

Poker Player Behavior After Big Wins and Big Losses

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Abstract

We find that experienced poker players typically change their style of play after winning or losing a big pot—most notably, playing less cautiously after a big loss, evidently hoping for lucky cards that will erase their loss. This finding is consistent with Kahneman and Tversky's break-even hypothesis and suggests that when investors incur a large loss, it might be time to take a vacation or be monitored closely.

Introduction

A substantial body of evidence indicates that decisions are shaped by a variety of cognitive biases. Hirshleifer (2001) gives an extensive literature survey of psychological influences on investor decisions. Thaler and Johnson (1990) discuss some problems with experimental data, including people's fears that they might lose money because they don't understand the instructions. We use data from an online poker site to investigate whether experienced poker players change their style of play after winning or losing a big pot. Poker is a very attractive source of data because it avoids many criticisms of artificial experiments; for example, that the subjects are inexperienced or that they are inattentive because the payoffs are small. We find that poker players tend to be less cautious after large losses, evidently attempting to recoup their losses quickly.

Behavioral Theories

Poker is a game of uncertainty that involves many unknown factors. Players do not know the cards that will be dealt, what cards their opponents hold, how their opponents will bet, or what their opponents' bets mean. However, poker players can assign probabilities, and the accuracy of these probabilities plays a crucial role in the implementation of a winning poker strategy.

Optimal decisions should focus on the marginal prospective benefits and costs, without regard for past gains and losses. In poker, every hand is new and unrelated to previous hands. In practice, history does matter because: (a) players may revise their assessments of their skills and strategy; and (b) outcomes do have psychological effects. We will summarize several different theories and their implied predictions about behavior after big wins and big losses.

Revised Assessment

Updated assessments are consistent with a Bayesian perspective in which players use wins and losses to assess ability. When large sums of money change hands, a player's decisions are validated or challenged and players may feel more confident or less sure of their ability to assign probabilities.

For experienced players, a small number of hands should have little effect on their assessment of their skills. Similarly, List (2004) argues that, "consumers with intense market experience behave largely in accordance with neoclassical predictions." If so, experienced poker players should be little influenced by wins and losses. But, of course, humans, are not dispassionate Bayesian statisticians and they often draw conclusions from limited data that should be unpersuasive (Kahneman and Tversky 1972).

If large losses cause poker players to lose confidence, they may subsequently be less certain of their ability to gauge probabilities and play more cautiously. Similarly, after large wins players may be more confident of their probability assessments and play less cautiously. If so, we might expect big losses to be followed by less aggressive play and big wins to be followed by more aggressive play.

On the other hand, calibration studies, which ask individuals to predict the outcome of an uncertain event (such as an election or the performance of a particular stock) and also to estimate the probability that their prediction will be correct, find that people are typically overconfident (Slovic, et al. 1976; Odean 1998) and maintain this misperception despite evidence to the contrary by attributing their successes to skill and their setbacks to bad luck (Langer and Roth 1975, Miller and Ross 1975, Fischhoff 1982). If so, wins and losses may matter little.

Prospect Theory and the Break Even Hypothesis

Many behavioral models are grounded in prospect theory (Kahneman and Tversky 1979, Tversky and Kahneman 1992), which uses a value function v to characterize potential gains and losses (in contrast to a utility function u that values potential levels of wealth) and a decision weight function π that is used in place of probabilities. Thus, if the reference level of wealth is W_0 and a gamble will result in wealth W_1 with probability p and wealth W_2 with probability $1 - p$, the value V of this prospect is

$$V = v[W_1 - W_0]\pi[p] + v[W_2 - W_0]\pi[1 - p]$$

in contrast to the expected value of utility

$$E[U] = u[W_1]p + u[W_2](1 - p)$$

Prospect theory is a general, flexible framework that can accommodate a wide variety of models. In practice, the experiments done by Kahneman and Tversky and others (typically involving survey questions or small laboratory gambles) support these characteristics:

1. The value function is S-shaped (convex for losses and concave for gains), since people tend to be risk averse for moderate probability gains (preferring a \$50 gain to a 0.50 probability of gaining \$100) and risk seeking for moderate probability losses (preferring a 0.50 probability of losing \$100 to a \$50 loss).
2. The value function is kinked at the origin and gives more importance to a loss than to a gain of the same magnitude, since most people are not attracted to wagers that give them an equal chance of winning or losing \$100.

3. The decision weight function treats extremely unlikely events as impossible and extremely likely events as certain. For less extreme probabilities, the decision weight function overweights small probabilities and underweights medium and large probabilities.

These characteristics of the value function and the decision weight function can explain otherwise puzzling behavior such as simultaneously investing conservatively and purchasing insurance and lottery tickets.

The framing of decisions is also thought to be very important (Kahnemann and Tversky 1979, 1981, Barberis and Thaler 2003, Barberis and Xiong 2009). For example, is the reference point W_0 equal to the current level of wealth? The level of wealth at the beginning of the day, week, or year? A target level of wealth?

Figure 1 shows how the reference point affects the value of a prospect. In this example, there is a 0.50 probability of winning \$1,000 and a 0.50 probability of losing \$1,000, and we assume that the decision weights are equal to the probabilities. If the reference point is $W_0 = 0$, the value of the prospect is negative because of the value function's loss aversion. The value of prospect is less than the value of the doing nothing. If, however, the reference point is $W_0 = -\$1,000$, perhaps because of an earlier loss, then the value of the prospect is higher than the value of $-\$1,000$ because the value function is convex for losses. The value of a 50 percent chance of $-\$2,000$ and a 50 percent chance of breaking even is larger than the value of $-\$1,000$.

There is considerable evidence that behavior is, in practice, affected by sunk costs (Arkes and Blumer 1985). Staw (1976) argues that adverse results often lead to an expanded commitment of resources in an attempt to justify the original investment. Laughhunn and Payne (1980) argue

that sunk costs and sunk benefits both affect decisions.

Kahneman and Tversky (1979, p. 287) observe that a “person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise.” Figure 1 illustrates how a prior loss can encourage a person to take a gamble he would otherwise avoid. If this person considers the gamble independently of previous outcomes ($W_0 = 0$), the gamble is unattractive. If, however, this person takes a prior loss of \$1,000 into account ($W_0 = -1,000$), the gamble is attractive.

Kahneman and Tversky (1979) observe that bets on long shots at horse races occur with greater frequency towards the end of the day, presumably because people are looking for a cheap opportunity to win back what they lost earlier in the day. Consistent with this argument, Thaler and Johnson (1990) argue that people who have suffered losses are attracted to gambles that offer them a relatively inexpensive opportunity to break even. They find that most people who have already lost \$30 would rather bet \$2 with 15-1 odds than bet \$30 on an even bet because the first bet offers a less expensive opportunity to break even.

An attraction to long shots might be explained in prospect theory by the combination of a value function that is convex for losses; a framing that incorporates prior losses, and an overweighting of small probabilities.

Moods

There is evidence that moods affect risk-taking; specifically, that people are more optimistic when they are in a good mood (Isen, Means, Patrick, and Nowicki 1982, Wright and Bower 1992). Similarly, there is some evidence that stock markets do better on sunny days than on cloudy days (Saunders 1993, Hirshleifer and Shumway 2003).

In poker, winning a big hand is exhilarating and losing a big hand is depressing. These emotions may carry over into subsequent hands, with players more likely to take unwarranted gambles after winning and less likely to do so after losing. It is possible that mood swings may cause even experienced poker players to change their style of play after a big win or loss.

House Money

It has been argued that gamblers who win wagers feel that they are now playing with other people's money ("house money") and can afford to be less cautious (Thaler and Johnson 1990). After a big win, players might be less concerned about losing what was not theirs to begin with. Similarly, they may be more cautious after a large loss because they feel they are now playing with their own money.

Gambler's Fallacy

Another possible reaction to gains and losses is based on the "gambler's fallacy"—the belief that the more often something has occurred (heads in coin flips, winning numbers in lotteries, bad hands in poker), the less likely it is to occur in the future. For example, Clotfelter and Cook (1993) looked at Maryland pick-three lottery bets before and after a winning number is selected. After a number is drawn, players choose that number at a far lower rate for around 80 days, evidently because of a belief that the probability that an event will occur is inversely related to the number of times it has occurred recently. Similarly, poker players often lament that they are "due for aces" or that they "will definitely hit their next flush." Players who believe in the gambler's fallacy may be less willing to bet after wins and more willing to bet after losses.

Hot and Cold Streaks

On the other hand, some players believe that cards can become "hot" or "cold." More

generally, a substantial literature on regression to the mean indicates that people underestimate the role of chance when they use observed data to assess underlying phenomena. For example, many investors misinterpret a temporary blip in a company's earnings as evidence of a permanent change in its profitability (Lakonishok, Shliefier, and Vishny 1994, La Porta 1996). Similarly, basketball players who make or miss two or three shots in a row are perceived to be hot or cold instead of lucky or unlucky (Gilovich, Vallone, and Tversky 1985). Poker players who believe in hot and cold streaks may be more willing to bet after wins and less willing to bet after losses.

Doyle Brunson Strategy

Poker players may have strategic reasons for changing their style of play. Doyle Brunson, two-time winner of the World Series of Poker main event, deliberately changes his play after large victories. In *Super System* (2003), the most acclaimed book on poker strategy, Brunson recommends loose-aggressive play (betting many hands and betting more than necessary to stay in the game) after big wins in order to bully opponents into submission. The successful outcome of this strategy is known as a rush. Brunson (p. 562) writes that, "Scientists don't believe in rushes, but sometimes rushes can make you a fortune. There's only one world-class poker player that I know of who doesn't believe in rushes. Well, he's wrong, and so are the scientists. Besides, how many of them can play poker anyway?"

Putting It All Together

Table 1 summarizes the predictions of these various theories. The revised-assessment argument is that a big win (or loss) makes players more (or less) confident of their ability. The break-even argument is that players who suffer big losses will be attracted to gambles that give

them an opportunity to win back what they have lost. The moods argument is that people in good (or bad) moods after a big win (or loss) will be more optimistic (or pessimistic) about their chances. The house-money argument is that players are less cautious after a big win because they feel that they are now playing with other people's money, and are more cautious after a big loss because they feel that they are playing with their own money. The gambler's fallacy counts on a change in a player's luck; the streaks argument predicts a continuation of one's luck. However, both of these theories seem more relevant after a string of wins or losses, rather than one big pot. The Doyle Brunson argument is that players who win big should bully their opponents by playing more aggressively.

Texas Hold 'Em

Texas Hold 'Em is a form of poker using a standard 52-card deck with four suits (spades, hearts, diamonds, and clubs) and 13 cards in each suit (ace, king, queen, jack, 10, 9, 8, 7, 6, 5, 4, 3, 2). In our study, we look at no-limit \$25/\$50 blind tables, with a maximum of six players at a table and the dealer position rotating around the table.

At the beginning of each hand, the player sitting directly to the left of the dealer for this hand puts a small blind of \$25 into the pot, and the player two seats to the left of the dealer puts in a big blind of \$50. Each player is then dealt two "hole cards" that only they are allowed to see. The players who have not already put money in the pot decide whether to play or fold. To play, the players must either "call" the big blind, \$50, or raise the bet above \$50, forcing the other players to match the highest bet on the table. The bets go clockwise around the table until the highest bet is called by all players who wish to remain in the hand, or all but one person folds.

If more than one player is still in, three community cards ("the flop") are dealt, which are

visible to everyone and can be used by each player to build the best possible hand. Another round of betting occurs, starting with the person to the left of the dealer. Until a bet is made, a player can check, which means the player waits to see what other people do. After this round of betting, a fourth community card (“the turn”) is dealt and there is another round of betting. Finally, the fifth community card (“the river”) is dealt and there is a final round of betting. The player with the best five-card hand, between their two cards and the five community cards, wins the pot.

The best five-card hand is a straight flush, five cards in sequence, all of the same suit (for example, the 10, 9, 8, 7, and 6 of hearts). An ace can be used as a low card (5, 4, 3, 2, ace) or as a high card (ace, king, queen, jack, 10). The next best hand is four of a kind (for example, four 8s and a 5), followed by a full house, which is a hand with three of a kind and a pair (for example, 8, 8, 8, 5, 5). Next best is a flush (five cards of the same suit), followed by a straight (five cards in sequence, but not all in the same suit), three of a kind (for example, 8, 8, 8, 5, 4), two pairs (for example, 8, 8, 5, 5, 4), and one pair (8, 8, 5, 4, 2). Last is a no-pair (or “nothing”) hand with none of the combinations listed previously. The ranking of the cards is used to break any ties. For example, a jack, 10, 9, 8, 7 straight beats a 10, 9, 8, 7, 6 straight, and a pair of aces beats a pair of kings.

Texas Hold ‘Em is considered a strategic game because there are several rounds of betting and the five community cards are visible to all players. The outcome of each individual hand depends on the luck of the draw; for example, a player with two aces in the hole may lose to a player with two 3s in the hole if another 3 shows up in the community cards. However, a player’s long-run success depends on making good betting decisions—“knowing when to hold ‘em and when to fold ‘em.”

Data

Full Tilt Poker is an online poker room launched in June 2004 with the involvement of a team of poker professionals. The company and its web site are regulated by the Kahnawake Gaming Commission in Canada's Mohawk Territory. Because it is outside U. S. jurisdiction, the web site is able to avoid U. S. regulations and taxes.

The main advantages of online play are the convenience, quick dealing, and low costs; the primary disadvantage is the absence of physical tells. In low-stakes or no-stakes games, online players tend to be unskilled and to bet more recklessly than the typical casino player. However, the players in online games that have substantial blinds are very experienced. In fact, Full Tilt Poker boasts the largest online contingent of professional poker players.

Using a program called PokerTracker, we gathered our data by recording online poker games at Full Tilt Poker from January 2008 to May 2008. With Full Tilt, PokerTracker can gather data on hands by simply observing rather than playing; we consequently monitored multiple tables continuously 24 hours a day. For consistency, we only looked at tables with blinds of \$25/\$50, which are considered high-stakes tables and attract experienced poker players.

Our data are split into two sets: six-player tables and two-player ("heads up") tables. Our unedited data set includes 1,609 different players and 226,351 hands at six-player tables and 1,069 players and 339,510 hands at two-player tables.

There are sometimes empty seats at a six-player table. Poker strategy is affected by the number of players at a table; for example, the chances that a pair of 8s in the hole will yield the best hand declines as the number of players increases. We consequently group the data for six-player tables according to the number of players at the table. We do not combine the data for

heads-up tables with the data for six-player tables with two players because the people who choose to play heads-up poker may have different styles than players who choose a six-player table but occasionally have four empty seats.

We consider a hand where a player wins or loses \$1000, twenty times the big blind, to be a significant win or loss. After a big win or loss, we monitor the player's behavior during the next 12 hands—two cycles around a six-player table. We follow two cycles because experienced players often make no voluntary bets, and twelve hands are still reasonably close to the time of the big win or loss.

For each of the 12 hands following a big win or loss, we record the number of players at the table and the bets made by the person who won or lost big. For example, a player might win \$1,200 one hand and, during the next 12 hands, play nine 6-player hands and three 5-player hands. In order to facilitate a comparison of play after winning and losing big pots, for each number-of-players category we restrict our attention to individuals who played at least 50 hands in the 12-hand window following big wins and at least 50 hands in the 12-hand window following big losses. For example, for a person to be included in the 5-player category, he must have played at least 50 5-player hands during the 12-hand windows following his big wins and at least 50 5-player hands during the 12-hand windows following his big losses. Then we are able to compare this person's play in 5-player hands played after big wins with his play in 5-player hands played after big losses.

Methods

Our objective is to investigate whether winning or losing a big hand has any impact on a person's playing style. There are two standard measures of playing style: looseness and

aggression.

The generally accepted measure of looseness is the percentage of hands in which a player voluntarily puts money into the pot. This can include a call or a raise, but does not include blind bets since these are involuntary. After a hand is dealt, the blinds force everyone other than the player who put in the big blind to bet or else fold before they see the 3-card flop. Thus, looseness generally measures how often a person puts money into the pot in order to see the flop cards. Tight players fold when their two hole cards are not strong; loose players stay in, hoping that a lucky flop will strengthen their hand. At large tables, people are typically considered to be very tight players if their looseness is below 20 percent and to be extremely loose players if their looseness is above 50 percent. For our data set, the average looseness values range from 51 percent at heads-up tables to 26 percent at full 6-player tables.

Aggressiveness measures how often a player bets or raises, as opposed to checking or calling, in order to force other players to either fold or call. The generally accepted measure of aggression is the ratio of the number of bets and raises to the number of checks and calls. Cautious players “limp in” by merely calling a bet, or checking if there is no need to bet. A cautious player tends to choose the least expensive way to continue playing the hand. Aggressive players bet more than necessary in order to force the other players to either put more money into the pot or fold. A player could bet aggressively because he has a good hand and wants more money in the pot or because he wants other players to fold before more community cards are dealt. An aggressive bet could also be a bluff that misrepresents a hand as being stronger than it really is. Players are typically considered to be passive if their aggression is below 1 and to be aggressive if their aggression is above 1.5. For our data set, the average values of aggression

were 1.2 at heads-up tables and 1.3 at full 6-player tables.

For both looseness and aggression, we summarize the data with medians and unweighted averages of the individual player looseness and aggression statistics. Otherwise, the results might be skewed by individuals who played a large number of hands and by the possibility that a player's style might affect the number of big wins and losses experienced. For example, if looser players tend to have lots of big losses and few big wins, this imbalance in the hands played after big wins and losses would increase the overall average looseness after big losses and reduce average looseness after big wins.

The first statistical test is the Wilcoxon signed-rank test for paired differences. The paired difference for each player is the difference between his looseness (or aggression) after a big loss and after a big win. For example, a player using the name ThePayBack1 played 910 6-player hands during the 12-hand window after big losses and played 1,064 6-player hands during the 12-hand window after big wins. His looseness was 30.88 after big losses and 27.26 after big wins, a difference of 3.62.

For each number-of-players category, the Wilcoxon test ranks the absolute values of the paired differences D_i across the n players, signs these ranks based on whether the difference is positive or negative, and sums these signed ranks R_i . With more than 40 observations, the probability distribution of the Wilcoxon test statistic

$$W = \frac{\sum_{i=1}^n R_i}{\sqrt{\sum_{i=1}^n R_i^2}}$$

is well approximated by the normal distribution. With fewer than 40 observations, we use the

exact P values.

We also tabulate the number of players who had a higher looseness (or aggression) statistic after a big win and the number for whom the reverse was true. The binomial distribution gives the exact p-value for a test of the null hypothesis that there is an equal chance of each player's statistic being higher or lower after big wins than after big losses.

All calculated p-values are two-sided because we are agnostic about how poker players' behavior might be affected by success and failure.

Results

Our final data set includes 346 players who met the various criteria. The median number of hands played is 1,738, with half of the players playing between 717 and 4,549 hands. Half of the players won or lost more than \$200,000, 10 percent won or lost more than \$1 million.

Table 2 shows the (unweighted) average values of the looseness and aggression statistics. Average looseness is inversely related to the number of players at the table because the chances that a given hand will turn out to be the winning hand is inversely related to the number of players at the table. There is no consistent relationship between the average value of the aggression statistic and the number of players.

Table 3 shows the median looseness values after big wins and losses. For each grouping of the number of players, median looseness is higher after a big loss than after a big win. Figure 2 shows side-by-side box plots for the paired differences in looseness after big losses and big wins.

Furthermore, Table 3 shows that it is consistently the case that more players are looser after a big loss than after a big win; for example, with 6 players at the table, 135 players were looser after a big loss than after a big win, while the reverse was true for only 68 players. The Wilcoxon

and binomial tests are least statistically persuasive for the 6-player tables with 2 or 3 players, perhaps because of the small sample sizes, but are highly persuasive at heads-up tables and at 6-player tables with more than 3 players.

Table 4 shows the median values of aggression after big wins and losses and the number of players who were more aggressive after big wins or after big losses. Figure 3 shows side-by-side box plots for the paired differences in aggression after big losses and big wins. Players tend to be more aggressive after a big loss than after a big win, although the only p-values less than 0.05 are at the 2-player and 6-player tables.

Cumulative Wins and Losses

Our study was motivated by anecdotal evidence that poker players react strongly to winning or losing big pots and our empirical data confirm this hypothesis. Nonetheless, another possibility is that poker players are affected by cumulative wins and losses; for example, losing a total of \$1,000 over several hands.

A comparison of player reactions to one-pot losses and cumulative losses might allow us to distinguish between the break even hypothesis and the gambler's fallacy as explanations for our results. If players are more apt to change their style of play after a string of wins or losses than after a single big win or loss, this suggests that the players change their play because they believe that a run of good or bad luck is due to be reversed. If players are more apt to change their style of play after a single big win or loss, this suggests that a dramatic chip swing is the reason.

There is no way of knowing for certain when to start tabulating an individual player's cumulative wins and losses, and our data have a fixed starting point that precludes looking backwards indefinitely. As a compromise, we looked at each player's cumulative profits over the

preceding 12 hands. If the cumulative profits are larger than \$1,000 or less than -\$1,000, we consider this to be a large cumulative win or loss. Then, as before, we look at the next 12 hands played.

Tables 5 and 6 show that the results for cumulative wins and losses are generally in the same direction as with single losses, but somewhat diluted. For example, at 6-player tables, 68 of 203 (67%) players were looser after a single big loss than after a single big win ($p = 0.000002$), while 202 of 348 (58%) were looser after a cumulative big loss than after a cumulative big win ($p = 0.004$). This suggests that our original conjecture is correct: winning or losing a big pot is memorable event that may affect a person's subsequent style of play.

Smaller Wins and Losses

Kahneman and Tversky's argument regarding a "person who has not made peace with his losses" is modeled in prospect theory by a framing that incorporates prior losses. Presumably, larger losses are more memorable than smaller losses and consequently more likely to affect behavior. Table 7 tests this presumption that large losses are more meaningful than are small losses. In every case, a majority of the players play looser after a large loss than after a large win. However, the fraction playing looser consistently increases as the size of the large loss increases.

Table 7 also shows that the effects are consistently smaller for large cumulative wins and losses than for a single large win or loss, confirming our earlier observation that the break even hypothesis is a better explanation for our results than is the gambler's fallacy.

Is Riskier Play Punished?

In our data set, most players play looser after a large loss. Is this change in strategy profitable or unprofitable? It is possible that experienced players generally play too tight, in which case

playing looser after a big loss improves their chances of winning. It seems more likely that experienced players are using profitable strategies and that departures caused by large wins or losses are detrimental.

Let's see what the data say. The generally accepted metric of success in poker is defined as big blinds won per 100 hands. For example, SamH133 played a total of 21,646 hands and won \$79,616.83, for a success of 7.36 (7.36 big blinds per 100 hands):

$$\begin{aligned}\text{success} &= \frac{\$79,616.83 / \$50}{21,646 / 100} \\ &= 7.36\end{aligned}$$

In our data set, the values of success ranged from -2,981.39 to 2,907.29, with a mean of -3.62. With \$50 big blinds, a success of -3.62 big blinds per 100 hands is an average loss of \$1.81 per hand.

For those players who played looser after a big loss than they normally played, their success rate, on average, fell by 18.42, though this observed difference is not statistically persuasive due to the relatively small number of observations combined with the large variance in success measured during the 12-hand window after big losses. The two-sided p-value is 0.75 for a test of the null hypothesis that the average change in the success rate is equal to 0.

Discussion

Our data indicate that experienced poker players tend to play looser after a big loss. This is consistent with the hypothesis that players remember big losses and are eager to return to their previous chip level. A loose strategy is essentially staying in the game with weak hands in order to see the flop—a speculative gamble that can allow players to win a big pot quickly if weak hole cards hit a miraculous flop.

There is also some evidence here that after winning big pots, most players play less aggressively than they do after big losses. This is unexpected since it is the opposite of Doyle Brunson's recommended strategy of aggressive play after big wins.

We also see that this tendency to become more aggressive after a big loss is most persuasive at two-player tables. This makes sense in that at a two-player table you only need to knock out one other player in order to win the pot. At a six-player table, it is likely that someone will call a raise; so, a lucky flop is a more promising way to cover an earlier loss.

The predictions of most of the theories listed in Table 1 are not supported by these data. For example, the house-money hypothesis predicts that people will be less cautious after a gain and more cautious after a loss. However, in their seminal discussion of the house-money effect, Thaler and Johnson (1990, p. 658) note that the break-even effect may override the house-money effect: "when prior losses are present, gambles which offer the prospect of changing the sign of the status of the current account will be treated differently from those which do not." Specifically, they agree with Kahneman and Tversky (1979) that "while an initial loss may induce risk aversion for some gambles, other gambles, which offer the opportunity to break even, will be found acceptable."

The gambler's fallacy is roughly consistent with our results but, as noted earlier, it is more applicable to a string of wins and losses than to a single big pot. In contrast, prospect theory's break-even hypothesis makes the same predictions after one large win or loss and a recent large cumulative win or loss. The fact that poker players are more likely to change their play after a single large win or loss than after a cumulative win or loss suggests that the break even hypothesis is a better explanation for our results than is the gambler's fallacy.

Overall, the theory that is most supported by our data is the break-even argument that a poker player who has lost a big pot may feel that the cheapest way to break even is to hit a long shot flop with a weak hand—for example, staying in with a pair of deuces in the hope of flopping another deuce.

The observed changes in poker play may be applicable to other decisions. Ken Warren, a well-respected poker writer, once said about Texas Hold-Em: “More money is lost by players who know what the right thing to do is, but don't do it, than for any other reason. Having a strategy, a game plan and the discipline to stick to it are, along with a sufficient bankroll, the four most important things that a player needs to be a winner.” David Nelson, the Senior Vice President of Legg Mason Funds, writes of Ken Warren’s observation, “You could say the same thing about investing. Game plan, strategy, discipline and obviously, bankroll.” Steenbarger (2007) also draws parallels between poker and investing, although there are important differences. For example, investing is not a zero-sum game, and deception is central to poker.

If investors are like poker players, their behavior might well be affected by large gains and losses; for example, making otherwise imprudent long-shot investments with the hope of offsetting a prior loss cheaply. There is some evidence of this behavior. Coval and Shumway (2005) find that Treasury bond futures traders are much more likely to take greater risks in the afternoon if they have morning losses instead of morning gains. Locke and Mann (2004) find that futures floor traders on the Chicago Mercantile Exchange (CME) increase their risk exposure after losses. Garvey, Murphy, and Wu (2007) similarly find that professional day traders who lose money in the morning trade more aggressively in the afternoon.” Crum, Laughhunn and Payne (1981) argue that major mutual funds and portfolio managers who are not

performing up to their target levels “exhibit risk-seeking behavior in an attempt to increase the return on their portfolios and thereby to achieve their targets.” Kumar (2009) found that in bad economic times, sales of lottery tickets increase as do investments in “lottery stocks” which are relatively inexpensive and usually unprofitable, but offer a small chance of a huge payoff. A February 2009 article in *The Wall Street Journal* reported that many investors were responding to their stock market losses by making increasingly risky investments: “the financial equivalent of a ‘Hail Mary pass’—the desperate attempt, far from the goal line and late in a losing game, to fling the football as hard and as high as you can, hoping it will somehow come down for a score and wipe out your deficit.” (Zweig 2009). All of these actions are consistent with a “break-even” mentality.

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Table 1 Predicted Play after a Big Win or Loss

	Big Win	Big Loss
Revised assessment	less cautious	more cautious
Break even		less cautious
Moods	less cautious	more cautious
House money	less cautious	more cautious
Gambler's fallacy	more cautious	less cautious
Hot and cold streaks	less cautious	more cautious
Doyle Branson strategy	less cautious	

Table 2 Unweighted Average Looseness and Aggression Statistics

Players at Table	Number of Observations	Average Looseness	Average Aggression
heads-up	228	51.27	1.15
2	40	46.49	1.38
3	33	34.68	1.55
4	75	28.50	1.63
5	150	25.93	1.42
6	203	25.53	1.34

note: heads-up hands occur at two-player tables; the other hands are at 6-player tables with 0 to 4 empty seats.

Table 3 Looseness After Big Wins and Losses

Players at Table	Median Looseness				Players Looser After		
	Big Win	Big Loss	Other	Wilcoxon P	Big Win	Big Loss	Binomial P
heads-up	49.46	50.73	50.33	1.0×10^{-7}	74	154	1.2×10^{-7}
2	44.72	46.15	46.10	0.150	17	23	0.430
3	32.63	34.86	32.98	0.026	11	22	0.080
4	25.73	28.93	28.57	0.000084	21	54	0.00018
5	24.53	25.75	24.57	0.000094	53	97	0.00040
6	22.67	25.00	23.45	1.0×10^{-7}	68	135	0.000002

note: heads-up hands occur at two-player tables; the other hands are at 6-player tables with 0 to 4 empty seats.

Table 4 Aggression After Big Wins and Losses

Players at Table	Median Aggression				Players More Aggressive After		
	Big Win	Big Loss	Other	P-Value	Big Win	Big Loss	P-Value
heads-up	1.00	1.20	1.14	3.1×10^{-8}	47	181	9.8×10^{-20}
2	1.21	1.59	1.38	0.0026	12	28	0.017
3	1.39	1.28	1.31	0.249	11	22	0.080
4	1.38	1.54	1.49	0.796	41	34	0.489
5	1.19	1.25	1.21	0.131	71	79	0.568
6	1.06	1.20	1.16	0.013	85	117	0.035

note: heads-up hands occur at two-player tables; the other hands are at 6-player tables with 0 to 4 empty seats.

Table 5 Looseness After Cumulative Big Wins and Losses

Players at Table	Median Looseness				Players Loser After		
	Big Win	Big Loss	Other	Wilcoxon P	Big Win	Big Loss	Binomial P
heads-up	50.50	51.12	50.00	6.0×10^{-7}	143	240	8.0×10^{-7}
2	46.58	46.57	45.33	0.274	41	48	0.525
3	34.13	35.25	33.33	0.079	35	50	0.128
4	27.84	28.24	27.73	0.012	59	88	0.021
5	25.16	25.71	25.00	0.022	116	165	0.005
6	23.88	24.29	23.43	0.005	146	202	0.004

note: heads-up hands occur at two-player tables; the other hands are at 6-player tables with 0 to 4 empty seats.

Table 6 Aggression After Cumulative Big Wins and Losses

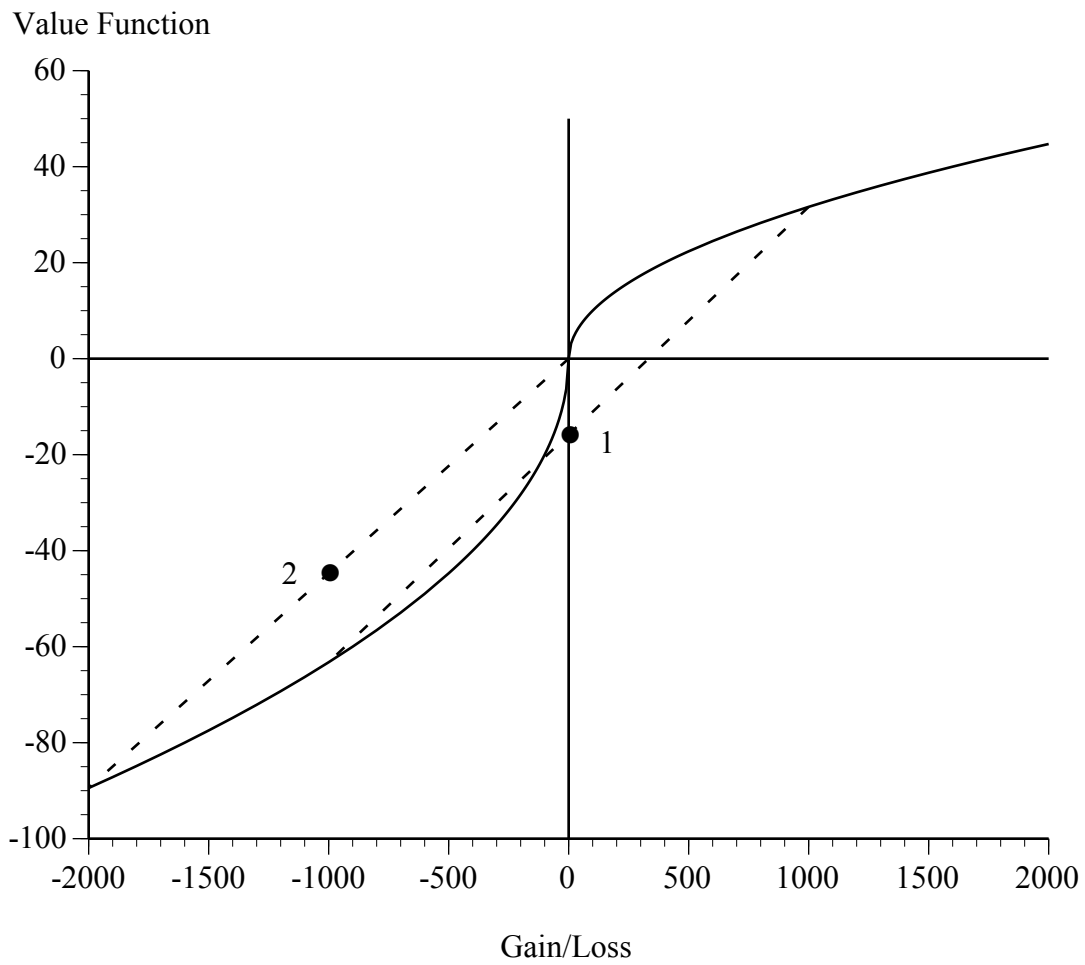
Players at Table	Median Aggression				Players More Aggressive After		
	Big Win	Big Loss	Other	P-Value	Big Win	Big Loss	P-Value
heads-up	1.00	1.11	0.86	1.0×10^{-12}	111	272	6.2×10^{-17}
2	1.22	1.30	1.12	0.056	38	51	0.203
3	1.45	1.45	1.00	0.815	41	44	0.828
4	1.38	1.44	1.26	0.943	71	76	0.742
5	1.19	1.17	1.19	0.544	126	155	0.108
6	1.00	1.10	1.09	0.015	157	192	0.069

note: heads-up hands occur at two-player tables; the other hands are at 6-player tables with 0 to 4 empty seats.

Table 7 Fraction of Players Who Play Looser After a Large Loss than After a Large Win

Win/Loss	Single Win/Loss		Cumulative Win/Loss	
	6-player Table	Heads Up	6-player Table	Heads Up
\$250	0.629	0.615	0.560	0.592
\$500	0.633	0.642	0.579	0.613
\$1000	0.661	0.675	0.582	0.627

note: 6-player tables have 0 to 4 empty seats; heads-up hands are at two-player tables.



1: Value of prospect with reference point $W_0 = 0$

2: Value of prospect with reference point $W_0 = -1000$

Figure 1 The Value of a Prospect Depends on the Reference Point

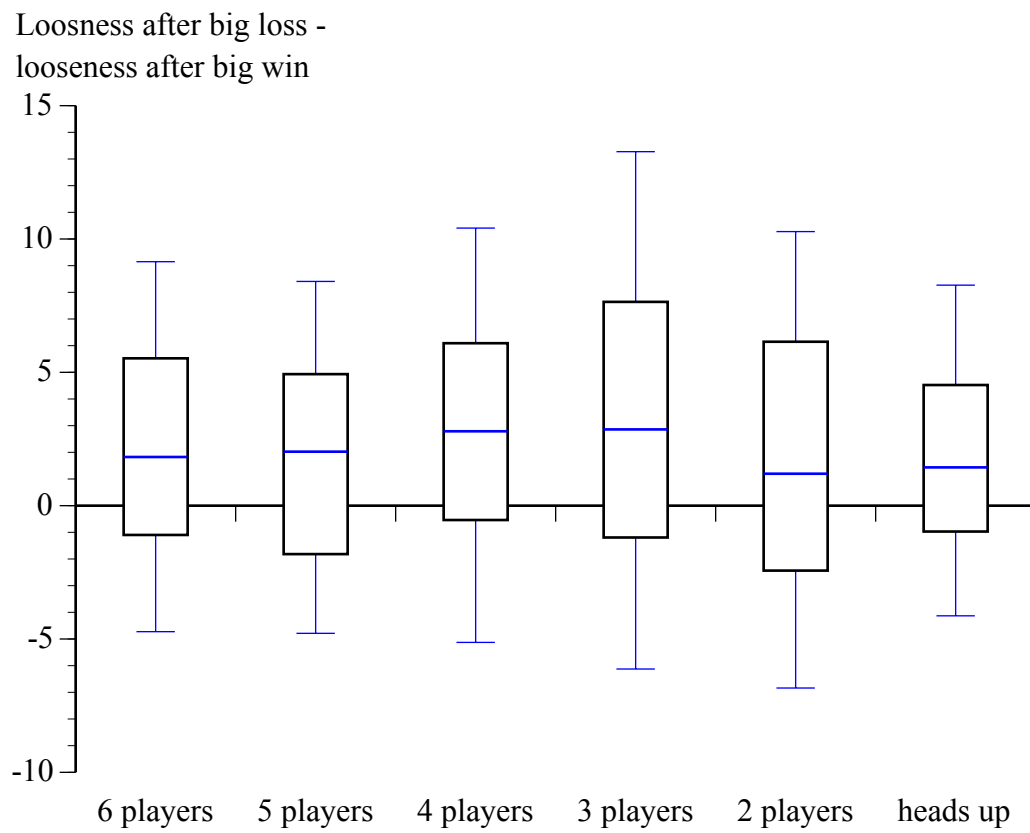


Figure 2 Distribution of the Difference Between Looseness After a Big Loss and After a Big Win

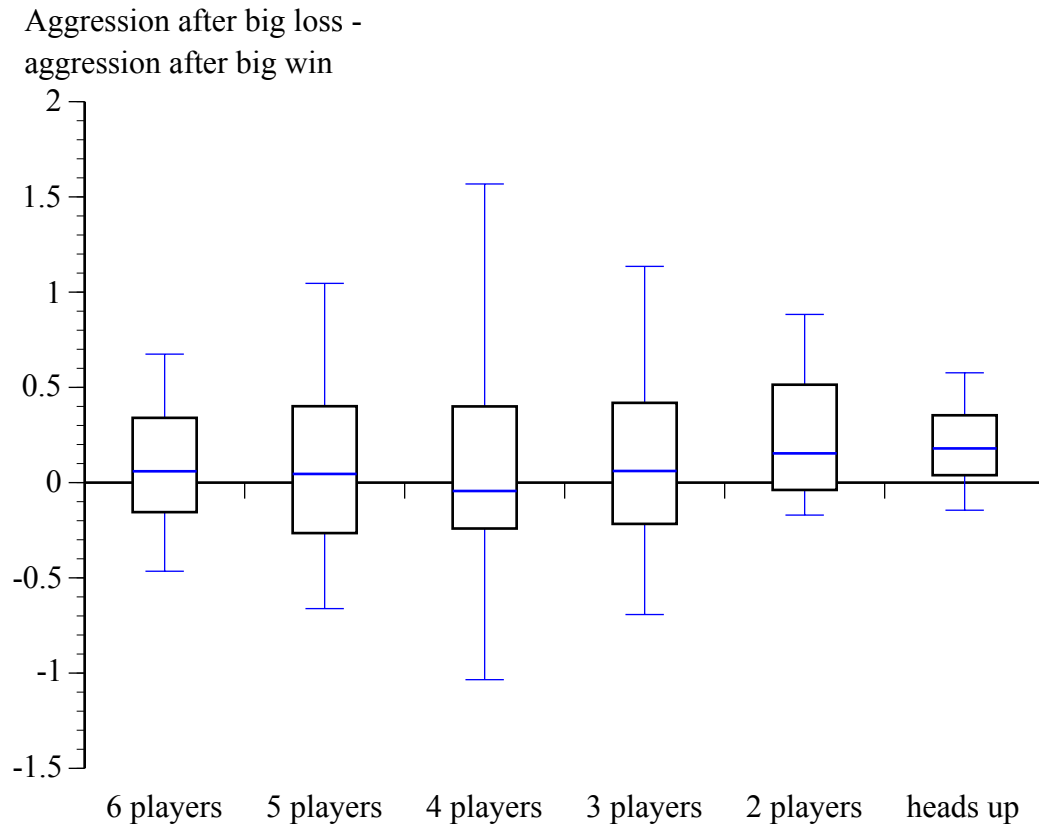


Figure 3 Distribution of the Difference Between Aggression
After a Big Loss and After a Big Win