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9396
2021

November 2021

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
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CESifo *Working Paper No. 9396*

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Abstract

Overbidding in second-price auctions (SPAs) has been shown to be persistent and associated with cognitive ability. We study experimentally to what extent cross-game learning can reduce overbidding in SPAs, taking into account cognitive skills. Employing an order-balanced design, we use first-price auctions (FPAs) to expose participants to an auction format in which losses from high bids are more salient than in SPAs. Experience in FPAs causes substantial cross-game learning for cognitively less able participants but does not affect overbidding for the cognitively more able. Vice versa, experiencing SPAs before bidding in an FPA does not affect bidding behavior by the cognitively less able but, somewhat surprisingly, reduces bid shading by cognitively more able participants, resulting in lower profits in FPAs. Thus, cross-game learning has the potential to benefit bidders with lower cognitive ability whereas it has little or even adverse effects for higher ability bidders.

JEL-Codes: C720, C910, D440, D830.

Keywords: cognitive ability, cross-game learning, experiment, auction, heuristics, first-price auctions, second-price auctions.

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November 2, 2021
We thank Dirk Engelmann, Florian Englmaier, Sander Onderstal, Gyula Seres, Michel Tolksdorf, Ro'i Zultan and participants of the 2021 ESA Global Conference for very helpful comments. Financial support by Deutsche Forschungsgemeinschaft through CRC TRR 190 “Rationality and Competition” (project number 280092119) is gratefully acknowledged.

1. Introduction

Since the seminal work by Kagel et al. (1987), overbidding (bidding above the own value) has been shown to occur frequently in second-price sealed-bid auctions (see, e.g., Kagel and Levin, 1993; Rutström, 1998; Harstad, 2000; Aseff, 2004; Andreoni et al., 2007; Cooper and Fang, 2008; Drichoutis et al., 2015; Georganas et al., 2017; Karmeliuk and Kocher, 2021). Although bidding one's value is a weakly dominant strategy in second-price private-value auctions (henceforth SPAs), there is substantial heterogeneity in bidding behavior, even among experienced bidders (Garratt and Wooders, 2010). Li (2017) suggests that overbidding in SPAs may result from the fact that a cognitively limited agent may not recognize true-value bidding as the weakly dominant strategy in SPAs, and, indeed, recent contributions indicate that cognitive ability may predict overbidding in SPAs (see, e.g., Bartling and Netzer, 2016; Lee et al., 2020). Bidders with higher cognitive ability are more likely to adhere to true-value bidding whereas cognitively less able bidders are prone to overbid, and, among those who overbid, deviations from true values are stronger for cognitive less able bidders.[1] It is thus important to understand how bidders with lower cognitive ability can compensate for their lack of ability.

A natural way of compensation through which bidders with lower cognitive ability may learn not to overbid is feedback about bidding mistakes. However, feedback-based learning within SPAs is difficult. Overbidding and winning an SPA does not necessarily provide the required feedback because winners paying the second highest bid may still pay a price below or equal to their value (Kagel, 1995a). As SPAs often mask overbidding errors, overbidding is not only frequent but also persistent.[2] A promising alternative approach to learning within an auction format is cross-game learning. Cross-game learning may allow decision makers integrating important elements of one situation into their "mental models" and recalling them in similar situations (see also Wickens, 1992; Kagel, 1995b; Grimm and Mengel, 2012). That is, bidders may benefit from experience in other, but similar, auction formats if these formats render reasonably acceptable prices and potential losses from high bids salient (see Kagel et al., 1987; Harstad, 2000).

We hypothesize that such cross-game learning opportunities are particularly helpful to reduce differences in overbidding due to differences in cognitively ability and study experimentally whether cross-game learning can indeed help to reduce the extent of cognitively less able bidders' bidding mistakes. In our laboratory experiment, we focus on a simple form of cross-game learning and study experimentally how experience in first-price auctions (henceforth FPAs) affects subsequent bidding behavior in SPAs. FPAs are common and render potential losses from high bids particularly salient. However, FPAs are not strategically equivalent to SPAs. Hence, cognitively able decision makers may realize that there is no lesson to be learned for optimal bidding in SPAs from experience in FPAs, whereas cognitively less able bidders may transfer a simple bidding heuristic from FPAs to SPAs ("Don't bid too high"). If so, experience in FPAs may help to reduce differences in the inclination to overbid due to cognitive ability. More specifically, we first proxy cognitive ability using Raven's Progressive Matrices (Raven, 1962) before participants encounter the two different auction formats. We employ an order-balanced design that allows

[1] Lee et al. (2020) presents evidence from second-price auctions with private values and Casari et al. (2007) finds that bidders with lower SAT/ACT scores are more susceptible to the winner's curse in common value auctions.

[2] See, e.g., Kagel et al. (1987), Kagel and Levin (1993), Harstad (2000), Aseff (2004), Andreoni et al. (2007), Cooper and Fang (2008), Drichoutis et al. (2015), Georganas et al. (2017), and Karmeliuk and Kocher (2021).

us to study the role of cognitive ability for participants' bidding behavior with and without being exposed to the opportunity of cross-game learning. Participants bid in pairs in computerized private-values sealed-bid auctions, and each participant either bids first in a series of FPAs followed by a series of SPAs, or vice versa. Importantly, when experiencing the first auction format, participants are not aware that they will encounter another auction format subsequently. This way, we can naturally study how cognitive ability relates to bidding behavior without experience, as well as how experience in one auction format affects behavior in the other.

The main objective of our study is to understand whether cross-game learning through experience in FPAs can help cognitively less able participants to improve their bidding behavior in SPAs, and to what extent highly cognitively able participants may benefit at all from learning across games. Further, our order-balanced experimental design allows us to shed light on how experience in SPAs may affect bidding behavior in FPAs. Bidders with lower cognitive ability are expected to overbid in SPAs. As outlined above, there is also little room for these bidders to learn from bidding in SPAs for optimal bidding in FPAs. Bidders with higher cognitive ability are more likely to bid true values within in SPAs and may – with experience – even form a habit of true-value bidding. Although cognitively more able bidders should be aware that FPAs are not strategically equivalent to SPAs, they may erroneously stick with their simple heuristic of true-value bidding when switching to FPAs. It is thus possible that experience in SPAs worsens in fact the performance of cognitively more able bidders.

Our experimental results are threefold: First, we find that cognitive ability predicts overbidding in SPAs without experience in another auction format. The majority of bids by less cognitively able bidders are larger than their true values whereas the majority of bids by higher cognitively able bidders correspond to their induced values. Second, and most importantly, we find strong cross-game learning among cognitively less able participants. After experiencing FPAs, the majority of bids in SPAs by cognitively less able bidders correspond to their values. Cross-game learning reduces overbidding by less cognitively able participants by about 40 percent (this corresponds to 20 percentage points), while the fraction of cognitively more able bidders who overbid remains the same. Third, experiencing SPAs before participating in FPAs does not substantially alter bidding behavior in FPAs by less cognitively able participants. However, participants with higher cognitive ability who experienced SPAs first reduce their bid shading in FPAs and thus perform worse in terms of payoffs compared to highly cognitively able participants that bid in FPAs first.

Our findings advance the literature on the causes of overbidding in SPAs and the means to reduce it (see, e.g., Cooper and Fang, 2008; Kagel and Levin, 2016, and references therein). We find that overbidding by cognitively less able bidders can be reduced substantially by cross-game learning, but that cross-game learning can have adverse effects. Building on the finding that overbidding is much less pronounced in strategically equivalent English auctions, Kagel et al. (1987) have shown that experience in English auctions can reduce overbidding in SPAs. Harstad (2000) confirms the latter finding and extends this work by showing that experience in an auction that avoids bidding dynamics of the English auction but still renders acceptable prices salient (such as Price Acceptance List auctions) reduces overbidding in SPAs too. Although his experiment does not focus on experience in FPAs, in one of his many treatments, fourteen participants bid in SPAs after experiencing FPAs. Harstad's (2000) main finding is that experience in all three auction formats reduces overbidding in SPAs, but also that overbidding and learning across games is very heterogeneous. Our analyses advance his work and provide guidance on how the observed heterogeneity comes about. Without prior experience in other auction formats, cognitively less able bidders overbid more frequently in SPAs than cognitively more able bidders. With experience in FPAs, this difference is reduced substantially. When experiencing FPAs before SPAs, cognitively less able bidders start with rather high bids in FPAs but learn to lower their bids when bidding repeatedly in FPAs. Lower ability bidders benefit from adjusting their strategy when subsequently bidding in SPAs, in which they then overbid substantially less. Highl cognitively able bidders benefit less from experience in FPAs, because they bid profitably in FPAs early on (by substantially shading their bids). Thus, they do not encounter salient forgone profits due to high bids in FPAs. Further, overbidding in SPAs without prior experience in other auction formats is much less prounounced among cognitively more able bidders such that overall, they have less scope to benefit from experience in FPAs.

Our results further complement recent contributions on the relationship of cognitive ability and overbidding in SPAs with private values (Bartling and Netzer, 2016; Lee et al., 2020). We show that cognitive ability is a robust predictor of overbidding in SPAs when participants have no prior experience in other auction formats, but not when participants have experienced bidding in FPAs. These findings connect also to the literature on learning across games more broadly (see, e.g., Grimm and Mengel, 2012), highlighting that experience in SPAs may yield payoff losses for cognitively more able participants, when they afterwards bid in FPAs, in which no dominant bidding strategy exists.

Finally, our findings deliver some practical implications. Cross-game learning can be beneficial to cognitively less able bidders, in particular, when lessons learned in one game yield simple and useful heuristics for other games. In turn, simply fostering experience in FPAs may help inexperienced low ability bidders. Similarly, if low ability bidders misinterpret SPAs as FPAs (see e.g., Ockenfels and Roth, 2002, 2006) they may be less likely to overbid. However, our results also serve as a warning. Bidders do not learn to bid optimally, but rather learn simple heuristics. When bidders adopt simple heuristics (such as true-value bidding), they may also suffer from simplified bidding strategies when bidding in more complex environments (such as FPAs), even if they exhibit relatively high levels of cognitive ability.

The remainder of the paper is organized as follows. Section 2 introduces the experimental design, Section 3 presents the results, and Section 4 provides a discussion and conclusion. The appendix contains further analyses as well as the experimental instructions (translated from German).

2. Experimental design

Our experimental design aims at understanding how cognitive ability shapes bidding behavior in first- and second-price auctions and how cross-game learning changes bidding behaviors by cognitively more and cognitively less able bidders. We therefore structured the experiment in four independent parts and informed participants at the beginning of the experiment that they would receive instructions for each of the four parts only after completion of the previous part. Part I elicited cognitive ability. Part II assessed participants' risk attitudes. In Part III and part IV, each participant either bids first in a series of FPAs followed by a series of SPAs or vice-versa.

Elicitation of cognitive ability (Part I):

To proxy participants cognitive ability, participants were given five minutes to answer as many (out of 22) Raven's Progressive Matrices as possible in Part 1. The matrices were of progressing difficulty, and participants were aware of this. Each matrix had eight potential answers, exactly one of which was correct. Participants could only solve one matrix at a time, and they could not revisit earlier matrices. For each correctly solved matrix, participants could earn EUR 0.30. Participants also had the possibility to familiarize themselves with the matrix task in two unpaid dry runs. Performance feedback on Part I was provided only at the very end of the entire experiment to avoid behavioral effects from wealth accumulation or other behavioral complementarities in performance between parts.

Elicitation of risk preferences (Part II):

In Part II, we elicited subjects' risk attitudes following Holt and Laury (2002). Participants made ten binary lottery choices with payoffs given in EUR. One of the ten choice items was randomly selected and implemented for real payment. A risk-neutral subject should choose the less risky lottery four times before switching to the more risky lottery. Thus, a higher switch point indicates a relatively higher level of risk aversion. Most of our participants are risk averse. The average switch point in our sample was 5.74 (median 6). The estimated individual risk preferences range from -0.315 at the 5th percentile to 0.98 at the 95th percentile, with a median level of 0.55.[3] There are no significant differences between treatments in the distributions of the observed switch points as well as of the estimated risk preferences ($p = 0.926$, resp. $p = 0.384$, t-tests). Similar to Part I, participants were informed of their income from Part II only at the very end of the experiment.

Auctions (Parts III and IV):

Parts III and IV consisted of 20 two-bidder private-value auctions, either of the FPA- or the SPA-format. Each participant either bid first in a series of 20 FPAs, followed by a series of 20 SPAs, or vice-versa, and we varied the order of the auction formats (between subjects) at the session level. After each auction, participants were randomly rematched within matching groups of 10 participants.[4] Participants first received instructions for Part III, and only after completion of Part III, they received instructions for Part IV. This approach exclude 'reverse' spillovers that would complicate the interpretation of learning effects from one auction format to the other. In each auction, every participant received a private value (resale value) that was independently drawn from a uniform distribution of integer numbers on $[0, 100]$. Each participant was required to submit a bid in each auction. Participants could choose non-negative integer bids.[5] In the FPA, the highest bidder wins, and she has to pay her bid. In the SPA, the highest bidder wins, and she has to pay the second highest bid. If both bids were equal, the buyer was randomly chosen with equal probability. After each auction, participants were informed about whether they won (or not), the final price to be paid by the winner, the rival's bid, their own profit, and we reminded participants about their own private value and bid. Values, bids, and profits were stated in Experimental Currency

[3] For the estimation of participants' risk preferences we used an exponential utility function of the form $U(x) = (x)^{(1-\alpha)}/(1-\alpha)$, where α is the Arrow-Pratt measure of relative risk aversion. This specification implies risk seeking for $\alpha < 0$, risk neutrality for $\alpha = 0$, and risk aversion for $\alpha > 0$. When $\alpha = 1$, the natural logarithm, $U(x) = ln(x)$, is used (Holt and Laury, 2002).

[4] Doing so, we obtained six independent matching groups for each treatment.

[5] No upper bid limit was mentioned explicitly, but to avoid extreme losses, the highest possible bid was set to 200.

Units (ECU, with a pre-announced exchange rate of 1 ECU = 0.03 EUR).[6] At the beginning of Part III and Part IV, participants received an endowment of 30 ECU to cover potential losses. Further, losses in single auctions could be compensated by gains in other auctions, since all auctions were payoff-relevant.

Post-experimental questionnaire and procedures:
After the four main parts, participants had to fill in a post-experimental questionnaire that contains among other things, a self-assessed, hypothetical measure of risk attitude on a 0–10 scale (German Socio-Economic Panel, question no. 154, (2013)), gender, age, field of study, and number of semesters at university.

Altogether, the experiment encompasses a total of 4,720 bidding decisions (2,360 for each auction format by 118 participants (43% female) by 60 participants experiencing FPAs first (FPA/SPA: 1.200 decisions) and 58 participants experiencing SPAs first ("SPA/FPA": 1.160 decisions). The experiment was conducted at Technische Universität Berlin. Participants were students from the local participant pool, mostly from economics, engineering, or the natural sciences. Participants were invited to the experiment with ORSEE (Greiner, 2015). All experimental sessions were conducted using z-Tree (Fischbacher, 2007). The average length of a session was 75 minutes. The average total earnings per subject amounted to 24.26 EUR. Earnings were paid out in cash directly after the end of the experiment.

3. Results

We structure our experimental results along our research questions. First, we ask whether differences in cognitive skills explain overbidding in private-value SPAs. Second, we study who benefits the most from cross-game learning through experience in FPAs. Third, we document how cognitive ability relates to bidding behavior in FPAs, and finally, we study whether experience in SPAs also shapes bidding behavior in FPAs, taking cognitive ability into account.

3.1. Cognitive ability

We calculate each participant's score in the Raven's progressive matrix test, i.e. the number of correctly solved matrices, to proxy cognitive ability. We find substantial heterogeneity in participants' cognitive ability. Individual scores range from five up to 16 correctly solved matrices, with an overall average score of 11.14 matrices and a standard deviation of 2.61. Importantly, Raven's scores do not differ across the order of auction formats (SPA/FPA vs. FPA/SPA, (t-test: $p = 0.245$, Kolmogorov-Smirnov test: $p = 0.333$, see also Table 1) and do not correlate with risk attitude measured in the Holt-and-Laury task in our sample (Spearman's $\rho = -0.0535$, $p = 0.5650$). To study whether cognitive ability predicts behavior in auctions as well as participants' scope to benefit from cross-game learning, we categorize bidders' into two groups. A participant belongs to the lower cognitive ability group (**LC**) if their Raven's score is below the total average score (11.14) of all 118 participants and to the high ability group (**HC**), otherwise.[7] Table 1 illustrates this classification.

[6] 1 EUR= 1.15 USD at the time of the experiment.

[7] Our classification follows similar approaches used in the literature (e.g., Lee et al., 2020; Grimm and Mengel, 2012; Bergman et al., 2010). The median score in our sample is 11, such that our categorization coincides with a median split in

Treatment (Order of formats)		**LC** (Below average)	**HC** (Above average)	CA Overall
FPA/SPA	Avg. CA	9.14	13.46	10.87
	(std. dev.)	(1.42)	(1.28)	(2.53)
	No. of subj.	36	24	60
SPA/FPA	Avg. CA	9.07	13.48	11.43
	(std. dev.)	(1.96)	(1.15)	(2.72)
	No. of subj.	27	31	58
Both treatments	Avg. CA	9.11	13.47	11.14
	(std. dev.)	(1.66)	(1.20)	(2.63)
	No. of subj.	63	55	118

Table 1: Definition of cognitive ability groups based on Raven's test scores

3.2. Second-price auction

Although the dominant strategy in SPAs is to bid one's true value, research has shown that a substantial fraction of bidders overbid in SPAs (see, e.g., the surveys by Kagel, 1995a; Kagel and Levin, 2016). Figure 1 shows the relative frequency of overbidding, $b_i > v_i$, underbidding, $b_i < v_i$, and true-value bidding, $b_i = v_i$. The figure illustrates that cognitive ability is an important driver of overbidding without experience in other auction formats. For the LC–group without experience (Panel (A)), more than 50 percent of bids are larger than the own value, whereas overbidding is much less pronounced among participants in the HC–group (Panel (B)), whose members overbid about half as often (Mann-Whitney, $p = 0.005$), without prior experience of another auction format.[8] Vice-versa, true-value bidding is the modal choice in the HC–group, and participants of the HC–group bid true values almost twice as often as participants of the LC–group (Mann-Whitney, $p = 0.013$).

Result 1. *Without prior experience in FPAs, bidders with lower cognitive ability overbid substantially more often in SPAs than bidders with higher cognitive ability.*

Experiencing FPAs before bidding in SPAs substantially reduces overbidding by bidders with lower cognitive ability (see Panel(C), Mann-Whitney, $p = 0.011$), whereas bidders with high cognitive ability do not overbid substantially less in SPAs when experiencing FPAs first (see Panel (D), Mann-Whitney, $p = 0.1598$). This is also reflected in a related measure, relative overbidding, defined as $(b_i - v_i)/v_i$, within each auction across treatments and bidder groups.

Figure 2 illustrates average relative overbidding over time in both treatments. The left panel depicts the treatment in which participants first experience SPAs and thereafter bid in FPAs, and the right panel shows the treatment FPA/SPA. Bidders of the LC–group overbid substantially when bidding first in 20 SPAs (left panel), whereas the average relative overbidding of bidders in the HC–group is stable and close

which the median is included in the group of less cognitively able participants. Further, our results are robust to alternative group classifications such as splitting groups based on the overall score within each treatment (the results are available on request).

[8] We test this difference non-parametrically across cognitive ability groups by calculating for each participant the number of auctions in which she overbids (and proceed analogously for true–value bidding, see below).

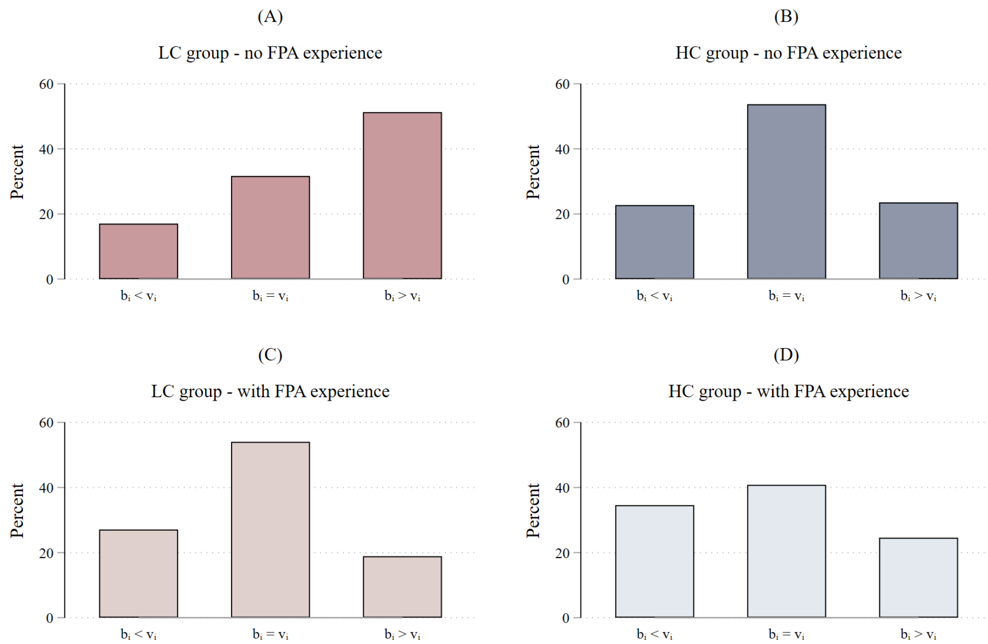

Figure 1: Bidding behavior in SPAs across treatments and cognitive ability groups.

to zero. After experiencing 20 FPAs this difference in relative overbidding between the LC–group and the HC–group vanishes.

Table 2 presents regression results underlining the important role of cognitive ability for overbidding of inexperienced bidders as well as for the benefits from cross-game learning. We focus on bid deviation from true-value bidding, $b_i - v_i$, and estimate generalized least squares (GLS) regressions, with random effects at the subject level and clustered standard errors at the matching group level to account for correlated decisions by the same subject and within the same matching group. We control for our three main variables of interest: direct effects of cognitive ability (the dummy CognD $= 0$ if LC; 1 if HC), learning within the 20 periods of the SPA (the dummy periodD $= 0$ if first 10 auctions; 1 if auctions 11-20), and cross-game learning from experience of FPAs prior to SPAs (the dummy CGL-D $= 0$ if order SPA/FPA, 1 if order FPA/SPA). Control variables include gender and risk attitude (switch point in the Holt/Laury-task; increasing in the degree of risk aversion). We also control for value and value squared because bid deviation from true value bidding can depend on the underlying value. Specifications without and with control variables are distinguished by the letters a and b, respectively. The subsample in Specification (1) includes only the observations in treatment SPA/FPA and hence focuses on overbidding in SPAs without bidding experience in FPAs. Specification (2) includes only observations from treatment FPA/SPA, i.e., focusing on bidding behavior of participants who experienced 20 SPAs in advance while specifications (3) and (4) include both treatments. Specification (1a) mirrors the pattern observed in the left panel of Figure 2, showing that cognitively more able bidders overbid substantially less when not having bid in FPAs before SPAs, and further, that overbidding is not reduced with experience within the SPA format. Hence, within-game learning does not lead to a convergence to the dominant strategy. This holds also when adding controls for risk attitudes and gender (see specification (1b)). In contrast, overbidding does

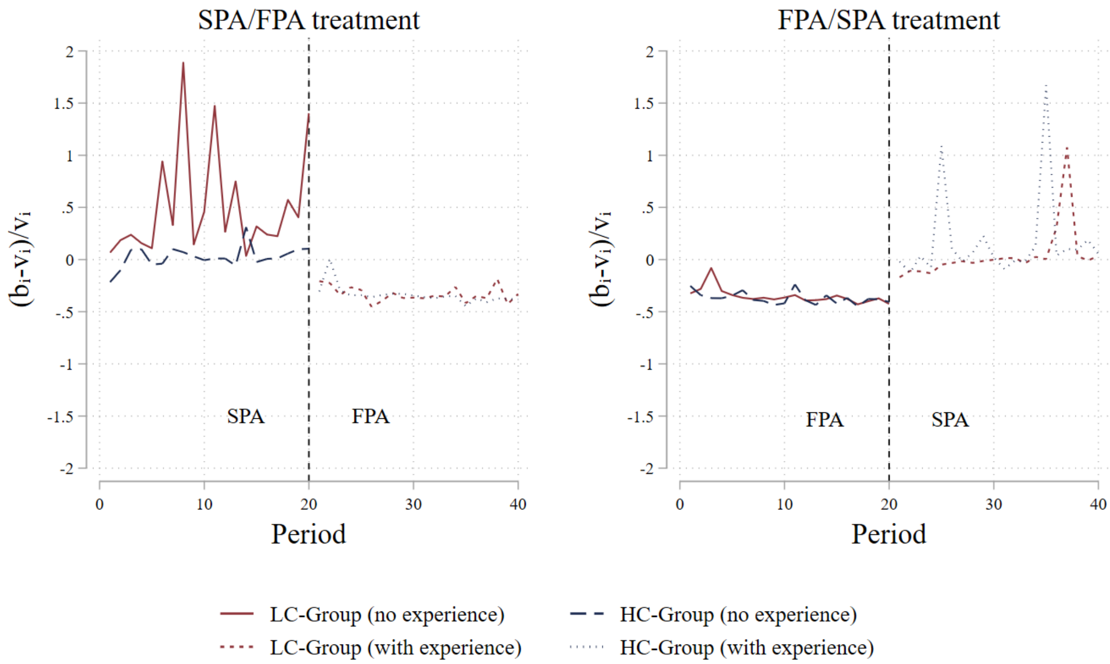

Figure 2: Average relative bid deviation, $(b_i - v_i)/v_i$, over time by treatment and cognitive ability group.

not significantly differ between the LC–group and the HC–group, when both groups have experienced 20 FPAs before bidding in the SPAs (see specifications (2a) and (2b)). Specifications (3) and (4) estimate the causal effect of experiencing the 20 FPAs on overbidding in SPAs and shows that such cross-game learning eliminates the significant difference between the LC–Group and the HC–group.

Result 2. *Bidders with lower cognitive ability benefit substantially from experience in FPAs. Cross-game learning reduces overbidding in SPAs for cognitively less able bidders, and thereby eliminates significant differences between low and high ability groups.*

3.3. First-price auction

To understand how the differential effects of experience in FPAs for cognitively more and less able bidders comes about, we now shed light on bidding behavior in FPAs. Figure 3 presents scatter plots of individual bids in FPAs by treatment and cognitive ability groups, conditional on induced values. Each panel of Figure 3 also includes three reference lines. From top to bottom, these lines indicate, respectively, true-value bidding, the fitted (observed) linear 'bid function', and the risk-neutral Nash-equilibrium (benchmark) bidding. In the FPA, bidding above the risk-neutral benchmark is rational for risk-averse bidders. However, a positive profit in the FPA requires bid shading, i.e. bidding below one's value, $b_i < v_i$. Thus, bidding at or above the true value cannot be rationalized. Hence, rational bids should fall between the

Table 2: SPA: Bid deviation from true-value bidding; GLS regressions.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Dependent Variable:	$b_i - v_i$	$b_i - v_i$	$b_i - v_i$	$b_i - v_i$	$b_i - v_i$	$b_i - v_i$	$b_i - v_i$	$b_i - v_i$
Reference category:	LC–Group (without CGL, first 10 auctions)				LC–Group (without CGL)		LC–Group (without CGL, first 10 auctions)	
Constant	4.078***	8.681**	-3.519**	-5.975***	6.080***	7.152***	4.135**	5.205***
	(1.529)	(3.911)	(1.726)	(2.175)	(1.650)	(0.655)	(1.765)	(0.903)
CognD (HC=1)	-6.394***	-6.080**	2.815	3.204*	-6.662***	-6.547***	-6.451***	-6.413**
	(2.120)	(2.371)	(1.985)	(1.782)	(1.442)	(1.687)	(2.311)	(2.566)
TimeD (auctions 11-20)	4.004***	4.107***	3.803***	3.678***			3.889***	3.834***
	(0.676)	(0.728)	(1.001)	(0.981)			(0.614)	(0.617)
CGL-D (FPA experience=1)					-7.698***	-7.881***	-7.698***	-7.880***
					(2.025)	(1.952)	(2.027)	(1.952)
CognD × TimeD	-0.536	-0.517	-2.107**	-2.038**			-0.421	-0.270
	(2.323)	(2.339)	(0.907)	(0.892)			(2.681)	(2.713)
CognD × CGL-D					8.424***	8.624***	9.310***	9.595***
					(2.073)	(2.182)	(2.772)	(2.889)
CognD × TimeD × CGL-D							-1.772	-1.939
							(3.148)	(3.179)
Value		-0.007		-0.015		-0.0119		-0.011
		(0.054)		(0.062)		(0.0405)		(0.042)
Value^2		-0.001		-0.000		-0.000445		-0.000
		(0.001)		(0.000)		(0.000468)		(0.000)
Female		1.518		0.941		1.083		1.082
		(2.066)		(1.891)		(1.695)		(1.698)
Switch point (H&L)		-0.517		0.636**		0.0988		0.099
		(0.862)		(0.307)		(0.450)		(0.451)
Incl. Obs.	SPA/FPA	SPA/FPA	FPA/SPA	FPA/SPA	All	All	All	All
Observations	1,160	1,160	1,200	1,200	2,360	2,360	2,360	2,360
Number of Subj.	58	58	60	60	118	118	118	118

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

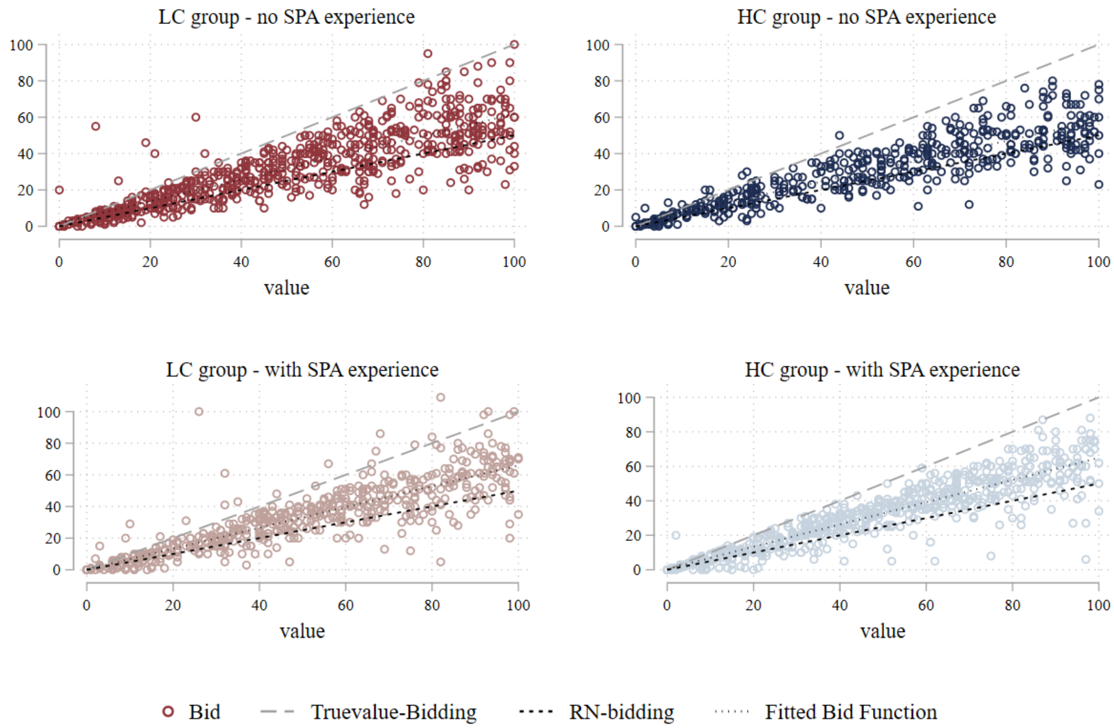

Figure 3: FPA: Scatter plots of individual bids by treatment and cognitive group.

two outer lines in Figure 3 . As can be seen, this is indeed the case for the overwhelming majority of observations. The few overbidding deviations in FPAs originate mainly from the low cognitive ability group.

Without experience in SPAs (see top panels in Figure 3), bidders in the LC–group shade bids less than bidders in the HC–group, particularly for higher values. However, these differences appear to be less pronounced, when bidders experience SPAs before bidding in FPAs.

Figure 4 depicts the average degree of relative bid shading, $(v_i - b_i)/v_i$, for less cognitively and more cognitively able bidders across values. Note that a higher level of bid shading is associated with bidding closer to the risk-neutral Nash equilibrium (RNNE), i.e. a larger profit in case of winning but a lower probability of winning (unless the bid is below the RNNE bid). We have grouped values into ten value bins in order to better distinguish participants' bidding behavior for low values from that for high values. The left panel shows that bid shading in FPAs by less cognitively able participants is not affected strongly by the preceding bidding experience in SPAs. However, for highly cognitively able bidders (right panel), and especially for high values, bid shading tends to 'deteriorate' when these bidders experienced SPAs before participating in FPAs. Note that if values are low, the expected profit from rational bidding will be low too. In contrast, for high values, stakes but also the probability of winning the auction are higher such that the own bid becomes payoff-relevant more often. There are different approaches in the literature to deal with the problem of unmotivated behavior that can interfere with data analysis when values are low (see e.g., Harstad, 2000; Lee et al., 2020). In our statistical analyses (Table 3), we follow Lee et al., 2020, p.1501, by providing estimations for all observations as well as for situations in which bidders encountered

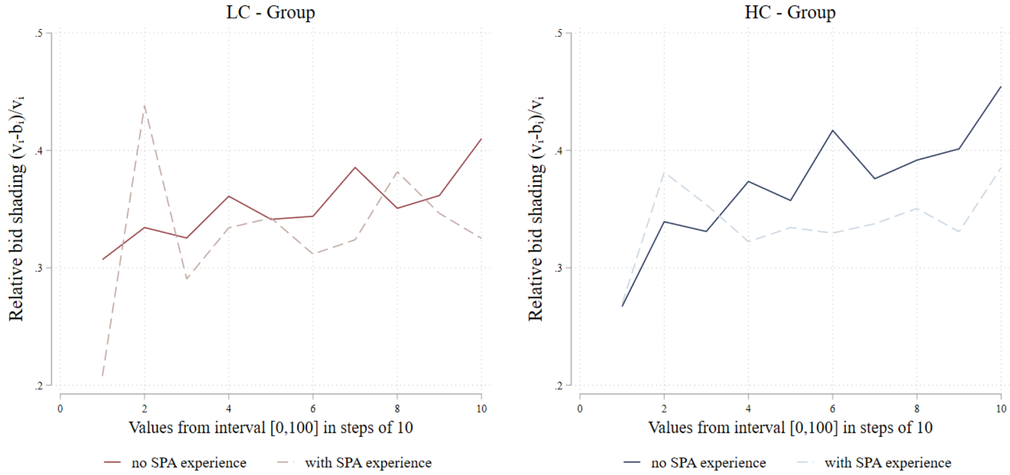

Figure 4: FPA: Average relative bid shading, $(v_i - b_i)/v_i$, by treatment and cognitive group.

higher values, for which incentives to consider one's bid more to carefully are stronger.

We focus on relative bid shading, $\frac{v_i - b_i}{v_i}$, and estimate how cognitive ability, cross-game learning (i.e. experience in SPAs before bidding in the FPA) and within-game learning affect participants' extent of bid shadings. Similar to our analysis of bidding behavior in SPAs, we include a "cross-game learning" treatment dummy CGL-D (=1 if bidders experienced SPAs before bidding in FPAs) and a dummy variable for belonging to the HC- group (CognD) as well as interaction variables. Regression specifications a/b include all induced values while specifications c/d include only high values, i.e. $v_i > 50$. Specifications a/c do not include additional control variables while we add controls for gender (dummy for female), risk attitudes and induced values in specifications b/d. Again, all specifications are generalized least squares (GLS) models with random effects at the subject level and clustered standard errors at the matching group level to account for correlated decisions by the same subject and within the same matching group. Mirroring the result from Figures 3 and 4, we find that without experience in SPAs, bidders in the HC–group tend to shade bids slightly more than bidders in the LC–group, particularly for values larger than 50 (see specification (1c) and the solid lines in both panels of Figure 4). Further, specification (1d) shows that more risk-averse bidders shade bids less (as expected), and gender does not affect bid shading. While the coefficient for cognitive ability (CognD) remains positive, this tendency is not statistically significant. Second, we observe that cross-game learning has no effect for the cognitively less able bidders, while, somewhat surprisingly, the cognitively more able bidders shade their bids less, in particular for high values when experiencing SPAs before bidding in FPAs (post-estimation Wald tests, $p-$values< 0.05, see Table 3, specifications (1c) and (1d)). Specifications (2a)-(2d) further document within-game learning for bidders in the LC–group, who shade bids more in the second as compared to the first half of bidding in FPAs (without experience). Thus, bidders in the LC–group indeed experience forgone profits in FPAs due to relatively high bids and adjust their bidding behavior accordingly. In contrast, within-game learning in FPAs is less pronounced for the HC–group, and vanishes completely with experience in SPAs (see post-estimation Wald tests for specifications (2c) and (2d)).

Table 3: FPA: Relative bid shading; GLS regressions.

	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Dependent Variable:	$\frac{v_i-b_i}{v_i}$	$\frac{v_i-b_i}{v_i}$	$\frac{v_i-b_i}{v_i}$	$\frac{v_i-b_i}{v_i}$	$\frac{v_i-b_i}{v_i}$	$\frac{v_i-b_i}{v_i}$	$\frac{v_i-b_i}{v_i}$	$\frac{v_i-b_i}{v_i}$
Reference category:	LC–Group (without CGL)				LC–Group (without CGL, first 10 auctions)			
Constant	0.352***	0.354***	0.366***	0.347***	0.319***	0.321***	0.345***	0.328***
	(0.038)	(0.040)	(0.032)	(0.023)	(0.050)	(0.046)	(0.030)	(0.025)
CognD (HC=1)	0.019	0.012	0.041*	0.030	0.043	0.035	0.048	0.038
	(0.034)	(0.034)	(0.024)	(0.023)	(0.035)	(0.033)	(0.032)	(0.030)
TimeD (auctions 11-20)					0.066**	0.064**	0.040***	0.041***
					(0.028)	(0.013)	(0.0126)	(0.053)
CGL-D (SPA experience =1)	-0.019	-0.023	-0.027	-0.031	0.004	-0.001	-0.037	-0.040
	(0.069)	(0.070)	(0.063)	(0.062)	(0.058)	(0.059)	(0.054)	(0.053)
CognD × TimeD					-0.047**	-0.045**	-0.014	-0.016
					(0.020)	(0.019)	(0.020)	(0.017)
CognD × CGL-D	-0.014	-0.007	-0.035	-0.025	-0.068*	-0.061	-0.029	-0.019
	(0.050)	(0.053)	(0.042)	(0.043)	(0.038)	(0.041)	(0.037)	(0.038)
TimeD × CGL-D					-0.046	-0.045	0.020	0.019
					(0.061)	(0.062)	(0.029)	(0.028)
CognD × TimeD × CGL-D					0.109*	0.109*	-0.012	-0.012
					(0.066)	(0.066)	(0.033)	(0.031)
Value		0.001		0.001***		0.001		0.001***
		(0.001)		(0.001)		(0.001)		(0.000)
Value^2		-3.44e-06				-4.11e-06		
		(8.62e-06)				(9.27e-06)		
Female		-0.015		-0.025		-0.016		-0.024
		(0.030)		(0.023)		(0.031)		(0.023)
Switch point (H&L)		-0.007		-0.008**		-0.007		-0.008**
		(0.006)		(0.003)		(0.006)		(0.003)
Value	all	all	value> 50	value> 50	all	all	value> 50	value> 50
Observations	2.339	2.339	1,172	1,172	2.339	2.339	1,172	1,172
Number of Subj.	118	118	118	118	118	118	118	118
Post estimation tests (Wald tests):								
H_0: HC: FPA (No CGL) = FPA (With CGL)	$p = 0.405$	$p = 0.465$	$p = 0.009$	$p = 0.017$				
H_0: HC; First 10 auctions: FPA (No CGL) = FPA (With CGL)					$p = 0.209$	$p = 0.264$	$p = 0.016$	$p = 0.022$
H_0: HC; Auctions 11-20: FPA (No CGL) = FPA (With CGL)					$p = 0.980$	$p = 0.964$	$p = 0.025$	$p = 0.045$
H_0: HC; No CGL: FPA (First 10 auctions) = FPA (Auctions 11-20)					$p = 0.5031$	$p = 0.5184$	$p = 0.140$	$p = 0.142$

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
(Note: relative bid shading not defined for $v_i = 0$)

Table 4: Average (hypothetical) profit (std. dev. in parentheses)

Treatment	Cogn. Ability	Hyp. Profit FPA	Actual Profit FPA	Actual Profit SPA	Actual Profit Both
FPA/SPA	LC	10.78 (15.620)	11.09 (15.407)	16.97 (25.245)	14.03 (21.111)
	HC	13.72 (14.111)	12.24 (16.330)	17.35 (24.604)	14.79 (21.201)
SPA/FPA	LC	10.31 (14.711)	10.24 (15.251)	14.42 (24.822)	12.33 (20.696)
	HC	11.62 (13.726)	10.48 (13.513)	15.98 (24.003)	13.23 (19.663)
Both	LC	10.58 (15.233)	10.72 (15.340)	15.87 (25.09)	13.30 (20.947)
	HC	12.54 (15.323)	11.25 (16.577)	16.58 (24.398)	13.91 (20.359)

Result 3. *Without prior experience in SPAs, (i) cognitively more able bidders tend to shade bids more than cognitively less able bidders, but (ii) less able bidders learn to lower their bids within the set of FPAs. After experiencing SPAs, cognitively more able bidders shade their bids less, while experience in SPAs does not significantly affect bid shading by cognitively less able bidders.*

3.4. Profits and (potential) benefits from cross-game learning

While in SPAs, bidding behavior itself is indicative of bidders' sophistication and profits, FPAs are strategically more complex, such that it is natural to study profits as a proxy for bidders' sophistication in the FPA format. In our setting, a subject's actual profit in each two-bidder auction depends not only on the sophistication of the own bid, but to a large extent on the rival bid as well as on the random values drawn in each given auction. To analyze bidders' sophistication in FPAs in greater detail, we calculate a subject's hypothetical profit (in each single auction), as the profit that would have been obtained if the subject had bid against the average bid of all participants in the FPA (31.96). The idea is that each subject plays against a rival that, in each auction, is randomly drawn from the population of participants.[9] Table 4 lists average profits and standard deviations by treatment and cognitive group. The third column contains hypothetical profits in the FPA, the last three columns state the actual profits in all formats. Results from GLS-regressions comparing hypothetical profits across treatments and cognitive groups in FPAs (see specifications (1a) and (1b) in Appendix, Table A1) reveal that, without experience, participants with high cognitive ability achieve significantly higher hypothetical profits in FPAs than participants with low cognitive ability. Interestingly, high-ability participants that bid in FPAs first (FPA/SPA) also earn more than the high-ability participants that bid in FPAs only after experiencing SPAs (see post-estimation Wald tests in specifications (1a) and (1b) in Table A1). That is, highly cognitively able participants do not benefit in FPAs from cross-game learning through experience in SPAs. If at all, they achieve lower profits in FPAs when experiencing SPAs before bidding in FPAs, because SPA experience reduces bid shading in FPAs for highly cognitively able bidders.[10]

[9] The results do not change if the hypothetical profit is determined using the average bid observed in the corresponding treatment.

[10] The results for realized profits in FPAs are qualitatively similar but statistically insignificant (see Table A1, specifications (2a) and (2b)).

In SPAs, high cognitively able participants do neither suffer nor benefit in terms of payoffs from cross-game learning through experience in FPAs, whereas FPA bidding experience reduces overbidding in SPAs by subjects with lower cognitive ability and thereby increases their profits (see specifications (3a) and (3b) in Table A1).

Finally, we compare total profit (FPA+SPA) between treatments. It turns out that both cognitive groups achieve higher profits in the treatment FPA/SPA, i.e., when FPAs is encountered first (see specifications (4a) and (4b) in Table A1), but they do so for different reasons: Prior experience of SPAs reduces bid shading by the cognitively more able bidders such that they benefit from bidding in FPAs first. Cognitively less able bidders are not affected by experience in SPAs, but benefit substantially from experience in FPAs before bidding in SPAs, which reduces overbidding by this group in SPAs. That is, cross-game learning helps the low cognitive group to improve bidding in SPAs while experience in SPAs appears irrelevant, or even counterproductive for the profits of highly cognitively able bidders in FPAs.

4. Discussion and conclusion

We study the role of cognitive ability, within-game learning, and cross-game learning for bidding behavior in first- and second-price private-value auctions. We first document that cognitive ability is indeed an important predictor for bidding behavior in other auction formats. Bidding quality in, both, SPAs and FPAs depends on cognitive ability: high-ability participants, when not having previous experience in other auction formats, exhibit less overbidding in SPAs and shade their bids more in FPAs than low-ability participants. Second, we complement previous findings on very limited within-game learning in SPAs, independent of cognitive ability. However, within FPAs, we find that low ability bidders learn to lower their bids when bidding repeatedly. Such learning within the set of FPAs is less pronounced for high ability bidders who seem to know how to shade bids early on.

Inspired by the work of Kagel (1995b) on cross-game learning, we then study whether cognitively less able bidders can indeed compensate for the lack of cognitive ability by experiencing FPAs before bidding in SPAs. Although FPAs and SPAs are not strategically equivalent, we find that with previous FPA experience, low ability bidders overbid substantially less such that cognitive ability is not indicative of bidding quality in SPAs anymore. In contrast, experiencing SPAs before bidding in FPAs does not improve bidding quality (in terms of bid shading in FPAs) by low ability bidders and, if at all, is irrelevant or even reduces bidding quality by high-ability bidders.

Our findings shed new light on the drivers of overbidding in SPAs. Several such drivers as well as potential means to reduce overbidding have been discussed in the literature. For example, Li (2017) has argued that overbidding in SPAs may result from the fact that a cognitively limited agent may not recognize true-value bidding as the weakly dominant strategy in SPAs and we find, indeed, that cognitive ability is an important predictor of overbidding in SPAs without prior experience in other auction formats. Hence, it is particularly cognitively less able bidders who misperceive the logic of SPAs. Further, Kagel et al. (1987) argued that overbidding in SPAs may occur due to an illusion that overbidding increases the probability of winning with often no immediate effects on profits. If so, rendering potential effects on profits more salient may reduce overbidding in SPAs. Experience in FPAs may not be a remedy for such an illusion in general. However, FPAs do render potentially forgone payoffs from high bids salient for cognitively less able bidders and thereby suggest simple bidding heuristics for bidding in SPAs: bidding (too) high may result in forgone profits. Our findings highlight that cognitively less able inexperienced bidders bid high in FPAs at the beginning but learn to reduce forgone profits by shading their bids more when bidding in FPAs repeatedly. Hence, less cognitively able participants learn within FPAs, that high bids may have negative effects on profits. In turn, they reduce their bids also in SPAs. As such it seems that FPA experience does not increase the general understanding of the logic of SPAs but rather provides low ability bidders with a simple bidding rules to follow also in SPAs.

Interestingly, we also observe that high ability bidders react when cross-game learning from SPAs to FPAs is possible. We find that bid shading in FPAs by high-ability participants is reduced after previous SPA experience. Here, a similar effect could be at play: prior experience of SPA bidding could induce an 'excessive' focus on the winning probability relative to the price being paid conditional on winning, leading to higher bids in the subsequent FPA. Given that bids in FPAs tend to be too high rather than too low (as compared to the risk-neutral benchmark) such an upwards adjustment of bids reduces participants' expected profits.

Overall, our findings suggest that experiencing other auction formats may be beneficial for some groups, but at the same time can also reduce bidding quality, as such experience does not necessarily enable bidders to learn or better understand the underlying logic of alternative auction formats but it seems to rather render particular aspects of their bidding strategy more or less salient. Therefore, cross-game learning is a potentially strong tool for improvement of bidding quality, but it can have heterogeneous effects, and does not necessarily benefit all groups.

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5. Appendix

5.1. Profits in FPAs and SPAs

Table A1 presents the regression results on hypothetical profits in FPAs and realized profits in FPAs and SPAs, as well as total profits (SPA+FPA).

Table A1: Profits (π); GLS regressions.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Dependent Variable:	Hyp. Profit: FPA		Profit: FPA		Profit:SPA		Profit: Total	
Reference category:	LC–Group (without CGL)		LC–Group (without CGL)		LC–Group (without CGL)		LC–Group (without CGL)	
Constant	10.78***	-8.971***	11.09***	-3.664***	14.42***	-10.29***	339.3***	415.5***
	(1.074)	(1.139)	(1.196)	(0.480)	(1.433)	(1.774)	(15.31)	(34.16)
CognD (HC=1)	2.934**	1.682*	1.154	0.201	1.562	1.697	7.611	1.471
	(1.384)	(0.992)	(1.241)	(1.065)	(1.951)	(1.534)	(22.70)	(21.46)
CGL-D (SPA Exp.=1)	-0.472	-1.034	-0.850	-1.344	2.545**	3.070***	-134.6***	-138.8***
	(1.439)	(1.204)	(2.018)	(2.170)	(1.233)	(1.016)	(28.37)	(31.63)
CognD $\times$ CGL-D	-1.623	-0.489	-0.915	0.118	-1.181	-0.860	-2.836	4.750
	(1.134)	(1.410)	(1.462)	(1.699)	(1.480)	(1.252)	(24.19)	(28.05)
Value		0.406***		0.336***		0.518***		
		(0.0128)		(0.0155)		(0.0103)		
Female		-2.155***		-1.179		-0.171		-9.571
		(0.396)		(0.853)		(1.053)		(22.70)
Switch point (H&L)		0.169		-0.195		-0.300*		-12.05*
		(0.164)		(0.166)		(0.180)	(5.311)	
Observations	2,360	2,360	2,360	2,360	2,360	2,360	118	118
Number of Subj.	118	118	118	118	118	118	118	118
Post estimation (Wald) tests, H_0: HC: π(No Experience) = π(With Experience):								
	$p = 0.0006$	$p = 0.0055$	$p = 0.1171$	$p = 0.2708$	$p = 0.2708$	$p = 0.1787$	$p = 0.0015$	$p = 0.0029$

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2. Instructions (SPA/FPA treatment, translated from German)

Instructions

Welcome to the experiment! From now on, please do not talk to other participants in the experiment.

Please read these instructions carefully. They are identical for all participants. If there is anything you do not understand, please indicate this by raising your hand. We will then come to you and answer your questions privately. You will make your decisions on the computer. All decisions remain anonymous. This means that you do not learn the identity of other participants and no participant learns your identity.

This experiment consists of four parts. The four parts are independent of each other; this means: your decisions in one part have no effect on other (later) parts. At the beginning of each part, you will receive detailed information about that part.

In each part of the experiment, you earn money. How exactly you earn money is described in the instructions.

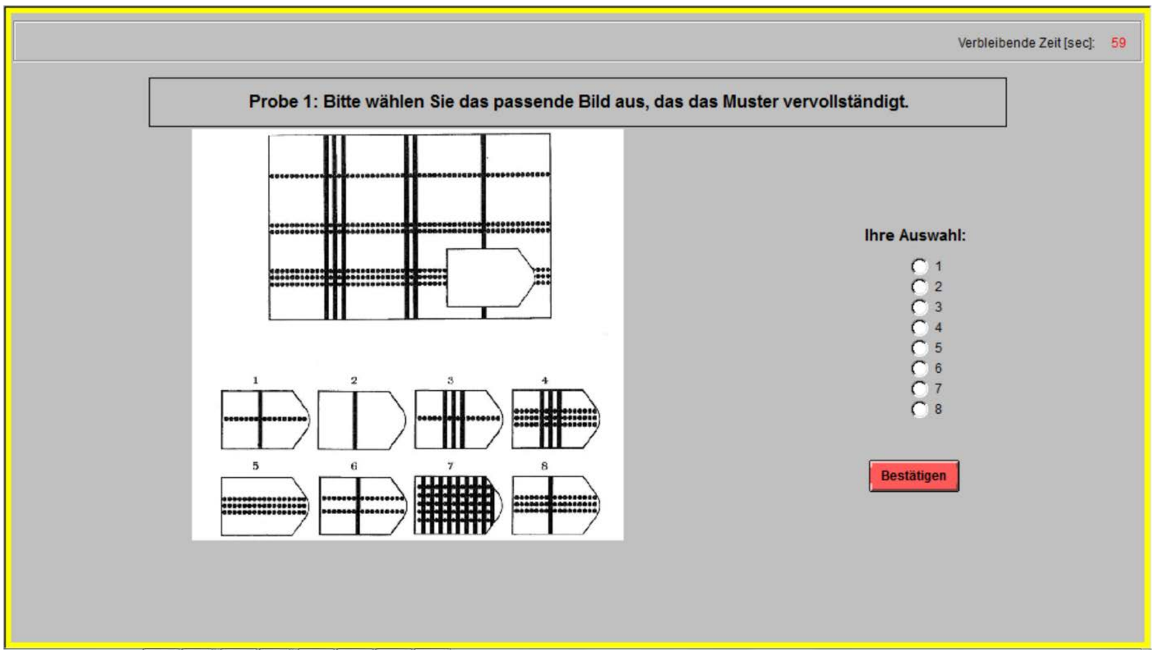
Your earnings in this experiment (sum of your earnings from all four parts) will be paid to you privately and in cash at the end of the experiment.

Part 1

In this part, you have to complete graphic patterns. There are 22 patterns of increasing difficulty in total. You have a total of **5 minutes (300 seconds)** to complete as many patterns as you can. There will always be eight possible answers per pattern. You will receive € 0.30 for each correct answer. At the end of the experiment, i.e. after part 4, you will be shown the result of part 1.

There are two example patterns at the beginning. These are intended to help you familiarize with the task. We will display the correct answers (only) for the two example tasks after you solved them. You do not have a time limit for solving the test patterns and the results do not influence your payout. Afterward, you continue directly with the part of the task that is relevant for your payment.

A screen always shows only one pattern and looks like this:



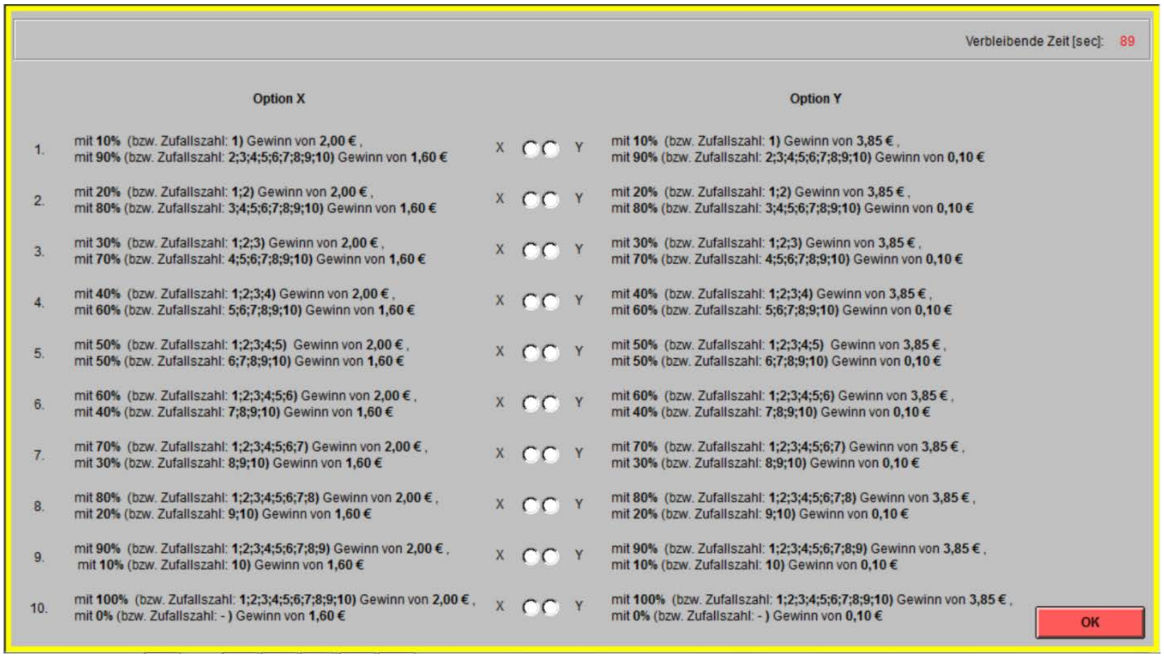
[Trial task 1: Please choose the picture that completes the pattern, your choice:…, Confirm].

In the left part of the screen, you will see the pattern shown and the eight possible answers. Only **one** out of the eight answers is correct. At the top right of the screen, you will see the remaining time you have for Part 1. To complete a pattern, select one of the numbers 1-8 in the right-hand side of the screen and click the "Confirm" button. Only then will you move on to the next pattern. It is not possible to jump back and forth between patterns.

If you still have questions, please raise your hand and an experimenter will come to you to clarify your question. This also applies if something is unclear to you during this part.

Part 2

In Part 2 you make 10 decisions. The screen with all 10 decision problems looks like this:



Verbleibende Zeit [sec]: 89

	Option X			Option Y
1.	mit 10% (bzw. Zufallszahl: 1) Gewinn von 2,00 € , mit 90% (bzw. Zufallszahl: 2;3;4;5;6;7;8;9;10) Gewinn von 1,60 €	X	Y	mit 10% (bzw. Zufallszahl: 1) Gewinn von 3,85 € , mit 90% (bzw. Zufallszahl: 2;3;4;5;6;7;8;9;10) Gewinn von 0,10 €
2.	mit 20% (bzw. Zufallszahl: 1;2) Gewinn von 2,00 € , mit 80% (bzw. Zufallszahl: 3;4;5;6;7;8;9;10) Gewinn von 1,60 €	X	Y	mit 20% (bzw. Zufallszahl: 1;2) Gewinn von 3,85 € , mit 80% (bzw. Zufallszahl: 3;4;5;6;7;8;9;10) Gewinn von 0,10 €
3.	mit 30% (bzw. Zufallszahl: 1;2;3) Gewinn von 2,00 € , mit 70% (bzw. Zufallszahl: 4;5;6;7;8;9;10) Gewinn von 1,60 €	X	Y	mit 30% (bzw. Zufallszahl: 1;2;3) Gewinn von 3,85 € , mit 70% (bzw. Zufallszahl: 4;5;6;7;8;9;10) Gewinn von 0,10 €
4.	mit 40% (bzw. Zufallszahl: 1;2;3;4) Gewinn von 2,00 € , mit 60% (bzw. Zufallszahl: 5;6;7;8;9;10) Gewinn von 1,60 €	X	Y	mit 40% (bzw. Zufallszahl: 1;2;3;4) Gewinn von 3,85 € , mit 60% (bzw. Zufallszahl: 5;6;7;8;9;10) Gewinn von 0,10 €
5.	mit 50% (bzw. Zufallszahl: 1;2;3;4;5) Gewinn von 2,00 € , mit 50% (bzw. Zufallszahl: 6;7;8;9;10) Gewinn von 1,60 €	X	Y	mit 50% (bzw. Zufallszahl: 1;2;3;4;5) Gewinn von 3,85 € , mit 50% (bzw. Zufallszahl: 6;7;8;9;10) Gewinn von 0,10 €
6.	mit 60% (bzw. Zufallszahl: 1;2;3;4;5;6) Gewinn von 2,00 € , mit 40% (bzw. Zufallszahl: 7;8;9;10) Gewinn von 1,60 €	X	Y	mit 60% (bzw. Zufallszahl: 1;2;3;4;5;6) Gewinn von 3,85 € , mit 40% (bzw. Zufallszahl: 7;8;9;10) Gewinn von 0,10 €
7.	mit 70% (bzw. Zufallszahl: 1;2;3;4;5;6;7) Gewinn von 2,00 € , mit 30% (bzw. Zufallszahl: 8;9;10) Gewinn von 1,60 €	X	Y	mit 70% (bzw. Zufallszahl: 1;2;3;4;5;6;7) Gewinn von 3,85 € , mit 30% (bzw. Zufallszahl: 8;9;10) Gewinn von 0,10 €
8.	mit 80% (bzw. Zufallszahl: 1;2;3;4;5;6;7;8) Gewinn von 2,00 € , mit 20% (bzw. Zufallszahl: 9;10) Gewinn von 1,60 €	X	Y	mit 80% (bzw. Zufallszahl: 1;2;3;4;5;6;7;8) Gewinn von 3,85 € , mit 20% (bzw. Zufallszahl: 9;10) Gewinn von 0,10 €
9.	mit 90% (bzw. Zufallszahl: 1;2;3;4;5;6;7;8;9) Gewinn von 2,00 € , mit 10% (bzw. Zufallszahl: 10) Gewinn von 1,60 €	X	Y	mit 90% (bzw. Zufallszahl: 1;2;3;4;5;6;7;8;9) Gewinn von 3,85 € , mit 10% (bzw. Zufallszahl: 10) Gewinn von 0,10 €
10.	mit 100% (bzw. Zufallszahl: 1;2;3;4;5;6;7;8;9;10) Gewinn von 2,00 € , mit 0% (bzw. Zufallszahl: -) Gewinn von 1,60 €	X	Y	mit 100% (bzw. Zufallszahl: 1;2;3;4;5;6;7;8;9;10) Gewinn von 3,85 € , mit 0% (bzw. Zufallszahl: -) Gewinn von 0,10 €

OK

In each of these decision problems you can choose between **two alternative options.** Your decision is not valid until you have made a choice for all problems (i.e. for each row) and confirmed your choice by clicking the OK button. Take enough time to make your decisions because your choice - as described below - will determine your payoff from Part 2. All figures in Part 2 are directly in € amounts.

Your payoff is determined as follows: The computer randomly draws two numbers between 1 and 10. The first random number determines the line from the table shown above. The option you choose in this row is then executed with the second randomly drawn number. The profit from this option is then paid to you at the end of the experiment.

For example: Assume that the computer randomly chooses the number 2 first, i.e. the decision problem in the 2nd row of the table, and you have chosen option X there. In this case, you will receive either €2 (with probability 20% or if the second randomly selected number is 1 or 2) or €1.60 (with probability 80%, that is, if the second randomly selected number is 3;4;5;6;7;8;9 or 10). Assuming the computer randomly chooses 9 as the second number, your payoff for part 2 of the experiment would be €1.60.

You only make your choices **once**. The random numbers are drawn after the end of part 4. Then you will be shown the result from part 2.

If you still have questions, please raise your hand and an experiment leader will come to you. This also applies if something is unclear to you during the part.

Part 3

In Part 3 you participate in 20 auctions. All entries in Part 3 are denoted in ECU (*Experimental Currency Unit*). Each auction consists of two bidders, i.e. you and one other bidder. This other bidder is another participant in the room who is randomly selected before each auction.

In each auction, a fictitious good is auctioned off. At the beginning of each auction, the bidders' personal product values are first determined. These values are integers from the interval *0* to *100 ECU* and are determined randomly. Every integer between 0 and 100 is equally probable. The personal product values of the different bidders are independent of each other, i.e. they will usually be different. Each bidder learns only his own product value, but not that of the other bidder. Then, knowing their product values, the bidders place a single integer bid for the good.

The following auction rule applies:

Second-price auction: The bidder with the highest bid receives the good. The bidder then pays the second-highest bid as the price. His profit is the difference between his product value and the price. The bidder with the second highest bid receives nothing and pays nothing, i.e. his profit is zero. If the bids are identical, the buyer is chosen by lot. In this case, the second-highest bid is equal to the highest bid.

After each auction you will find out whether you have won the auction. Furthermore, you will find out the price paid for the good, the bid of your fellow bidder and your own profit in this auction. However, you will not know the product value of the other bidder. For your information, your own product value and your own bid for this auction are displayed again.

Please note that losses are possible. Should the price in an auction be higher than your product value and should you win the auction, then you will make a loss. This will be offset against your winnings or the initial equipment. You will receive an initial endowment of 30 ECU for this part.

The exchange rate ECU to € is: 1 ECU = 0.03 €. At the end of the experiment, i.e. after part 4, you will be paid your earnings from all auctions in part 3.

If you still have questions, please raise your hand and an experiment leader will come to you. This also applies if something is unclear to you during the part.

Part 4

In Part 4 you participate in 20 auctions. All entries in Part 3 are denoted in ECU (*Experimental Currency Unit*). Each auction consists of two bidders, i.e. you and one other bidder. This other bidder is another participant in the room who is randomly selected before each auction.

In each auction, a fictitious good is auctioned off. At the beginning of each auction, the bidders' personal product values are first determined. These values are integers from the interval *0* to *100 ECU* and are determined randomly. Every integer between 0 and 100 is equally probable. The personal product values of the different bidders are independent of each other, i.e. they will usually be different. Each bidder learns only his own product value, but not that of the other bidder. Then, knowing their product values, the bidders place a single integer bid for the good.

The following auction rule applies:

First price auction: The bidder with the highest bid acquires the good. The bidder pays his bid as the price. His profit is the difference between his product value and the price. The bidder with the second highest bid receives nothing and pays nothing, i.e. his profit is zero. If the bids are identical, the buyer is chosen by lot.

After each auction you will find out whether you have won the auction. Furthermore, you will find out the price paid for the good, the bid of your fellow bidder and your own profit in this auction. However, you will not know the product value of the other bidder. For your information, your own product value and your own bid for this auction are displayed again.

Please note that losses are possible. Should the price in an auction be higher than your product value and should you win the auction, then you will make a loss. This will be offset against your winnings or the initial equipment. You will receive an initial endowment of 30 ECU for this part.

The exchange rate ECU to € is: 1 ECU = 0.03 €. At the end of the experiment, i.e. after this part, you will be paid your earnings from all auctions in this part.

We then ask you to answer a few more questions about yourself honestly and completely. Once all participants have completed answering these questions, you will be told your earnings from parts 1 to 4. We will then call you individually using your participant number. Your total earnings will then be paid to you privately and in cash.

If you still have questions, please raise your hand and an experiment leader will come to you. This also applies if something is unclear to you during the part.