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Statistical Analysis of Texas Holdem Poker

Table of contents

Overview

Objective

Use statistical analysis to determine maximum profit potential for Mike Linn's online poker games.

Abstract

Gathered lifetime online Poker data for Mike Linn. Attempted to analyze data to obtain information to maximize profit. Techniques included Univariate Analysis, Regression analysis, Anova analysis, Logistic Regression, and outlier Analysis. After the analysis, nothing of supreme importance or sustenance was found. Encountered issues with too much power. Results lead to plenty of statistical significance, but little practical significance. Results showed that the data did not provide all the answers that were being sought after, but there was some value in examining the data in a strict statistical manner.

Background

My roommate, Mike Linn, is a professional online poker player. He has had success profiting off less skilled players. I have spent many hours watching him play online and have learned some of the things that make him successful and others not. I have often wondered if there was a way to use my statistical analysis skills to quantify what things separate winning players from losing players. Linn plays primarily online; consequently, there is an abundance of data available to analyze. Linn has played and cashed in some live tournaments (including placing 81st in the main event of the World Series of Poker). For the purpose of this report we will only analyze his online play. When Mike sits down at his computer to play poker he generally opens six to eighteen tables and plays anywhere from thirty minutes to three hours. This will be referred to as a poker session. I will be doing the bulk of my analysis on a session by session basis. Sometimes Linn ends his session with more money than he started and sometimes not. As we know there is a fair bit of luck in poker but the winning players win in the long run not because of luck but because of their actions. The purpose of this report is to quantify what the actions Mike Linn takes to be a winning player.

Introduction

Mike plays online poker primarily on the site Poker Stars. His screen name on Poker Stars is Poly_Baller. Poker Stars (PS from now on) is required by law to record every hand they host. They record each hand using something called a hand history file. The hand history file is a text file that includes a comprehensive listing of everything that occurs at the online poker table for each hand. Here is an example of one hand recorded in the hand history.

EXAMPLE

Hand #20306

PokerStars Game #18467389778: Hold'em No Limit ($2/$4 USD) - 2008/06/29 15:44:31 ET
Table 'Klonios II' 6-max Seat #5 is the button
Seat 1: Huge Gloves ($103.25 in chips)
Seat 2: FastEddie267 ($394 in chips)
Seat 3: UffzBrasche ($216.10 in chips)
Seat 4: KKozhuKK ($709.15 in chips)
Seat 5: Poly_Baller ($867.65 in chips)
Seat 6: cdeez8 ($432 in chips)
cdeez8: posts small blind $2
Huge Gloves: posts big blind $4
*** HOLE CARDS ***
Dealt to Poly_Baller [3c 3d]
FastEddie267: folds
UffzBrasche: calls $4
KKozhuKK: raises $10 to $14
Poly_Baller: calls $14
cdeez8: folds
Huge Gloves: folds
UffzBrasche: calls $10
*** FLOP *** [As 3s Tc]
UffzBrasche: bets $4
KKozhuKK: raises $32 to $36
Poly_Baller: calls $36
UffzBrasche: calls $32
*** TURN *** [As 3s Tc] [Kc]
UffzBrasche: bets $4
KKozhuKK: raises $36 to $40
Poly_Baller: calls $40
UffzBrasche: calls $36
*** RIVER *** [As 3s Tc Kc] [6h]
UffzBrasche: bets $4
KKozhuKK: raises $196 to $200
Poly_Baller: calls $200
UffzBrasche: calls $122.10 and is all-in
*** SHOW DOWN ***
KKozhuKK: shows [Td Ad] (two pair, Aces and Tens)
Poly_Baller: shows [3c 3d] (three of a kind, Threes)
Poly_Baller collected $147.80 from side pot
UffzBrasche: mucks hand
Poly_Baller collected $651.30 from main pot
KKozhuKK said, "f***in a joke honestly"
*** SUMMARY ***

Total pot $802.10 Main pot $651.30. Side pot $147.80. | Rake $3
Board [As 3s Tc Kc 6h]
Seat 1: Huge Gloves (big blind) folded before Flop
Seat 2: FastEddie267 folded before Flop (didn't bet)
Seat 3: UffzBrasche mucked [4s Ac]
Seat 4: KKozhuKK showed [Td Ad] and lost with two pair, Aces and Tens
Seat 5: Poly_Baller (button) showed [3c 3d] and won ($799.10) with three of a kind, Threes
Seat 6: cdeez8 (small blind) folded before Flop

When I emailed PS they emailed me back with 24 .zip files. After unzipping the files they revealed 24 massive .txt files. There were 24 files because PS had Poly_Ballers hand histories on 24 different servers. Recently people have developed ways to read in these hand histories and convert them into poker data. The leading poker analysis software is called Poker Manager. I used this program to import all the hand histories that PS provided me. After taking an initial look at the data it was clear that the data were not complete. I may not have realized this if the month of February 2009 was not missing. This happened to be one of Mike's best months ever and there was simply no data on it. I emailed PS again and luckily they have very good customer service. They said they had made a mistake and there should in fact be 28 files instead of 24. I imported the new 28 text files and I believe these to be a complete representation of Poly_Ballers online poker play on PS. The 28 .txt files will be provided along with this report.

Explanation of No limit Texas Holdem Poker

To begin, anywhere from 2 to 10 players sit around a circular table. Before cards are dealt the forced bets must be paid, which are called the **big blind** and the **little blind**. The player one seat to the left of the dealer places the small blind. The player one seat to the left of the little blind places the big blind. The dealer will then deal two cards to each player face down. These are known as the **pocket cards** or hole cards. Each player must then decide if they wish to call the current bet (the big blind, which is the highest amount bet at this point) which means to match it, fold their hand without betting if they don't like their cards, or raise the bet by putting more money into the pot. Each player, starting with the seat to the left of the big blind, makes their choice and acts. If a player raises the bet, each player must now call the new amount, including those who may have already acted. At any time a player may re-raise, meaning that they raise it again beyond the amount it was raised previously. Once there are no more raises and everyone has acted the dealer will deal the **flop.** The flop is three cards placed face up in the middle of the table. These are the first community cards. Each player can use their two hole cards in conjunction with the three flop cards to make the best 5 card hand. The first player to the left of the dealer that is still in the hand is the first to act. They have the option to check or bet. Checking is defined as not committing any more money to the pot and continuing on to the next player. After everyone has had their chance to act, the dealer will deal another community card. This is known as the **turn.** Betting is done exactly the same as on the flop. After everyone has had their turn to act, the final card is dealt. This is known as the **river.** The collection of the five community cards is known as the **board.** There is a final round of betting. Anyone still in the hand is now at **showdown**. The player that can make the best 5 card hand will win the pot. Each player has the option to use zero, one, or both of their hole cards to make the best 5 card hand. This means if there are four spades on the board and I hold one spade in my hand I can play a flush. Since this is no limit Texas Holdem each player has the option to go wager all their chips and go **all in** at any time.

Glossary of terms

Poker has its own jargon that could be take many, many pages to explain. Below is a listing of the technical terms needed for this report.

Game Type – defined by the small and big blind of the limit being played. Also referred to by the maximum buy in. The max buy in is usually 100 times the big blind. e.g. no limit holdem with small blind of 2 and big blind 4 is referred to NL 400.
NL-No limit means a player can wager all his chips at any time during the hand
LIM- Players can only bet certain amounts on different streets that are proportional to the blinds.
EV-This is calculated by taking the actual amount won and either deducting or adding the amount you would have won with average luck.
Hands- Total number of hands played at the level specified.
$- Money won or lost at that limit. Loses documented in red and parentheses.
BB/100- Amount of Big Bets won per 100 hands. A **Big Bet** is defined by twice the big blind.
VPIP%- Voluntarily put money in pot percentage. This is a measure of how loose or tight a player is. VP$IP is expressed as a percentage of the time a player puts money into a pot to see a flop in Hold'em. The big blind is not considered voluntary, so if a player checks his big blind, that is not considered in the VP$IP calculation. However, if the big blind calls a raise, then it is considered for VPIP. If a player calls or raises only to fold to a further pre-flop raise, this also counts for VPIP%.
PFR%-PreFlop Raises. This is a measure of pre flop aggression. Simply, the percent of time a player raises before the flop.
3bet%-Percentage of time player 3 bets. A **3 bet** is defined by the player betting, getting raised, and then the player reraising.
WTSD%- Went to Show Down. This is a measurement of how willing a player is to stay in the hand until the end. Simply computed as number of hands showed down divided by hands played.
W$SD%- Percentage of time a player has money at show down. This can be used as a measure of how often a player bluffs.
Agg-This is the aggression factor. This is the aggressive actions divided by calls. This is found by adding total number of bets and raises and dividing by number of calls.
Agg%-This is the aggression frequency. This is often referred to as the best way to assess a player's aggression. It is found by [Times Raised + Times Bet] / [Times Raised + Times Bet + Times Called + Times Folded]. The higher the percentage the more likely the player is bluffing more hands.

Restriction of Analysis

I should mention that the analysis that follows in the rest of the report is for the most part inferential. However, the data I have is from a population and is not a random sample. If we can see the data as a "sample" of lifetime data then there is no issue. It is important to remember we are dealing with population data and not a random sample when making predictions, extrapolation and inference.

Univariate Analysis

Univariate reports are used to get a better idea of what the data looks like simply.

Data qualifications and parameters

For the purpose of this project I will only be analyzing data that was obtained between March 31, 2006 and Jan 15, 2010. In that span we have data on 2,178,217 hands. Mike is primarily a Texas Holdem player; however, he has played some Omaha. Omaha is a variant of Texas holdem. I decided to only analyze the holdem hands. The style in which one plays Omaha and holdem are completely different. Their winning strategies have many differences. I thought it would be more appropriate to only analyze Mike's holdem play. After removing all the Omaha hands there were now only 1,883,932 hands.

Univariate analysis by hands

Throughout this report the primary response variable is going to be profit. Below in *figure 1* is a time series graph provided by poker manager that shows every holdem hand played versus profit.

Figure 1

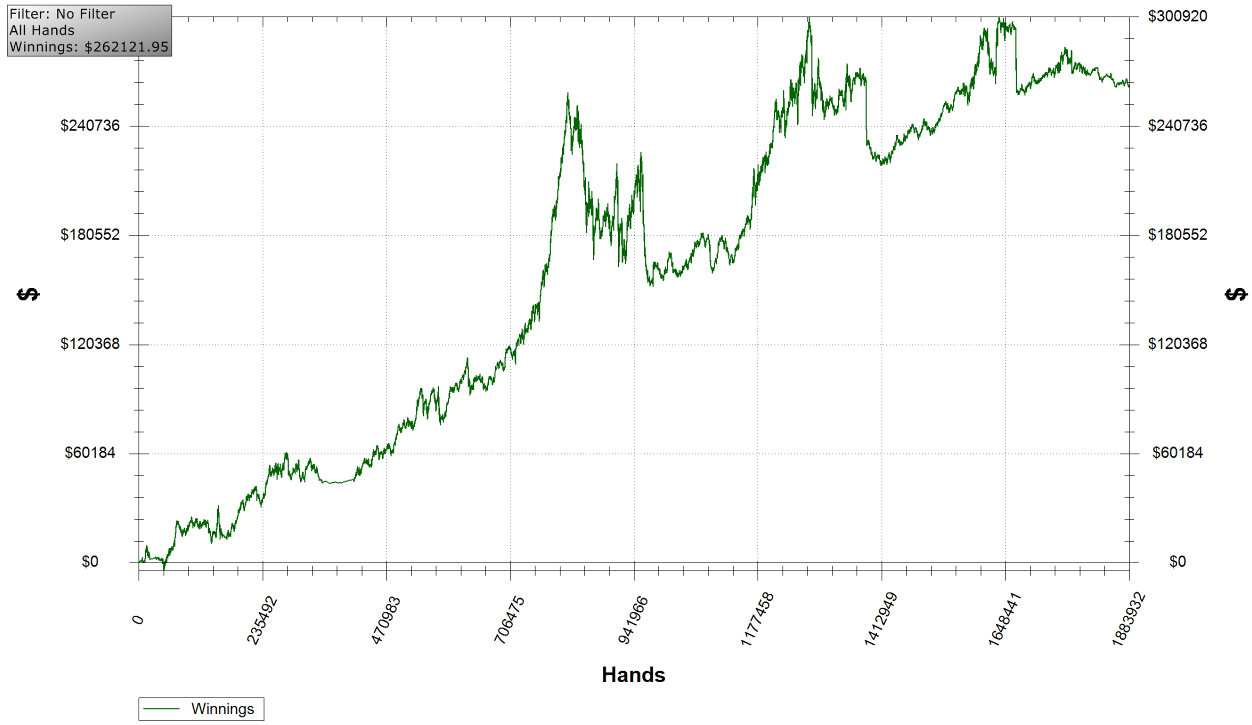


Figure 1 is essentially a time series graph with hands on the x-axis and profit on the y-axis

As you can see there are many up and down swings in the graph. My aim to try and figure out what makes the graph go up and down but more importantly, why it has a general upward trend.

Univariate analysis by Sessions

I initially thought that the bulk of my analysis would be based on sessions. These sessions were defined as Mike opening up a group of tables and playing for a period of time then closing all the tables. My initial thought would be that profit would be response variable. However, it became clear that using just profit would not be sufficient. If Mike won a 400 dollar pot while playing no limit 400 then it means we did well to get the entire chip stack of another player. However, if he is playing NL 5000 and he wins 400, then it means he won a very small pot and may not have had to play as well as he did at NL 400. Because of this fact it makes a lot more sense to look at a standardized version of profit. The most logical is BB/100. This will also be referred to as **win rate**. I could not develop a win rate variable for the session's data because he would often play different stakes during the same session. He might be playing 5 tables of NL 400 and 4 tables of NL 1000. This makes it impossible to convert profit to win rate. Thus, I had to break each session down to each table and look at the data that way. Regardless, *figure 2* shows the univariate stats for sessions.

Figure 2

Variable	Mean	StDev	Sum	Minimum	Median	Maximum
Start Time of Session	39454	342	89244702	38808	39434	40193
Minutes Played	76.33	53.11	172652.00	1.00	65.10	435.10
Hands	832.9	764.9	1883932.0	1.0	656.0	6283.0
$	115.9	2860.2	262121.9	-37265.7	186.9	18239.8
$/hr	247.2	2463.4	559269.1	-36306.6	196.5	16241.7
$ EV	149.3	2413.2	337617.5	-27332.7	98.8	18404.0
Avg Players	5.3766	0.4199	12161.8000	2.0000	5.4000	8.4000
VPIP%	31.756	7.427	71800.800	0.000	30.100	100.000
PFR%	21.417	5.973	48423.200	0.000	20.600	100.000
3Bet%	5.673	5.241	12833.400	0.000	5.100	100.000
Agg Factor	3.3632	2.0669	7607.5500	0.0000	3.0700	70.0000
WTSD%	25.910	7.660	58608.800	0.000	25.700	100.000
W$SD%	47.008	15.067	106332.000	0.000	47.800	100.000
Bin profit	0.6167	0.4863	1395.0000	0.0000	1.0000	1.0000

Figure 2 shows that the means for each variable match very closely to the means in figure 3. Also Bin profit shows that Mike won 61.67% of his sessions.

Univariate Analysis by Table Sessions

After looking at initial reports of the data it was clear that I would have to clean it up before it was usable. The first thing that became clear was that there were insanely large outliers in nearly every variable. In *figure 4* you can see all the outliers in each of the variables. The reason for all these outliers is that some of these sessions are only a few hands long. This small sample size of hands is making the variance very high. My aim was to lower the variance by only including sessions that contained more than a certain number of hands. I was unsure what an acceptable number to use was. I examined the sessions with only more than 25, 50, 75, and 100 hands. Because of the nature of the data an interesting thing happened. When I was only looking at sessions with more than 100 hands I had lost well over half the data in terms of sessions. There are 19069 sessions total and only 7698 sessions with more than 100 hands. However, there are 1.88 million total hands and about 1.3 million are included in the sessions with over 100 hands. Also, in my attempt to raise sample size by only including sessions with a substantial amount of hands I was actually lowering the sample size of number of sessions. Another very interesting thing happened when I was only analyzing sessions with more than 100 hands. Mike was actually a losing player. His profit was a negative 157,000 dollars. That means in sessions with less than 100 hands he was positive almost 300,000 dollars. This was a very promising result for my regression analysis to come. Another thing that caught my eye was that even though Mike was in the red 157 thousand dollars his win rate (i.e. BB/100) was still positive at 2.41. What this means to me is that for longer sessions Mike suffers great losses at higher stakes but can still win consistently at lower stakes to counteract those huge losing sessions. Since I would be looking at win rate and not straight profit I knew when I would run my regression analysis my coefficient for hands would not be as negative since the win rate only went from 6.63 to 2.41. After examining the scatter plots in *figure 3* I decided I would do all my session analysis on sessions that lasted longer than 50 hands. I made this decision because the scatter plot showed no substantial outliers and eliminated the least amount of data. It became clear after examining these scatter plots I was going to have a problem with constant variance for the residuals. I know that we are not supposed to just throw away data just because it is an outlier. However, with less than 50 hands the data is too dependent on the cards Mike is receiving and not on his playing style.

Figure 3

			All 19069 sessions			
Variable	Mean	StDev	Sum	Minimum	Median	Maximum
Minutes.Pl	61.157	47.203	1166198	0	51.6	429.6
Hands	98.796	75.852	1883932	1	83	883
Profit	13.7	967.5	262122	-24728	7.25	13783
ProfitPerH	48.4	1736.5	923718	-40678	14.3	82241.4
EV	17.7	819.7	337618	-22786.5	6.27	13783
Avg.Player	5.3543	0.6219	102101	1	5.5	9
VPIP%	30.359	9.343	578517	0	29.6	100
PFR%	20.879	7.886	397863	0	20.3	100
3Bet%	5.674	6.975	108201	0	4.5	100
Agg.Factor	4.2069	4.0523	80220.9	0	3	68
WTSD%	25.285	15.879	482168	0	25	100
W$SD	42.824	31.723	816603	0	45.5	100
Rake	14.702	12.29	280361	0	12.04	138.65
BBPer100	6.63	342.5	126497	-10000	4.74	35025

			more than 25, 16646 sessions			
Variable	Mean	StDev	Sum	Minimum	Median	Maximum
Minutes.Pl	68.92	45.545	1147242	4.8	57.9	429.6
Hands	111.28	73.2	1852358	25	94	883
Profit	14.6	1026	243858	-24728	14.8	13783
ProfitPerH	46.1	1058.8	767606	-24736.6	18	20735
EV	19.5	869.8	324667	-22786.5	13.7	13783
Avg.Player	5.393	0.5172	89771.9	2	5.5	9
VPIP%	30.149	7.029	501869	3.7	29.5	100
PFR%	20.883	6.008	347613	0	20.4	100
3Bet%	5.623	5.261	93608.6	0	4.9	100
Agg.Factor	4.4591	4.1438	74225.6	0	3.25	68
WTSD%	25.671	12.591	427317	0	25	100
W$SD	45.589	29.345	758869	0	50	100
Rake	16.565	12.058	275743	0.06	13.73	138.65
BBPer100	6.66	141.17	110845	-4071.25	5.81	1321.6

			more than 50, 13742 sessions			
Variable	Mean	StDev	Sum	Minimum	Median	Maximum
Minutes.Pl	78.625	44.416	1078102	9.8	67.3	429.6
Hands	127.19	71.11	1744033	50	108	883
Profit	7.46	1100.8	102234	-24728	17.9	13783
ProfitPerH	27.2	960	372874	-24736.6	16.3	20735
EV	13.9	930.7	190887	-22786.5	17.6	13783
Avg.Player	5.4017	0.4851	74067.5	2	5.5	9
VPIP%	30.105	6.351	412796	10	29.5	89.8
PFR%	20.903	5.471	286628	3.5	20.4	78
3Bet%	5.6145	4.5969	76986.5	0	5	61
Agg.Factor	4.4542	4.1814	61076.6	0	3.25	68
WTSD%	25.654	10.747	351767	0	25	100
W$SD	46.709	26.382	640480	0	50	100
Rake	18.948	11.957	259815	0.86	16.07	138.65
BBPer100	5.47	119.72	75003.1	-737.79	5.36	740

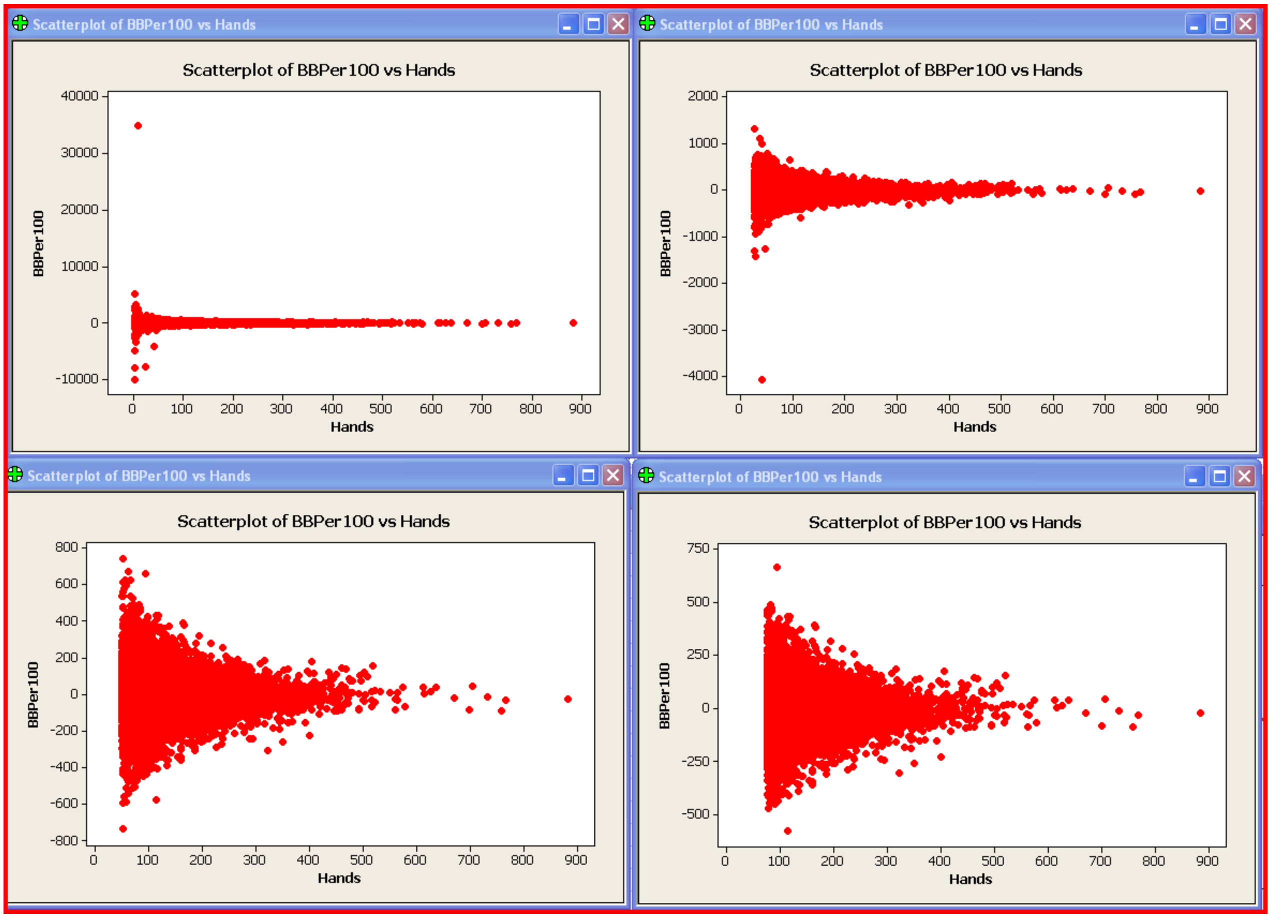
Figure 3 cont.

			more than 75 hands, 10666 sessions			
Variable	Mean	StDev	Sum	Minimum	Median	Maximum
Minutes.Pl	89.66	44.347	956040	15.8	77.6	429.6
Hands	145.82	70.2	1554854	75	126	883
Profit	-2.8	1171.3	-30384.4	-24728	21.5	11192
ProfitPerHr	15	878.3	160025	-24736.6	16.2	9256.1
EV	8.68	987.5	92546.7	-22786.5	20.1	11184.4
Avg.Players	5.3962	0.4702	57540	2	5.5	9
VPIP%	30.106	6.046	321016	10	29.5	89.8
PFR%	20.961	5.23	223509	6.4	20.5	78
3Bet%	5.5906	4.2698	59612.5	0	5	61
Agg.Factor	4.3307	4.0567	46177.9	0.29	3.22	68
WTSD%	25.665	9.664	273671	0	25	75
W$SD	47.263	23.711	503967	0	50	100
Rake	21.693	12.109	231313	0.86	18.87	138.65
BBPer100	4.83	108.57	51532.9	-578.71	4.92	661.38

			more than 100, 7698 sessions			
Variable	Mean	StDev	Sum	Minimum	Median	Maximum
Minutes.Pl	103.24	44.95	794730	27	90.8	429.6
Hands	168.7	70.17	1298642	100	148.5	883
Profit	-20.4	1253.5	-157112	-24728	14.1	11192
ProfitPerHr	-0.29	813.5	-2240	-24736.6	8.37	9256.1
EV	-3.3	1078.7	-25503.1	-22786.5	17.9	11184.4
Avg.Players	5.3918	0.4625	41506.2	2	5.5	8.4
VPIP%	30.176	5.718	232295	13.4	29.6	82.8
PFR%	21.048	4.956	162030	7.7	20.6	75
3Bet%	5.6284	3.993	43327.2	0	5.1	61
Agg.Factor	4.1847	3.8336	32213.8	0.33	3.2	58
WTSD%	25.672	8.848	197625	0	25.4	67.7
W$SD	47.168	21.278	363103	0	50	100
Rake	25.041	12.505	192763	2.05	22.3	138.65
BBPer100	2.41	99.36	18525	-578.71	2.83	433.27

Figure 3 shows the differences in basic statistics when we remove different amounts of the data. The data does not change much when all of it is present and when the sessions with less than 50 hands are removed.

Figure 4



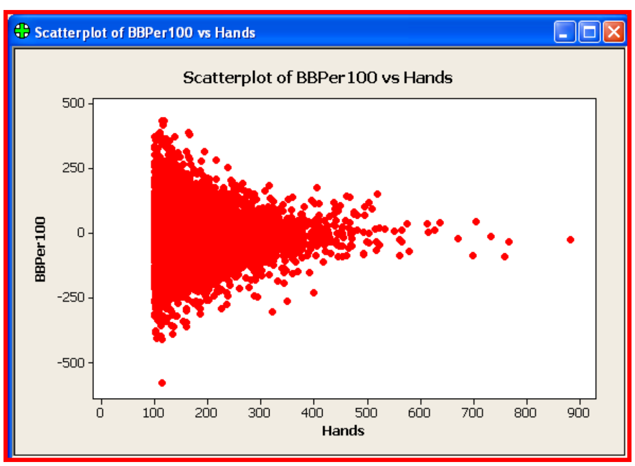
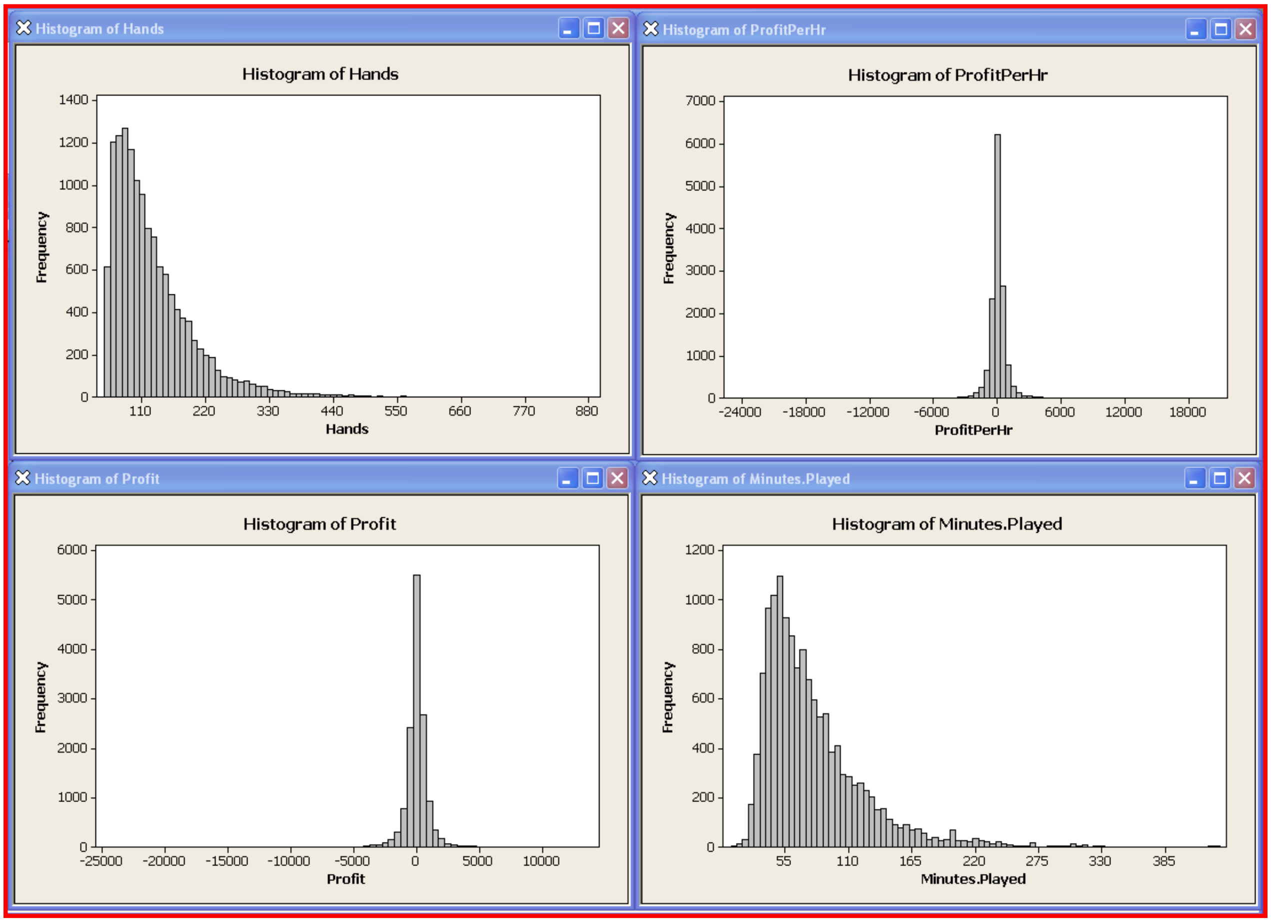


Figure 4 shows how we can get rid of the crazy outliers when we remove the short sessions. Top left has all the data, top right does not contain sessions with less than 25 hands, middle left contains sessions with more than 50 hands, then 75 hands, then 100 hands in bottom left.

The top left scatter plot shows hands vs. bbper100. It shows that there is a tremendous amount of variance when we include all the data, standard deviation=342. The next scatter plot (top right) has sessions with less than 25 hands removed. You can see that the variance is better but still not very good, standard deviation=141. The next three scatter plots have less than 50, 75, and 100 hand sessions removed. The variance does not improve significantly from 50 to 100, standard deviation goes from 119 to 99. This is why I decided to use 50 hands as my cut off. Even with removing the short sessions it is clear we are going to have issues with unequal variance.

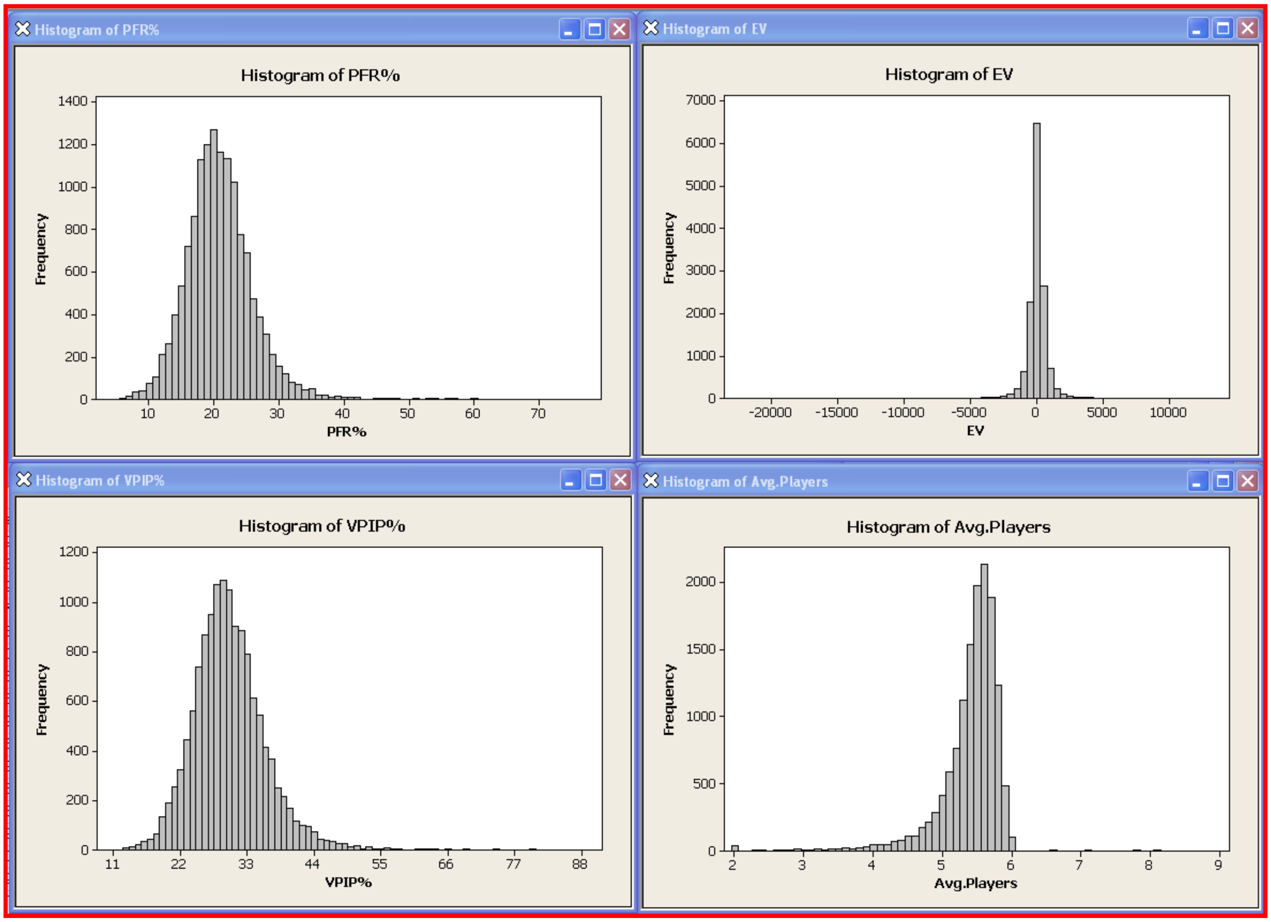
Figure 5, figure 6, and Figure 7 show basic histograms of the explanatory variables we will be dealing with in the analysis

Figure 5



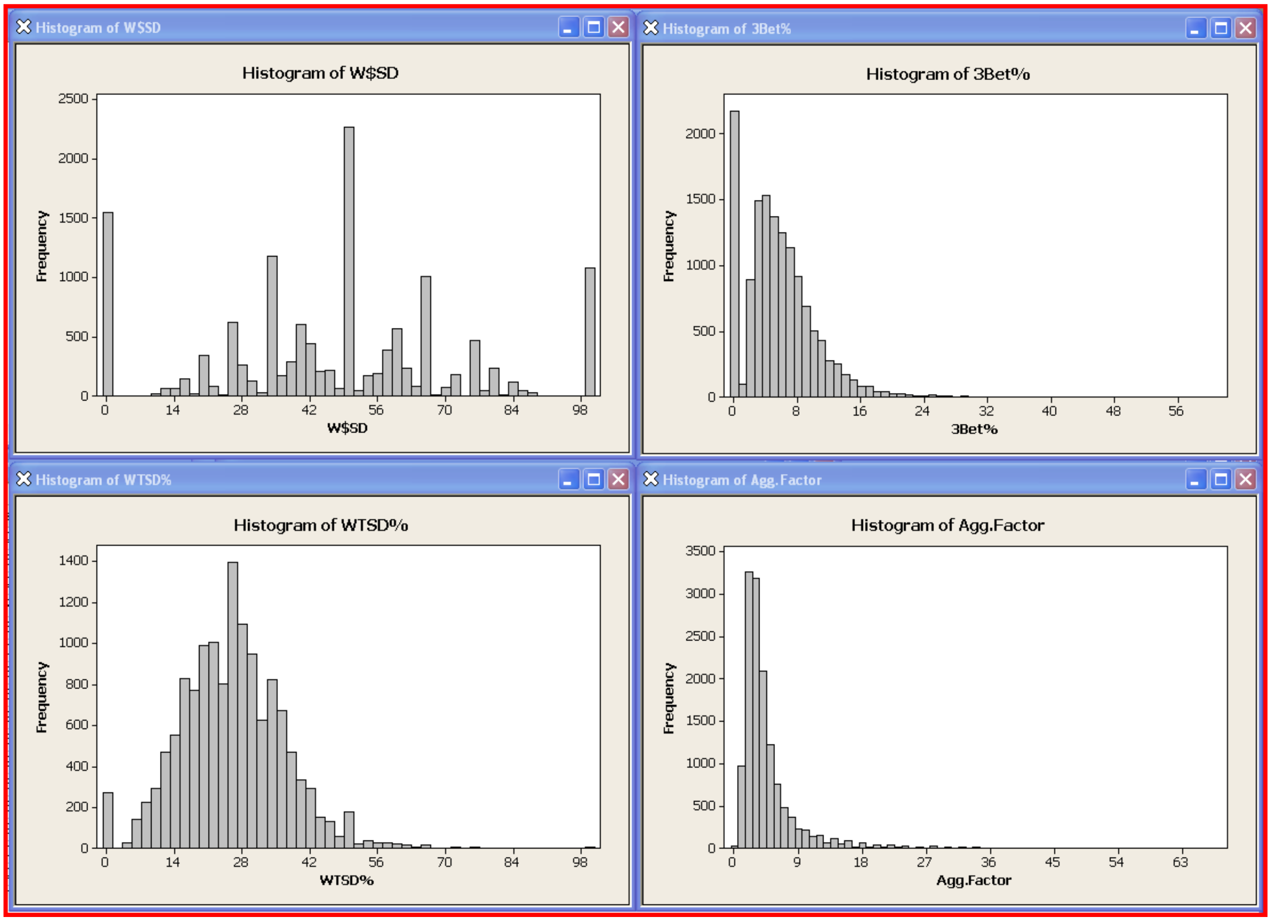
As you can see, hands is skewed right. Mike plays the bulk of his sessions with less than 200 hands. Profit per hour and profit look very similar. It appears they are symmetric around zero and bell shaped with some very large outliers on both sides. The minutes played group looks similar to hands, as it should. It looks like the bulk of Mike's sessions last about an hour.

Figure 6



The histograms for PFR% and VPIP% look quite similar. PFR% is centered around 20% as VPIP% is centered around 30%. EV looks like it is symmetric about zero and has some very large outliers on both sides. Average players histogram shows that Mike mostly plays at 6 person maximum tables that usually table 5 players.

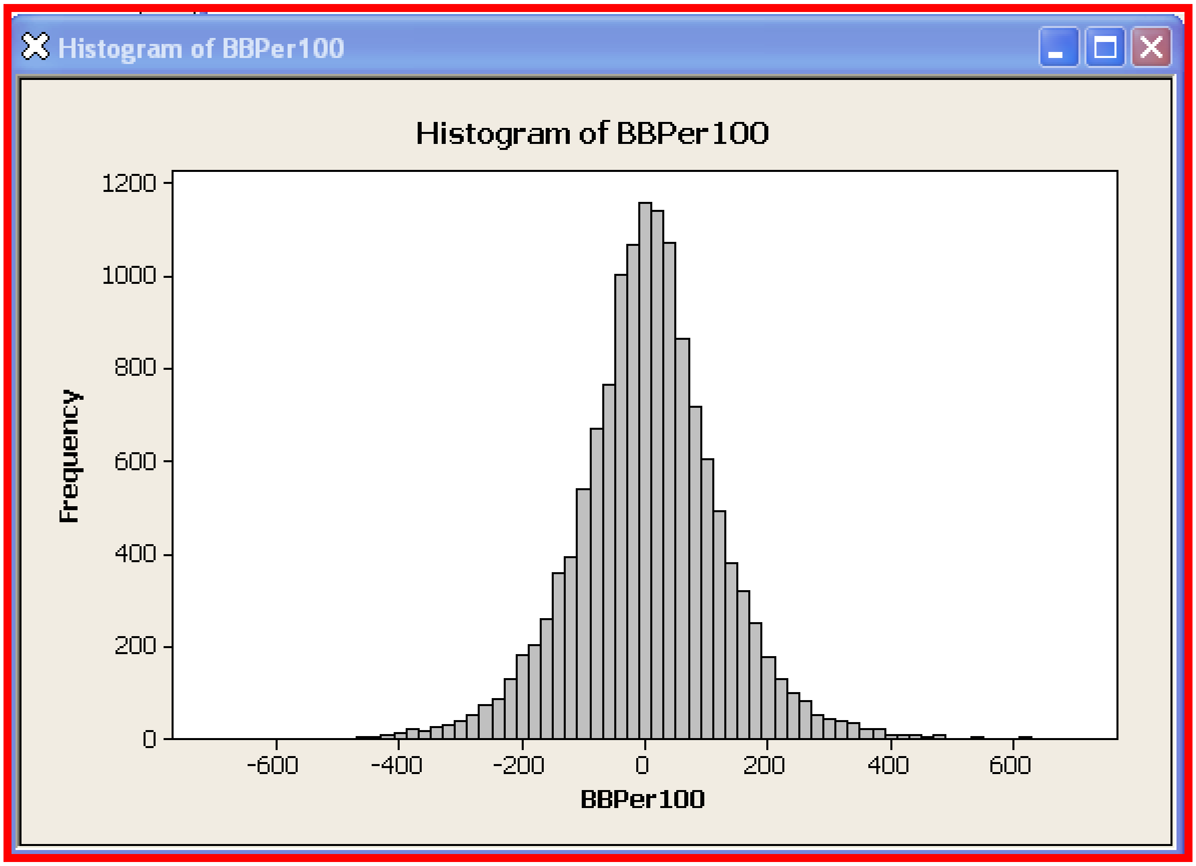
Figure 7



W$SD is a very interesting histogram. It ranges all the way from zero to one hundred. There is a substantial amount of data that is at the extremes as well. The 3 bet % is skewed right and never really gets above 25%. WTSD% is fairly normal and symmetric about 28%. Aggression factor is also skewed right and centered around 6.

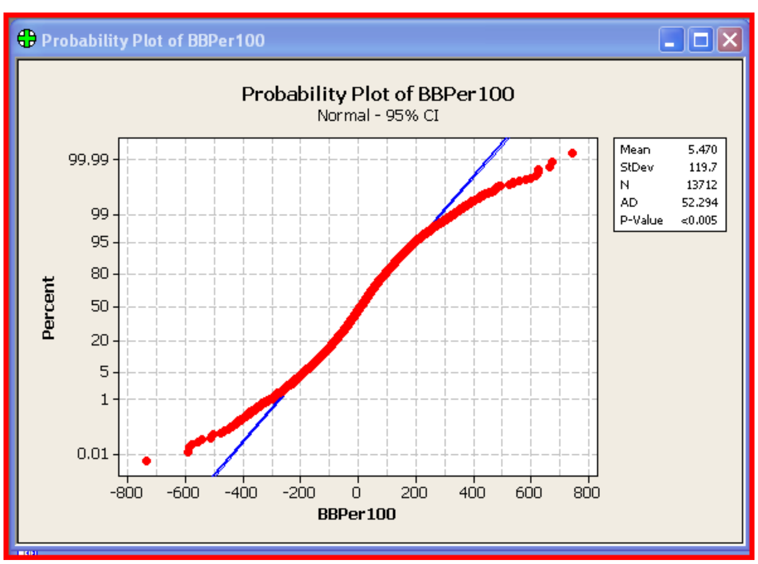
Figure 8 below shows the histogram for our response variable

Figure 8



The above figure is my response variable. The histogram shows that the data is looking quite nice, perhaps even normal. After looking at a normal probability plot in *Figure 9* it shows that although the data is symmetrical and bell shaped it is not normal.

Figure 9



There are actually 95% CI limits on *Figure 9*. However, since there is so much data they are very close to the normal line and barely visible. When we have such a large amount of data perfect normality is nearly impossible. Based on the histogram the data is behaving quite normally. Most statisticians would be very satisfied with the normality in *Figure 8* given the sample size

Univariate analysis by Stakes

Below in *Figure 10* is a chart that shows all the stats differentiated by the different stakes that Mike has played.

Figure 10

Game Type	Hands	$	bb/100	VPIP%	PFR%	3Bet%	WTSD%	W$SD%	Agg	Agg%
$25/50 NL	13949	($57,361.20)	-8.22	34.7	25	7.7	26.4	45.5	2.89	40.3
$30/60 LIM	205	$354.00	5.76	34	26.6	14.9	54.8	50	1.96	55
$10/20 NL	26601	($22,627.95)	-4.25	32.9	23.4	6.8	25.5	46.3	3	39.2
$15/30 LIM	56	($634.00)	-75.48	30.4	19.6	12	52.9	22.2	2.18	61.1
$5/10 NL	420238	$109,459.35	2.6	29.7	21	6.1	26.2	48.3	3	38.7
$10/20 LIM	371	($1,436.50)	-38.72	45.5	34.4	21.5	53	36.4	2.15	57.5
$3/6 NL	14360	$6,692.25	7.77	34	22.5	5.3	26.8	44.7	2.77	38
$5/10 LIM	2768	$999.00	7.22	40	25.8	11.9	37.1	48.9	2.57	52
$2/4 NL	1226761	$229,560.75	4.68	29.8	20.6	5.3	25.6	47.3	3.12	38.8
$4/8 LIM	4	($50.00)	-312.5	25	0	0	100	0	na	100
$2/4 LIM	105	$44.50	21.19	51	37	27.6	41.9	38.9	2.29	60
$1/2 NL	88156	($6,348.75)	-3.6	32.3	24.1	8.3	26.2	45.1	3.16	42
$1/2 LIM	10	($21.60)	-216	60	20	0	33.3	50	1.25	38.5
$0.5/1 NL	6446	($424.55)	-6.59	42.6	24.8	4.4	25.6	42.4	3.14	37.7
$0.25/0.5 NI	82409	$3,952.95	9.59	34	21.5	4.8	26.7	47	3	36.5
$0.5/1 LIM	23	($13.25)	-115.2	68.2	31.8	0	20	0	2.5	48.4
$0.1/0.25 NI	878	$14.60	6.65	32	23.4	6.7	19	40.5	4.44	54.5
$0.05/0.1 NI	318	($12.85)	-40.41	26.8	22.2	3.3	30.4	38.1	4.14	41.7
$0.02/0.05 N	96	($10.21)	-212.7	43.8	22.9	30.8	19.1	11.1	3.18	41.7
$0.02/0.04 L	19	($0.31)	-81.58	84.2	57.9	0	42.1	37.5	1.45	65.1
$0.01/0.02 N	159	($14.28)	-449.1	87.7	77.9	40.6	85.4	42.1	4.2	8.4

Figure 10 shows a breakdown of each variable by what stake Mike is playing.

It is clear from *Figure 10* that the best stake in terms of profit in NL 400 and his worst is NL 5000. Mike has also played the most hands at 2/4. There will be more in depth analysis on the impact of stakes in the ANOVA section of the report, page 35.

Regression Analysis

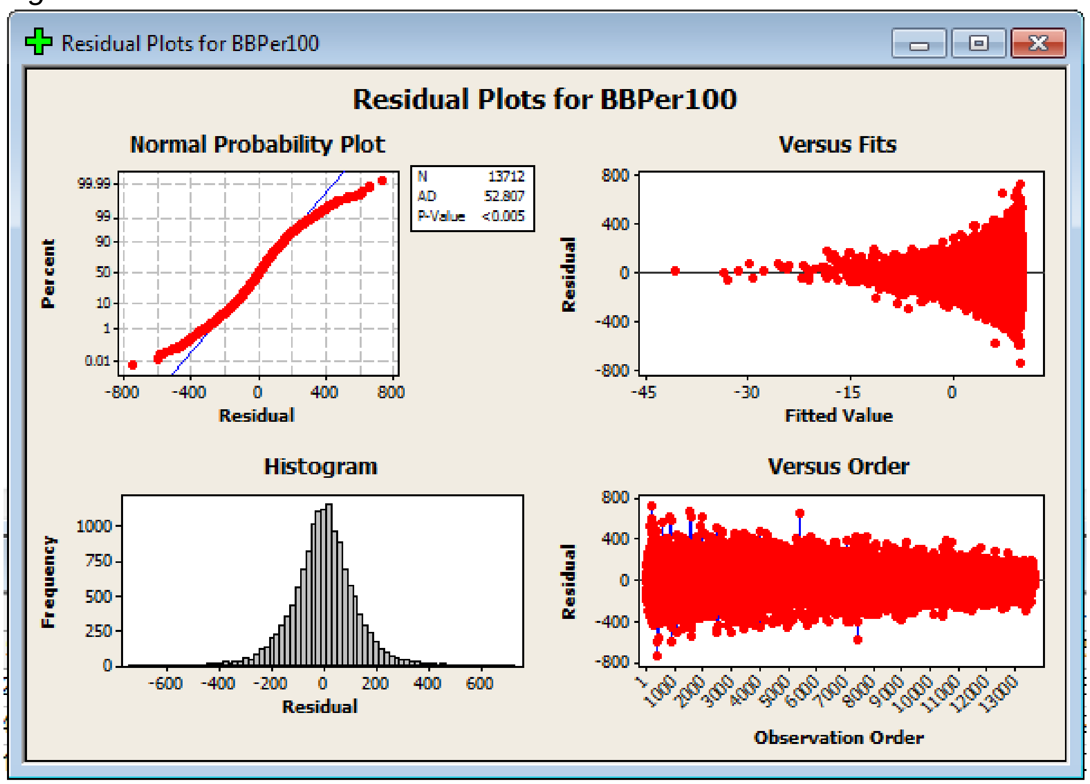
~As stated previously~

I thought the best way to start this analysis would be to look at it on a session-by-session basis. I thought there would be certain variables that would contribute to a winning or losing session. There are certain styles of play that often result in profit. I think that the variables I included can capture the different styles of play. For this portion of my analysis I am going to use dollars per 100 big blinds as my response. This is a way to standardize winnings. Since Mike plays many different stakes it makes the most sense to look at profit as a percentage of the big blind. The first problem I ran into with this approach was that sometimes Mike played different stakes during the same session. This would make it impossible to develop a bb/100 response variable. Luckily, Poker Manager is able to generate a .csv file that is partitioned by each individual table's session. I did the bulk of the analysis on this data frame.

Simple Regression

The first variable that I did regression analysis on was hands per session. My hypothesis was that the longer Mike played the worse he would perform. This is where I ran into my first problem. Below in *Figure 11* is the four in one graph of the residuals generated by this regression analysis.

Figure 11



The top right graph in Figure 11 shows a huge problem with unequal variance of the residuals

In *figure 11* above it is clear that there is a problem with the residuals vs fits. The residuals are also apparently not normal based on the normal probability plots, despite the histogram looking symmetric. This is significantly less of an issue considering the sample size. In an ill-fated attempt to fix the unequal variance and the problem with normality I tried some transformations. My first transformation attempted was to log the response. In order to do this I had to take the log of the absolute value of the bb/100 then get the negative sign back where it was needed. *Figure 12* shows the residual plots.

Figure 12

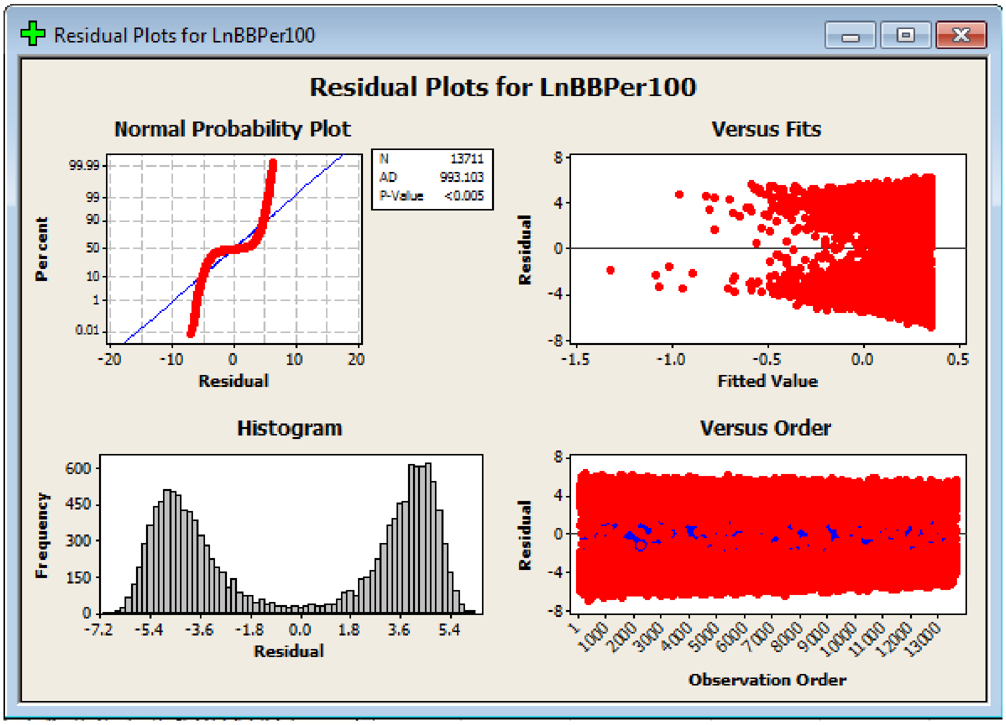
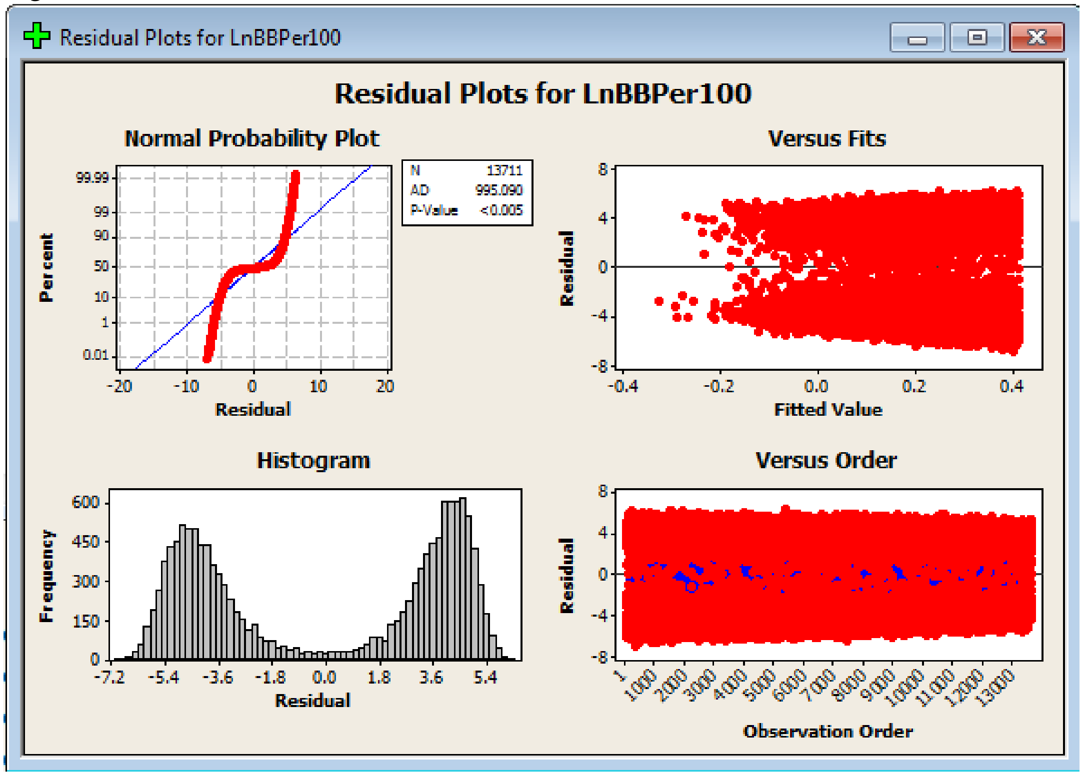


Figure 12 shows the transformation clearly did not work.

The next thought was to transform the X variable, by logging hands. *Figure 13* is the residual analysis.

Figure 13



Also an unsuccessful transformation shown in Figure 13

This also did not work. I tried every combination of natural logs, square roots, squaring and different powers. I could not obtain any combination of transformations that helped the residuals. The remarkable thing I noticed during these transforms was that no matter what I did the variable hands stayed significant. Below in *Figure 14* is the output that shows the original regression results.

Figure 14

Regression Analysis: BBPer100 versus Hands

```
The regression equation is
BBPer100 = 13.2 - 0.0610 Hands


Predictor      Coef   SE Coef      T      P
Constant     13.227     2.094   6.32  0.000
Hands      -0.06099   0.01437  -4.24  0.000


S = 119.646   R-Sq = 0.1%   R-Sq(adj) = 0.1%


Analysis of Variance

Source             DF          SS      MS      F      P
Regression          1      257905  257905  18.02  0.000
Residual Error  13710   196260740   14315
Total           13711   196518645
```

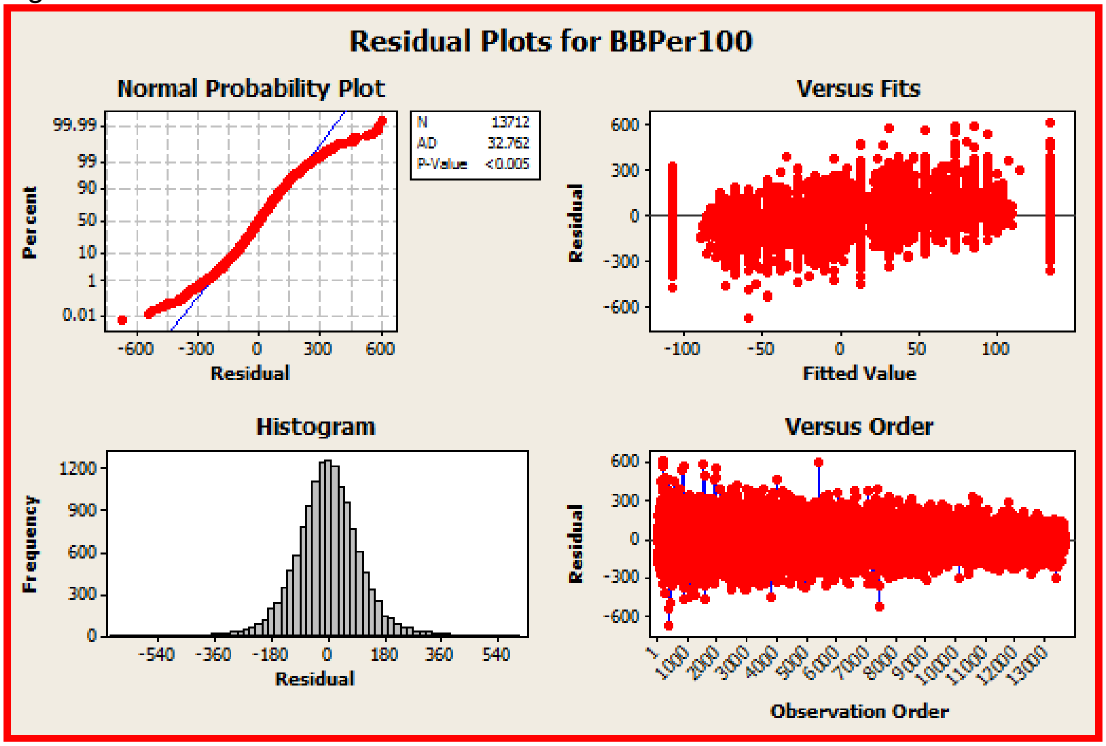
Output for simple regression analysis

Disappointingly, the R-squared value is essentially zero. It seems (based on this invalid analysis) that the length of the session does not explain any of the variance in Mike's win rate. However, as I suspected, the coefficient is negative and statistically significant. Since the sample size is so large it seems that no matter what variable is being used to predict bb/100, it will be a significant predictor. This was the first indication that there would be plenty of statistical significance but little practical significance. With sample sizes as large as I had, the power of each test was immense.

More simple regression

I decided to take a look at each of the explanatory variables as a single predictor for win rate. The variable W$SD looked the most promising. *Figure 15* shows the residual analysis.

Figure 15



These are much more promising residuals. There is some pattern in the residuals vs. fits however it is not that bad. The histogram of residuals looks very symmetric and normal. The normal probability does not look that bad even though there is a very small P-value suggesting non-normality. With these large sample sizes we almost never see perfect normality.

Figure 16 shows the output from Minitab on the regression analysis.
Figure 16

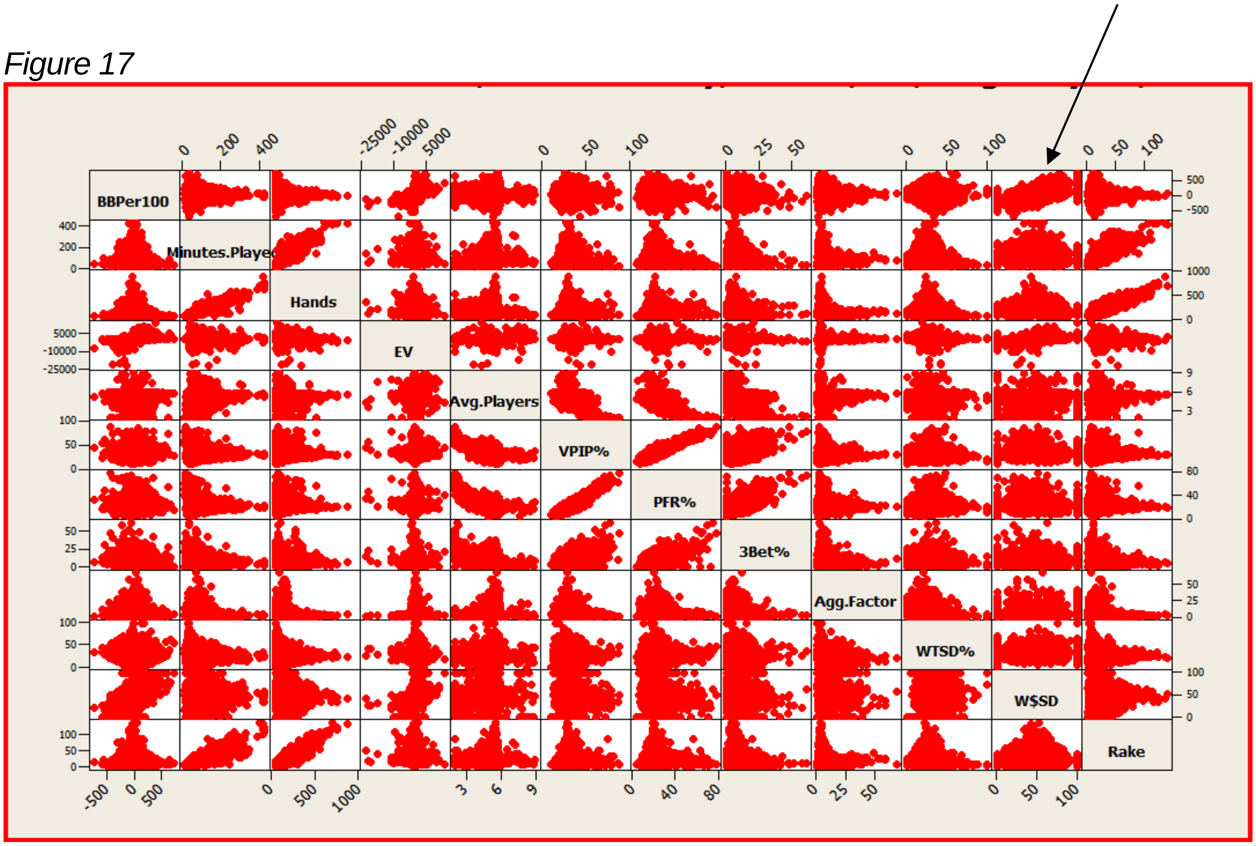
Regression Analysis: BBPer100 versus W$SD

```
The regression equation is
BBPer100 = - 108 + 2.42 W$SD


Predictor      Coef  SE Coef       T      P
Constant   -107.590    1.759  -61.18  0.000
W$SD        2.42050  0.03278   73.84  0.000


S = 101.271   R-Sq = 28.5%   R-Sq(adj) = 28.4%


Analysis of Variance

Source             DF         SS        MS        F      P
Regression          1   55911950  55911950  5451.75  0.000
Residual Error  13710  140606695     10256
Total           13711  196518645
```

The intercept is interpretable in this case and it is significant. If mike does not win any money at showdown he can expect an average win rate of -108. This is a significant loss. As such, the coefficient for W$SD is quite positive and very significant. The corresponding t-value is a high 73.84 leading to an incredibly small P-value. The R-squared value is 28.5%, which is not great but promising for only one predictor. This is certainly an upgrade from .1% from the previous simple regression analysis.

Below in *Figure 17* is a matrix plot for all the variables of interest. You can see that W$SD clearly has the best linear association with win rate.

Figure 17



You can see that none of the other predictors had strong linear associations with BB/100. However there were some instances of association between certain explanatory variables. The strongest correlation, based on the correlation matrix in *Figure 18*, was between minutes played and hands. The Pearson correlation being .94 is not surprising. PFR% and VPIP% also had a high Pearson correlation of .837. This is also expected because a PFR is considered as volunteering money in the pot.

Figure 18

	Minutes.Played	Hands	EV	Avg.Players
Hands	0.940			
	0.000			
EV	-0.040	-0.041		
	0.000	0.000		
Avg.Players	0.073	-0.040	0.002	
	0.000	0.000	0.805	
VPIP%	0.015	0.048	-0.020	-0.425
	0.080	0.000	0.018	0.000
PFR%	0.011	0.062	-0.016	-0.464
	0.204	0.000	0.062	0.000
3Bet%	-0.009	0.014	-0.018	-0.278
	0.270	0.102	0.032	0.000
Agg.Factor	-0.095	-0.103	0.039	0.029
	0.000	0.000	0.000	0.001
WTSD%	-0.006	0.009	-0.012	-0.065
	0.499	0.317	0.159	0.000
W$SD	0.008	0.010	0.278	-0.017
	0.374	0.240	0.000	0.043
Rake	0.843	0.878	-0.040	0.014
	0.000	0.000	0.000	0.104
BBPer100	-0.043	-0.036	0.518	-0.031
	0.000	0.000	0.000	0.000

	VPIP%	PFR%	3Bet%	Agg.Factor
PFR%	0.837			
	0.000			
3Bet%	0.357	0.500		
	0.000	0.000		
Agg.Factor	-0.058	0.030	0.009	
	0.000	0.000	0.290	
WTSD%	0.053	0.084	0.091	-0.207
	0.000	0.000	0.000	0.000
W$SD	-0.006	-0.022	-0.025	-0.046
	0.494	0.009	0.003	0.000
Rake	0.059	0.021	-0.024	-0.093
	0.000	0.012	0.005	0.000
BBPer100	0.005	-0.009	-0.028	0.026
	0.558	0.309	0.001	0.003

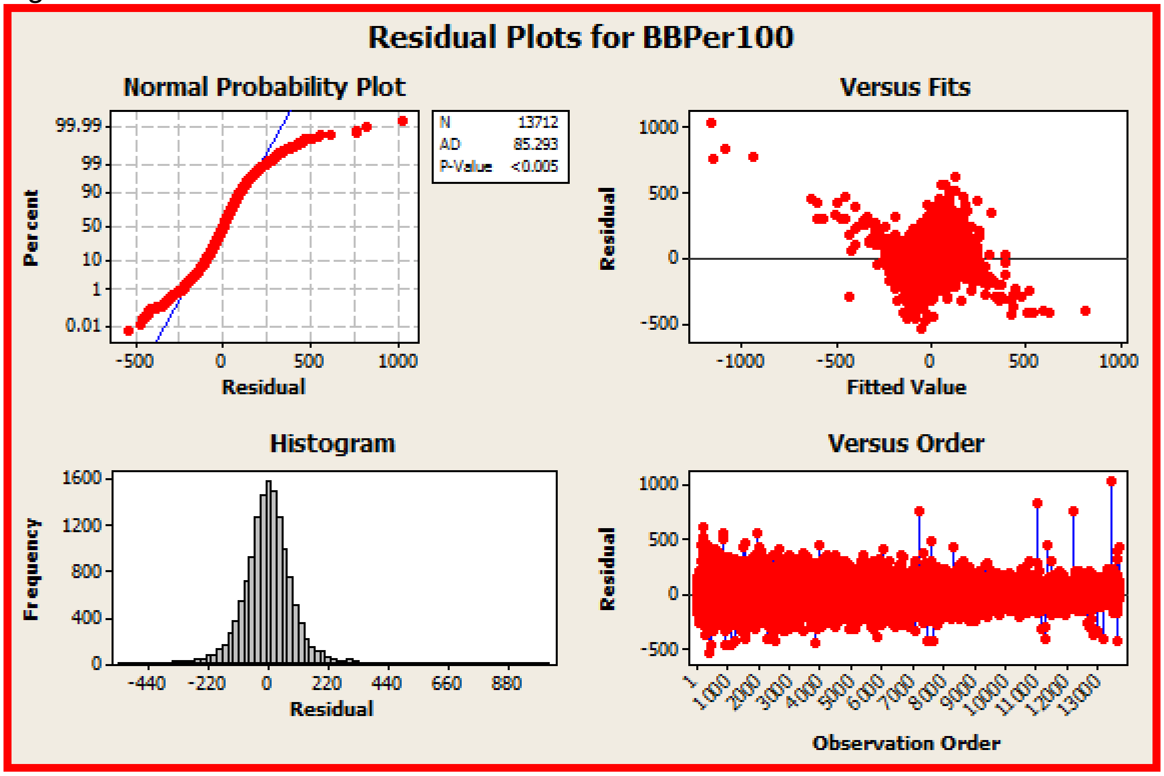
	WTSD%	W$SD	Rake
W$SD	0.093		
	0.000		
Rake	0.016	0.015	
	0.055	0.076	
BBPer100	0.006	0.533	-0.034
	0.474	0.000	0.000

Cell Contents: Pearson correlation
P-Value

Multiple Regression Analysis

Now, with the simple regression complete I can begin the multiple regression. I am going to start with the saturated model. Below is the analysis. *Figure 19* shows the residual analysis.

Figure 19



Residual vs. fits shows some issues but there are only a few points that do not behave.

The residual plots carry the same story as previously. They are not the best but they are acceptable considering the sample size and I am going to continue the analysis. There are only a few observations that are making the residual vs. fits graph look imperfect. This is acceptable.

Below, *Figure 20* is the Minitab output for the saturated model.

Figure 20

Regression Analysis: BBPer100 versus Minutes.Played, Hands, ...

The regression equation is

```
BBPer100 = - 52.7 - 0.122 Minutes.Played + 0.0554 Hands + 0.0511 EV
           - 5.64 Avg.Players + 0.662 VPIP% - 0.540 PFR% - 0.429 3Bet%
           + 0.754 Agg.Factor - 0.258 WTSD% + 1.93 W$SD - 0.145 Rake
```

Predictor	Coef	SE Coef	T	P
Constant	-52.67	12.82	-4.11	0.000
Minutes.Played	-0.12158	0.05413	-2.25	0.025
Hands	0.05542	0.03837	1.44	0.149
EV	0.0511005	0.0008619	59.29	0.000
Avg.Players	-5.635	1.892	-2.98	0.003
VPIP%	0.6621	0.2310	2.87	0.004
PFR%	-0.5402	0.2914	-1.85	0.064
3Bet%	-0.4293	0.1957	-2.19	0.028
Agg.Factor	0.7542	0.1921	3.93	0.000
WTSD%	-0.25799	0.07406	-3.48	0.000
W$SD	1.93027	0.03053	63.22	0.000
Rake	-0.1450	0.1375	-1.05	0.292

S = 89.9535   R-Sq = 43.6%   R-Sq(adj) = 43.5%

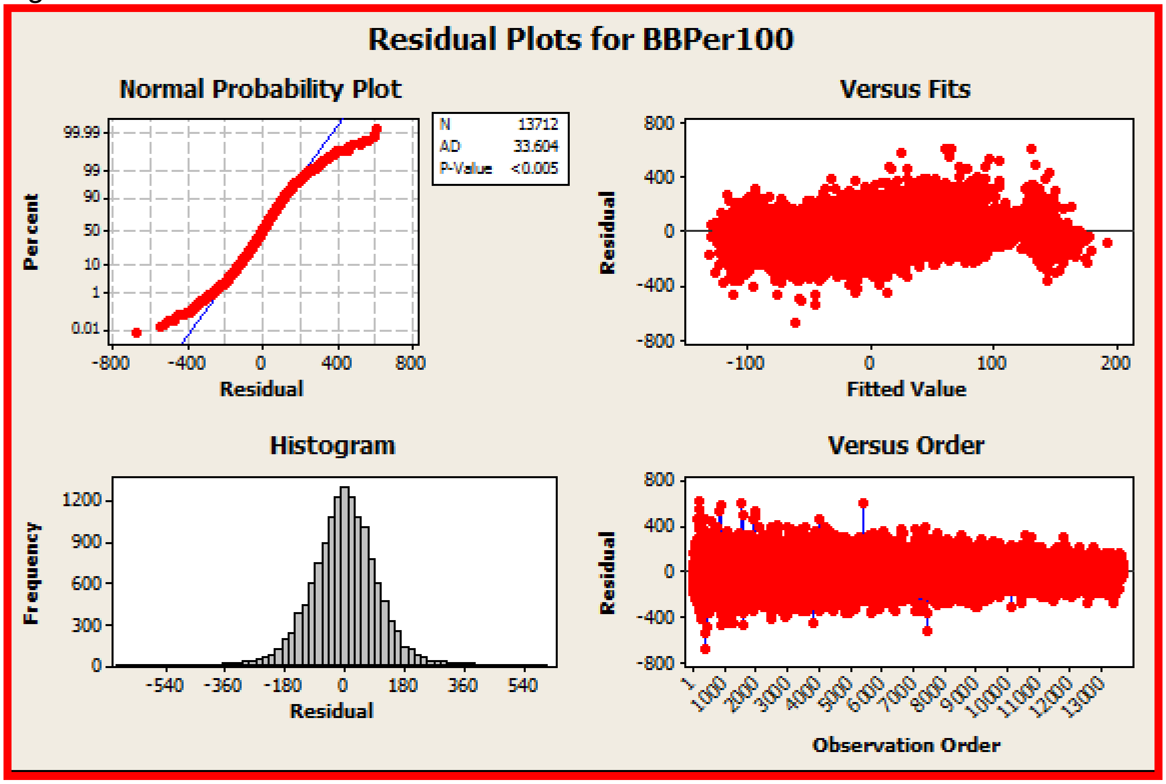
Analysis of Variance

Source	DF	SS	MS	F	P
Regression	11	85663190	7787563	962.42	0.000
Residual Error	13700	110855455	8092		
Total	13711	196518645			

This is the first time in my report that I realized that it would not be acceptable to include EV as an explanatory variable. Poker Manager calculates EV as a function of profit. It takes the actual expected values (as statisticians know the term) and then takes the difference of that number and the actual profit earned. This does not work for my analysis because then I have the problem of predicting BB/100 (which is a function of profit) with EV, which is also a function of profit. Thus, I will not be using EV for the rest of my analysis.

Figure 22 shows the new saturated model without EV. While *Figure 21* shows the residual analysis.

Figure 21



Residual plots actually look a little better without EV in the model.

Figure 22

Regression Analysis: BBPer100 versus Minutes.Played, Hands, ...

```
The regression equation is
BBPer100 = - 68.2 - 0.133 Minutes.Played + 0.0474 Hands - 5.65 Avg.Players
           + 0.474 VPIP% - 0.377 PFR% - 0.531 3Bet% + 1.21 Agg.Factor
           - 0.386 WTSD% + 2.44 W$SD - 0.222 Rake
```

Predictor	Coef	SE Coef	T	P
Constant	-68.22	14.37	-4.75	0.000
Minutes.Played	-0.13328	0.06067	-2.20	0.028
Hands	0.04741	0.04301	1.10	0.270
Avg.Players	-5.651	2.121	-2.66	0.008
VPIP%	0.4735	0.2589	1.83	0.067
PFR%	-0.3768	0.3266	-1.15	0.249
3Bet%	-0.5309	0.2193	-2.42	0.016
Agg.Factor	1.2072	0.2151	5.61	0.000
WTSD%	-0.38647	0.08298	-4.66	0.000
W$SD	2.44063	0.03284	74.33	0.000
Rake	-0.2216	0.1542	-1.44	0.151

S = 100.833   R-Sq = 29.1%   R-Sq(adj) = 29.1%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	10	57217127	5721713	562.76	0.000
Residual Error	13701	139301518	10167		
Total	13711	196518645			

The first thing to notice is that the R-Squared value went down a lot. It turns out that EV was accounting for a large amount of the variation in win rate. The new R-squared is not even 1% higher than the model with only W%SD. Yet, 6 out of 10 predictors are significant at the .05 level. The new R-squared value is about 30%. This was disappointing for me. This means that there was still 70% of variation in win rate unaccounted for. I believe the explanatory variables included are a fairly good representation of the skill accounted for poker. Perhaps I am missing a key variable. Perhaps that variable is luck. The most profound discovery I may have found in this report is that poker is 30% skill and 70% luck. Poker analysts have not found a clear and exact way to quantify luck in poker without knowing every players cards from the beginning of the hand. Although, every poker player will tell you how unlucky they are.

I noticed that the two Betas that had the lowest t values and highest P-values were also two of the variables that had the highest correlation. First, I took Minutes Played out first since we have been speaking in terms of hands rather than time for most of this report. My thought was that this would now make hands significant. However, Hands remained insignificant. So, I put Time played back in the model and took out Hands. Hands remained significant. The model did not change in terms of residuals or R-squared adjusted.

Next, I took out rake. Rake had a high p-value. Again nothing happened. No change in R-squared adjusted or residuals. None of the other variables coefficients' or P-values' changed significantly. Next, I took out PFR%. This was not a variable I would suspect as being insignificant. In the poker community it is often one of the most discussed statistics when determining good play. Given the high p-value for PFR%, not surprisingly, things remained the same after the removal.

Now there remained only one insignificant variable, VPIP%. I removed that variable and arrived at my first multiple regression model. Seen below in *Figure 23*.

Figure 23

```
The regression equation is
BBPer100 = - 55.0 - 0.111 Minutes.Played - 6.80 Avg.Players - 0.526 3Bet%
           + 1.15 Agg.Factor - 0.397 WTSD% + 2.44 W$SD


Predictor           Coef  SE Coef      T      P
Constant          -55.02    10.86  -5.07  0.000
Minutes.Played  -0.11127  0.01954  -5.69  0.000
Avg.Players       -6.801    1.856  -3.66  0.000
3Bet%            -0.5264   0.1959  -2.69  0.007
Agg.Factor        1.1475   0.2118   5.42  0.000
WTSD%           -0.39693  0.08266  -4.80  0.000
W$SD             2.44080  0.03282  74.37  0.000


S = 100.837   R-Sq = 29.1%   R-Sq(adj) = 29.1%


Analysis of Variance

Source            DF         SS       MS       F      P
Regression         6   57166141  9527690  937.03  0.000
Residual Error  13705  139352504    10168
Total           13711  196518645
```

It seems the best regression equation I could find is:
BB/100 = 55 - .111 Minutes.Played – 6.8 Avg.Players - .526 3Bet% + 1.15 Agg.Factor - .397 WTSD% + 2.44 W$SD

The significant variables I found were Minutes played, average players, 3 bet %, Aggression factor, WTSD% and W$SD. These variables were all statistically significant for the regression analysis. However, the R sq. is quite low. I was hoping for a value closer to 80% when I started this project. The problem with having such a high sample size is that almost any variable can be found to be statistically significant but few are practically significant. If we compare this model with many predictors to the model with just W$SD we are only gaining about 1% of R-sq. This tells me that although the rest of the predictors are statistically significantly different from zero they may not be practically significant.

I was curious to see if a partial F test would even say this was a substantially better model from the simple regression with only W$SD.

Partial F-test

$H_o: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$

H_1: At least one differs from zero

$$F = \frac{\frac{140600695 - 139352504}{5}}{(139352504)/13705}$$

F= 24.55

P-value ≈ 0

Reject the null hypothesis meaning the final multiple regression model is in fact adding additional information. However, I am skeptical it added any practical value.

Forward and backward stepwise selection yielded the same optimal model, seen in *Figure 24*.

Figure 24

Alpha-to-Enter: 0.05 Alpha-to-Remove: 0.05

Response is BBPer100 on 10 predictors, with N = 13712

Step	1	2	3	4	5	6
Constant	-107.59	-114.50	-105.05	-94.25	-64.92	-55.02
W$SD	2.420	2.431	2.432	2.445	2.444	2.441
T-Value	73.84	74.21	74.31	74.52	74.50	74.37
P-Value	0.000	0.000	0.000	0.000	0.000	0.000
Agg.Factor		1.44	1.33	1.11	1.13	1.15
T-Value		6.97	6.39	5.26	5.33	5.42
P-Value		0.000	0.000	0.000	0.000	0.000
Minutes.Played			-0.114	-0.116	-0.112	-0.111
T-Value			-5.84	-5.98	-5.73	-5.69
P-Value			0.000	0.000	0.000	0.000
WTSD%				-0.401	-0.416	-0.397
T-Value				-4.88	-5.05	-4.80
P-Value				0.000	0.000	0.000
Avg.Players					-5.4	-6.8
T-Value					-3.04	-3.66
P-Value					0.002	0.000
3Bet%						-0.53
T-Value						-2.69
P-Value						0.007
S	101	101	101	101	101	101
R-Sq	28.45	28.70	28.88	29.00	29.05	29.09
R-Sq(adj)	28.45	28.69	28.87	28.98	29.03	29.06
Mallows Cp	121.4	74.6	42.3	20.5	13.2	8.0

Best subsets also shows that the model I found is optimal, based on the lowest Mallows Cp. Shown in *Figure 25*. Every method I used to get from the saturated model to the final model yielded the same significant variables. I am confident the final model I obtained is the best model available.

Figure 25

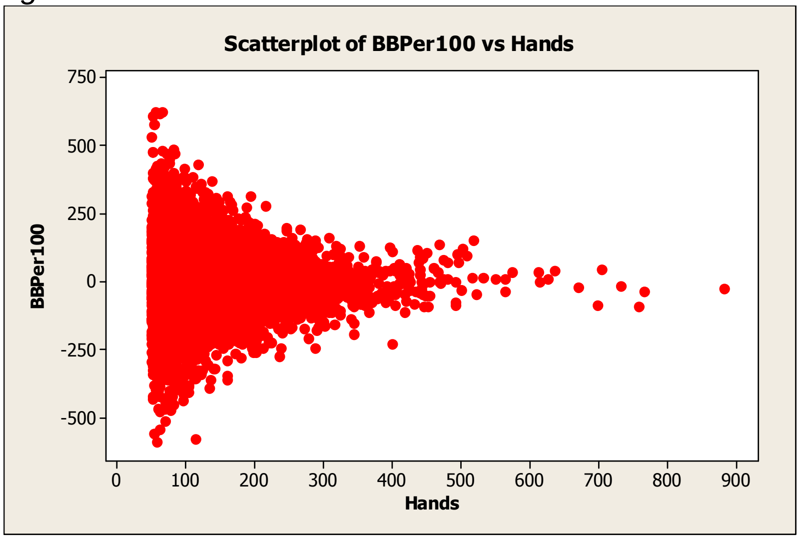
Response is BBPer100

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Minutes.Played	Hands	Avg.Players	VPIP%	PFR%	3Bet%	Agg.Factor	WTSD%	W$SD	Rake
1	28.5	28.4	121.4	101.27									X	
1	0.2	0.2	5585.5	119.62	X									
2	28.7	28.7	74.6	101.10							X		X	
2	28.7	28.7	81.3	101.12	X								X	
3	28.9	28.9	42.3	100.97	X						X		X	
3	28.9	28.8	46.1	100.99	X							X	X	
4	29.0	29.0	20.5	100.89	X						X	X	X	
4	29.0	28.9	28.5	100.92							X	X	X	X
5	29.1	29.0	13.2	100.86	X		X				X	X	X	
5	29.0	29.0	18.1	100.88		X	X				X	X	X	
6	29.1	29.1	8.0	100.84	X		X			X	X	X	X	
6	29.1	29.0	12.6	100.85		X	X			X	X	X	X	
7	29.1	29.1	8.2	100.83	X		X	X		X	X	X	X	
7	29.1	29.1	9.3	100.84	X		X			X	X	X	X	X
8	29.1	29.1	9.2	100.83	X		X	X		X	X	X	X	X
8	29.1	29.1	9.3	100.83	X		X	X	X	X	X	X	X	
9	29.1	29.1	10.2	100.83	X		X	X	X	X	X	X	X	X
9	29.1	29.1	10.3	100.83	X	X	X	X		X	X	X	X	X
10	29.1	29.1	11.0	100.83	X	X	X	X	X	X	X	X	X	X

Multiple regression Analysis for NL400

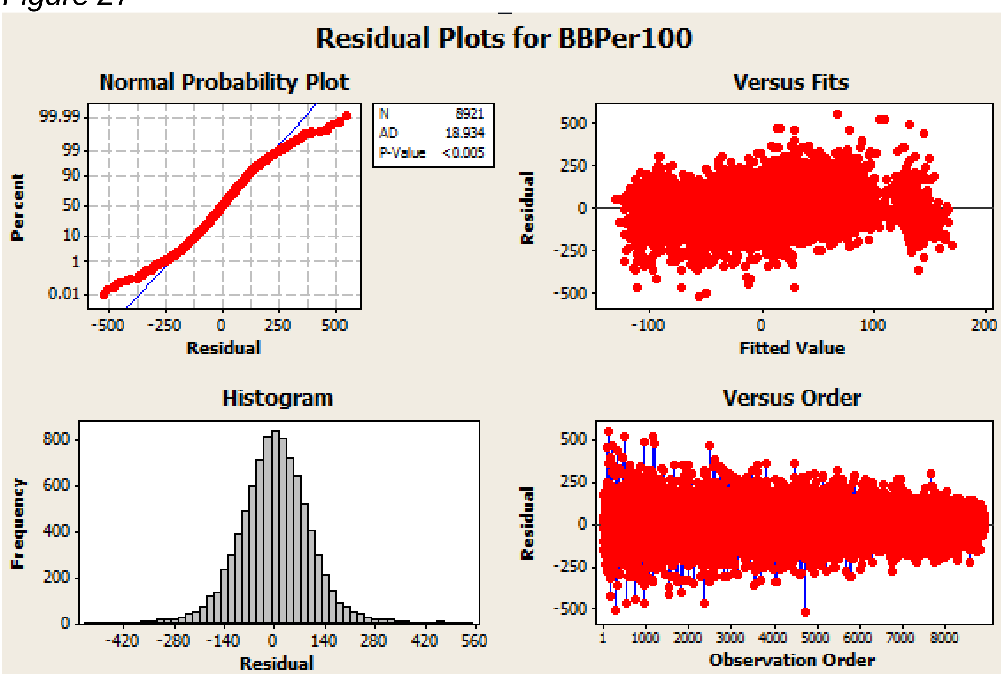
I decided to do a multiple regression analysis on only one limit of play. Mike has played the most hands, by far, at No limit 400. Mike has played 1226761 hands at this stake and profited 229,460.75 dollars. This is also by the far the most profit he has made at any stake. Like in the complete analysis I had to remove the sessions that were less than 50 hands. Below in *Figure 26* is a scatter plot of hands Vs Win Rate, without any sessions with less than 50 hands.

Figure 26



Below is the saturated model residual analysis and results.

Figure 27



The residual analysis actually looks pretty good. There is a slight problem with normality but nothing ghastly. Also, there seems to be a bit of an upward trend in the residual vs fits graph but also nothing too terrible.

Figure 28

Regression Analysis: BBPer100 versus Minutes.Played, Hands, ...

```
The regression equation is
BBPer100 = - 49.1 - 0.211 Minutes.Played + 0.0822 Hands - 8.93 Avg.Players
           + 0.712 VPIP% - 0.746 PFR% - 0.238 3Bet% + 1.17 Agg.Factor
           - 0.459 WTSD% + 2.40 W$SD - 0.051 Rake
```

Predictor	Coef	SE Coef	T	P
Constant	-49.07	19.16	-2.56	0.010
Minutes.Played	-0.21098	0.07712	-2.74	0.006
Hands	0.08225	0.05404	1.52	0.128
Avg.Players	-8.932	2.882	-3.10	0.002
VPIP%	0.7124	0.3487	2.04	0.041
PFR%	-0.7459	0.4245	-1.76	0.079
3Bet%	-0.2380	0.2796	-0.85	0.395
Agg.Factor	1.1654	0.2637	4.42	0.000
WTSD%	-0.4590	0.1031	-4.45	0.000
W$SD	2.39575	0.03982	60.16	0.000
Rake	-0.0514	0.2466	-0.21	0.835

S = 98.3316   R-Sq = 29.3%   R-Sq(adj) = 29.2%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	10	35651306	3565131	368.71	0.000
Residual Error	8910	86151676	9669		
Total	8920	121802982			

The regression analysis looks similar to the saturated model that included every stake. The R-squared are nearly identical, as are some of the coefficients. I came to the final model in a similar approach as I performed with all the data. *Figure 29* shows the final model.

Figure 29

```
The regression equation is
BBPer100 = - 41.9 - 0.0950 Minutes.Played - 10.1 Avg.Players + 0.703 VPIP%
           - 0.814 PFR% + 1.14 Agg.Factor - 0.462 WTSD% + 2.40 W$SD


Predictor           Coef   SE Coef      T      P
Constant          -41.86     18.43  -2.27  0.023
Minutes.Played  -0.09500   0.02412  -3.94  0.000
Avg.Players      -10.069     2.770  -3.64  0.000
VPIP%             0.7027    0.3244   2.17  0.030
PFR%             -0.8142    0.3833  -2.12  0.034
Agg.Factor        1.1442    0.2631   4.35  0.000
WTSD%            -0.4618    0.1027  -4.49  0.000
W$SD             2.39651   0.03982  60.19  0.000


S = 98.3347   R-Sq = 29.2%   R-Sq(adj) = 29.2%


Analysis of Variance

Source            DF          SS       MS       F      P
Regression         7    35616886  5088127  526.19  0.000
Residual Error  8913    86186096     9670
Total           8920   121802982
```

This analysis proved to be slightly different in terms of what variables are included in the model. *Figure 30* is a chart that illustrates the differences.

Figure 30

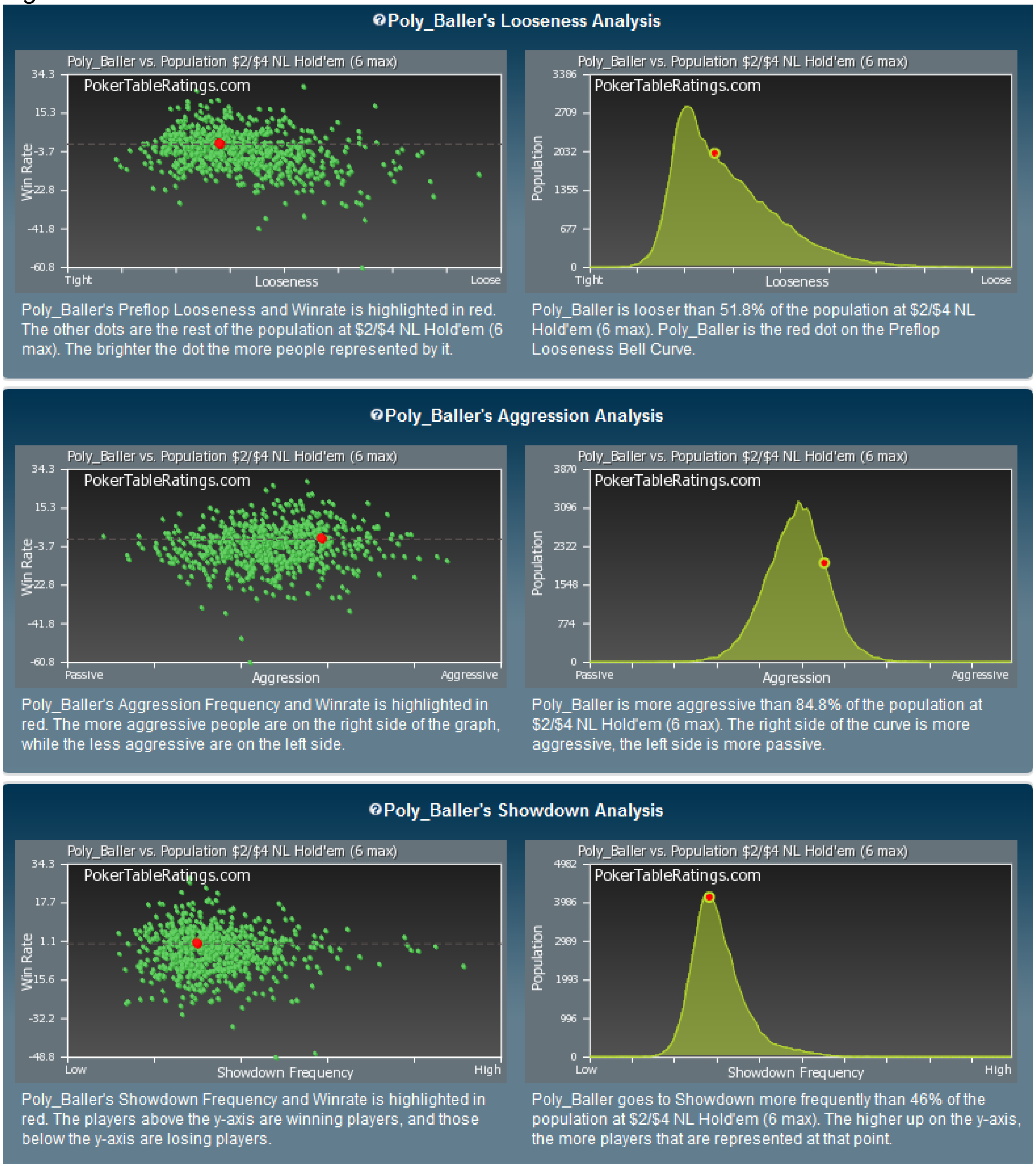
Variable	All stakes	NL 400
Minutes Played	-.111	-.095
Average players	-6.801	-10.069
3 bet%	-.5264	
VPIP%		.7027
Aggression factor	1.1475	1.1442
PFR%		-.8142
WTSD%	-.39693	-.4618
W$SD	2.4408	2.39651

For the most part the coefficients are very similar for the overlapping explanatory variables. The NL 400 model penalizes a bit more for more people at the table. The NL 400 model also has one more significant variable. The variables in both models that do not have their counterpart in the other model are all small, meaning close to zero and more in the model because of their statistical significant but not their practical significance.

Poker Tracker Analysis

The output shown below in *Figure 31* is from Pokertableratings.com or PTR. PTR is a free online site that aims to track every player's performance that plays online poker. It is useful for quickly checking the statistics of opponents you meet online. It is effective for getting a general idea of a player. There are drawbacks though. The site only has data for the last year and a half, roughly. Also it tends to miss some sessions for whatever reason. So, it is not perfect, but many players use it as a general guide to look at different player's playing style. The output below compares Mike's play at NL 400 to other players at the same stakes. It shows that mikes play is pretty average in terms of looseness but he is quite aggressive compared to others. It also shows that his win rate is right in the middle of the y axis maybe a bit higher than average. The bottom two graphs show his show down frequency as being fairly average because his point is right at the peak. They do not explicitly explain how they arrive at their scale for looseness and aggression but it seems to be a composite of some of the variables I have included in my report.

Figure 30


Poly_Baller's Looseness Analysis
Poly_Baller vs. Population $2/$4 NL Hold'em (6 max)
PokerTableRatings.com
34.3
15.3
-3.7
-22.8
-41.8
-60.8
Win Rate
Tight
Looseness
Loose
Poly_Baller vs. Population $2/$4 NL Hold'em (6 max)
PokerTableRatings.com
3386
2709
2032
1355
677
0
Population
Tight
Looseness
Loose
Poly_Baller's Preflop Looseness and Winrate is highlighted in red. The other dots are the rest of the population at $2/$4 NL Hold'em (6 max). The brighter the dot the more people represented by it.
Poly_Baller is looser than 51.8% of the population at $2/$4 NL Hold'em (6 max). Poly_Baller is the red dot on the Preflop Looseness Bell Curve.
Poly_Baller's Aggression Analysis
Poly_Baller vs. Population $2/$4 NL Hold'em (6 max)
PokerTableRatings.com
34.3
15.3
-3.7
-22.8
-41.8
-60.8
Win Rate
Passive
Aggression
Aggressive
Poly_Baller vs. Population $2/$4 NL Hold'em (6 max)
PokerTableRatings.com
3870
3096
2322
1548
774
0
Population
Passive
Aggression
Aggressive
Poly_Baller's Aggression Frequency and Winrate is highlighted in red. The more aggressive people are on the right side of the graph, while the less aggressive are on the left side.
Poly_Baller is more aggressive than 84.8% of the population at $2/$4 NL Hold'em (6 max). The right side of the curve is more aggressive, the left side is more passive.
Poly_Baller's Showdown Analysis
Poly_Baller vs. Population $2/$4 NL Hold'em (6 max)
PokerTableRatings.com
34.3
17.7
1.1
-15.6
-32.2
-48.8
Win Rate
Low
Showdown Frequency
High
Poly_Baller vs. Population $2/$4 NL Hold'em (6 max)
PokerTableRatings.com
4982
3986
2989
1993
996
0
Population
Low
Showdown Frequency
High
Poly_Baller's Showdown Frequency and Winrate is highlighted in red. The players above the y-axis are winning players, and those below the y-axis are losing players.
Poly_Baller goes to Showdown more frequently than 46% of the population at $2/$4 NL Hold'em (6 max). The higher up on the y-axis, the more players that are represented at that point.

ANOVA Analysis

I wanted to see if Mike played differently at different stakes. In theory, Mike should play the same no matter what stakes he is playing. If it is a winning strategy at one level then in theory it should work at other stakes because you are still playing the same game. The first variable I wanted to test was his Win Rate. *Figure 31* shows the 1-way ANOVA analysis.

Figure 30

One-way ANOVA: BBPer100 versus Stakes

```
Source     DF         SS     MS     F      P
Stakes     12     116716   9726  0.68  0.774
Error   13699  196401929  14337
Total   13711  196518645

S = 119.7   R-Sq = 0.06%   R-Sq(adj) = 0.00%


                                    Individual 95% CIs For Mean Based on
                                    Pooled StDev
Level              N    Mean  StDev ---+---------+---------+---------+------
$0.02/0.05 NL      1  -222.4      *  (-----------*-----------)
$0.1/0.25 NL       8    15.1  104.4                    (---*---)
$0.25/0.5 NL     615    12.0  131.7                       (*
$0.5/1 NL         48     8.6  176.8                      (*-)
$1/2 NL          626     3.3  127.7                       *)
$10/20 LIM         1   -18.5      *           (-----------*-----------)
$10/20 NL        180     2.4  137.9                      (*)
$2/4 NL         8921     5.3  116.9                       *
$25/50 NL         98    -9.8  148.1                     (-*)
$3/6 NL          101    15.1  138.6                       (*)
$30/60 LIM         2     5.4   15.8                (-------*--------)
$5/10 LIM         21     6.4   17.5                     (-*--)
$5/10 NL        3090     5.5  120.4                       *
                                    ---+---------+---------+---------+------
                                    -400      -200         0       200

Pooled StDev = 119.7
```

Clearly, I need to remove the stakes where he has not played many sessions with more than 50 hands. I decided to remove the stakes where Mike has played less than 50 sessions. Below is the new analysis.

Figure 31

One-way ANOVA: BBPer100 versus Stakes

```
Source     DF         SS     MS     F      P
Stakes      6      62981  10497  0.73  0.622
Error   13624  194850420  14302
Total   13630  194913401

S = 119.6   R-Sq = 0.03%   R-Sq(adj) = 0.00%


                                  Individual 95% CIs For Mean Based on
                                  Pooled StDev
Level            N  Mean  StDev  -------+---------+---------+---------+--
$0.25/0.5 NL   615  12.0  131.7                    (----*----)
$1/2 NL        626   3.3  127.7                (----*---)
$10/20 NL      180   2.4  137.9           (--------*--------)
$2/4 NL       8921   5.3  116.9                    (-*)
$25/50 NL       98  -9.8  148.1   (-----------*-----------)
$3/6 NL        101  15.1  138.6               (-----------*----------)
$5/10 NL      3090   5.5  120.4                    (-*-)
                                 -------+---------+---------+---------+--
                                      -20         0        20        40

Pooled StDev = 119.6
```

The output suggests that there is no difference in the mean win rates at each stake.

The next variable that I wanted to check was the aggression factor. Mike plays quite aggressive compared to other players. Often one of the consequences of playing at higher stakes is that players get timid, and thus not as aggressive. Below in *Figure 32* is the ANOVA analysis.

Figure 32

One-way ANOVA: Agg.Factor versus Stakes

Source	DF	SS	MS	F	P
Stakes	6	119.4	19.9	1.13	0.340
Error	13624	239138.3	17.6		
Total	13630	239257.7			

S = 4.190   R-Sq = 0.05%   R-Sq(adj) = 0.01%

Level	N	Mean	StDev
$0.25/0.5 NL	615	4.313	4.718
$1/2 NL	626	4.498	4.120
$10/20 NL	180	4.846	4.543
$2/4 NL	8921	4.472	4.127
$25/50 NL	98	4.436	4.868
$3/6 NL	101	3.590	2.501
$5/10 NL	3090	4.448	4.271

```
              Individual 95% CIs For Mean Based on Pooled StDev
Level           +---------+---------+---------+---------
$0.25/0.5 NL                     (----*---)
$1/2 NL                             (---*----)
$10/20 NL                           (--------*--------)
$2/4 NL                                (*)
$25/50 NL                   (----------*-----------)
$3/6 NL         (----------*-----------)
$5/10 NL                             (--*-)
                +---------+---------+---------+---------
              2.80      3.50      4.20      4.90
```

Pooled StDev = 4.190

Once again there is no difference in mean aggression factors across all stakes.

I found one significant ANOVA analysis that I did not expect to find. It turns out that the number of people at the table has a significant difference. Analysis in *Figure 33.*

Figure 33

One-way ANOVA: Avg.Players versus Stakes

Source	DF	SS	MS	F	P
Stakes	6	55.140	9.190	40.09	0.000
Error	13624	3122.839	0.229		
Total	13630	3177.979			

S = 0.4788   R-Sq = 1.74%   R-Sq(adj) = 1.69%

```
                                    Individual 95% CIs For Mean Based on
                                    Pooled StDev
Level            N    Mean   StDev  --------+---------+---------+---------+-
$0.25/0.5 NL   615  5.4039  0.3792         (*)
$1/2 NL        626  5.4262  0.5216          (*)
$10/20 NL      180  5.2383  0.8371  (--*-)
$2/4 NL       8921  5.4102  0.4211          *)
$25/50 NL       98  6.0755  1.5398                             (---*--)
$3/6 NL        101  5.3663  0.4746      (--*--)
$5/10 NL      3090  5.3628  0.5413        (*
                                    --------+---------+---------+---------+-
                                          5.40      5.70      6.00      6.30
```

Pooled StDev = 0.4788

It appears that at the highest stake, 25/50, Mike tended to play with more people. This is interesting because in the regression analysis avg.Players was a significant predictor with a negative coefficient. Also 25/50 is the only stake that Mike has a negative win rate.

Figure 34

One-way ANOVA: VPIP% versus Stakes

```
Source     DF        SS      MS      F      P
Stakes      6   19034.0  3172.3  83.15  0.000
Error   13624  519750.8    38.1
Total   13630  538784.8

S = 6.177   R-Sq = 3.53%   R-Sq(adj) = 3.49%


                                   Individual 95% CIs For Mean Based on
                                   Pooled StDev
Level            N    Mean  StDev  -------+---------+---------+---------+--
$0.25/0.5 NL   615  33.773  6.730                          (--*--)
$1/2 NL        626  32.440  7.368                  (--*--)
$10/20 NL      180  32.488  8.270               (-----*-----)
$2/4 NL       8921  29.659  5.924    *)
$25/50 NL       98  34.318  9.277                         (------*-------)
$3/6 NL        101  34.265  7.905                         (------*-------)
$5/10 NL      3090  29.503  6.185  (*-)
                                   -------+---------+---------+---------+--
                                       30.4      32.0      33.6      35.2

Pooled StDev = 6.177
```

Figure 34 shows VPIP% had at least one significantly different mean at the different stakes. It appears when Mike plays 2/4, his most profitable stake, he has a lower VPIP%. This may be an indication that a lower VPIP% is better but the regression analysis showed that it had a slightly positive slope. I wouldn't say that the difference in means is only statistically significant and not practically significant either. There is about a 4% difference in the mean at 2/4 compared to the other group of means.

Figure 35

One-way ANOVA: PFR% versus Stakes

```
Source     DF        SS      MS      F      P
Stakes      6   10142.3  1690.4  58.19  0.000
Error   13624  395797.4    29.1
Total   13630  405939.7

S = 5.390   R-Sq = 2.50%   R-Sq(adj) = 2.46%


                                   Individual 95% CIs For Mean Based on
                                   Pooled StDev
Level            N    Mean  StDev  ----+---------+---------+---------+-----
$0.25/0.5 NL   615  21.275  4.952     (--*--)
$1/2 NL        626  23.980  6.631                       (--*--)
$10/20 NL      180  23.140  7.552               (----*-----)
$2/4 NL       8921  20.525  5.096  (*)
$25/50 NL       98  25.003  9.209                          (------*------)
$3/6 NL        101  22.666  6.088          (------*------)
$5/10 NL      3090  20.873  5.674    (*)
                                   ----+---------+---------+---------+-----
                                    21.0      22.5      24.0      25.5

Pooled StDev = 5.390
```

The means for PFR% seem to be all over the place, each mean being different from almost all the other means. The only thing that could be intelligible from this is that Mike has the highest PFR% at 25/50 which is the highest stakes he played and his only stake where he has a losing win rate.

Figure 36

One-way ANOVA: 3Bet% versus Stakes

```
Source     DF        SS      MS      F      P
Stakes      6    6571.7  1095.3  53.65  0.000
Error   13624  278159.2    20.4
Total   13630  284730.9

S = 4.519   R-Sq = 2.31%   R-Sq(adj) = 2.27%


                                   Individual 95% CIs For Mean Based on
                                   Pooled StDev
Level            N   Mean  StDev  ---+---------+---------+---------+------
$0.25/0.5 NL   615  4.891  4.532   (--*--)
$1/2 NL        626  8.132  5.676                            (--*--)
$10/20 NL      180  6.622  4.923               (----*-----)
$2/4 NL       8921  5.279  4.278        (*)
$25/50 NL       98  7.778  6.166                      (-------*------)
$3/6 NL        101  5.280  4.618  (------*------)
$5/10 NL      3090  6.064  4.829              (-*)
                                  ---+---------+---------+---------+------
                                   4.8       6.0       7.2       8.4

Pooled StDev = 4.519
```

This ANOVA analysis may be a case of statistical significance but not practical significance. The difference between the lowest and highest is only a little more than 2%.

Figure 37

One-way ANOVA: WTSD% versus Stakes

```
Source     DF       SS   MS     F      P
Stakes      6     2833  472  4.10  0.000
Error   13624  1568987  115
Total   13630  1571820

S = 10.73   R-Sq = 0.18%   R-Sq(adj) = 0.14%


                                   Individual 95% CIs For Mean Based on
                                   Pooled StDev
Level            N   Mean  StDev  -----+---------+---------+---------+----
$0.25/0.5 NL   615  26.51   9.03              (----*---)
$1/2 NL        626  26.18  11.33             (---*---)
$10/20 NL      180  24.53  10.30  (-------*------)
$2/4 NL       8921  25.35  10.47            (*)
$25/50 NL       98  27.26  10.49            (---------*----------)
$3/6 NL        101  27.15   8.32           (----------*---------)
$5/10 NL      3090  26.13  11.71               (-*-)
                                  -----+---------+---------+---------+----
                                     24.0      26.0      28.0      30.0

Pooled StDev = 10.73
```

The same case here as above. There is only statistical significance but not practical differences. The lowest mean is only 2 percent lower than the highest which is not much.

Figure 38

One-way ANOVA: W$SD versus Stakes

Source	DF	SS	MS	F	P
Stakes	6	7097	1183	1.70	0.117
Error	13624	9499828	697		
Total	13630	9506925			

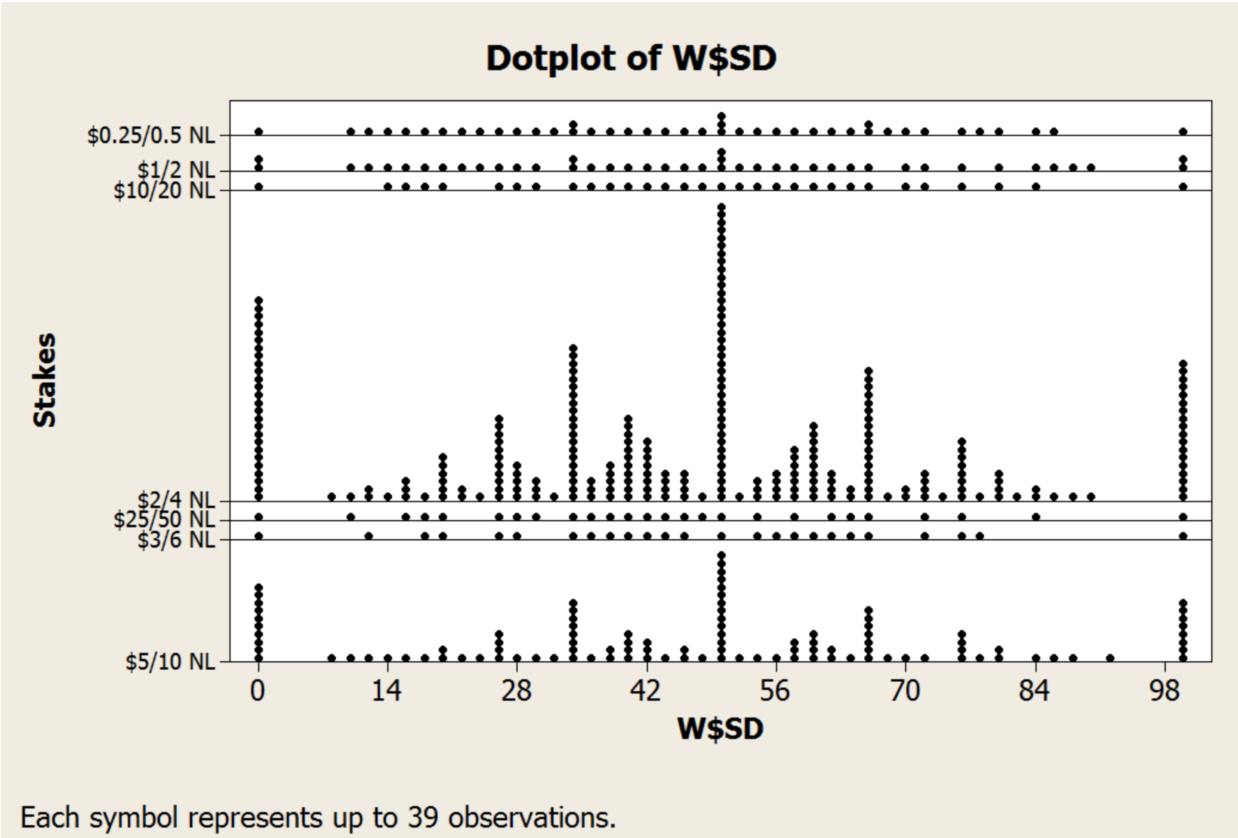
S = 26.41   R-Sq = 0.07%   R-Sq(adj) = 0.03%

Level	N	Mean	StDev
$0.25/0.5 NL	615	47.16	21.10
$1/2 NL	626	45.46	27.61
$10/20 NL	180	46.68	26.65
$2/4 NL	8921	46.54	26.29
$25/50 NL	98	41.13	25.91
$3/6 NL	101	45.30	20.32
$5/10 NL	3090	47.60	27.59

```
              Individual 95% CIs For Mean Based on Pooled StDev
Level            +---------+---------+---------+---------
$0.25/0.5 NL                            (----*----)
$1/2 NL                            (-----*----)
$10/20 NL                         (---------*--------)
$2/4 NL                                   (*-)
$25/50 NL        (------------*------------)
$3/6 NL                    (------------*------------)
$5/10 NL                                    (-*-)
                 +---------+---------+---------+---------
              36.0      40.0      44.0      48.0

Pooled StDev = 26.41
```

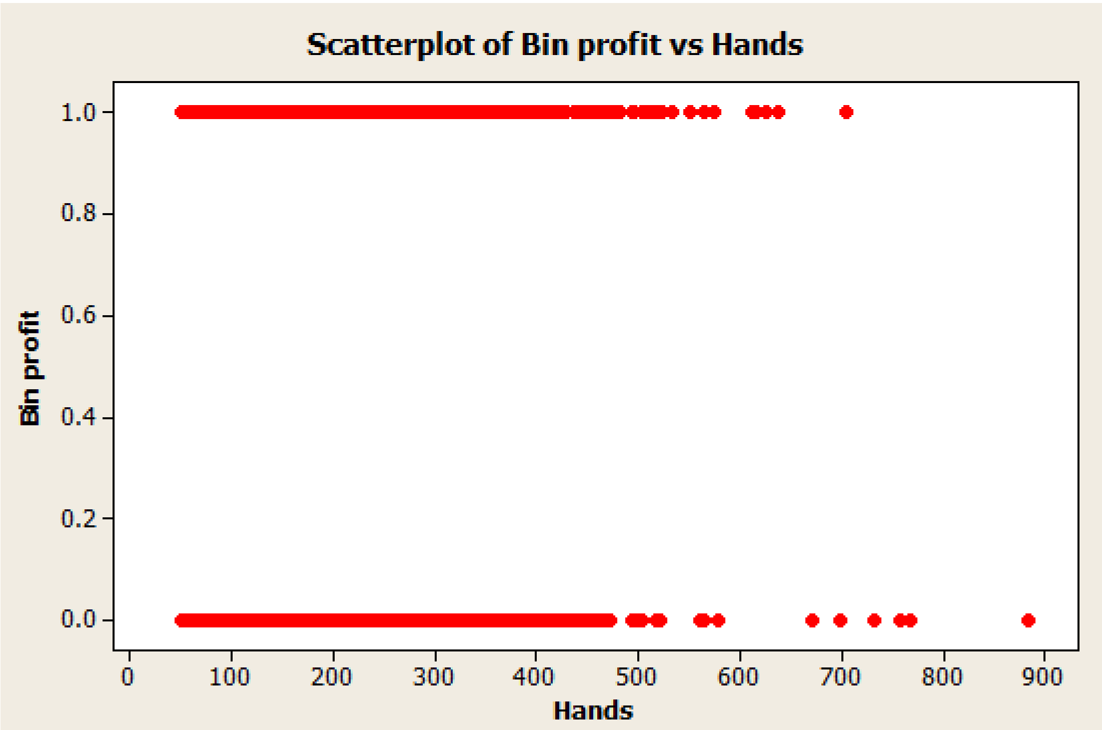
W$SD did not show any statistical differences in means. This was surprising since in the last two analyses we had a problem with too much statistically significant evidence. If you compare the standard deviations for W$SD to all the other explanatory variables you will see that they are much higher for W$SD. This can be explained by looking at the histogram for W$SD. Below in *Figure 39* is a dot plot chart that shows that the distribution of W$SD looks basically the same for each stake.

Figure 39


Dotplot of W$SD
Stakes
$0.25/0.5 NL
$1/2 NL
$10/20 NL
$2/4 NL
$25/50 NL
$3/6 NL
$5/10 NL
0
14
28
42
56
70
84
98
W$SD
Each symbol represents up to 39 observations.

Logistic Regression Analysis

I thought it would be pertinent to analyze the session analysis using logistic regression. This would allow me to look at whether or not certain aspects of Mike's game result in profit or loss. I would also be able to look at which variables contributed to increased odds of success. I made the Profit variable dichotomous by assigning it a value of 1 if the session resulted in any gains above zero dollars. Similarly, I assigned a zero to any losing sessions. I started with simple logistic regression. The first model I fit was just using hands as a predictor. Below is a scatter plot or hands vs the dichotomous profit variable.



The plot shows no real difference in the groups but I suspect there will be a very slightly negative coefficient based on the graph and the previous regression analysis, although probably still significant. The SAS output is seen in *Figure 40*.

Figure 40

Model Information

Data Set	WORK.PROJECT	
Distribution	Binomial	
Link Function	Logit	
Dependent Variable	Bin_profit	Bin profit
Observations Used	13712	

Response Profile

Ordered Value	Bin_ profit	Total Frequency
1	0	6541
2	1	7171

PROC GENMOD is modeling the probability that Bin_profit='0'. One way to change this to model the probability that Bin_profit='1' is to specify the DESCENDING option in the PROC statement.

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	14E3	18969.1468	1.3836
Scaled Deviance	14E3	18969.1468	1.3836
Pearson Chi-Square	14E3	13712.0003	1.0001
Scaled Pearson X2	14E3	13712.0003	1.0001
Log Likelihood		-9484.5734	

Algorithm converged.

Analysis Of Parameter Estimates

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-0.1924	0.0351	-0.2611	-0.1236	30.05	<.0001
Hands	1	0.0008	0.0002	0.0003	0.0013	10.74	0.0010
Scale	0	1.0000	0.0000	1.0000	1.0000		

The regression equation is

$$\ln\left(\frac{\pi}{1-\pi}\right) = -0.1924 + .0008x$$

Remember the regression equation should be converted to make is interpretable. Shown below.

$$\hat{\pi} = \frac{e^{-0.1924+.0008x}}{1+e^{-0.1924+.0008x}}$$

The estimated odds of a winning session multiply by $(e^{.0008})$ = 1.00080032 for each 1 hand increase in the number of hands per session. This is incredibly close to 1, meaning it does not affect the estimated odds of a successful session very much. Here is another case of a statistically significant predictor that is not practically significant.

Next I fit a multiple logistic regression model. I started with the saturated model and started removing insignificant variables, starting with the least significant, until everything was significant. *Figure 41* shows the final model.

Figure 41

The GENMOD Procedure

Model Information

Data Set	WORK.PROJECT	
Distribution	Binomial	
Link Function	Logit	
Dependent Variable	Bin_profit	Bin profit
Observations Used	13712	

Response Profile

Ordered Value	Bin_ profit	Total Frequency
1	1	7171
2	0	6541

PROC GENMOD is modeling the probability that Bin_profit='1'.

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	14E3	15339.5288	1.1192
Scaled Deviance	14E3	15339.5288	1.1192
Pearson Chi-Square	14E3	14714.1236	1.0736
Scaled Pearson X2	14E3	14714.1236	1.0736
Log Likelihood		-7669.7644	

Algorithm converged.

Analysis Of Parameter Estimates

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-1.8847	0.1097	-2.0997	-1.6696	295.05	<.0001
Minutes_Played	1	-0.0023	0.0004	-0.0032	-0.0015	30.01	<.0001
PFR_	1	0.0093	0.0036	0.0023	0.0164	6.70	0.0096
Agg_Factor	1	0.0296	0.0051	0.0195	0.0397	33.09	<.0001
WTSD_	1	-0.0148	0.0020	-0.0187	-0.0110	55.86	<.0001
W_SD	1	0.0488	0.0010	0.0469	0.0508	2427.16	<.0001
Scale	0	1.0000	0.0000	1.0000	1.0000		

It seems we are not going to see a lot of practical significance. The odds ratios are all very close to zero. It is interesting that we yielded less significant variables in logistic regression than regular multiple regression. Below is a chart of each estimate in exponential form.

Figure 42

Variable	Exp^estimate
Minutes played	.9977
PFR%	1.0093
Aggression factor	1.03
WTSD%	.9853

W$SD	1.0500

All of these odds estimates are very close to one. This indicates that none of the predictors practically significantly increase or decrease the predicted odds of a successful winning session, holding all other variables constant. The logistic regression portion of the analysis proved not to be as fruitful as expected. I was going to run a cross validation test but my computer could not handle that many calculations and I am very confident the cross validation test would yield results right around 50%, showing the model is better than random guessing.

Outlier Analysis

I wanted to do an outlier analysis that would look at the all the extremely good and bad results Mike had encountered. I wanted to look at the most winning and losing sessions Mike endured and try to figure out why they happened. I also wanted to look at which players have taken the most money from Mike and which players Mike has profited the most from. Below is a chart showing the players Mike has profited from the most and who has won the most against Mike.

Figure 43

Opponent	Wins	Losses	20BB+ Wins	20BB+ Losses	50BB+ Wins	50BB+ Losses	Largest Win	Largest Loss	$
Killer_ooooo (ps)	264	211	18	8	6	3	$5,442.00	($2,068.00)	$24,475.50
thorladen (ps)	120	58	7	3	4	1	$5,000.00	($5,000.00)	$19,407.50
DerekJC9954 (ps)	2484	1969	78	63	33	19	$1,738.25	($1,199.50)	$14,649.19
twin-caracas (ps)	1167	905	89	107	35	65	$1,590.00	($2,402.00)	($16,002.89)
ADZ124 (ps)	472	346	14	28	7	11	$6,595.00	($8,515.15)	($19,167.15)
BrynKenney (ps)	763	499	29	41	12	16	$5,771.00	($10,361.00)	($34,686.45)

Figure 43 shows the top three most winning and losing players vs. Mike. The largest winner, BrynKenney has taken nearly 35 thousand from Mike. This is a very substantial amount of money considering Mike has played against over 54,000 players. On the other hand, Mike is up about 24 thousand against killer_ooooo. This is also very substantial. If you consider the fact that Mike's total profit is about 260 thousand and one player has accounted for almost 10 percent of total profit, it is quite remarkable. The first thing I wanted to look at was if there was any difference between the 3 winning players and 3 losing players as a whole. I looked at a series of 2 sample t tests to see if there were any differences in the style of play between the 3 winning players and the three losing players. Each test was a two sided test. It is very important to note that I only looked at these tests and their p-values informally and only as a starting point. Since there was certainly no random sampling going on here in the outlier analysis. Any procedures in *Figure 44* are informal.

Figure 44

Two-sample T for **Minutes Played**

win lost N Mean StDev SE Mean

mike lost 173 36.4 46.2 3.5
mike won 461 38.1 35.2 1.6
Difference = mu (mike lost) - mu (mike won)
Estimate for difference: -1.66
95% CI for difference: (-9.30, 5.98)
T-Test of difference = 0 (vs not =): T-Value = -0.43 P-Value = 0.669 DF = 250

Two-sample T for **Hands**

win lost N Mean StDev SE Mean
mike lost 173 56.3 72.8 5.5
mike won 461 53.6 49.2 2.3
Difference = mu (mike lost) - mu (mike won)
Estimate for difference: 2.68
95% CI for difference: (-9.13, 14.48)
T-Test of difference = 0 (vs not =): T-Value = 0.45 P-Value = 0.656 DF = 233

Two-sample T for **Avg Players**

win lost N Mean StDev SE Mean
mike lost 173 5.88 1.27 0.096
mike won 461 5.561 0.708 0.033
Difference = mu (mike lost) - mu (mike won)
Estimate for difference: 0.318
95% CI for difference: (0.118, 0.519)
T-Test of difference = 0 (vs not =): T-Value = 3.13 P-Value = 0.002 DF = 213

Two-sample T for **VPIP%**

win lost N Mean StDev SE Mean
mike lost 173 29.0 16.3 1.2
mike won 460 23.9 12.8 0.60
Difference = mu (mike lost) - mu (mike won)
Estimate for difference: 5.10
95% CI for difference: (2.39, 7.82)
T-Test of difference = 0 (vs not =): T-Value = 3.71 P-Value = 0.000 DF = 255

Two-sample T for **PFR%**

win lost N Mean StDev SE Mean
mike lost 173 21.0 15.7 1.2
mike won 460 17.6 10.6 0.49
Difference = mu (mike lost) - mu (mike won)
Estimate for difference: 3.40
95% CI for difference: (0.86, 5.95)
T-Test of difference = 0 (vs not =): T-Value = 2.63 P-Value = 0.009 DF = 233

Two-sample T for **3Bet%**

win lost N Mean StDev SE Mean
mike lost 173 6.9 10.9 0.83
mike won 461 6.57 9.00 0.42
Difference = mu (mike lost) - mu (mike won)
Estimate for difference: 0.326
95% CI for difference: (-1.503, 2.156)
T-Test of difference = 0 (vs not =): T-Value = 0.35 P-Value = 0.726 DF = 264

Two-sample T for **Agg Factor**

win lost N Mean StDev SE Mean
mike lost 173 2.61 2.72 0.21
mike won 461 3.59 4.21 0.20
Difference = mu (mike lost) - mu (mike won)
Estimate for difference: -0.977
95% CI for difference: (-1.537, -0.417)
T-Test of difference = 0 (vs not =): T-Value = -3.43 P-Value = 0.001 DF = 475

Two-sample T for **WTSD%**

win lost N Mean StDev SE Mean

```
mike lost  173  21.5   21.4      1.6
mike won   461  21.1   23.5      1.1
Difference = mu (mike lost) - mu (mike won)
Estimate for difference:  0.40
95% CI for difference:  (-3.46, 4.26)
T-Test of difference = 0 (vs not =): T-Value = 0.20  P-Value = 0.838  DF = 337
```

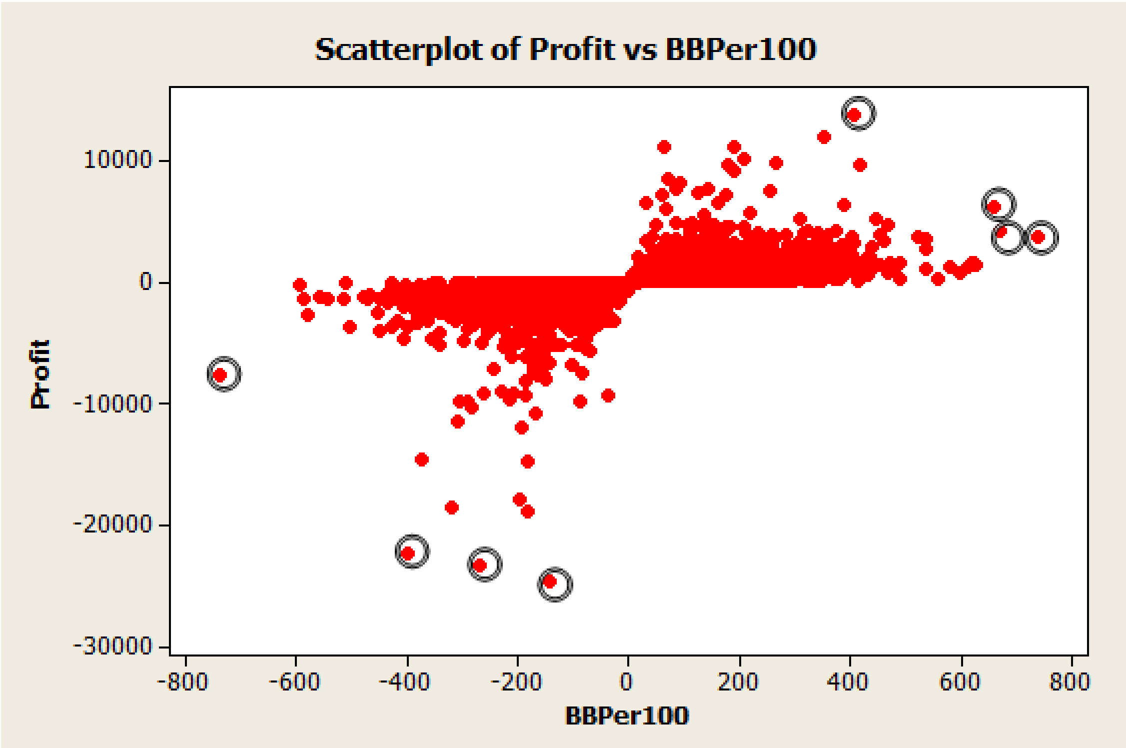
```
Two-sample T for W$SD%

win lost     N  Mean  StDev  SE Mean
mike lost  173  38.9   39.3      3.0
mike won   461  33.3   39.7      1.8
Difference = mu (mike lost) - mu (mike won)
Estimate for difference:  5.63
95% CI for difference:  (-1.28, 12.55)
T-Test of difference = 0 (vs not =): T-Value = 1.60  P-Value = 0.110  DF = 311
```

Again, it is important to note that these P-values are not valid because these are not random samples. I simply used them as a guide to measure some differences.

Average players, VPIP%, PFR%, and agg factor yielded significant P-values at the alpha = .01 level. I am not so sure that there is a practical difference between the two groups in terms of average players. Both groups seem to be playing in 6 max games. There does seem to be a practical difference for VPIP%. The players that beat Mike had a much higher VPIP% than those who lost money to Mike. This means that players that are more willing to put money in the pot did better against Mike. This makes sense because a lot of Mike's game is trying to get other people to fold their hands. PFR% was also significantly different for the two groups. It was higher for the players that took money from Mike. This also makes sense in terms of Mike's strategy because his aggressive style works better against people who do not raise pre flop because Mike wants to be the only pre flop raiser. Aggression factor was also significant. Less aggressive players can take advantage of Mike's aggressive play. In this case Mike did better against players that had a higher aggression factor. It might be the case that since Mike plays aggressively he can take advantage of other players that play aggressive as long as Mike is more aggressive. Mike's own aggression factor is 4.45, which is higher than both groups which may account for this.

Now I wanted to look at Mike's best and worst sessions. I was not sure whether to qualify the best and worst in terms of straight profit or bb/100. Below in *Figure 45* is a scatter plot of bb/100 vs profit.

Figure 45



I circled the sessions that I deemed outliers that I wanted to do additional analysis on.

Figure 45 looks interesting because there is no data in quadrants II and IV. This makes sense because you cannot have a positive win rate and negative profit and vice versa. The plot is fairly symmetric however if examined carefully you can see that there are more very negative profit sessions and they are a lot more negative than the most positive sessions. We have seen this before in this report. Mike wins more often than he loses but when he loses he tends to lose a lot more money.

Figure 46 is the same chart shown earlier (*Figure 10*) but is included again to reference and compare Mike's normal play to the outlier sessions.

Figure 46

Game Type	Hands	$	bb/100	VPIP%	PFR%	3Bet%	WTSD%	W$SD%	Agg	Agg%
$25/50 NL	13949	($57,361.20)	-8.22	34.7	25	7.7	26.4	45.5	2.89	40.3
$30/60 LIM	205	$354.00	5.76	34	26.6	14.9	54.8	50	1.96	55
$10/20 NL	26601	($22,627.95)	-4.25	32.9	23.4	6.8	25.5	46.3	3	39.2
$15/30 LIM	56	($634.00)	-75.48	30.4	19.6	12	52.9	22.2	2.18	61.1
$5/10 NL	420238	$109,459.35	2.6	29.7	21	6.1	26.2	48.3	3	38.7
$10/20 LIM	371	($1,436.50)	-38.72	45.5	34.4	21.5	53	36.4	2.15	57.5
$3/6 NL	14360	$6,692.25	7.77	34	22.5	5.3	26.8	44.7	2.77	38
$5/10 LIM	2768	$999.00	7.22	40	25.8	11.9	37.1	48.9	2.57	52
$2/4 NL	1226761	$229,560.75	4.68	29.8	20.6	5.3	25.6	47.3	3.12	38.8
$4/8 LIM	4	($50.00)	-312.5	25	0	0	100	0	na	100
$2/4 LIM	105	$44.50	21.19	51	37	27.6	41.9	38.9	2.29	60
$1/2 NL	88156	($6,348.75)	-3.6	32.3	24.1	8.3	26.2	45.1	3.16	42
$1/2 LIM	10	($21.60)	-216	60	20	0	33.3	50	1.25	38.5
$0.5/1 NL	6446	($424.55)	-6.59	42.6	24.8	4.4	25.6	42.4	3.14	37.7
$0.25/0.5 NL	82409	$3,952.95	9.59	34	21.5	4.8	26.7	47	3	36.5
$0.5/1 LIM	23	($13.25)	-115.2	68.2	31.8	0	20	0	2.5	48.4
$0.1/0.25 NL	878	$14.60	6.65	32	23.4	6.7	19	40.5	4.44	54.5
$0.05/0.1 NL	318	($12.85)	-40.41	26.8	22.2	3.3	30.4	38.1	4.14	41.7
$0.02/0.05 NL	96	($10.21)	-212.7	43.8	22.9	30.8	19.1	11.1	3.18	41.7
$0.02/0.04 LIM	19	($0.31)	-81.58	84.2	57.9	0	42.1	37.5	1.45	65.1
$0.01/0.02 NL	159	($14.28)	-449.1	87.7	77.9	40.6	85.4	42.1	4.2	8.4

Below in *Figure 47* shows the 8 outliers that I chose to analyze. You can compare *Figure 46 to Figure 47* to see if Mike was playing any differently in his outlier sessions.

Figure 47

Start.Time.of.Session	Minutes.Play	Stakes	Hands	Profit	ProfitPerHr	EV	Avg.Players	VPIP%	PFR%	3Bet%	Agg.Factor	WTSD%	W$SD	Rake	BBPer100
7/1/2007 12:27	34.4	$10/20 NL	52	-7673	-13402.62	-7653.37	5.3	44	32	5.9	0.67	33.3	20	13.3	-737.788
1/10/2009 8:22	54.3	$25/50 NL	112	-22366	-24736.59	-21993.2	3.6	57.7	46.2	22	1.67	41.4	25	16.6	-399.393
4/19/2008 16:09	68.2	$25/50 NL	174	-23419	-20608.39	-20791.4	4.8	40.3	33.3	8.2	3.13	42.3	27.3	14.9	-269.186
4/19/2008 9:33	136	$25/50 NL	348	-24728	-10908.07	-22786.5	4.3	44.3	33.7	14.2	1.81	26.8	42.1	52.4	-142.115
10/30/2008 14:03	39.9	$25/50 NL	68	13783	20734.98	13783	4.3	46	41.3	20	2.75	18.2	100	6.71	405.3824
10/11/2008 18:12	78.2	$5/10 NL	94	6217	4768.01	5260.51	5.8	30.4	22.8	8.3	2.88	38.1	75	20.7	661.3777
10/14/2008 1:05	42.6	$5/10 NL	62	4164	5871.68	3789.75	5.8	29.5	24.6	13.3	2.33	62.5	80	7.97	671.6129
2/23/2008 5:26	32.9	$5/10 NL	51	3774	6882.67	422.96	5.8	27.1	14.6	0	5.5	55.6	100	11.3	740

You can already tell there are some differences in the winning and losing outlier sessions.

Figure 48

Two-Sample T-Test and CI: W$SD, win/loss

```
Two-sample T for W$SD

win/loss  N   Mean  StDev  SE Mean
loser     4  28.60   9.50      4.8
winner    4   88.8   13.1      6.6

|
Difference = mu (loser) - mu (winner)
Estimate for difference:  -60.15
95% CI for difference:  (-81.00, -39.30)
T-Test of difference = 0 (vs not =): T-Value = -7.42  P-Value = 0.001  DF = 5
```

I performed t tests on each of the variables for the outlier sessions. There was only one significant test, shown in Figure 48. Again, these are not valid t-tests but only there to get a gage of what the differences are.

In the winning outlier sessions Mike's W$SD percentage was higher than the losing sessions. This variable seems to be coming up a lot in analysis as a key component. The only way to win money without it coming on the river is to have everyone else in the hand fold to your bet. Often times the biggest bets are made on the river. If a player is able to have the best hand at showdown then he is guaranteed the biggest pot possible. To a certain extent having the best hand at showdown comes down to what you were dealt which is based on luck. The skill is knowing when to make it to showdown with your cards. In these outlier sessions Mike was able to hold the best cards at showdown a very high percentage of the time. Holding the best cards at showdown contributes to a very lucrative session.

The rest of the variables were not statistically significant however, since the sample size for each group is only four and they are not random samples it might be more effective to just examine the differences in the variables informally. Besides the one losing session at 10/20 the losing sessions are a lot longer than the winning sessions. This reinforces my original hypothesis that the longer he plays the worse he does. After he has made a lot of money he might be more inclined to quit because he is satisfied with his winnings. If he has lost a lot of money he might be more inclined to play more because he thinks he can win it all back. VPIP% is also higher in almost every winning session. A higher VPIP% indicates a looser playing style which is more inclined to spew money to opponents. Mike's aggression factor was also quite a bit higher in most of his winning sessions. Conventional wisdom says that being aggressive is almost always better than being passive. At Mike's most winning stake his aggression factor was about 4.5 which is certainly higher than all the losing sessions.

I was curious to see what the regression model would predict for these outlier sessions. I decided to enter the winning and losing sessions into the optimal regression equations I found earlier and find point estimates and confidence intervals. Seen in *Figure 48 and 49.*

Figure 48

Losing outlier sessions.

```
Predicted Values for New Observations

New
Obs      Fit  SE Fit        95% CI               95% PI
  1  -42.789   2.265  (-47.229, -38.350)  (-240.493, 154.914)


Values of Predictors for New Observations

New
Obs  Minutes.Played  Avg.Players  3Bet%  Agg.Factor  WTSD%  W$SD
  1            73.2         4.50   12.6        1.80   36.0  28.6
```

Compared to the actual -387 average win rate that Mike achieved over these 4 worst sessions, the predicted fit of -42.8 is not actually that low. The size of the residual is very large; however, it does show that the model did predict him to lose money.

Figure 49

Winning outlier sessions.

```
Predicted Values for New Observations

New
Obs      Fit  SE Fit        95% CI              95% PI
  1  100.389   2.354  (95.775, 105.002)  (-97.318, 298.096)


Values of Predictors for New Observations

New
Obs  Minutes.Played  Avg.Players  3Bet%  Agg.Factor  WTSD%  W$SD
  1            48.4         5.42   10.4        3.36   43.6  88.8
```

The actual average win rate for these 4 most wining sessions was 619.6. This is a lot higher than the estimate or the confidence limits. This might indicate that luck may have been an important factor in these sessions.

The winning and losing outlier sessions were not identical. This is to say that it was not just really bad luck or good luck to account for the differences. Perhaps if Mike had used a different playing style he could have turned the monstrously bad sessions into moderately bad sessions. After all, if Mike had decided to go play basketball instead of play in these four bad sessions he would be up another 78,000 dollars or 30% of total profit. (Just something to think about).

Conclusions

Suggestions for Mike

The whole purpose for this report was to figure a way to make Mike more profitable. My thought was that I could use my skills in statistics to do a thorough report and figure out a method to increase profit. One such hope I had was that I could tell Mike at what point in his session that he should quit. An optimal playing time was not found. My results slightly suggest that the longer the session, the worse it goes. I think the better advice is to continue a session when you are playing well and end a session when you are not. My other goal was to define what is playing well and what is playing poorly. I was not able to fully accomplish this goal either. I think poker is too dependent on what the other players are doing at the table to only look at one player's stats. However, I did find that Mike wins more table sessions than he loses (717 more). However, his biggest losing sessions are a lot bigger than his biggest wining sessions. Cēterīs paribus, the higher the stakes the better the players and higher potential for great loss. The most money in terms of profit and win rate was no limit 400. My advice would be to continue at that level. Every once in a while I think it would be profitable to look at your recent stats and make sure you are staying in line with your winning strategy. Even though I was not able to find an overwhelming amount of evidence to suggest the explanatory variables explain everything, I was able to find to some evidence they are important.

Overview

This project was plagued with one big problem. There was way too much data. Throughout the entire report I had issues with finding statistical significance but not practical significance. At the beginning of the project I was very optimistic to find some significant results. It was disappointing that I was not able to find something more concrete. I had always thought that there was always an optimal move in poker. I thought eventually some super computer would be built that could beat the game of poker, similar to chess, well almost beat. After this report I think that the game is too dependent on what the other players at the table are doing. So often I hear Mike say something along the lines of, “oh, this guy always check raises the turn”, or something to that extent. The problem with my analysis was that it solely dependent on what Mike was doing. The model could not really take into what other players were doing. I thought that since I was looking at averages I would take into account all the different scenarios Mike could encounter. This did not seem to be the case. I do think there is some value in looking at all the statistics. At the time of this report Mike rarely, if ever, looks at personal or opponents stats. He thinks they over simplify things too much. I am not sure if there is a way to optimize explanatory variables to maximize profit. I also think that different playing styles will yield optimal results. However, I think for individual players it is important to keep an eye on personal statistics. For instance if a player is in a down swing he might want to make sure they are not changing their playing style from their winning strategy. In short, I think my report was not able to show exactly the perfect way to play, but showed that there is some value in looking at these variables.

What I learned?

I learned the pitfalls of having too much data. The power of each test I was making simply way too much. I also learned the importance of having good notes. I was able to reteach myself stat 418 in less than an hour. I hadn’t taken Stat 418 in over a year but I had really good notes from Dr. Doi’s class and I am grateful I made them so nice to follow and thorough. I also had to relearn a bit of SAS which I had not used in a while since switching to R. Good notes were also helpful there. Stat 465 certainly helped me prepare for this report but this definitely they largest report I have put together. I learned how to manage different sections and put it together in a coherent manner. Lastly, Dr. Smidt did not set many, if any, deadlines for me and I think I did a pretty good job at time management. I was able to make sure everything got done in timely fashion.