices are identical in both ex-ante and ex-post formats given the same value of γ .

Next, we incorporate risk aversion into the SCP model, referring to it as the SCP model with risk aversion. One can derive the optimal reserve prices for this model for each of the two considered auction frames from the first order conditions to the auctioneer's maximization of expected surplus problem²⁰ and find, the predicted ex-post reserve price is

$$\hat{r}_p = v - \gamma \frac{\Phi(\hat{r}_p)}{\Phi'(\hat{r}_p)},$$

and the predicted ex-ante reserve price is

$$\hat{r}_a = v - \gamma \frac{Z(\hat{r}_a)}{\bar{Z}(\hat{r}_a)}.$$

Table 9 presents the estimation results for the risk averse and the SCP with risk aversion models in the two reserve price formats of Experiment 1. Surprisingly, while the risk aversion model estimation does find significant risk aversion, once we allow for subject conditional probability judgements via the SCP with risk aversion model the estimated values of γ are essentially one, i.e. risk neutrality. Likelihood ratio tests reject the risk averse models (17) and (19) in favor of the SCP with risk aversion models (18) and (20). However, likelihood ratio tests do not reject the original SCP model

¹⁹ These reserve prices are derived from the first order condition of $r^* = v - \gamma \frac{F(r^*)}{f(r^*)}$ that maximizing the expected payoff function of $E[\pi_a(r_a; v)] = (v - r_a)^\gamma B(r_a) + \int_0^{r_a} (v - y)^\gamma f_{(2)}(y) dy$, as well as the expected payoff function of $E[\pi_p(r_p; v, c_2)] = \max\{(v - c_2)^\gamma, (v - r_p)^\gamma (F(r_p)/F(c_2))\}$.

²⁰ The expected payoff functions, developed from Eq. (7) and (6), are $E[\pi_a(r_a; v)] = (v - r_a)^\gamma Z(r_a) + \int_0^{r_a} (v - y)^\gamma f_{(2)}(y) dy$ in ex-ante format, and $E[\pi_p(r_p; v, c_2)] = \max\{(v - c_2)^\gamma, (v - r_p)^\gamma \Psi(r_p)\}$ in ex-post format.

Table 9

Estimates of the risk averse model and the SCP model with risk aversion for Experiment 1.

Variable	EP-U treatment		EA-U treatment	
	Risk averse Model(17)	SCP with RA Model(18)	Risk averse Model(19)	SCP with RA Model(20)
μ	-	1.42*** (<0.01)	-	1.47*** (<0.01)
λ	-	1.23*** (<0.01)	-	1.55*** (<0.01)
γ	0.73*** (<0.01)	0.99*** (0.03)	0.85*** (<0.01)	1.05*** (<0.01)
Log(scale)	13.18*** (0.13)	12.67*** (0.13)	16.42*** (0.16)	15.35*** (0.15)
ln(Likelihood)	-19198.1	-19061.7	-24293.4	-23898.2
LR test(p-value)	-	<0.01	-	<0.01
Number of observations	5760	5760	5760	5760

Standard deviations are in parentheses. RA is the abbreviation of the term of risk aversion. * Coefficient is significant at the 10% level, ** 5% level and *** 1% level. Notes, we compare the SCP models with and without risk aversion. The p -value of LR-test for the comparison between Model(7) and Model(18) is 0.18, and between Model(9) and Model(20) is 0.27. That means adding the risk averse parameter does not significantly improve the goodness of fit of the SCP model.

(7) and (9) when there is comparison between the SCP models with and without risk aversion factor.

6.2. The SP model: Transformations of conditional and unconditional probabilities

In this type of alternative model, we extend our base SCP model to allow transformations on the unconditional probability judgement in the ex-ante auction format. We call this the SP - subjective probability - model. Explicitly, we incorporate a subjective transformation of the unconditional probability of $F_{(2)}(r_a)$. With this extension, the SP's predicted ex-ante reserve price has the similar structure to that of the standard SPC given by Eq. (3):

$$r_a^* = v - \frac{ZZ(r_a^*)}{ZZ(r_a^*)},$$

where $ZZ = \psi_{con}(G(r_a))(1 - \psi_{uncon}(F_{(2)}(r_a)))$, and $\tilde{ZZ}(r_a) = ZZ'(r_a) + \psi'_{uncon}(F_{(2)}(y))$.²¹

The function ψ_{con} , with parameters of $(\mu_{con}, \lambda_{con})$, transforms conditional probabilities and the function of ψ_{uncon} , with parameters of $(\mu_{uncon}, \lambda_{uncon})$, transforms unconditional probabilities. We consider two cases for the shape parameters of the SP model. In the restricted version, unconditional and conditional probabilities are transformed by the same function, i.e. $(\mu_{con}, \lambda_{con}) = (\mu_{uncon}, \lambda_{uncon})$. In the unrestricted version, these shape parameters may differ for the two types of probabilities. Table 10 reports the parameter estimates of the SP model using the data from Experiment 1.

By looking over the estimates in Table 10, the S-shaped transformation on conditional probability is very stable while μ_{con} and λ_{con} are larger than 1 in two models. In the unrestricted model, the unconditional probability transformation with parameters of (2.06, 0.90). These parameter values generate a strictly convex transformation function of unconditional probabilities. A behavioural intuition of such transformation is that an auctioneer under-weights the probability of the auction price setting the purchase price. This interesting insight survives likelihood ratio specification tests reject both the restricted model in favor of the unre-

²¹ The ex-ante reserve price is derived from maximizing the auctioneer's expected utility function of $E[\pi_a(r_a; v)] = (v - r_a)\psi_{con}(G(r_a))(1 - \psi_{uncon}(F_{(2)}(r_a))) + \int_0^a (v - y)d\psi_{uncon}(F_{(2)}(y))$.

Table 10

Estimates of the SP model for the EA-U treatment.

Variable	Restricted ($\mu_{con} = \mu_{uncon}, \lambda_{con} = \lambda_{uncon}$) Model (21)	Unrestricted Model (22)
μ_{con}	1.53*** (<0.01)	1.48*** (<0.01)
λ_{con}	1.70*** (<0.01)	1.59*** (<0.01)
μ_{uncon}	-	2.06*** (<0.01)
λ_{uncon}	-	0.90*** (<0.01)
Log(scale)	15.48*** (0.12)	15.28*** (0.15)
ln(Likelihood)	-23953	-23875
LR test(p-value)	-	<0.01
Number of observations	5760	5760

Standard deviations are in parentheses. * Coefficient is significant at the 10% level, ** 5% level and *** 1% level. Notes, we compare Model (22) to Model (9). The LR-test reject Model(9) in favor of Model (22) with p -value < 0.01 .

Table 11

Out-of-sample prediction performance of alternative models.

	$n = 1$	$n = 2$	$n = 3$	Pooled
MSE of predicted ex-ante reserve price				
Risk averse model	76.54	106.13	131.19	104.62
SCP with RA	46.84	77.25	82.84	68.98
SCP	49.48	81.47	89.35	73.50
SP with restricted parameters	46.53	78.22	84.58	69.78
SP with unrestricted parameters	46.86	77.09	84.22	69.39
MSE of predicted ex-post reserve price ^a				
Risk averse model	92.43	75.60	59.96	77.22
SCP with RA	77.97	62.57	48.39	64.10
SCP	78.34	63.57	50.60	65.22
Ex-post auction outcome rejection and acceptance consistency				
Risk averse model	0.70	0.65	0.66	0.67
SCP with RA	0.85	0.81	0.76	0.81
SCP	0.85	0.80	0.74	0.80

^a Reserve price conditional on auction outcome rejection. Note, the MSE is computed by the formula of $\frac{1}{5760} \sum_{i=1}^{5760} (r_i - \hat{r}_i)^2$, for 5760 observations, where r_i is the actual reserve price in observation i and $\hat{r}_i$ is the corresponding model prediction on reserve price for observation i .

stricted model and the original SCP model (9) in favor of the unrestricted model (22).

6.3. Prediction performance assessments of alternative models and the SCP model

Based on the estimates of Model (17) - (22), we use these estimated parameters to predict out-of-sample the corresponding reserve prices under the left-skewed cost distribution. MSE is again used to measure the prediction performance. Table 11 reports the prediction performances of risk averse model, SCP model with risk aversion (RA), and the SP model with and without restricting the shape parameters of the transformation function. We additionally provide the predictions based on the SCP model as a benchmark. First, the overall high MSE and low consistency rates based on risk averse model demonstrate that risk aversion alone is a poor alternative to SCP model and its variants. For example in the ex-post format, the SCP forecasts generate an improvement over the risk averse forecasts of average MSE that range from 30 to 50% for the different number of bidders; this improvement is approximately 18% for the different number of bidders in the ex-ante format. Second, incorporating either risk aversion or unconditional probability into the SCP model improves the prediction performance. However, the improvements from SCP to the SP models are limited. Incorporating transformed unconditional probabilities improves the average MSE by approximately 6% in the ex-ante format, and incorpo-

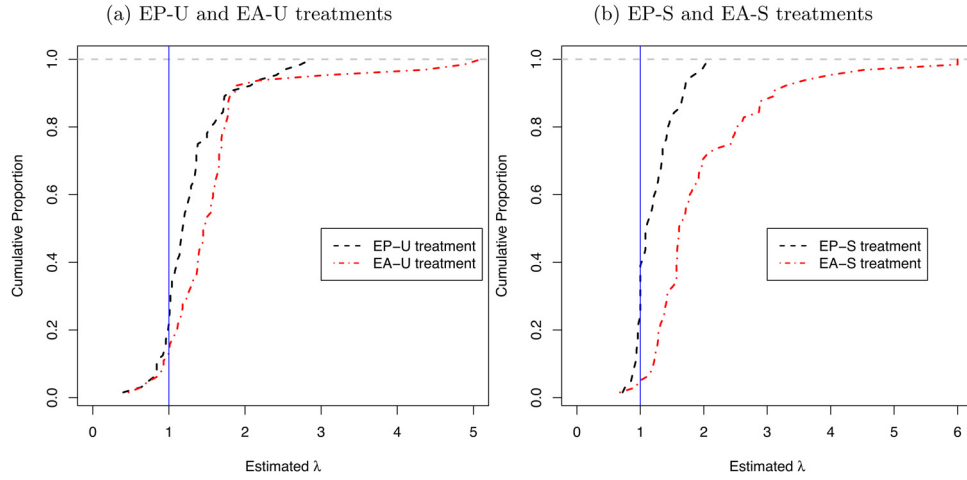


Fig. A1. Estimates of λ in SCP model, 64 subjects in each treatment.

rating risk aversion into the SCP model improves the average MSE by less than 5% in the ex-post format and up to 9% in the ex-ante format.

7. Conclusion

We introduce a behavioral model for setting reserve prices based on upon subjective judgement of conditional probabilities. We use controlled laboratory experiments, establish the robustness of the behavioral model vis-a-vis rational and other common models with respect to the English auction format, number of bidders, and distribution of supplier costs. The first experiment addresses two counter-intuitive prescriptions: first, the optimal ex-ante reserve price is invariant to the number of bidders; second, the optimal ex-post reserve price is independent of auction prices. The experimental results show that ex-ante reserve prices decrease with the number of bidders and ex-post reserve prices increase with auction prices. The anticipated regret (Davis et al., 2011) effectively explains the first finding but provides an inaccurate prediction of the second. Although the SCP model successfully explains the two findings, it does not dominate the anticipated regret explanation for ex-ante reserve prices. Hence, it is not clear whether auctioneers use format-specific models or the unified SCP model across auction formats.

The second experiment is designed to assess these two explanations, by redrawing costs from a left-skewed distribution. The experimental result shows the unified SCP model has a better performance of predicting auctioneers' behavior in this experiment. In addition, although the specific values of (μ, λ) pair are varied over treatments, the S-shaped transformed function always hold according to the SCP structural model estimation.

The extent to which procurement professionals subjectively transform conditional probabilities remains unknown, which requires future field studies. However, we do know that correcting this subjective judgement bias is challenging. Providing a decision support tool is a natural intervention, one would reasonably believe confronting decision makers with the objective probabilities and consequences over outcomes from potential decision would stem the value loss. However, there is evidence that this type of subjective judgement is difficult to correct with such support tools. Shachat & Tan (2015) reported an experimental treatment in which auctioneers are provided such support tool, and find auctioneers' judgement bias is more severe. The challenge of framing an effective support system to correct this subjective judgement bias remains open. Perhaps auctioneer screening is a more effective solution to mitigating auctioneers' judgement biases.

Appendix A

A1. Proofs

Proof of Proposition 3. The first order condition for expected utility maximization of Eq. (7) is,

$$-Z(r_a^*) + (v - r_a^*)\tilde{Z}(r_a^*) = 0.$$

Let $\tilde{Z}(r_a^*) = Z'(r_a^*) + f_{(2)}(r_a^*)$ and then rewrite the first order condition,

$$r_a^* = v - \frac{Z(r_a^*)}{\tilde{Z}(r_a^*)}.$$

To guarantee r_a^* is interior maximum, the second order condition needs to satisfy

$$-Z'(r_a^*) - \tilde{Z}(r_a^*) + (v - r_a^*)\tilde{Z}'(r_a^*) < 0.$$

Furthermore, substituting r_a^* for $v - \frac{Z(r_a^*)}{\tilde{Z}(r_a^*)}$, the second order condition comes to

$$\frac{Z'(r_a^*)\tilde{Z}(r_a^*) - Z(r_a^*)\tilde{Z}'(r_a^*) + \tilde{Z}(r_a^*)^2}{\tilde{Z}(r_a^*)} < 0.$$

Since $\tilde{Z}(r_a^*) > 0$, the negative of the numerator has to be $Z'(r_a^*)\tilde{Z}(r_a^*) - Z(r_a^*)\tilde{Z}'(r_a^*) + \tilde{Z}(r_a^*)^2 > 0$. $\square$

Proof of Proposition 4. Differentiate r_a^* with respect to n at the optimal solution to obtain

$$\begin{aligned} \frac{\partial r_a^*}{\partial n} &= \frac{-Z'(r_a^*)\tilde{Z}(r_a^*) + Z(r_a^*)\tilde{Z}'(r_a^*)}{\tilde{Z}(r_a^*)^2} \frac{\partial r_a^*}{\partial n} \\ &\quad + \frac{-\frac{\partial Z(r_a^*)}{\partial n}\tilde{Z}(r_a^*) + Z(r_a^*)\frac{\partial \tilde{Z}(r_a^*)}{\partial n}}{\tilde{Z}(r_a^*)^2} = 0. \end{aligned} \quad (A.1)$$

Rearranging terms,

$$\frac{\partial r_a^*}{\partial n} = \frac{Z(r_a^*)\frac{\partial \tilde{Z}(r_a^*)}{\partial n} - \tilde{Z}(r_a^*)\frac{\partial Z(r_a^*)}{\partial n}}{Z'(r_a^*)\tilde{Z}(r_a^*) - Z(r_a^*)\tilde{Z}'(r_a^*) + \tilde{Z}(r_a^*)^2}. \quad (A.2)$$

The second order condition implies $Z'(r_a^*)\tilde{Z}(r_a^*) - Z(r_a^*)\tilde{Z}'(r_a^*) + \tilde{Z}(r_a^*)^2 > 0$. Thus the sign of Eq. (A.2) is determined by the numerator. When the numerator is strictly negative, the partial derivative is strictly less than 0. $\square$

Proof of Proposition 5. Since $D(r_p|c_2) = \frac{F(r_p)}{F(c_2)}$, if $v - c_2 > 0$, the first order condition for maximizing the second argument of

$E[\pi_p(r_p; v, c_2)]$ is,

$$l(v - c_2) \frac{f(r_p^*)}{F(c_2)} + (-1 - w'(r_p^*)) \frac{F(r_p^*)}{F(c_2)} + (v - r_p^* - w(r_p^*)) \frac{f(r_p^*)}{F(c_2)} = 0.$$

Substituting $l(v - c_2) = \delta_l(v - c_2)$ and $w(r_p^*) = \delta_w(r_p^* - k(r_p^*))$ into the first order condition and dividing it by $\frac{F(c_2)}{f(r_p^*)}$ on both sides,

$$\delta_l(v - c_2) + (-1 - \delta_w + \delta_w k'(r_p^*)) \frac{F(r_p^*)}{f(r_p^*)} + (v - (1 + \delta_w)r_p^* + \delta_w k(r_p^*)) \frac{f(r_p^*)}{f(r_p^*)} = 0.$$

Rearranging terms,

$$V(r_p^*) + \delta_l(v - c_2) + \delta_w M(r_p^*) = (1 + \delta_w)r_p^*,$$

where $V(r_p^*) = v - \frac{F(r_p^*)}{f(r_p^*)}$ and $M(r_p^*) = k(r_p^*) - \frac{F(r_p^*)}{f(r_p^*)}(1 - k'(r_p^*))$. Dividing by $1 + \delta_w$,

$$r_p^* = \frac{1}{1 + \delta_w} \left(V(r_p^*) + \delta_l(v - c_2) + \delta_w M(r_p^*) \right).$$

If $v - c_2 < 0$, since the lose regret has $l(x) = 0$, the second term $\delta_l(v - c_2)$ has to be 0. Generally,

$$r_p^* = \frac{1}{1 + \delta_w} \left(V(r_p^*) + \delta_l \max\{0, v - c_2\} + \delta_w M(r_p^*) \right).$$

□

Proof of Proposition 6. To obtain the relationship between r_p^* and c_2 , we differentiate Eq. (9) with respect to c_2 ,

$$\frac{\partial r_p^*}{\partial c_2} = \frac{1}{1 + \delta_w} \left(V'(r_p^*) \frac{\partial r_p^*}{\partial c_2} - \delta_l + \delta_w M'(r_p^*) \frac{\partial r_p^*}{\partial c_2} \right).$$

Rearranging terms,

$$\frac{\partial r_p^*}{\partial c_2} = \frac{-\delta_l}{1 + \delta_w - V'(r_p^*) - M'(r_p^*)}.$$

Since the denominator is the negative of the second order condition, $1 + \delta_w - V'(r_p^*) - M'(r_p^*) > 0$. As $\delta_l > 0$, $\frac{\partial r_p^*}{\partial c_2} < 0$. □

Proof of Proposition 7. The first order condition for maximizing $E[\pi_a(r_a; v)]$ is

$$-\frac{\partial l(v - r_a^*)}{\partial r_a^*} (1 - F(r_a^*)) + l(r_a^*) n f(r_a^*) + (-1 - w'(r_a^*)) n F(r_a^*) + (v - r_a^* - w(r_a^*)) n f(r_a^*) = 0.$$

Substituting $l(r_a^*) = \delta_l(v - r_a^*)$ and $w(r_a^*) = \delta_w(r_a^* - k(r_a^*))$ into the first order condition,

$$\delta_l - \delta_l F(r_a^*) - n F(r_a^*) - \delta_w (1 - k'(r_a^*)) n F(r_a^*) + v n F(r_a^*) - r_a^* n f(r_a^*) - \delta_w (r_a^* - k(r_a^*)) n f(r_a^*) + \delta_l (v - r_a^*) n f(r_a^*) = 0.$$

Dividing by $n f(r_a^*)$,

$$v - \frac{F(r_a^*)}{f(r_a^*)} + \delta_l \left(\frac{1 - F(r_a^*)}{f(r_a^*)} \frac{1}{n} + v \right) + \delta_w \left(k(r_a^*) - \frac{F(r_a^*)}{f(r_a^*)} (1 - k'(r_a^*)) \right) = (1 + \delta_w + \delta_l) r_a^*.$$

Dividing by $1 + \delta_w + \delta_l$ on both sides,

$$r_a^* = \frac{1}{1 + \delta_l + \delta_w} \left(V(r_a^*) + \delta_l L(r_a^*, n) + \delta_w M(r_a^*) \right),$$

where $\delta_l \geq 0$, $\delta_w \geq 0$, $V(r_a^*) = v - \frac{F(r_a^*)}{f(r_a^*)}$, $L(r_a^*, n) = v + \frac{1 - F(r_a^*)}{f(r_a^*)} \frac{1}{n}$ and $M(r_a^*) = k(r_a^*) - \frac{F(r_a^*)}{f(r_a^*)} (1 - k'(r_a^*))$. □

Table A1

Estimates of intermediate linear models for Table 2: EP-U and EA-U.

Variable	EP-U treatment		EA-U treatment
	Model(23)	Model(24) ^f	Model(25)
Intercept	17.73*** (2.18)	-18.34*** (2.25)	21.55*** (1.92)
$\mathbb{1}_{\{n=2\}}$	-6.65*** (0.90)	4.24*** (1.10)	-4.10*** (1.05)
$\mathbb{1}_{\{n=3\}}$	-10.44*** (1.31)	6.26*** (1.16)	-7.20*** (1.75)
Value	0.41*** (0.02)	0.39*** (0.02)	0.38*** (0.02)
Auction price	-	0.38*** (0.03)	-
Log(scale)	2.75*** (0.03)	2.62*** (0.03)	-
R^2	-	-	0.35 ^a
ln(Likelihood)	-19640	-19180 ^b	-23909 ^c
Number of observations	5760	5760	5760

Standard deviations clustered by subject are in parentheses. *** Coefficient is significant at the 1% level.

^f The coefficients of $\mathbb{1}_{\{n=2\}}$ and $\mathbb{1}_{\{n=3\}}$ become to be positive because the added variable of auction price decreases with the number of bidders.

^a Comparing Models (25) and (5), F test rejects Model (25) in favor of Model(5), where p -value < 0.01.

^b Comparing Model (24) and (2), LR test rejects Model (24) in favor of Model (2), where p -value < 0.01.

^c Log-likelihood is extracted from OLS estimations.

Proof of Proposition 8. Differentiate r_a^* with respect to n yields,

$$\frac{\partial r_a^*}{\partial n} = \frac{1}{1 + \delta_l + \delta_w} \left(V'(r_a^*) + \delta_l \frac{\partial L(r_a^*, n)}{\partial r_a^*} + \delta_w M'(r_a^*) \right) \frac{\partial r_a^*}{\partial n} + \frac{\delta_l}{1 + \delta_l + \delta_w} \frac{\partial L(r_a^*, n)}{\partial n}.$$

Rearranging terms,

$$\frac{\partial r_a^*}{\partial n} = \frac{\delta_l \frac{\partial L(r_a^*, n)}{\partial n}}{(1 + \delta_l + \delta_w) - \left(V'(r_a^*) + \delta_l \frac{\partial L(r_a^*, n)}{\partial r_a^*} + \delta_w M'(r_a^*) \right)}$$

The denominator is the negative of second order condition. Therefore the denominator is strictly positive. Consider the terms in the numerator. $\frac{\partial L(r_a^*, n)}{\partial n} = -\frac{1 - F(r_a^*)}{f(r_a^*)} \frac{1}{n^2} > 0$, where $1 - F(r_a^*) > 0$. The strict inequality is implied by r_a^* being an interior solution. Hence, the partial derivative has $\frac{\partial r_a^*}{\partial n} < 0$. □

A2. Heterogeneity

Fig. A1 plots the estimates of λ in SCP Model, for 64 subjects in each treatment.

A3. Additional empirical analyses

In Fig. A2, The SCP model predictions are calculated at the expected auction prices: 100 for $n = 1$, 66.7 for $n = 2$ and 50 for $n = 3$. Table A2~A5 present the results of the in-sample prediction performance and estimates of the alternative models.

Appendix B. Instruction translation

B1. EP-U Treatment - N varying from 1 to 3

Preliminary Remark

You are participating in an experiment studying individual decision-making in auctions. Contingent on your decisions in this experiment, you can earn money in excess of your participation fee of 5 RMB. Therefore, it is very important that you read the instructions very carefully.

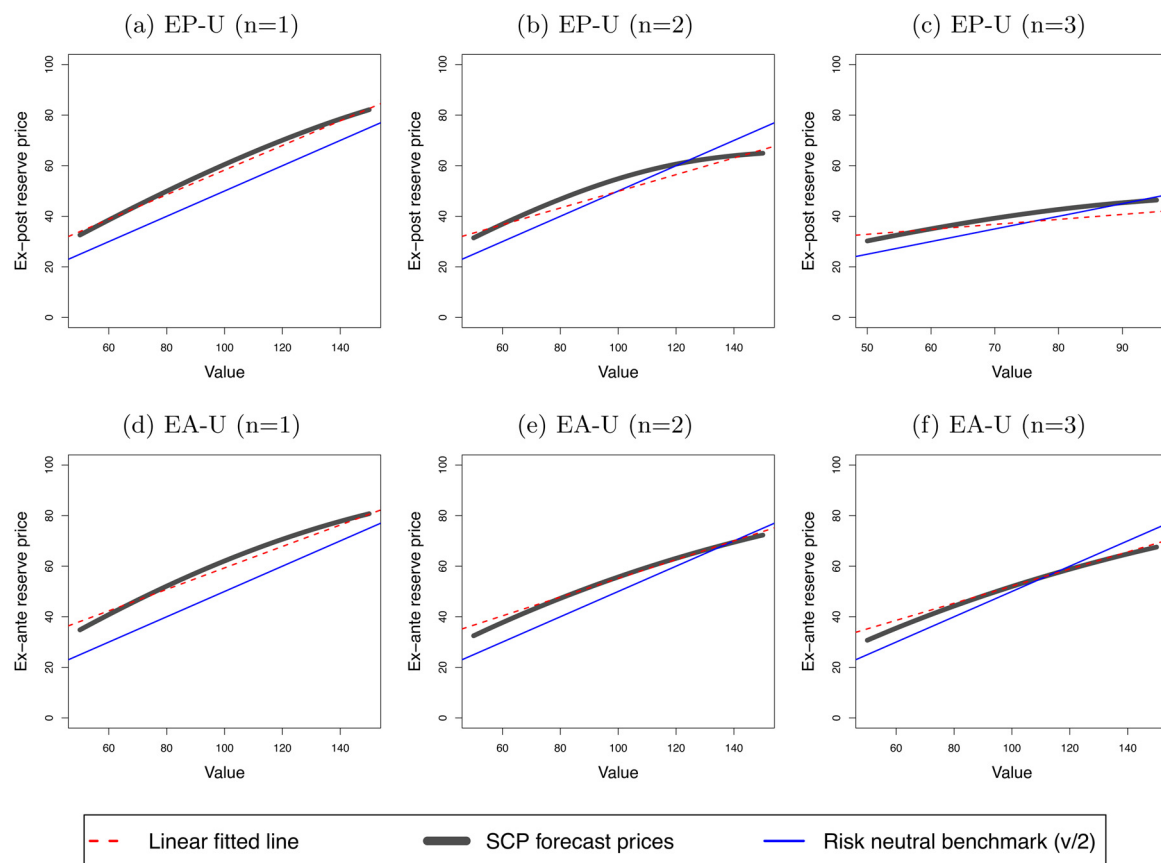


Fig. A2. SCP forecasts of reserve prices: EP-U and EA-U treatments.

Table A2

In sample prediction performance of alternative models for Experiment 1.

	$n = 1$	$n = 2$	$n = 3$	Pooled
MSEs of predicted ex-ante reserve price				
Risk averse model	187.78	224.38	346.45	252.87
SCP with RA	147.24	226.93	367.15	247.10
SCP	149.43	212.59	343.50	235.17
SCP with UPT-RE	147.27	228.44	350.96	242.22
SCP with UPT-UN	146.66	246.69	398.94	264.10
MSEs of predicted ex-post reserve price^a				
Risk averse model	469.28	335.33	225.26	361.51
SCP with RA	174.97	125.60	101.00	139.36
SCP	175.36	129.74	108.57	142.86
Ex-post auction outcome rejection and acceptance consistency				
Risk averse model	0.64	0.46	0.50	0.53
SCP with RA	0.97	0.83	0.72	0.84
SCP	0.97	0.79	0.70	0.82

^a Reserve price conditional on auction outcome rejection. The abbreviations are, RA: risk aversion; UPT-RE: unconditional probability transformation with restriction; UPT-UN: unconditional probability transformation without restriction.

In the experiment, we request you to switch off your hand phones and other devices; except for the experimental software application do not open other applications on the computer. Please read instruction quietly if there is a lull. Please do not talk with the other subjects in the entire experiment, or look at other' computer monitors. If at some point you have a question, please raise your hand and we will address it as soon as possible. If you do not observe these rules, we will have to exclude you from this experiment and all associated payments, and ask you to leave.

Today the experiment will consist of 90 rounds and you will receive earnings from each round. In the experiment, all monetary amounts are donated in experimental currency denoted as \$. Any

Table A3

Estimates of the risk averse model and the SCP model with risk aversion for Experiment 2.

Variable	EP-S treatment		EA-S treatment	
	Risk averse Model(26)	SCP with RA Model(27)	Risk averse Model(28)	SCP with RA Model(29)
μ	-	1.35*** ($<.001$)	-	0.75*** ($<.001$)
λ	-	1.18*** ($<.001$)	-	1.68*** ($<.001$)
γ^a	0.65*** ($<.001$)	1.05** (0.03)	0.68*** ($<.001$)	0.51*** ($<.001$)
Log(scale)	8.49*** (0.09)	8.27*** (0.14)	10.08*** (0.09)	8.28*** (0.08)
ln(Likelihood)	-16680.44	-16598.66	-21480.74	-20339.69
LR-test(p-value)	-	<0.01	-	<0.01
Number of observations	5760	5760	5760	5760

Standard deviations are in parentheses. * Coefficient is significant at the 10% level, ** 5% level and *** 1% level. ^a The utility function of risk averse auctioneers is $U(x) = x^\gamma$. LR-test is a comparison between the models with and without risk aversion.

earnings will be converted to RMB at the exchange rate $\$60 = 1$ Yuan RMB. All payments will be made privately at the conclusion of the experiment.

You will participate in a procurement auction in each round. In an auction, the buyer may purchase a single unit of a fictitious good from one of the N sellers, the auction winner. You are the buyer and the computer plays the role of sellers.

How are your earnings calculated?

As a buyer, each round you will have a unit value of the good. These values generated by the computer varies over rounds. We will provide more details later about generating a value. If you purchase a unit, your earnings are

Table A4
Estimates of the SCP model with UPT for EA-S treatment.

Variable	Restricted ($\mu_{con} = \mu_{uncon}$, $\lambda_{con} = \lambda_{uncon}$) Model (30) (Restricted)	Unrestricted Model (31) (Unrestricted)
μ_{con}	-	1.16*** (0.001)
λ_{con}	-	1.86*** ($<.001$)
μ_{uncon}	-	0.28*** ($<.001$)
λ_{uncon}	-	2.48*** ($<.001$)
$\mu_{con} = \mu_{uncon}$	1.44*** (0.04)	-
$\lambda_{con} = \lambda_{uncon}$	1.81*** (0.02)	-
Log(scale)	8.31*** (0.08)	8.20*** (0.08)
ln(Likelihood)	-20366.9	-20294.9
LR test(p-value)	-	<0.01
Number of observations	5760	5760

Standard deviations are in parentheses. * Coefficient is significant at the 10% level, ** 5% level and *** 1% level.

Table A5
SCP model and learning in Experiment 1.

Variable	EP-U treatment		EA-U treatment	
	1st half data	2nd half data	1st half data	2nd half data
μ	1.38*** (0.002)	1.51*** ($<.001$)	1.48*** ($<.001$)	1.67*** ($<.001$)
λ	1.29*** (0.03)	1.23*** (0.02)	1.45*** ($<.001$)	1.40*** ($<.001$)
Log(scale)	12.84*** (0.19)	12.47*** (0.19)	15.48*** (0.19)	15.06*** (0.08)
ln(Likelihood)	-9640.55	-9405.75	-11976.94	-11897.77
Number of observations	2880	2880	2880	2880

Standard deviations are in parentheses. * Coefficient is significant at the 10% level, ** 5% level and *** 1% level.

Buyer's profit = unit value – purchase price

You are not obligated to purchase a unit, and if you do not make a purchase your earnings for that round are zero. For example, if a buyer's unit value is \$131.00 he purchases a unit at the price of \$75.00, then his profit in a round is \$56.00 (\$131.00 - \$75.00). Your earnings in each round will be recorded and be summed up to pay you at the end of the experiment. Notice that, a buyer's profit can be negative in a round. Please make a decision seriously.

How do you buy a unit of fictitious good?

You can purchase a unit of fictitious good through procurement auction in each round. As previously stated, today's experiment consists of 90 rounds. Each round is an independent procurement auction. As a buyer, you will engage in the procurement auction to buy a good. In the rounds of 1 - 30, you will be matched with 1 computer seller in each round; in the rounds of 31 - 60, you will be matched with 2 computer sellers; In the rounds of 61 - 90, you will be with 3 computer sellers.

- The Auction Stage which computer sellers take part in: When an auction begins, the price starting at \$100 will be dynamically reduced at a constant speed. At any point a seller can drop out the auction, but once a seller exits he cannot re-enter the auction. The current price when a seller drops out

becomes his drop-out price. The auction is over once all N seller exit. The last seller to exit is the auction winner. The auction price is the price when the $N - 1$ th seller exit the auction. Notice that, when $N=1$, there is no $N - 1$ th seller and therefore the auction price will be the initial price of \$100. In this experiment, a computer seller will exit the auction when the price reaches his own cost.

- The Decision Stage which you take part in: After the auction outcome is presented, you have two options: accept the price or make a counter offer.
 - ✓ If you accept the auction price, you will purchase a unit of the fictitious good at the auction price, and this round will end.
 - ✓ If you make a counter offer (to less than the auction price, with a minimum unit of 0.01). There are two possible results: **If your counter offer is lower than the auction winner's drop-out price**, this round ends up without a transaction and your profit in this round is zero. **If your counter offer is higher than or equal to the winner's drop-out price**, this round ends up with a transaction. You can purchase a unit of the fictitious good at the price of counter offer.

Note that the auction winner's drop-out price is invisible to you.

How are costs and unit values determined?

At the beginning of a period, each seller's cost is randomly selected to be between \$0.00 and \$100.00. Every cost level within this range is equally likely. Similarly, your unit value is randomly selected to be between \$50.00 and \$150.00. Every value level within this range is equally likely. Note that all sellers' costs and other buyers' unit values have no influence on your unit value. This random determination of costs and unit values is done every period, and the realization of these values is not influenced by past realizations nor they will influence future realizations.

A simple example

Let's consider an example. Suppose computer Seller1's unit cost is \$25.00 and that computer Seller2's unit cost is \$67.00. In the auction, computer Seller 2 first drops out the auction at \$67.00 and computer Seller 1 drops out at \$25.00 (invisible to you). Auction ends and Computer Seller 1 becomes to the auction winner. The auction price is equal to computer Seller2's drop-out price of \$67.00. The buyer, whose value is \$108.00, has two choices: accept the price \$67.00 or send a counter offer lower than \$67.00.

If the buyer accept the auction price of \$67, this round is over and the buyer would receive a profit of \$41.00 (buyer's value - auction price, or \$108.00 - \$67.00).

If the buyer chooses to send a counter offer of \$29.00 to the auction winner (computer Seller 1), which is higher than the winner's drop-out price, the buyer receives a profit of \$79.00 (buyer's value - offer price, or \$108.00 - \$29);

Or, if the buyer sends a counter offer of \$20.00 to the auction winner, which is lower than his drop-out price. The buyer cannot purchase and earn \$0 in this round.

How to use the computer program

After all participants have read the instructions and successfully completed the attached quiz, the experimenter will start the computerized auctions. There will be two phases in each round: an Auction and a bargaining phase.

Fig. B.1 gives an example of what your computer screen looks like in the Auction phase. The left hand side window shows the price of computer seller exiting chronologically: price and W.

- Shows W, he is the auction winner, and his drop-out price is not visible;

Current period
5 Total 6

AUCTION

Bidding Process

Bidder 1

\$ 72.01

Bidder 2

\$ 61.39

Bidder 3

W

W=the winner
\$XX.XX= a drop-out price

Your Value: **\$ 85.28**
Auction price: **\$ 61.39**

Accept the auction price or bargain:

Accept the auction price
Bargain

Period	Your Value	Auction Price	Bargain or not	Your Offer	Offer is accepted or not	Profit	TotalProfit
1	140.71	100.00	N	-	-	40.71	40.71
2	136.40	100.00	Y	32.00	Y	104.40	151.11
3	96.31	96.19	Y	32.00	Y	64.31	215.42
4	74.39	93.99	N	-	-	-19.60	195.82

Fig. B1. A screen-shot for the Auction Phase.

Current period
5 Total 6

There are 3 bidders in the auction

Your Value: **\$ 60.74**

Auction Price: **\$ 66.62**

Please type into your offer:

OK

Period	Your Value	Auction Price	Bargain or not	Your Offer	Offer is accepted or not	Profit	TotalProfit
1	103.84	100.00	Y	23.00	N	0.00	0.00
2	114.61	100.00	Y	32.00	N	0.00	0.00
3	86.02	8.46	Y	3.00	N	0.00	0.00
4	124.77	28.34	N	-	-	96.44	96.44

Fig. B2. A screen-shot for the Bargaining Phase.

- Show price \$XX.XX, he is not the winner, and his drop-out price is XX.XX.

In this screen, you will be informed of your unit value and auction price in this round. You can choose “accept auction price” or “bargain”. To accept the auction price you can simply click the “Accept” button and you will purchase the fictitious good at the auction price.

If you choose 'Bargain', the next page will display (as shown in Fig. B.2). You enter your counter offer into the “Your Offer” box and then click button “OK”.

In the review page, you will be informed of the results, including whether you purchased or not, accept the auction price or send a counter offer, the purchase price, and your profit.

B2. EA-U Treatment - N varying from 1 to 3

Preliminary Remark

(The same as in EP-U treatment)

How are your earnings calculated?

(The same as in EP-U treatment)

Current period
2 Total 3

In this period, 3 bidders are in the auction.

Your value: **\$ 129.39**

Please input your reserve price:

0 s

Period	Your Value	Reserve price	Purchase or not	Purchase Price	Profit	TotalProfit
1	\$4.55	23.00	Y	auction price	\$7.39	\$7.39

Fig. B3. A screen-shot for the phase to setting reserve price.

Current period
2 Total 3

AUCTION
Auction duration: 5s
Auction time left: 0 s

Bidding Process

Reserve Price	Bidder 1	Bidder 2	Bidder 3
\$ 23.00	D	\$ 19.57	W

D= a drop-out price higher than your reserve price
W= the winner
\$XX.XX= a drop-out price not higher than your reserve price

Result

Your value: **\$ 129.39**
Your reserve price: **\$ 23.00**

**More than 1 bidders' drop-out prices are less than your reserve price.
You can purchase in this period.**

The purchase price is the auction price: \$ 19.57
Your profit: **\$ 109.82**

Enter the next period

Period	Your Value	Reserve Price	Purchase or not	Purchase Price	Profit	TotalProfit
1	\$4.55	23.00	Y	auction price	\$7.39	\$7.39
2	129.39	23.00	Y	auction price	109.82	117.21

Fig. B4. A screen-shot for the phase to reviewing auction outcome.

How do you buy a unit of fictitious good?
(The same as in EP-U treatment)

- The Auction Stage which computer sellers take part in:(The same as in EP-U treatment)
- The Decision Stage which you take part in:Before the auction begins, you will know the value of the good in current round. You need to decide a reserve price for the auction. The reserve price is the highest price which you would like to pay for the fictitious good in this round. The reserve price is over the range of from 0 to 100 with a minimum unit of 0.01. After the auction stage concludes, the auction price becomes the purchase price if it is lower than your reserve price; or your reserve price becomes the purchase price if

your reserve price lower than the auction price and higher than the auction winner's drop-out price; or you cannot purchase if your reserve price less than all drop-out prices.

Note that the auction winner's drop-out price is invisible to you.

How are costs and unit values determined?
(The same as in EP-U treatment)

A simple example

Let's consider an example. Suppose 2 computer sellers participate in an auction, your unit value for a fictitious good is \$90 and you set up a reserve price of \$X. Computer Seller 1 has a unit cost

of \$88 and Computer Seller 2 has a unit cost of \$66. The following process (your invisible information) will run in the system:

- In the auction, Computer Seller 1 first drops out the auction when the current price is \$88;
- Computer Seller 2 drops out the auction when the current price is \$66;
- Computer Seller 2 becomes the auction winner, and the auction price is \$88.

Based on your reserve price of \$X decided before auction, the following circumstances will occur (take three examples) (your visible information):

- ✓ If your reserve price is $X=89$, it is higher than the auction price. You will observe that the penultimate seller exiting the auction at the price of \$88 and the winner being indicated as W. You will purchase the fictitious good at the auction price of \$88 and will yield a profit of \$2 in this round (unit value - auction price, or $90 - 88$);
- ✓ If your reserve price is $X=77$, it is lower than the auction price but not less than the winner's drop-out price. You will learn that one seller's drop-out price is higher than your reserve price, by observing of D (More details provided later). You will also learn that the winner's drop-out price is not higher than your reserve price, by observing of W. You will purchase the fictitious good at the price of \$77 and will yield a profit of \$13 (unit value - reserve price, or $90 - 77$).
- ✓ If your reserve is $X=55$, it is less than all drop-out prices of computer sellers. You will know it by observing two D. You will not purchase in this round and your profit will be \$0.

How to use the computer program

After all participants have read the instructions and successfully completed the attached quiz, the experimenter will start the computerized auctions. There will be two phases in each round: a phase to setting reserve price and a phase to reviewing auction outcome.

Fig. B.3 gives a screen-shot of setting up a reserve price before auction. You are informed of your unit value and the number of bidders. You have to decide a reserve price (from 0.00 to 100.00) and type it into the box and then press "confirm".

Fig. B.4 gives an example of what your computer screen looks like in auction phase. The duration of an auction is 5 seconds. After that, the left hand side window shows the price of computer seller exiting chronologically: D, W or price.

- Shows D, the drop-out price of this computer seller higher than the reserve price;
- Show price \$XX.XX, the drop-out price of this computer seller lower than the reserve price but he is not the auction winner. The drop-out price (bid) is XX.XX.
- Shows W, this computer seller's drop-out price less than the reserve price and he is the auction winner. If all cards dis-

play D, it means your reserve price less than all drop-out prices. There is no auction winner in the auction and you cannot purchase in that round. The right hand side window shows the result of a round, including reserve price, whether purchase or not, purchase price and profit.

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