AUCTION MECHANISMS AND BIDDER COLLUSION: BRIBES, SIGNALS AND SELECTION

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Auction Mechanisms and Bidder Collusion: Bribes, Signals and Selection[*]

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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. In equilibrium, collusive negotiations are either successful or are avoided altogether, hence such analysis neglects the effects of failed collusion attempts. In such contingencies, information revealed in the negotiation process is likely to affect the bidding behavior in first-price (but not second-price) auctions. We test experimentally a setup in which collusion is possible, but negotiations often break down and information is revealed in an asymmetric way. The existing theoretical analysis of our setup predicts that the first-price mechanism deters collusion. In contrast, we find the same level of collusion in first-price and second-price auctions. Furthermore, failed collusion attempts distort the bidding behavior in the ensuing auction, leading to loss of efficiency and eliminating the revenue dominance typically observed in first-price auctions.

Keywords: auctions, collusion, bribes, experiment.

JEL classification: C72, C91, D44

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1 Introduction

Auctions are a prominent market mechanism. They are commonly used by governments to purchase goods and services, to sell assets and to fund the national debt,[1] and are also widely spread in the private sector, especially with the recent growth in electronic commerce (Ockenfels et al., 2006). 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).[2] and it is now acknowledged as a major challenge for optimal auction design (Klemperer, 2002; Marshall et al., 2014).

Successful collusion requires that cartel members share information and uphold the collusive agreement. Auction design can take this into account to create incentives for cartel members to misrepresent their private information—thus inhibiting successful collusive negotiations—or to renege on the collusive agreement once it is reached. A large body of literature analyzed 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 collusive agreement (e.g., Marshall and Marx, 2007; Robinson, 1985). In contrast, in this paper we focus on the *signaling properties* of collusive bargaining. Bidders' actions in the bargaining process that precedes the auction serve as indirect signals of their private valuations. In case of negotiations breakdown (which in many theoretical models never happens in equilibrium), these signals, combined with the selection at the bargaining stage, may drastically affect behavior in the auction stage.[3]

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 for staying out of the auction, leaving the remaining bidder free to win the auction at the seller's reserve price. The collusive agreement is reached through a simple ultimatum bargaining protocol, in which one bidder (the *proposer*)

[1] The Bureau of the Public Debt in the United States Department of the Treasury website states that "Annually, we auction and issue $4.7 trillion in marketable securities and 4.8 trillion in non-marketable securities, including $195 billion in savings bonds." (`http://www.publicdebt.treas.gov/whatwedo/what_we_do.htm`, accessed September 7, 2014).

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

[3] 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.

can make a take-it-or-leave offer to the other bidder (the *responder*). The responder can choose between accepting the offer and refraining from bidding in the auction versus rejecting the offer and proceeding to the auction.

This particular type of bargaining protocol is well suited for an experimental examination for at least two reasons. First, it is highly structured and simple to understand—thus serving as an ideal environment to study the implications of the signaling properties of the bargaining. Second, it has been analyzed in the theoretical literature for second-price auctions (Eső and Schummer, 2004) and for first-price auctions (Rachmilevitch, 2013), providing a theoretical background highlighting the role of the auction mechanism in deterring bargaining over collusive agreements. 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.

The intuition for the theoretical results is the following. In second-price auctions, where bidders have a weakly dominant strategy to bid their true value, the private information revealed during negotiation over the collusive agreement does not affect bidding behavior if negotiations break down. In first-price auctions, however, such information has substantial implications for bidding behavior. The existing theoretical analysis suggests that this effect creates incentives for bidders to misrepresent their private information, leading to a complete breakdown of collusion in equilibrium and thus to increased revenue and efficiency.

Our results can be organized into two main findings. First, the experimental data reject the prediction based on the existing theoretical literature, namely there are no substantial differences in bribing behavior between first-price and second-price auctions. The observed loss of efficiency due to collusion is much less than predicted by theory for 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 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), consequentially winning 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.

Although we are the first to test the signaling effects of collusion, several experiments have studied how the auction mechanism affects collusion when collusion is not directly enforceable. 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 (2014) 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 to each of the 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 higher gains to be made from colluding 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 settings and unlike in those of Agranov and Yariv (2014) and Hinloopen and Onderstal (2014)—designated losers could not use any private information revealed in the knockout auction as they already committed to not bidding in the preceding voting stage. Consequently, there was no room for signaling effects arising from collusion attempts.

Our paper differs from these papers in that bargaining may break down, and otherwise the agreement is with commitment, allowing us to cleanly identify the signalling effect of 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.

The remainder of the paper is organized as follows. The theoretical model is developed in Section 2. Sections 3 and 4 describe the experimental design and results, respectively, and Section 5 concludes.

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

2 Model

2.1 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 an amount b for the responder to refrain from bidding. If the responder accepts the offer, the proposer automatically wins the auction at the reserve price set at zero. If the receiver rejects the offer, both bidders proceed to the *auction* stage, which can take the form of either a first-price or a second-price auction. In the auction stage, both bidders simultaneously bid for the object and the bidder with the highest bid gets the object. 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, $b : [0, 100] \rightarrow \mathbb{R}_+$ and $c_p(\theta_p)$ is a bidding function mapping types into bids, $c_p : [0, 1] \rightarrow \mathbb{R}_+$. 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, $c_p : \mathbb{R}_+ \times [0, 100] \rightarrow \mathbb{R}_+$.

2.2 Equilibria

Eső and Schummer (2004) analyzes and characterizes the equilibria of this game for second-price auctions. Eső and Schummer (2004, page 309) shows that when types are distributed uniformly, there exists a unique sequential equilibrium in continuous bribing strategies. The equilibrium takes the following form:

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

and in case of proceeding 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 $b \leq \frac{100}{3}$ 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 expected payoff will be $\min(0, \theta_r - 2b)$, hence any $b \geq \frac{\theta_r}{3}$ should be accepted.

The unique equilibrium features two intersting 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) analyzes the case for the first-price auction. Rachmilevitch (2013) shows that if the bribing function is monotonic and continuous, 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. 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 is zero on some interval $[0, \theta']$. If $\theta' = 0$, all positive types have an incentive to offer an arbitrarily small bribe $b(\epsilon)$ and bid ϵ^+ if the bribe is rejected. Since the responder will bid in equilibrium no more than the highest undominated bid ϵ, by deviating the proposer can gain arbitrarily close to her full value as ϵ goes to zero. 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.

3 Experimental design and procedure

The experiment implemented the game described in Section 2. 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, a round consisted of a collusion stage and an auction stage. In the baseline treatments FPA-NOCOL and SPA-NOCOL, collusion was not possible, so that 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. Proposers and responders were rematched in each round within matching groups of eight participants.[5]

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.

[5] See the appendix for a translation of the Instructions.

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 to the responder for staying out of the auction. Proposers could choose not to make an offer 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.[6]

We took the following steps 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 2–5 practice rounds, in which each participant made all of the decisions in both roles. This allowed participants to freely experiment with different bribing and bidding strategies. Lastly, the feedback provided at the end of each round included the full round history, including the (typically unobservable) value and bid of the other player.

The sessions were conducted in May 2013 and April 2014 at the BonnEconLab. We ran two sessions with 24 participants in each session for each of the four treatments, and 192 participants in total. The experiment was programmed using z-Tree (Fischbacher, 2007) and the invitation of participants was managed using ORSEE (Greiner, 2004), 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.

3.1 Hypotheses

The results presented in section 2 and evidence from previous studies provides some hypotheses for the different treatments that we summarize in this subsection. Drawing on the existing theoretical literature, we formulate our main hypothesis:

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

Previous studies have established that, without collusion, seller revenue is higher

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

in FPA, whereas efficiency is higher in SPA.[7] Hypothesis 1 implies that the FPA is even more preferable from the perspective of the seller when collusion is possible. Unlike in the baseline no-collusion auctions, however, efficiency is higher in FPA-COL than in SPA-COL, where collusion substantially reduces efficiency.

Hypothesis 2a. *Efficiency is higher in SPA-NOCOL than in FPA-NOCOL.*

Hypothesis 2b. *Efficiency is higher in FPA-COL than in SPA-COL.*

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

Hypothesis 3. *Collusion reduces seller revenue in SPA more than in FPA. That is, Revenue in SPA-NOCOL − Revenue in SPA-COL > Revenue in FPA-NOCOL − Revenue in FPA-COL.*

4 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 stage to show that the bargaining process in the first stage has substantial effects on bidding behavior in FPA but not in SPA.

4.1 The collusion stage

4.1.1 Proposer behavior

Figure 1 depicts bribing behavior in the collusion stage. Panel (A) presents the raw bribes in treatments FPA-COL and SPA-COL, and mean bids by value intervals of 5. Panel (B) displays the cummulative distribution of bribes in the two treatments. 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, the auction type, interactions and period.[8] Although the effect of the proposer's value on the offered bribe is slightly different in SPA compared to FPA, this difference disappears in the second half of the experiment. Furthermore, the

[7] In FPA, bids are higher than in the risk-neutral Nash equilibrium benchmark—leading to an increase in seller revenue compared to SPA—and the variance is substantial—leading to inefficient allocations. Both observations can be rationalized by risk aversion (see, e.g., the CRRAM model in Cox et al., 1982, 1988).

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

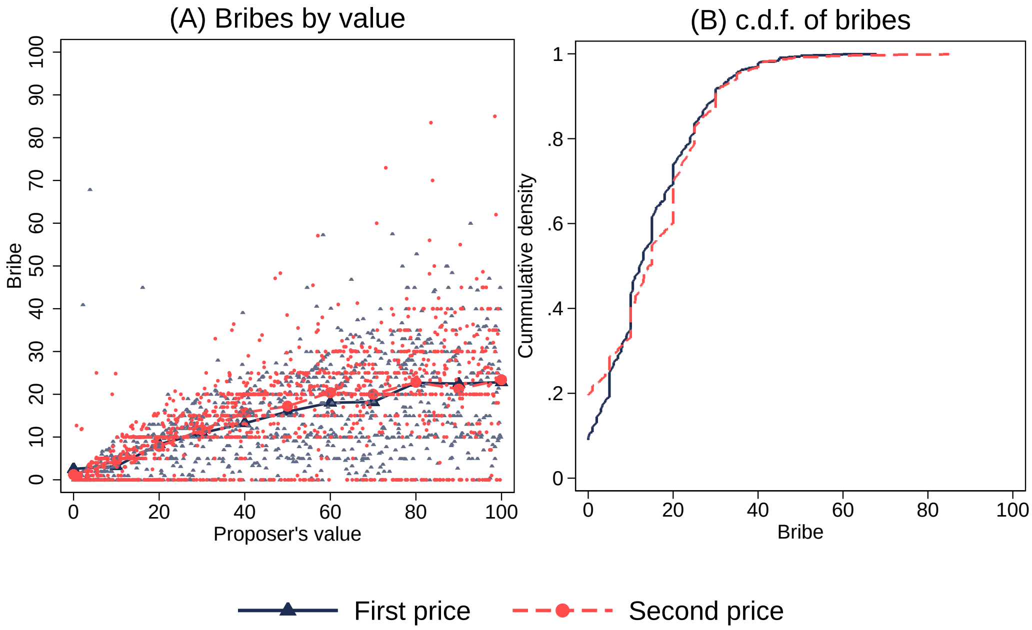

Figure 1: Bribes in first-price and second-price auctions

marginal effect of the auction mechanism on the bribe, calculated using the Delta method 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, with mean bribes decreasing over the first part of the experiment and stabilizing later.

Result 1. *Contrary to Hypothesis 1, the first-price auction mechanism does not deter collusion, with bribing behavior similar to that under the second-price mechanism.*

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

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

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. In line with the equilibrium prediction, bribes 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

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.

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

of the bribing function β_1 equal to 0.2 and significantly below the predicted 0.5. Indeed, 81.9% of all bribes observed in SPA are lower than predicted.[9]

Result 2. *Bribes in SPA are substantially and significantly lower than predicted by the equilibrium analysis.*

4.1.2 Responder behavior

Figure 2 depicts the acceptance responses in the FPA and SPA as a function of the responder's value and the bribe. Dark regions indicates acceptance and light indicates rejection. Recall that the equilibrium strategy in SPA is to accept any bribe that is above one third of the responder's value. This strategy is marked by the black line in the figure. As with proposer behavior, acceptance choices are very similar in FPA and SPA. Choices roughly follow the SPA equilibrium strategy, as the equilibrium line in the figure can be seen to separate the acceptance and rejection regions.

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. Finally, responders learn to accept more bribes with experience.[10]

Recall that the SPA equilibrium prediction is for responders to accept any offer above one third of their value, implying that increasing the bribe by one unit has an equivalent effect to decreasing the responder's value by three units. We test this implication by estimating the ratio of the coefficients for value and bribe from the regressions, as reported at the bottom of the table. The ratio in SPA is not significantly different from the theoretical prediction of $\frac{1}{3}$. While the ratio in FPA

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

[10] 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). As we discuss below, responders often reject offers that are higher than their expected payoff in the continuation auction, hence learning is in the direction implied by money maximization. None of the interaction terms of period with auction mechanism, bribe and responder value is statistically significant if included in the models.

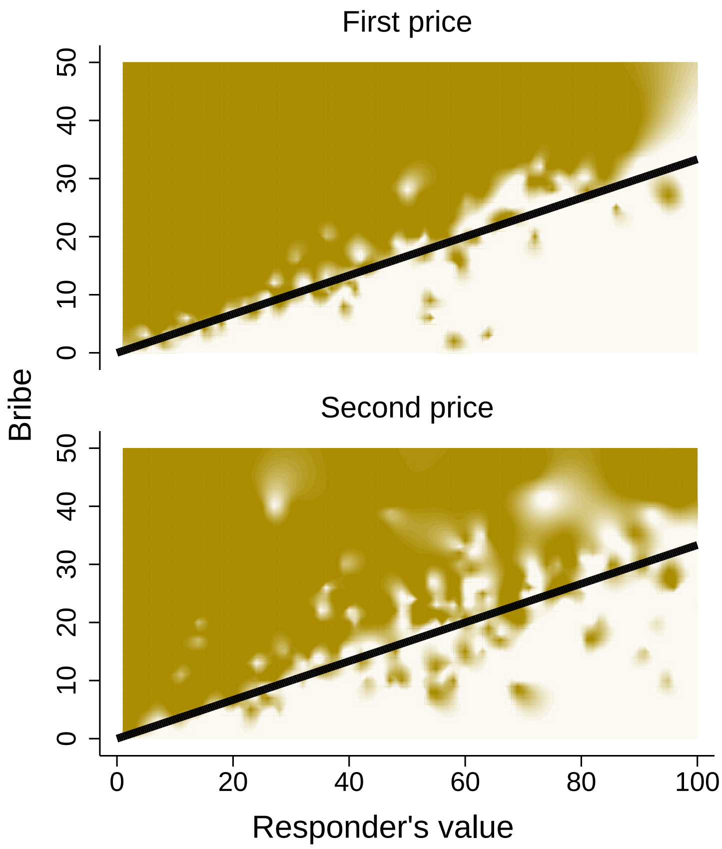

Figure 2: Bribe acceptance in first-price and second-price auctions

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

Table 3: Regressions for 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.

Table 4: Collusion inefficiency

Auction mechanism	Proportion of inefficient allocations		Efficiency loss	
	Predicted	Observed	Predicted	Observed
FPA	0.00%	6.00%	0.000%	0.092%
SPA	16.67%	6.42%	1.852%	0.097%

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

Note that although acceptance behavior in SPA appears to conform with the equilibrium prediction, it is not an optimal response to the actual proposer behavior as reported in the previous section. In fact, proposers bid, on average, less than one half their value (as in the theoretical equilibrium). Consequently, the expected proposer value is more than double the bribe offer, so that money maximizing responders should accept bribes well below one third of their value.[11] We develop and test this argument in Section 4.3.

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. The other is that bribe rejections are motivated similarly to rejections in the ultimatum game (see Güth and Kocher, 2013, for a recent review of the literature). That is, consider a responder who receives a relatively low bribe offer. He may believe that the proposer has a high value and reject the offer as unfair. On the other hand, he may believe that the proposer has a low value and will likely bid low in the auction, making the auction attractive for the responder. The results for the responder behavior in the collusion stage are summarized in the following result:

Result 3. *Responder acceptance strategies are similar for FPA and SPA. Responders often reject bribe offers lower than one third of their own value although their expected gain in the auction is, on average, less than that amount. The tendency to over-reject can be explained by overconfidence in the probability of winning the auction or by fairness considerations.*

4.1.3 Collusion (in)efficiency

An inefficient allocation due to collusion happens when the bidder that has the lower value is able to bribe the bidder with the higher value to refrain from bidding and thus win the auction. We will refer to this type of efficiency loss as *collusion*

[11] Possible risk aversion potentially lowers the acceptance threshold further.

inefficiency to distinguish from *auction inefficiency*, which occurs when the lower-value bidder wins the auction by placing the highest bid.

We use two measures of efficiency. The first measure is the *proportion of inefficient allocations*. The theoretical analysis predicts a substantial proportion of inefficient allocations due to accepted bribes in SPA (Eső and Schummer, 2004) but no inefficient allocations in FPA (Rachmilevitch, 2013). In the SPA equilibrium such inefficient allocations occur $\frac{1}{6}$ of the time.[12] The previous measure does not reflect the magnitude of the efficiency loss. We therefore define the *relative efficiency loss* as one minus the ratio of the value of the auction winner (realized surplus) to the maximum of the two values (maximal possible surplus). In the SPA equilibrium, the expected loss of efficiency is $\frac{1}{54}$.

Table 4 displays the observed levels of inefficiency in the experiment and the theoretical predictions. The proportion of inefficient allocations in SPA is three times less than predicted, and the efficiency loss is an order of magnitude smaller than predicted. Collusion inefficiency is not noticeably lower in FPA with any 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. Accordingly, we state our next result:

Result 4. *Efficiency loss due to collusion in SPA are substantially less than predicted by theory, as proposers refrain from offering bribes and responders reject profitable bribes. Contrary to Hypothesis 2b, efficiency loss in FPA is similar to that in SPA.*

The theoretical literature draws two conclusions: SPA are susceptible to, and FPA deter, collusion and associated inefficiencies. We conclude this section by restating the two main empirical findings: *Collusion in SPA is marginal in comparison to the theoretical predictions, and FPA do not deter collusion in comparison to SPA.*

4.2 Auction stage

Figure 3 depicts the bidding behavior. Panel (A) presents the raw bidding function in terms of the scatter plots and mean bids by value intervals of 5. Panel (B) presents the results of a mixed effects linear regression with random effects on subjects 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.[13]

The figure shows that bidding in SPA is mostly in equilibrium, with 62.9% of the bids set exactly at the value, 79.2% set at the value± 1 overall, and no sig-

[12] Given proposer and responder values, v_i and v_j, respectively, a bribing allocation can only be inefficient if $v_i > v_j$, which is true with probability 0.5. In equilibrium, the responder accepts bribe offers made by proposers with value $v_i > \frac{2}{3}v_j$, which, conditional on $v_i < v_j$, happens with probability $\frac{1}{3}$.

[13] Although the marginal effect of experience is highly significant ($p < 0.001$), the coefficient on period 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. The detailed regression results can be found in the appendix.

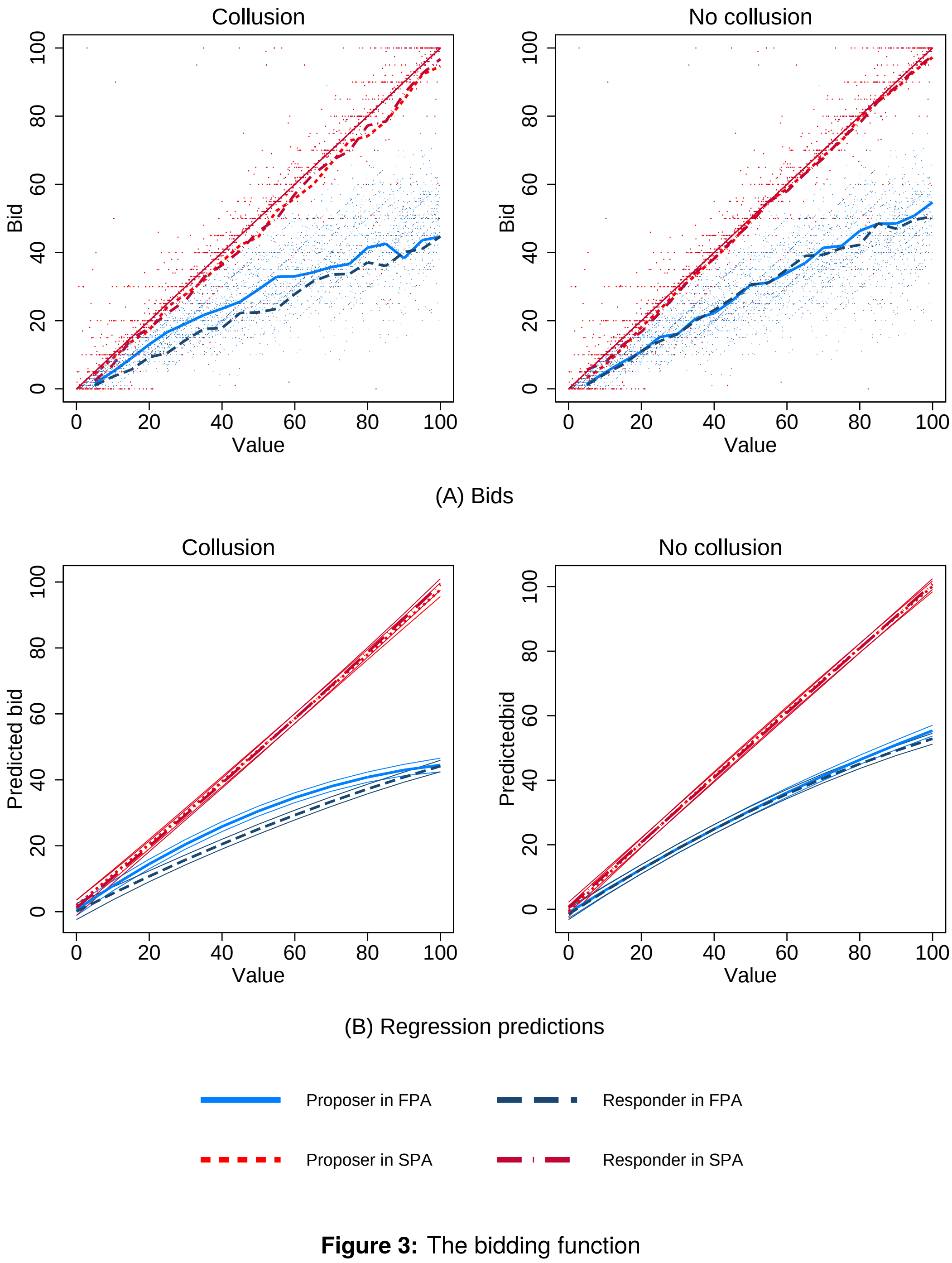

Figure 3: The bidding function

Table 5: 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]

nificant difference across treatments or across roles. Table 5 presents the average marginal slopes of bids on values by treatments and roles. Indeed, the slopes in SPA are close to the rational benchmark of 1, although proposers in SPA-COL bid slightly but significantly below their value. Evidently, proposers sometimes play the weakly dominated strategy of bidding below their value—in the knowledge that any responder who rejected a substantial bribe offer is not likely to place a high bid.

The typical overbidding with regard to the risk neutral Nash equilibrium prediction of bidding 0.5 of the value 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 clearly seen 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, this gap is driven by the selection at the collusion stage. As Figures 1 and 2 show, 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 by role. [14]

To control for the selection effect, panel (B) of the same figure 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

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

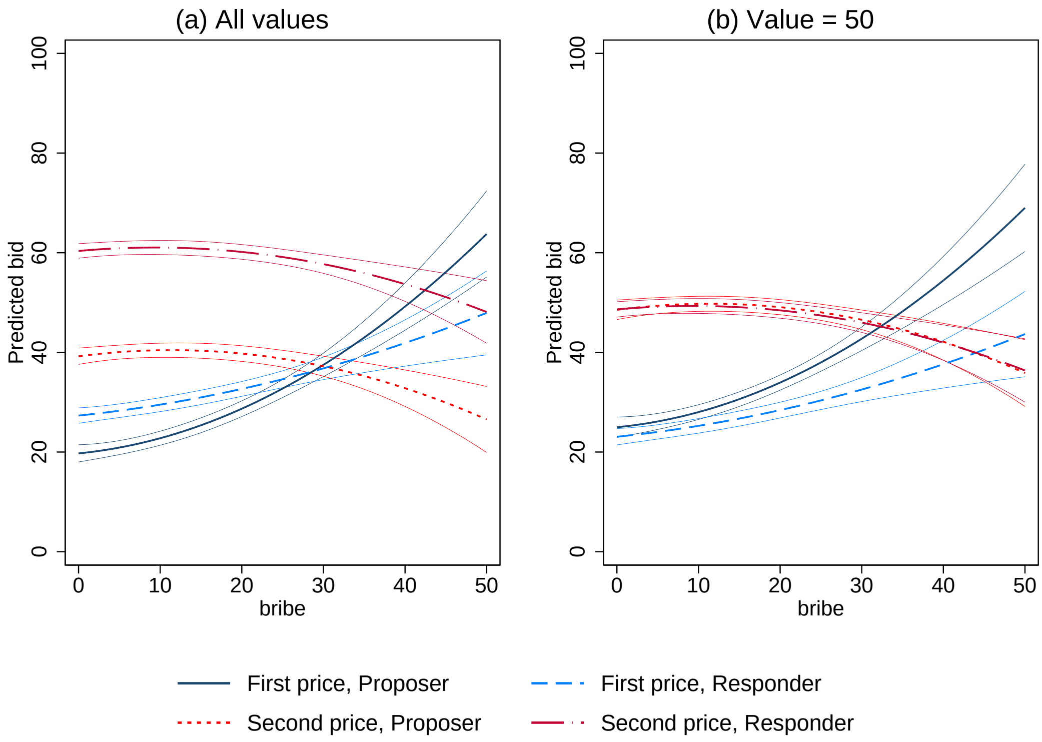

Figure 4: Bids by treatment and (rejected) bribe

responder bids in SPA[15] but a clear difference in FPA, stated in the next result:

Result 5. *In first-price auctions with collusion, proposers bid above responders when controlling for the private value and the rejected bribe.*

The mean marginal effect of role is not large, with proposers bidding 1.95 above responders ($p < 0.05$). Nonetheless, it is enough to distort the auction outcomes, as we report in the next section.

4.2.1 Auction (in)efficiency

Allocation 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. Figure 6 plots

[15] The equilibrium bid in Figure 4(A) is 50. One should not make much of the fact that predicted bids following a bribe above 30 are lower, as less than 9% of bribe offers are that high, and the rate diminishes repeated play.

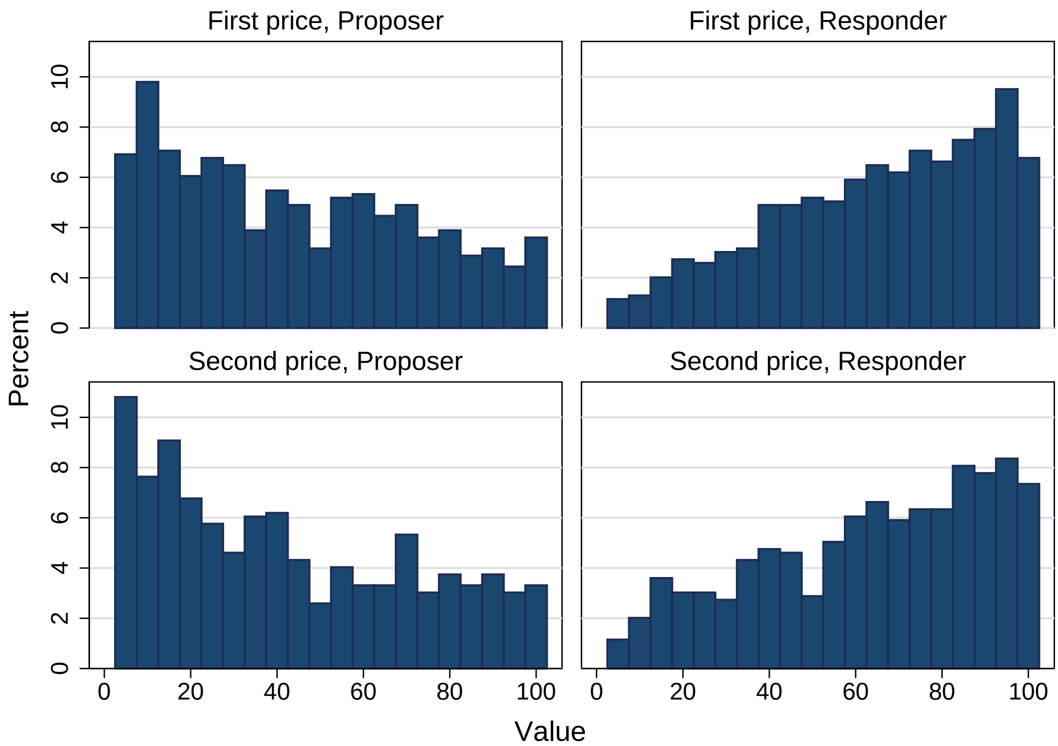

Figure 5: Histogram of valuations in the auction stage

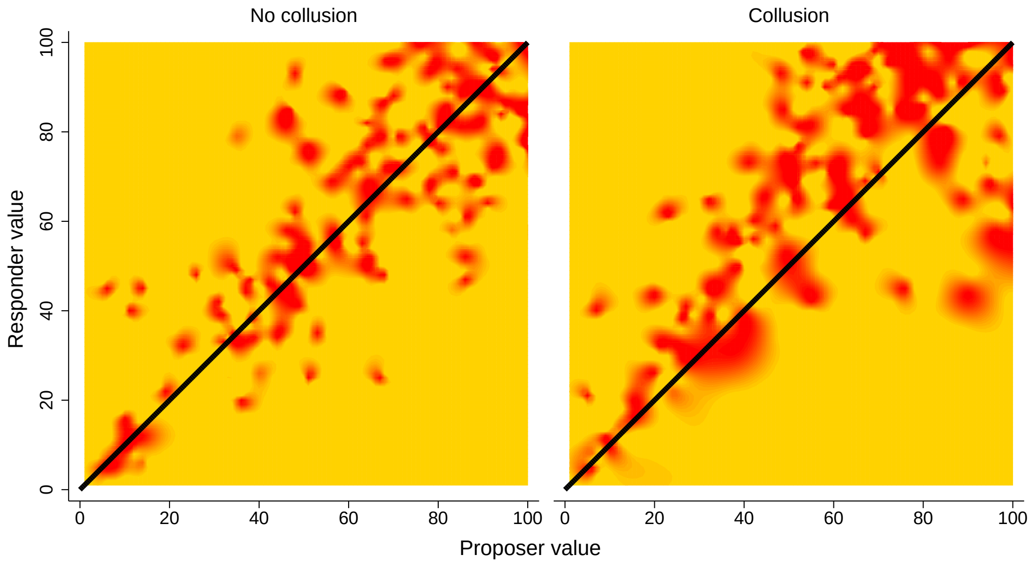

Figure 6: Efficiency in first-price auctions

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.

(in)efficient allocations as a function 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 6 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 5, namely that proposers bid higher than responders in FPA-NOCOL.

Result 6. *In line with Hypothesis 2a, we observe more inefficient allocations in FPA compared to SPA. However, not predicted by the theoretical analysis, collusion leads to more inefficient allocations in first-price auctions compared to auctions without collusion, as proposers become more likely to win the auction when having the lower value.*

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 16.7% of inefficient allocations in FPA-COL compared to only 7.9% in SPA-COL.

Table 6: Regressions for 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	0.936	0.023**	0.141	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			1.007	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***	0.010	0.958***
	(0.276)	(0.005)	(0.298)	(0.005)
Observations	3,789	3,788	3,789	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.

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 7. *Contrary to Hypothesis 2b, first-price auctions are overall less efficient than second-price auctions under collusion.*

4.3 Best response analysis

Clearly, bidders in the first-price auction with collusion do not play according to the no-bribing equilibrium described in Section 2. Nonetheless, bidding behavior may be in line with some mixed-strategies equilibrium.[16] 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 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 the previous section.

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. Figure 7a plots the optimal bids compared to the observed bids (cf. Figure 3). 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 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 briefly discussed in section 4.2. Successful collusion disproportionally removes from the auction proposers with high values and responders with low values (as it was clear from 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, namely the proposer (Güth et al., 2005; Maskin and Riley, 2000).

In Result 3 we made the claim that responders reject profitable bribe offers. We can now test this assertion formally using the best-response analysis of the auction data. Specifically, we calculate for each responder in each round her expected payoff if bidding optimally. A risk-neutral responder should accept the bribe if it is higher than the expected auction payoff. i Figure 8 plots the predicted probability of accepting a bribe by responder's value and depending on whether the highest obtainable expected payoff in the auction is lower or higher than the bribe.[17] We

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

[17] Based on a mixed effects logistic regression of acceptance decisions on payoff-maximizing strategy

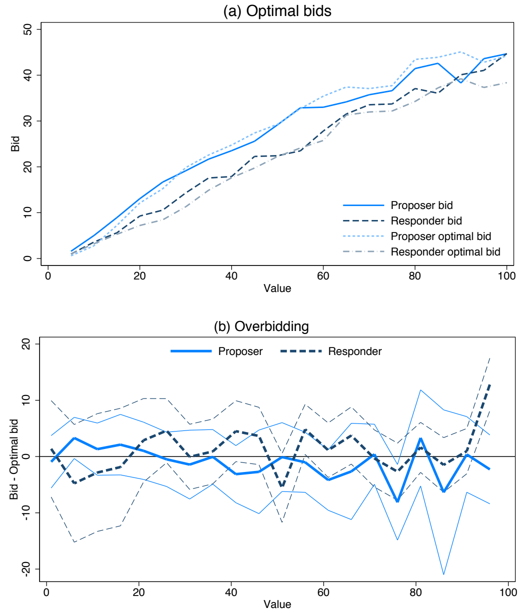

Figure 7: Optimal bids in first-price auctions with collusion stage

see that when the bribe is lower than the highest obtainable expected payoff 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 risk aversion or because the mean obtained auction payoff may be less than the highest obtainable. 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. See Section 4.1.2 for a discussion of this result.

4.4 Seller revenue

We conclude the Results section with reporting the effects of the auction mechanism on the seller revenue under collusion. Table 7 reports the marginal effects of two mixed effects linear regressions of seller revenue on auction mechanism, collusion treatment, and proposer and responders values and their interactions with the treatments. The regression reported in columns (1)–(3) include the plays in which

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.

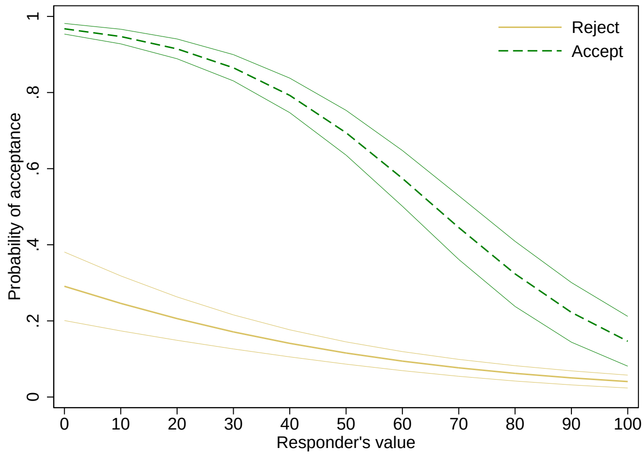

Figure 8: Observed and optimal acceptance decisions

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

the bribe offer was accepted and the seller received zero revenue. The regression reported in columns (4)–(5) included 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 and without a preceding collusion stage. In FPA, in contrast, the effect is two-fold, as the low bribes push the bids down (cf. Table 5, 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 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, is is more sensitive to the responder value in the former and to 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. We summarize the analysis in the final result.

Result 8. *Contrary to Hypothesis 3, collusion is more detrimental to seller revenue in FPA than in SPA. Under collusion, the auction mechanism has no perceptible effect on seller revenue. In first-price auctions, an increase in the proposer value leads to a decrease in seller revenue.*

5 Summary and concluding remarks

Robinson (1985) suggested that the robustness of first-price auctions to collusion offers one justification for their prevalence. First-price auctions deter collusion in his argument by providing an incentives to members of the colluding cartel to renege on the collusive agreement by entering the auction after accepting a side payment for not doing so. Such agreements are, however, often feasible to enforce, for example if the auction requires prior and public registration. Even so, first-price auctions may still deter collusion by providing incentives to misrepresent private information, thus impeding collusive negotiations.

This paper studies this aspect of the auction mechanism by experimentally implementing a simple negotiation protocol which (a) was formally analyzed in the theoretical literature, and (b) allows for 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 in second-price) auctions. This distortion may eliminate desirable features of the auction mechanism and, as in our experimental auction, reduce efficiency.

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

Our paper joins other experimental papers that compared auction mechanisms with respect to robustness to collusion, and highlights a new channel through which collusion affects auction outcomes. 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). Other studies that reach the same result include Hinloopen and Onderstal (2014) for centralized cartel formation without commitment and Agranov and Yariv (2014)

Table 7: 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. *,** ,*** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

for free communication without commitment.[18]

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 individual characteristics of the negotiators to institutional restrictions on communication and/or transfers. Our experimental design brings the implications of 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.

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[18] See also Fischer et al. (2014), who found that first-price auction 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 A: Regression results

Table 8: Regressions for auction efficiency

	Bids
COL	1.664
	(1.229)
SPA	0.462
	(1.214)
Responder	-0.442
	(1.205)
COL x Responder	-0.065
	(1.952)
SPA x Responder	1.599
	(1.710)
Value	0.704***
	(0.023)
Value^2	-0.001***
	(0.000)
Period	0.019***
	(0.005)
Constant	-1.554
	(0.861)
Observations	7,576
Number of groups	24

Notes: Mixed effects linear regression with random effects for subjects nested in matching groups used to generate Figure 3 and Table 5. Standard errors in parentheses. *,** ,*** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

Appendix B: 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!