

Stockholm School of Economics
Department of Economics
Course 5350: Thesis in Economics
2012-2013

Do Prior Wins and Losses Affect Risk Taking Behaviour in Texas Hold ‘em Poker?

Peter Gray (40232)
Emelie Kullenberg (21400)

Supervisor: Magnus Johannesson

Abstract: This thesis investigates if and how prior wins and losses affect the risk taking behavior of professional poker players. Using a dataset based on a series of televised poker tournaments, we build upon the findings of Smith, Levere and Kurtzman (2009), who demonstrate the break-even effect of prospect theory in a field study of experienced online poker players. While we are unable to exactly replicate the results of Smith, Levere and Kurtzman (2009), our estimates are improved by using a number of model refinements made possible by our dataset. In particular, when explicitly controlling for the privately held information of each player, we find evidence that individuals take more risk following a large loss, and play more conservative following a large win. Based on these results, we find evidence that suggests that more experienced players are less affected by prior wins and losses than less experienced players. This thesis also argues in favour of using poker data to study economic behaviour and the importance of model selection when analysing such data.

Keywords: prospect theory, poker, risk preference, loss aversion, break-even effect

JEL Classification: D03, D81, G02

Examiner: Yoichi Sugita

Presentation: 2012-05-22

Acknowledgements:

We would like to thank our supervisor Magnus Johannesson for his advice and support throughout the entire thesis process. We are extremely grateful for his help.

Table of Contents

1	INTRODUCTION	1
2	THEORETICAL FRAMEWORK	3
2.1	EXPECTED UTILITY THEORY	3
2.2	PROSPECT THEORY	5
3	EMPIRICAL BACKGROUND	9
3.1	THE HOUSE MONEY EFFECT	9
3.2	BREAK-EVEN EFFECT	9
3.3	GAMBLER’S AND HOT HAND FALLACIES	10
3.4	THE ROLE OF EXPERIENCE	11
3.5	NOVEL FIELD STUDIES OF RISK TAKING BEHAVIOUR	12
3.6	THE POKER CONTEXT	13
3.7	SMITH ET AL. (2009)	14
4	RESEARCH QUESTIONS	16
5	NO-LIMIT TEXAS HOLD ‘EM POKER	17
6	DATA	19
7	METHODOLOGY	21
7.1	LOOSENESS	21
7.2	AGGRESSION	22
7.3	DISCRETE IDENTIFICATION OF WINS AND LOSSES	23
7.4	CONTINUOUS IDENTIFICATION OF WINS AND LOSSES	24
7.5	CONTROL VARIABLES	25
7.5.1	<i>Probability</i>	25
7.5.2	<i>Number of Players</i>	26
7.5.3	<i>Relative Position</i>	27
7.6	ESTIMATION MODELS	27
7.6.1	<i>Fixed vs. Random Effects</i>	29
7.7	CONTROLLING FOR EXPERIENCE	30
8	RESULTS	32
8.1	LOOSENESS	32
8.2	AGGRESSION	33
8.3	THE EFFECT OF EXPERIENCE	37
9	DISCUSSION	41
9.1	FUTURE RESEARCH	46
10	CONCLUSION	47
11	REFERENCES	49
12	APPENDIX	53

1 Introduction

Numerous authors have argued that expected utility theory inadequately describes the manner in which individuals behave in the face of risk and uncertainty. Using both real world data from financial markets and laboratory experiments, it has been shown that individuals routinely and regularly act in a manner that contradicts the predictions of expected utility theory. In a landmark study, Kahneman and Tversky (1979) demonstrate preference reversal about an individual's reference point. They find that individuals tend to be risk averse for positive gambles and risk seeking for negative gambles.

Kahneman and Tversky (1979) argue that both field studies and conventional laboratory experiments are problematic when studying choices made under risk and uncertainty. Field studies can provide only crude approximations of risk preferences as the true probability distribution is rarely known, and researchers cannot directly observe the subjective beliefs of participants. Conversely, laboratory experiments typically involve contrived gambles for small sums of money. Kahneman and Tversky (1979) instead present the participants of their study a series of hypothetical alternatives. However this set up is again problematic, in that it assumes individuals do not respond to hypothetical choices differently than they would act in a real world context.

To avoid the limitations which Kahneman and Tversky (1979) identify, a growing number of studies have utilised data from unconventional sources, such as televised game shows. In a similar vein, we use a novel dataset of our own construction, based on a series of televised poker tournaments. Poker is a particularly advantageous medium to study behaviour under risk and uncertainty. Players voluntarily participate in a repeated game with high stakes and are able accurately approximate the game's true probability distribution. Our use of poker in this way is similar to the work of Smith, Levere, and Kurtzman (2009) – henceforth referred to as Smith et al. (2009) – as well as Siler (2010) and Engelbergs (2010).

The purpose of this thesis is to investigate the effect of prior wins and losses upon risk taking behaviour. We base our prior expectations on the results of Smith et al. (2009), who demonstrate the break-even effect of prospect theory in a field study of highly experienced online poker players. Our initial hypothesis is that prior wins and losses significantly and inversely affect individual risk preferences. The framework used is also based on prospect theory, first introduced by Kahneman and Tversky (1979), as well as the extensions made for repeated games by Thaler and Johnson (1990).

The primary advantage of our dataset over previous poker studies is that we are able to explicitly control for each player's privately held information. Furthermore, we are able to utilise a set of publically available rankings as a proxy for experience. Using these rankings, which cover our entire sample, we investigate whether more experienced individuals are less affected by prior wins and losses in a poker context. This element of our thesis is based on the findings of authors such as List (2003, 2004), and Palacios-Huerta and Volij (2009).

The remainder of this paper is organised as follows. Sections 2 and 3 present the theoretical underpinnings of our paper and the empirical results from a number of closely related studies. Section 4 explicitly states our research questions. Section 5 provides a basic overview of Texas Hold 'em Poker for readers unfamiliar with the game. Section 6 summarises our data and section 7 describes our methodology in depth. Section 8 presents our results. A more detailed discussion of these results, including their relevance to the previous literature, can be found in section 9. Section 10 concludes the thesis.

2 Theoretical Framework

2.1 Expected Utility Theory

Expected utility theory attempts to explain why individuals, when faced with uncertain or risky decisions, typically act in a manner inconsistent with simply maximising their expected payoff (Machina 2008). The theory – as modelled by von Neumann and Morgenstern (1944) – is that individuals maximise the expected utility derived from each outcome. For instance, when faced with the decision between receiving an amount c with certainty and the gamble in which she wins either x_1 , with probability p , or x_2 , with probability $1 - p$, an individual maximises her expected utility: $p * U(x_1) + (1 - p) * U(x_2)$ compared to $U(c)$. This is in contrast to a comparison of her expected payoff: $p * x_1 + (1 - p) * (x_2)$, for the gamble, or c with certainty. This leads to a range of different risk preferences depending on the specific functional form of an individual's utility function. Depending on how an individual favours a risky situation relative to a certainty equivalent, they can be described as risk averse, risk neutral or risk seeking/risk loving.

Figure 1 and 2 present the utility functions of a risk averse and risk seeking individual offered the gamble between x_1 and x_2 with a certainty equivalent of c . For a risk averse individual, the certainty equivalent lies below the expected payoff of the gamble, while the converse is true for a risk seeking individual.

Although expected utility theory is widely used as a model of decision making under risk, it relies on the assumption that preferences are linear with respect to probability. Furthermore, there exists a large body of literature that is critical of the theory. Numerous authors have demonstrated that the behaviour of individuals frequently contradicts the predictions of expected utility theory. For instance, when testing Allais' eponymous paradox, various authors have found evidence of preference reversals (Machina 2008). Others such as Ellsberg (1961) find that individuals violate probabilistic sophistication when faced with uncertainty rather than risk.

Figure 1. Utility Function of a Risk Averse Individual

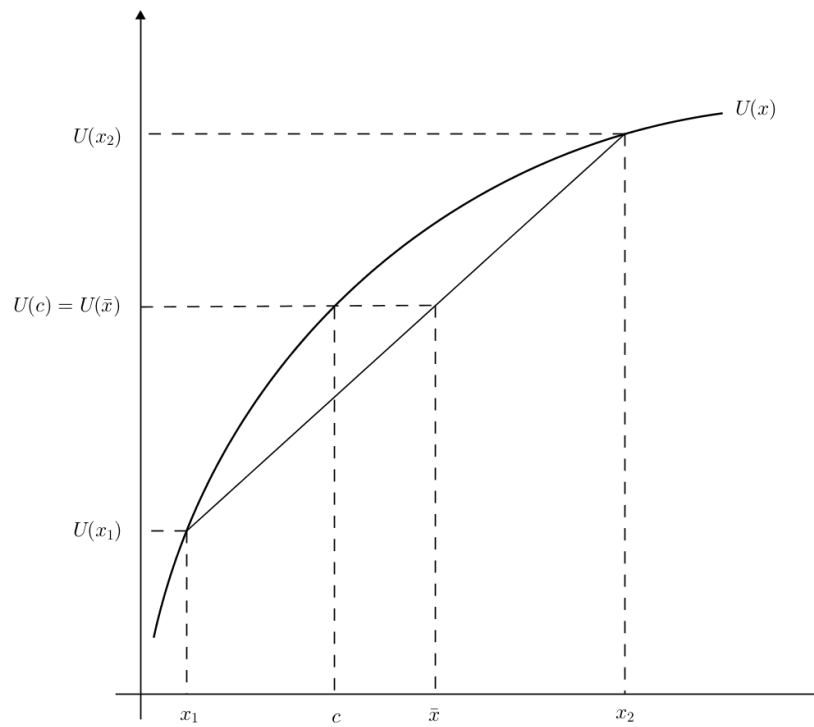
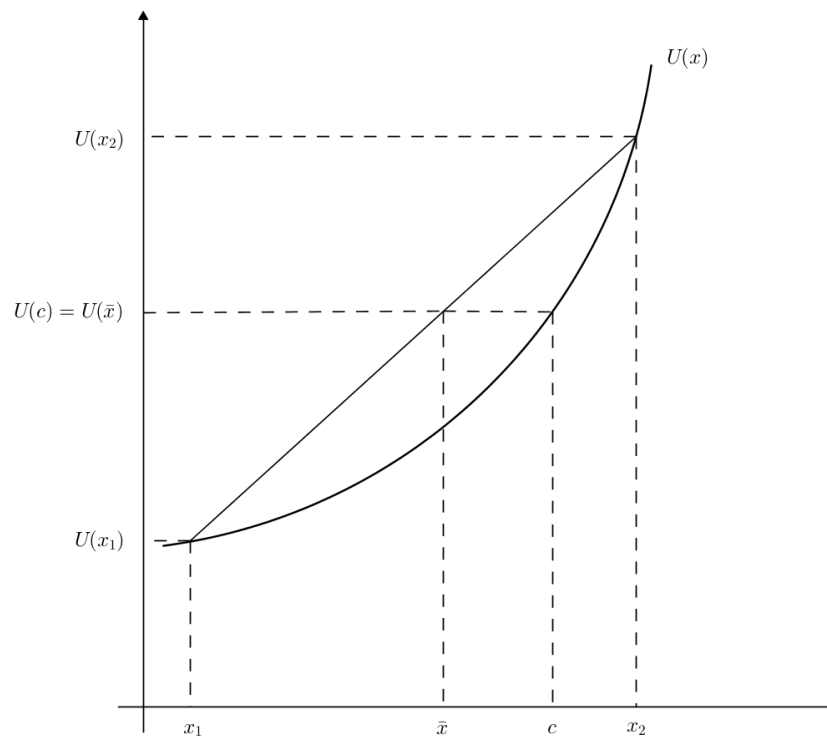


Figure 2. Utility Function of a Risk Seeking Individual



2.2 Prospect Theory

In their landmark paper “Prospect Theory: An Analysis of Decision Under Risk”, Daniel Kahneman and Amos Tversky (1979) demonstrate by way of experimentation “several classes of choice problems in which preferences systematically violate the axioms of expected utility theory” (p. 262). They identify two key effects: the certainty effect and the reflection effect. To explain this behaviour, Kahneman and Tversky (1979) present prospect theory as an improvement on expected utility theory.

The certainty effect is based on the observation that individuals place too great a weight on outcomes that they considered “certain”, which in turn underweights events with a low probability of occurring. For example consider Tables 1 and 2, which summarise two experiments run by Kahneman and Tversky (1979). In both situation 1 and 2, individuals are given the choice between two options. These two scenarios differ only by the probability of their outcomes, such that the probability of C and D are scaled down to a quarter that of A and B. The substitution axiom of expected utility theory predicts that if an individual prefers A to B, they will also prefer C to D. Similarly, individuals that prefer B to A are predicted to prefer D to C. Kahneman and Tversky (1979) instead find that the majority of subjects (80%) preferred B to A and C to D (65%). This suggests that around 40% of respondents revealed preferences in violation of expected utility theory.

Table 1. Choice Between Prospects A & B

Option	Payoffs	Probability	Expected Payoff	% of Subjects
A	4,000 0	$p = 0.8$ $p = 0.2$	3,200	20%
B	3,000 0	$p = 1$ $p = 0$	3,000	80%

Table 2. Choice Between Prospects C & D

Option	Payoffs	Probability	Expected Payoff	% of Subjects
C	4,000 0	$p = 0.2$ $p = 0.8$	800	65%
D	3,000 0	$p = 0.25$ $p = 0.75$	750	35%

Table 1 and 2 are reproduced from Kahneman and Tversky, 1979, p. 266.

The reflection effect is based on the observation that individuals tend to be risk averse in gains and risk seeking in losses. They argue that individuals are loss averse, and experience the pain of losing to a greater extent than they enjoy winning. The authors further find that if the loss-framed treatment is first endowed with an amount that equates the expected payoff to that of the win-framed treatment, the reflection effect remains. For an example, consider the experiment summarised in Tables 3 and 4. In both scenarios, individuals are given the choice between a risky and a safe option. These scenarios differed only in that the first frames the decision as a win and the second frames it as a loss. When framed as a win, the overwhelming majority of people (80%) chose the safe option, consistent with risk aversion. Conversely, when framed as a loss, 92% chose the risky decision, consistent with risk seeking preferences.

Table 3. Positive Gamble (Win) – E & F

Option	Payoffs	Probability	Expected Payoff	% of Subjects
E – risky	4,000 0	$p = 0.8$ $p = 0.2$	3,200	20%
F – risky	3,000 0	$p = 1$ $p = 0$	3,000	80%

Table 4. Negative Gamble (loss) – G & H

Option	Payoffs	Probability	Expected Payoff	% of Subjects
G – risky	-4,000 0	$p = 0.8$ $p = 0.2$	-3,200	92%
H – risky	-3,000 0	$p = 1$ $p = 0$	-3,000	8%

Source: Table 3 and 4 are reproduced from Kahneman and Tversky, 1979, p. 268.

Based on these findings, Kahneman and Tversky (1979) propose a model in which the value of a prospect is the resulting change in wealth or welfare, rather than the final outcome. Thus the value of a prospect is dependent upon an individual's reference point. The authors liken this to temperature, hot and cold being comparative states relative to the temperature at which one is accustomed. Another important element is

that individuals assess each prospect with a decision weight based on the probability. From this, individuals maximise the value, V , of a prospect:

$$V = \pi(p) * v(x_1) + \pi(1 - p) * v(x_2)$$

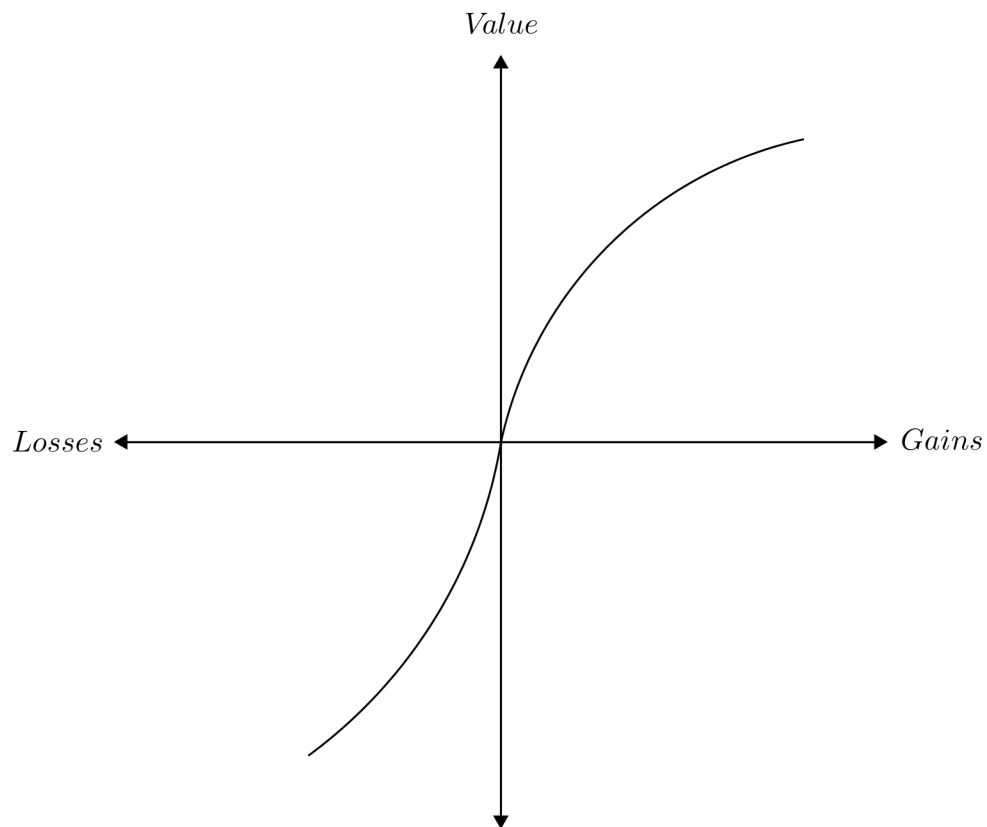
Where $\pi(p)$ is a decision weight dependent on the probability p , such that:

$$\pi(p) + \pi(1 - p) < 1, \quad \text{in general}$$

$$\pi(p) > p, \quad \text{when } p \text{ high}$$

$$\pi(p) < p, \quad \text{when } p \text{ low}$$

Figure 3. Value Function



The S-shaped feature of the value function is due to the reflection effect. The concavity in the positive domain (wins) and the convexity in the negative domain (loss) indicate risk aversion in gains and risk seeking in losses. This is dependent upon a reference point defined at the origin. The function is steepest

around the reference point (origin), as individuals tend to overestimate very unlikely events, and steeper in losses than in gains, as a loss hurts more than a gain gratifies.

Beyond prospect theory, there has been substantial development of other non-expected utility theories. For further and more comprehensive reading, we recommend Hirshleifer (2001) and Starmer (2000). Below we briefly summarise a number of empirical findings from behavioural economics, which build upon Kahneman and Tversky (1979) and are relevant for our analysis. We specifically emphasise findings upon the effects of prior wins and losses upon decision-making under risk.

3 Empirical Background

3.1 The House Money Effect

A natural extension of Kahneman and Tversky (1979), who use one-shot hypothetical experiments, is to investigate how the decision making process is influenced by the outcome of prior events. Thaler and Johnson (1990), using a framework based on prospect theory, stress the importance of an individual's reference point in isolating the effect of prior gains and losses upon risk taking behaviour. They argue that as the pain of losing is cushioned by previous gains, people are more likely to accept a risky gamble if they have already made money in previous rounds. It is easier to lose these gains, from a psychologically perspective, than to lose one's own money. Thaler and Johnson (1990) refer to this effect as the *house money effect*.

Using data on investor behaviour, Barberis, Huang and Santos (2001) find evidence for such an effect. Their results suggest that investors show signs of being less risk averse when their asset return exceeds index price.

In a poker context, the house money effect suggests that when current wealth exceeds a player's reference point, typically her initial bankroll, the player will play worse hands and bet more than she otherwise would. Thus while Kahneman and Tversky (1979) observe greater risk aversion for wins, the implication of the house money effect is that in a repeated game, individuals are less risk averse after having already won.

3.2 Break-Even Effect

Thaler and Johnson (1990) further suggest that individuals are similarly less risk averse following a prior loss. They note that people are typically more willing to accept a risky prospect if it provides them with the possibility to break even. Thaler and Johnson describe this effect as the *break-even effect*. Andrade and Iyer (2009) similarly find that people tend to bet significantly more than planned following a loss, but remain relatively constant after an equivalent win.

Coval and Shumway (2005), using data from traders from the Chicago Board of Trade, find that a trader with a morning loss is 15.5% more likely to take greater risk in the afternoon compared to a trader that had a morning gain. Odean (1998), similarly using stock market data, finds evidence that investors are

reluctant to realise losses as opposed to gains, holding onto poorly performing stock for a relatively longer duration than for profitable stock.

The implication of the break-even effect is that while a player who is up for the night may play safe to retain her winnings, a losing player may take more risks in an attempt to win back her lost money.

3.3 Gambler's and Hot Hand Fallacies

Another explanation for deviations from expected utility theory is that individuals are susceptible to a misperception of random events. The *gambler's fallacy* is the effect that people typically believe that there is a negative correlation between non-correlated random sequences (Rabin 2002). An example is provided by Croson and Sundali (2005): a girl tossing a coin, who has previously thrown three consecutive heads, may believe she is due for a tails and that the probability of throwing a fourth head is less than 50%. This contradicts the true probability of 50%, regardless of previous throws.

Terrell (1994) finds that when a certain number has recently been drawn as a winning lottery number, less people bet on that number in subsequent draws. Croson and Sundali (2005) investigate this phenomenon in a field study of gamblers playing roulette at a casino. They find that while a streak of less than five has no statistically significant effect on individual behaviour, a streak of more than five affects behaviour in line with the gambler's fallacy, significant at the 5% level.

A similar concept is the *hot hand fallacy*, which is the inverse of the gambler's fallacy. It refers to a belief in a positive correlation between non-correlated random sequences. For instance, individuals tend to believe a favourable (unfavourable) outcome is more likely if it follows previously favourable (unfavourable) events, such as hot and cold streaks.

Using basketball data, Camerer (1989) finds that people tend to believe a "hot" player, who has just scored a free throw, is more likely to score the next free throw than a player who just missed. Although, the existence of the hot hand fallacy requires that said "hot" player is not more likely to score again. Gilovich, Vallone, and Tversky (1985) find that the success of a player to be independent of past performance, which suggests the hot hand fallacy is merely an illusion. However, Aharoni and Sarig (2012), who find evidence of hot hand effects across a complete season, suggest that teams may change their playing strategy when a player is considered to be hot. They suggest that this change in strategy drives the relationship between with success and past performance.

In our setting, the gambler's fallacy suggests that a player who has just won by a long shot, will behave more conservatively in the proceeding rounds as she does not expect such good luck again. Conversely, the hot hand fallacy instead predicts that that same player will behave less conservatively, as she will consider herself to be "hot" or on form. These cognitive biases predict behaviour in opposite directions. However, our sample consists of professional poker players who are well acquainted with the concepts of chance and probability. It is unlikely that these fallacies are plausible explanations in the context of our research.

3.4 The Role of Experience

Another important aspect of our research is the question of how individual behaviour and strategies are affected by experience. List (2004) uses a field experiment, conducted at a sports card swap meet using both experienced and inexperienced traders. List finds that while experienced traders behave largely inline with expected utility theory, inexperienced individuals were significantly biased towards their endowment. List (2003, 2004) finds that this bias appears to be attenuated as experience increases.

Alevy, Haigh and List (2007) compare the behaviour of professional traders from the Chicago Board of Trade to that of college students to investigate the notion of "information cascades". They find significant difference between the more experience group (the professionals) and the student group. While the behavior of the market professionals was reasonably consistent across gains and losses, the students acted in a manner indicative of loss aversion.

Similarly, List and Haigh (2005) test if the independence condition in expected utility theory holds true when professionals from the Chicago Board of Trade and students participate in an Allais paradox experiment, similar to that conducted by Kahneman and Tversky (1979). They find that both groups violate expected utility theory, but that the students do so to a greater extent than the professionals.

Palacios-Huerta and Volij (2009) conduct a trial of a one-shot centipede game with a sample consisting of both typical student subjects and professional chess players.¹ They argue that the professional players are "very likely characterized by a high degree of rationality" (p. 1620). When conducted with only chess players, the authors find that 69% of the games ended in the sub-game perfect equilibrium (the game theory prediction). This increases to 100% when the authors only consider games in which a grandmaster

¹ For a description of the centipede game and a discussion of the traditional prediction of game theory, we recommend Rosenthal (1981).

played first. When conducted with a mixed sample, the authors find that only 37.5% games ended in the sub game equilibrium when a chess player moved first against a non-chess player. Furthermore, they find that only 3% of games with two students ended in the sub game equilibrium. As such, the authors argue that it is not rationality in itself that contributes to the sub game equilibrium, but the degree of common knowledge of rationality among the players.

However, a study by Levitt, List and Sadoff (2011) fails to replicate the results of Palacios-Huerta and Volij (2009). The authors instead find that professional chess players behave remarkably similar to less experience players, such as students, in the centipede game.

Our sample consists of top-ranked poker players with substantial poker experience. The above findings suggest that our sample may be less affected by prior events, such as large wins and losses, than a less experienced sample. This may have important implication on our results, particularly in relation to previous literature, and is discussed in more detail below.

3.5 Novel Field Studies of Risk Taking Behaviour

Although ubiquitous in the behavioural literature, Kahneman and Tversky (1979) suggest that both conventional field studies and laboratory experiments are problematic when attempting to capture the aforementioned inconsistencies with expected utility theory. Kahneman and Tversky (1979, p. 265) comment:

Field studies can only provide for rather crude tests of qualitative predictions, because probabilities and utilities cannot be adequately measured in such contexts. Laboratory experiments have been designed to obtain precise measures of utility and probability from actual choices, but these experimental studies typically involve contrived gambles for small stakes, and a large number of repetitions of very similar problems. These features of laboratory gambling complicate the interpretation of the results and restrict their generality.

However, there are a growing number of studies that attempt to avoid these issues through use of novel data sources. A prime example is the use of televised game shows such as “Jeopardy” (Lindquist and S  ve-S  derbergh 2012), “Deal or No Deal?” (de Roos and Sarafidis 2010; Blavatskyy and Pogrebna 2010) and “Who Wants to be a Millionaire” (Johnson and Gleason 2009) as a proxy for a controlled lab experiment.

Post, Van Den Assem, Baltussen and Thaler (2008) study the behaviour of contestants from a number of international versions of “Deal or No Deal?” and find results largely in line with reference-dependent theories rather than expected utility theory. They also find evidence that previous outcomes affect the degree of loss aversion in line with the break-even and house money effects. For instance, loss aversion increases and decreases in line with changes in a player’s expected payoff. The authors note that the drawback with non-experimental research is that in most real-life situations, individuals cannot know the true probability distribution and researchers cannot know their subject’s beliefs. However, as both contestants and researchers know the probability distribution in “Deal or No Deal?”, they argue that the setting overcomes these limitations (p. 38-39).

Casino and casino game data has also been used in a similar manner as those from the televised game shows in studies by Delfabbro and Winefield (1999), Carlin and Robinson (2009), and Keren and Wagenaar (1985). Poker in particular, played in both casinos and online, can provide a detailed dataset of individual behaviour based on real life instances of risk, uncertainty, imperfect information and competition (Siler 2010).

3.6 The Poker Context

To our knowledge, the closest credible papers to our study, that use data from poker players to study risk preferences and rationality, are those of Smith et al. (2009), Engelbergs (2010) and Siler (2010). Smith et al. (2009) is a particularly important forerunner to our work, and is described in greater detail below.

Siler (2010) and Engelbergs (2010) are of less direct comparison. While Siler (2010) use a similarly constructed dataset to Smith et al. (2009), the primary focus is the evaluation of various poker strategies and their associated payoffs, rather than the behavioural implications.

Engelbergs (2010) similarly presents a very thorough and extensive analysis of behavioural theories in his dissertation with a strong emphasis on testing for psychological biases. In the most relevant section, Engelbergs tests whether behaviour deviates significantly when a player’s bankroll is above or below their reference point, defined as the money brought to the table at the beginning of the session. Engelbergs finds weak evidence that suggests that risk aversion falls (increases) when current wealth is above (below) the reference-point.

The data used by Englebergs (2010) was gathered from a database of IRC Poker, an extremely early version of online poker. There are significant differences between IRC Poker and our dataset, which

limits direct comparison. Firstly in IRC Poker, individuals play for hypothetical stakes rather than real money. Secondly, our players are able to raise the stakes by any amount they wish, while they are limited by a maximum bet in IRC Poker. Finally, our players are all equally endowed at the start of the session.

These authors, Smith et al. (2009), Engelbergs (2010) and Siler (2010), all argue that the use of data on online poker presents a number of unique and valuable opportunities. Namely: the accessibility to an extensive and detailed data on individual behaviour; the nature of the game which involves real life situations of interest such as risk, uncertainty, imperfect information and competition; and the fact that the players participate voluntarily and act in a self-motivated manner without prior knowledge of their participation.

In addition, the high stakes naturally limits the typical concerns related to the low stakes of laboratory experiments. For instance, although Cameron (1999) find only small effects when increasing the stakes in the ultimatum game, Andersen et al. (2011) recently found much larger effects. Moreover, by using data based on real values one naturally avoids the issue of *hypothetical bias*. Hypothetical bias describes the concern that individuals may respond to choices differently in a hypothetical context than they would in a real context, such as overstating their true valuation of alternatives (Harrison and Rutström 2008).

3.7 Smith et al. (2009)

“Poker Player Behavior After Big Wins and Losses” by Gary Smith, Michael Levere and Robert Kurtzman – referred to as Smith et al. (2009) – is the work most similar to our own, and a large influence upon both our methodology and prior expectations. Smith et al. (2009) use data collected from an online poker site to study the behaviour of experienced poker players following big wins and losses. They find evidence that prior wins and losses affect the risk preferences of individuals in the poker context, in line with the reflection effect of prospect theory.

Using computer software, the authors were able to observe every hand played on the online poker site Full Tilt Poker over a five-month period. Through this method they are able to record all information that is common knowledge to all players, such as number of players, the community cards, and all bets made. The most significant limitation is that they are unable to observe each player’s hole cards. The authors restrict their study to 6 player tables and head-up tables (2 players only) with no limit on bets. This results in a raw dataset consisting of 1609 players, 226,351 hands played at the 6 seat tables and 339,519 hands at the heads up tables.

They test for the effect of large wins and losses by first defining a large win/loss as a change in bankroll in a single hand of at least \$1000, which for their sample is 20 times the big blind (a compulsory bet). After every large win or loss the authors identify the 12 proceeding hand, based on two rotations around a six-player table. They then conduct a Wilcoxon signed-rank test, which pairs the post-win and post-loss observations for each individual. For robustness, the authors consider only players with a sufficient number of both wins and losses, for a minimum of 50 hands post-win and post-loss. To control for any systematic relationship between behaviour and the number of players, the authors split their data by the number of players at the table. This further controls for probability, albeit indirectly, in that the probability of winning is inversely related to the number of players at the table

The behavioural indicators used are two measures of playing style: looseness, “the percentage of hands in which a player voluntarily puts money into the pot”; and aggression, “the ratio of the number of bets and raises to the number of checks and calls” (p. 1551).

The results of the Wilcoxon test suggest that individuals tend to play more hands (looser) and more aggressively in hands following a large loss, compared to hands following a large win. Generally speaking, looser play is indicative that players play worse hands on average, indicative of decreased risk aversion. For looseness, these findings are statistically significant in the majority of cases, although the significance is mixed for aggression. The authors conclude that wins and losses do have an effect on the playing behaviour of experienced poker players.

4 Research Questions

The overarching goal of our thesis is to test whether prior wins and losses affect risk-taking behaviour in a repeated game. As a player's privately held information is an arguably important behavioural determinant, the omission of this information is a potentially serious limitation. With our dataset we are able to extend the methodology of previous studies and estimate the effect of large wins and losses in a poker context. The main questions of our thesis are the following:

- 1. For a new dataset, are we able to replicate the results of Smith et al. (2009), that risk preferences are affected by prior wins and losses?**
- 2. Are the estimates of how prior outcomes affect behaviour dependent on whether a continuous, rather than discrete, measure of prior wins and losses is used?**
- 3. Is the effect of prior wins and losses affected by controlling for privately held information?**
- 4. Are more experienced players affected less by prior wins and losses than relatively less experienced players?**

We begin by attempting to replicate the findings of Smith et al. (2009) with our new dataset. Although we are unable to exactly recreate their methods, our baseline model closely follows their methodology. Furthermore, our analysis is based on more advanced and nuanced econometric techniques. We investigate our second and third research questions by extending the baseline model by both explicitly controlling for each individual's probability of winning and using a more appropriate method to isolate the effect of prior wins and losses. Our expectations are that both these extensions will improve our estimations relative to our baseline results. However we have no a priori expectations as to the exact nature of how these additions will affect our estimates.

Finally we investigate whether experience affects the behavioural bias of prior wins and losses. We split our dataset based on experience level and estimate the effect separately. Our final expectation is that a sample of more experienced players will be affected to a smaller degree by prior wins and losses, than a sample of relatively less experienced players.

5 No-limit Texas Hold ‘em Poker

From a game theory perspective, poker is an n -player, non-cooperative, zero-sum game with imperfect information. The game consists of a series of independent and identical repeated rounds played sequentially. In the following section we present a basic primer on No-limit Texas Hold ‘em Poker for readers unfamiliar with the game’s format. The description given is based on the specific rule set used within our dataset.

Texas Hold ‘em Poker is a card game played using a standard 52 card deck between 2-6 players. Each game consists of a series of hands or rounds in which each player is dealt two *hole* cards, the value of which is known only to that player. In a series of four betting rounds, players bet each other that they hold the highest-ranking hand at the table.² Players are able to either match or raise the current bet, as all players must wager the same amount to continue. Alternatively, a player may exit the game voluntarily by folding her cards and is not required to wager any further money.

All wagers are placed in the centre of the table in what is known as the *pot*. If at least two players continue without folding for four complete rounds, those players show their cards and the player with the highest-ranking hand wins the pot.³ If all players fold, voluntarily exiting the game, the last remaining player wins the pot and no player is required to show their cards. Common variants of Texas Hold ‘em Poker are limit and no-limit Texas Hold ‘em. While the former places a restriction on how much a player may wager, the later does not and allows a player to ultimately bet all her money. Our dataset, as well as that of Smith et al. (2009), is based on a no-limit variant of the game.

In each hand of no-limit Texas Hold ‘em, the cards are dealt clockwise starting from the player to the immediate left of the dealer. To the dealer’s left sits the player known as the *small blind* and next to her sits the *big blind*. Blinds are compulsory bets that these players must make at the start of each hand. The size of big blind is always twice the amount of the small blind, and increases as the tournament progresses. The dealer position, as well as the small and big blind positions, rotates clockwise around the table each hand.

² For a ranking of the hands, see Appendix B.

³ The word *hand* has two different interpretations in this context: (1) the cards a player holds in combination with the community cards (five cards in total) or (2) one round of play, consisting of at most four betting rounds, where each hand leaves a winner with the amount of money in the pot.

In addition to each player's hole cards, there are five additional community cards, which are initially dealt face down upon the table. These cards are used by all players to form the best five-card hand possible from the seven cards available to them (2 hole plus 5 community) and are revealed in a specific order. After the first round of betting the first three community cards (the flop) are revealed and betting continues. After the second round of betting the fourth card (the river) is revealed, and between the third and fourth betting rounds the fifth and last card (the turn) is revealed. Due to this structure, the information available to each player is altered throughout the game and players must update their beliefs.

An important distinction needs to be made between a cash game and a tournament. In a cash game, a player can join or leave a table whenever she wants. If the player leaves the table, she then takes with her the amount of money that she has won less what she has lost. If a player has won a hand, she can choose to quit the game, leave the table and enjoy her gain. In a tournament, each player brings to the table a pre-determined amount of money and plays until they are either eliminated or the final remaining player. The tournaments in our dataset are winner take all, the eliminated players leave with nothing, having lost the amount brought with them.

Since the game structure differs between cash games and tournaments, this may affect the optimal strategy of play between the two variants. Players eliminated in a tournament earn nothing, which as Englebergs (2010) suggests, may incentivise more conservative play. Similarly, as players can only leave with nothing or everything, the break-even effect is less applicable in tournaments than in cash games.

Another important issue is the difference between online poker and that played live and in person. Most significantly, the anonymity of online poker has several potential effects upon the game and therefore our analysis. Firstly, without information regarding an opponent's ability such as age, gender and playing style, it is more difficult for players to adjust their strategy in response to these factors in online rather than in live poker. Secondly, the anonymity veils visual indicators, which increases a player's ability to bluff their opponents (Hurtig and Lundgren 2006, p. 20). The impact on behaviour from these differences are themselves separate bodies of economic literature. For instance, Charness and Gneezy (2008) and Hoffman, McCabe and Smith (1996) find that dictators in the dictator game, offered a larger share as social distance decreased, although the implications of this within the current game structure is unclear and outside the scope of this research. However, it is important to note that these differences do exist.

6 Data

Our data is based on 17 televised poker tournaments as part of NBC's "Poker After Dark". Each of these invitational tournaments feature six professional players and follow the standard no-limit Texas Hold 'em rule set. Each player begins with an initial bankroll of \$20,000 and is eliminated when this bankroll is exhausted, the final remaining player winning the total \$120,000. Starting blinds are \$100/\$200 and increased regularly throughout the tournament.

These 17 tournaments are taken from season two (10) and season five (7) of "Poker After Dark", taped in Las Vegas during May 2007 and December 2008 respectively. Tournament choice was based in large part on episode availability as well as to exclude special tournaments with a non-standard rule set. These 17 tournaments represent 85 episodes of poker play, which required roughly 60 hours to observe.

In each episode, the audience is informed of a player's privately held hole cards and other important information – such as remaining bankroll, current bet and action history – by way of summary boxes present on screen. The hole cards were captured by "lipstick" cameras installed in the table specifically to inform the audience without revealing them to the other players. On average, roughly 120 hands of each tournament were aired. However, during these episodes it is implied that some editing was done in order to fit the entire tournament into five episodes. As a result, a small number of hands are not present in our dataset.⁴

For each hand we record the number of players, all dealt cards and for each player we recorded table position, current bankroll and net profit. We also record every action made by each player in each hand, such as betting and raising, as well as the corresponding amounts staked. In addition, we have also gathered data on each player's world ranking based on total career earnings in open and invitational tournaments. This data was gathered from the "All Time Money List" (The Hendon Mob 2012) and is current as of April 2012.⁵

The basic statistics of our dataset are presented in Table 5. Of the 62 individuals within our sample, only 6 are female. This unfortunately limits our ability to estimate whether the behavioral bias of prior wins and losses differs across gender. This underrepresentation of females is consistent with the general poker

⁴ Although we are unsure exactly how many hands were not shown, we are confident that only a small number are missing and that the hands following a large win/loss were very rarely omitted. The focus of the show is to follow the discussion of the players at the table and features only limited commentary. Players naturally discuss the result of important hands in the subsequent rounds, which are as such included in the broadcast.

⁵ The maximum rank available at the time of writing is 199,667.

playing population, which is widely acknowledged to consist primarily of male players (Williams and Wood 2007). Although most of individuals participated in a single tournament, 25 individuals participated in at least two tournaments. The benefit of individuals having played in multiple tournaments is the increase in data points for that individual, improving estimation.

Table 5. Summary Statistics – Total Sample

Total (N=62)	Mean	Standard Deviation	Min	Median	Max
Age	41	10.72	21	39	75
Games	1.65	0.94	1	1	5
Hands	131	72.46	10	108	320
Rank	2049	9539	1	78	70063

Note: “Age” is measured in years. “Games” refers to the number of tournaments in which a player participated. “Hands” refers to the total number of hands played by a player. “Rank” corresponds to the ranking of the players.

7 Methodology

The primary focus of our analysis is to estimate the effect of large wins and losses upon behaviour and risk preferences. Our methodology is largely based on that of the previous literature, particularly with regard to the behavioural variables of interest and the identification of a large win or loss. Whilst we commence with the framework of Smith et al. (2009), we extend this basic framework by explicitly controlling for privately held information. We further improve the identification of large wins and losses and conduct our analysis with more rigorous econometric techniques than those used in previous studies.

We use two behavioural measures, which are commonly used measures of behaviour within the context of poker: looseness and aggression. These are important concepts both in the standard poker literature (Sklansky 1997) and are widely used in the academic literature (Engelbergs 2010; Smit et al. 2009; Siler 2010).

7.1 Looseness

Looseness is a measure of how many hands in which a player participates relative to the total number of hands in which that player is dealt cards. We define the looseness of player i as the number of hands in which she does not fold during the first round of betting (pre-flop), relative to the total number of hands in which she is dealt cards. Explicitly:

$$L_i = \frac{\sum_{h=1}^{H_i} SawFlop_{i,h}}{H_i} \in [0,1]$$

Where $SawFlop_{i,h}$ is a binary variable equal to 1 if player i in hand h does not fold pre-flop, and hence sees the first three community cards dealt (the flop), and zero otherwise. The denominator, H_i , is the total number of hands in which player i is dealt cards before being eliminated from the game (or winning).

$$SawFlop_{i,h} = 1, \quad \text{if does not fold pre-flop}$$

Thus to capture the effect of wins and losses on looseness on a hand by hand basis, we use $SawFlop_{i,h}$ as a dummy dependent variable in the regression analysis below.

The choice of looseness as a dependent variable is motivated by the direct relationship between looseness and risk. Holding all things equal, a risk averse individual will have a lower $L_{i,h}$, playing fewer hands, than a baseline risk neutral individual with $L_i = L_i^{RN}$, while a risk seeking individual will have a higher L_i and play more hands.

Risk averse:	$L_i = L_i^{RA} < L_i^{RN}$
Risk neutral:	$L_i = L_i^{RN}$
Risk seeking:	$L_i = L_i^{RS} > L_i^{RN}$

For instance, if a player is able to correctly calculate the probability of winning for each starting hand, and assuming she prefers to play the highest strength cards possible, her looseness will determine the average probability of hands played. Given that the cards in poker are random and uniformly distributed with respect to probability, the average strength of hands played must necessarily fall as looseness increases across a large enough set of hands. This in turn increases a player's risk exposure. While the role of strategy is an important consideration – for instance a player may bluff and play a weak hand in a manner indicative of a much stronger hand – a loose player faces greater risk than a tight player, regardless of strategy.

7.2 Aggression

Aggression, $A \in [0,1]$, is a measure that captures how a player influences the size of the pot, and hence the amount staked, by betting (b) and raising (r) as opposed to merely checking or calling (c). For our purposes, we define the aggression of player i in hand h as the following:

$$A_{i,h} = \frac{b_{i,h} + r_{i,h}}{c_{i,h} + b_{i,h} + r_{i,h}} \Bigg|_{SawFlop_{i,h}=1} \in [0,1]$$

Where $b_{i,h}$ is the number of bets, $r_{i,h}$ is the number of raises, and $c_{i,h}$ is the number of checks and calls player i makes during hand h . The aggression of player i in hand h is defined conditional on player i not folding, $SawFlop_{i,h} = 1$, as it is undefined when $b_{i,h} = r_{i,h} = c_{i,h} = 0$.

By necessity we have deviated from the definition used by of Smith et al. (2009) who define aggression as “the ratio of the number of bets and raises to the number of checks and calls” (p. 1551). This measure is problematic in that it is undefined when a player neither checks nor calls in a hand. This problem is

further exacerbated within our framework as we calculate aggression per hand, while Smith et al. (2009) calculate aggression across a number of hands, which reduces the likelihood that a player neither checks nor calls.

Aggression is similarly related to risk in that an aggressive player actively increases the size of the pot, and hence the magnitude of the risky investment. Thus for a given probability of winning, an aggressive player risks losing a larger amount relative to an otherwise identical passive player, *ceteris paribus*.

7.3 Discrete identification of Wins and Losses

Following the methodology of Smith et al. (2009), who calculate looseness and aggression across the 12 hands immediately following a large win or loss, we firstly define a large win and loss as a net profit in a single hand of more than 20 times the big blind in absolute terms. For example, with a big blind of \$200, a large win (loss) is defined as a win (loss) of more than \$4000. Given the structure of the tournaments in question, this amount increases as the game progresses. A large win, $W_{i,h}$, and a large loss, $L_{i,h}$, are explicitly defined as:

$$W_{i,h} = 1, \quad \text{if } \pi_{i,h} > 20 * B_h$$

$$L_{i,h} = 1, \quad \text{if } \pi_{i,h} < -20 * B_h$$

Where $\pi_{i,h}$ is the net profit of player i in hand h , and B_h is the size of the big blind in hand h .

For estimation purposes we then generate a pair of dummy variables, $Win_{i,h}$ and $Loss_{i,h}$, that equals 1 if player i in hand h had a large win or loss during the preceding 12 periods. The choice of 12 rounds is based on two rotations around a table with six players. The number is somewhat of a trade off between enough hands to capture an effect of wins and loss, and not too many so as to dilute the effect. Firstly, players tend to only participate in hands in which they are either the small or big blind, and are forced to make compulsory bets. Thus 12 hands results in an individual playing the small and big blind positions at least twice.

$$Win_{i,h} = 1, \quad \text{if } \sum_{j=1}^{12} W_{h-j} \geq 0$$

$$Loss_{i,h} = 1, \quad \text{if } \sum_{j=1}^{12} L_{h-j} \geq 0$$

Using these dummy variables as explanatory variables indicates whether players behave differently in hands following either a large win or loss against a baseline of having neither a large win nor a large loss in the preceding 12 periods. In line with the reflection effect, we expect to find an inverse effect of winning than for losing, with the former being a negative effect and the latter a positive effect. For example, a negative coefficient for $Win_{i,h}$ upon $SawFlo_{i,h}$ suggests that a large win increases the likelihood that a player folds pre-flop (increased risk aversion), while a positive coefficient for $Loss_{i,h}$ suggests that a large loss reduces this likelihood (decreased risk aversion).

The major drawback of the discrete construction is the implicit assumption that all large wins and loss affect behaviour to an equal degree, independent of size. Furthermore, the definition of a “large” win and loss and how that definition evolves across time is somewhat arbitrary. We begin with this identifier, as it is central to the methodology of Smith et al. (2009). However, the definition of 20 times the big blind is to a large degree arbitrary and its choice is not explained or motivated.

7.4 Continuous Identification of Wins and Losses

As an alternative to the measure above, we further estimate the effect of wins and losses through the use of a continuous measure $cum12_{i,h}$, which is equal to the cumulative net profit of player i from the preceding 12 hands. The choice of 12 hands is based on two rotations around a six-player table. For ease of interpretation, the variable $cum12_i$ is scaled relative to the initial bankroll such that a $cum12_i = 1$ is interpreted as a net gain of \$20,000.

$$cum12_{i,h} = \frac{\sum_{j=1}^{12} \pi_{i,h-j}}{20,000}$$

The use of the single variable $cum12_{i,h}$ captures the reflection effect, as wins and losses will inversely affect behaviour. For example a negative coefficient upon $cum12_{i,h}$, with looseness as the dependent variable, would indicate that a cumulative win would decrease looseness making players more risk averse, while a cumulative loss makes players more risk seeking. However, this set up further assumes that the effects of a win and a loss are inversely proportional to each other. However, as discussed in the results presented in the following section, we see an indication of this relationship using the discrete identification.

7.5 Control Variables

Beyond the win/loss identification variables defined above, we use the following control variables, which approximate a player's information set at each point of the game. While decisions are heavily influenced by a large set of non-tangible, qualitative variables, such as visual "tells", these control variables constitute the quantitative information available.

7.5.1 Probability

By virtue of having observed each player's hole cards, we are able to explicitly control for the strength of each player's hand by using the control variable $probability_{i,h}$, which is the probability that player i 's hole cards in hand h will form a hand of higher ranking than her opponents. This probability is calculated pre-flop from each player's perspective and depends upon their hole cards, $HoleCards_{i,h}$, and the number of players at the table, $players_h$. Specifically, the probability that a specific pair of cards will win falls as the number of players at the table increases, as the number of opportunities for better cards to be dealt increases with the number of players.

$$probability_{i,h} = f(HoleCards_{i,h}, players_h) \in [0,1]$$

Where $HoleCards_{i,h}$ are the hole cards dealt to player i in hand h – which are independent and identically distributed – and $players_h$ are the number of non-eliminated players in hand h

Our expectation is that $probability_{i,h}$ will have a positive effect upon both $SawFlop_{i,h}$ and $A_{i,h}$. As the probability of winning increases, the risk faced by individuals decreases. In turn, we expect the likelihood that a player plays the hand to similarly increase, and for players to play the hand more aggressively, both of which maximise a player's expected profit from the hand. Underlying this expectation is the assumption that the players in our sample are able to correctly calculate this probability.

By controlling for probability, we hope to improve the estimates of $Large_Win_{i,h}$, $Large_Loss_{i,h}$ and $cum12_{i,h}$, by further isolating their effects. The implication of including probability depends on how the estimates for our win/loss identification variables are affected. Finding an effect of wins/losses upon behaviour, which is relatively robust to the inclusion of probability, adds further credibility to findings of previous studies. Conversely, non-robustness to probability would have the opposite implications on these results.

To estimate the true probability that player i in hand h with $HoleCards_{i,h}$ facing $players_h$ will win, we use a Monte Carlo simulation. For every possible $HoleCards_{i,h}$ we simulate 100,000 iterations in which all unknown cards at the table (two hole cards for each opponent and five community cards) are randomly dealt and the winning player determined. From this we estimate the probability as the number of iterations that $HoleCards_{i,h}$ formed the highest ranked hand divided by the total number of iterations. The estimated probabilities for a sample of potential starting hands are presented in Appendix E.

The need to use Monte Carlo simulation arises from the sheer number of unique games with a standard 52-card deck. With just two players, both are dealt two cards, $\binom{52}{2} * \binom{50}{2}$, and five further cards are dealt facedown on the table as community cards, $\binom{48}{5}$. This results in over two trillion possible combinations.⁶ Even controlling for the fact that within our framework each player already knows her own cards, there remain over two billion unique combinations of the seven remaining unknown cards in play.⁷ Further, this number grows exponentially as the number of players is increased from two to six.

To limit the number of calculations, we note that of the possible 1326 starting hands, a significant number are of equivalent value from a probability standpoint. As the four suits are of equal value, the strength of a hand prior to the reveal of the community cards depends only upon whether or not they are of matching (suited) or non-matching (unsuited) suits. For example, the pair ($K♥$, $A♠$) has the same probability of winning as ($K♠$, $A♥$), while ($K♦$, $A♦$) is more likely to win. Taking this into account there are 13 unsuited matching pairs, $78 \left(\frac{13*12}{2}\right)$ non-matching suited pairs, and 78 non-matching unsuited pairs.

7.5.2 Number of Players

Within our sample the number of players at the table decreases as the games progress. To control for any systematic effect upon behaviour from changing the number of players, we include the control variable $players_h$, which is equal to the number of non-eliminated players remaining in hand h . The number of players is important in that the $probability_{i,h}$ of a specific hand, as described above, is inversely affected by $players_h$. To control for this effect, Smith et al. (2009, p. 1552) group their data according to the number of players at the table and find that average looseness increased from 25.53 to 51.27 as the

⁶ $\binom{52}{2} * \binom{50}{2} * \binom{48}{5} = 1,326 * 1,225 * 1,712,304 = 2,781,381,002,400$

⁷ $\binom{50}{2} * \binom{48}{5} = 1,225 * 1,712,304 = 2,097,572,400$

number of players fell from six to two. We include $players_h$ in all specifications of the following models.

7.5.3 Relative Position

Our final control is for a player's relative table position, which is an important factor in poker strategy. Position is an important consideration as moving later provides players with additional information, revealed by their earlier moving opponents. Late moving players can base their decisions on this additional information. The probability of holding the highest-ranking hand increases as the earlier moving players fold and the number of opponents declines. Sklansky (1997, p. 13) suggests that a player in an early position, who moves with less information relative to late moving players, faces a greater degree of risk.

We define the relative position of player i in hand h by the following:

$$position_{i,h} = \frac{TurnOrder_{i,h}}{players_h} \in [0,1]$$

Where $TurnOrder_{i,h}$ is player i 's order in the sequence of play, and $players_h$ is the number of non eliminated players remaining in hand h . We divide $TurnOrder_{i,h}$ by the number of players, to account for the fact that the value of a specific position in the sequence order will change as the tournament progresses and the number of players decreases. For instance, being second goes from being a very weak position when there are six players, to the most valuable position when only two players remain.

7.6 Estimation Models

For each dependent variable we estimate the effect of wins and losses with eight different model specifications through panel data regression techniques. These 16 regressions are presented in the result section below. The basic models we use are the following four combinations of our two dependent variables and our alternative win/loss identifiers, where the $X_{i,h}$ are our control variables.

We further augment each of these four models with both a *baseline* and *extended* specification of our control variables. While the extended model includes all the above control variables, the baseline model excludes probability and table position. The specification of the baseline model is in line with Smith et al. (2009) and controls only for the number of players at the table. For both the baseline and extended

model we include the dummy variable *Season5* – equal to 1 if the hand was played in a tournament from the fifth season of the source material – which is included to control for any systematic difference between the datasets.

$$\text{1. Looseness/Discrete:} \quad SawFlop_{i,h} = a_W Win_{i,h} + a_L Loss_{i,h} + \beta X_{i,h}$$

$$\text{2. Looseness/Continuous:} \quad SawFlop_{i,h} = a_C Cum12_{i,h} + \beta X_{i,h}$$

$$\text{3. Aggression/Discrete:} \quad A_{i,h} = a_W Win_{i,h} + a_L Loss_{i,h} + \beta X_{i,h}$$

$$\text{4. Aggression/Continuous:} \quad A_{i,h} = a_C Cum12_{i,h} + \beta X_{i,h}$$

$$\text{A. Baseline Model:} \quad \beta X_{i,h} = \beta_{pl} players_h + \beta_s Season5_h$$

$$\text{B. Extended Model:} \quad \beta X_{i,h} = \beta_{pr} probability_{i,h} + \beta_{po} position_{i,h} + \beta_{pl} players_h + \beta_s Season5_h$$

Finally, to control for any unobserved individual effects we use both fixed effects and random effects for each of our different model specifications. Similarly, all standard errors presented are robust. It is the 16 permutations of these key factors that we present in the following section.

An important assumption we make when estimating these models is that each hand in a tournament is independent from each other, as the cards are iid. Given that all hands are independent, a prior win/loss has no influence of the probability of winning later hands. The implication is that rational individuals will behaviour in a consistent manner across all hands, regardless of when individuals experience a large win or loss. For instance, under expected utility theory it is irrational for a player to play a certain set of cards in one hand but fold the same set of cards in a later hand, *ceteris paribus*.

Care needs to be taken in the interpretation of the coefficients in the various models above. The first and second models above have a dummy dependent variable, $SawFlop_{i,h} \in \{0,1\}$. In such a linear probability model, the estimated coefficients are interpreted as the influence of the explanatory variables upon the likelihood that the dependent variable equals 1. For instance, a positive estimate of β_{pl} suggests that as $players_{i,h}$ increases, the likelihood that $SawFlop_{i,h} = 1$ also increases. Similarly, $a_{W_{i,h}}$ and a_L , are the discrete change in the likelihood that $SawFlop_{i,h} = 1$ when $Win_{i,h}$ and $Loss_{i,h}$, themselves dummy

variables, are equal to 1. It is also important to note that an increase in $probability_{i,h}$ of $\frac{x}{100}$, should be interpreted as an increase in the probability x percentage points (pp), rather than $x\%$.

The significant difference between our methodology and that of Smith et al. (2009) is that they use the Wilcoxon signed-rank test, while we are unable to use this test due to sample size. The test requires that an individual's post-loss behaviour facing n players and her post-win behaviour facing n players are paired and the difference ranked against the total sample. This test is then conducted separately for each relevant number of players. Given our sample size and the infrequency of such large wins and losses, only a small number of observations, at most 10, meet all the requirements of each scenario.

7.6.1 Fixed vs. Random Effects

Individual effects are an important consideration due to the high degree of error correlation within the observations of each individual. For instance, there are up to 11 periods common to the calculations of and individual's $cum12_{i,h}$ measure in nearby periods. Furthermore, it is important to consider that a player who plays more hands is more likely to experience large wins and losses than a tight player, *ceteris paribus*. In addition, whether a player has more wins or losses than others may be influenced by unobserved individual characteristics, such as skill or experience.

As our data is organised at the individual level and constructed as a panel dataset, estimation techniques exist which allow us to control for these unobserved individual effects. The fixed effect model and the random effect model are such estimators that control for potential omitted variable biases. The difference between the models is that the fixed effect model allows a correlation between the unobserved individual effect and the explanatory variables while the random effect model does not. As we have no a priori beliefs of which model best fits our data, we conduct a Hausman test to evaluate the choice. The Hausman test uses the null hypothesis that the random effect estimator is consistent, a rejection of which suggests that the unobserved effects are correlated with the regressors and the random effect estimator is not consistent (Wooldridge 2009, p. 493).

We find that the Hausman test strongly rejects the null when $SawFlop_{i,h}$ serves as the dependent variable in both the discrete model (p-value = 0.000) and the continuous model, regardless of the controls used (see Appendix C for complete results). These results suggest the use of fixed effects for estimation of the *Looseness* model. However, when $Aggression_{i,h}$ is the dependent variable, we fail to reject the null for all model specifications. This suggests the use of random as opposed to fixed effects. For completeness,

we present both the fixed effect and random effect model for all our model specifications in our results below.

We also conduct Breusch-Pagan Lagrange multiplier tests for our various model specifications, which compares the use of random effects to pooled OLS estimation. The null hypothesis is that the variance across individuals is equal to zero, which suggests OLS is consistent. The test strongly rejects the null (p-value = 0.0000) for all model specifications, suggesting that OLS would produce inconsistent estimates in favour for the random effect model.

7.7 Controlling for Experience

While the sample of Smith et al. (2009) consists of both professional and experienced amateurs, our sample is almost exclusively high-ranking professional players. For example, our dataset features 20 of the top 40 poker players of all time (The Hendon Mob, 2012).⁸ The results of Palacios-Huerta and Volij (2009) suggest that experience, and especially the experience of one's opponents, may have a large effect on playing style. Furthermore, Sklansky (1997, p. 106) suggests that the ability to calculate the probability of winning may improve with experience.

To capture such an effect, we split our sample into three roughly equal subsamples based on the player's total career earnings and estimate the above models separately for each subsample. We then test whether the estimated coefficients in each subsample are statistically different from each other. Our subgroups are the following:

Table 6. Summary Statistics – Rank-dependent Subgroups

Subgroup	N	Mean rank	Mean hands	Total hands	Hands/game
High-ranked	21	17.29	160.3	3366	78.3
Mid-ranked	21	99.30	136.8	2872	79.8
Low-ranked ⁹	20	6585	94.5	1890	82.2

⁸ Based on total career earnings unadjusted for inflation and current as of April 2012

⁹ A rank is not available for three individuals in the low-ranked group whose career earning place them outside of the top 199,667 players (the ranks maximum value as of writing). They are excluded from the mean rank.

For each subsample we estimate the effect of prior wins and losses using the continuous identifier and extended control specification. The choice to use this model is motivated by the results of our regression analysis using the entire sample, which is presented below. The results suggest that this specification best isolates the effect of interest. Estimates are again presented for both fixed and random effects.

We further test the null hypothesis that the estimates of the effect is equal for each of the subsamples. To conduct this test we generate dummy variables for the high and low-ranked groups and estimate the extended model with a continuous win/loss identifier using interaction variables between these dummies and the other explanatory variables, the output of which is not presented. The tests presented in the Appendix D are based on whether the interaction terms between $cum12_{i,h}$ and the rank dummies are equal to zero.

The decision to split our data into three subsamples is based on observations made during the data collection process. The idea is to capture a number of key trends in relation to the experience or skill level of the sample. One such observation is that around one third of the players in our sample, while high-ranked globally, are well ranked based on either a single large win or a series of moderate wins. However, there are a number of players that have regularly won large tournaments throughout their entire careers. For instance, Phil Hellmuth, Doyle Brunson and Johnny Chan have collectively won 31 tournaments at the World Series of Poker, and both Brunson and Chan have won the main-event twice and in consecutive years. We also wish to control for a final group of individuals that are noticeably lower ranked than the rest of the sample. For instance, for three individuals there is no rank available. To capture this general grouping, we split the sample into *high*, *mid* and *low* rank-dependent subgroups.

To identify our rank-dependent subsamples, we use total career earnings in tournaments unadjusted for inflation. We favour the unadjusted rank to acknowledge that all players are still currently active as professionals, who regularly compete against one another. This also allows for inflation to work as a proxy for human capital depreciation. For example, consider two players, A and B, who both compete in the main event of the World Series of Poker in 2000 and again in 2010, but no tournaments in between. If player A wins \$7 million in 2000 and player B wins \$8 million 10 years later in 2010, player A would outrank player B in 2000, while the converse is true in 2010. However, player A would outrank player B both before and after B's win, if her earnings are measured in $\$US_{2000}$. For our purposes, we consider the rank of each player in 2012, when B's more recent win is indicative of greater current form in 2012, relative to player A.

8 Results

The following section is broken down as follows. We first present our main findings in Table 7 and Table 8, which summarise the results of the 16 regression models we run to estimate the effect of prior wins and losses upon looseness and aggression. Secondly, we present the results in Tables 9 and 10 from investigating the role of experience on playing behaviour. This section is intended as an overview, while a more detailed discussion of how our results relate to our research questions and the previous literature is presented in section 9 below.

8.1 Looseness

The results of our regression analysis on our looseness measure $SawFlop_{i,h}$ are presented in Table 7. In general we find evidence that supports our prior expectations of how wins and losses affect behaviour. Although this evidence is weak for certain models, we find statistically significant results for our improved model specification. We also find strong evidence to support our expectation that both table position and the probability of winning are important determinants of individual behaviour. For all models, we find only minor variation when estimation with either fixed or random effects.

If we first consider columns 1 and 2, the discrete baseline model, we find weak evidence of large wins and losses affecting behaviour in line with our prior expectations. The likelihood that a player plays a given hand decreases following a large win and increases following an equivalently large loss. However, as we are unable to reject the null hypothesis of $\beta_W = \beta_L$ (see bottom row of table), we conclude that the estimates of $Win_{i,h}$ and $Loss_{i,h}$ are neither statistically significant nor statistically different from each other.

If we include further controls, the discrete extended model of columns 3 and 4, we find that the estimates for $probability_{i,h}$ and $position_{i,h}$ are both positive and highly significant. The interpretation is that a 1 percentage point increase in the probability of winning, increases the likelihood that a player plays a hand by 2.8 percentage points, and that she is similarly more likely to play the later she makes her decision relative to their opponents. This fits our prior expectations that these are important determinants of player behaviour. However, the estimates of the effect of large wins and losses remain insignificant and relatively unchanged.

If we shift our attention to columns 5-8, the continuous models, we first note that the estimates of our control variables remain highly significant and relatively consistent with the equivalent discrete model. In line with our prior expectations we find a negative relationship between a cumulative win and the likelihood that a player plays a specific hand. Thus a player is less likely to play a hand if her cumulatively net profit in the preceding 12 hands is positive. However, this effect is only statistically significant when controlling for probability and position. The interpretation of the coefficient on $Cum12_{i,h}$ is that a cumulative net profit of \$20,000 across the preceding 12 hands reduces the likelihood that the player plays the hand by 0.4 percentage points in the baseline model and 1.4 percentage points in the extended model.

When estimating the baseline specification, the number of players at the table is found to have a negative relationship with looseness. For both the discrete and continuous identifiers, an additional player reduced the likelihood that a player plays to the flop by around 9.5 percentage points. However, we find that by controlling for probability and table position the $players_h$ coefficient becomes positive, increases in magnitude, and remains highly significant. Furthermore, this change is consistent for aggression (see Table 8). Driving this result is the high correlation between $players_h$ and $probability_{i,h}$, and the value of the latter depending on the former.¹⁰ While $position_{i,h}$ similarly depends on $players_h$, the correlation is significantly smaller.¹¹ Thus, the implication is that when we control for a player's probability of winning, a player is more likely to play a given hand as the number of opponents increase.

8.2 Aggression

The results of our regression analysis of aggression are presented in Table 8. As with looseness, we generally find evidence that wins and losses affect aggression in line with our prior expectations. Although the estimated coefficients are relatively constant across the eight model specifications, we find greater significance with the continuous model. We similarly find evidence that both table position and the probability of winning are important determinants of individual behaviour. Again, our results are not significantly affected by controlling for fixed rather than random effects.

From columns 1-4, the discrete model, we find weak evidence that a large win reduces predicted aggression, while a large loss has the opposite effect and increases predicted aggression. Both effects are

¹⁰ $corr(players_h, probability_{i,h}) = -0.7336$

¹¹ $corr(players_h, position_{i,h}) = -0.1465$

relative to hands in which the player has not experienced either a large win or a large loss in the preceding 12 hands. The interpretation is that given a player does not fold pre-flop, her predicted aggression decreases by 3-5 percentage points following a large win, and increases by 2-2.5 percentage points following a large loss. These estimates range in significance from no significance for the baseline model, to mixed or boarder line significance for the extended model (large wins significant at the 5% level). However, when testing the hypothesis that the difference between these estimates is not statistically significant from zero, we are able to reject the null hypothesis in every case. These results are presented in the last two rows of Table 8.

From columns 5-8, the continuous models, we find significant estimates of the win/loss effect for the baseline model (10%) and the extended model (5%). The effect is roughly consistent across both the extended and baseline models. Given a player does not fold pre-flop, a cumulative net profit of \$20,000 across the preceding 12 hands reduce her predicted aggression by 1.7-1.8 percentage points.

Considering our control variables, we see that when $probability_{i,h}$ and $position_{i,h}$ are controlled for in the extended specification, the estimates are highly significant and the magnitude is independent of which win/loss identification is used. The interpretation of $probability_{i,h}$ is that a 1 percentage point increase in the probability of winning, increases predicted aggression by around 0.9 percentage points. This fits our prior expectations that probability is an important determinant of player behaviour. Conversely to looseness, we find that predicted aggression instead falls the later their position in the order of play. However, this is most likely a result of poker strategy rather than behavioural bias. Finally, we find the significance of $players_h$ is more erratic than for looseness, and the sign is affected by controlling for $probability_{i,h}$, due to the high correlation between the two variables.

Table 7. The Effect of Wins and Losses on Looseness

<i>SawFlop_{i,h}</i>	Discrete Identification				Continuous Identification			
	Baseline Model		Extended Model		Baseline Model		Extended Model	
	FE	RE	FE	RE	FE	RE	FE	RE
<i>Win_{i,h}</i>	-0.017 <i>0.0184</i> 0.359	-0.0078 <i>0.019</i> 0.679	-0.0166 <i>0.0157</i> 0.294	-0.0108 <i>0.0156</i> 0.488	-	-	-	-
<i>Loss_{i,h}</i>	0.0054 <i>0.0231</i> 0.817	0.0292 <i>0.0234</i> 0.212	0.0099 <i>0.0183</i> 0.588	0.0253 <i>0.0198</i> 0.201	-	-	-	-
<i>Cum12_{i,h}</i>	-	-	-	-	-0.004 <i>0.0085</i> 0.64	-0.0039 <i>0.0083</i> 0.643	-0.0142 <i>0.008</i> 0.080	-0.0141 <i>0.0078</i> 0.071
<i>probability_{i,h}</i>	-	-	2.8699 <i>0.0683</i> 0.000	2.8683 <i>0.069</i> 0.000	-	-	2.8726 <i>0.0688</i> 0.000	2.8716 <i>0.0693</i> 0.000
<i>position_{i,h}</i>	-	-	0.3134 <i>0.0151</i> 0.000	0.3132 <i>0.0152</i> 0.000	-	-	0.3137 <i>0.0152</i> 0.000	0.3133 <i>0.0152</i> 0.000
<i>players_h</i>	-0.0949 <i>0.0062</i> 0.000	-0.0928 <i>0.0063</i> 0.000	0.1287 <i>0.0065</i> 0.000	0.13 <i>0.0065</i> 0.000	-0.0949 <i>0.0061</i> 0.000	-0.0938 <i>0.0062</i> 0.000	0.1281 <i>0.0062</i> 0.000	0.1287 <i>0.0062</i> 0.000
<i>Season5_h</i>	0.013 <i>0.0243</i> 0.595	-0.0197 <i>0.0189</i> 0.298	0.0248 <i>0.0233</i> 0.292	-0.003 <i>0.0185</i> 0.873	0.0137 <i>0.0237</i> 0.567	-0.0122 <i>0.0191</i> 0.523	0.0253 <i>0.0231</i> 0.279	0.0027 <i>0.0189</i> 0.884
<i>Constant</i>	0.8574 <i>0.039</i> 0.000	0.8592 <i>0.0386</i> 0.000	-1.21 <i>0.0509</i> 0.000	-1.2041 <i>0.0506</i> 0.000	0.8557 <i>0.0376</i> 0.000	0.863 <i>0.0383</i> 0.000	-1.2076 <i>0.0488</i> 0.000	-1.1989 <i>0.0484</i> 0.000
#Obs.	8128	8128	8128	8128	8128	8128	8128	8128
Groups	62	62	62	62	62	62	62	62
<i>R^S (within)</i>	0.0490	0.0484	0.3435	0.3431	0.0489	0.0486	0.3437	0.3435
<i>R^S (between)</i>	0.1426	0.2232	0.2872	0.3600	0.1452	0.1895	0.2857	0.3340
<i>R^S (overall)</i>	0.0518	0.0550	0.3414	0.3441	0.0518	0.0539	0.3416	0.3436
H0: Win = Loss								
Test Stat.	0.60	1.65	1.31	2.46				
P-Value	0.442	0.199	0.258	0.117				

Note: Estimated coefficient in bold, standard error and p-value below

Table 8. The Effect of Wins and Losses on Aggression

$A_{i,h}$	Discrete Identification				Continuous Identification			
	Baseline Model		Extended Model		Baseline Model		Extended Model	
	FE	RE	FE	RE	FE	RE	FE	RE
$Win_{i,h}$	-0.036 <i>0.0243</i> 0.143	-0.0315 <i>0.0233</i> 0.177	-0.0467 <i>0.0225</i> 0.043	-0.0431 <i>0.0215</i> 0.046	-	-	-	-
$Loss_{i,h}$	0.0261 <i>0.0212</i> 0.222	0.0266 <i>0.0202</i> 0.189	0.0223 <i>0.0222</i> 0.320	0.0207 <i>0.0218</i> 0.342	-	-	-	-
$Cum12_{i,h}$	-	-	-	-	-0.0175 <i>0.0091</i> 0.058	-0.0169 <i>0.0089</i> 0.056	-0.0182 <i>0.0073</i> 0.015	-0.0174 <i>0.0072</i> 0.016
$probability_{i,h}$	-	-	0.9423 <i>0.1034</i> 0.000	0.9349 <i>0.1032</i> 0.000	-	-	0.946 <i>0.1035</i> 0.000	0.9383 <i>0.1034</i> 0.000
$position_{i,h}$	-	-	-0.5064 <i>0.0377</i> 0.000	-0.5049 <i>0.0373</i> 0.000	-	-	-0.5046 <i>0.0376</i> 0.000	-0.5032 <i>0.0372</i> 0.000
$players_h$	-0.0069 <i>0.006</i> 0.253	-0.0081 <i>0.0057</i> 0.157	0.0507 <i>0.0084</i> 0.000	0.0488 <i>0.0082</i> 0.000	-0.0079 <i>0.0061</i> 0.200	-0.0091 <i>0.0058</i> 0.115	0.0503 <i>0.0088</i> 0.000	0.0485 <i>0.0085</i> 0.000
$Season5_h$	0.0456 <i>0.02</i> 0.026	0.0487 <i>0.0173</i> 0.005	0.0394 <i>0.0248</i> 0.118	0.0435 <i>0.0202</i> 0.031	0.0456 <i>0.02</i> 0.026	0.0484 <i>0.0172</i> 0.005	0.04 <i>0.0249</i> 0.113	0.044 <i>0.0202</i> 0.029
$Constant$	0.486 <i>0.0285</i> 0.000	0.4863 <i>0.0299</i> 0.000	0.2502 <i>0.0818</i> 0.003	0.2538 <i>0.0785</i> 0.001	0.4904 <i>0.0284</i> 0.000	0.4913 <i>0.0292</i> 0.000	0.2475 <i>0.0838</i> 0.004	0.2514 <i>0.0801</i> 0.002
#Obs.	3186	3186	3186	3186	3186	3186	3186	3186
Groups	62	62	62	62	62	62	62	62
R^S (within)	0.0028	0.0027	0.1963	0.1962	0.0028	0.0028	0.1959	0.1959
R^S (between)	0.0545	0.0601	0.0430	0.0491	0.0659	0.0686	0.0515	0.0567
R^S (overall)	0.0049	0.0049	0.1839	0.1841	0.0051	0.0051	0.1837	0.1839
	H0: Win = Loss							
Test Stat.	4.83	4.58	7.16	6.49				
P-Value	0.032	0.032	0.010	0.011				

Note: Estimated coefficient in bold, standard error and p-value below

8.3 The Effect of Experience

To investigate whether more experienced players are less affected by prior wins and losses, we split our sample into three roughly equal subsamples conditional on total career earnings. We then estimate the continuous extended model for each sub group separately. These results are presented in Table 9 with looseness as the dependent variable and in Table 10 with aggression as the dependent variable. Again we estimate each model with both a fixed effects and random effects model specifications.

If we consider looseness, Table 9, we firstly observe that splitting the sample into three subgroups has very little effect upon the estimates of $probability_{i,h}$, $position_{i,h}$ and $players_{i,h}$. These controls are all highly significant and similar to the equivalent estimates presented in Table 7. However, the primary result from Table 9 is how the estimates of $Cum12_{i,h}$ differ across our rank-dependent subgroups. Our expectations are that estimates of $Cum12_{i,h}$ for high (low) ranked players will be smaller (larger) in magnitude then for mid-ranked players. Considering the fixed effects specification, we find a striking difference between the estimates across these groups. Specifically, the estimate of the effect for mid and low-ranked players is roughly 30 times that of high-ranked players. Similarly, while the effect for mid and low-ranked players is significant at the 10% and 5% levels respectively, the effect is not significant for high-ranked players.

When testing the differences between the estimates of $Cum12_{i,h}$ (see Appendix D), we are able to reject the null hypothesis of coefficient equality high-ranked subgroup ($Cum12_{i,h} * high_i$) and low-ranked subgroup ($Cum12_{i,h} * low_i$) at the 5% level (p-value = 0.0238). We are similarly able to reject the joint null hypothesis of coefficient equality across all three subsample at the 5% level (p-value = 0.0455) and find borderline significance of the difference (p-value = 0.0297) between the high and mid-groups (p-value = 0.1044). That we are unable to reject the null hypotheses of no difference between the low and mid samples, which is unsurprising if we consider the difference is only 0.0008.

Turning our attention to Table 10, and if we consider the random effects model, we see a similar relationship between the magnitude of the effect of wins/losses and the group ranking. Although the difference in the estimates of $Cum12_{i,h}$ for the high-ranked group compared to the mid-ranked group are smaller in magnitude (0.0209) than for looseness, the difference between the mid and low-ranked players is larger (0.0291). In general, the results suggest that less experienced players are affected to a greater extent by the outcome of prior hands than high-ranked players.

When testing the differences between the estimates of $Cum12_{i,h}$, we find strong to borderline significance of the difference between the high and low groups depending on the whether fixed effects (p-

value = 0.0833) or random effects (p-value = 0.1384) are used. We are unable to reject the null hypothesis of coefficient equality for the remaining combinations. Similarly, we find considerably more variation in the estimates for the remaining controls variables, which are all significant at the 1% level. The driving factor behind these irregularities, and an overall limitation of this type of analysis, is the limited sample size caused by splitting our sample into three smaller groups. This issue is further compounded by the definition of aggression, which by limiting the analysis to observations in which a player does not fold effectively halves the sample size.

Table 9. The Effect of Wins and Losses on Looseness, by experience

<i>SawFlop_{i,h}</i>	HIGH RANKED		MID RANKED		LOW RANKED	
	FE	RE	FE	RE	FE	RE
<i>Cum12_{i,h}</i>	-0.0013	-0.0028	-0.0310	-0.0252	-0.0390	-0.0344
	<i>0.0090</i>	<i>0.0091</i>	<i>0.0159</i>	<i>0.0159</i>	<i>0.0138</i>	<i>0.0118</i>
	0.884	0.756	0.066	0.113	0.011	0.004
<i>probability_{i,h}</i>	2.9019	2.9091	2.9712	2.9635	2.7266	2.7133
	<i>0.0770</i>	<i>0.0769</i>	<i>0.1454</i>	<i>0.1452</i>	<i>0.1270</i>	<i>0.1246</i>
	0.000	0.000	0.000	0.000	0.000	0.000
<i>position_{i,h}</i>	0.2843	0.2841	0.3411	0.3405	0.3273	0.3269
	<i>0.0219</i>	<i>0.0219</i>	<i>0.0215</i>	<i>0.0216</i>	<i>0.0372</i>	<i>0.0373</i>
	0.000	0.000	0.000	0.000	0.000	0.000
<i>players_h</i>	0.1327	0.1353	0.1209	0.1218	0.1081	0.1092
	<i>0.0100</i>	<i>0.0099</i>	<i>0.0134</i>	<i>0.0135</i>	<i>0.0115</i>	<i>0.0120</i>
	0.000	0.000	0.000	0.000	0.000	0.000
<i>Season5_h</i>	0.0048	-0.0068	0.0635	0.0373	-0.0146	-0.0302
	<i>0.0273</i>	<i>0.0253</i>	<i>0.0501</i>	<i>0.0389</i>	<i>0.0367</i>	<i>0.0264</i>
	0.861	0.788	0.219	0.338	0.694	0.253
<i>Constant</i>	-1.1997	-1.2046	-1.2014	-1.1883	-1.0945	-1.0860
	<i>0.0618</i>	<i>0.0569</i>	<i>0.1082</i>	<i>0.1107</i>	<i>0.0906</i>	<i>0.0972</i>
	0.000	0.000	0.000	0.000	0.000	0.000
<i>#Obs.</i>	3365	3365	2872	2872	1890	1890
<i>Groups</i>	21	21	21	21	20	20
<i>R^s (within)</i>	0.3285	0.3284	0.3525	0.3522	0.3652	0.3651
<i>R^s (between)</i>	0.0660	0.0872	0.4289	0.4915	0.2918	0.3143
<i>R^s (overall)</i>	0.3223	0.3234	0.3566	0.3587	0.3670	0.3686

Note: Estimated coefficient in bold, standard error and p-value below

Table 10. The Effect of Wins and Losses on Aggression, by experience

$A_{i,h}$	HIGH RANKED		MID RANKED		LOW RANKED	
	FE	RE	FE	RE	FE	RE
$Cum12_{i,h}$	-0.0170	-0.0120	-0.0380	-0.0329	-0.0718	-0.0620
	<i>0.0101</i>	<i>0.0110</i>	<i>0.0207</i>	<i>0.0205</i>	<i>0.0300</i>	<i>0.0245</i>
	0.107	0.274	0.082	0.109	0.027	0.011
$probability_{i,h}$	1.0767	1.0773	0.8796	0.8469	0.9011	0.8845
	<i>0.1459</i>	<i>0.1457</i>	<i>0.1781</i>	<i>0.1751</i>	<i>0.2629</i>	<i>0.2549</i>
	0.000	0.000	0.000	0.000	0.003	0.001
$position_{i,h}$	-0.4260	-0.4222	-0.6248	-0.6303	-0.4558	-0.4516
	<i>0.0605</i>	<i>0.0597</i>	<i>0.0577</i>	<i>0.0566</i>	<i>0.0446</i>	<i>0.0437</i>
	0.000	0.000	0.000	0.000	0.000	0.000
$players_h$	0.0518	0.0501	0.0251	0.0250	0.0312	0.0362
	<i>0.0156</i>	<i>0.0156</i>	<i>0.0115</i>	<i>0.0118</i>	<i>0.0138</i>	<i>0.0141</i>
	0.003	0.001	0.029	0.047	0.036	0.010
$Season5_h$	0.0044	0.0278	0.0539	0.0266	0.0625	0.0369
	<i>0.0327</i>	<i>0.0318</i>	<i>0.0418</i>	<i>0.0353</i>	<i>0.0191</i>	<i>0.0308</i>
	0.894	0.382	0.212	0.452	0.004	0.230
$Constant$	0.1611	0.1470	0.4951	0.5121	0.3244	0.3144
	<i>0.1291</i>	<i>0.1236</i>	<i>0.1260</i>	<i>0.1200</i>	<i>0.1411</i>	<i>0.1398</i>
	0.226	0.234	0.001	0.000	0.033	0.025
#Obs.	1339	1339	1172	1172	675	675
Groups	21	21	21	21	20	20
R^S (within)	0.1803	0.1796	0.2454	0.2449	0.1808	0.1802
R^S (between)	0.0076	0.0990	0.0208	0.0350	0.0307	0.0287
R^S (overall)	0.1635	0.1685	0.2307	0.2331	0.1627	0.1654

Note: Estimated coefficient in bold, standard error and p-value below

9 Discussion

From the results above, we generally find evidence in support of our initial hypothesis: that within a poker environment, risk preferences are inversely affected by large wins and losses. As the outcome of previous rounds has no bearing on a player's expected payoffs, all rounds being independent of each other, this effect is inconsistent with the predictions of expected utility theory. Our results, in line with Englebergs (2010), are indicative that individuals are loss averse below their reference point. For a repeated game, this phenomenon is typically described as the break-even effect. Following a large loss, individuals in our sample generally took greater risks than they otherwise did, in an attempt to reclaim the lost wealth. However we find conflicting results from those suggested by the house money effect, which suggests that individuals are less risk averse following a large win. We conversely find that individuals in our sample generally played more conservatively after such a win.

The hot hand fallacy predicts that a player who has just won may believe they are on a hot streak and are more likely to win than objective probability would suggest. Although we do not explicitly address this prediction, within our framework the hot hand fallacy may have presented itself as decreased risk aversion after enjoying a large win. We do not find evidence of this effect. On the contrary, we find evidence that suggests that beliefs move in the opposite direction, in line with the gambler's fallacy. The gambler's fallacy suggests that players believe that in repeated simulations, deviations from expected probability are followed by deviations in the opposite direction. Hence, players take greater risks following a large loss, as they believe that they are "due" for a win.

We do not believe that it is the gambler's fallacy that is driving our results. Firstly, one would expect professional poker players to be adept at calculating probabilities, a belief supported in the poker literature (Sklansky 1997, p. 106). Secondly, our observations during the data collection process confirm this expectation. For example, there are moments throughout the game when the players will openly discuss the probability the certain events will occur, such as when a player "goes all-in" (bets all their remaining money) and another player "calls" (matches the amount staked). As there is no possibility for additional betting, both players are required to reveal their cards and the remaining cards are dealt. During such situations, the probability estimates, made by the players and announced to the table, are uncannily accurate.

For a new dataset, are we able to replicate the results of Smith et al. (2009), that risk preferences are affected by prior wins and losses?

Using the Wilcoxon signed-rank test, Smith et al. (2009) are able to strongly reject the hypothesis that looseness is identical in rounds preceded by either a win or a loss, in all cases except tables with only two players. For aggression, they find mixed results and are only able to reject this hypothesis for tables with two and six players, as well as for heads-up tables. The relevant results of Smith et al. (2009) are recreated and presented in Appendix A. We are unable to exactly replicate these results when closely following their methodology with our discrete baseline model. Although, our estimates are indicative of the same direction, for both looseness and aggression, we are unable to reject the null hypothesis that the effect is not significantly different from zero.

A possible explanation for this is that the effect is less significant in tournaments than the cash games used by Smith et al. (2009). In a cash game players may leave the game at any time with their current bankroll, while eliminated players in the tournaments of our sample leave with nothing. This may naturally affect the optimal strategy of participants. For instance, if a tournament player is concerned primarily with the tournament as a whole, as opposed to the individual hands, tournaments may incentivise more conservative play (Englebergs 2010, p. 231). Following this logic, the break-even effect makes less sense for tournaments compared to cash games, as players are not truly able to break even and walk away. Similarly, as the games buy-in is a sunk cost, all money is in a sense the house's money. Furthermore, while players are unable to bring additional money to the table, as they are in cash games, a large loss will have the effect of limiting a player's ability to play more aggressively. This also weakens our assumption that every hand is independent of each other. Unfortunately we are unable to control for, or estimate, the effect of using tournaments rather than cash games. However, given that we are able to find an effect using our refined methodology, we feel that there is indeed a behavioural bias from prior wins and losses with respect to risk preferences.

A similar explanation is that the effect may be less significant for samples of more experienced players. Our sample is on average more experienced and more homogenous with respect to experience. Thus if more experienced players are less influenced by prior wins and losses, which is indeed what we find, an effect will be harder to isolate. Furthermore, this explanation may in itself exaggerate the smaller effect in tournaments than in cash games. As well as being less affected by prior wins and losses, a more experienced player may focus on the end goal of the tournament to a greater degree than less experienced players. This is very likely as our experience proxy, based on career earnings, more directly captures

ability or success. One would naturally expect that success to in large part be based on a player's ability to play rationally and analytically.

Another possible explanation is that our estimates have less statistical power than those of Smith et al. (2009). Although we have included as great a number of players as possible, our dataset is somewhat modest in scope compared to the previous studies of Smith et al. (2009), Engelbergs (2010) and Siler (2010). This reduced sample size is a result of using televised tournaments, which allowed us to observe the hole cards of each player, rather than online poker. We believe that this is the most plausible explanation as to why we are unable to exactly replicate the results of Smith et al. (2009).

Are the estimates of how prior outcomes affect behaviour dependent on whether a continuous, rather than discrete, measure of prior wins and losses is used?

While we are unable to find statistically significant and robust results when using the win/loss definition of Smith et al. (2009), we see an indication of their presence. We believe that the discrete nature of this definition and its arbitrary definition are confusing our results, especially within our modest sample. The comparison between the estimates of the discrete and continuous win/loss identifiers supports this belief. Specifically we find that the win/loss estimates almost universally improve when moving from the discrete to continuous model.

While the discrete measure arbitrarily identifies a win or a loss as either large or small, our continuous measure is more neutral in its construction. By not specifying the necessary magnitude required for a win or a loss to affect behaviour, our continuous measure allows large wins and losses to affect behaviour to a greater degree than smaller wins and losses. The continuous measure also allows us to use more data points to estimate the effect. While the discrete identifier restricted analysis to hands following an arbitrarily defined win or loss, the continuous measure estimates the effect across a greater number of hands by naturally weighting the effect based on the size of the prior win or loss.

We conclude that by utilising an improved model design, we can better estimate the behavioural bias from prior gains and losses in a smaller sample. The particular value of this improved measure is that we are able to find a statistically significant effect of prior wins and losses on aggression, while Smith et al. (2009) find only mixed results for this measure. In fact, while they find substantially more compelling results for looseness, our results for aggression are significant at the 5% level of significance.

The major limitation of this identifier is that we may be indirectly capturing the effect of wealth rather than isolating the influence of prior wins and losses. Especially early in a tournament there is a high correlation between wealth and our continuous identifier. Thus an alternative interpretation of the result

that a player is more likely to take risks following a large loss, is that a player with low wealth is more likely to take risks. Similarly, the fact that the correlation between wealth and our continuous identifier changes across a tournament generally complicates the interpretation of how prior wins and loss affect behaviour. However, one must note that the effect we find with the continuous model is in line with the effect from the previous literature and that implicated by the discrete model.

Is the effect of prior wins and losses affected by controlling for privately held information?

When extending our framework to control for an individual's probability of winning, we find that the estimates of the effect of prior wins and losses increase. The estimates of probability are highly statistically significant for all model specifications, as are those for relative table position. Our results go so far as to suggest that as the probability of winning increases, the likelihood a player plays that hand increases more than the actual increase in probability. Furthermore, we see significant increases in the R^2 values of the extended model compared to the baseline model. Based on these findings, it is clear that the probability of winning is a significant determinant of an individual's behaviour in the poker context, which is hardly surprising.

Given that controlling for this privately held information should further isolate the effect of prior wins and losses, this increase is a result of a more refined analysis. This improvement is most noticeable when the extended and continuous models are combined, and only slight when using the discrete measure. Similarly, the improvement is most noticeable for looseness than for aggression, which makes sense given the smaller effect that probability generally has upon an individual's aggression. This runs converse to the findings above, in which moving from the discrete to the continuous model greatly improved the aggression estimates.

When comparing our results to those of Smith et al. (2009), one can argue that as sample size increases, the importance of explicitly controlling for the hole cards decreases. However, Smith et al. (2009) find only borderline significance for aggression and the results of Engelbergs (2010) are similarly mixed. Conversely, our results are stronger for aggression than for looseness. We conclude that while a large enough sample will naturally reduce the effect of probability on behaviour, the inclusion of this control is an important consideration for future research.

Are more experienced players affected less by prior wins and losses than relatively less experienced players?

By using public records of their career wins, we are able to rank the individuals within our sample as a proxy for experience. We believe the external validity of these rankings give an appropriate measure of ability and experience within our sample. We find that the highest ranked players are less affected by previous wins and losses than the lowest ranked players. This result is inline with our prior expectations based on the findings of Alevy, Haigh and List (2007), List and Haigh (2005), and Palacios-Huerta and Volij (2009). We consider this result to be the most important contribution of our thesis.

The most serious limitation of our investigation of experience is that our tests have quite low statistical power when testing coefficient equality across our subgroups. This is a consequence of having split and already small dataset into three smaller subgroups. Despite this, our results suggest that while the lowest ranked individuals are affected by prior wins and losses, the behaviour of the highest ranked individuals remains relatively consistent across hands following both losses and wins. Our findings are indicative that the effect decreases with respect to experience.

This result is also important in relation to our other research questions. Compared to that of Smith et al. (2009), our sample is more experienced on average and more homogenous with respect to experience. This may further explain why we are unable to exactly replicate their results with our sample. Given that more experienced players are less affected and our sample is generally more experienced, it is natural to conclude that the effect should be smaller within our sample. Following this line of reasoning, the value of our refined methodology is made all the more apparent. Using the extended continuous model, we find evidence of a significant effect even amongst a highly experience sample, which we cannot with the discrete baseline model.

An unexplored question is whether the effect of prior wins and losses is affected by a combination of one's own experience, and the experience of one's opponents. Palacios-Huerta and Volij (2009) find that an experienced chess player in a centipede game is much more likely to follow game theoretic predictions if their opponent is also an experienced chess player, rather than a university student. Based on this, there is the possibility that a highly experienced poker player is less affected by prior wins and losses if she is playing a similarly experienced opponent.

9.1 Future Research

As we note above, poker presents an important compromise between a controlled laboratory experiment and a field study. This is particularly useful for the study of risk behaviour and preferences, in that players can be assumed to know the probability of the game. Furthermore, the game is played for real money, which increases the external validity of such a study. Beyond the current research, such datasets remain relatively under-utilised, primarily due to the relatively large size of the dataset required. However, partnership with a provider of online poker services would provide access to an existing database of considerable scope. Online poker providers are legally obligated to store very detailed data of the games played on their services. This is a source of very valuable data for research and analysis. Furthermore, a partnership with a poker provider could allow the construction of a randomised field experiment. For instance, providing players with a randomised endowment would manipulate the effect of an individual's reference point on risk preferences.

10 Conclusion

The aim of this thesis was to investigate the effect of prior wins and losses upon risk taking behaviour. We use televised poker tournaments as a proxy for a controlled laboratory experiment. The advantage of such data is that participants play for large, non-hypothetical stakes and are assumed to know the game's true probability distribution. However, our study is important beyond the poker context, as we are able to empirically estimate the effect of prior outcomes in a series of repeated one-shot games. In doing so, we capture the behavioural bias of individuals facing risky and uncertain decisions. In particular, our thesis specifically addresses three key elements:

Firstly, we attempt to replicate the results of Smith et al. (2009) using our new dataset. While our dataset is of a modest size, particularly in relation to a number of previous studies, we are able to find evidence in line with our prior expectations. The primary results are that an individual's risk-preferences are reference point dependent in a repeated game. We find that individuals tend to be less risk averse in rounds following a prior loss, and more risk averse in rounds following a prior win. This influence of previous outcomes on behaviour, while inconsistent with expected utility theory, is supportive of the reference point predictions of prospect theory.

Secondly, we employ a number of improvements to the standard estimation procedures of empirical poker research. We find greatly improved results when using our refined methodology. These improvements are two fold: controlling for privately held information and the use of more reliable econometric techniques. For the former, we explicitly control for each player's probability of winning, which is based on his or her private information. For the later, we use individual fixed effects and a more appropriate continuous measure of prior wins and losses. In our smaller sample these extensions allow us better to isolate the effect of interest, where the standard methods were unsuccessful.

Finally, we test our hypothesis that more experienced individuals are less affected by prior wins and losses. We are able to exploit the unique characteristics of our dataset to identify a set of rank-dependent subgroups, based on total careers earnings. These rank-dependent subgroups allow us to contribute to the literature on how experience affects risk-taking behaviour. We consider this to be the most important contribution of our thesis. Our analysis demonstrates that there are significant and systematic differences in how prior wins and losses affect our subsamples. We find a clear trend of this effect diminishing as average experience increases.

This result adds further credibility to our primary results. Firstly, it presents a reasonable explanation as to the sensitivity of our results to the estimation method. We consider an effect that we find to be less significant for more experienced individuals, and estimate this effect using a sample of highly experienced individuals. Secondly, that we do find an effect is suggestive that an individual's risk preference is indeed dependent on the outcomes of prior events, at least within the poker context.

11 References

- Aharoni, G., and Sarig, O.H., 2012. Hot hands and equilibrium. *Applied Economics*, 44(18), pp. 2309-2320.
- Alevy, J. E., Haigh, M. S. and List, J. A., 2007. Information cascades: evidence from a field experiment with financial market professionals. *Journal of Finance*, 62(1), pp. 151-180.
- Andersen, S., Ertac, S., Gneezy, U., Hoffman, M. and List, J.A., 2011. Stakes matter in ultimatum games. *American Economic Review*, 101(7), pp. 3427-3439.
- Andrade, E. and Iyer, G., 2009. Planned versus actual betting in sequential gambles. *Journal of Marketing Research*, 46(3), pp. 372-383.
- Barberis, N., Huang, M. and Santos, T., 2001. Prospect theory and asset prices. *Quarterly Journal of Economics*, 116(1), pp. 1-53.
- Blavatsky, P. and Pogrebna, G., 2010. Endowment effects? "Even" with half a million on the table!. *Theory and Decision*, 68(1-2), pp. 173-192.
- Camerer, C., 1989. Does the basketball market believe in the 'hot hand'? *American Economic Review*, 79(5), pp. 1257-1261.
- Cameron, L.A., 1999. Raising the stakes in the ultimatum game: experimental evidence from Indonesia. *Economic Inquiry*, 37(1), pp. 47-59.
- Carlin, B.I. and Robinson, D.T., 2009. Fear and loathing in Las Vegas: evidence from blackjack tables. *Judgement and Decision Making*, 4(5), pp. 385-396.
- Charness, G. and Gneezy, U., 2008. What's in a name? Anonymity and social distance in dictator and ultimatum games. *Journal of Economic Behavior and Organization*, 68(1), pp. 29-35.
- Coval, J.D. and Shumway, T., 2005. Do behavioral biases affect prices?. *Journal of Finance*, 60(1), pp. 1-34.
- Croson, R. and Sundali, J., 2005. The gambler's fallacy and the hot hand: empirical data from casinos. *Journal of Risk and Uncertainty*, 30(3), pp. 195-209.

- Delfabbro, P.H. and Winefield, A., 1999. Poker-machine gambling: an analysis of a within session characteristics. *British Journal of Psychology*, 90(3), pp. 425-439.
- de Roos, N. and Sarafidis, Y., 2010. Decision making under risk in deal or no deal. *Journal of Applied Econometrics*, 25(6), pp. 987-1027.
- Ellsberg, D., 1961. Risk, ambiguity and the Savage axioms. *Quarterly Journal of Economics*, 75(4), pp. 643-669.
- Engelbergs, J., 2010. *Judgements under competition and uncertainty: empirical evidence from online-poker*. Ph.D. Rheinisch-Westfälischen Technischen Hochschule Aachen University.
- Gilovich, T., Vallone, R. and Tversky, A., 1985. The hot hand in basketball: on the misperception of random sequences. *Cognitive Psychology*, 17(3), pp. 295-314.
- Harrison, G.W. and Rutström, E.E., 2008. Experimental evidence on the existence of hypothetical bias in value elicitation methods. In: C.R. Plott and V.L. Smith, eds. 2008. *Handbook of Experimental Economics Results*. Amsterdam: North-Holland, pp. 752-767.
- Hirshleifer, D. 2001. Investor psychology and asset pricing. *Journal of Finance*, 56(4), pp. 1533–1597.
- Hoffman, E., McCabe, K. and Smith, V.L., 1996. Social distance and other-regarding behavior in dictator games. *American Economic Review*, 86(3), pp. 653-660.
- Hurtig, A. and Lundgren, K., 2006. *Pokerturningar på internet*. Stockholm: Albert Bonniers Förlag.
- Johnson, D.K.N. and Gleason, T.R., 2009. Who really wants to be a millionaire? Gender differences in game show contestant behavior under risk. *Social Science Quarterly*, 90(2), pp. 243-261.
- Kahneman, D. and Tversky, A., 1979. Prospect theory: an analysis of decision under risk. *Econometrica*, 47(2), pp. 263–291.
- Keren, G., and Wagenaar, A.W., 1985. On the psychology of playing blackjack: normative and descriptive considerations with implications for decision theory. *Journal of Experimental Psychology: General*, 114(2), pp. 133-158.
- Levitt, S.D., List, J.A. and Sadoff, S.E., 2011. Checkmate: exploring backward induction among chess players. *American Economic Review*, 101(2), pp. 975-990.

- Lindquist, G.S. and S  ve-S  derbergh, J., 2012. Securing victory or not? Surrendering optimal play when facing simple calculations – a natural experiment from the Swedish and US Jeopardy. *Applied Economics*, 44 (6), pp. 777-783.
- List, A.J., 2003. Does market experience eliminate market anomalies?. *Quarterly Journal of Economics*, 118(1), pp. 41-71.
- List, A.J., 2004. Neoclassical theory versus prospect theory: evidence from the marketplace. *Econometrica*, 72(2), pp. 615-625.
- List, J.A. and Haigh, M.S., 2005. A simple test of expected utility theory using professional traders. *Proceedings of the National Academy of Science*, 102(3), pp. 945-948.
- Machina, M.J., 2008. Expected utility hypothesis. In: S.N. Durlauf and L. E. Blume, eds. 2008. *The New Palgrave Dictionary of Economics*. 2nd ed. Palgrave Macmillan. The New Palgrave Dictionary of Economics Online. Palgrave Macmillan. Available at: <http://www.dictionaryofeconomics.com.ez.hhs.se/article?id=pde2008_E000178> [Accessed 14 March 2012].
- Odean, T., 1998. Are investors reluctant to realize their losses?. *Journal of Finance*, 53(5), pp. 1775-1798.
- Palacios-Huerta, I. and Volij, O., 2009. Field centipedes. *American Economic Review*, 99(4), pp. 1619-1635.
- Post, T., Van Den Assem, M.J., Baltussen, G. and Thaler, R.H., 2008. Deal or no deal? Decision making under risk in a large-payoff game show. *American Economic Review*, 98(1), pp. 38–71.
- Rabin, M., 2002. Inference by believers in the law of small numbers. *Quarterly Journal of Economics*, 117(3), pp. 775-816.
- Rosenthal, R.W., 1981. Games of perfect information, predatory pricing and the chain-store paradox. *Journal of Economic Theory*, 25(1), pp. 92-100.
- Siler, K., 2010. Social and psychological challenges of poker. *Journal of Gambling Studies*, 26 (3), pp. 401-420.
- Sklansky, D., 1997. *Hold ‘em poker*. Las Vegas: Two Plus Two Publishing.

- Smith, G., Levere, M. and Kurtzman, R., 2009. Poker player behavior after big wins and big losses. *Management Science*, 55(9), pp. 1547-1555.
- Starmer, C., 2000. Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, 38(2), pp. 332–382.
- Terrell, D., 1994. A test of the gambler's fallacy: evidence from pari-mutuel games. *Journal of Risk and Uncertainty*, 8(3), pp. 309-317.
- Thaler, H.R. and Johnson, J.E., 1990. Gambling with the house money and trying to break even: the effects of prior outcomes on risky choice. *Management Science*, 36(6), pp. 643–660.
- The Hendon Mob, 2012. *All time money list*. [online] Available at: <http://pokerdb.thehendonsmob.com/ranking/1> [Accessed 11 April 2012].
- von Neumann, J. and Morgenstern, O., 1944. *Theory of games and economic behavior*. Princeton: Princeton University Press.
- Williams, R.J. and Wood, R.T., 2007. *Internet gambling: a comprehensive review and synthesis of the literature*. Ontario: Ontario Problem Gambling Research Center.
- Wooldridge, J.M., 2009. *Introductory econometrics: a modern approach*. 4th ed. Mason: South-Western Cengage Learning.

12 Appendix

Appendix A – Results from Smith et al. (2009)

Table A1. Looseness after Big Wins/Losses

Players	Big win	Big loss	Other	P-value
Heads up	49.46	50.73	50.33	1.0×10^{-7}
2	44.72	46.15	46.10	0.150
3	32.63	34.86	32.98	0.026
4	25.73	28.93	28.57	0.000084
5	24.53	25.75	24.57	0.00094
6	22.67	25.00	23.45	1.0×10^{-7}

Table A1 is reproduced from Smith et al. 2009, p. 1552.

Table A2. Aggression after Big Wins/Losses

Players	Big win	Big loss	Other	P-value
Heads up	1.00	1.20	1.12	3.1×10^{-8}
2	1.21	1.59	1.38	0.0026
3	1.39	1.28	1.31	0.249
4	1.38	1.54	1.49	0.796
5	1.19	1.25	1.21	0.131
6	1.06	1.20	1.16	0.013

Table A2 is reproduced from Smith et al. 2009, p. 1552.

Appendix B – Poker Hands Ranking

The rank is based on the probability of getting that hand, such that the most common hands are ranked lower than comparatively less frequent hands.

Table B1. Poker Hands by Rank

	Name	Description	Example
1	Royal Flush	Ace, King, Queen, Jack and 10 of the same suit	A♠, K♠, Q♠, J♠, 10♠
2	Straight Flush	Five suited cards of sequential value	2♣, 3♣, 4♣, 5♣, 6♣
3	Four of a kind	Four cards of equal value (plus another card)	8♣, 8♠, 8♦, 8♥, 2♠
4	Full House	Three cards of equal value, plus a pair	8♣, 8♠, 8♦, 2♠, 2♦
5	Flush	Five suited cards not in sequence	2♥, 5♥, 9♥, 10♥, A♥
6	Straight	Five unsuited cards of sequential value	4♥, 5♥, 6♣, 7♦, 8♦
7	Three of a Kind	Three cards of equal value (plus two other cards)	8♣, 8♠, 8♦, 2♠, 10♠
8	Two Pair	Two pairs (plus another unmatched card)	8♣, 8♠, 2♠, 2♦, 10♠
9	Pair	Two cards equal value (plus three other cards)	8♣, 8♠, 2♠, 10♠, 9♥
10	High Card	Ranked from Ace (highest) to 2 (lowest)	

Appendix C – Model Specification Tests

Table C1. Hausman Test for Various Model Specifications

Hausman Test	Looseness		Aggression	
	Baseline Model	Extended Model	Baseline Model	Extended Model
Discrete	35.99	36.29	1.40	4.58
	0.000	0.000	0.844	0.599
Continuous	9.00	10.68	0.76	3.92
	0.029	0.058	0.860	0.560

Table C2. Breusch-Pagan Test for Various Model Specifications

Breusch-Pagan	Looseness		Aggression	
	Baseline Model	Extended Model	Baseline Model	Extended Model
Discrete	149.08	205.58	45.90	157.98
	0.000	0.000	0.000	0.000
Continuous	177.70	231.44	45.85	160.63
	0.000	0.000	45.90	157.98

Appendix D – The Effect of Experience

Table D1. Testing Estimate Equality across Rank-dependent Subgroups

	Looseness - $SawFloP_{i,h}$		Aggression - $A_{i,h}$	
	FE	RE	FE	RE
H0: High = Low				
Test Statistic	5.38	3.12	3.10	2.20
P-value	0.0238	0.0774	0.0833	0.1384
H0: High = Low = Mid				
Test Statistic	3.25	3.74	1.79	2.25
P-value	0.0455	0.1543	0.1762	0.3243
H0: High = Mid				
Test Statistic	2.72	1.58	0.86	0.29
P-value	0.1044	0.2084	0.3581	0.5930
H0: Low = Mid				
Test Statistic	0.15	0.00	0.89	0.96
P-value	0.7041	0.9990	0.3502	0.3260
Test Type	F-test	χ^2 -test	F-test	χ^2 -test

Appendix E – Estimated Probability of Winning

Table E1. Probability for a Sample of Stating Hands (Monte Carlo Simulation)

Hole Cards		2 players	3 players	4 players	5 players	6 players
A♥	A♠	0.874	0.775	0.691	0.622	0.565
A♥	K♥	0.718	0.570	0.481	0.420	0.369
A♥	K♠	0.698	0.537	0.444	0.377	0.326
A♥	Q♥	0.706	0.553	0.462	0.399	0.351
A♥	Q♠	0.685	0.523	0.423	0.354	0.304
K♥	K♠	0.852	0.736	0.644	0.571	0.513
K♥	Q♥	0.685	0.531	0.441	0.383	0.337
K♥	Q♠	0.661	0.500	0.401	0.339	0.289
T♥	T♠	0.788	0.639	0.526	0.451	0.394
T♥	9♥	0.597	0.440	0.356	0.301	0.260
T♥	9♠	0.564	0.400	0.312	0.253	0.212
T♥	2♠	0.506	0.346	0.266	0.221	0.188
T♥	2♥	0.469	0.296	0.212	0.165	0.132
7♥	7♠	0.717	0.548	0.441	0.369	0.323
7♥	5♥	0.493	0.351	0.277	0.230	0.199
7♥	5♠	0.456	0.307	0.229	0.180	0.148
7♥	2♥	0.447	0.301	0.236	0.195	0.166
7♥	2♠	0.405	0.251	0.181	0.139	0.111
5♥	5♠	0.670	0.494	0.392	0.328	0.291
2♥	2♠	0.596	0.420	0.339	0.292	0.268