PREFERENCE ADAPTATION AND THE CHALLENGE OF POKER[1]

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ABSTRACT: Poker is a competitive, social game of skill and luck, which presents players with numerous challenging strategic and interpersonal decisions. To maximize chances for profitability, players implement strategies to handle the competitive interactions in the game. The adaptation of poker into a game played over the internet provides an unprecedented opportunity for data mining, and to quantitatively analyze extremely large numbers of hands and players. This paper analyzes roughly twenty-seven million hands played online in small-stakes, medium-stakes and high-stakes games. Using PokerTracker software, statistics are generated to a) gauge the types of strategies utilized by players (i.e. the 'strategic demography') at each level and b) examine the various payoffs associated with different strategies at varying levels of play. The results show that competitive edges attenuate as one moves up levels, and tight-aggressive strategies – which tend to be the most remunerative – become more prevalent. Further, the payoffs for winning hands, and different combinations of cards, varies between levels, showing how strategic payoffs are derived from competitive interactions. These varying payoffs reveal a meta-game of rationality and psychology which underlies the card game. Adopting risk-neutrality to maximize expected value, aggression and appropriate mental accounting, are cognitive burdens on players, and underpin the *rationality work* – reconfiguring of personal preferences and goals – players engage in to be competitive, and maximize their winning and profit chances.

Keywords: Poker, Games, Risk, Uncertainty, Competition, Behavioral Economics.

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INTRODUCTION

Poker is a social and strategic card game of imperfect information, which is often invoked as a microcosm or metaphor for economic, existential (Hayano, 1982: 138-140), eand strategic dilemmas people face in life (Sklansky, 2009). The game involves a complex tapestry of skill and luck, rationality and intuition, mathematics and psychology, fraught with uncertainty over outcomes, best practices and their relationships to success. Thus, poker provides a fertile context to observe micro-level economic and social behaviors in contexts of risk and uncertainty. The advent of internet poker in the late 1990's spurred a major increase of interest in and adoption of the game, due to its relative convenience, ability to solve co-ordination problems for people previously unable to find others to play a game, and affordable free and small-stakes niches. Reflective of the "poker boom", the number of entrants in the annual $10,000 buy-in World Series of Poker Main Event increased from 512 in 2000, to a high of 8,773 in 2006. Internet poker has also enabled new and more complex understandings of poker, both when played online and in person, via the analysis of quantitative data.

With millions of players online, wagering hundreds of millions of dollars, competition is fierce. Some players use poker as their sole, or a partial means of income, others use it as a lucrative avocation, while others play as recreational gamblers. Thus, online poker provides an ideal laboratory for observing the economic decisions between risk and rewards people make with their money, in different competitive contexts. Since information is almost always imperfect, and reinforcement schedules are erratic for making correct moves, due to luck, or ‘noise’ in the game, formulating correct strategies cannot be done through operant conditioning, or other objective decision-frames alone (Tallman and Gray, 1990). Given its complex and social nature, decision-making in poker almost always possesses some degree of subjectivity. Since poker is a game of uncertainty and imperfect information, the issue of how people deal with uncertainty is important. Tversky and Kahneman (1974) famously posited that when people are faced with making difficult decisions under conditions of uncertainty, they adopt *heuristics* – subjective rules and strategies – to come to a resolution. Given that poker is rife with such situations, and poker literature offers a variety of strategies for approaching the game, and numerous styles, or belief systems (Hayano, 1982: 106) have been observed throughout the history of the game (Boyd, 1976; Harrington, 2004).

THEORETICAL OVERVIEW

The confluence of short and long-term incentives and information is another large part of the allure and challenge of poker. The long-term *strategic* heuristics of online poker players interact with contrasting short-term *tactical* interests, as each hand and pot is contested. As participants play numerous hands and iterate interactions, their strategies become at least partially revealed through their actions in the game. Blumer (1986) posited that people know things via the meanings of symbols, which are created and changed through social interaction. Thus, a bet from a player which appears loose-aggressive player, as defined via interactions in the game, acquires a very different meaning (and thus, a different response, as devised by the player’s strategy and tactics), than an equivalent bet from a player employing a tight-passive strategy. As per Berger and Luckmann (1966), individuals interact and create perceptions about their own behaviors and others, while occupying niches and roles based on those perceptions. In turn, impression management (Goffman, 1959) in poker is as much about controlling one's own behavior in consort with one's impressions (i.e. "table image" in poker parlance) as it is influencing the perceptions of others. Advantages are derived in poker from the strategic and tactical use of betting patterns, which double as information-rich market signals (Spence, 1973). Ideally, a player is able to control and exploit the definitions and interactions of players (including themselves). Part of the challenge of poker is not only concealing information, but also propagating bad, or *lemon* (Akerlof, 1970) information, for one's own benefit.

While strategic orientations impact long-term returns, those results are the aggregate of numerous tactical interactions in each hand, influenced by the larger strategic and interactional context. Analogously, Chen and Ankenman (2006) contrast *exploitative* and *non-exploitative* strategies in poker. Exploitative strategies are tactical in nature and involve altering one's play on a given hand in response to a perception of the opponent's tendencies in that moment. A problem with such play is that it results in deviating from one's own strategies, and often optimal play. Further, it renders the player vulnerable to counter-exploitation. In turn, poker games and interactions can turn into a complex infinite regress of moves and decisions calibrated by an equally complex history of competitive interactions and outcomes. Non-exploitative strategies are rooted in game theory, and involve randomly choosing one's levels of aggression and bluffing at an optimal point to maximize profitability. Due to the random nature of such strategies, they are non-exploitable. However, such strategies may also miss short-term opportunities to exploit profits in isolated, idiosyncratic situations scattered throughout the long-term.

Given these contrasts, it is not surprising that poker has been of interest both to game theorists (von Neumann and Morgenstern, 1944; Chen and Ankenman, 2006) and symbolic interactionists (Goffman, 1972; Boyd, 1976; Hayano, 1982). Analogous to exploitative play, symbolic interactionism focuses on contextual meanings and utterances, seeking to illuminate details out of even the smallest and most subtle symbols. In contrast, game theory is axiomatic and deductive. Players are supposed to optimize frequencies of various moves (e.g., raising, bluffing) for the game, then implement them randomly, so opponents cannot pick up a pattern in their decision-making. Both theoretical perspectives focus on the strategic effects of interaction, and how actors modify their behaviors in accordance to other's actions. The two major ways internet poker differs from live poker modifies the relevance of the two theories to the game. Firstly, internet poker removes in-person social interaction, so symbols or 'tells', like personal gestures, facial expressions, voice tenor, braggadocio and body posture, which are famously important in live poker (Caro, 2003). Secondly, the increased speed of online poker hands, in addition to the ability to play multiple hands at once, has increased the number of hands a player can play in an hour tenfold. These large size increases allow players to more quickly even out effects of short-term luck. Additionally, players can acquire larger sample sizes on their own play, as well of their opponents, and have a deeper context to interpret actions in the game. With this improved information on opponents, players can make tactical exploitative moves based on a deeper knowledge of the meta-strategies in the game Thus, game theory and symbolic interactionism are complementary and overlapping theories, particularly in poker, whether live or online.

In poker, information and interactions are used to make decisions regarding how to make the most competitive and profitable decisions in an uncertain game of chance. Knight's (1921) distinction between *risk* and *uncertainty* is particularly germane to this challenge. Risk involves uncertain outcomes, where the probabilities of those potential outcomes are known. Uncertainty also involves uncertain outcomes, but where information is less complete and perfect, and numerical probabilities cannot be accurately assigned to various potential outcomes. Both risk and uncertainty are omnipresent in poker, and part of the challenge of the game is the ability to *commensurate* (Espeland and Stevens, 1998) uncertainty into risk, so precise and profitable quantitative decisions can possibly be made regarding how to handle one's money in each particular scenario. Chen and Ankenman (2006: ch. 1) argue that Bayesian reasoning is what underlies the conversion of uncertainty to risk, based on the premises and evidence a player is able to collect about the known. Even in conditions when it is rendered entirely or mostly clear, risk itself provides a challenge for players to manage the mathematically inevitable ups and downs of gambling intelligently and responsibly.

Since poker is an emotionally evocative game rife with uncertainty, reflective of its strategic diversity, numerous forms of mental and monetary accounting can emerge. This may be problematic, because poker strategy advocates maximizing utility, which presupposes risk-neutrality (see von Neumann and Morgenstern, 1944). Since game theory and rational choice are rendered problematic by uncertainty (Harsanyi, 1986; Tallman and Grey, 1990: 410), a more nuanced approach is needed to understand decision making and heuristic formation in poker. Prospect theory (Kahneman and Tversky, 1979) provides a lens for understanding idiosyncratic, subjective accounting processes and decisions people make under conditions of uncertainty. While humans tend to be risk-averse with gains, they tend to be risk-loving with losses. Of note is that the difference between a ‘gain’ and a ‘loss’ can often be a subjective matter of framing and perception. Thus, just as bets, actions and strategies in poker games can carry a diversity of genuine, obfuscated and lemon information, the social meanings of money (Zelizer, 1997) in a poker game are also part of the mental accounting that players engage in to handle risk and uncertainty. Choosing between varied perceptions of actions and consequences (Blumer, 1986) is also necessary. Whether chips represent fun, a bigger house, a status symbol, next month’s rent and groceries, and/or one’s self-worth, also impacts the subjective framing and accounting decisions which influence perceptions and orientations to risk and uncertainty. These framing and interpretation issues are part of the cognitive challenge of poker.

This study maps out the ‘strategic demography’ of players at different levels of play (from small-stakes to high-stakes), and analyzes which strategies are conducive to winning at these different levels. In turn, this sheds light on how reward structures and the strategic demography of players interact at different levels. Since players must cope with uncertainty and risk, examining strategies helps reveal the heuristics and economic dispositions they enact in response to these challenges. These data and analyses show hierarchies of knowledge and competition, and sheds light on why poker is challenging beyond the mere nuts and bolts of the card game.

Beneath the card game of poker is a meta-level competition of rationalities and handling the burdens of different cognitive stresses. To maximize profitability, players must reconfigure their preferences and behaviors in a manner which goes against normal human preferences. For example, risk neutrality straightens out concave marginal utility curves, treating a dollar to keep one out of poverty the same way it treats a dollar serving as tip money at a fancy restaurant. Relatedly, Gray and Tallman (1987) found that the risk and cost sensitivity characteristic of most people's preferences leads to decisions which do *not* maximize gains and minimize losses. Losing these sensitivities and adopting a risk-neutral frame for decision-making may maximize income potential, but also requires effort to reconfigure often deeply rooted human preferences. This challenging and deliberate reconfiguration of preferences and behaviors in the interests of some desired end – in this case, profitability in poker games – is dubbed *rationality work.*

The poker game used as the empirical example in this study is No-Limit Texas Hold'em (NLHE), with six seats at the table ('6Max'), with at least five players at the table. Famously called the "Cadillac of poker", this most famous variant of poker is characterized by its simplicity of rules (and thus, easy adoption), and the fact that any single hand can involve players risking their entire stack of chips. Due in part to this freedom in the game and its inherently social nature, NLHE has a significant "psychological" component, in addition to the technicalities of the card game. Further, subterfuge and deception in poker often trump mathematics, as encapsulated in the climactic scene of the 1962 movie, *The Cincinnati Kid*, where the triumphant player muses, "[I]t's all about…making the wrong move at the right time." Due to these frequent twists in logic, and the need for responsiveness to similarly twisted moves by opponents, computer scientists have not yet been able to create a NLHE bot competitive at elite levels (Boyle, 2007). This lies in contrast with checkers, which has been entirely solved; chess, where the game has been solved to the point that the best bot and computer has surpassed the best human player alive, and Fixed-Limit Texas Hold'em, where programmers have devised bots which are very competitive with the best players in the world. Thus, No-Limit Hold'em is an ideal context to study heuristics, rationality and strategy from a human and psychological perspective, as the game transcends logic and mathematics. As poker legend Doyle Brunson (1979: 17) famously posited in his seminal strategy text *Super/System*, "Poker is a game of people. That is the most important lesson you should learn from my book." This human element further complexifies the hundreds of millions of permutations and combinations of cards that can be dealt.

DATA

Online poker sites automatically transcribe records of hands into .txt files as they are being played. The data for this study were acquired from HandHQ.com, a business which observes online poker games, then sells archives of these .txt files for numerous poker rooms. Many players use these data to supplement sample sizes of hands on their opponents, so they can have more reliable summary statistics of the play of their opponents, thus enabling them to make better and more profitable decisions. The datasets used for this research are comprised of 17.25 million hands at NL50 (small-stakes game), 6.79 million hands at NL200 (medium-stakes game) and 2.87 million hands at NL1000 (high-stakes game). The names of these games refer to the standard buy-in at the game, which is one hundred big blinds (e.g., NL50 has a standard buy-in of $50, with big blinds of $0.50). This yielded databases with 212,224 players[2] (NL50), 64,262 players (NL200) and 18,596 players (NL1000) respectively. All records of players were anonymized. Hands were culled from December 2008 to April 2009. All money values are in United States dollars.

METHODS

These data were uploaded and analyzed using PokerTracker; software designed to cull and archive information from .txt files, which serve as records of hands played on poker sites. PokerTracker yields a substantial number of statistics on every player uploaded to its database. Using the simple summary statistics used in this study, PokerTracker was used by a small group of ingenious and vigilant players to inductively expose major inside-job cheating scandals at two prominent online poker rooms. More commonly, PokerTracker is also used by almost all serious players, to gather quantitative information on their own play, as well as that of their opponents. Thus, PokerTracker

[2] Due to computational limitations, only 120,000 of these NL50 players could be rated by PokerTracker. Regardless, this is still an enormous sample.

presents the unprecedented opportunity to operationalize and quantify strategies – and in turn the economic decisions and behaviors – of tens of thousands of players.[3]

For this study, information on the number of hands played, the cards dealt to players, win (or loss) rates, percentage of hands won, strategy type and overall amount won, were compiled. Labeling strategies is subjective and derived from behavioral tendencies of how frequently players bet or raise at different parts of the hand. Regardless of how boundaries of strategies are demarcated and gerrymandered, what is most important is the relative performance and tendencies of the player, since poker is a contextual, interactive game. As Boyd (1976) observes, someone labeled a 'tight' player in one game, might be a 'loose' player in another game, while implementing the same strategies. The rules for assigning strategy types yielded a fairly well-dispersed population of players across all levels (See Appendix A for rating criteria and definitions).

Player strategy types were labeled as a function of their propensity to play hands (i.e. looseness or tightness), and then the amount they are inclined to bet and raise as the hand progresses (i.e. play aggressively or passively). The PokerTracker rating procedure entails interaction effects between the three strategic components of proportion of hands played, proportion of hands raised and degree of post-flop aggression (i.e. betting and/or raising). Finally, to facilitate comparisons between levels, win rates (big blinds won per

3 While this methodology is ideal for understanding the actual behaviors and consequences of players, from a "pure poker" standpoint the theoretical relationships between strategies, win rates and variance (i.e. standard deviations of win rates) would be better handled by simulation studies, which could keep player abilities, interactions, games and luck constant.

100 hands) were adjusted to account for the average rake taken from the hand. Poker sites profit from online poker by siphoning off $0.05 to $3.00 of every pot which involves community cards being dealt. As one moves up limits, players pay more rake at an absolute level, but lesser proportion of rake of the total money on the table; this is a small incentive for players to play higher-stakes games. While beating the rake (in addition to beating the other players at the table) is a vital part of being a profitable poker player, adjusted big blinds/100 hands rates are reported to facilitate equivalent comparisons between levels. The adjusted rate is merely the raw BB/100 rate (i.e. win rate), plus a correction factor for the rake taken at each level. At NL50, the adjustment was +4.98 BB/100; NL 200, +3.00 BB/100 and NL1000, +0.95 BB/100.[4]

RESULTS

STRATEGIC PAYOFF STRUCTURES AND DEMOGRAPHY

Tables 1a, 1b and 1c show the payoffs for various strategies. Payoffs are operationalized by big blinds won per one hundred hands, to enable comparisons between levels. Additionally, the tables show the "strategic demographics" of games at the various stakes, via the proportion of total players labeled with a given strategy at each level.

-- Insert Tables 1a, 1b and 1c about here –

[4] Except where noted, analyses where conducted while weighting by the number of hands each player participated in. For example, the results of a player who played 100,000 hands will be weighted five times more heavily than a player who played 20,000.

In general tight and aggressive strategies have the best returns across all levels. Semi-loose aggressive strategies also are relatively successful. As one moves up stakes, win-rtes get smaller as games get tighter, more aggressive and competitive. Profitable tight-aggressive niches get more crowded, and the strategy becomes less novel and remunerative. Additionally, passivity gets increasingly punished as one moves up levels.

The most obvious trend in regards to the strategic demographics of the various levels, is the increased proportion of aggressive players as one moves up stakes. The tables also show that as one moves up levels to higher stakes, the number of passive players decreases. This may be linked to the fact that the win rate coefficients for passive strategies decreased at higher stakes. While the number of loose players decreases somewhat, there is a large increase in semi-loose players. As a result of these trends, there is a notable convergence of players around similar Tight-Aggressive and Semi-Loose-Aggressive strategies. Since most leading poker instructional texts advocate this type of strategy (Sklansky and Miller, 2006; Harrington, 2004), this is not a surprise. An implication of this is that as strategies become isomorphic, this may make the game more tactical than strategic, or create niches for other strategies. The attenuation of the negative coefficient at the NL1000 level for Loose-Aggressive-Aggressive strategy is particularly interesting. With the large standard deviation, although the mean coefficient is slightly negative, there are also numerous players who now play this strategy effectively. This may be a function of this audit study, where better players, capable of playing this notoriously lucrative but risky and difficult strategy (Harrington, 2004: 42) tend not to occupy small-stakes games, while recreational players may utilize this same strategy with disastrous results.

Another way of understanding the incentives and payoffs associated with various strategies involves examining the characteristics of the biggest winners and losers at each level. This will be done first by win rate (big blinds/100 hands), then by overall amount won.

GETTING RICH QUICK, OR THE ROAD TO RUIN?

Tables 2a, 2b and 2c show the representation of different strategies amongst the players with the highest and lowest win rates (or loss rates) at each level.

-- Insert Tables 2a, 2b and 2c about here –

Notable is the consistent overrepresentation of loose and aggressive players amongst both the top and bottom hundred players. Such strategies are much more overrepresented amongst losing than winning players. This raises the question of to what degree these divergent values are out of skill and luck. If loose-aggressive strategies are more difficult to play, it stands to reason, particularly at lower levels, that such strategies would be particularly overrepresented amongst the biggest losers. However, it could also be expected that there would be a reasonable proportion of such players who have mastered the difficult and stressful strategy who also occupy the upper tail of the bell curve. This thesis would be supported by the data, as would an additional or hypothesis that it is merely luck and variance causing these outliers. Since loose-aggressive strategies appear to have significantly higher standard deviations, it is inevitable that some players would be placed on the high end of the relatively wider bell curve, regardless of their skill level. This dilemma illustrates the fusion of skill and luck in poker, and how difficult the two entities are to parse out from one another.[5]

GRINDING FOR GOLD

When one looks at the top players by actual amount won, a different trend emerges. Tables 3a and 3b show summary statistics of the top twenty winners and losers at each level, while Tables 4a and 4b shows the strategic demographics of those categories.

-- Insert Tables 3a, 3b and Tables 4a, 4b about here –

The most notable trend in the tables is that the mean win-rates are relatively modest. None of the biggest winners at any of the levels were even close to being in the top hundred win rates. The average win rates in Table 3a work out to the 76th percentile of win rates for the entire population of NL50 and NL200 players, and the 68th percentile for NL1000. The way these players distinguished themselves to be the biggest winners in the sample was by playing an enormous volume of hands at a moderately profitable rate.

[5] As this research is an audit study, it reveals information about the behavior of real people, and is not ideal for solving theoretical and philosophical problems such as the relationship between chance and skill. Simulation work, which can control the population and skill of players may be the way to go about solving that problem. However, such work is well beyond the scope of this paper.

There are a number of potential explanations for this phenomenon. Firstly, players with a higher (or lower) win rate are likely to move up or down stakes, and thus fall outside of the sample in the study. Secondly the big winners are the inevitable upward outsiders of numerous players playing large volumes of hands. Thirdly, some players might get "stuck" at a level, where they are good enough to break even or profit, but do not feel comfortable moving up any higher, where the stakes are higher, and their already razor-thin win rate will be eroded. Fourthly, some poker players adopt a standard tight-aggressive "grinding" (Matros, 2005: 69) strategy, oriented towards low-risk outcomes, via capitalizing on occasional mistakes of others. While such a strategy puts a glass ceiling on one's win rate, it is simple and low-variance enough to play at an extremely high volume, playing multiple games simultaneously online to generate these substantial winnings. Finally, the results of these high-volume players suggest that in the long-run, where the aggregate effects of luck and chance are diminished, competitive edges in online poker may be relatively modest.

Figure 1 shows the adjusted win rates for players with a minimum of 750 hands at NL200, showing that while win rates can be very volatile in the short-term, through some combination of players moving up or down stakes (or in some cases, going broke), long term win rates converge slightly above zero[6], after the rake adjustment.

-- Insert Figure 1 about here --

[6] This is largely because players who did not play 750 hands tended to be losing players, or 'donators.'

PATIENCE AND PYRRHIC VICTORIES

Another cognitive challenge in online poker which differentiates winners and losers – particularly at lower stakes – is distinguishing the difference between winning lots of hands and winning money. As Table 5 shows, a high win percentage (i.e. the percentage of total hands won by a player) is *negatively* correlated with win rate, although this value attenuates somewhat as you move up stakes.[7]

-- Insert Table 5 about here --

This is an unusual and seemingly counterintuitive incentive structure. After all, is not the object of every hand in poker to win it? This phenomenon can be explained by the fact that players who win large proportions of hands lose money because they lose a few hands of great value. In other words, these players overweight frequent small gains vis-à-vis occasional large losses. This is an issue particularly germane to No-Limit Hold'em, where on any given hand, all of a player's chips can be put at risk. It also appears that patience is rewarded, although the more aggressive and skilled games at NL1000 attenuates this somewhat, as players cannot rely on winning big pots off of mistake-prone players as often as in lower limit games. Since one of the tenets of prospect theory (Kahneman and Tversky, 1979; Degeorge and Zeckhauser, 1993: 1331) is that people

[7] Removing the weights of hands played of high volume players (who tend to be tight-aggressive) decreased all of the coefficients by roughly 0.2, which also rendered the still negative NL1000 coefficient statistically insignificant.

tend to underweight large losses and overweight small gains, it makes sense that many players employ strategies influenced by this unprofitable disposition. An additional explanation for this is that money online assumes a non-material form, which is easily thrown around. Studies in behavioral economics have shown that people tend to be more profligate spenders with credit cards over cash (Feinberg, 1986). Thus, while winning hands may be cognitively satisfying and reinforces learning, the occasional large loss, represented similarly as pixels on a computer screen, does not carry a proportional cognitive or accounting impact for many.

POKER HANDS AND PROSPECT THEORY

While Texas Hold'em is a very complex game, it is governed by simple rules. Players are initially dealt two hole cards concealed to the other players, which give the player a payoff structure depending on the five visible community cards that are to come, or have been dealt. These simple two card combinations have been categorized by poker experts into general categories, based on the general payoff structures they represent. For this article, I will also further clarify these incentive structures, by introducing the concepts of initial *strength*, *certainty* and *speculativity* to understand the hand categories. These categories are adapted from Billings et al.'s (2002) artificial intelligence model of poker. Strength entails the likelihood that a hand will be best after five random community cards are drawn. Uncertainty involves the need for additional information (via additional – and preferably all five – face-up community cards to be dealt) to gauge and the strength, or lack thereof, of the hands. For further details on the combinations of cards yield these categories, see Appendix B. Of note is that these strategic categories entail broad boundaries, and there still remains heterogeneity in strategies and tendencies of players within each category. However, the categories serve as a solid starting point to sort out the relative strategies employed by players.

No-Limit Hold'em is a game defined by *implied odds* (Sklansky and Miller, 2006: 33), which often makes chasing speculative and uncertain hands profitable, even if the chances of them are slim. In other words, connecting with unlikely combinations of hands seldom occurs. However, since such hands have the potential for large payoffs, they can be extremely valuable, and are part of a player's portfolio. In contrast, strong hands suffer from *reverse implied odds* (58), as they have fewer options for improvement as the community cards get dealt and the hand progresses. Implied odds offer the prospect of large losses in the future, against small losses in the present, while reverse implied odds offer the prospect of small gains in the present against potentially large losses in the future. Thus, stronger and more certain hands provide a payoff structure more conducive to frequent small to medium wins and occasional large losses.[8] As shown in Table 5, this incentive structure (frequent small gains, occasional large losses) is particularly dangerous for weaker players. In contrast, uncertain and weaker hands offer an incentive structure based on frequent small losses, tempered by the prospect of occasional large wins.

[8] Even if such hands are winning, they are frequently affected by the prospect of large losses, even if they occur less frequently than wins. Playing for a large pot with even a strong pair is usually daunting after community cards are dealt.

Big pairs are the hands with the strongest initial strength, and carry high levels of certainty, as a high pair is often the winning hand, even after all of the community cards are dealt. However, like all pairs, they are relatively less likely to improve as community cards are dealt. Further, when big pairs improve, it is often superfluous and prone to scaring off further bets, so they have little speculative value. Medium pairs have moderate initial strength, and may end up being the winning hand unimproved. Like all pairs, its value tends to be very certain, whether the hand is improved by the community cards or not. While medium pairs are much less rarely winning hands than their big pair counterparts, they do have high speculative value. Finally, small pairs have low initial strength, but have high certainty and high speculative value.

Similarly, Broadway cards are primarily oriented towards becoming pairs, so they share the characteristics of pairs of having high certainty. Since they rely on community cards to make a pair, their initial strength is moderate, and their speculative value is nil.

Suited and connected cards are drawing hands oriented towards making straights and flushes; uncertain drawing hands which only become certain after all community cards are dealt. Betting patterns and incentives (which can make players fold) can often preclude all of the hands being dealt, so these hands are both uncertain and speculative. Since these include many low cards, their initial value is very low.

Suited Broadway cards simultaneously possess both of the differing incentive structures of suited connectors and offsuit Broadway cards.

Table 6 shows the distributions of different hand categories at different stakes, in addition to their payoffs.

-- Insert Table 6 about here--

These data reveal, at least in part, the differing incentive structures of each level.

The larger coefficients associated with most hand categories at NL1000 may be reflective of a greater willingness to play hands to completion, which is a consequence of the increased aggression at that level. In particular, the increased proportion of big and medium pairs shown down suggest that due to the aggressive context, higher-stakes players often need to intelligently accept uncertain risks and propositions to be profitable, even though they involve the potential for large losses. This increased competitiveness and aggression is tantamount to a game of chicken, where players who continually avoid risk, uncertainty and conflict, will be prone to being dominated. Further, it may be the cognizance of potential large losses disproportionate to the frequent small gains of big pair hands (which are dominant early in the hand, but are generally more brittle afterwards) which may explain the higher payoff coefficient at higher stakes.

Another interesting finding is that the gap between the profitability of medium and small pairs widens as one moves up limits, as does their frequency of being shown down. Notably, the value of medium pairs is *less* than small pairs at NL50, despite the fact that medium pairs are a stronger hand. Small pairs are speculative and acquire fairly certain values, so they are generally easy to play at all levels. Thus, the differences in payoffs and proportions played between the limits are relatively small compared to other hand categories. However, medium pairs also possess showdown value (the possibility the hand will remain a winner unimproved), which add reverse implied odds and marginally (un)profitable bets to their incentive structure. These data suggest that on the whole, these payoff sets are difficult for the relatively less skilled players at NL50 to handle, and are increasingly mastered as one moves up stakes. As competition gets fiercer as one moves up stakes, and value is more difficult to extract out of low-risk and obvious positions, the challenge of skimming narrow value out of dangerous hands with reverse implied odds distinguishes winners and losers across an increasingly narrow gap.

The results for suited connectors – weak, speculative and uncertain hands – show some of the risks and consequences of aggression at higher stakes. The progressively lower proportion of hands of this category, and lower coefficients suggest at higher levels suggest that as one moves up stakes, one must take gambles with uncertain values in order to be successful. Gordon (2005: 245) suggests that one of the big innovations of high-stakes poker players in the internet age, is to play uncertain or marginal hands very aggressively, to capitalize on fold equity (winning the pot uncontested by making opponents fold). The increased speed and quantity of hands that online poker allows also makes the absorption of the high variance of such moves and strategies possible. This strategy is in part a counter-exploitation of the scenario that players at higher skill levels are generally skilled enough to shape incentives to discourage uncertain hands from acquiring additional information by getting to see one additional card cheaply. In contrast, players at NL50 are less skilled and less aggressive, and thus allow uncertain and/or speculative hands to see all of the community cards, which allows them to acquire certainty and be shown down profitably more often; hence, the higher proportion and coefficient at NL50 relative to those at higher stakes.

The offsuit Broadway results suggest that at higher stakes, players use these hands more selectively, but more profitably. These moderately strong, certain and non-speculative hands are often deceptively attractive to weaker players. The lower proportion of shown down hands offsuit Broadway hands suggests that at higher stakes, players are more likely to fold these hands, which are very conducive to reverse implied odds. As a result, the profitability of these hands increases. This is in contrast to the results for big and medium pair hands, which suggested that their dangerous reverse implied odds incentive structures were more frequently played at higher limits, in part due to their concealed nature. This is in contrast to Broadway hands, which rarely assume concealed values. The implication of this is that part of the development of a high-stakes poker player is an understanding of the value of information concealment. Finally, suited Broadway hands – which are comprised of both the incentives of suited connectors and Broadway hands – are more played and profitable at higher levels. This appears to speak to the ability of high stakes players to reconcile complex and complementary incentive structures.

A limitation of this audit study is that hand information is only available when hands are played to their conclusion, and are not shown down. As evidenced by the extremely large proportion of hands that were mucked (i.e. folded at some point during the hand), such hands comprise the vast majority of the sample data.[9] While these datasets are still large enough to yield extremely large sample sizes for each of the hand categories, it is important to remember that they are being drawn from an inherently biased sample. Comparing the proportions of hands shown down and available in the dataset provides data to suggest which hands are more prone to being mucked, and filling in these lacunae in the datasets. Even though a 0.5% difference in N values between stakes works out to only one hand in two hundred, this is an important difference, considering these premium hand categories only comprise roughly one in fifteen hands and that hands are rarely shown down (as shown by the large mucked proportions). Further, the trends showing consistent directions across limits (with the exception of small pairs) also suggest that there are subtle, but profound changes in the behaviors and incentive structures when one moves up stakes.

IMPLICATIONS

Akerlof and Shiller (2009) and DiMaggio (2002) adapted Keynes' (1936) famous edict that "animal spirits" shape economic behavior and the economy, emphasizing the role of "emotional buoyance" in economic success. Analogously, the results in this study suggest that, on the whole, aggression is a profitable strategy in the uncertain realm of online poker. However, the heavy losses often associated with loose-aggressive play, suggests that there is a fine line between aggression and foolhardiness for many players.

[9] The only way to get information about folded hands would be to receive data directly from the online poker companies themselves. Despite repeated overtures, such businesses have been very reluctant to release such data, even anonymously, citing legal concerns.

To be successful in poker, animal spirits must be stoked, but also intelligent, refined and channeled strategically. As Holden (2005) mused about Lee Jones' tight-aggressive strategy suggestions, "I only hope I can summon the self-discipline to play [them.]" The optimal tradeoffs between aggression and restraint can be difficult to reach, given the contradictions between the two elements. Given that animal spirits are most important under conditions of Knightian uncertainty (DiMaggio, 2002: 80), the successful channeling and regulation of these human impulses and cognitions is key to success in poker, and beyond. Much like some degree of physical fitness is a prerequisite for proper athletic technique in numerous sports, cognitive fitness plays an analogous role in underpinning successful poker strategy.

Most elite high-stakes players are known for prominently employing loose-aggressive strategies (Harrington, 2004). Given the high standard deviations of win rates associated with such strategies, this raises the question of to what degree extreme positive outliers enjoy their status due to luck or skill. Taleb (2004) suggested that many successful investors with suboptimal strategies can become rich, due to the fact that there are so many people in the population taking chances, and even suboptimal strategies have a modest chance of succeeding. In a population of thousands, it is inevitable that some unskilled people will sneak through. Thus, being able to distinguish random but powerful trends as caused by skill or luck (Gilovich, Vallone and Tversky, 1985) is a recurrent challenge in poker.

As the research suggests, competitive edges in high-stakes games are relatively modest, and elite players generally play higher-stakes and more competitive games than NL1000. Thus, it is not surprising that stories abound of wealthy and successful professional poker players who have gone deeply into debt (Duke, 2006: 198) or broke on numerous occasions (Greenstein, 2005: 9) throughout their careers. As Malmuth muses (1999: 35), the difference between *good* and *great* gamblers is that the latter are willing to take marginal gambles with favorable odds, often with standard deviations higher than their win rate, or competitive edge. Accordingly, some great gamblers will go broke – sometimes repeatedly – in their careers. This raises the paradox and cognitive framing issue that high-stakes players must treat money and their decisions with reverent strategic care, yet also willing to be daring and cavalier with them. Money is simultaneously all-important and worthless. The line between riches and ruin can be extremely precarious and volatile, which presents a difficult incentive structure for risk-averse humans to handle. Despite this, framing issues are very important for poker players in order to optimize their expected value and rationality, given that framing and adaptive preferences formation are the two main means by which people alter their preferences with (Elster, 1983: 25-26).

There are a number of cognitive challenges inherent to successful poker strategy. Coupled with the need for “refined aggression”, profitable players must learn to not overweight high frequencies of small gains vis-à-vis rare large losses. However, at the same time, such players also benefit from a willingness to accept gambles with reverse implied odds intelligently, and sometimes be willing to not swerve in a chicken game of aggression encapsulated within the larger game of poker. Further, successful loose-aggressive players need to accept the stress and high variance of their high-variance play, in addition to mastering the technical complexities of the strategy. With all of these cognitive challenges, players must also try to distinguish between skill and luck effects to learn more about the game, their opponents and refine their strategies. The process of dealing with these challenges and shaping ones behaviors and preferences accordingly is dubbed *rationality work* (also see: Elster, 1983; Sally, 2000). This is a similar concept to Hochschild's (1983) emotion work, which similarly involves the channeling of psychological impulses in socially appropriate manners. Rationality work differs in that it involves reconfiguring one's preferences from one's initial cognitive and emotional impulses (or at least attempting to).[10] As prospect theory (Kahneman and Tversky, 1979) suggests, many of these impulses and predispositions toward risk and uncertainty are widespread amongst humans, and thus, it requires a concerted effort for many to reconfigure such preferences in a more profitable manner. Not surprisingly, some elite poker players have exhibited an inability to harness their attitudes towards risk in other less appropriate contexts in their lives, with disastrous consequences (Dalla and Also, 2006).

In addition to this myriad of cognitively challenging incentive structures, players still must learn how to appropriately distinguishing skill and luck as causal factors in the game, to learn and refine strategies. As it is impossible to parse skill and luck out

[10] Poker is rife with emotion work as well, from concealing one's true feelings about the situations they are in (i.e. "keeping a poker face") and dealing with adversity and maintaining emotional control and staying off "tilt", where emotions cloud the ability of a player to make intelligent and optimal decisions (Browne, 1989).

perfectly, poker players are particularly prone to committing the *fundamental attribution error*. Heider (1958) divided internal (in this case, skill) and external (luck) factors into four main attributes (Hayano, 1982: 109). Difficulty of the task and luck serve as external attributes, while skill and effort function as internal attributes. Hayano (110) found that losing players highly emphasized the role of luck in explaining their losses. While this allowed them to retain their self-image as competent poker players[11], albeit at a cost of further justifying and perpetuating their incompetence and further losses. In contrast, winning players were prone to including personal responsibility and efficacy in their explanations for winning or losing. In turn, poker provides the sort of context where a player can be “unskilled and unaware of it” (Kruger and Dunning, 1999), which is a large source of profits for skilled players. Thus, receiving and filtering feedback appropriately to facilitate learning and strategic and tactical adjustments is important, and is another cognitive challenge poker presents.

Utility maximization and most poker strategy guides (Harrington, 2004; Sklansky and Miller, 2006) emphasize the importance of maximizing expected value for playing winning poker. This is a theory where risks and bets are taken, regardless of their variance, or payout structure, as long as they have a positive expected value. Maximizing expected value often involves taking risks with frequent low or negative payouts, as long as they are outweighted by relatively rare positive events. Risk neutrality is assumed by such a valuation frame, which lies in contrast to marginal utility theory and prospect theory, which have both found that humans tend towards risk aversion, particularly when

[11] Keeping a positive self-image might not only be pleasant, but also be important for playing well, given that confidence is a prerequisite with being able to play profitable aggressive strategies. Granted, few losing players are likely able to realize such a connection anyways, given their cognitive blinders.

dealing with gains. Thus, adopting risk neutrality (or even risk-loving) dispositions is part of challenge of poker, and is part of the emotional and preference management poker players engage in. Given that poker is an emotionally evocative game (Browne, 1989), and players often have a variety of economic, psychological, house-holding and social pressures hinging on the results of their play (Hanusa, 1989), implementing “non self-weighting” strategies (Malmuth, 1999: 20) and adopting a risk-neutral orientation of maximizing expected utility can be very difficult, emotionally, if not also cognitively.

CONCLUSION

Poker is a very complex game, and the nuts and bolts strategy of the card game takes a great deal of effort and intelligence to master. However, mastering the card game is only part of the challenge of becoming a successful poker player in the long run. Rationality work is vital, as many “best strategies” in poker implicitly involve adopting dispositions towards risk, uncertainty and accounting that often go against the normal economic preferences of most humans. Ideally, a successful player will adapt their preferences towards risk neutrality to maximize expected value, even if this may entail wider swings of income. Relatedly, players must learn to appropriately weight and account for occasional large wins and losses accurately vis-à-vis more frequent small wins and losses. Aggression is almost always a valuable trait, yet this “animal spirit” must be refined, either through patient tight-aggression, or through very skilled and brave loose-aggression. When dealing with the mercurial vicissitudes of chance and luck in poker, players need to learn how to parse out correctly what they can and cannot control, without attributing errors to chance or external circumstances in defense of their self-image and control. At the same time, they must also retain the confidence to stay aggressive and keep playing.

The rationality work poker players do comprises meta-game of orientations to risk, which underlies the more visible game of cards being played. Doyle Brunson was right to say that poker is primarily a game of people. However, the biggest opponent for many players is themselves, given the challenges of optimizing one’s mindset and strategies, both in the card game, and the meta-games of psychology and rationality which hover beneath it.

Appendix A. Rating Criteria and Operationalizations for Various Strategies

Strategy	% Hands Played	% Hands Raised	Aggression Factor*
Loose-Aggressive/Aggressive	>=35	>=12	>=2.0
Loose-Aggressive/Passive	>=35	>=12	<2.0
Loose-Passive/Aggressive	>=35	<12	>=2.0
Loose-Passive/Passive	>=35	<12	<2.0
Semi-Loose-Aggressive/Aggressive	25 < 35	>=12	>=2.0
Semi-Loose-Aggressive/Passive	25 < 35	>=12	<2.0
Semi-Loose-Passive/Aggressive	25 < 35	<12	>=2.0
Semi-Loose-Passive/Passive	25 < 35	<12	<2.0
Tight-Aggressive/Aggressive	<25	>=12	>3.0
Tight-Aggressive/Neutral	<25	>=12	2.0 < 3.0
Tight-Aggressive/Passive	<25	>=12	<2.0
Tight-Passive/Aggressive	<25	<12	>2.0
Tight-Passive/Passive	<25	<12	<2.0

* The formula for Aggression Factor is (Total Times Bet + Total Times Raised) / (Total Times Called). See PokerTracker Manual (2009).

Appendix B. Poker Hand Classifications

Big Pairs: AA, KK, QQ.

Medium Pairs: 88, 99, TT, JJ.

Small Pairs: 22, 33, 44, 55, 66, 77.

Suited Connectors: 32s, 42s, 43s, 53s, 54s, 64s, 65s, 75s, 76s, 86s, 87s, 97s, 98s, AKs, AQs, J9s, JTs, KJs, KQs,, KTs, QJs, QTs, T8s, T9s. (Note: Two and three-gap suited connectors (e.g., 96s, J7s) could arguably also be included, but for these purposes, a more focused sample is preferable.)

Suited Broadway: AJs, ATs, AKs, AQs, JTs, KJs, KQs, KTs, QJs, QTs.

Offsuit Broadway: AJo, AKo, AQo, ATo, JTo, KJo, KQo, KTo, QJo, QTo.

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Table 1a. Adjusted Counts and Big Blind Win Rates for Various Strategies - NL1000 (N=1962)

Strategy	Adjusted BB/100	Standard Deviation	N	N (% of total)
Loose-Aggressive/Aggressive	-2.59	18.44	129	6.57
Loose-Aggressive/Passive	-10.17	20.27	110	5.61
Loose-Passive/Aggressive	-9.12	14.48	19	0.97
Loose-Passive/Passive	-11.55	18.45	55	2.80
Semi-Loose-Aggressive/Aggressive	0.89	13.16	366	18.65
Semi-Loose-Aggressive/Passive	-1.31	14.78	170	8.66
Semi-Loose-Passive/Aggressive	-3.42	14.69	55	2.80
Semi-Loose-Passive/Passive	-3.32	14.28	66	3.36
Tight-Aggressive/Neutral	0.34	10.05	333	16.97
Tight-Aggressive/Aggressive	1.62	8.97	419	21.36
Tight-Aggressive/Passive	-0.58	10.79	96	4.89
Tight-Passive/Aggressive	0.28	9.25	77	3.92
Tight-Passive/Passive	-1.79	11.24	67	3.41

* minimum 750 hands played

Table 1b. Adjusted Counts and Big Blind Win Rates for Various Strategies - NL200 (N=5659)

Strategy	Adjusted BB/100	Standard Deviation	N	N (% of total)
Loose-Aggressive/Aggressive	-5.19	17.87	614	10.85
Loose-Aggressive/Passive	-7.39	15.98	371	6.56
Loose-Passive/Aggressive	-4.32	15.01	243	4.29
Loose-Passive/Passive	-8.32	15.73	366	6.47
Semi-Loose-Aggressive/Aggressive	1.00	12.40	768	13.57
Semi-Loose-Aggressive/Passive	-0.94	11.80	336	5.94
Semi-Loose-Passive/Aggressive	0.07	10.55	326	5.76
Semi-Loose-Passive/Passive	-3.02	11.93	355	6.27
Tight-Aggressive/Neutral	3.09	8.28	688	12.16
Tight-Aggressive/Aggressive	3.27	7.78	893	15.78
Tight-Aggressive/Passive	0.24	12.07	161	2.85
Tight-Passive/Aggressive	1.70	8.23	336	5.94
Tight-Passive/Passive	1.47	9.20	202	3.57

* minimum 750 hands played

Table 1c. Adjusted Counts and Big Blind Win Rates for Various Strategies - NL50 (N=9313)

Strategy	Adjusted BB/100	Standard Deviation	N	N (% of total)
Loose-Aggressive/Aggressive	-6.24	19.49	893	9.59
Loose-Aggressive/Passive	-9.47	18.62	507	5.44
Loose-Passive/Aggressive	-5.03	16.35	468	5.03
Loose-Passive/Passive	-9.38	19.29	715	7.68
Semi-Loose-Aggressive/Aggressive	2.62	12.89	701	7.53
Semi-Loose-Aggressive/Passive	0.07	13.31	376	4.04
Semi-Loose-Passive/Aggressive	1.65	10.71	636	6.83
Semi-Loose-Passive/Passive	-0.80	11.47	603	6.47
Tight-Aggressive/Neutral	4.18	9.72	542	5.82
Tight-Aggressive/Aggressive	4.08	10.6	1743	18.72
Tight-Aggressive/Passive	2.92	10.91	274	2.94
Tight-Passive/Aggressive	3.89	7.93	1433	15.39
Tight-Passive/Passive	2.14	9.41	422	4.53

Table 2a. Proportions of Strategies among Top and Bottom 100 (BB/100 hands rates) Players, NL1000

	Bottom 100 Players			Top 100 Players		
Strategy	N (bottom 100)	% of entire sample	Over(under)-representation	N (top 100)	% of entire sample	Over(under)-representation
Loose-Aggressive/Aggressive	14	6.57	7.43	13	6.57	6.43
Loose-Aggressive/Passive	19	5.61	13.39	2	5.61	-3.61
Loose-Passive/Aggressive	2	0.97	1.03	0	0.97	-0.97
Loose-Passive/Passive	13	2.80	10.2	2	2.80	-0.8
Semi-Loose-Aggressive/Aggressive	11	18.65	-7.65	30	18.65	11.35
Semi-Loose-Aggressive/Passive	12	8.66	3.34	13	8.66	4.34
Semi-Loose-Passive/Aggressive	3	2.80	0.2	3	2.80	0.2
Semi-Loose-Passive/Passive	5	3.36	1.64	3	3.36	-0.36
Tight-Aggressive/Neutral	9	16.97	-7.97	9	16.97	-7.97
Tight-Aggressive/Aggressive	6	21.36	-15.36	14	21.36	-7.36
Tight-Aggressive/Passive	4	4.89	-0.89	5	4.89	0.11
Tight-Passive/Aggressive	0	3.92	-3.92	3	3.92	-0.92
Tight-Passive/Passive	2	3.41	-1.41	3	3.41	-0.41

Table 2b. Proportions of Strategies among Top and Bottom 100 (BB/100 hands rates) Players, NL200

	Bottom 100 Players			Top 100 Players		
Strategy	N (bottom 100)	% of entire sample	Over(under)-representation	N (top 100)	% of entire sample	Over(under)-representation
Loose-Aggressive/Aggressive	33	10.85	22.15	19	10.85	8.15
Loose-Aggressive/Passive	19	6.56	12.44	7	6.56	0.44
Loose-Passive/Aggressive	7	4.29	2.71	4	4.29	-0.29
Loose-Passive/Passive	25	6.47	18.53	7	6.47	0.53
Semi-Loose-Aggressive/Aggressive	5	13.57	-8.57	19	13.57	5.43
Semi-Loose-Aggressive/Passive	1	5.94	-4.94	7	5.94	1.06
Semi-Loose-Passive/Aggressive	0	5.76	-5.76	6	5.76	0.24
Semi-Loose-Passive/Passive	7	6.27	0.73	1	6.27	-5.27
Tight-Aggressive/Neutral	0	12.16	-12.16	7	12.16	-5.16
Tight-Aggressive/Aggressive	0	15.78	-15.78	12	15.78	-3.78
Tight-Aggressive/Passive	3	2.85	0.15	2	2.85	-0.85
Tight-Passive/Aggressive	0	5.94	-5.94	5	5.94	-0.94
Tight-Passive/Passive	0	3.57	-3.57	4	3.57	0.43

Table 2c. Proportions of Strategies among Top and Bottom 100 (BB/100 hands rates) Players, NL50

	Bottom 100 Players			Top 100 Players		
Strategy	N	% of overall sample	Over(under)-representation	N	% of overall sample	Over(under)-representation
Loose-Aggressive/Aggressive	36	9.59	26.41	19	9.59	9.41
Loose-Aggressive/Passive	19	5.44	13.56	4	5.44	-1.44
Loose-Passive/Aggressive	9	5.03	3.97	5	5.03	-0.03
Loose-Passive/Passive	32	7.68	24.32	13	7.68	5.32
Semi-Loose-Aggressive/Aggressive	0	7.53	-7.53	13	7.53	5.47
Semi-Loose-Aggressive/Passive	1	4.04	-3.04	7	4.04	2.96
Semi-Loose-Passive/Aggressive	0	6.83	-6.83	8	6.83	1.17
Semi-Loose-Passive/Passive	1	6.47	-5.47	5	6.47	-1.47
Tight-Aggressive/Neutral	0	5.82	-5.82	3	5.82	-2.82
Tight-Aggressive/Aggressive	0	18.72	-18.72	14	18.72	-4.72
Tight-Aggressive/Passive	1	2.94	-1.94	2	2.94	-0.94
Tight-Passive/Aggressive	0	15.39	-15.39	5	15.39	-10.39
Tight-Passive/Passive	0	4.53	-4.53	2	4.53	-2.53

Table 3a. Summary Statistics of Top 20 Winning Players (Amount Won) at Various Stakes

Stakes	Avg. Hands	Min	Max	Avg. Amount Won	Min	Max	Avg. BB_100	Min	Max
NL50	76418	13632	268658	2313	1712	4172	5.33	1.21	13.99
NL200	78416	28343	199848	13586	9961	24402	5.10	2.3	9.29
NL1000	90049	30966	195516	67227	39641	188983	4.53	1.17	11.01

Table 3b. Summary Statistics of Top 20 Losing Players (Amount Lost) at Various Stakes

Stakes	Avg. Hands	Min	Max	Avg. Amount Lost	Min	Max	Avg. BB_100	Min	Max
NL50	22152	1801	106096	2839	2052	4856	28.96	1.96	156.00
NL200	53982	5256	241193	7399	5706	24939	11.43	0.87	82.71
NL1000	32914	4224	134729	34804	21874	75935	16.82	1.12	61.73

Table 4a. Strategies of Top 20 Winning Players (Amount Won) at Various Stakes

	NL50	NL200	NL1000
Semi-Loose-Aggressive/Aggressive	1	1	4
Tight-Aggressive/Aggressive	9	14	9
Tight-Aggressive/Neutral	3	6	7
Tight-Aggressive/Passive	1	0	0
Tight-Passive/Aggressive	6	1	0

Table 4b. Strategies of Top 20 Losing Players (Amount Won) at Various Stakes

	NL50	NL200	NL1000
Loose-Aggressive/Aggressive	5	3	1
Loose-Aggressive/Passive	3	1	2
Loose-Passive/Passive	4	0	2
Semi-Loose-Aggressive/Aggressive	1	0	3
Semi-Loose-Aggressive/Passive	2	2	1
Semi-Loose-Passive/Aggressive	0	1	0
Semi-Loose-Passive/Passive	2	0	1
Tight-Aggressive/Aggressive	1	5	3
Tight-Aggressive/Neutral	0	6	7
Tight-Aggressive/Passive	1	1	0
Tight-Passive/Aggressive	1	1	0

Table 5. Regression of Big Blind Win Rates (per 100 hands) on Win Percentage at Various Stakes

Stakes	NL1000	NL200	NL50
Win Percentage	-.348***	-.734***	-.876***
	(.001)	(.000)	(.000)
Constant	7.08***	14.44***	17.20***
	(.015)	(.008)	(.007)
N (hands)	15520695	35948809	49521492
R-square	.011	.072	.092

* weighted by number of hands played per player

Note: Numbers in parentheses are standard errors.

+ p <.10; * p <.05; ** p <.01; *** p <.001 (two-tailed tests)

Table 6. Regression of Big Blind Win Rates (per 100 hands) on Hand Type at Various Stakes

Stakes	NL1000	NL200	NL50
Hand Type			
Big Pair	958.31***	797.78***	713.53***
	(56.77)	(41.82)	(36.95)
N	50906	83426	343102
% Total N	11.18	10.78	10.67
Medium Pair	341.69***	274.23***	274.82***
	(49.36)	(36.37)	(32.13)
N	57957	90855	355731
% Total N	12.73	11.73	11.07
Small Pair	296.15***	260.19***	280.91***
	(-40.62)	(29.93)	(26.44)
N	50817	85405	360583
% Total N	11.16	11.03	11.22
Suited Connectors	73.48**	74.44***	87.72***
	(24.50)	(18.05)	(15.95)
N	95358	164778	690270
% Total N	20.95	21.28	21.47
Suited Broadway	107.23**	91.23**	73.01**
	(35.95)	(26.49)	(23.40)
N	65199	108596	447924
% Total N	14.32	14.03	13.93
Offsuit Broadway	61.13+	51.05*	51.51*
	(31.96)	(23.55)	(20.80)
N	134990	241174	1017006
% Total N	29.65	31.15	31.64
Mucked	-74.41	-74.07	-82.80
	(97.53)	(71.86)	(63.49)
N	15480211	23986034	92013486
% Total N	97.14	96.87	96.62
Constant	63.86***	61.60***	67.27***
	(8.81)	(6.49)	(5.74)

R-Square	.704	.757	.779
Total N (Hands)	15935438	24760268	95228102

Note: Numbers in parentheses are standard errors.
For hand type categories, % of Total N values do not include Mucked N.

+ p <.10; * p <.05; ** p <.01; *** p <.001 (two-tailed tests)

Figure 1 – Scatterplot Regression of Adjusted Win Rate on Hands Played by Player, NL 50 (N=9313)