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Abstract

It is generally thought that market outcomes are improved with the provision of market information. As a result, the use of repeated rounds with price feedback has become standard practice in the applied experimental auction valuation literature. We conducted two experiments to determine how rationally subjects behave with and without price feedback in a second price auction. Results from an auction for lotteries show that subjects exposed to price feedback are significantly more likely to commit preference reversals. However, this irrationality diminishes in later rounds. Results from an induced value auction indicate that price feedback caused greater deviations from the Nash equilibrium bidding strategy. Our results suggest that while bidding on the same item repeatedly improves auction outcomes, this improvement is not the result of price feedback.

JEL codes: D44

Keywords: bid affiliation; posted prices; induced value experiment; preference reversals; lotteries

1. Introduction

Value elicitation has become standard practice in testing economic theory and carrying out cost-benefit analysis. Because of the skepticism surrounding the validity of values obtained from stated preference methods, economists have turned to experimental approaches that involve the exchange of real goods and real money. Among these experimental methods, perhaps none has been more popular than auction-based approaches.

The appeal of auction-based methods is both conceptual and practical. Conceptually, certain types of auctions are incentive compatible, meaning people have a dominant strategy to submit bids equal to their value for the auctioned good. Practically, the analyst receives bids from each person, which by-passes the need to formally specify a functional form for the utility function or the need to use econometric modeling to derive willingness-to-pay. Given these advantages, it is not surprising that economists have published well over 100 studies using experimental auctions to value goods as diverse as meat, cars, coffee mugs, sports cards, and lotteries (Lusk and Shogren 2007).

As the use of experimental auctions has expanded and knowledge of the approach has matured, a few areas of controversy have arisen. One such controversy is the appropriateness of conducting auctions using repeated rounds with price feedback. This controversy is of major interest to experimental auction practitioners because it directly relates to whether the incentive compatibility property holds. The controversy is of interest to economists more generally because it speaks to the question of how values are formed, the factors that influence how people come to value goods, and how people respond to price feedback in markets.

Like any controversy, the debate over this topic has become heated as competing camps have found and emphasized different results, e.g., Harrison (2006) and Shogren (2006). What is needed is for the divided parties to collaboratively design and conduct a set of experiments to help settle some of the uncertainties. Bateman et al. (2005) have persuasively argued for the need for researchers to engage in such "adversarial collaborations" to move forward the state of knowledge. Our paper represents an explicit attempt to implement an adversarial collaboration as it relates to the appropriateness of using repeated rounds with price feedback in experimental auctions. The authors of this paper have divergent opinions about whether such a practice should be used when conducting experimental auctions.

In what follows, we first provide background on repeated round auctions to set the stage and illustrate why the topic is important and to clearly define some of the terms. Then, we describe two sets of experiments designed by all of the authors as a way to help move the debate forward. The first experiment compares the results from a choice experiment and a series of auctions for lotteries to test whether price feedback reduces the frequency of preference reversals. The second set of experiments use induced-value auctions to test whether price feedback motivates subjects to submit bids closer to their induced values. The following sections discuss the results and include our interpretations of the results.

2. Background and State of the Controversy

Experimental economists have used repeated rounds in induced value experiments since the dawn of the field of inquiry. In his first papers using the double oral auction to determine whether buyers and sellers could arrive at the competitive outcome, Smith (1962) showed that it took several rounds for prices to converge to the equilibrium. Moreover, when psychologists first demonstrated that subjects gave more in voluntary contribution games than theory predicted, economists quickly found that this was a static result that tended to dissipate over repeated rounds (Ledyard, 1995). As a result of such findings, the standard practice in experimental economics is to use repeated rounds with price feedback (e.g., Davis and Holt, 1993, Kagel and Roth, 1995).

When economists ventured to elicit "homegrown" values rather than inducing them, some adopted the standard practice of running several rounds of bidding with price feedback. This move was motivated in part because it was consistent with standard experimental practices, but also because of conceptual reason and empirical evidence. Conceptually, Plott (1996) offered the discovered preference hypothesis suggesting people's preferences are learned through experience and market exposure. Empirically, several studies suggested that people become more "rational" over repeated rounds with price feedback, e.g., Cox and Grether (1996) and Shogren et al. (2001). As a result, the use of repeated auctions round with price feedback became standard practice.

However, Milgrom and Weber's (1982) theoretical work and Kagel, Harstad, and Levin's (1987) induced value experiments showed that the incentive compatibility property of auctions such as Vickrey's second-price auction break down if values are affiliated. Some researchers became concerned that repeatedly exposing subjects to market price information might cause their values to become affiliated – in which case their bids could no longer be assumed to equal their true values. Over the following years, several studies attempted to determine whether and to what extent bid affiliation was a problem. We will discuss some of these studies momentarily; however, before proceeding it is important to precisely define what is meant by the term "affiliation" because the term has been used in various ways throughout the literature. Indeed, much of the controversy in this literature has arisen because the term has been used in different ways by different researchers to refer to related but slightly different phenomena.

Affiliation has come to be used to describe an outcome in which subjects' bids in one round are correlated with market prices in a previous round. A common approach used in previous research to investigate whether affiliation exists is to estimate a regression where bids are regressed on prices posted in previous rounds and a time trend variable or round dummy variables. Studies commonly find that bids are significantly related to prices posted in previous rounds and are also influenced by the trend variable. Previous research has tended to attribute either or both effects to "affiliation." And it is here that the controversy and confusion lies. Why the correlation occurs and what the correlation means are the key questions at issue. Thus, we consider several possible explanations for the correlation. In what follows, we propose a taxonomy of explanations for the correlation between bids and prices, namely:

- the *value interdependence effect*,
- the *anchoring effect*,
- the *detachment effect,*
- the *learning effect*, and
- the *competitive effect*.

3. Potential explanations for correlation between posted prices and bids

3.1 The value interdependence effect

We first consider the *value interdependence effect*. In their classic work, Milgrom and Weber (1982) use the term affiliation to refer to the situation in which individuals' values are interrelated. Affiliation, in this context, implies that individual i's value depends on individual j's value. Thus, individual i's value for a good can be written as $v_i = \alpha t_i + \beta \sum_{i \neq j} t_j$, where t_i is individual i's own "signal" of value for the good, t_j is the "signal" of value of the other j people, and where α and β are the respective weights assigned to individual i's signal versus all other individuals' signals. In the extreme, $\alpha = \beta$ and a pure common value situation arises in which everyone shares the same value. In this case, the well known winner's curse can arise. Assuming all bidders' values are independently and uniformly distributed, Klemperer (1999) shows that a person's optimal bid in a second-price auction is $b_i^* = (\alpha + (n/2)\beta)t_i$, where n is the number of bidders. Thus, an individual only submits a bid equal to their own true value (i.e., $b_i^* = t_i$) if $\beta = 0$, meaning values are independent.

In the context of value interdependence, Milgrom and Weber (1982) show that providing information can increase a seller's revenue, implying that information provision increases bids. Thus, if values are interrelated, then revealing the market price in repeated-round auctions might signal the quality of the good and/or the availability of field substitutes and, in so doing, increase bids.

If the correlation between prices and bids results from value interdependence, two problems arise. First, as shown above, people do not have an incentive to bid their own signal of value, and as such the second-price auction is no longer incentive compatible. Second, values for the good change over rounds as more information enters the market. Thus, if values are interdependent, there is no "true" value to observe that is independent of what one bidder thinks of another. Thus, the second-price auction will not give incentives for people to bid an amount equal to whatever their signal of value is in any particular round.

The existence of value interdependence in auctions for goods with homegrown values would have profound implications for the experimental valuation literature, in that it would suggest that researchers should abandon second-price auctions and other similar mechanisms. When values are inter-related, auction mechanisms like those developed by Dasgupta and Maskin (2000) or Perry and Reny (2002) would be required to address this issue. Such mechanisms are complicated and require people to submit a bid *function* relating their bid to other individuals' bids. Margolis and Shogren (2004) showed that this mechanism has some promise in eliciting values in induced-value laboratory experiments; however, they suggest that the complicated nature of the mechanisms might require multiple bidding rounds and experience to achieve its full theoretical potential.

Moreover, if value interdependence exists, then it is insufficient to simply conduct single-shot or single-round auctions as suggested by Harrison, Harstad and Rutström (2004). Such advice assumes values are not interdependent when subjects walk into the experiment, but only through the act of bidding in repeated rounds with price feedback do their values *become* interdependent. It seems more likely that values were interrelated before the auction even began, and as is shown above, even single-round bidding does not escape the critique that the second-price auction mechanism is not incentive compatible.

Whether such value interdependence exists in the typical settings in which applied experimental auctions are applied is an open question. As noted, finding a positive correlation between bids in one round and prices in previous rounds is not sufficient to conclude that value interdependence exists. One argument is that people use posted prices to partially infer the quality of the good, causing values to become affiliated. If true, *relative* values of quality-differentiated goods should be affected by posted prices. Lusk and Shogren (2007) show, however, that the *differences* between bids for meat of different qualities remain roughly constant across rounds despite the fact that the overall level of bids increased. Relative preferences did not change with the price information, implying that people are not using posted prices to signal unknown quality or availability.

Another way to look at the issue is to compare bidding behavior across mechanisms that utilize different levels of price feedback. For example, Lusk, Feldkamp, and Schroeder (2004) and Rutström (1998) both found that the BDM mechanism and English auctions generated statistically equivalent results. This is fascinating because the English auction permits the greatest possible amount of market feedback as every individual can see exactly what every other individual is doing (and thus has the greatest potential for bid affiliation), whereas the BDM permits no feedback about other individuals' values (and thus has no potential for development of bid affiliation). The fact that the English auction and BDM yield similar results suggests that values are not influenced by what one person sees another person doing.

Because of these findings and because value interdependence would imply that researchers should abandon second-price auctions altogether, in this paper we rely on lottery and induced-value experiments designed to eliminate value interdependence. This allows us to focus on four other explanations of why bids in later rounds may be correlated with prices posted after earlier rounds..

3.2 The anchoring effect

The anchoring effect is named for the psychological phenomenon of "anchoring and adjustment" (Tversky and Kahneman, 1974). Namely, when formulating a numerical estimate, individuals begin with an initial figure which they adjust to arrive at a final estimate. While the anchoring effect bears superficial similarity to value interdependence, it is different in that the anchoring effect may be present even for strictly private-values good. Ariely, Loewenstein, and Prelec (2003) allow subjects to bid for the opportunity to hear an annoying noise. All subjects heard a sample of the noise at the experiment's outset, which the authors argue "makes the valuations of others prescriptively irrelevant" (p. 89). Depending on the treatment, subjects were asked whether they would be willing to accept either \$0.10 or \$0.50 in exchange for hearing the sound again, and were then asked to submit WTA bids in a series of BDM auctions for noises of varying duration. WTA bids submitted by subjects asked to consider the \$0.50 offer were on average 50% higher than those submitted by subjects asked to consider the $0.10 offer. Building on this experiment, Tufano (2010) also showed that market participants adjusted their bids towards the price observed in previous market periods when, by design, individuals' values should not be affiliated with the market price.

The presence of an anchoring effect is consistent with the results from a series of three closely related studies finding: (a) WTA and WTP for familiar private goods converge in repeated second-price auction rounds where posted prices reflect the upper end of the value distribution for potential buyers and the lower end of the value distribution for potential sellers (Shogren et al., 1994), (b) the WTA-WTP gap persists in repeated BDM rounds where posted prices contain no information about subjects' valuations (Shogren and Hayes, 1997), and (c) WTP and WTA *diverge* in repeated ninth-price auction rounds where posted prices reflect the *lower* end of the value distribution for potential buyers and the *upper* end of the value distribution for potential sellers (Knetch et al., 2001). While these results are not conclusive by themselves, combined they suggest that subjects' bids may be systematically influenced by posted prices, with relatively high prices leading to higher average bids.

More formally, in the presence of anchoring, individual *i*'s value for a good can be written as $v_i = \alpha t_i + \beta \mathrm{A}$, where t_i is individual *i*'s own "signal" of value for the good, *A* is an anchor, and α and β are the respective weights assigned to individual *i*'s original signal versus the anchor. In repeated-round auctions, the anchor *A* is the posted price in a previous auction round. In this setting, even if subjects bid truthfully, their bids reflect both their own signal as well as the anchor adjustment: $b_i = \alpha t_i + \beta \mathrm{A}$. Assuming researchers wish to observe t_i, bids obtained in the *first* round of bidding best reflect this signal.

3.3 The detachment effect

The detachment effect relates to whether subjects view the auction exercise as salient. Although the second-price auction is theoretically incentive compatible for private-value goods, it does not motivate "off-margin" bidders to bid truthfully in practice (see Shogren, et al., 2001). For example, consider a subject who bids $0.50 in the initial rounds of an auction where the prices posted after rounds 1, 2, and 3 are $4.50, $4.75, and $5.00. This subject may decide that since her chances of winning subsequent auction rounds are virtually nil, there is no incentive to bid truthfully in later rounds. The cost of misbehaving, in other words, is extremely low for off-margin bidders (Harrison, 1992, Lusk et al., 2007). Posting prices in a second-price auction may exacerbate this problem by reinforcing just how far off-margin bidders' valuations are from those at the upper end of the value distribution. Detachment may also partly explain the results from Shogren et al. (1994), Shogren and Hayes (1997), and Knetsch, Tang and Thaler (2001) discussed above. Off-margin bidders in second-price and ninth-price auctions could have become detached and let their bids drift toward the posted price, increasing average bids in a second-price auction and decreasing average bids in a ninth-price auction.

However, as Lusk, Alexander, and Rousu (2007) show, a median-value auction tends to provide the highest incentives for all types of bidders (high, medium, and low value) to bid truthfully.[1] Using repeated median-value auction or a random *n*th-price auction rounds and price feedback highlights that any bid (high, medium, or low) might be binding, and thus increase incentives for truthful bidding.

Price feedback provides information about the likelihood of winning an auction. Depending on the mechanism employed and the magnitude of subjects' value, feedback can

[1] In a median-value auction, the selling price equals the median bid and all bidders who submitted higher bids pay the median price in exchange for the good.

serve to motivate or de-motivate a bidder to carefully consider a bidding strategy. In the case of repeated second-price auction rounds, mid to low value bidders may become detached as they learn that they have little chance of winning. If price feedback leads to detachment, bids equal $b_{it} = v_i + \eta_{it}$, where η_{it} is a random variable with zero mean and a variance that increases with $|v_i - p_{t-1}|$ or the absolute difference between *i*'s value and the posted price from the previous round. If the detachment effect is the cause of the correlation between bids and prices, bids obtained in the *first* round of bidding most accurately reflect true preferences. Bid variance should increase across rounds as off-margin bidders become detached.

3.4 The learning effect

Another explanation for the correlation between bids and prices is a phenomenon we refer to as the learning effect. The incentives to bid truthfully are not always transparent to auction participants even if told. In many auctions, and in everyday bargaining experiences, individuals have likely developed heuristics such as "buy low" even if told that optimal behavior is to bid true value. Repeated rounds with price feedback help people learn that this heuristic is not applicable in the laboratory auction environment. That is, suppose a person, based on previous buying behavior in other field contexts, adopts a strategy of understating their true valuation in a misunderstood attempt to garner additional surplus. Posting a high price will force them to reevaluate this strategy and increase their bid, and the higher the price the more pronounced the departure from the heuristic. Such a finding would be quite positive as people would bid closer to true value.

If the learning effect exists, people submit bids that equal their true value, v, *less* an additional profit/surplus, π, they mistakenly try to accrue: $b_{it} = v_i - \pi_{it}\left(price_{t-1}, n\right)$, where individual *i*'s bid in round *t* depends on their value, and on the perceived profit they believe they can make, which depends on the number of other bidders, *n*, and the price in the previous round. When people observe higher prices from previous rounds, they realize they cannot seek the profit they hoped to obtain, and because expected profits fall, bids increase. If the learning effect exists, underlying values stay the same throughout the bidding rounds, but people adjust bids upward toward their values as they learn about the incentives inherent in the mechanism. If the learning effect is the cause of the correlation between bids and prices, bids obtained in the *last* round of bidding would be expected to most accurately reflect true preferences.

3.5 The competitive effect

Posting prices might also cause people to change their bids as a result of a *competitive effect*. The competitive effect is similar to the learning effect except for the underlying assumption about the motivation for submitting bids not equal to the true value. Whereas the learning effect asserts that people adjust their bid to try to garner additional monetary surplus, the competitive effect asserts that people adjust their bid because they get additional utility from winning the auction. Under the competitive effect, bids equal $b_{it} = v_i + winner_{it}\left(price_{t-1}, n\right)$, where *winner* is the extra utility (stated in dollar terms) derived from winning an auction. Here, a higher price in a previous round will cause an increase in bids as people try to gain the extra utility of winning. If the competitive effect is the cause of the correlation between bids and prices, bids obtained in the *first* round of bidding most accurately reflect true preferences.

3.6 Summary

Price-feedback advocates argue that subjects need experience to learn that bidding truthfully is indeed in their best interest so as to gain the positive benefits of the learning effect. Skeptics argue that there are alternative training regimens that avoid the shortcomings of price feedback. To reach consensus, we investigate whether the potential benefits from the learning effect outweigh the combined effects of competitive, detachment, and anchoring effects. This is the empirical question we aim to answer with the experiments detailed in section 5.

4. Previous Research on Affiliation

Before proceeding, it is worth looking more specifically at research conducted on the effects of using repeated-round auctions with price feedback. List and Shogren (1999) conducted one of the first studies on the issue. They found that repeated auction rounds with price feedback caused a slight increase in median bids for unfamiliar goods. A $1 increase in the posted price was associated with an eight cent increase in the median bid for unfamiliar goods. By contrast, they found that median bids for familiar goods were not affected by posted prices. They further found that non-price information attenuated the affiliation effect for unfamiliar goods.

Alfnes and Rickertsen (2003) also found that posted prices caused a small increase in bids; however, they showed that the trend in bid increases was similar across all goods investigated in their study leading them to conclude, as in List and Shogren (1999), that the learning effect is primarily responsible for the increase in bids across rounds.

Harrison, Harstad, and Rutström (2004) reanalyzed the data in Hoffman et al. (1993) and showed that controlling for price feedback in regression analysis reversed one of the original study's main conclusions. This led Harrison, Harstad, and Rutström (2004) to argue against using repeated auction round. They also showed that bids for beef steaks were affected by prices in previous rounds and argued that such an effect was due to affiliation. One important caveat about the Hoffman et al. (1993) study is that bids in every round were binding – a fact that would itself induce a trend in bids over a rounds; subsequent studies tend to select one round as binding to avoid demand reduction effects.

Lusk and Shogren (2007) showed that some of the previously observed results may be due to inadequate attention paid to modeling individual heterogeneity. They showed that although bids were affected by posted prices in previous rounds using a traditional aggregate regression model, posted prices did not significantly affect bids using individual-specific regressions despite the fact that other variables, such as steak quality, were significant.

Corrigan and Rousu (2006) exogenously varied the posted price via the use of confederate bidders solicited before the auction and instructed to submit unusually high bids. Their results show that the confederates' bids, and thus the market prices, significantly influenced others' bids for familiar private-value goods. For example, the authors found that mean WTP for a candy bar increased by 96% over the course of 10 auction rounds with confederate bidders, while mean WTP increased by just 3% across rounds in the absence of confederates.

Drichoutis et al. (2009) criticized the econometric models used in these previous studies, in which bids were regressed against prices in previous rounds, because of the potential for endogeneity between bids and prices. They used three datasets from previously published studies that employed second-price auctions with repeated rounds and price feedback. Once the endogeneity problem was corrected econometrically using a dynamic panel estimator, they found a significant correlation between bids and prices from previous rounds.

5. Experiments

While the studies discussed in the previous section differ in their conclusions regarding the appropriateness of using repeated rounds with market feedback, what they have in common is that they all focus on conventional goods with homegrown values. We believe that the reliance on homegrown-value goods largely explains why researchers have struggled to reach consensus on the usefulness of price feedback. Because it is impossible to know *ex ante* what a homegrown-value good is worth to auction participants, researchers have not been able to definitively show whether repeated rounds with price feedback motivate participants to submit bids that better represent their underlying valuations.

To address this shortcoming, we developed two experiments which parallel the design commonly used in the experimental auction valuation literature in every regard except that we replace the use of conventional homegrown value goods with goods that allow us to objectively observe whether market feedback improves auction outcomes. The first experiment focuses on preference reversals in the market for lotteries. Lotteries are homegrown-value goods, but assuming rationality, individuals' rankings of two lotteries should be the same whether they are participating in a choice task or submitting separate bids for the two lotteries in an experimental auction. Comparing the frequency of preference reversals across treatments with and without price feedback allows us to objectively determine whether price feedback leads to increased rationality.

The second experiment uses induced values. Because we know what the goods are worth to auction participants *ex ante*, we can compare the difference between induced values and bids across treatments with and without price feedback. This allows for a cleaner test of whether price feedback leads to demand-revealing bidding than if we used homegrown-value goods.

5.1 Experiment 1: The rationality experiment

5.1.1 Description of the experiment

A conventional lab experiment was conducted using z-Tree software (Fischbacher, 2007).[2] subjects were undergraduate students at Agricultural University of Athens. During recruitment, the nature of the experiment and the expected earnings were not mentioned.

A second-price auction was used to determine subjects' selling price for lotteries. A between-subject 2x2 design was adopted varying the extent of training (minimal vs. extensive training) and posting of market-clearing prices (posting vs. no posting of the second-highest price). Each subject participated in only one treatment. The size of the groups varied from 17 to 18 subjects per treatment. Each treatment lasted no more than an hour. In total, 71 subjects participated in our experiments, which were conducted in March 2009.

Each session included four phases: the training phase, the choice phase, the auction phase and the post-auction phase. Subjects were given prior instructions on the overall layout of the session and were also reminded about the procedures at the beginning of each phase.

5.1.2 The training phase

A second-price Vickrey auction (1961) was used to elicit subjects' values for lotteries. After arriving at the lab, subjects were randomly assigned to a computer. Subjects were given €15 as a participation fee at the end of the experiment. We emphasized that although they were not given the money at the beginning of the experiment, the €15 was theirs to use as they please and that they should think that they have this money already. To control for possible monetary endowment effects, subjects were also told that a random amount of money between €0.50 and €3 was going to be assigned to each one of them.[3] Everyone then received a random draw

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[2] z-Tree is a software package designed to facilitate computer-based economic experiments including experimental auctions. According to Google Scholar more than 1900 studies cite the paper documenting z-Tree (Fischbacher, 2007).

[3] In every step that involved random drawings by the computer, we reassured subjects that the drawing was fair and that extra care was taken by the programmer to make sure that this is the case.

determining their individual-specific extra fee, which was added to their participation fee as soon as the computerized phase of the experiment began. We emphasized to the subjects that the endowment they received was private information and that they should not communicate this information to other subjects in the lab. All transactions were completed at the end of the experiment.

Subjects in the extensive training treatments watched a short PowerPoint presentation to familiarize them with the auction and procedures. The presentation included a short explanation of the second-price auction, along with a numerical example demonstrating why it is in subjects' best interest to bid truthfully. Subjects then took a short computerized test regarding the procedure, after which the monitor explained the correct answers.

Next, subjects bid in five *hypothetical* multi-product auction rounds.[4] The monitor emphasized that while these rounds were simply intended to familiarize subjects with the auction procedure, they should bid as if they were in a real auction. The monitor also emphasized that one binding round and product would be randomly chosen at the end of these rounds. A screen displayed subjects' hypothetical payoffs after these rounds.

Subjects then bid in five *real* multi-product auction rounds.[5] The monitor emphasized that these rounds were real and that winners would actually pay for the products. Again, one round and one product were randomly chosen as binding at the end of these rounds.

Subjects who participated in the minimal training treatment were not exposed to the full training as described above. Subjects in the minimal training treatment were not provided with a numerical example of how a second-price auction works, were not given a computerized test and

[4] The products were a packet of gums, a bag of cookies and a bag of potato chips.
[5] The products we used were a Tobleron chocolate, a pack of Soft Kings cookies and Kraft's Lacta chocolate.

were not explicitly informed about the incentive compatibility of the auction. They also participated only in the hypothetical rounds.

5.1.3 The choice phase

Subjects indicated their preference for each of three pairs of lotteries with the understanding that one pair would be randomly selected as binding. Table 1 presents the bet pairs with their probabilities and expected payoffs. The ordering of bet pairs was randomized across subjects to avoid order effects

Bet pairs 1 and 3 were adopted from Cox and Grether (1996). Bet pair 2 was added as a medium expected payoff category. Each bet pair included a “P-bet” and a “$-bet”. A P-bet lottery involves a bet with a high probability of winning a modest amount and a low probability of losing an even more modest amount. A $-bet involves a bet with a modest probability of winning a large amount and a high probability of winning a modest amount. Preference reversal studies typically find that a significant fraction of subjects state prices that are opposite to the choices made out of the respective lotteries (see Seidl, 2002 for a review). Notice that for bet pair 1, the bad outcome for the $-bet is worse than that for the P-bet. The opposite is true for bet pair 3, while for bet pair 2 the bad outcomes are equal.

5.1.4 The auction phase

Subjects bid on the same six lotteries shown in table 1, indicating how much, if anything, they were willing to pay to buy each lottery. Lottery order was again randomized across subjects. Subjects repeated the bidding task for ten consecutive rounds with the understanding that only one lottery and one round would be randomly chosen as binding. In the price-feedback treatment, subjects observed the second-highest price and winner's ID after each round. In the no-feedback treatment subjects only observed the winner's ID.

5.1.5 The post-experimental phase

Subjects provided information about their age, household size and income. Experimental instructions are available at https://sites.google.com/site/postedprices/.

5.1.6 Econometric analysis

Figure 1 depicts mean rates of preference reversals by treatment across rounds.

Figure 2 shows mean bids over all lotteries across rounds and treatments. It is obvious that mean bids increase across rounds. There is no difference, however, across treatments for the first three rounds and it is only after round 4 that bids begin to differ. Subjects in the price-feedback treatment bid higher, on average, than in the no-feedback treatment. In addition, subjects in the extensive-training treatment bid on average higher than subjects in the minimal-training treatment.

To account for the panel nature of our data, we estimate a random parameters probit model, where the probability of observing a preference reversal is specified as:

$$\text{(1)} \qquad \operatorname{Prob}\left[y_t = 1\right] = F\begin{pmatrix} b_{0i} + b_{1i}t + b_{2i}Price + b_{3i}Train + b_{4i}Price \times t \\ +b_{5i}Price \times Train + b_6 TotalFee + \mathbf{b'Dem} \end{pmatrix},$$

where *t* is a time trend variable, *Price* is a dummy indicating whether subjects received price feedback, *Training* is a dummy indicating whether subjects received extensive training, *TotalFee* is the total fee endowed to each subject (recall a portion of this fee was randomly determined) and the **Dem** vector includes demographic variables such as gender, age, household size, and household's relative economic position (as a proxy for income). We also included an interaction between rounds (t) and the price treatment dummy (*Price*) to capture differences across rounds in the price-feedback treatment as well as an interaction between the (*Price*) and (*Train*) treatment dummies. F is the standard normal cumulative distribution function.

Coefficient estimates of a probit model are not directly interpretable, so we estimated the marginal changes[6]. However, the interaction term makes estimates of marginal changes more complicated since one needs to consider the fact that the interacted variables appear in the interaction term as well. Standard software estimates ignore this distinction because it is impossible for the software to know whether a variable is the product of other variables in the model. We derive corrected estimates of marginal changes following Drichoutis and Nayga (2010). For example, the marginal effect for the time trend variable is calculated as:

$$(2)\qquad \begin{aligned} ME_t &= \frac{\partial \Pr\left(y_i = 1 \mid \mathbf{x_i}\right)}{\partial t}, \\ &= \left(b_{1i} + b_{4i} Price\right) f\begin{pmatrix} b_{0i} + b_{1i}t + b_{2i}Price + b_{3i}Train + b_{4i}Price \times t \\ +b_{5i}Price \times Train + b_6 TotalFee + \mathbf{b'Dem} \end{pmatrix}, \end{aligned}$$

where b with subscript i indexes the random parameters and f is the probability density function of the normal distribution. The expression is evaluated at the sample mean $E\left[\mathbf{b}_i\right] = \mathbf{b}$ for *Price* = 0 and 1.

The corresponding marginal change for a dummy variable (i.e., a discrete change) is evaluated for a change of the variable from the start value of 0 to the end value of 1. For example, the formula for the *Price* variable is calculated as:

[6] Greene (2007, p. E18-23) argues that significance tests of the influence of a variable for non-linear models should be based on the coefficients alone. Marginal effects in the case of non-linear models are a highly non-linear function of all the coefficients in the model and the hypothesis that this function equals zero is not equivalent to the hypothesis that the coefficient is zero or that the variable in question is not a significant determinant of the outcome. Given that, coefficient estimates are presented in an online appendix at https://sites.google.com/site/postedprices/. Statistical significance for marginal effects is indicated in Table 2. However, claims about a variable being a significant predictor of the outcome should be based on tests over coefficients.

$$
\begin{aligned}
&\mathrm{DC}_{Price} = \mathrm{Prob}\left[y_i = 1 \mid Price = 1\right] - \mathrm{Prob}\left[y_i = 1 \mid Price = 0\right], \\
(3) \qquad &= F\left(b_{0i} + b_{1i}t + b_{2i} + b_{3i}Train + b_{4i}t + b_{5i}Train + b_6 TotalFee + \mathbf{b'Dem}\right) \\
&-F\left(b_{0i} + b_{1i}t + b_{3i}Train + b_6 TotalFee + \mathbf{b'Dem}\right),
\end{aligned}
$$

which can be evaluated at various values of the time trend t and the *Train* dummy.

Standard errors for expressions (2) to (3) where calculated with the delta method. Limdep v9 was used in all estimation steps.

Table 2 shows the estimated marginal changes for each bet pair. In general, the probability of a preference reversal decreases across rounds, although the effect is positive for the high expected payoff bet pair in the no-posted prices treatment. The effects are statistically significant in most cases as well. There is also indication that subjects exposed to posted prices were more likely to reverse their preferences, although the effect attenuates in most cases by round 5. By round 10 the effect of market feedback is statistically indistinguishable from the no-feedback treatment, although it remains positive in most cases with the exception of the high-expected-payoff bet pair in the extensive-training treatment (-0.132 coefficient). Training with the auction mechanism does not seem to alleviate the effect either. It does seem to reduce the rate of preference reversals, although the effect is statistically significant only for the low-expected-payoff bet pair in the no-feedback treatment (-0.037 coefficient).

Total fee endowment has a positive effect and increases the probability of a preference reversal for the high- and medium-payoff bet pairs. The practice of providing stochastic fees in the laboratory is important given that Rutström (1998) has found that provision of stochastic participation fees to subjects is responsible for small income effects. Harrison et al. (2009) have also found that it generates samples that are more risk averse than would have been observed otherwise. Therefore, the introduction of stochastic fees can control for possible income and sample-selection effects in bidding behavior and should be considered as an important factor in any experimental design.

Figure 3 depicts average predicted probabilities of a preference reversal over all bet pairs across rounds for treatments with and without price feedback. In general, we find that price feedback generates a higher probability of preference reversals across rounds. The difference in the probabilities of a preference reversal between the price-feedback and the no-feedback treatment diminishes across rounds and is practically negligible by round 10.

5.1.7 Comments on findings

While we find preference reversals in all treatments, we observe a higher level of preference reversals with price feedback. Consistent with the *learning effect*, repeated exposure to price feedback lowers the rate of preference reversals. However, the level of preference reversals in price-feedback treatments is never meaningfully lower than in contemporaneous rounds in the no-feedback treatments and is often much higher. Apparently the knowledge that prices *would be* posted caused subjects to act differently in early rounds. Although providing price feedback is meant to illustrate that subjects cannot "game" the mechanism, perhaps price feedback lets subjects know that there is a game to be played. Subjects, knowing that more information on relative valuations will be forthcoming, may be inclined to "play" with their initial bids in an attempt to garner additional perceived surplus.

One somewhat surprising result from this experiment is that additional training with the auction mechanism has no effect on the rate of preference reversals. This result suggests that, at least for preference-reversal experiments, additional training and the provision of posted prices are *not* substitutes as has been found by previous authors in the context of the WTP-WTA disparity (e.g., Plott and Zeiler, 2005).

5.2 Experiment 2: The induced value experiment

5.2.1 Description of the experiment

A conventional induced-value lab experiment was conducted among undergraduate students at Susquehanna University and Kenyon College. During the recruitment, the nature of the experiment and the expected earnings were not mentioned.

As with experiment 1, subjects participated in a second-price auction. However, instead of auctioning lotteries, we conducted two different induced-value experiments. Both experiment 2A and 2B consisted of two treatments: posting vs. no posting of the second-highest price. Each subject participated in only one treatment. In experiment 2A, subjects received a $5 fee; bid on an induced value drawn from a [$0, $5] interval; received training but did not participate in a practice round; and were in groups with 23 to 29 subjects. In experiment 2B, subjects received a $15 fee; bid on an induced value drawn from a [$0, $15] interval; participated in a practice round; and were in groups with 8 to 14 subjects. Comparing experiments 2A and 2B allows us to examine whether price feedback is more likely to influence bids when stakes are smaller, the probability of winning is smaller (i.e., group size is larger), and without practice rounds.

The experimental design closely follows Corrigan and Rousu (2006). Each session included three phases: the training phase, the auction phase and the post-auction phase.

5.2.2 The training phase

After arriving at the lab, subjects received a packet of written instructions. Because packets were randomly shuffled, it was not obvious to subjects what their neighbors' identification numbers would be. Subjects received their participation fee ($5 or $15) at the end of the experiment. We emphasized that although they were not given the money at the beginning of the experiment, the fee ($5/$15) was theirs and they should behave as if they have this money already. All transactions were completed at the end of the experiment.

Subjects received both written and oral instructions on the second-price auction. These instructions emphasized that the participants should not communicate with each other. Subjects were given a short introduction on how the second-price auction works, a short example of how bids are sorted in a descending order, and of how the second-highest bid and the winner are selected. Subjects were explicitly informed that bidding truthfully was in their best interest.[7] Subjects then took a short quiz regarding the procedure. After all subjects had completed the quiz, the questions and the correct answers were read aloud and explained. Participants in experiment 2B then participated in a practice auction round, while those in experiment 2A proceeded immediately to the induced-value auction phase.

5.2.3 The auction phase

After the training phase, subjects took part in ten rounds of bidding on an induced-value token. Because we hoped to follow the procedures from homegrown auctions as closely as possible, only one of these ten rounds was chosen to be binding. Subjects submitted their bids by filling out a paper bid form. The highest bidder's ID number was posted after every round in both price-feedback and no-feedback treatments. In the price-feedback treatment, the second-highest bid was also posted after every round. At the end of ten rounds of bidding, the monitor randomly determined the binding round and announced the winner's ID number and the selling price.

[7] While subjects in many induced value experiments are not informed of their optimal bidding strategy, our aim was to parallel the design of homegrown value experiments as closely as possible. Therefore, we follow the standard practice in that literature (Plot and Zeiler, 2005).

5.2.4 The post-experimental phase

After the experiment, we collected standard socio-demographic information about subjects' gender, age, class year, employment status, and disposable income. Subjects were then dismissed individually and any transactions were carried out in private. Experimental instructions are available at https://sites.google.com/site/postedprices/.

5.2.5 Econometric analysis

Figure 4 shows mean and median bids across rounds for both the price-feedback and no-feedback treatments. Notice that mean bids from both treatments show the frequently observed pattern of increasing during the first several rounds before stabilizing in later rounds (e.g., Corrigan et al., 2009, Lusk and Shogren, 2007, Shogren et al., 1994). Median bids also increase across rounds.

Figures 5a and 5b present summary statistics for the absolute difference between subjects' induced value and their bid, i.e., $\left|bid_{it} - induced\ value_i\right|$. If market feedback motivates subjects to bid truthfully—possibly as a result of the *learning effect*—we might expect $\left|bid_{it} - induced\ value_i\right|$ to be smaller in later rounds of the price-feedback treatment than in the corresponding rounds in the no-feedback treatment. This is not the case. Figure 5a summarizes results from experiment 2A with larger group sizes and lower stakes. Here the median absolute difference between induced values and bids are at (or near) zero by round 10 in both treatments. This suggests that either auction design ultimately motivates the median participant to bid truthfully. However, in none of the rounds does the price-feedback treatment outperform the no-feedback treatment, and while the median absolute difference is never greater than \$0.07 in the non-posted price treatment, that difference is initially \$0.46 in the earliest rounds of posted price treatment. As in experiment 1, the knowledge that prices *would be* posted may have prompted subjects to behave differently in early rounds. Knowing they will receive more information about relative valuations, subjects may strategically shade their initial bids in a misguided attempt to earn additional profit. The contrast between treatments is starker when focusing on the *mean* absolute difference between induced values and bids. While the difference shrinks modestly on average in the no-feedback treatment, the difference grows on average with price feedback.

Figure 5b summarizes results from experiment 2B with smaller group sizes and higher stakes. Here the differences between treatments are less pronounced, though these results do not suggest that the price feedback reduces absolute bid differences. Note that while the absolute bid differences are larger in figure 5b than in figure 5a, absolute differences as a proportion of induced value are comparable across treatments.

Next we specify the absolute value of difference between subject *i*'s induced value and her bid in round *t* as:

(4) $$AbsDifference_{it} = b_{0i} + b_{1i}t + b_{2i}Price + b_{3i}Price \times t + \mathbf{b'Dem}.$$

We estimate equation (4) using a random parameters model with panel structure. Table 3 presents the estimated marginal changes for equation (4). We also estimated a pooled regression model where we included an experiment dummy (Experiment2B=1 for experiment 2B, else=0) and its interaction with the *Price* dummy. The table also presents several conditional marginal effects. For example, "Experiment 2B, Price=0" refers to the marginal effect of the variable Experiment 2B *conditional* on the variable Price taking the value of 0. Likewise, "t, Price=1" refers to the marginal effect of rounds *conditional* on Price taking the value of 1. In other words, "t, Price=1" captures the round effect in the price-feedback treatment. As in experiment 1, we were careful to derive marginal changes that take into account the interaction term.[8] The results

[8] Standard coefficient estimates (software output) and additional data plots are available at https://sites.google.com/site/postedprices/.

show that in round 1 $\left|bid_{it} - induced\ value_i\right|$ is significantly greater (lower) in the price-feedback treatment in experiment 2A (2B). The difference grows significantly across rounds and by round 10 is equivalent across the two induced-value experiments (absolute differences of 0.837 and 0.735 respectively). Results from the pooled regression also show that $\left|bid_{it} - induced\ value_i\right|$ increases across rounds in the price-feedback treatment. Figure 6 shows this relationship graphically. The significant increase in absolute bid difference across rounds in the price-feedback treatment is likely due to some combination of the anchoring, detachment, and competitive effects. There is no clear theoretical explanation for why the absolute bid difference should initially be greater in the market feedback treatment in experiment 2A or why it should be lower in experiment 2B. The two experiments differ in incentive fee (\$5 vs. \$15), stakes for the induced values (\$0-\$5 vs. \$0-\$15), and practice round training. Future research may wish to determine whether this finding is caused by any or all of those features.

5.2.6 Comments on findings

Both our regression analysis and a comparison of mean bids from experiments 2A and 2B show that price feedback leads to bids that are farther away from participants' induced values, with the distance increasing across rounds. On the other hand, consistent with List and Shogren (1999), we find that price feedback has no significant impact on median bids in later rounds. The balance of evidence from experiments 2A and 2B suggest that posting prices in repeated round auctions does not lead to a better estimate of individual's values. Any benefits from the learning effect seem to be outweighed by some combination of the competitiveness, detachment, and anchoring effects. Neither do the results support the single-round auctions Harrison, Harstad, and Rutström

(2004) advocate. Regression results from both experiments show that the absolute difference between bids and induced values decreases across rounds in the no-feedback treatment.

6. Conclusions

We engaged in an adversarial collaboration to explore the appropriateness of using repeated experimental auctions with price feedback. The authors of this paper came into the project with divergent opinions about whether such a practice should be used when conducting experimental auctions. The use of price feedback in repeated auctions has resulted in a heated debate lasting more than a decade. We therefore designed and executed two sets of experiments that allowed us to examine (a) the rate of preference reversals in repeated rounds with and without price feedback (experiment 1) and (b) the difference between bids and induced values in repeated rounds with and without price feedback (experiments 2A and 2B).

Results from experiment 1 show that subjects behave significantly more irrationally in the price-feedback treatment. However, the rate of preference reversals tends to decrease across rounds in both treatments. The difference, however, is negligible. Results from the experiments 2A and 2B show that price feedback leads to bids that are farther away from participants' induced values.

Overall, the lesson from our experiments is that any learning effect from price feedback is more than offset by the combined effects of competitiveness, detachment, and anchoring. Therefore, we cannot advocate posting prices in repeated auction rounds. However, this does not mean that researchers should instead embrace one-shot institutions as proposed by Harrison (2006) and Corrigan and Rousu (2006). We find that even without price feedback, repeated rounds improve auction performance, therefore we recommend repeated auction rounds without price feedback in situations where a second-price auction is preferable to other auction mechanisms (e.g., when only a small quantity of the good of interest is available). Because high posted prices may intensify the anchoring, detachment, and competitive effects as well as the learning effect, researchers' intent on providing price feedback may be safer using repeated median-price or random nth-price auctions where posted prices do not solely reflect the upper end of the value distribution. Determining whether repeated median-price or random nth-price auctions perform better with or without price feedback is a topic for future research.

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Table 1. Lotteries used in the experiment

Lottery	Bet type	Bet pair	Probability of win	Amount of win	Probability of loss	Amount of loss	Expected payoff
A	P-bet	1	90%	4	10%	1	3.50
B	$-bet		28%	16	72%	1.5	3.40
C	P-bet	2	80%	3	20%	1	2.20
D	$-bet		24%	12	76%	1	2.12
E	P-bet	3	75%	2	25%	1	1.25
F	$-bet		18%	9	82%	0.5	1.21

Table 2. Marginal effects and discrete changes for random parameters probit model

		High expected payoff		Medium expected payoff		Low expected payoff	
		Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
TotFee		0.117***	0.030	0.033***	0.013	0.003	0.002
t,Price=1		-0.009	0.010	-0.004	0.004	-0.009**	0.004
t,Price=0		0.018*	0.011	-0.012***	0.003	-0.002*	0.001
Price, Train=1	*t=1*	0.197**	0.083	-0.016	0.057	0.270***	0.092
	t=5	0.093	0.062	0.025	0.030	-0.012	0.007
	t=10	-0.132	0.125	0.114	0.070	-0.002	0.002
Price, Train=0	*t=1*	0.254***	0.089	-0.006	0.051	0.193*	0.112
	t=5	0.168**	0.070	0.028	0.028	-0.054**	0.021
	t=10	0.044	0.103	0.033	0.028	-0.010	0.009
Train, Price=1		-0.007	0.077	0.003	0.035	-0.0002	0.001
Train, Price=0		0.071	0.053	0.006	0.017	-0.037**	0.018

Note: ***, **, * = Significance at 1%, 5%, 10% level. This analysis also controls for gender, age, household size, and income. Results including these variables are available in an online appendix. This table presents several conditional marginal effects. For example, "*t*, *Price*=1" refers to the marginal effect of rounds *conditional* on *Price* taking the value of 1. In other words, "*t*, *Price*=1" captures the round effect in the price-feedback treatment. Likewise, "*Price*, *Train*=1, *t*=1" refers to the discrete change of *Price conditional* on *Train* and *t* taking the value of 1. In other words, "*Price*, *Train*=1, *t*=1" captures the effect of price feedback in the extensive training treatment in round 1.

Table 3. Coefficient estimates for random parameters model

		Experiment 2a			Experiment 2b			Pooled		
		Coef.	Std. Err.	t-ratio	Coef.	Std. Err.	t-ratio	Coef.	Std. Err.	t-ratio
Constant		0.786	0.501	1.568	7.469***	1.375	5.432	1.021	0.735	1.390
t,Price=1		0.031***	0.011	2.838	0.186***	0.034	5.500	0.118***	0.017	6.817
t,Price=0		-0.031***	0.009	-3.178	-0.047	0.037	-1.256	-0.034**	0.017	-2.025
Price	*t=1*	0.272***	0.082	3.311	-1.365***	0.280	-4.880			
	t=5	0.523***	0.053	9.823	-0.431***	0.158	-2.730			
	t=10	0.837***	0.087	9.636	0.735***	0.277	2.655			
Experiment 2B, Price=0								1.860***	0.116	16.043
Experiment 2B, Price=1								0.712***	0.104	6.843
Price, Experiment 2B=0	*t=1*							0.080	0.155	0.518
	t=5							0.688***	0.111	6.201
	t=10							1.448***	0.155	9.340
Price, Experiment 2B =1	*t=1*							-1.067***	0.146	-7.313
	t=5							-0.460***	0.094	-4.864
	t=10							0.300**	0.141	2.132

Note: ***, **, * = Significance at 1%, 5%, 10% level. This analysis also controls for gender, age, employment, and income. Results including these variables are available in an online appendix. This table presents several conditional marginal effects. For example, "*t*, *Price*=1" refers to the marginal effect of rounds *conditional* on *Price* taking the value of 1. In other words, "*t*, *Price*=1" captures the round effect in the price-feedback treatment. Likewise, "*Price*, *t*=1" refers to the discrete change of *Price conditional* on *t* taking the value of 1. In other words, "*Price*, *t*=1" captures the effect of price feedback in round 1.

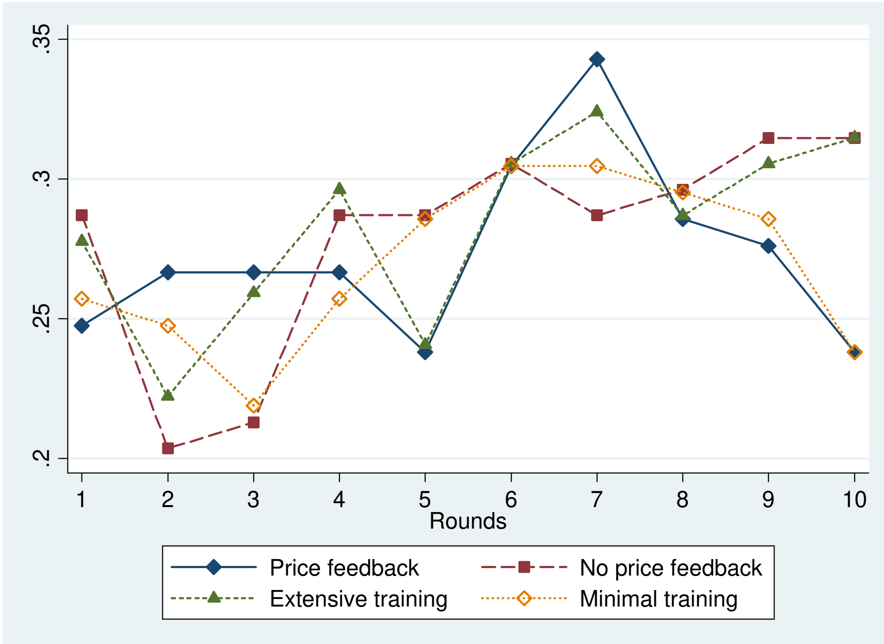

Figure 1. Mean rates of preference reversals across rounds by treatment

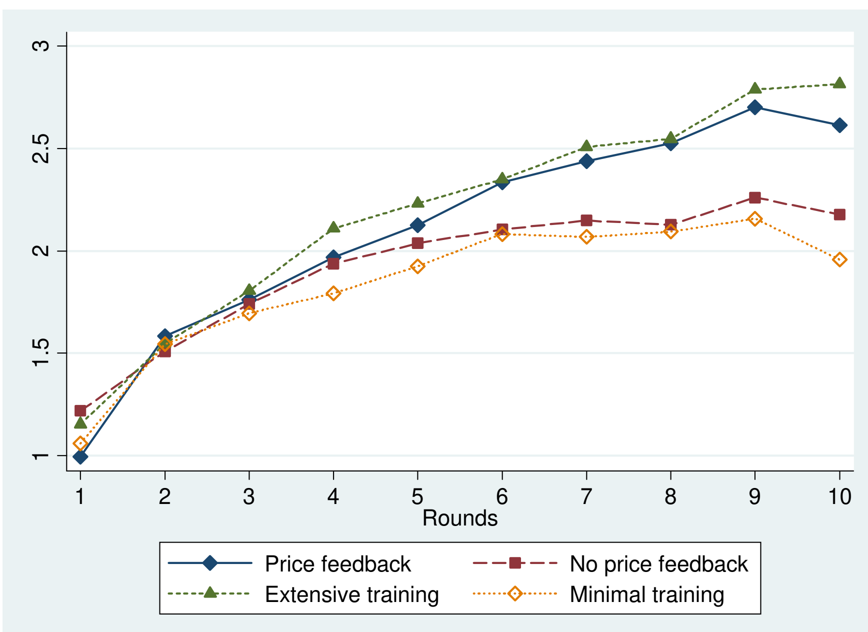

Figure 2. Mean bids for lotteries across rounds and treatments

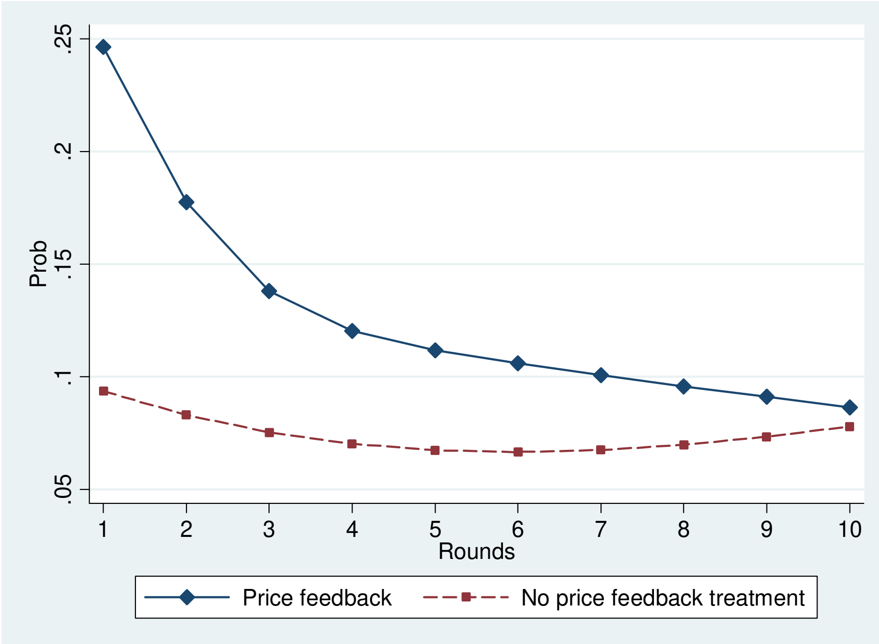

Figure 3. Average Predicted probabilities of a preference reversal across bet pairs

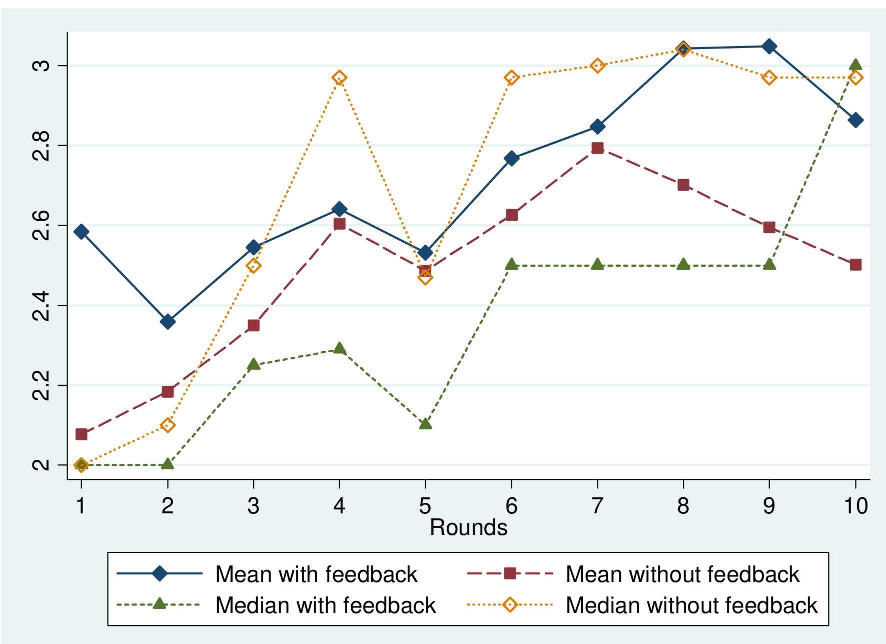

Figure 4. Bids submitted across rounds

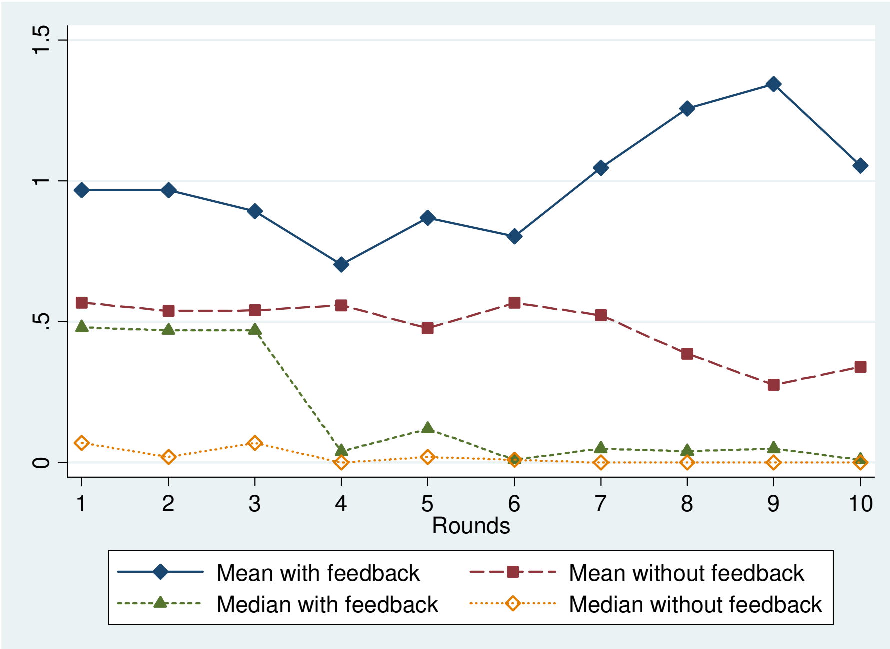

Figure 5a. Absolute value of the difference between induced value and bid submitted across rounds (Experiment 2a)

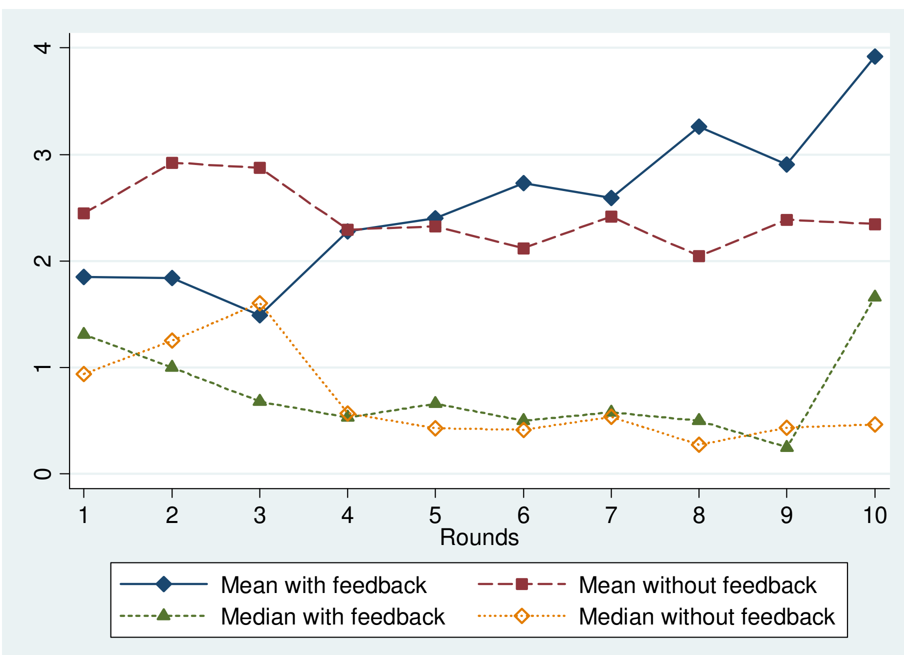

Figure 5b. Absolute value of the difference between induced value and bid submitted across rounds (Experiment 2b)

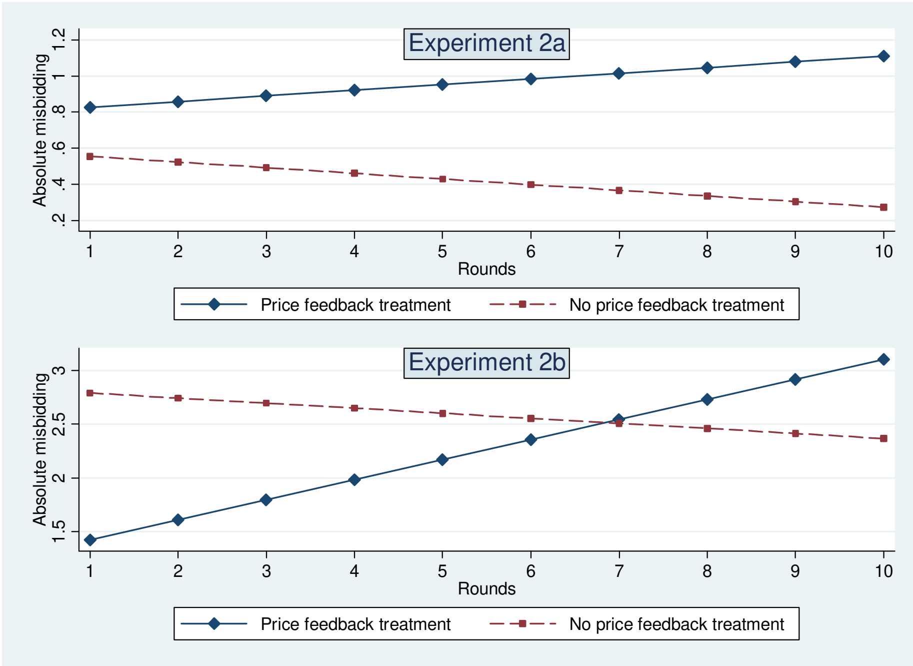

Figure 6. Predicted absolute difference between induced value and bid submitted across rounds