Collusion and Information Revelation in Auctions[*]

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Abstract

The theoretical literature on collusion in auctions suggests that the first-price mechanism can deter the formation of bidding rings. However, such analyses neglect to consider the effects of failed collusion attempts, wherein information revealed in the negotiation process may affect bidding behavior. We experimentally test a setup in which theory predicts no collusion and no information revelation in first-price auctions. The results reveal a hitherto overlooked failing of the first-price mechanism: failed collusion attempts distort bidding behavior, resulting in a loss of seller revenue and efficiency. Moreover, the first-price mechanism does not result in less collusion than the second-price mechanism. We conclude that, while the features of the first-price mechanism may have the potential to deter bidder collusion, the role of beliefs in guiding bidding behavior make it highly susceptible to distortions arising from the informational properties of collusive negotiation. Auction designers should take this phenomenon into account when choosing the auction mechanism.

Keywords: auctions, collusion, experiment.

JEL classification: C72, C91, D44

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1 Introduction

Bidder collusion poses a major impediment for auctions. By colluding, members of the colluding cartel—also known in the literature as a *bidding ring*—can improve their respective outcomes and substantially reduce the auctioneer's revenues. Recent studies have documented the prevalence of bidder collusion across sundry domains (Asker, 2010; Hendricks and Porter, 1989; Pesendorfer, 2000; Porter and Zona, 1999)[1] and it is now acknowledged as a major challenge for optimal auction design (Klemperer, 2002; Marshall et al., 2014).

Collusive negotiations reveal private information and affect the bidders' beliefs regarding private values of other bidders. If negotiations break down and bidders bid competitively, the effect on beliefs may extend to altering bidding strategies. The auction designer can take this into account, creating incentives for cartel members to misrepresent their private information, thus inhibiting successful collusive negotiations.[2] Specifically, theory predicts that the first-price mechanism deters collusion due to the opportunities to manipulate the other party's beliefs that arise in the bargaining process, as compared to the second-price mechanism, where optimal bidding does not depend on beliefs. On the other hand, if information is revealed but negotiations break down (which in many theoretical models never happens in equilibrium), the effect on the bidders' beliefs may drastically distort bidding in first-price auctions, whereas the second-price mechanism is immune to such distortions.

In this paper, we study the implications of information revelation in collusive bargaining in first-price and second-price auctions. We test the theoretical prediction that the first-price mechanism deters collusion, and provide the first systematic study of the effects of failed collusive bargaining on subsequent bidding. We study experimentally first-price and second-price private-values auctions with two bidders. The baseline treatments follow the tradition of the seminal papers that study first-price and second-price sealed-bid auctions (Cox et al., 1982; Kagel and Levin, 1993). In these treatments, subjects bid for an object without previous interaction with the other bidder. In the collusion treatments, one bidder can 'bribe' the other bidder to stay out of the auction, leaving the remaining bidder free to win the auction at the seller's reserve price.[3]

[1] A large proportion of court cases pursued under U.S. antitrust laws deal with auction markets (Agranov and Yariv, 2014; Froeb and Shor, 2005).

[2] Deterrence can also be achieved by way of sanctions levied on cartel members. We abstract from such considerations to isolate the effects of the incentives created by the auction mechanism on top of existing legal mechanisms.

[3] In order to focus on the effects of information revelation, we assume that bribes are committing. This is possible when the cartel can prevent members from bidding (McAfee and McMillan, 1992), or can submit bids in the name of the members (Marshall and Marx, 2007). A large body of literature analyzes the commitment problem, showing that, under general assumptions, first-price auctions have the potential to deter collusion. As the bidder assigned by the cartel to win the auction must place a low bid, other cartel members can enter and win the auction contrary to the terms of the collusive agreement (e.g., Marshall

In the experiment, the collusive agreement is reached through a simple ultimatum bargaining protocol, in which one bidder (the *proposer*) can make a take-it-or-leave-it offer to the other bidder (the *responder*). The responder can choose whether to accept the offer and consequently refrain from bidding in the auction or to reject the offer and participate in the auction.

This particular type of bargaining protocol is well suited for our experimental examination for several reasons. First, it is highly structured and simple to understand, thus serving as an ideal environment in which to study the implications of information revelation in collusive bargaining. Second, it has been analyzed in the theoretical literature for second-price auctions (Eső and Schummer, 2004) and first-price auctions (Rachmilevitch, 2013). These papers illuminate the deterrence properties of the first-price mechanism. Whereas Eső and Schummer (2004) proved the existence (and, under a mild refinement, uniqueness) of a collusive equilibrium in second-price auctions, Rachmilevitch (2013) proved that, assuming undominated bidding and a pure, continuous, and monotonic bribing function, no bribes are offered in the unique equilibrium of the first-price auction. This result illustrates how the effects of information revelation on bidding in first-price—but not second-price—auctions lead to the breakdown of collusion, as proposers have incentives to misrepresent their private information.

Finally, the simple bargaining protocol is well suited for the study of failed collusive bargaining, as it generates such failures as a natural part of the mechanism. The theoretical model we build on thus provides a useful benchmark to guide this first experimental study of failed collusive bargaining. As such, it should be viewed as a workhorse designed to capture the essential features of collusive bargaining that we aim to study rather than a realistic model of real-world collusion.

Our results can be organized into two main findings. First, the experimental data reject the theoretical prediction that there are substantial differences in bribing behavior between first-price and second-price auctions. Second, the bargaining process has dramatic effects on bidding behavior in first-price (but not second-price) auctions, leading to a substantial drop in seller revenue and efficiency. Our empirical analysis is able to attribute this loss of efficiency to a selection effect arising from failed bargaining. Bribe offers are likely to be accepted when proposers have a relatively high value and responders a relatively low value. This leads to a positive bias in the distribution of responder values in the auction and a negative bias for the proposer values. Proposers in the resulting asymmetric auction bid higher than responders who have the same private value (but face a lower distribution of opponents' values). Consequently, proposers often win the auction even if the responder's value is higher. A best-response analysis confirms that rational bidders should bid asymmetrically in the auction and that actual bids follow, on average, the optimal pattern.

Thus, our paper brings to light an hitherto overlooked principle: while the features of the first-price mechanism may have the potential to deter bidder collusion,

and Marx, 2007; Robinson, 1985).

the role of beliefs in guiding bidding behavior make it highly susceptible to distortions arising from the informational properties of collusive negotiation. In this, our paper contributes to two distinct literatures. First, the literature informing auction design, specifically on how to use the auction mechanism to counter collusion attempts. The consensus in the theoretical literature is that the first-price mechanism has the power to deter bidder collusion (Marshall and Marx, 2012). We bring to the discussion a new consideration, which auction designers should take this phenomenon into account when choosing the auction mechanism. Second, our paper contributes to the literature on bargaining. Most theoretical and empirical analyses of bargaining assume that failure to reach an agreement results in a known disagreement allocation. Recent treatments in cooperative game theory have explored the implications of endogenizing the disagreement point as a function of the strategic environment (Bozbay et al., 2012; Vartiainen, 2007). In contrast, we explore an environment in which the disagreement point depends on private information and on the players' actions in the bargaining stage.

2 Related literature

Although we are the first to test the informational effects of collusion on bidding behavior, several experiments have studied the more general question of how the auction mechanism affects collusion. These mostly look at situations where collusion is not directly enforceable, where the first price mechanism can deter collusion by providing opportunities for cartel members to renege on the collusive agreement (Lopomo et al., 2011; Marshall and Marx, 2007; Robinson, 1985). In a pioneer experiment, Isaac and Walker (1985) found that unstructured communication substantially increases collusion in first price auctions, mainly through bid rotation in repeated interactions.[4] Later experiments introduced other auction mechanisms and compared their success in deterring collusion in different environments. Several studies found that, even without communication or side payments, an ascending bid mechanism results in more collusion than uniform or discriminatory sealed bid mechanisms in multi-unit auctions (Alsemgeest et al., 1998; Burtraw et al., 2009; Goeree et al., 2013; Kwasnica and Sherstyuk, 2007). Agranov and Yariv (2014) compared first-price and second-price auctions with unstructured communication and side payments, using a stranger design to rule out bid rotation. They found that post-auction side payments dramatically increased collusion, while the auction mechanism had no significant effect on collusion with or without side payments.

Hinloopen and Onderstal (2013) tested the Robinson (1985) model explicitly, comparing first-price and ascending-bid auctions in a minimal setting where all three bidders share a commonly known value and vote on whether to collude. Side payments were exogenously set at one-quarter of the value paid to each of the

[4] Vyrastekova and Montero (2002) did not find that structured communication had any effect in a setting where restricted bid space gives rise to a collusive equilibrium in a repeated game.

two designated losers. In this setting, all cartels break down under the first-price mechanism, reducing the loss of revenue from collusion compared to the ascending-bid mechanism. Hu et al. (2011) studied a richer environment with private values, where the revelation mechanism used to form the cartel includes a knockout auction and the collusive agreement is enforceable. Bidders were more likely to collude under the first-price mechanism compared to the ascending-bid mechanism, which the authors attribute to the higher gains expected from collusion given overbidding in first-price auctions. In asymmetric auctions, where strong bidders can collude, a premium auction format was more successful in deterring collusion than both the first-price and the ascending-bid mechanisms. Although the cartel agreement in Hu et al. (2011) was committing—as in our setting, and unlike in that of Agranov and Yariv (2014) and Hinloopen and Onderstal (2013)—designated losers could not use any private information revealed in the knockout auction, as they had already committed to not bidding in the preceding voting stage. Consequently, there was no scope for any effects of information revelation on bidding behavior.

Our paper differs from these papers in that collusive agreements are committing, but bargaining may break down. This allows us to cleanly identify the effects of information revelation in collusive bargaining. Furthermore, by specifying the bargaining protocol we are able to generate theoretical predictions without assuming a centralized revelation mechanism, which is not always feasible as it requires an impartial third party to implement.

3 Model

3.1 Setup

The experiment implements a special case of the model introduced by Eső and Schummer (2004). Two risk-neutral bidders, p (the proposer) and r (the responder), are bidding for a single indivisible object for which they have valuations θ_p and θ_r respectively. θ_p and θ_r are drawn independently from the uniform distribution over $[0, 100]$. Everything is commonly known except the valuations, which are privately known by the bidders.

The game proceeds in two stages. In the *collusion* stage, the proposer can offer any amount b to the responder to refrain from bidding. If the responder accepts the offer, the proposer automatically wins the auction at the reserve price, which is set at zero.[5] If the receiver rejects the offer, both bidders proceed to the *auction* stage, which can take the form of either a first-price or second-price auction. In the auction stage, both bidders simultaneously bid for the object and the bidder with

[5] We set the reserve price at zero in order to simplify the experimental design. The comparative statics and the hypotheses in this section are robust to positive reserve prices as long as they are below the maximum possible valuation (see p. 302 in Eső and Schummer (2004) and p. 220 in Rachmilevitch (2013) for the predictions in the collusion treatments).

the highest bid receives it. In the first-price auction the winner pays her posted bid, while in the second-price auction the winner pays the bid posted by the other bidder.

Formally, the strategy of the proposer is a tuple $\{b(\theta_p), c_p(\theta_p)\}$, where $b(\theta_p)$ is a bribing function mapping types into offers, $b : [0, 100] \to \mathbb{R}_+$, and $c_p(\theta_p)$ is a bidding function mapping types into bids, $c_p : [0, 100] \to \mathbb{R}_+$. The strategy of the responder is a tuple $\{a(b, \theta_r), c_r(b, \theta_r)\}$, where $a(b, \theta_r)$ is an acceptance function determining whether a bribe is accepted for each bribe offered and responder type, $a : \mathbb{R}_+ \times [0, 100] \longrightarrow \{0, 1\}$, and $c_r(b, \theta_r)$ is a bidding function mapping types and bribes into bids, $c_p : \mathbb{R}_+ \times [0, 100] \to \mathbb{R}_+$.

3.2 *Equilibria*

Consider first the game without the collusion stage. In the case of a second-price auction, bidders should play their weakly dominant strategy of bidding their value. In the first-price auction, for the case of the uniform distribution, bidders should bid half of their valuation. This results in efficient allocations and equivalent revenues across mechanisms (Krishna, 2009).

Let us turn now to the game with the collusion stage. Eső and Schummer (2004) characterized the sequential equilibria for the case of second-price auctions, restricting the analysis to continuous bribing strategies, and assuming that players play the weakly dominant strategy in the auction stage. Eső and Schummer (2004, page 309) showed that when types are distributed uniformly, there exists a unique sequential equilibrium in continuous bribing strategies. The equilibrium takes the following form:

$$\begin{aligned} b(\theta_p) &= \begin{cases} \frac{1}{2}\theta_p & \text{if } \theta_p \in [0, \frac{200}{3}), \\ \frac{100}{3} & \text{if } \theta_p \in [\frac{200}{3}, 100], \end{cases} \\ a(b, \theta_r) &= \begin{cases} 1 & \text{if } b \geq \frac{\theta_r}{3}, \\ 0 & \text{if } b < \frac{\theta_r}{3}, \end{cases} \end{aligned} \tag{1}$$

and in the case where they proceed to the auction stage, both bidders play their dominant strategy and bid their valuation—i.e., $c_p(\theta_p) = \theta_p$ and $c_r(b, \theta_r) = \theta_r$. As the bribe does not affect the auction behavior, the equilibrium bribing function $b(\theta_p)$ simply balances the probability that the responder accepts and the amount that the proposer needs to pay in case the responder accepts. Similarly, the acceptance function $a(b, \theta_r)$ is based on a simple comparison of the bribe to the expected profit in the auction. Given the equilibrium bribing function, a responder who is offered a bribe $b < \frac{100}{3}$ believes that the proposer's value is $\theta_p = 2b$. It follows that if both bidders go to the auction and bid their true values, the responder's payoff will be $\max(0, \theta_r - 2b)$, hence any $b \geq \frac{\theta_r}{3}$ should be accepted. If the bribe is $b = \frac{100}{3}$, then the expected value of going to the auction is lower than b, and therefore the bribe should always be accepted.

The unique equilibrium features two interesting properties. First, bribes are offered and accepted with positive probability. Second, equilibrium allocations are not necessarily efficient. Specifically, if $\theta_p \in \left(\frac{2}{3}\theta_r, \theta_r\right)$, the responder accepts the bribe offer made by the proposer, who consequently wins the auction despite having a lower value.

Rachmilevitch (2013) analyzed the case for the first-price auction to show that if the bribing function is monotonic and continuous,[6] and under the assumption that no player bids more than her true value, the unique weak-perfect Bayesian equilibrium in pure strategies is a trivial equilibrium in which no bribe offers are made.[7]

The intuition for this result is the following. In equilibrium, a proposer with valuation 0 must offer a bribe of 0. Continuity and monotonicity imply that $b(\theta_p) = 0$ on some interval $\theta_p \in [0, \theta']$. If $\theta' = 0$, all positive types have an incentive to offer an arbitrarily small bribe $b(\epsilon)$, leading the proposer to believe that the proposer has a low value ϵ. Consequently, the responder will believe that a bid of ϵ or above is weakly dominated for the proposer. The responder will therefore bid at most ϵ. The proposer can thus gain close to her full value by deviating to a bribe offer of $b(\epsilon)$ and a bid of slightly higher than ϵ in the ensuing auction. If $\theta' > 0$, the θ' type has an incentive to deviate and offer a small positive bribe $b(\theta' + \delta)$, which will be accepted by all types $\theta < \theta' + \delta$, who believe they will lose the auction. Note that his result holds for any level of risk aversion. We refer the reader to Rachmilevitch (2013) for the complete proof.

4 Experimental design and procedure

The experiment implemented the game described in Section 3. We manipulated the availability of collusion and the auction mechanism in a 2×2 between-subjects design. Participants in the experiments played 50 rounds of the game. In treatments FPA-COL and SPA-COL, each round consisted of a collusion stage and an auction stage (first price and second price, respectively). In the baseline treatments FPA-NOCOL and SPA-NOCOL, collusion was not possible, so each round started directly with the auction stage. The roles of proposer and responder were randomly assigned at the beginning of the session and remained fixed throughout the session. Each session consisted of 12 proposers and 12 responders, who were rematched in

[6] Kotowski and Rachmilevitch (2014) showed that the proof also requires that the cumulative value distribution to be weakly concave, which is satisfied by the uniform distribution that we study.

[7] Rachmilevitch (2013) also showed the existence of other equilibria when bidding above the valuation is allowed. In such equilibria, bidders with low valuations reveal their identity through the bribing function and all higher types offer a common bribe. In case of reaching the auction stage, proposers with lower valuations bid above their value and the responders bid slightly above that. While this is technically possible, bidding above the valuation is rare in the data and happened in only 3 out of 1388 observations in the first-price auction with collusion treatment.

each round within matching groups of eight participants.[8] See the appendix for a translation of the instructions.

Private valuations were (known to be) independently drawn from a uniform distribution over $[0, 100]$. To keep with the theoretical assumption of continuity, values could be any round multiplication of 0.01 within the range. Bribe offers and bids were similarly restricted to be in the range $[0, 100]$ in steps of 0.01. That is, values, offers, and bids could each take one of $10,001$ different values.

In each round, participants were first informed of their private values. In the FPA-COL and SPA-COL treatments, the proposer was then asked to choose an amount to offer the responder in exchange for staying out of the auction. Proposers could choose not to make an offer to the responder by entering an offer of zero, in which case the two participants proceeded directly to the auction stage. If a positive offer was made, the responder was asked to choose whether to accept or reject the offer. Acceptance resulted in the round ending, with the proposer receiving her private value minus the offered amount and the responder receiving the offered amount. In case of rejection, the auction stage commenced. In the auction stage, both players entered a bid, with the highest bidder receiving her private value and paying her bid (in the FPA treatments) or the other player's bid (in the SPA treatments). The round ended with a feedback screen, providing participants with complete information about the round.[9]

Since the reasoning behind the unraveling of bribing in first-price auctions is subtle and requires several steps, we took the following steps in all treatments to facilitate understanding of the game and provide participants with an optimal environment for reaching equilibrium. First, we made sure that participants understood the payoff structures using standard control questions. Second, after the control questions and before the role assignment, participants played a number of practice rounds, in which each participant made all of the decisions in both roles.[10] This allowed participants to freely experiment with different bribing and bidding strategies. Last, the feedback provided at the end of each round encompassed the full round history, including the (typically unobservable) value and bid of the other player.[11]

The sessions were conducted in May 2013 and April 2014 at the BonnEconLab. We ran two sessions per treatment, with 24 participants in each session, and 192

[8] This matching scheme balances the aim of maximizing the number of independent observations and the aim of minimizing repeated play effects. To further minimize repeated play effects, participants were not told that rematching would be within subgroups of eight.

[9] Feedback included the valuations of both players, the bribe amount and whether it was accepted or rejected, and in the case where they went to auction, both bids.

[10] Participants received 10 minutes, in which they could repeat the procedure for at least two, but not more than five, rounds.

[11] The evidence of the effect of feedback is mixed. Filiz-Ozbay and Ozbay (2007) found that revealing the losing bid instead of the winning bid increases bidding. Katušcák et al. (2015) found that ex ante knowledge of posterior feedback has no systematic effect on bidding behavior. To the best of our knowledge, there is no study that studies the effect of revealing both bids and valuations.

participants in total. The experiment was programmed using z-Tree (Fischbacher, 2007), and the invitation of participants was managed using ORSEE (Greiner, 2015), which guaranteed that no subject participated in more than one session. Five of the 50 rounds were randomly chosen for payment. Experimental earnings were specified in Experimental Currency Units (ECU), which were converted to euros at the end of the experiment at a conversion rate of 10 ECU = 1 €. Final payoffs ranged from 3 € to 37 €, with an average of 17.92 € per participant.

4.1 Hypotheses

Based on the results presented in section 3, we formulate our research hypotheses.

Hypothesis 1. *Proposers are more likely to offer bribes and offer, on average, higher bribes, in SPA than in FPA.*

Hypothesis 1 implies that outcomes in FPA-COL are more efficient than in SPA-COL, where collusion substantially reduces efficiency. We measure efficiency both by the proportion of auctions resulting in an efficient allocation and by the relative loss of efficiency, defined as the ratio of the value of the auction winner to the higher value of the two.

Hypothesis 2. *The proportion of inefficient allocations and relative loss of efficiency are higher in SPA-COL than in FPA-COL.*

Finally, a consequence of the theoretical results is that the revenue equivalence theorem (Myerson, 1981; Riley and Samuelson, 1981) breaks, leading to higher revenues in FPA.

Hypothesis 3. *Seller revenue is higher in FPA-COL than in SPA-COL.*

Interestingly, Hypotheses 2 and 3 run contrary to the typical observation in experimental auctions that first-price auctions lead to higher seller revenue and lower efficiency than in second price auctions (Kagel, 1995). To allow for these empirical consistencies, we ran the no-collusion FPA-NOCOL and SPA-NOCOL treatments; this provided a benchmark against which to test Hypotheses 2 and 3.[12]

5 Results

We start this section by describing and analyzing the collusion-stage behavior and outcomes. After establishing that, contrary to the theoretical predictions, the auction mechanism has little effect on collusion, we proceed with analyzing the auction

[12] Note that a model of heterogeneous risk aversion (e.g., the CRRAM model in Cox et al., 1982, 1988) is able to accommodate both our theoretical predictions and the empirical consistencies observed in the experiments, as the assumption of risk neutrality plays no role in the proof of Theorem 1 in Rachmilevitch (2013) (which states that no bribes are offered in the continuous equilibrium of the first-price auction). In the second-price auctions analyzed by Eső and Schummer (2004), risk aversion would alter the functional form of the equilibrium specified in (1), but not its existence.

stage to show that the bargaining process in the first stage has substantial effects on bidding behavior in FPA but not in SPA. We conclude the results section by reporting efficiency and seller's revenue, followed by a best-response analysis. We report the results based on all 50 periods. Although we observe some learning, changes in behavior are fairly homogeneous across treatments, such that all the results hold if we restrict the analysis to second half of the experiment.

5.1 *The collusion stage*

5.1.1 Proposer behavior

Figure 1 depicts bribing behavior in the collusion stage. The figure displays the raw bribes and mean bids by value intervals of 5 in treatments FPA-COL (Panel (a)) and SPA-COL (Panel (b)). The comparison of bribes presented in Figure 1 reveals that, contrary to Hypothesis 1, bribe levels are very similar in FPA and SPA. Although bribes are higher in SPA for intermediate values, the difference is negligible. The regressions presented in Table 1 confirm this conclusion. Table 1 reports regressions of bribes on the value of the proposer, auction type, interactions, and period.[13] In contrast to the theoretical prediction, the significant constant term in the regressions shows that bribes are significantly positive even for values close to zero. Although the effect of the proposer's value on the offered bribe slightly differs between SPA and FPA, this difference disappears in the second half of the experiment. Furthermore, the marginal effect of the auction mechanism on the bribe, calculated using the Delta method (Dorfman, 1938) from the regression equation in column (1), is not significant at any level of the proposer's value ($p > 0.390$ for all comparisons). There is some evidence of learning in the initial periods, with mean bribes decreasing over the first part of the experiment and stabilizing later. Notwithstanding this evidence, all of the following analyses are based on the full dataset. All of the results hold if we restrict the analysis to the second half of the experiment, where no further learning effects are apparent.

Recall that the equilibrium strategy in SPA is piecewise linear, which can only be approximated with the polynomial equation estimated in the regressions. Therefore we estimated a piecewise linear model of the form

$$\text{Bribe} = \begin{cases} \alpha + \beta_1 \text{Value} & \text{if Value} < \gamma, \\ \alpha + \beta_1 \gamma + \beta_2 \text{Value} & \text{if Value} \geq \gamma. \end{cases} \tag{2}$$

The equilibrium prediction is $\alpha = 0, \beta_1 = 0.5, \beta_2 = 0$, and $\gamma = 100 \cdot \frac{2}{3}$. Table 2 presents the result of a non-linear regression with robust standard errors clustered on matching groups.[14] In line with the equilibrium prediction, bribes

[13]We include $Value^2$ in the regression due to the curvature observed in the average bribe functions in Figure 1.

[14] The corresponding analysis for FPA yields essentially identical results. We do not report it here, as the theoretical benchmark is not relevant for FPA.

Table 1: Regressions on bribes.

	(1) All Periods	(2) First 25 Periods	(3) Last 25 Periods
Value	0.374***	0.304***	0.415***
	(0.029)	(0.047)	(0.031)
Value^2	-0.001***	-0.001	-0.002***
	(0.000)	(0.000)	(0.000)
SPA	-0.858	-3.011	0.342
	(1.927)	(2.465)	(1.877)
SPA x Value	0.089*	0.190**	0.042
	(0.041)	(0.065)	(0.044)
SPA x Value^2	-0.001*	-0.002**	-0.000
	(0.000)	(0.001)	(0.000)
Period	-0.308***	-0.586***	-0.260
	(0.042)	(0.133)	(0.261)
Period^2	0.005***	0.015**	0.004
	(0.001)	(0.005)	(0.003)
Constant	4.548**	6.680***	4.400
	(1.439)	(1.908)	(4.999)
Observations	2,400	1,200	1,200
Number of groups	12	12	12

Notes: Random effects for subjects nested in matching groups. Standard errors in parentheses. *,** ,*** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

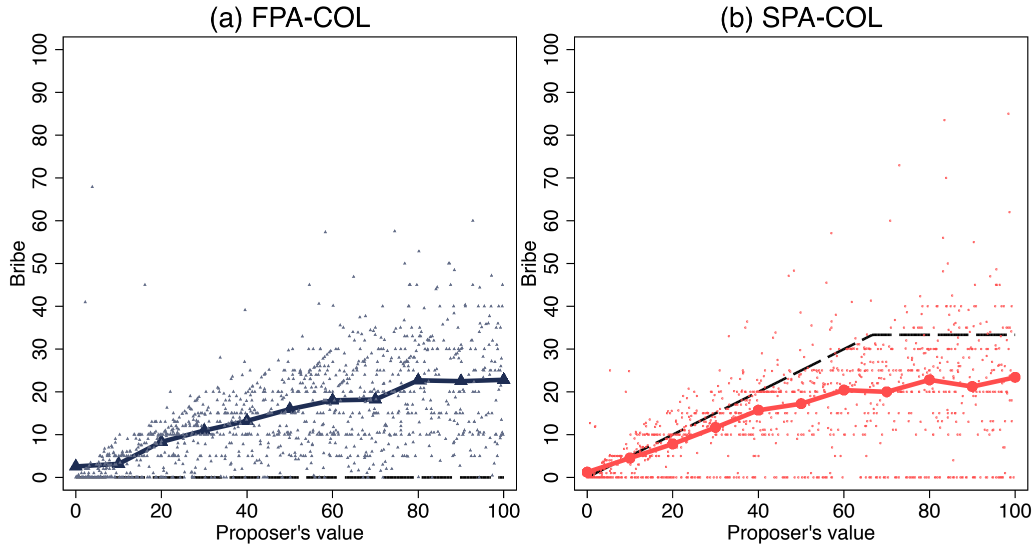

Figure 1: Bribes in first-price and second-price auctions.

Note: Scatter plot of raw bribes and mean bids by value intervals of 5. The thin dashed line marks the theoretical equilibrium predictions.

do not increase above a certain cutoff point, as β_2 is not significantly different from zero. The estimated cutoff point γ is, however, significantly lower than the theoretical cutoff point of $\frac{200}{3}$. Bribes are significantly lower than predicted, with the estimated slope of the bribing function β_1 equal to 0.2 and significantly below the predicted 0.5.[15] As a result, 81.9% of all bribes observed in SPA are lower than predicted.

Result 1. *Contrary to Hypothesis 1, we observe no significant differences in bribing behavior between first-price and second-price auctions. Bribes in FPA (SPA) are substantially and significantly higher (lower) than predicted by the equilibrium analysis.*

5.1.2 Responder behavior

Figure 2 depicts the acceptance responses in FPA and SPA as a function of the responder's value and the bribe. Dark regions indicate acceptance, and light ones indicate rejection. Recall that the theoretical equilibrium strategy in SPA is to accept any bribe that is above one third of the responder's value. This strategy is

[15] Constraining the non-significant β_2 to be zero, we find that the estimated γ is 55.180, which is not significantly lower than predicted in equilibrium. The estimated β_1 is 0.182, even slightly lower than in Table 2, and significantly lower than the equilibrium prediction.

Table 2: Piecewise linear regression on bribes.

	coefficient	Robust S.E.	95% CI		Equilibrium
α	7.586	0.413	6.523	8.648	0
β_1	0.200	0.026	0.134	0.267	0.5
β_2	0.028	0.038	-0.070	0.126	0
γ	47.110	3.901	37.082	57.138	66.66

Notes: Non-linear regression estimating Equation (2) with robust standard errors clustered on matching groups.

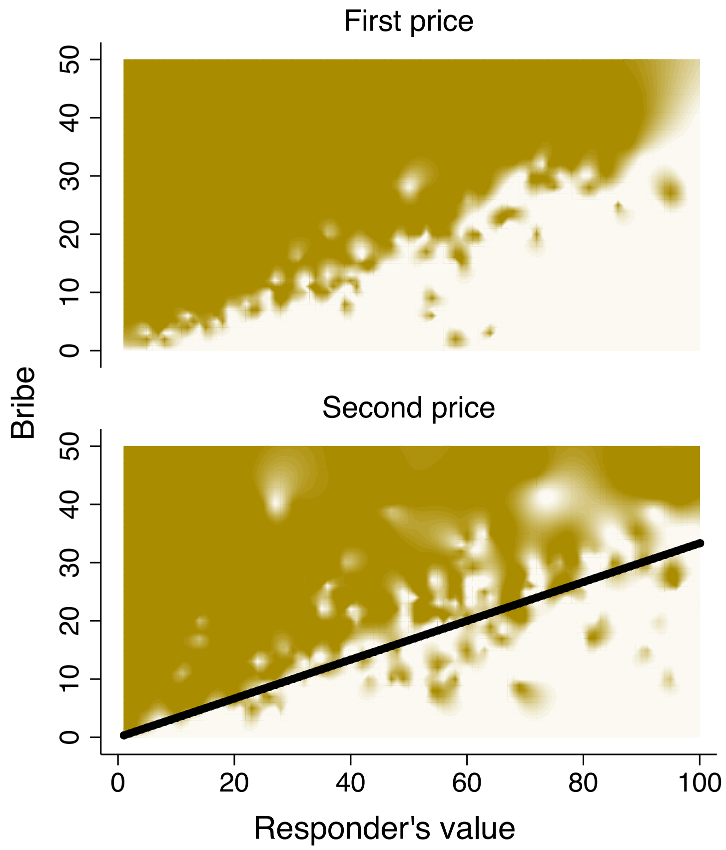

Figure 2: Bribe acceptance in first-price and second-price auctions.

Note: Acceptance choices by responder's value and offered bribe. Dark regions indicate acceptance and light ones indicate rejection. The black line marks the theoretical acceptance threshold in SPA.

Table 3: Regressions on bribe acceptance.

	(1) FPA	(2) SPA	(3) FPA & SPA
Value	-0.204***	-0.110***	-0.200***
	(0.017)	(0.008)	(0.015)
Bribe	0.535***	0.308***	0.523***
	(0.044)	(0.021)	(0.040)
SPA			-1.034
			(0.537)
SPA x Value			0.089***
			(0.016)
SPA x Bribe			-0.211***
			(0.043)
Period	0.040***	0.027***	0.032***
	(0.010)	(0.008)	(0.006)
Constant	-0.318	-1.037*	-0.149
	(0.457)	(0.422)	(0.407)
Observations	1,200	1,200	2,400
Number of groups	6	6	12
Value/Bribe ratio in FPA	0.382		0.382
95% CI	[0.361 – 0.404]		[0.360 – 0.404]
Value/Bribe ratio in SPA		0.357	0.356
95% CI		[0.327 – 0.386]	[0.327 – 0.386]

Notes: Mixed effects logistic regression with random effects for subjects nested in matching groups. Standard errors in parentheses. *,** ,*** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

marked by the black line in the figure. Choices roughly follow the theoretical equilibrium strategy, as the equilibrium line in the figure can be seen to separate the acceptance and rejection regions. As with proposer behavior, acceptance choices in FPA are very similar to the ones in SPA.

Table 3 reports a set of logistic regressions of the acceptance decision on responder's value and offered bribe. As can also be seen in Figure 2, responders are more likely to accept the bribe offer when it is higher and when their own value is lower. The significant interaction terms with auction mechanism indicate that acceptance is more sensitive to both bribe and value in FPA than in SPA; however, these differences are minor. Finally, responders learn to accept more bribes with experience.[16]

The regression results also serve to characterize the acceptance threshold by estimating the line where responders are indifferent between acceptance and rejection. In terms of the regression, this implies a predicted probability of 0.5 for acceptance. We assume, in line with the theoretical analysis, that the bribe at which the responder is indifferent increases linearly with the responder's value. We estimate the slope of this line by estimating the ratio of the coefficients for value and bribe. The results are presented at the bottom of Table 3. Interestingly, although the proposer behavior deviates from the theoretical equilibrium, the estimated ratio in SPA is not significantly different from the 1:3 ratio implied by the theoretical analysis.[17] We analyze the acceptance behavior further by comparing it to the best response to the observed proposer behavior in Section 5.3.

The main result for the responder behavior in the collusion stage is the following:

Result 2. *Although there are some systematic differences between the two auction mechanisms, responder acceptance strategies are similar for FPA and SPA.*

Taken together with the previous result, Result 2 implies that successful collusion is similar across the two auction mechanisms. Overall, we find that with both mechanisms, 42% of all auctions end in successful collusion. Nonetheless, the auction mechanism has substantial effects on behavior in the auction stage, as we discuss next.

5.2 Auction stage

Figure 3 depicts the bidding behavior in terms of the scatter plots and mean bids by value intervals of 5. In order to test our next claims formally, we estimate the bid function using a mixed effects linear regression with random effects on subjects

[16] This learning takes place at the initial part of the experiment, and is not apparent in a regression restricted to the second half of the experiment (not reported here). None of the interaction terms of period with auction mechanism, bribe, and responder value are statistically significant if included in the models.

[17] While the ratio in FPA is significantly higher than $\frac{1}{3}$, it is not significantly different from the ratio in SPA ($\Delta = 0.026$, $z = 1.36$, $p = 0.173$).

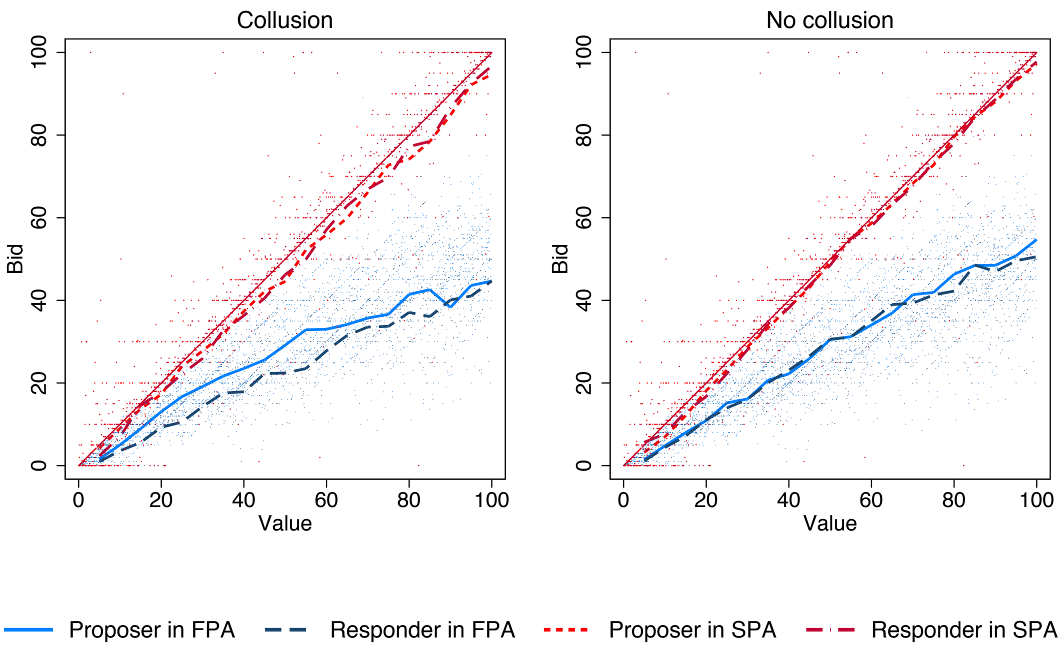

Figure 3: The bidding function.

Note: Scatter plot of raw bids and mean bids by value intervals of 5 for each type and treatment. What appears as a 45 degrees line is, in fact, bids set at the bidder's value.

nested in matching groups, regressing the bid on collusion treatment, auction mechanism, role, period, and the bidder's value and value squared with their interactions with treatment, auction, and role. Table 4 presents the average marginal slopes of bids on values by treatments and roles.[18]

Figure 3 shows that bidding in SPA is mostly concentrated around the weakly dominant strategy. Across treatments and roles, 62.9% of the bids are set exactly at the value, and 79.2% set at the value$\pm$1, with no significant difference between treatments or roles. Indeed, the marginal slopes in SPA presented in Table 4 are close to the rational benchmark of 1, although proposers in SPA-COL bid slightly but significantly below their value.[19]

[18] The marginal effect of the period variable is highly significant ($\beta = 0.019, p < 0.001$). However, the coefficient is of negligible magnitude, indicating an average increase in bids of 0.019 per period and less than one unit over the 50 periods of the experiment. See the appendix for the complete regression.

[19] This result contrasts with the data reported by Kagel and Levin (1993), who found slight overbidding in second-price auctions, but it is in line with Coppinger et al. (1980) and Cox et al. (1982). Kagel (1995, p. 511) suggested that the difference is due to Cox et al. (1982) explicitly prohibiting any bids above the value. We did not prohibit this, but we did explicitly state in the experimental instructions that bidding above the value may lead to negative payoffs, which may explain underbidding in our data (see appendix).

Table 4: Marginal effects of private values on bids.

Treatment	Role	Marginal slope	Std. Error	95% CI	
FPA-NOCOL	—	0.556	0.004	[0.548	0.564]
FPA-COL	Proposer	0.493	0.008	[0.477	0.510]
FPA-COL	Responder	0.412	0.010	[0.392	0.431]
SPA-NOCOL	—	1.005	0.004	[0.996	1.013]
SPA-COL	Proposer	0.952	0.009	[0.935	0.968]
SPA-COL	Responder	0.994	0.009	[0.976	1.012]

Notes: Average Marginal slopes of bids on values by treatments and rolesbased on the regression presented in Table A1.

The typical overbidding with regard to the risk-neutral Nash equilibrium prediction of bidding 0.5 of the value (Kagel, 1995) is observed in FPA-NOCOL. The opportunity to collude, however, leads to lower bids for both proposers and responders ($p < 0.001$ for both comparisons). Furthermore, responders bid significantly less than proposers holding the same value ($p < 0.001$), as can be seen clearly in Figure 3. The same pattern is apparent when controlling for the (rejected) bribe. Panel (a) in Figure 4 plots the predictions of a new regression, conducted on the Collusion treatments and incorporating the bribe and bribe squared and their interactions with the treatment and role. The results show that, on average, responders bid higher than proposers. However, part of this gap is driven by the selection at the collusion stage. Recall that high-value proposers are likely to offer a high bribe, which in turn is likely to be accepted, whereas responders are more likely to accept a bribe as their value decreases. Consequently, the value distribution of proposers who reach the auction stage is shifted down, with a mean value of 40.7 and a standard deviation of 28.9, whereas the value distribution of responders who reach the auction stage is shifted up, with a mean value of 62.0 and a standard deviation of 25.9. This is evident in Figure 5, which plots a histogram of valuations by auction and role. [20]

To control for the selection effect, panel (b) of Figure 4 plots the predicted bids fixing the bidder value at 50. The new plot is generated by replacing each observation with the bid predicted for the same subject given the actual bribe and a value of 50. The regression results show no difference between proposer and responder bids in SPA[21] but a clear difference in FPA, which is stated in the next result:

[20]We report the aggregate distributions across all bribe levels. Nonetheless, the asymmetries arising from selection remain when controlling for the rejected bribe.

[21] It is somewhat odd that predicted bids decrease with higher levels of rejected bribes. This is probably due to misunderstanding, as less than 9% of bribes were in the high range of above 30, and the rate of underbidding in such cases diminishes with repeated play.

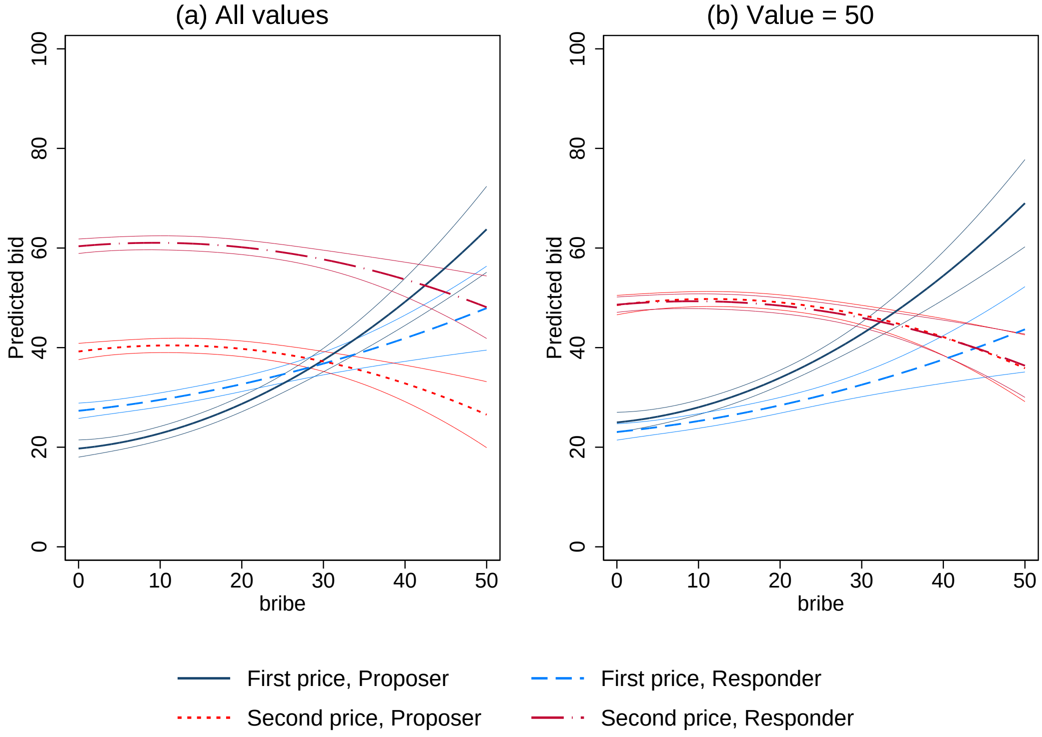

Figure 4: Bids by treatment and (rejected) bribe.

Note: Predicted bid based on OLS regression incorporating the bribe and bribe squared and their interactions with the treatment and role. Panel (a) presents the mean predicted bid. Panel (b) presents the mean predicted bid fixing the bidder's value at 50.

Result 3. *In first-price auctions with collusion, proposers bid above responders when controlling for the private value and the rejected bribe. No difference between proposers and responders is apparent in second-price auctions with collusion.*

The mean marginal effect of role in FPA-COL is not large, with proposers bidding on average 1.95 above responders ($p < 0.05$). Nonetheless, it is enough to distort the auction outcomes, as we report in the following sections.

5.3 *Best response analysis*

Clearly, bidders in the first-price auction with collusion do not play according to the no-bribing equilibrium described in Section 3. Nonetheless, we cannot rule out

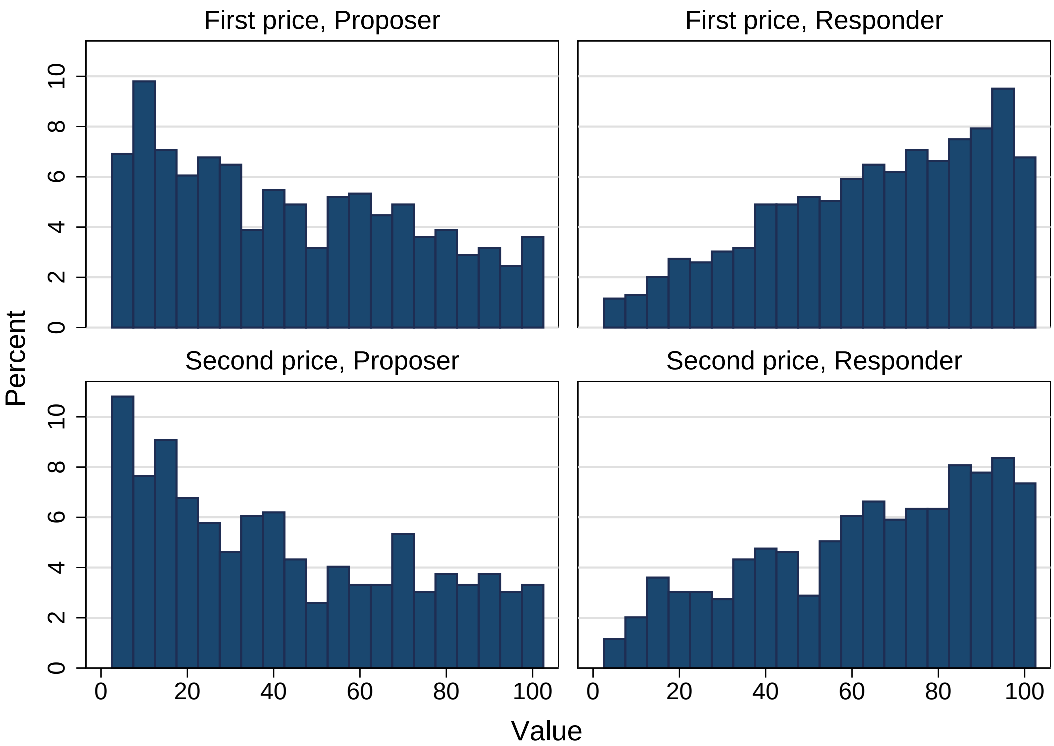

Figure 5: Histogram of valuations in the auction stage.

Note: Frequency of bidder valuations conditional on reaching the auction stage in treatments FPA-COL and SPA-COL.

that bidding is consistent with some mixed-strategies equilibrium.[22] In this section we compare the bidding behavior in FPA-COL to the best response strategies based on the empirical bids observed in the treatment throughout the experiment. This analysis serves to test the conjecture that bidders are, on average, best-responding to the behavior of others, and at the same time provides an insight into the sources of the inefficiency in first-price auctions with collusion reported in Section 5.5.

For each player and each round, we calculated the optimal bid as the expected payoff-maximizing bid given the distribution of bids placed by all players in the opposite role following a rejection of the same bribe as the one offered or rejected by the player, rounded to an integer, throughout the experiment.[23] Panel (a) in Figure 6 plots the optimal bids compared to the observed bids. Panel (b) in the same figure plots the predicted difference between the bid and the optimal bid with 95% confidence intervals based on a mixed effects linear regression by role and rounded value with random effects for subjects nested in matching groups. Bids are generally close to optimal, suggesting that strategies in the auction subgame approximate, on average, equilibrium behavior. Importantly, optimal bids mirror the differences between proposers and responders observed in actual behavior. This effect in the best-response bids is clearly driven by the selection at the collusion stage that was briefly discussed in Section 5.2. Successful collusion disproportionally removes proposers with high values and responders with low values from the auction (as made clear in Figure 5). This gives rise to an asymmetric auction, which is inherently inefficient as the strong bidder—the responder who rejected a bribe offer—shades her bid more than the weak bidder—the proposer (Güth et al., 2005; Maskin and Riley, 2000).

In Section 5.1.2 we saw that responder behavior roughly matches the theoretical prediction despite the divergent proposer behavior. We can now use the best-response analysis of the auction data to compute the responders' optimal acceptance strategies. Specifically, we calculate for each responder in each round her expected payoff if bidding optimally. A risk-neutral responder should accept a bribe if and only if it the bribe is higher than the expected auction payoff. To test whether acceptance decisions are empirically optimal, Figure 7 plots the predicted probability of accepting a bribe by responder's value, separately for optimal accept (i.e., the bribe is higher than the expected payoff in the auction under optimal bidding) and optimal reject.[24] We see that when the bribe is lower than what the responder can expect to obtain in the auction, responders generally do the right thing and reject the bribe. The 20%–30% acceptance levels for low values may be driven by

[22] The theoretical analysis of Rachmilevitch (2013) is restricted to pure strategies.

[23] Naturally, this information is not available to the players themselves. The analysis is aimed at exploring whether behavior in the auction approximates an equilibrium.

[24] The figure is based on a mixed effects logistic regression of acceptance decisions on payoff-maximizing strategy and responder value and their interactions with the auction mechanism with random effects for subjects nested in matching groups. The two auction mechanism yield an essentially identical picture, and are therefore collapsed in the figure.

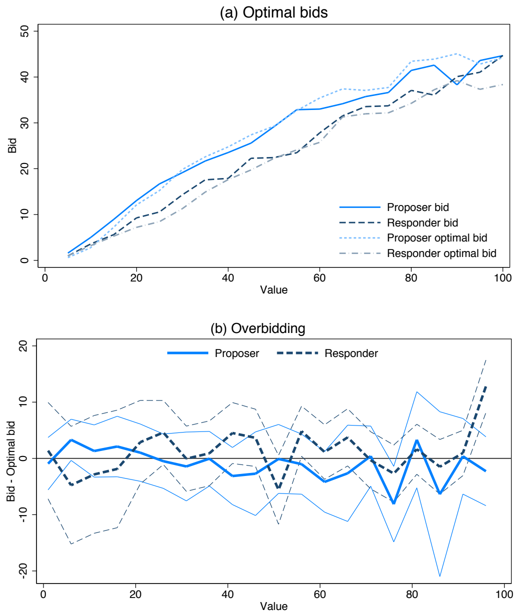

Figure 6: Optimal bids in first-price auctions with collusion stage (FPA-COL).

Note: Panel (a) plots the optimal bids and the observe bids. Panel (b) plots the predicted difference between the bid and the optimal bid with 95% confidence intervals based on a mixed effects linear regression by role and rounded value with random effects for subjects nested in matching groups.

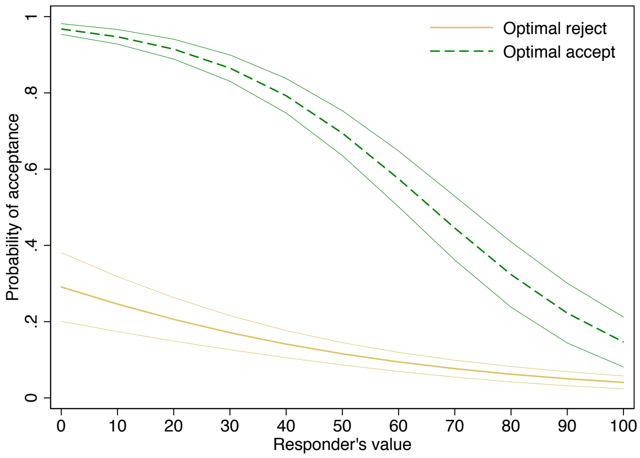

Figure 7: Observed and optimal acceptance decisions in FPA-COL.

Note: Predicted probability of accepting bribes when the expected-payoff maximizing decision is to accept or to reject.

risk aversion—the bribe is certain while the auction payoff is not—or because the optimal-bid expected payoff in the auction is higher than what bidders actually receive on average. Conversely, responders with high values are likely to reject bribes even when they are not expected to gain more in the auction. For example, when the responder's value is above 80, unprofitable bribes are rejected in 94.87% of the cases, but profitable bribes are also rejected as high as 82.05% of the time.

Why are responders rejecting profitable bribes? We see two possible explanations. One is that responders underestimate the proposer's value and thus overestimate their chances of winning the auction. However, given that responders bid, on average, close to their expected payoff-maximizing bid, this explanation does not appear to be sufficient. Alternatively, bribe rejections may be motivated by the same considerations as rejections in the ultimatum game (see Güth and Kocher, 2014, for a recent review of the literature). On average, proposers offer a bribe equal to 35.3% of their value, so that the proposer stands to receive almost three times the payoff of the receiver if the bribe is accepted. Conversely, when a profitable bribe (according to our analysis) was rejected, the responder won 43.5% of the ensuing auctions, with a mean payoff of more than half that of proposers. Thus, responders may be willing to forgo some of their payoff in order to reduce the inequality and increase fairness.[25]

[25] Both outcome- and intention-based notions of fairness can rationalize rejections of offers that favor the proposer (see, e.g., Falk and Fischbacher, 2006). As this is not directly related to the main aims of the experiment, we do not develop a formal model of bribe rejections and leave this explanation as a conjecture.

5.4 Seller revenue

In this section we analyze the effects of the auction mechanism on the seller revenue under collusion. Table 5 reports the marginal effects of two mixed effects linear regressions of seller revenue on auction mechanism, collusion treatment, and proposer and responder values and their interactions with the treatments. The regressions reported in columns (1)–(3) include the plays in which the bribe offer was accepted and the seller received zero revenue. The regressions reported in columns (4)–(5) include only data from the auction stage.

Without collusion, seller revenue is significantly higher in FPA than in SPA due to overbidding in FPA ($z = .4.9, p < 0.001$). With collusion, seller revenue is substantially lower and does not differ significantly with the auction mechanism ($z = 0.06, p = 0.953$). The effect of collusion on the seller's revenue is predominantly due to successful collusion. Indeed, the mean price set in the SPA auction is the same with or without a preceding collusion stage. In FPA, in contrast, the effect is two-fold, as the low bribes push the bids down (cf. Table 4), leading to a loss of seller revenue on top of the revenue lost due to successful collusion.

The effect of the bidders' values on seller revenue provides an insight into the processes determining the seller revenue under collusion. Naturally, without collusion the mean seller revenue increases with both proposer and responder value under both auction mechanisms. Collusion introduces two new effects. In the collusion stage, a higher proposer value implies a higher chance of acceptance of the bribe offer and thus a lower mean seller revenue, and vice versa for responders. In the auction stage, the selection effect implies that responders have, on average, higher values than proposers. Since the final price in FPA is determined by the high bid and in SPA by the low bid, it is more sensitive to the responder value in the former and the proposer value in the latter. The two effects lead to a counterintuitive result in FPA-COL: since a higher proposer value facilitates collusion and only has a mild effect on the auction price, seller revenue is *negatively* correlated with proposer value. The next result summarizes the findings with respect to the seller revenue.

Result 4. *Contrary to Hypothesis 3, collusion is more detrimental to seller revenue in FPA than in SPA. Under collusion, both auction mechanisms generate the same seller revenue. In first-price auctions, an increase in the proposer value leads to a decrease in seller revenue.*

5.5 (In)Efficiency

Inefficient allocations arise when the good is allocated to the bidder with the lower valuation. These can be generated either because (i) the bidder who has the lowest value is able to bribe the bidder with the higher value to refrain from bidding and thus win the auction or (ii) the lower-value bidder wins the auction by placing the highest bid. We refer to the former as *collusion inefficiency* and the latter as

Table 5: Regressions on seller revenue.

	Overall			Auction stage only		
	(1) Seller revenue	(2) Marginal effect of proposer value	(3) Marginal effect of responder value	(4) Seller revenue	(5) Marginal effect of proposer value	(6) Marginal effect of responder value
FPA-NOCOL	38.894	0.300***	0.270***	38.894	0.300***	0.270***
	[37.232 – 40.555]	[0.273 – 0.327]	[0.243 – 0.297]	[37.799 – 39.988]	[0.279 – 0.321]	[0.249 – 0.291]
FPA-COL	19.024	-0.048***	0.487***	32.956	0.170***	0.325***
	[17.363 – 20.686]	[-0.075 – -0.021]	[0.460 – 0.513]	[31.742 – 34.170]	[0.141 – 0.199]	[0.292 – 0.357]
SPA-NOCOL	33.943	0.480***	0.530***	33.943	0.480***	0.530***
	[32.281 – 35.604]	[0.453 – 0.507]	[0.503 – 0.556]	[32.848 – 35.037]	[0.459 – 0.501]	[0.510 – 0.550]
SPA-COL	19.006	0.197***	0.485***	33.204	0.633***	0.278***
	[17.344 – 20.667]	[0.171 – 0.223]	[0.458 – 0.511]	[31.987 – 34.420]	[0.606 – 0.661]	[0.248 – 0.309]
Observations	4,800	4,800	4,800	3,788	3,788	3,788

Notes: Mixed effects linear regressions with random effects for subjects nested in matching groups. Ninety-five percent confidence intervals in brackets. Note that the coefficients in Column (1) reflect the mean final price. *,** ,*** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

Table 6: Inefficient allocations.

Treatment	Observations	Proportion of inefficient allocations: Predicted	Observed	Relative efficiency loss: Predicted	Observed
		Collusion Stage			
FPA-COL	506 (42.17%)	0.00%	14.23%	0.00%	4.07%
SPA-COL	506 (42.17%)	25.00%	15.22%	4.17%	4.48%
		Auction Stage			
FPA-COL	694 (57.83%)	0.00%	18.44%	0.00%	4.30%
SPA-COL	694 (57.83%)	0.00%	2.59%	0.00%	0.66%
FPA-NOCOL	1,200 (100%)	0.00%	10.92%	0.00%	2.03%
SPA-NOCOL	1,200 (100%)	0.00%	3.58%	0.00%	0.75%
		Overall			
FPA-COL	1,200	0.00%	16.67%	0.00%	4.21%
SPA-COL	1,200	16.67%	7.92%	2.78%	2.28%
FPA-NOCOL	1,200	0.00%	10.92%	0.00%	2.03%
SPA-NOCOL	1,200	0.00%	3.58%	0.00%	0.75%

Notes: Proportion of efficient allocations and relative efficiency loss in the collusion stage (conditional on accepted bribe), in the auction stage (conditional on reaching the auction stage), and at the aggregate level.

auction inefficiency. Table 6 displays the observed levels of inefficiency both at the aggregate level and disaggregated by the type of inefficiency. The table displays two different measures. The first measure is the *proportion of inefficient allocations*. While informative, the previous measure does not reflect the magnitude of the efficiency loss. We therefore define the *relative efficiency loss*: one minus the ratio of the value of the auction winner (realized surplus) to the maximum of the two values (maximal possible surplus).

Let's analyze the two stages in turn, starting with the collusion stage. The theoretical analysis predicts a substantial proportion of inefficient allocations due to accepted bribes in SPA (Eső and Schummer, 2004): 25% of accepted bribes result in an inefficient allocation and the expected loss of efficiency is 4.17%. The observed proportion of inefficient allocations in SPA in the collusion stage is 10 percentage points lower than predicted. Regardless, the observed magnitude of efficiency loss is sometimes higher than in the theoretical equilibrium. Recall than in equilibrium, the lowest possible efficiency is obtained when a proposer with a value of 66.67 bribes a responder with a value of 100 for a relative efficiency loss of $\frac{1}{3}$. In the experiment, however, proposers with very low values are sometimes successful in bribing responders with very high values. Consequently, the mean relative efficiency loss is even slightly higher than predicted despite the lower rate of successful collusion.

Rachmilevitch (2013) predicts no inefficient allocations in FPA. However, collusion inefficiency is not noticeably lower in FPA with either of the two measures. This is in line with the results reported above, namely that both bribe offers and (conditional on bribe) acceptance levels are lower than predicted by theory.

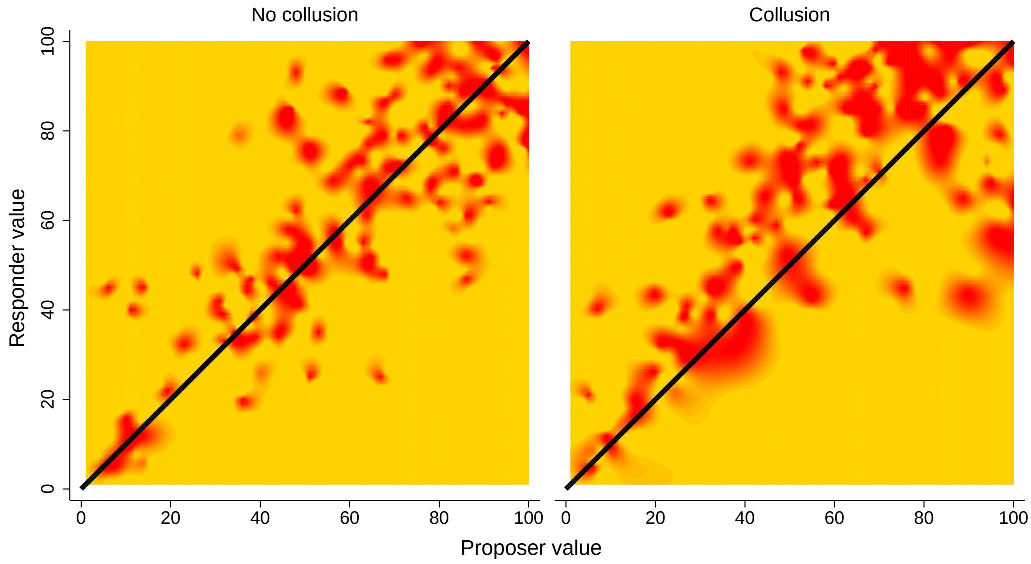

Figure 8: Efficiency in first-price auctions.

Note: Efficient allocations in the auction by proposer and responder value. Dark (red) regions indicate that the bidder with the lower value won the auction.

Next we analyze efficiency in the auction stage. Allocations in SPA tend to be efficient, with the high-value bidder winning in 96.4% of all cases in SPA-NOCOL and 97.4% in SPA-COL—not surprising, given that bidders generally bid their value. In comparison, allocations in FPA-NOCOL are efficient only in 89.1% of the time, dropping to 81.6% with collusion.[26] Figure 8 plots (in)efficient allocations as a function

[26] The inefficiency levels in the no-collusion treatments are similar to those previously observed in the literature. Efficiency in Cox et al. (1982), for example, is remarkably similar to our findings, with 12.14% and 6.00% inefficient allocations and efficiency losses of 1.12% and 0.35% in FPA and SPA, respectively. Kagel and Levin (1993), on the other hand, observed higher proportions of inefficient allocations, 18% and 21% in FPA and SPA, respectively. See Footnote 19 above for a related discussion.

Table 7: Regressions on auction efficiency.

	(1) Allocation[a]	(2) Efficiency[b]	(3) Allocation[a]	(4) Efficiency[b]
COL	-0.689*	-0.022***	0.174	-0.001
	(0.341)	(0.006)	(0.420)	(0.008)
SPA	1.565***	0.013*	1.401***	0.008
	(0.374)	(0.005)	(0.423)	(0.006)
COL x SPA	0.928	0.023**	0.120	0.009
	(0.558)	(0.008)	(0.709)	(0.011)
Proposer low			-0.070	-0.004
			(0.207)	(0.004)
COL x Proposer low			-1.177***	-0.027***
			(0.347)	(0.008)
SPA x Proposer low			0.357	0.010
			(0.393)	(0.006)
COL x SPA x Proposer low			1.026	0.015
			(0.705)	(0.011)
Difference in values	0.081***	0.000***	0.085***	0.000***
	(0.006)	(0.000)	(0.006)	(0.000)
Period	0.018***	0.000***	0.018***	0.000***
	(0.005)	(0.000)	(0.005)	(0.000)
Constant	0.033	0.957***	0.009	0.958***
	(0.276)	(0.005)	(0.298)	(0.005)
Observations	3,788	3,788	3,788	3,788
Number of groups	24	24	24	24

Notes: Mixed effects [a]logistic and [b]linear regressions with random effects for subjects nested in matching groups. Allocation refers to the frequency of efficient allocations. Efficiency refers to relative efficiency. Proposer Low is a dummy indicating that the proposer has a lower value. Standard errors in parentheses. *,** ,*** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

of the proposer and responder value in the FPA treatments. While the plot is symmetric along the diagonal in FPA-NOCOL, it is markedly asymmetric in FPA-COL, with most of the inefficient allocations appearing above the diagonal (i.e., when the responder has a higher value than the proposer). The mixed effects logistic regressions reported in Table 7 support this observation. Not surprisingly, auction efficiency is higher in second-price auctions, after the bidders gain experience, and when the difference between the two values is large. Efficiency is significantly reduced with collusion only in the first-price auction—but not when the proposer has a higher value. This is a consequence of the observation summarized in Result 3—namely that proposers bid higher than responders in FPA-NOCOL.

Given that direct loss of efficiency due to collusion is similar in FPA and SPA, it is not surprising that the last result carries over to overall efficiency. Taking together loss of efficiency due to accepted bribes and loss of efficiency at the auction stage, we find a 16.7% rate of inefficient allocations in FPA-COL compared to only 7.9% in SPA-COL. Relative loss of efficiency is 4.2% in FPA-COL compared to only 2.3% in SPA-COL. Mixed effects linear and logistic regressions confirm that the difference is significant ($p < 0.001$ for both measures).

Result 5. *Contrary to Hypothesis 2, first-price auctions are* ***less*** *efficient than second-price auctions under collusion. Loss of efficiency in the collusion stage is similar under both auction mechanisms; the differences are generated in the auction stage.*

6 Summary and concluding remarks

The theoretical literature on collusion in auctions suggests that first-price auctions deters collusion by providing incentives to misrepresent private information. This paper studies this claim by experimentally implementing a simple negotiation protocol that (a) was formally analyzed in the theoretical literature and (b) allows for the breakdown of negotiations and is therefore conducive to studying the effects of collusion on continuation auctions.

While we don't find any systematic differences in collusion between first-price and second-price auctions, the results give rise to a new insight hitherto lacking from the analysis of collusion in auctions: Unsuccessful collusive attempts distort the auction behavior in first-price (but not second-price) auctions.[27] This distortion may eliminate desirable features of the auction mechanism and, as in our experimental auction, reduce revenue and efficiency. Looking at the expected revenue of the auctioneer, we find that collusion eliminates the advantage of first-price auctions, which systematically results in higher revenues without collusion (Kagel and Levin, 1993).

This conclusion may appear to depend on the asymmetry imposed by the ultimatum bargaining protocol, which is admittedly stylized and unrealistic. Nonetheless,

[27] Similarly, Kirchkamp et al. (2009) have shown that the introduction of outside options affects the theoretical equilibrium bids, as well as the empirical deviation from equilibrium, in FPA but not in SPA.

asymmetries are likely to arise in natural settings as well. Side payments may be made more easily by one competing firm than by another for financial or organizational reasons; for example, if one firm is a supplier of the other, or if one has liquidity constraints. Bargaining power can also vary for various reasons from the individual characteristics of the negotiators to the economic and political assets of the firms. Our setup should be viewed as an extreme case of more natural environments, which we use as a controlled workhorse with which to study the basic issues associated with collusion negotiation than for its ecological plausibility.

While our results clearly demonstrate that information revelation in failed collusive negotiations distort bidding behavior in first-price auctions, more work is needed to determine how and which of the specific effects generalize beyond the specific protocol. In particular, the loss of efficiency may be mitigated if the colluding cartel can choose the identity of the designated winner endogenously. However, Noussair and Seres (2017) studied second-price auctions with affiliated values, where collusion is predicted to reduce efficiency by efficiently assigning the identity of the designated winner. Contrary to this prediction, both the opportunity to collude and actual successful collusion resulted in loss of efficiency, suggesting that allowing for endogenous choice of the designated winner will not alter our qualitative conclusions. Therefore, more empirical evidence is required to determine the boundaries of our results.

Our paper joins other experimental papers that compare auction mechanisms with respect to robustness to collusion, but highlights a new channel through which collusion affects auction outcomes. Other studies that have found that first-price auctions are not as robust to collusion as theory predicts include Hinloopen and Onderstal (2013) for centralized cartel formation without commitment and Agranov and Yariv (2014) for free communication without commitment.[28] Our results introduce the role of information revelation, and reveal the potentially negative harmful implications of using the first-price rule.

The theoretical treatment of collusion in auctions typically assumes fully rational players and frictionless bargaining, leading to successful and efficient collusion when the collusive agreement is enforceable (e.g., Marshall and Marx, 2007). In practice, however, collusion attempts may fail for various reasons ranging from the individual characteristics of the negotiators to institutional restrictions on communication and/or transfers. Our experimental design brings the implications of a failure to collude to the fore. Future research will determine the conditions under which the detrimental effects of collusion in first-price auctions that are apparent in our experimental setup are likely to arise.

[28] See also Fischer et al. (2014), who found that first-price auctions do not generate higher seller revenue compared to second-price auctions if there is a non-negligible probability that one bidder's bid leaks to the other bidder.

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Appendix: Regression for Table 4

Table A1: Regression on the bidding function.

VARIABLES	(1) bid	(2) bid
1.treatment	1.664	
	(1.229)	
2.auction	0.462	0.540
	(1.214)	(1.210)
2.role	-0.442	-0.134
	(1.205)	(1.490)
1.treatment#2.role	-0.065	
	(1.952)	
2.auction#2.role	1.599	-0.050
	(1.710)	(2.056)
value	0.704***	0.606***
	(0.023)	(0.036)
c.value#c.value	-0.001***	-0.003***
	(0.000)	(0.000)
period	0.019***	0.076***
	(0.005)	(0.008)
Constant	-1.554	1.767***
	(0.861)	(0.089)
Constant	-14.382***	-1.019
	(4.172)	(1.290)
Constant	1.214***	1.091***
	(0.056)	(0.014)
Constant	1.749***	-0.685
	(0.008)	(0.889)
Observations	7,576	2,776
Number of groups	24	12

Notes: Mixed effects linear regression with random effects for subjects nested in matching groups. Standard errors in parentheses. *,** ,*** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

Appendix: Instructions for FPA-COL and SPA-COL

Welcome and thank you for participating in this experiment. Please remain quiet and switch off your mobile phone. It is important that you do not talk to other participants during the entire experiment. Please read the instructions carefully, the better you understand the instructions the more money you will be able to earn. The instructions are the same for all participants. If you have further questions after reading the instructions, please give us a sign by raising your hand out of your cubicle. We will then approach you in order to answer your questions personally. Please do not ask aloud.

The experiment consists of **two phases**. The first phase is a **practice phase**, in which you will have the opportunity to familiarize yourself with the software and the rules of the experiments in a non binding way. In the **second phase** you will interact in **50 rounds** with other participants. In each of these 50 rounds you can earn money. How much money you earn will depend on your own decision, those of the other participants and partly on chance. At the end of the experiment, the computer will randomly select 5 rounds and you will earn the payoffs you obtained in these rounds. Each of the 50 rounds has the same chance of being selected.

During the experiment all sums of money are listed in ECU (for Experimental Currency Unit). Your earnings during the experiment will be converted to € at the end and paid to you in cash. The exchange rate is **10 ECU = 1 €.** The earnings from all parts will be added to a participation fee of €4. If the earnings are negative, we will subtract them from your participation fee.

Instructions for the experiment

At the beginning of the second phase of the experiment, all participants will be assigned a role. Half of the participants will be assigned the **role** of **Person X** and the other half will be assigned the role of **Person Y**. These roles will **remain fixed** throughout the experiment. In each round, two participants, one in the role od **X** and one in the role of **Y** will interact with each other. Which participant in the other role you interact with will be **randomly chosen** at the beginning of each round.

The sequence of the round

A round consists of two stages, which are explained in detail below. In the *second* stage, **Person X** and **Person Y** participate in an auction. Both participants can bid for a token. The token is worth a certain amount to each participant, which we call the participant's **Value**. The computer will determine this Value **separately** for **each participant** in **each round** by choosing a two decimal number between **0 and 100**, where each number is **equally likely** to be chosen. detailed instructions for this second stage follow the instructions for the first stage below.

Detailed instructions for Stage 1

In Stage 1, **Person X** can offer to pay a certain amount to **Person Y** not to participate in the auction (in Stage 2). **Person X can choose any two decimal number between 0 and 100 to offer to Person Y**. **Person X** can also choose **not to make an offer** by choosing an **amount of 0**.
If **Person X** decides to not to make an offer or if **Person Y** rejects the offer, Stage 1 will end and the participants will proceed to Stage 2.
If **Person Y** accepts the offer, **Person X** will receive the Value that the token has for him or her minus the amount offered to **Person Y**. **Person Y** will receive the offered amount regardless of the Value the token has for him or her. This will end the round, and the participants will be rematched for the next round.

Detailed instructions for Stage 2

First-price auction

In this stage, each participant will choose how much to **bid** in the auction. This Bid can be any two decimal number between **0 and 100**. The participant who makes the **higher Bid** receives the Value the token has for him or her. Out of this value he or she pays **his or her Bid**. The participant who makes the **lower Bid** receives nothing, and his or her payoff for that round is zero. In the case that both participants make the same bid, the computer will randomly select one of the participants and the selected participant will receive the Value the token has for him or her. Out of this value he or she pays **his or her Bid**. The participant who is not selected receives nothing, and his or her payoff for that round is zero.

Note that if you get the token by bidding higher that the value it has for you, you will receive a negative payoff. You can guarantee not to receive a negative payoff in the round by bidding no more than the value the token has for you.

Second-price auction

In this stage, each participant will choose how much to **bid** in the auction. This Bid can be any two decimal number between **0 and 100**. The participant who makes the **higher Bid** receives the Value the token has for him or her. Out of this value he or she pays **the Bid made by the other participant**. The participant who makes the **lower Bid** receives nothing, and his or her payoff for that round is zero. In the case that both participants make the same bid, the computer will randomly select one of the participants and the selected participant will receive the Value the token has for him or her. Out of this value he or she pays **the Bid of the other participant** (which in this case, is equal to his bid). The participant who is not selected receives nothing, and his or her payoff for that round is zero.

Note that if you get the token by bidding higher that the value it has for you, you might receive a negative payoff. You can guarantee not to receive a negative payoff in the round by bidding no more than the value the token has for you.

The end of the round

At the end of the round you will be reminded of the Value the token has for you and your decisions. We will also inform you about the **Value the token has for other participant**, **his or her choices** in the round, and **your payoff for the round**.

The practice phase

Before the main part of the experiment starts, you will be able to familiarize yourself with the procedure in a practice phase. In this phase you will decide as both **Person X** and as **Person Y**. That is, you will first decide on an offer as **Person X**. If you make an offer, you will decide as **Person Y** whether to accept or reject it. If you decide not to make an offer as **Person X** or to reject an offer as **Person Y**, you will proceed to the second stage. Here, again, you will decide as both **Person X** and as **Person Y**. You will receive 10 minutes, in which you can repeat the procedure for as many rounds as you wish.

The end of the experiment

After you have completed the fifty rounds, your final payoff will be calculated and presented to you. We will then ask you to complete a short questionnaire, which we need for the statistical analysis of the experimental data. The data of the questionnaire, as well as all your decisions during the experiments will be anonymous. Please remain seated until your cabin number is called.

Thank you for participating in this experiment and have a nice day!