BRACKETING AND REFERENCE-DEPENDENT PREFERENCES AMONG ONLINE POKER PLAYERS

YI SUN

Abstract. We investigate bracketing and reference-dependent preferences among online poker players via an empirical study. We examine the impact of both cumulative and recent results on both winning and losing players' determination of when to end sessions of play and how often to enter a hand. We find that there are significant differences in these effects for winning and losing players, and we speculate that these differences result from differences in motivations between the two groups of players.

1. Introduction

Since the introduction of prospect theory by Kahneman and Tversky in [7], studies have focused on deviations from the neoclassical view of consumer behavior caused by reference-dependent preferences. Such models stipulate that individuals fix a given level of consumption, called a *reference point*, and determine their utility based on deviations from that reference point. This utility is often highly loss-averse, distorting individual choices away from what would be observed in the neoclassical case. While the theory of behavior given an exogenously specified reference point is relatively well-developed, less is known about how individuals choose reference points and over what timescales they choose them. The latter determination is known as *bracketing*.

Some recent literature has explored the structure of bracketing and reference-dependent preferences by studying labor supply in the case where workers may choose their own hours. Such studies have largely focused on employment, with most participants motivated to work in order to earn income. In this paper, we consider online poker, another activity where participants may freely determine the length of their participation. However, our study is distinguished from the existing literature by the fact that there are fundamentally different motivations for participation among online poker players. For instance, recreational players play for enjoyment or excitement, while professional players play to earn income. This variety in motivation may manifest itself in differences in players' mental accounting. Our goal in the present paper is to study their impact on bracketing and choice of reference points.

In particular, we examine the influence of previous results on choices made by winning and losing players to end playing sessions and to play particular poker hands. Our findings indicate significant differences in the nature of these effects. Our results are consistent with bracketing within sessions by winning players in reaction to cumulative results, with a smaller effect for recent results. Losing players appear to respond to previous results by changing their quitting frequency more often than by changing their proportion of hands played, perhaps due to a lack of sophistication. We provide some further speculation on these differences in Section 5.

The remainder of this paper is organized as follows. In Section 2, we introduce some relevant results from the recent literature. In Section 3, we describe the structure of our data and introduce some relevant concepts from poker. In Section 4, we introduce and estimate our theoretical models. Section 5 concludes.

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2. Previous Work

In this section we give an overview of the existing literature on reference-dependent preferences in labor supply determination and some existing studies on poker players.

2.1. Literature on Reference Points and Labor Supply.

Recent attention has been drawn to the problem of whether reference-dependent preferences play a role in labor supply decisions. In particular, many of these studies have focused on workers who are able to choose their own working hours; some examples include cabdrivers, stadium vendors, and bicycle messengers. In this subsection, we give a brief overview of this literature as it relates to our study.

In [1], a study of the (self-determined) working hours of New York City cabdrivers found that drivers' choice of working hours is significantly negatively correlated with their daily wage. The authors infer that drivers determine a stopping time for their shift based upon a fixed target for their daily earnings, providing evidence for daily bracketing.

However, studies done for stadium vendors in [12] and bicycle messengers in [6] found a positive elasticity of wage supply consistent with neoclassical theory. In these studies, the authors found that workers increased their hours worked to take advantage of opportunities for higher wages, suggesting that in these cases the workers were bracketing along time frames on the order of months (the time scale of these studies).

These findings seem to be inconsistent with the earlier study of cabdrivers. Indeed, in the later papers [3], [4], and [5], a reanalysis of the data using different econometric models found little evidence for such bracketing. Instead, using an optimal stopping model in [5], Farber finds that drivers do have reference-dependent preferences but that the reference are variable between days and rarely achieved, leaving open the question of how to interpret the importance of their role. Farber posits the major difficulty as how to deal with wage reference points that differ by day.

2.2. Literature on Rationality in Poker.

A number of previous studies have also focused on the rationality of decision making among poker players. We briefly summarize these studies in this subsection. In [2], the authors conclude that the outcome of poker tournaments is largely determined by skill. In [10], Liley and Rakow examine the ability of moderately experienced poker players to estimate common probabilities associated to poker. They find that players provide relatively accurate estimates of these probabilities, concluding that they are able to avoid several common estimation biases. These studies suggest that several important aspects of poker are dominated by rational decision-making, creating a more interesting context for the following two studies about deviations from the rational model.

In [2], Lee examines risk-taking among entrants in WPT poker tournaments and concludes that players are much more sensitive to possible losses than possible gains, which is consistent with reference-dependent preferences. The metric used for the amount of risk taken by players is the frequency of hands played. However, it should be noted that aggressive play may reduce risk late in tournament play by allowing players to avoid the effect of rising blinds, so the link to risk aversion should be viewed in this light.

In [13], Smith, Levere, and Kurtzman study the influence of winning or losing a large pot on behavior among experienced players in the short run. They find that recent results are negatively correlated with the frequency of hands that players play soon thereafter. The authors interpret this as evidence that players are reference-dependent, hence willing to accept greater risks in order to "chase their losses." On the other hand, they would tend to play more cautiously after wins to preserve them. However, we note that it is a commonly used strategy to play more hands when one has more money on the table (since one can make up for small preflop mistakes by winning a greater amount of money after the flop), hence it might be possible to interpret this effect as an appropriate adjustment made by very skilled players.

3. Data

In this section, we describe the hand history data used in our empirical study in more detail.

3.1. **Texas Hold'em Poker.**

Texas Hold'em is currently the most popular form of poker played online. It is played using a standard deck of cards. In each hand, every player is dealt two cards, and the objective is to make the best five card poker hand using the combination of these cards with five common community cards. The sequence of play during every hand proceeds as follows:

(1) Before the hand starts, two players (determined in a rotating manner around the table) are designated to be the small blind (SB) and big blind (BB) and must place forced bets of a fixed size.
(2) Beginning with the player after the BB, each player may either fold, forfeiting the opportunity to win that hand, call, matching the bet, or raise, increasing the bet. This is known as the *preflop* round of betting and ends when all players have called or folded.
(3) Three community cards, known as the *flop*, are dealt, followed by a round of betting beginning with the SB.
(4) One more community card, known as the *turn*, is dealt, followed by a round of betting beginning with the SB.
(5) One final community card, known as the *river*, is dealt, followed by a round of betting beginning with the SB.
(6) Players who have not folded reveal their cards, and the player with the best five card poker hand wins the accumulated bets, known as the *pot*.

Online play at Texas Hold'em tables consists of a series of hands played consecutively at the same table. In addition, it is possible for the same player to simultaneously play at multiple tables at once to increase the rate of hands seen, a practice known as *multitabling*. The two largest online poker sites are Full Tilt Poker and PokerStars, with over 100,000 players online at once at all times.

3.2. **Poker Statistics.**

There are several statistics often used in poker to track performance and playstyle. For each player, we may track the rate of money won (winrate), the proportion of hands that the player voluntarily puts additional money into the pot for (VPIP), and the proportion of hands where the player raises before the flop (PFR). The last two are often used as a measure of how "loose" or "aggressive" a strategy a player is using (a higher VPIP is looser and a higher PFR is more aggressive). The winrate is usually measured in terms of big blinds won per 100 hands played (bb/100); we note here that the rake, a portion of each pot collected by PokerStars, is deducted from this winrate, so the average winrate of all players should be negative.

It is widely believed in the poker community that a sustainable long-run winrate at these stakes is between 5bb/100 and 10bb/100 and that observing 20000 hands is necessary to determine if one is a winning player due to variance inherent to Texas Hold'em. Indeed, the relative ranking of hands can reverse completely depending on the value of a single card, meaning that player winrates can be very difficult to accurate estimate. However, the frequency with which players play poker also varies widely; of the players in the sample, 2181 have played at least 1000 hands, but over half have played less than 100 hands. To eliminate some outliers in these statistical measures, we only use hands from players who have played at least 10 hands in our sample.

We use a player's winrate over our sample as an estimate of their long-run winrate. We postulate that a player with a winrate of greater than 5bb/100 in our sample is winning and that a player with a winrate of less than -5bb/100 is losing, and we will examine the differences in decision-making between these two groups.

3.3. **Description of Data.**

Our data consists of transcripts of a complete sample of Texas Hold'em hands played with a \$0.10 small blind and a \$0.25 big blind (this stake is known as NL25) at 6-person tables on PokerStars on 07/27/09. This comprises 270,000 hands with 27000 players. We note here that much more data of this type is available, but we faced time constraints that limited our computational capacity. For each hand, we are able to observe all actions taken by all players and the final result of the hand. Note, however, that players' hands are only known to us if they were revealed during the course of online play. In addition, we have a unique identifier and timestamp for each hand.

We group the hands played by each player into *sessions*, which are groups of hands played (possibly on multiple tables) in a continuous block of time. As a simple heuristic, we assume that two hands belong to the same session if they are played within 5 minutes of each other. We may then compute the following statistics for each player:

- For each session, the number of hands and the winrate in that session.
- For each hand, the number of hands played so far in the session, the winrate so far in the session, and the winrate for the previous 12 hands in the session.

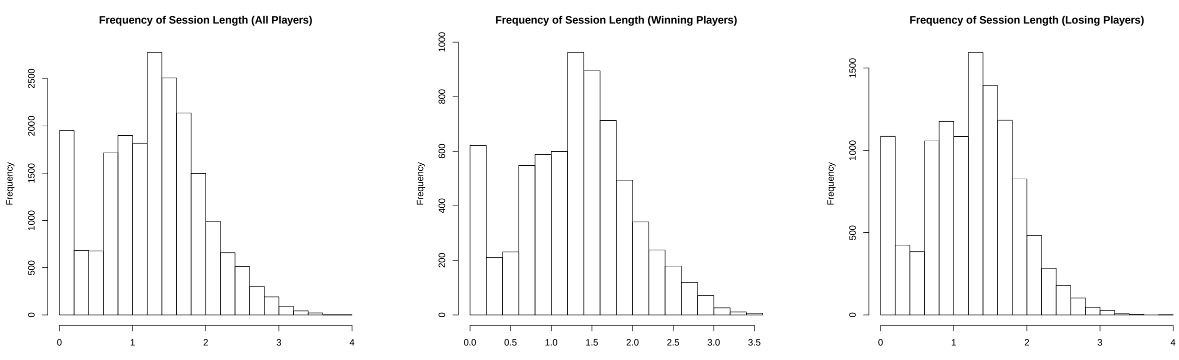
We use this data to represent players' past performance within a session.

4. Analysis and Results

In this section, we describe our analysis. We first give some summary statistics for winrate and session length and then develop and estimate two empirical models.

4.1. **Preliminary Analysis.** We begin by examining the relationship between the lengths of sessions that players play and their winrates. Comparing histograms of the frequency of session lengths for winning and losing players in Figure 1, we see that they are distributed very similarly, suggesting that we may do a crude first evaluation by looking at the mean winrate conditional on session length.

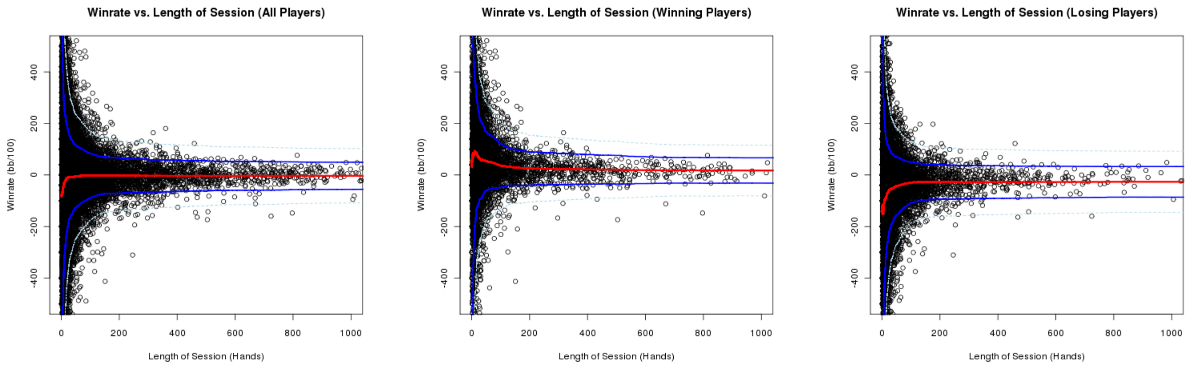
Figure 1. Frequency of Session Lengths.



In Figure 2, we have plotted a smoothed version of the mean winrate conditional on session length. The red line indicates the mean, and the two blue lines represent variations of 1 and 2 standard deviations from the mean.

Notice that the magnitude of players' average winrates are largest for short sessions and decay to smaller absolute magnitudes with an increase in hands. We interpret the large initial magnitude as a manifestation of players quitting after large initial wins or losses or simply playing small numbers of hands, thus producing larger variance in winrates. Note further that the variance in session length is quite high, with most players playing sessions of less than 100 hands, but a fair number of players playing much longer sessions. This motivates our more systematic study of how players determine session length in the next few sections.

FIGURE 2. Winrate vs. Length of Session.



4.2. **Empirical Models.** In this subsection, we develop an empirical discrete choice model of online poker player behavior. We will use this model to study the dependence of (1) players' decisions to end sessions and (2) players VPIP on their results in the preceding session. Here we follow the general methodology taken in [4]; in our case, however, the use of a discrete choice model is an exact reflection of the situation rather than an approximation of an optimal stopping model.

During any hand during a session, a player must make two binary choices. First, he can either commit preflop money to the hand or not, which determines his VPIP for the hand. Second, he can decide to continue to play future hands or to end the session. We model both of these choices using a probit model. Explicitly, we postulate that the player's choice to do the action X (either commit money preflop or play the next hands) has conditional distribution

$$\mathbb{P}[X_i \mid p, w] = \Phi(\gamma_p p + \gamma_w w + \varepsilon_{ipw}),$$

where Φ is the standard probit link function and i indexes the player under consideration. The quantity p measures the profit of the player thus far in the session, and w measures the recent winrate of the player. Here we define recent to encompass the previous 12 hands in the session (or the entire session if the session is less than 12 hands long).

We choose our regressors p and w to provide two different measures of prior performance. We use p to measure players' response to their overall performance during a (possibly long) session, and we take w to measure effects from short-run fluctuations in results. While players will of course be aware of the approximate value of w during play, it is worth noting that there is pervasive tracking software that allows some players to actively monitor p as well. Therefore, it is likely that some more sophisticated players will be able to actively factor w and p into their decision-making processes.

4.3. **Predictions.** We now briefly point out some possible predictions for the result of these empirical models. These predictions are motivated by informal observations of online poker play and several different online poker players at different skill levels, some recreational and some professional. In our investigation, we will take winrate as a proxy for experience and sophistication, so we phrase our predictions in this language.

(1) **Losing players will be influenced more than winning players by recent results.** There is a great deal of variance in poker, and more sophisticated players might become habituated to it, reducing the effect of any reference points set by recent results.
(2) **Winning players will exhibit more cumulative "break-even" reference point effects than losing players.** Sophisticated players may be more concerned with their results, either for monetary or goal oriented reasons and should therefore be more likely to be affected by single-session bracketing and preset reference points. In particular, informal

observations find that even professional poker players often play exceptionally long sessions in order to return to a break-even point. Recreational players, on the other hand, may have a less goal oriented approach (while still attempting to make correct decisions), causing them to be less susceptible to narrow bracketing.

In the remainder of this section, we implement the models from the previous subsection and discuss the consequence of the results for our predictions.

4.4. **Preflop Looseness.** We first consider players' preflop looseness. As a first step, we compute players' VPIP for several extreme ranges of p and w. Here, p is measured in dollars and w in bb/100. A p of 75 corresponds to a profit of 3 initial buyins, while a w of 800 corresponds to a profit of 1 initial buyin in the previous 12 hands. Such variations are among the largest in magnitude to occur in a typical session. These results are given in Table 1; note that the sample sizes are given below the VPIP values.

TABLE 1. VPIP for various ranges of p and w.

	$p < -75$	$p < -25$	$p > 25$	$p > 75$	$w < -800$	$w < -200$	$w > 200$	$w > 800$	total
All	20.3	22.8	23.1	19.7	34.1	36.1	33.5	34.1	25.5
	(37k)	(177k)	(170k)	(31k)	(11k)	(104k)	(112k)	(9k)	(1113k)
Winning	24.1	23.6	24.5	21.7	31.9	34.0	33.6	34.6	25.4
	(7.4k)	(38k)	(79k)	(12k)	(2.7k)	(29k)	(46k)	(4.4k)	(374k)
Losing	19.2	25.6	26.4	21.8	38.8	40.9	37.3	37.7	29.6
	(19k)	(76k)	(32k)	(4k)	(5.3k)	(50k)	(38k)	(4.0k)	(406k)

As can be seen in Table 1, players' average VPIP appears to be slightly larger when they have experienced large recent losses than for large recent gains, while there does not appear to be an effect for a recent loss or gain. This is consistent with the findings of [13] for games at much higher stakes, providing a consistency check for our data. In addition, we observe that players' average VPIP is generally higher than the overall mean after recent large variations, while it is lower when their cumulative profits are large. This may simply be the result of players who have higher VPIP using a more volatile playstyle and hence higher magnitude of w, while players with lower VPIP remain in higher magnitude values of p for a longer time period. However, this does not seem like an entirely satisfactory explanation.

We now estimate our empirical probit model; the results of our regression are shown in Table 2. Here *** denotes significance at the 0.01% level. The χ^2 test statistic is 2.5×10^{-25} and a pseudo R^2 of 0.54. Our fit is therefore highly significant. Note that the low absolute values of the coefficients for p and w are due to their large absolute values.

As can be seen from Table 2, winning and losing players appear to change their VPIP in different ways depending on past results. The reaction of winning players to cumulative profits is consistent with the hypothesis in [13] of bracketing of results within sessions, as winners play more hands when losing and fewer hand when winning. Counterintuitively, losers, who we assume to be less sophisticated, exhibit the opposite tendencies.

On the other hand, the reactions to short-run results exhibit the opposite trend. Winners appear to react to such results in a rational manner, while losers seem to chase losses by playing more hands. In the short run, at least, the greater skill or sophistication of the winners seems to aid their decision making.

TABLE 2. Probit Regression Results for VPIP.

All	Estimate	Std. Error	z-value	$\Pr(>\lvert z\rvert)$	
(Intercept)	-0.5870	0.0011	-519.45	$< 2 \times 10^{-16}$	***
p	2.995×10^{-4}	2.846×10^{-5}	10.52	$< 2 \times 10^{-16}$	***
w	-1.495×10^{-5}	4.249×10^{-6}	-3.52	4.37×10^{-4}	***
Winning	Estimate	Std. Error	z-value	$\Pr(>\lvert z\rvert)$	
(Intercept)	-0.600	0.0020	-302.97	$< 2 \times 10^{-16}$	***
p	-4.695×10^{-4}	5.398×10^{-5}	-8.699	$< 2 \times 10^{-16}$	***
w	1.903×10^{-4}	7.173×10^{-6}	26.53	$< 2 \times 10^{-16}$	***
Losing	Estimate	Std. Error	z-value	$\Pr(>\lvert z\rvert)$	
(Intercept)	-0.4481	0.0018	-251.76	$< 2 \times 10^{-16}$	***
p	1.565×10^{-3}	4.418×10^{-5}	35.42	$< 2 \times 10^{-16}$	***
w	-1.588×10^{-4}	6.170×10^{-6}	-25.73	$< 2 \times 10^{-16}$	***

4.5. **Session Length.** Our measures of player response to outcomes via VPIP changes leave out a frequent occurrence – leaving the table. Some observed practices of this type seen in the poker community include (a) ending a session after a large win or loss, (b) setting a predetermined cap on losses during a session, or (c) playing until results reach a predetermined point (usually the break-even point). We test for these phenomena in this section.

We first consider the probability that a player decides to end a session after each hand conditional on several ranges for p and w. This is shown in Table 3, where we have also shown the results when restricted to players who are large winners or large losers in our sample.

TABLE 3. Quitting Probability for various ranges of p and w.

	$p < -25$	$-25 < p < 0$	$0 < p < 25$	$25 < p$	$w < -200$	$w > 200$	total
All	.005	.011	.011	.005	.018	.011	.009
	(177k)	(396k)	(378k)	(170k)	(105k)	(114k)	(1124k)
Winning	.003	.009	.014	.006	.012	.013	0.009
	(38k)	(108k)	(152k)	(79k)	(30k)	(47k)	(377k)
Losing	.008	.017	.013	.004	.026	.011	.013
	(76k)	(174k)	(128k)	(32k)	(51k)	(38k)	(411k)

We make several observations here. First, we see that players have a much higher probability of quitting when the magnitude of p is small, probably because longer sessions are more rare. Second, we find an interesting dichotomy in the reaction of players to high volatility in the short-run. Losing players tended to quit much more frequently after a large loss than winning players, while such an effect is not present for large wins. This difference appears to contradict our hypothesis of daily bracketing and a break-even reference point; however, the lack of a similar discrepancy among winning players suggests that this may be associated to an experience or skill effect.

We now estimate our empirical probit model; the results are shown in Table 4. For these regressions, the χ^2 test statistics are less than 2×10^{-5}, and the pseudo-R^2 values are 0.095, 0.098, and 0.122, respectively. While these pseudo-R^2 values are somewhat low, this is perhaps explained by the infrequent nature of the end of sessions.

In all cases, we see that cumulative profit is positively correlated with quitting probability, which is consistent with the hypothesis posited in [13] that players attempt to preserve wins and make back losses. However, we see that the effect of short-run profit differs for winning and losing

Table 4. Probit Regression Results for Quitting Probability

All	Estimate	Std. Error	z-value	Pr($>\|z\|$)	
(Intercept)	-2.3566	0.0036	-645.70	$< 2 \times 10^{-16}$	***
p	5.066×10^{-4}	8.56×10^{-5}	5.92	3×10^{-9}	***
w	-2.646×10^{-4}	1.586×10^{-5}	-16.69	$< 2 \times 10^{-16}$	***
Winning	Estimate	Std. Error	z-value	Pr($>\|z\|$)	
(Intercept)	-2.345	.0063	-371.7	$< 2 \times 10^{-16}$	***
p	1.491×10^{-4}	1.554×10^{-4}	0.960	.337	
w	1.096×10^{-4}	2.617×10^{-5}	4.187	2.8×10^{-5}	***
Losing	Estimate	Std. Error	z-value	Pr($>\|z\|$)	
(Intercept)	-2.234	0.0055	-403.23	$< 2 \times 10^{-16}$	***
p	1.59×10^{-3}	1.42×10^{-4}	11.22	$< 2 \times 10^{-16}$	***
w	-4.91×10^{-4}	2.08×10^{-5}	-23.59	$< 2 \times 10^{-16}$	***

players. Winners react the same way to short-run and long-run profits, while losers appear to treat the situations differently. In particular, losers are much more likely to end a session in the period following a large short-run loss and much less likely to book an immediate win. Such behavior is more consistent with rational preferences in the short run than the behavior of winning players. Paradoxically, however, the magnitude of the "break-even" influence of cumulative results is much greater for losing players than for winning players, suggesting that losing players' success in the short run here may not be a sign of greater sophistication.

5. Discussion

5.1. **Motivations and Bracketing.** We have provided some evidence for differences in reactions to prior results among two populations of online poker players, with the corresponding implications for differences in bracketing. We provide some speculations here on the differences between these populations.

In [1], [4], [5], and [12], the authors examine bracketing and reference-dependent preferences among sophisticated agents motivated to maximize their income from their jobs. In these cases, we may view any instance of narrow bracketing as a cognitive mistake or mistaken optimization. Previous studies on online poker have established a segment of the poker-playing population as having many of these attributes; as seen in [9] and [10], agents are clearly sophisticated in estimation of poker-related probabilities. However, studies such as [13] point to limits to this sophistication, even among high-level professional players, perhaps suggesting that these effects are fundamentally psychological in nature.

The present study includes a large population of *unsophisticated* poker players. While such players may also be trying to optimize their returns from poker, it appears from our results that their approach leads to a different type of bracketing. Of course, one might attempt to explain these differences as simply similar deviations applied to incorrect heuristics rather than the (assumed good) optimization of sophisticated players. However, it seems that the psychological basis for bracketing derives not from the analytical act of optimization but rather the effort expended by individuals to apply it (for instance, expert poker players are aware of cognitive biases of the type studied in [13] and work rationally to eliminate them). Therefore, one might attribute the differences in bracketing among player types to differences in the effort expended and the rigidity of the (self-imposed) framework in which the interaction occurs.

5.2. **Future Directions.** We conclude by discussing some possible improvements and extensions.

5.2.1. *Statistical Issues.* Our statistical analysis in the present paper is still somewhat incomplete due to time constraints. Firstly, we were unable to run our analysis on a larger data set in our possession due to computational time constraints. Further, some systemic problems with our analysis could be improved.

In particular, the pseudo R^2 and log likelihood values we reported to test for goodness of fit in our regressions are somewhat crude measures. Given more time and computational power, we could address this issues by cross-validating our model between a training and test data set.

In addition, we determined whether players were winning or losing from the same data as was used to find their cumulative profit and recent winrate among sessions. While the effect on recent winrate is not be large, this choice introduces creates an unintended correlation between p and our two player types, which may bias the p coefficients in our regressions of winning players to be closer to the coefficients in the overall player pool. To correct this, we could attempt to find winning and losing players in an independent sample of hands and examine the (unbiased) winrates of these players in a different later sample.

Finally, our analysis aggregates hands of all players together in the analysis, losing a significant amount of hierarchical information. In particular, the fact that different session were played by the same player does not play a large role in our analysis. We might address this by introducing a hierarchical probit model that parametrized players by some learned attributes (e.g. level of sophistication, susceptibility to reference-dependence). We might fit such a model using the flexible BUGS statistics package developed to handle such hierarchical models (see [11]).

5.2.2. *Choice of Data Set.* Our specific data set was chosen due to ready availability for a quick study and has several disadvantages over some similar data sets. In particular, 6-player Texas Hold'em has quite variance due to the large number of possible situations that can occur. There is also a large amount of hand history data for 2-player Texas Hold'em available for purchase online, and it may be fruitful to examine this data instead.

This would have two advantages. First, because there are fewer possible poker-related situations, bracketing and reference point effects may play a larger role, improving the quality of our regressions. Secondly, our current data set has a relatively small number of hands per player relative to its overall size. This makes it infeasible to obtain statistically significant estimates of winrate for individual players, which would be extremely useful for classifying types of players. Using 2-player data, we might be able to classify individual players more cleaning and thereby draw stronger conclusions on the group level.

Finally, our data set consisted of hands at the $25 dollar buyin level, which consists of mostly amateur players with a range of interest levels. It might be interesting to conduct a similar study with data at the $100 or $200 buyin tables. At these stakes, players are able to make a full-time living from poker, meaning that the player pool is a mixture of professionals and recreational players. This contrast might allow us to draw stronger conclusions about differences in bracketing behavior between the two groups.

5.2.3. *Model.* Our work in this study has been almost entirely empirical due to a lack of intuition about what effects should take place. Given our increased knowledge of the data, our ultimate goal would be to find a more theoretically grounded model that distinguishes between the types of players. An approach to this seems challenging, as it would need to combine information about playing styles with additional information about individual participants, but perhaps a first step would be to attempt to learn to distinguish types of players based on their observed playstyle.

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206 Cabot Mail Center, Cambridge, MA 02138
E-mail address: `yisun@fas.harvard.edu`