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The Price is Right: Analyzing Bidding Behavior on Contestants' Row

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The Price is Right: Analyzing Bidding Behavior on Contestant's Row

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Abstract

The TV game show "The Price is Right" features a bidding auction called Contestant's Row that rewards the player (out of four) who bids closest to an item's value without overbidding. By exploring 903 game outcomes from the 2000-2001 season, we show how player strategies are significantly ineffi-cient, and compare the empirical results to probability outcomes for optimal bid strategies found in Kvam (2018). Findings show that the last bidder would do better using the naïve strategy of bidding a dollar more than the highest of the three bids. We use the EM algorithm to model the predicted merchandise value as a function of player bids. These estimates allow us to demonstrate how one player's observed bid effects another player's evaluation of the same merchandise.

Keywords: Anchoring, Auction, EM Algorithm, Logistic Regression, Order statistics

1 Introduction

The Price Is Right (TPiR) is a game show that has been running on American television as early as 1956. With over 8000 episodes aired since its debut, TPiR is one of the most well known and longest running game shows in US history. The show features several games in which contestants from the audience compete to win prizes by guessing the retail price of some featured merchandise. We have particular interest in the segment called *Items up for bid*, in which four contestants from the audience guess the value of a piece of merchandise, and the bidder who is closest without going over the actual value wins the merchandise. This asymmetric risk makes the TPiR game complicated, in terms of bidding strategy. Because of the overbidding penalty, players tend to place a bid below what they believe is the true value of the merchandise.

Each player (we will label them Player 1 through Player 4) reveals their bid in sequence, starting with Player 1. This gives players who bid later a distinct advantage, because they can sometimes increase their chance of winning by bidding a dollar more than a previous player. According to the rules of the game, this action virtually eliminates that other player's chance of winning. It is clear that such a strategy is optimal for the last bidder (Player 4). For example, suppose the first three player bids are \$700, \$800 and \$900. It can be easily seen that the best bid for Player 4 would be one dollar more than one of the previous bids, or if they believe the value of the merchandise is less than \$700, they would bid one dollar.

In this paper, we examine the game outcomes of 903 *Items up for Bid* segments from the 2000-2001 TPiR show. There is a modest amount of literature that considers this type of auction, and we review some main findings in Section 2. The data are introduced and summarized in Section 3, and in Section 4, we compare how actual bidders contrast with the optimal strategies derived in Kvam (2018) as well as the past results in Berk, et al Berk, et al. (1996). We examine what the data reveal about player bidding behavior, and specifically on how a player's actions may be influenced by a player who bids before they do. These effects are akin to "anchoring", which we discuss in Section 5.

2 Background

Most applied game theory models are based on auctions in which players are not aware of the bids from other participants (Lorentziadis, 2015). In this TPiR auction, the bid order is crucial for player strategy and imposes a unique asymmetry. With no chance to win by overbidding, all players are motivated to bid below the perceived value. At the same time, players gain information and distinct advantage by knowing their opponents' bid, so being the first bidder is a significant drawback. Player 4, as mentioned earlier, has four rational bids to make that will optimize the chance of winning: bidding one dollar more than one of the three previous bids, or simply bidding a dollar in case the other three players have all overbid.

Past research has considered both the economic principles and behavioral modeling for player bids using past game data. Berk, et al. (1996) showed apparent faults with contestants' strategies and proposed simple rules for rational bidders. Their results were based on a limited number of games from the 1994-1995 season, showing it was advantageous to bid last. They also demonstrated that contestants tend to improve their strategies if they play repeatedly.

Estelami (1998) studied the impact of product-related factors on the players' understanding of different product categories. Heally and Noussair (2004) conducted an experimental study that showed similar suboptimal bidding behavior that was found in Berk, et al. (1996) and Lorentziadis (2015). Lee, et al. (2011) used the bids of the individual players to construct an aggregate bid that is superior to estimates of individual players. Holbrook (1993) considers fundamental relationships between the bidding behavior of the players and the kinds of merchandise that is up for auction, and specifically the way television (TPiR in particular) affects that relationship. Mendes and Morrison (2014) present optimal strategies for symmetric games (each player has equal footing), including those where overbidding disqualifies the bidder.

Kvam (2018) considered optimal bidding strategies for all four players, including marginal strategies (when only one player shows strategy while the other three players bid their perceived value) and conditional strategies, in which players adjust their marginal strategy knowing the other players are simultaneously optimizing their bid. If all four players use conditional strategies, Player 4 maintains a large advantage over the other three players, winning 56.7% of the time in simulated outcomes. In contrast, Player 3 would win 21.7% of the games, Player 2 wins 11.6%, and Player 1 wins only 7.4%. When all players use conditional strategy, there is a 2.5% chance they all overbid. Note that if all players gave independent assessments of the merchandise, with a 50% chance of underestimating its value, then we would expect them to overbid as a group with probability $1/16 = 0.0625$.

Berk, et al. (1996) explored how players use suboptimal bidding on TPiR and offer simple rules for the bidding behavior they observed. In this paper we use statistical methods to characterize the bid behavior of the contestants, knowing they are not always bidding their perceived value of the merchandise. We use actual data from the TPiR 2000-2001 season, described in the next section. Bid behavior is not thoroughly studied in the literature, but research exists to study auction scenarios in which bid collusion is suspect (Graham and Marshall, 1987, Ballesteros-Perez, et al., 2015). If we fail to acknowledge that players use concealment in bidding, it is not possible to directly test the optimal bidding strategies in Kvam (2018) in order to see how they applied to actual data. In this paper, we try to model the bidding behavior using the opaque information provided by contestants.

3 Data From The 2000-2001 Season

We collected data from 903 games during the 2000-2001 season of The Price is Right from the website titled "The Price is Right Stats" (see references). There are usually six games per episode, but some data are missing due to typos from the webpage or problems with uploading the data. During the game show, if all contestants overbid, the host starts the bidding over. We only collected the first segment (when all four contestants overbid) for those instances. Players who fail to win the first time the game is played can reappear on the second game, and the evolution of bid behavior for players who participate in more than one game is aptly studied in Berk, et al. (1996). We do not have information on player identity, which could be an important factor because players who lose in an *Items Up For Bid* segment will continue on (with a new player selected from the audience) the next time that game is played.

As a consequence, we have no information on the random effects of players which may affect sequences of two or more games.

3.1 Frequency of Winners

From the 903 games, Player 4 was predictably most successful, winning 41% of the time. Players 1, 2, and 3 won 16.2%, 17.1% and 17.9% of the games, respectively. In 7.9% of the games, all four players overbid. Similar results were obtained by Berk, et al. (1996) in a sample of 48 auctions from 55 show broadcasts, presumably during the early 1990s. In their sample, Player 4 won 40% of the time. Over the 2000-2001 season, we observed that contestants underbid a majority of the time (68%, 68%, 67%, 74% for Players 1 through 4, respectively). This is in line with a coherent strategy, given the asymmetric loss incurred by overbidding.

We would not assume player bids are independent. The challenge in measuring the actual correlation between bids is masked by the way players adjust their bids in reaction to another player's bid. This is especially true for bids that are a dollar more than a previous bid, or with games in which a player bids one dollar. A one-dollar bid, most frequently used by Player 4, signals that the player believes the value of the merchandise is less than the previous bids on display. We will refer to this strategy as *plus-one bidding*, even using this action to describe bids that are within $10 of other bids.

It has been demonstrated that the plus-one bidding strategy is key to maximizing a player's win probability (mostly for Player 4, the last bidder), and we will reaffirm from the data that many players failed to apply such a strategy. We consider the reasons and consequences of plus-one bids, and how we can estimate a player's perceived value of the merchandise that is up for bid using this biased data. Next, we consider a naïve strategy for Player 4 that is based only on previous bids and not on the player's random assessment of the merchandise.

3.2 Naïve Bidding Strategy

We noted that all players have a tendency to bid below the value of the merchandise, and this can be seen if we consider the four bids as order statistics. As a simple example, suppose players are independently bidding the value they believe for the merchandise, and their belief is such that they are just as likely to overbid as to underbid. According to probability, the second smallest bid will most frequently win (the probability of two bids under and two bids over, assuming the likelihood of an exact guess is negligible, is $6/16 = 0.375$). That is, based on binomial probabilities, the probability of winning, from the lowest to the highest bid are $\frac{4}{16}$, $\frac{6}{16}$, $\frac{4}{16}$ and $\frac{1}{16}$, with a probability $\frac{1}{16}$ that no one wins due to everyone overbidding.

The data demonstrate that players do not bid independently this way. In the 2000-2001 season data, the lowest bid won 15.1% of the time. The second lowest bid won 15.4% of the games, the third lowest won 13.7%, and the highest bid won 47.8% of the games. Because we understand players are more likely to bid below the merchandise value, these observed frequencies are not expected to match the probabilities of the order statistics, and this is borne out in the data.

During the TPiR season, Player 4 won the auction around 40% of the time, but the findings here suggest Player 4 may do better by ignoring their judgement on the merchandise value and simply bidding a dollar higher than the highest previous bid. This what we call the naïve strategy. If we consider only the bids from the first three players across the 903 games, all three players bid below the merchandise value 48.8% of the time. This means Player 4 would have won nearly half the games using the naïve strategy, which is 20% more often than Player 4 actually won during the 2000-2001 season.

3.3 Player Evaluation and Plus-One Bidding

Consistent with Berk, et al. (1996) and Kvam (2018), Holbrook (1993) shows it is frequently advantageous to use plus-one bidding (including a bid of one dollar), and it is always optimal for the last bidder to do so. Players 2 and 3 always risk having subsequent bidders boxing them out of the game by bidding one dollar more than their bid, so they have incentive *not* to underbid, making every player's game strategy more complicated.

In the 2000-2001 data, players bid $1 in approximately the same frequency as the optimal strategies found in Kvam (2018): the fourth player put in a minimum bid of one dollar 18% of the time, while the other three players did this less than 1% of time. Even though the strategy of bidding $1 may be optimal in theory, it was not to the advantage of the players, overall. In fact, the low bidder (the player who bid $1) won less than one percent of the time. Given the frequency and the large scale of underbidding by all players, the dollar bid has less chance of succeeding because the probability that one of the previous bids was already under the merchandise value is high.

Although plus-one bidding served as an optimal strategy for many game scenarios, the data reflect the findings in Berk, et al. (1996) that players failed to use this approach as frequently as they should have. In only 65% of the games played were there any bids within ten dollars of each other (we expanded the range of bid differences because players occasionally bid a few dollars more than a previous bid, as if to generously grant their competitor a modest interval of potential values that will allow them to win). In only 3% of the games did Player 2 bid under 10 dollars or within 10 dollars of Player 1. In 11% of the games, Player 3 bid under 10 dollars or within 10 dollars of a previous bid. Most surprisingly, in only 60% of the games did Player 4 bid under 10 dollars or within 10 dollars of a previous bid. In only one game (out of 903) did more than two bids deliberately top a previous bid by a dollar, and that was game #683, in which Players 1 to 4 bid (respectively) 1000, 1001, 1002, and 1003 dollars for merchandise that was valued at $1030 (so Player 4 won).

These statistics suggest that there may be an implicit social cost for bidding one dollar more that a previous bidder. Since Player 4 bid close to a previous bid (or bid near one dollar) only 60% of the time, that player was using a clearly suboptimal strategy for the other 40% of the games. The bidding data might suggest a social norm is being enforced since players who bid one dollar more than a previous bidder essentially eliminate them from competing for the prize in that game. There is no explicit cost to this apparently efficient strategy, but the risk of appearing ruthless to the audience or just to the other players might be an influence the player's behavior.

Because the presence of one-dollar bids and plus-one bids obscures our ability to assess the bidding behavior of the four players, in the next section we consider how the information from player bids is related to the actual value of the merchandise, and how variability between players and variability between games (or merchandise) effects this relationship. If players show a bias by underbidding, that bias may depend on the merchandise value. With the presence of plus-one bids, we treat the player's bid as a censored information.

4 Do Players Use Optimal Strategy?

The optimal strategies established in Kvam (2018) rely on simulation-based empirical results in which players obtain their assessed value of the items up for bid independently. Each player's strategy uses information provided by the previous bidders. We denote the merchandise evaluations of Player 1 to Player 4, respectively, as X_1, X_2, X_3, X_4, implying that player evaluations are governed by some joint distribution, while the actual evaluations (x_1, x_2, x_3, x_4) are not revealed by the players. Instead, we observe their respective bids as b_1, b_2, b_3, b_4. Optimal player strategies are summarized as follows:

1. Player 1 maximizes the win probability by bidding $b_1 = 0.975x_1$.

2. For Player 2, who observes the first bid as b_1, if $x_2 > b_1$, then the win probability is maximized by bidding $b_2 = b_1 + 0.345(x_2 - b_1)$. If $x_2 < b_1$, then Player 2 maximizes winning probability by bidding $b_2 = 0.975x_2$.

3. For Player 3, who observes bids ordered $b_{1:2} < b_{2:2}$, if $x_3 < b_{1:2}$, then the probability of winning is maximized by $b_3 = 0.963x_3$. If $b_{1:2} < x_3 < b_{2:2}$, then Player 3 should bid $b_3 = b_{1:2} + 0.249(x_3 - b_{1:2})$, and if $b_{2:2} < x_3$, the bid should be $b_3 = b_{2:2} + 1$.

4. Player 4 maximizes win probability by bidding a dollar more than the largest bid under x_4, and by bidding a dollar if x_4 is smaller than the three previous bids.

If all four players use this optimal strategy, their respective win probabilities will be 0.075, 0.116, 0.216, 0.569.

The data do not allow us to see directly whether the players are using this type of optimal strategy. Specifically, we want to know each player's assessed value of the merchandise (x_i) but the data reveal only the observed bid value b_i. If we replace the bid by Player 1 with an optimal bid, for example, the bids that follow (from Players

2, 3, 4) no longer represent player strategy, because those players were reacting to the original bid, not the more optimal one.

In order to examine how player bids matched optimal strategies, we need to generate a better guess of the player assessment than what is provided by the observed bid. The adjustment presented below will provide an improved estimate on player evaluations. To address the second point, we will construct optimal bids for a player, and then consider the subset of the 903 games in which that player's bid is relatively close to that optimal bid. For those games, the subsequent bidders are reacting to what is an approximately optimal strategy, and we will compare how often that player wins in those games, compared to how frequently that player wins overall.

4.1 Modeling Player Evaluations

If we treat plus-one bids as censored variables, we may be able to get a better understanding about the underlying bidding behavior of the players. For example, if we observe $b_i = 1$ from Player i, we may assume the player's evaluation x_i is actually between \$1 and the smallest bid observed up to that point. In general, if a player bids one dollar more than a previous bid, we treat that as right-censored data (or possibly interval censored if it was not the highest bid observed at that point).

In this section, we model the observed player bids as a function of merchandise value using a basic regression model and treating plus-one bids as censored observations. We model the joint density of the four bids using the marginal distribution of the first player's bid, the conditional distribution of the second player's bid (given the first), and so on. For computational convenience, we use an EM-algorithm (McLachlan and Krishnan, 2014) to avoid likelihood formulations with censored data. That is, we initially replace censored values with naïve estimates of the data (e.g., midpoints) and then use EM-iterations to improve the estimated regression coefficients until the model converges.

Because the bids from Players 2, 3, and 4 are affected by the previous bids, the most useful evidence of bias (toward underbidding) in a player's bidding behavior is provided by the initial bid from each of the 903 games.

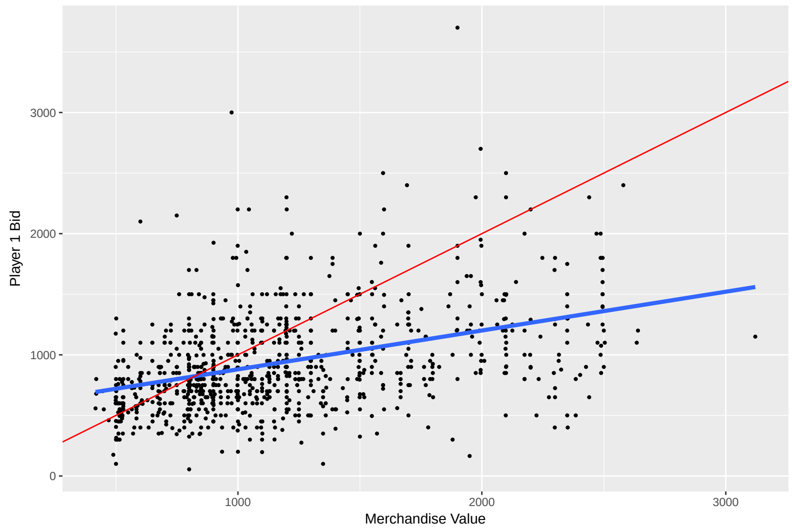

Figure 1: First player bid (regression on blue line) compared to merchandise value (red line). Regression estimates $\hat{\beta}_0 = 559.8$ (s.e. $= 32.3$), $\hat{\beta}_1 = 0.320$ (s.e. $= 0.025$), $\hat{\sigma} = 384.0$.

Figure 1 shows the linear regression of the first player's bid as a function of merchandise value. In the regression, we see a large amount of variance across different values of merchandise, along with the effect that players tend to overestimate the lesser-valued merchandise and underestimate merchandise of high value. This is expected, and presents a reasonable model of player behavior. If b_1 represents the bid from the first player, and v represents merchandise value, then the regression model $E(b_1) = \beta_0 + \beta_1 v$ provides a convenient way to estimate player bias. For any game with an item up for bid of value v, players, on average, will underbid an amount $\tau(v) = v - (\beta_0 + \beta_1 v) = (1 - \beta_1)v - \beta_0$.

Let b_{ki} be the actual bid from Player k in game i, where $k \in \{1, 2, 3, 4\}$ and $i = 1, 2, \cdots, 903$. Then we estimate the player's perceived value of the merchandise to be

$$y_{ki} = b_{ki} + (v_i - \hat{\beta}_0 - \hat{\beta}_1 v_i) = b_{ki} + \hat{\tau}_i(v_i)$$

where $\hat{\tau}_i(v_i) = v_i(1 - \hat{\beta}_1) - \hat{\beta}_0$ is the estimated bias for merchandise with value v_i based on Player 1 bid data for all 903 games.

With data $(b_{1i}, b_{2i}, b_{3i}, b_{4i}, v_i)$, we generate estimates of player evaluations using simple linear regressions on player bid data. The details for these regressions are relegated to the appendix. With incomplete data, we apply the EM Algorithm to find maximum likelihood estimates of the regression parameters, and also use the missing-data estimates to illustrate the variability between player bids and how it changes as a function of merchandise value. As a result, the plus-one bids will not fully obscure our ability to characterize this variability.

Step 1. Generate initial estimates of player evaluations based on plus-one bids using midpoints for interval censored bids (and one-dollar bids), and adding 20% for left-censored bids.

Step 2. Use regression to model first bid as a function of value and estimate player bias $\tau(v)$ as a function of value.

Step 3. Model second bid as a function of value and Player 1 bid.

Step 4. Model third bid as a function of value and bids from Players 1 and 2.

Step 5. Model fourth bid as a function of value and previous bids.

Step 6. Use current regression model to estimate censored bids (E-step in the EM Algorithm), and repeat regressions until estimated player evaluations converge.

The initial guess for the interval censored bids (we added 20% to the actual bid) is admittedly arbitrary, but the EM iterations converge in a uniform manner for any reasonable selection with this data, and required fewer iterations with this initial condition.

4.2 Results of Study

After estimating player evaluations for each game, we went back to the optimal bidding rules in Kvam (2018) to determine if players who bid optimally actually performed better than expected. Optimal bids are a function of player evaluations (x_1, x_2, x_3, x_4), and in their place we use the estimated player evaluations from the EM iterations. To determine whether or not a player bid optimally, we selected the subset of bidders from each game who bid within 50 dollars of the optimal rule. This occurred between 19% and 58% of the time for the four players. Each optimal bid was considered individually, so some games may have no optimal bids, and some could have more than one.

- Player 1 has the smallest chance of winning, overall, winning 16% of the games. Out of 903 games, Player 1 bid optimally (within 50 dollars of the optimal bid) 18.9% of the time, and won in 25.3% of those games.

- During the 2000-2001 season, Player 2 won 17% of the time. In 22.5% of the games played that year, the second player's estimated merchandise evaluation led to a bid within 50 dollars of the optimal bid. In those games, Player 2 won 30.0% of the games.

- In the 903 games played that season, Player 3 actually won 17.9% of the time. In 22.6% of the 903 games, Player 3 bid optimally, and from those games, Player 3 won slightly more often (20.6% of the games).

- Player 4 bid optimally 58% of the time, which means that in 42% of the games, Player 4 chose not to bid using the plus-one bidding rule. For those games in which Player 4 did use the optimal bid, they won 47.1% of the games. Over all games, Player 4 won 41% of the time, and in games where Player 4 did not employ plus-one bidding, they won only 32% of the games.

The results show that all four players would have improved their winning chances by using the optimal bids. The bid rules mostly help the first two players, who improve their win probabilities by 58% and 76%, respectively. Players 3 and 4 improve win probability by 15%.

5 Anchoring & Bid Correlation

The available data for the 2000-2001 TPiR season gives us an opportunity to measure and test how a player's evaluation of the merchandise might be affected by another player's revealed bid for that particular merchandise. For example, suppose the contestants are bidding on a gourmet outdoor grill with stainless steel grates and built-in propane gas supply for six burners. Further suppose that Player 2 recalls coveting such a grill with similar properties during a recent visit to Home Depot, but does not recall any of the actual grill prices. If pressed on the subject, Player 2 would guess the value of the grill displayed on the stage would be between $1000 and $2000. However, after Player 1 bids $3300 for the grill, Player 2 starts to believe this initial evaluation was too low, and they end up bidding $2400.

This example of one player's influence on another is akin to anchoring; the first bid serves as an "anchor" for the other players. Anchoring is a cognitive bias that leads people do depend too heavily on some information that may be only slightly related to the merchandise they are assessing. For example, wine sellers may use anchoring to great benefit by showcasing expensive bottles of wine to buyers as they shop and think about a reasonable price to pay for the bottle they will purchase and take home. The seller has no expectation of selling the prominently displayed $400 bottle of Château Margaux, but after seeing this expensive wine, some buyer might lose some resistance to spending over $40 on more affordable bottle of Bordeaux.

Anchoring is also used in models where an initial auction price is treated as an outlier (Ariel, et al. 2003). Although anchoring is typically associated with irrelevant information (in terms of the item up for bid), recent studies by Beggs, et al. (2009) and Ku, et al. (2006) have considered extended application for anchor models, and Yang, et al. (2012) considered information gleaned from prior bidders.

We model the probability of underbidding using a simple logistic regression. In Figure 2, the blue line represents the empirical probability Player 1 underbids, as a function of merchandise value. Only for the least expensive merchandise ($500 and less) is Player 1 apt to bid higher than the actual value. The probability of underbidding, on the other hand, keeps increasing as the value of merchandise increases, and for the most expensive items up for bid, Player 1 almost always underbids.

The red line in Figure 2 represents the conditional probability that Player 2 underbids *given that Player 1 underbids.* The bid by Player 1 serves as a potential anchor for Player 2, and we can see that the conditional probability of underbidding increases noticeably. The green line represents the conditional probability that Player 3 underbids, given both of the previous players have entered a bid below the merchandise value. Again, the probability is higher, suggesting anchoring is a plausible factor for the observed bidding behavior.

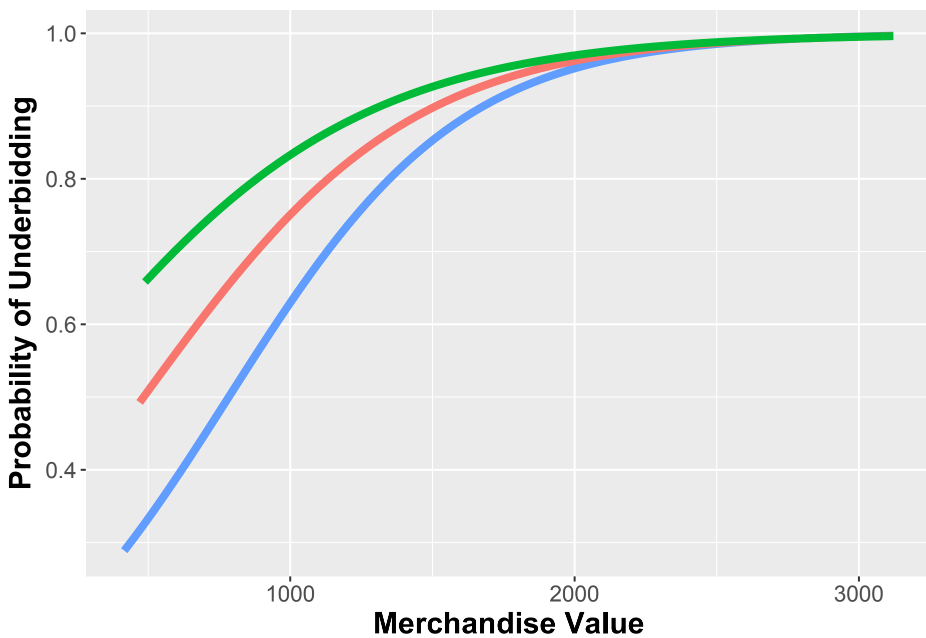

Figure 2: Conditional probabilities of underbidding for Player 2 (red) and Player 3 (green) along with probability of underbidding for Player 1 (blue).

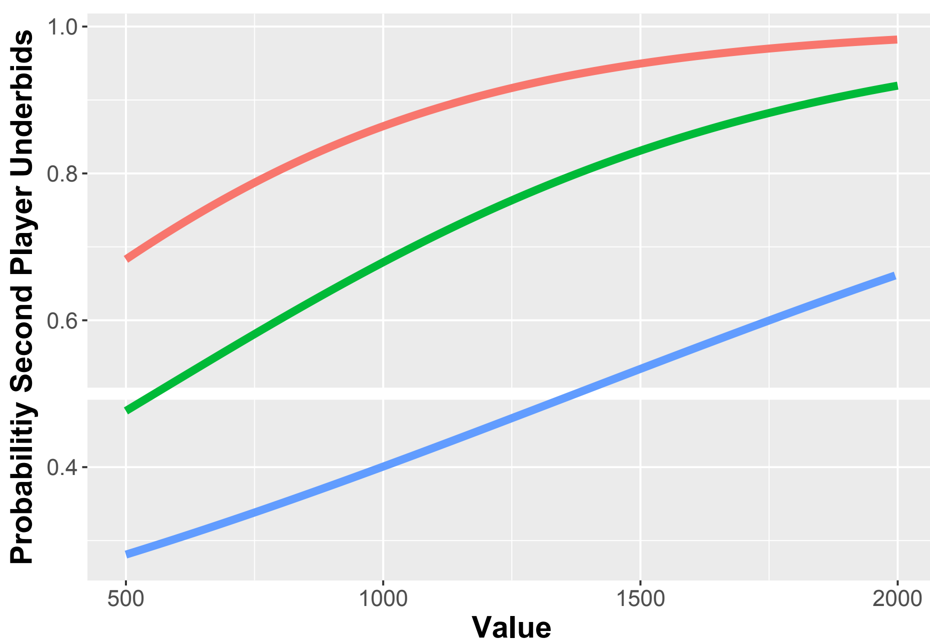

Figure 3: Conditional probabilities of underbidding for Player 2 when Player 1 bids less than 67% of the true value (red), when Player 1 bids between 67% and 100% (green) and when Player 1 overbids (blue).

In Figure 3, we see the frequency of underbidding for Player 2 broken into three difference cases: (1) the red line shows the probability Player 2 underbids when the first bid is at most 2/3 the actual value of the merchandise, (2) the green line shows the probability when the first bid is higher than 2/3 of the value but still under the actual value, and (3) the blue line shows the probability Player 2 underbids when Player 1 overbids. This figure illustrates how the initial bid by Player 1 can affect how Player 2 evaluates the same merchandise, but it also shows that this anchoring effect is not as significant as the effect the merchandise value has on how frequently a player overbids or underbids.

Figure 4 shows the probability Player 2 underbids as a function of first bid, in terms of its proportion of the merchandise value. In this case, we are averaging over the actual merchandise value, and focusing on how much (in percentage value) the first player overbids or underbids. This result is based on a simple (linear) logistic regression. For example, if the first bid is only half the value of the merchandise, the second player (if properly informed) would benefit by bidding higher. However, in the actual games, Player 2 underbids 84% of the time, on average, in this situation. On the other hand, when Player 1 overbids by 50%, the second bidder has ample opportunity to increase their chance of winning by staking a lower bid. Nonetheless, in these scenarios, Player 2 enters a bid that is below the merchandise value less than 25% of the time.

6 Discussion

This study examined player bidding behavior on the "Items Up For Bid" section of the daily game show The Price Is Right. Readers familiar with the game show and the potential irrationality of player behavior in a reality TV environment would not be surprised at the suboptimal player behavior exhibitied and quantified in this study. However, these results also give us a unique perspective of player behavior in an asymmetric auction and helps to illustrate how one player's bid may affect the way other players conceive their own evaluation of the merchandise up for bid.

The results in Section 2 reaffirm many of the results found in Berk et al. (1996). Not only do players bid suboptimally for all varieties of merchandise, but we found

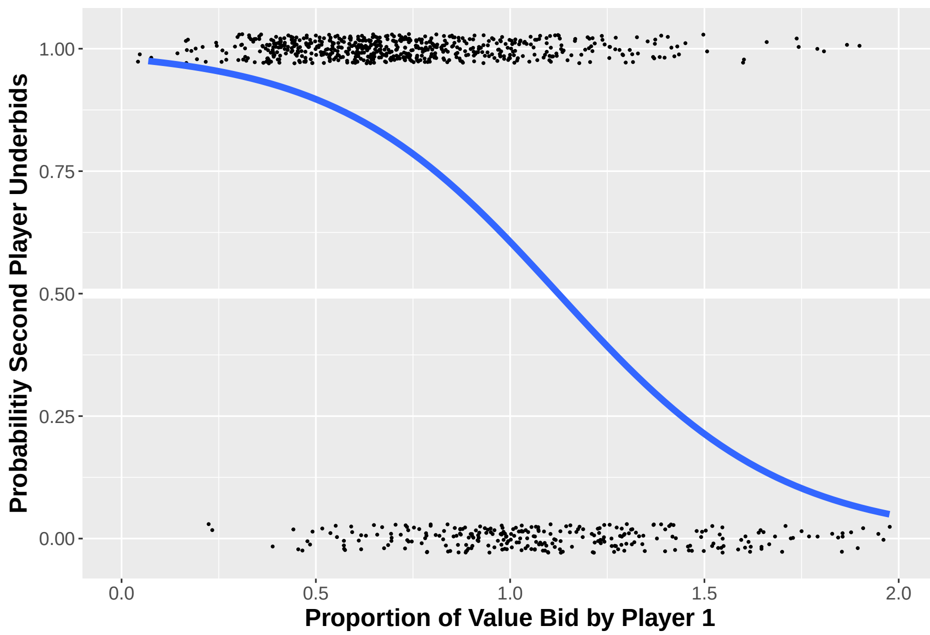

Figure 4: Logistic Regression showing probability Player 2 underbids as a function of how much Player 1 underbids.

that during the 2000-2001 season, the last bidder could have improved their winning percentage by employing a naïve strategy. That is, Player 4 would have have won 20% more frequently by ignoring any preconception they have about the value of the merchandise and just bidding one dollar more than the highest bidder.

The probability model to determine optimal bidding in Kvam (2018) was tested using the 2000-2001 TPiR data. Those bidding rules rely heavily on plus-one bidding, along with bid-shrinking (lowering a bid below the perceived assessed value) in order to maximize winning probability. To test these heuristics, we needed to estimate player assessment (potentially different from what they actually bid) using linear regression and the EM algorithm, treating plus-one bids as censored responses. The optimal rules show that players can significantly improve their winning probability, especially for Players 1 and 2.

Finally, we consider how the first bid might anchor the second player and affect their bidding behavior. Using simple logistic regressions, we show that player bids may be greatly affected by how close the first bidder is to the actual merchandise value, but the effect also depends on the value of the merchandise. The data show that if the first player grossly underbids, the second player is much more likely to do the same. What the study does not consider, however, is how correlated those bids might be due to the uniqueness of the merchandise up for bid. That is, the values of some types of merchandise are much more likely to be underestimated, so this is a confounded effect. However, Figure 4 shows that across all values of merchandise, the probability Player 2 underbids is strongly dependent on just how close Player 1's bid is to the actual merchandise value.

We saw in Figures 2 and 3 that effect of anchoring strongly depends on the value of the merchandise. Figure 5 shows more detail about how the data are quantified. The red arrows (downward) show how much (in percentage bid) the second bid decreases after the first bid, while the blue arrows (upward) show how the second bid increases after the first. We see that Player 1 often stakes out a bid well below the actual value, and in those cases the observed increase in the second bid is not surprising.

Berk et al. (1996) was able to focus on repeated game data from the same players. Player identity was not used in our analysis, but it would provide a valueable insight not only into measuring the suboptimal bidding behavior of the TPiR players, but also the potential anchoring behavior exhibited by the same player over repeated trials.

7 Appendix

The EM algorithm application from Section 4 is based on linear regressions. With the assumption of normal errors in the traditional regression model, the joint likelihood for assessment values is normal, constructed using the conditional distributions from the individual regressions. Each player evaluation ($\hat{x}_i$) is estimated using the merchandise value and the previous bids. Transformations for the explanatory variables or the response (using Box-Cox transformations) did not provide appreciable improvements. For the case of $\hat{x}_3$, regression models used ordered bids $b_{1:2}$ and $b_{2:2}$ as explanatory variables. The model fits for the individual linear regressions are not impressive (R^2 values for evaluations for Player's 1 to 4 are in the neighborhood of 0.16, 0.39, 0.46 and 0.17), but the purpose of the regression is not to generate

Figure 5: Second Bidder trends (after first bidder)

an exact prediction for player evaluations, but provide a coherent input to test the optimality properties using the guidelines in Kvam (2018). The regression and the E-step estimates are sufficient in this regard. The EM estimates converge sufficiently in four iterations.

It is worth noting that the EM sequences may not be necessary; the results of the study in Section 4.2 are nearly identical to the results obtained using the initial estimates (based on midpoints) obtained in Step 1 of the algorithm described in Section 4.1.

References

Ariely D., Simonson I. (2003) Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions. *Journal of Consumer Psychology*, **13**: 113-123.

Ballesteros-Perez, P., Skitmore, M., Das, R., del Campo-Hitschfeld, M.L. (2015) Quick Abnormal-Bid-Detection Method for Construction Contract Auctions. *Journal of Construction Engineering and Management*, **141**: no. 04015010.

Beggs, A., Graddy, K. (2009) Anchoring Effects: Evidence from Art Auctions. *American Auction Review*, **99**: 1027-1039.

Berk J.B., Hughson E., Vandezande K. (1996) The Price is Right, But are the Bids? An Investigation of Rational Decision Theory. *The American Economic Review*, **86**: 954-970.

Estelami H. (1998) The Price Is Right...or is it? Demographic and category effects on consumer price knowledge. *Journal of Product & Brand Management*, **7**: 254-266.

Graham D.A., Marshall R.C. (1987) Collusive Bidder Behavior at Single-Object 2nd-Price and English Auctions. *Journal of Political Economy*, **95**: 1217-1239.

Healy P., Noussair C. (2004) Bidding behavior in the price is right game: an experimental study. *Journal of Economic Behavior & Organization*, **54**: 231-247.

Holbrook M.B. (1993) *Daytime television game shows and the celebration of merchandise : the Price is right*, Bowling Green State University Popular Press, Bowling Green, Ohio.

Ku G., Galinsky A.D., Murnighan, J.K. (2006) Starting low but ending high: A reversal of the anchoring effect in auctions. *Journal of Personality and Social Psychology*, **90**: 975-986.

Kvam, P.H. (2018) The Price is Right: Probability Model for Bidding on Contestants' Row. *Decision Analysis*, to appear.

Lee M.D., Zhang S., Shi J. (2011) The wisdom of the crowd playing The Price Is Right. *Memory and Cognition*, **39**: 914-932.

Lorentziadis P.L. (2015) Optimal bidding in auctions from a game theory perspective. *European Journal of Operations Research*, **248**: 347-371.

McLachlan G., Krishnan T. (2014) *The EM Algorithm and Extensions*, 2^{nd} Edition, Wiley Press, NY.

Mendes A., Morrison K.E. (2014) Guessing Games. *American Mathematical Monthly*, **121**, 33-44.

Perrigne I., Vuong Q. (2007) Identification and Estimation of Bidders' Risk Aversion in First-Price Auctions. *The American Economic Review*, **97**: 444-448.

Tenorio R., Cason T.N. (2002) To Spin or Not to Spin? Natural and Laboratory Experiments From the Price Is Right. *The Economic Journal*, **112**: 170-195.

The Price is Right Stats. (2000) `http://tpirstats.com`.

Yang Z.M., Zhang Z.K., Zhou T. (2012) Anchoring bias in online voting. *EPL*, **100**.