

Revenue Implications of Strategic and External Auction Risk*

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Abstract

Two experimental treatments are used to study the effects of auction risk across five mechanisms. The first canonical, baseline treatment features only *strategic risk* and replicates the standard results that overbidding relative to the risk neutral Nash equilibrium is prevalent in all common auction mechanisms except for the English auction. We do not find evidence that bidders' risk preferences can explain these patterns of overbidding. To enhance salience, we introduce a second novel treatment with *external risk*. This treatment captures the risk, prevalent in online auctions, that winners will not receive a good of value. We find that dynamic auctions – including the English – are particularly susceptible to overbidding in this environment. We conclude with a brief discussion of research implications.

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1 Introduction

Bidders in the field must confront two sorts of risk. The first, and the principal focus of most economic studies, is *strategic risk*. Bidders who weigh how much to “shade their bids” in a first price sealed bid auction, for example, are engaged in strategic risk management.

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The second, which has drawn less attention from economists, is *external risk*. The prospect that, when all is said and done, the prize over which bidders compete proves to be defective is an example of external risk.

This second sort of risk has particular practical importance given the prevalence of online auctions, in which bidders are often unable to inspect goods or even ensure receipt after winning (Bajari and Hortagsu 2004, Kazumori and McMillan 2005). Auction fraud, defined as the misrepresentation of or the failure to deliver goods, is among the top two internet crimes reported in the United States each year [Jin and Kato 2006; Internet Crime Complaint Center Report 2014).¹ Even in the absence of intentional seller deception, there is external risk for bidders who must accept goods “as is,” without prior inspection, a common requirement of auctions for surplus or confiscated items. It is therefore surprising that the empirical literature on the response to such risk, or on differences in “risk pricing” across mechanisms, is thin. While some researchers have found that seller reputation ratings, particularly negative ratings, have a small but significant influence on prices (Melnik and Alm 2002, Houser and Wooders 2005, Canals-Cerda 2012), it has proven difficult, in the absence of data on bidders’ values and beliefs, to determine whether adjusted prices reflect actual risk. Furthermore, because almost all of these studies concern online variants of the English auction, mechanism-specific effects are never considered.

Induced value lab experiments offer an important platform from which to explore these questions, as bidder values, receipt risk, and mechanism can all be controlled. There is now a large literature that compares auction revenue across formats in induced independent private value auctions, in which one of the most robust findings is the presence of “overbidding” (Kagel 1995, Kagel and Levin 2008), relative to the risk neutral Nash equilibrium (RNNE), under

¹In a recent high profile case, Tiffany’s purchased silver jewelry being sold under its name on eBay and determined 76% was counterfeit. The FBI estimates that the majority of memorabilia bearing the autographs of high profile athletes and celebrities are forgeries and that \$100 million in forged memorabilia is sold in the United States annually (FBI.gov). Jin and Kato (2006) purchased ungraded baseball cards on eBay and report that 11% were never delivered or were fake. And the case of Glafira Rosales, the Long Island art dealer who sold \$80 million worth of counterfeit paintings over 15 years, is a recent, if extreme, manifestation of a widespread problem, not all of which reflects dealer fraud.

the first-price, Dutch, and all-pay mechanisms. With some important exceptions (Lusk and Rousu 2006, Noussair, Robin, and Ruffieux 2004), overbidding is also not uncommon in second-price auctions. A common, but much debated, explanation for overbidding in the first two formats centers on risk preferences: risk averse bidders in both the first-price and Dutch auction should be willing to trade off the size of the surplus, conditional on winning, against an increase in the likelihood of winning. Direct tests of whether overbidding in FP and Dutch auctions is related with an individual's risk aversion in other contexts is limited. In one such test, Isaac and James (2000) find that estimates of risk aversion derived from FP auctions are *negatively* correlated with estimates derived from a Becker-DeGroot-Marschak task.

In contrast to the overbidding observed in other formats, participants in induced value English auctions tend to bid just up to their values, consistent with the RNNE prediction (Kagel 1995). There is some evidence, however, that outside the induced values context, English auction bidders can be mistake-prone: Hossain and Morgan (2006), for example, find that higher shipping costs are not priced into bids, while Ku, Malhotra and Murnighan (2005) conclude that bidders in dynamic auctions often bid above their stated maximum willingness to pay. These studies suggest that English auction bidders might not necessarily be as successful in environments where their value for the good is not given by an explicitly assigned, certain payoff. Auctions with external risk offer the opportunity to test in a controlled environment whether English auction bidders are also susceptible to overbidding outside of a riskless induced value setting.

To better understand the overbidding phenomenon in a salient and practical environment, we introduce a much simplified form of external risk: namely, a fixed likelihood that the winner will never receive the value of the item. In particular, we use an induced independent private values lab experiment to study revenues under five common mechanisms – first-price sealed bid (FP), second-price sealed bid (SP), English (E), Dutch (D) and all-pay (AP) – and two risk conditions, one in which the winner receives her private value with

certainty, and another in which there is a 20% likelihood that the winner receives nothing at all. The advantage of this approach is that we are able to control bidder beliefs about the likelihood of loss. In the absence of concerns about misperceived risk, betrayal aversion or other social preferences, we obtain cleaner measures of bidder response under each mechanism. We are agnostic about the interpretation of the external risk, but the possibilities include stylized representations of seller fraud, or the purchase of counterfeit or defective goods, or the acquisition of goods that, through no fault of the seller, otherwise prove to be valueless. In contrast to standard independent private value auctions, the introduction of this second risk in auctions with risk averse bidders should *suppress* overbidding relative to the RNNE prediction, with *underbidding* expected in both the English and SP. If, however, consistent with Hossain and Morgan (2006), bidders fail to price the “terms of sale” into the bids or, following Ku et al (2006), revise WTP upward during auctions, we should observe *more* overbidding, especially in the English auction.

We make the following contributions to the literature. First, in the absence of external risk, and consistent with previous experimental results, we find that most participants overbid relative to the RNNE prediction in all but the English auction and that, as a result, revenues in all auctions but the English are greater than predicted. Second, we find direct evidence for the proposition that the all-pay auction generates more revenue than the FP, or any other winner-pay auction, in practice. Third, we directly measure risk aversion of each bidder using both an externally-validated survey question and an incentivized lottery choice. However, we find no evidence that risk aversion is positively correlated with overbidding or revenues under any mechanism. We are not aware of a similar direct test of whether elicited risk preferences predict overbidding under different mechanisms, but we note that our findings are in line with Isaac and James (2000)’s comparison of behavior in first price auctions and in a Becker-DeGroot-Marschak procedure. We are therefore able to replicate some common results and to provide new evidence against one popular explanation for these results. Our main innovation, however, is the introduction of external auction risk. As ex-

pected, revenues under all mechanisms decline with the introduction of external risk, but revenues exceed the RNNE prediction in just the two “real time” mechanisms - that is, the English and the Dutch - and AP.

2 Background and Predictions

In the canonical case with risk neutral bidders whose independent and private values are drawn from some common distribution, the theoretical implications of external risk are straightforward. In each mechanism, the winner now receives, in expectation, $(1 - \theta)v_i$, where θ is the likelihood that the buyer never receives the value of the good, and v_i is her private value. In effect, the second form of risk is the equivalent of an ad valorem tax on the value of the prize to the winner. It follows that in the symmetric equilibrium for each mechanism, bids and therefore expected revenue are scaled down θ percent, so that revenue equivalence is preserved. There is no need to (re)derive these well-known bid functions here. Instead, we note that in the special case of interest here, in which the private values of four bidders are drawn from a uniform $[0,100]$ distribution, FP bidders should submit, and D bidders should stop the auction when, $\sigma^{FP}(v) = \sigma^D(v) = 0.75(1 - \theta)v$; SP bidders should submit, and E auction bidders should drop out when, $\sigma^{SP}(v) = \sigma^E(v) = (1 - \theta)v$; and AP bidders should submit $\sigma^{AP} = (7.5 \times 10^{-7})(1 - \theta)v^4$. Under all five mechanisms, expected revenue is therefore equal to $60(1 - \theta)$. For the two cases considered here, $\theta = 0$ and $\theta = 0.2$, the introduction of external risk should cause mean revenues to fall, from 60 to 48.

When $\theta = 0$, risk averse bidders will bid above the RNNE prediction in FP and D, but not SP or E. It follows that risk averse expected revenues are 60 in SP and E but more than 60 in FP and D. Expected revenues in AP auctions with risk averse bidders can be higher or lower than the RNNE (Fibich et al. 2006). When $\theta = .2$, however, risk preferences should matter even in SP and E auctions: in particular, risk averse bidders should underbid relative to the RNNE prediction, and submit a bid equal to the certainty equivalent in a $[0.8, v_i; 0.2, 0]$ lottery. In the D and FP, the presence of risk averse bidders should generate

less overbidding relative to the case of $\theta = 0$.

3 Experimental Design

The experiment took place at Middlebury College in April 2014. All participants completed a survey approximately one week before participating, which asked demographic questions as well as about risk preferences and included an incentivized choice among six lotteries (as in Carpenter and Cardenas 2013). Ten sessions were conducted and 148 students participated in total. Each session consisted of 15 auction periods, with the auction mechanism held constant for the session. The auctions were computerized using the software z-Tree (Fischbacher 2007). At the start of each period, participants were randomly matched into groups of four bidders and each participant was assigned a value for the item being auctioned. The values were in experimental dollars and were randomly drawn from a uniform distribution on the $[0,100]$ interval.

In the sealed bid sessions (FP, SP, AP), participants each typed a bid, up to one decimal point. The highest bidder won the item and he was required to pay either his own bid (FP) or the bid of the second highest bidder (SP). In the AP sessions, all participants paid their own bids, regardless of whether they won. In the E sessions, a clock ticked upwards from 0 to 100 experimental dollars, in 10 cent increments. Participants could exit the auction at anytime. The last remaining bidder in the auction won the item and paid the price at which the second to last bidder exited. Finally, in the D sessions, a clock ticked downwards from 100 to 0 experimental dollars, in 10 cent increments. The first player to hit a “Buy Now” button won the auction and paid the price displayed when the button was pressed.

External risk was introduced in the form of a fixed likelihood that the winning bidder would receive the item. Upon learning their values at the start of the period, participants also learned whether the winner would receive his value with probability 1, in which case the auction period was “safe” (S), or with probability 0.8, in which case it was “risky” (R). One could interpret this as the experience of learning about the item and the seller’s rating or reputation at the same time, although other interpretations are possible: e.g., a memorabilia

collector may view an online auction while inferring the likelihood that the good will be of value from the posted photographs, or an art collector will sometimes learn that a painting has become available at the same time as doubts about its provenance are revealed. Eight of fifteen auction periods were R periods. Which periods were S vs. R, as well as which R periods resulted in an actual loss, was determined randomly before the experiment and then fixed across all auction groups and sessions to ensure that bidder experience was the same across treatments.

Winners who did not receive the item were still required to pay the relevant price. After each period, bidders learned the price paid and whether the item was received. All bidders received an endowment of 100 experimental dollars, ensuring that a participant who bid the maximum value and sustained a loss would not finish the experiment with negative earnings. To incentivize subjects to treat each auction separately and ensure that the risk was salient across all periods, participants were compensated using the random decision selection mechanism (Hey and Lee 2005): At the end of the experiment, one period was selected randomly and participants were paid their profits from this period only, at the exchange rate of 15 experimental dollars = 1 US dollar.

4 Results

Our central question is whether RNNE revenues obtain - and, if not, the nature of the deviation - with and without the presence of external risk. The first four columns of Table 1 report, in the form of regression coefficients, mean revenues for each format, with stars indicating whether the revenue differs from the theoretical predictions in S (60) and R (48) auctions. (For expositional purposes, we choose, following Suits (1984), to include the full set of indicators and no constant.)

We begin with the benchmark S auctions (Col. 1) in which, with few exceptions, we replicate earlier findings. First, we observe that AP revenues far exceed those in any of the winner pay formats, and are double the RNNE prediction of 60. As Decheneux, Kovenock and Sheremeta (2012) observe in their review, overbidding is a recurrent feature of all-pay

auctions, and “excess revenues” of this magnitude aren’t uncommon. In an experiment that was similar to our S periods, Noussair and Silver (2006) find that AP revenues are almost 150% of the RNNE prediction. Further, they conclude that AP revenues are also much greater than those in the FP auctions of Cox et al. (1982, 1988) but caution that methodological differences and the need to rescale data complicate comparisons. Our results provide direct confirmation that the AP mechanism generates more revenue than the FP ($p < .01$) or indeed any of the other winner pay auctions.

Second, as alluded in the introduction, overbidding relative to the RNNE prediction is common in the D, FP and sometimes SP lab auctions, but E auction bidders tend to dropout at their induced values. We, too, find that revenue is significantly greater than the RNNE prediction under all formats but the E, where mean revenues equal 60.69. At the bid level, the percentages of overbids in the FP, SP, and D are all are significantly greater than in the E. To ensure that our results are robust, we also compare observed revenue with the RNNE prediction conditional on the particular private value draws in the auction. The dependent variable in models (5) through (10) is Percent Excess Revenue = $(\text{Revenue} - \text{RNNE})/(\text{RNNE})$. We can reject the null hypothesis that this is equal across the four winner pay formats ($p < .01$ or $p = .05$ when including session controls) and we find significant excess revenues in all but the E and SP. The replication of these common findings thus serve as a “sanity check” for our main results, which are based on the behavior of the same individuals.

We next consider whether risk preferences can explain some or all of the overbidding in our experiment. On the surface, the revenue data are at least *consistent* with such an explanation, since excess revenues in the FP and D auctions, where risk aversion should produce higher bids, is significantly greater than the excess revenues in the SP and E auctions, where risk aversion doesn’t alter the dominant strategy of “sincere bidding” ($Z = 4.3, p < .01$). Likewise, our AP results are consistent with the theoretical prediction in Fibich, Gavious, and Sela (2006), who find that when bidders are risk averse, those with low values should un-

derbid, while those with high values should overbid, and with the particular pattern observed in Noussair and Silver (2006): bidders whose values fall in the lower half of the distribution bid zero most of the time while those with values in the upper half overbid 72% of the time.

Our survey data on risk preferences afford a more direct test of this claim, however. Models (2) and (6) in Table 1 interact the average level of subjective risk aversion among bidders in each auction with each of the mechanism indicators.² We find that risk aversion does *not* have a significant effect on revenue or excess revenue under any format, with the possible exception of the AP, in which risk aversion *suppresses* excess revenue. Likewise, the (insignificant) coefficient on risk-aversion is negative for the D and FP auctions. We therefore find little evidence that overbidding is the result of risk aversion in any winner pay format. In the case of the FP and Dutch auctions, revenue may be correlated with the risk aversion of the high value bidder. Alternatively, a more direct test of the effect of risk aversion on revenue would be to consider only the risk aversion of the individual(s) whose bid sets the revenue of a given auction: the winning bidder in the FP or D, the second-highest bidder in the SP or E, and all bidders in the AP. Thus, as a robustness check Table 2 replicates Table 1 with these updated, auction-specific definitions of risk aversion. Again, we find no evidence that risk aversion drives overbidding in the FP or D auctions: the coefficients are now significantly *negative*. The only auction format in which we find that risk aversion is weakly positively associated with Safe auction revenue is the E, where risk aversion should not play a role, and this association disappears when we consider Percent Excess Revenue rather than raw Revenue. The results are also robust to other specifications not reported here, including the substitution of the risk preferences of the highest (second highest) value bidders in the FP and D (SP and E), or using the incentivized auction choice rather than the survey question.

Turning to the results for R auctions (Col. 3), we start with the observation that the AP once more generates the most revenues, in this case about 170% of the (now reduced)

²The inclusion of risk aversion controls (Col. 2 and 6) does not alter the size or significance of the coefficients in the S auctions.

RNNE prediction. Otherwise, the introduction of external risk defies conventional wisdom. In particular, mean revenues are now significantly greater than predicted in the E and D auctions, a striking result. To rephrase, the English mechanism - the one format that produced sincere bidding and RNNE predicted revenue when there was no doubt about the value of the prize - now becomes susceptible to overbidding too. Further, we note that this result is *prima facie* inconsistent with risk aversion, which unambiguously predicts underbidding relative to the RNNE under the English mechanism. On the other hand, we do not observe overbidding in either the FP or SP, where mean revenues are, respectively, 51.8 and 47.3. Column 4 also confirms that risk aversion is not a source of revenue differences across mechanisms and we note no changes with the inclusion of these controls except that FP is now marginally significant.

At the individual level, we find that overbidding is much more frequent in the E and D auctions than other formats including the AP. Returning to percent excess revenue (relative to RNNE) in Col. 7, we find that the E and D mechanisms each generate revenues 20% greater than predicted and, including session controls, the hypothesis that excess revenue is zero can be rejected at all reasonable levels. Furthermore, with the same controls in place, we can reject the null hypothesis that excess revenue in the dynamic (E and D) auctions is equal to their isomorphic counterparts (SP and FP, respectively). Finally, columns 4 and 8 include risk aversion controls and confirm one of the emergent themes of this note: risk preferences do not contribute much to the determination of excess revenue.

5 Conclusion

We use the conclusion to underscore the importance of two distinct lines of current and perhaps future research within the context of our work. First, our “safe” auctions replicate now common violations of RNNE *and* provide additional evidence that risk preferences, even when consistent with these violations, do not explain them, and we note that research on bidder motivation is, and will remain, important. The second follows from the striking result that the two “real time” auction formats, the English and Dutch, seem to “underprice” the

introduction of substantial, if simple, external risk. It is tempting to speculate that this is the result of “heat of the moment” or impulse bidding, or a consequence of decision-making under (time) pressure - both of which are topics of ongoing research - but since neither was observed in safe English auctions, it is not clear if additional risk “activated” these behaviors or if overbidding occurs more generally in environments when bidders do not have set values.

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