Determinants of Point Rankings and Win Rate in the ATP: What Fuels the Success of Top Tennis Players?

Billy Altantulkhuur

ECON 190

Professor Andrabi

May 4th, 2022

Section I: Introduction

Growing up as a tennis player, I always appreciated the complexities and dynamics of the game, especially at the professional level. There are numerous factors in play that determine the outcome of a match, both performance related and non-performance related. In this paper I seek to discover and analyze the impact of some of these factors by looking at the pro men's singles tour governed by the Association of Tennis Professionals (ATP). Specifically, I want to learn the effects of these variables on the level of success of the top 200 players, represented by their point rankings. Particularly, I am interested in three performance related variables: break points converted, double faults, and ties-breaks won. The main variable of interest is break points converted but I am also curious to see the effect of double faults and tie-breaks won. These statistics are important to consider because of their suspected effect on a player's mental game. Tennis at the top levels not only requires peak physical performance but strong mental fortitude as well. It is a game of momentum, considering that matches can last hours and exert both a physical and mental toll on the players. Mistakes are bound to happen for even the best players but being able to stay consistent and generate momentum in their favor is what I believe to be a key differentiator for the players at the top of the rankings.

Section II: Literature Review

The factors that affect the performance of a tennis player is a topic that many economists and other academics have studied in the past. With regard to the physical aspects of a player's game, some variables that have been researched include height, age and handedness (Ovaska and Sumell, 2014).

Height is a critical aspect of a player's serve and volley game. Taller players have a sharper angle to serve the ball downwards, making it more difficult for their opponent to return as the angle translates to a higher bounce on the return side. Besides having a better angle to work with, taller players can theoretically generate more power on a serve as they have longer arms to generate more torque. Height is also an advantage on the return side as having longer arms also means that they can reach a couple extra inches that shorter players could not. Ovaska and Sumell note that at the net, shorter players would also have more difficulty lobbing balls over their taller opponents. However, after analyzing over 20,000 matches over a nine year period, the empirical results from their paper indicate that taller players (above 6'5") only had a significant advantage over shorter players of 5'8" or below.

Age is another factor to consider. There are both benefits and disadvantages as a player gets older. On one hand, players gain more experience and mental toughness as they age, but their physical capabilities also diminish while being more susceptible to injury. Yet empirically, Ovaska and Sumell concluded that the marginal effect of age led to a higher ranked older player being 5.4% less likely to win a match compared to a higher ranked younger player. Furthermore, for each additional year, the probability that a higher ranked older player wins decreases by 0.7%. Thus, they imply that "the effect of experience on winning may be overrated" (Ovaska and Sumell, 2014).

Being left-handed in tennis is a trait that has often been called advantageous. Some of the most notable left-handed players include Rafael Nadal, John McEnroe, Rod Laver, and Jimmy Connors. The idea is that left-handed players have different patterns of gameplay than their right handed counterparts, most notably being able to hit balls to their opponents' backhands more easily. This was most prominent a few decades ago when backhands were considered the weaker returning side. However, this may not be the case today where players have developed their two and one handed backhands into powerful weapons. Lefties also prefer serving on the “ad” side (left side of the court), versus the “deuce” side (right side) that righties prefer since these sides open up a greater range of mobility during a serve with the respective hand. This translates to an advantage as there are a greater number of chances (due to scoring) to serve on the advantage side when a game is one point away from closing. Ovaska and Sumell also point out that lefties are more in tune with the right hemisphere of the brain, which is responsible for spatial awareness and perception (essential skills needed for tennis). However, in their analysis, they found no evidence of an advantage.

The nationality of a player is another aspect that may affect the rankings of the top tennis players. Countries that have historically embraced tennis more than others are arguably better suited to develop top talent on a systemic level. Tennis is more popular among higher income countries and thus, have larger talent pools for reaching the top levels of tennis. The presence of elite tennis academies are another advantage that some countries have over others. Ovaska and Sumell point out the U.S., Germany, Sweden, Australia and Spain as these countries that have exceptional aptitude for generating talent.

Analysis of performance related variables and their effect on the chance of winning a men’s singles match in a Grand Slam was conducted by Ma et al (2017). They looked at longitudinal data from 1991 to 2008, comprising over 9000 men’s singles matches at these tournaments. In their logistic models, the variables that had higher proportions of first serve points won, second serve points won, aces, first serves returned, second serves returned, and converted and saved break points had the most impact on the chance of winning a match. They stated that their study confirms the importance of the serve and return as the most important skills in tennis. In my analysis however, I only want to focus on break points converted, double faults, and tie-breaks won because I suspect that these particular variables have a distinct effect on the mental state of the player which in turn affects their ability to win games and attain a higher ranking or win rate.

In Cohen-Zada et al's 2017 paper, they discuss "choking" under pressure in tennis by analyzing match-level data at the 2010 Grand Slam tournaments. This paper is useful in understanding the mental side of tennis games. They defined a game as high stakes by looking at a few different pressure measures, such as the probability of winning a set when the score was tight (both players won at least 4 games), the probability of winning the entire match as a result of winning or losing the current game, and looking at the importance of individual points. Furthermore, the paper compared the effect of these pressures by gender, and ultimately found that men consistently choke more than women in the more crucial stages of a match. The results of their study have implications on the psychological effects of momentum in a match and they note that their findings align with the biological literature on cortisol. Higher levels of cortisol, a stress hormone, negatively impacts the performance of both men and women, but more so for men. Their findings also agree with previous tennis literature by Gauriot and Page (2014) that found a momentum effect among men but not among women.

The idea of psychological momentum (PM) is explored in greater depth by Iso-Ahola and Dotson in their 2016 paper, which was published in a psychology journal. When referring to the efficiency of people in task completion, they state that "perceptions of positive PM enhance their sense of success in goal pursuit. When they initially experience success, their self-confidence and competence grow, leading to heightened expectations, expanded mental and physical effort in task performance, increased perceptions of positive PM, and a greater likelihood of success." From their research of various studies that looked at PM in sports, one important conclusion they made was that psychological processes, including PM, play a more critical role at increasing levels of skilled performance. Considering that my paper looks at the top singles players of men's tennis, PM is likely to be a key factor in their performance.

Section III: Theory of Equations

In reference to the research done by previous literature, the model I am constructing consists of both performance related and non-performance related variables of the tennis players I am analyzing. The base multivariate regression model is first constructed with the four variables mentioned in the literature that are non-performance related.

$$Points = \beta_0 + \beta_1 Height + \beta_2 Lefthanded + \beta_3 Age + \beta_4 Nationality + \mu$$

Points is the dependent variable of interest that represents a player's total points on the ATP men's singles ladder. Total points are calculated by ATP as the sum of the points gained from the four Grand Slam tournaments, the eight mandatory ATP Masters 1000 tournaments, the ATP Finals, and the six best results from all ATP 500, 250, Challenger and Futures tournaments. Tournament results and the subsequent points awarded are only valid for a rolling 52 week period so if a player ceases play for over a year, they will lose all their points. Players gain more points depending on how far they make in a tournament and the type of tournament, with Grand Slams awarding the most points. Because of the nonlinear hierarchy of points awarded by tournament, the handful of players who perform well at larger competitions gain much more than those who do not. Consequently, this variable is skewed to larger values, making sense to transform it into a logarithmic scale.

The relevant physical characteristics of players that influence success are addressed by the variables *Height* and *Lefthanded*. The effects of these factors have already been observed in the literature as determinants of winning in tennis, which in turn should affect a player's place on the rankings. *Height* measures the height of a player in centimeters. Taller players can play with steeper downward angles on their serve and can generally create more power as well due to the superior torque produced by their longer arm length. In addition, they have more reach which is useful for returning serves and playing at the net. The coefficient for this variable is expected to be positive. *Lefthanded* is a dummy variable that registers as 1 if the player is left handed and 0 if right handed. Left handed players are believed to have an advantage in tennis for a variety of reasons including having more chances to close out a game when serving on their preferred side, being able to hit to their opponents backhands more easily, and having better spatial awareness and perception. I expect this coefficient to be positively correlated with points.

The other two variables in this model, *Age* and *Nationality,* are player characteristics that have also been studied in the literature. As players grow older, their physical abilities deteriorate and their bodies are often more prone to injury. Thus, the coefficient for *Age* is expected to be negative. *Nationality* is another dummy variable that captures the benefits of coming from a country that has the pedigree and systemic capabilities to be able to develop top tennis talent at a higher rate than other countries. The countries mentioned in the literature are the U.S., Australia, Germany, Sweden, and Spain. If a player comes from one of these countries, then *Nationality* will be a 1, and 0 if not.

Next, I add the three performance-related variables to the equation that influences success through confidence and psychological momentum. This will be the first main regression of interest.

$$Points = \beta_0 + \beta_1 Breakpoints\_converted + \beta_2 Double\_faults + \beta_3 Tiebreaks\_won + \beta_4 Age + \beta_5 Height + \beta_6 Nationality + \beta_7 Lefthanded + \mu$$

Breakpoints_converted is the main explanatory variable of interest in my paper, measured by percentage. A break point in tennis is defined as a situation when one player is a point away from winning a game and the other player is on serve. If the player on return wins the point, the break point is converted. It is difficult to convert a break point since serving is a massive advantage in tennis. The serve is the one shot in the game that a player has total control over. The server can change up their technique, adjust their power and angle, and aim where they want the ball to bounce on the returning player's service box. Thus, the pressure on the returning side to win the game on this point is immense, especially with their disadvantage. I hypothesize that winning a break point is a boost to the player's confidence that is greater than winning a regular point because statistically they are unlikely to win a game when their opponent is on serve. Furthermore, converting a break point will likely harm the morale of their opponent who knows their best chances of winning games are on their serve. I expect the coefficient on this variable to be positive.

Double_faults is the percentage of double faults (missing both serves) out of total service points played. Since the serve is the one shot that players have total control over, doing a double fault can be particularly frustrating, especially at crucial points of a game when the score is tighter. Beginner players are taught to have a safer second serve (weaker) that is easier to land in the event that they miss their first. Professional players also follow this rule to some extent because of the inherent riskiness of producing a second serve that is as big as the first. However, sometimes players will decide to serve big on their second try if they are confident enough. There are risks to both options, as safer serves are easier to execute but also easier for the opponent to return, while a big second serve has a higher chance of failure but harder to return. Regardless of what kind of second serve a player chooses, performing a double fault is still damaging to a player's confidence. Thus, I expect the coefficient on this variable to be negative.

Tiebreaks_won is the percentage of tie-break sets won. A tie-break set occurs when the score becomes 6-6 in a given set. This set is much shorter as it ends when a player reaches seven points. The competitive pressure in a tie-break set is expected to be immense because the score is so tight. Losing a tie-break set can be very demoralizing due to both narrowly losing and the set disadvantage that the player now faces. The intensity of closer sets means that players have to exert more effort (both physical and mental) to stay on par and losing a tie-break can make one feel as if this effort was all for nothing. The opposite effects are in play for the winner of the tiebreak who now has additional momentum for the remaining sets. This variable is expected to be positively correlated with the dependent variable.

Points is the measure I am using to model the level of success for a player but it is not a perfect one. Due to the system that ATP uses, players have an incentive to participate in tournaments frequently and consistently to avoid losing points and to achieve the best results they can from smaller competitions in order to reach larger ones like the Grand Slams. However, players that do not have the large sponsorship deals or the financial means to support the various costs of being on tour (travel, coaching staff, etc) are at a disadvantage. Having more money also improves the likelihood of avoiding injuries due to having both a greater number and a superior quality of resources for injury prevention. Thus, a secondary regression that uses career win rate in place of points to represent success will be included. Since I am using career win rate here, the three performance variables will also be on a career basis (denoted with a C in front).

$$Winrate = \beta_0 + \beta_1 CBreakpoints\_converted + \beta_2 CDouble\_faults + \beta_3 CTiebreaks\_won + \beta_4 Age + \beta_5 Height + \beta_6 Nationality + \beta_7 Lefthanded + \mu$$

For both of these models, it would be interesting to run an additional regression that drops the Big Three players (Nadal, Djokovic, and Federer). Since their talents are far above the rest of the competition, they may skew the data to some extent. Finally, I will also run two simple side regressions to understand the correlation between the main variable of interest (break points converted) and the two dependent variables.

1) $Points = \beta_0 + \beta_1 Breakpoints\_converted + \mu$
2) $Winrate = \beta_0 + \beta_1 CBreakpoints\_converted + \mu$

Section IV: Data

The data used in this paper is derived from Ultimate Tennis Statistics, which in turn bases their data from the ATP open source tennis repository on GitHub by Jack Sackmann. For my analysis, I gathered both 2019 end-of-year data and career data on the top 200 ATP men's singles players and for the performance related variables. I chose 2019 because this was the last 'normal' year before the pandemic, which disrupted the professional tennis tour. Unfortunately, a lot of the data for players ranked below was missing both on Ultimate Tennis Statistics and the ATP website, so I chose to keep it at the top 200. The data was also compiled on a basis of all tournament levels, all types of court surfaces, all rounds, and versus all ranks of opponents. Controlling for these factors would not be helpful since my dependent variables *Points* and *Winrate* already encompass these situations.

Figure 1, shown below, is a scatterplot showing the relationship between breakpoints converted and ranking points for the 200 players at the end of 2019. This shows that most players have breakpoint converted percentages that are between 30% and 40%. Within this range, there is a slight upward trend. Although players at the top of the points ranking have percentages greater than this range, this figure overall does not paint a clear picture. However, Figure 2 shows a much clearer linear positive trend. Here, I look at career breakpoints converted and career win rate. This may suggest that winning breakpoints have a more direct impact on win rate as opposed to points, which can be affected by how active a player is (which is impacted by injury, costs, etc). With the addition of the controls provided by the other variables in the regression, a broader view of the magnitude of this performance statistic on points and win rate will be presented.

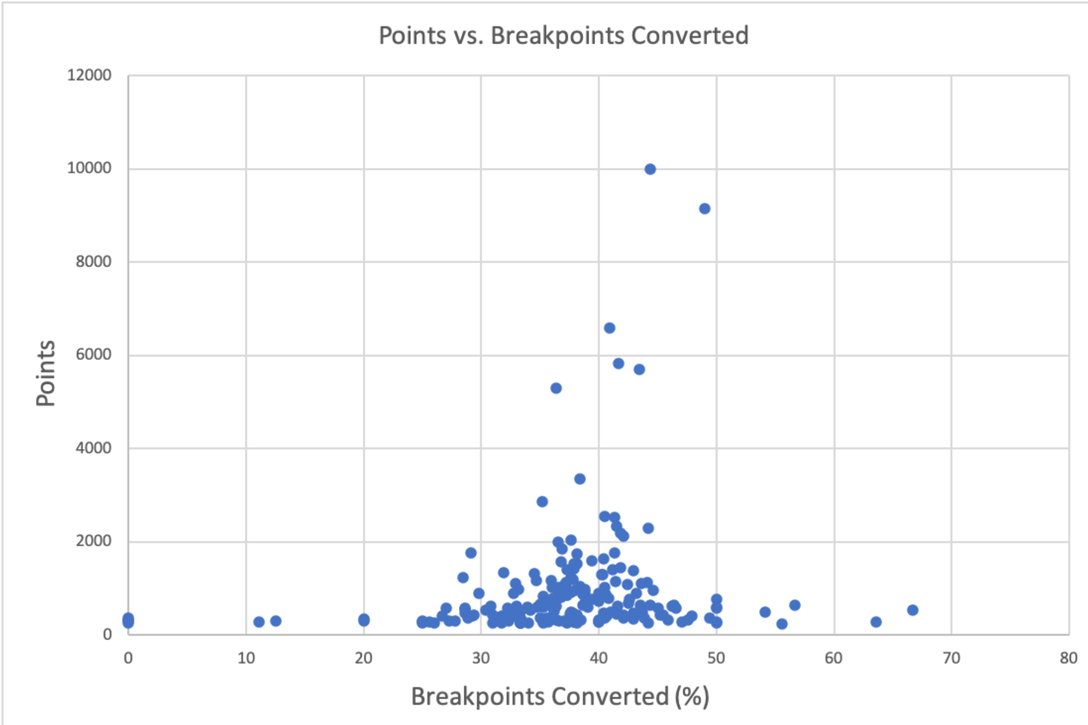

Figure 1: Breakpoints converted (%) vs Points (2019)

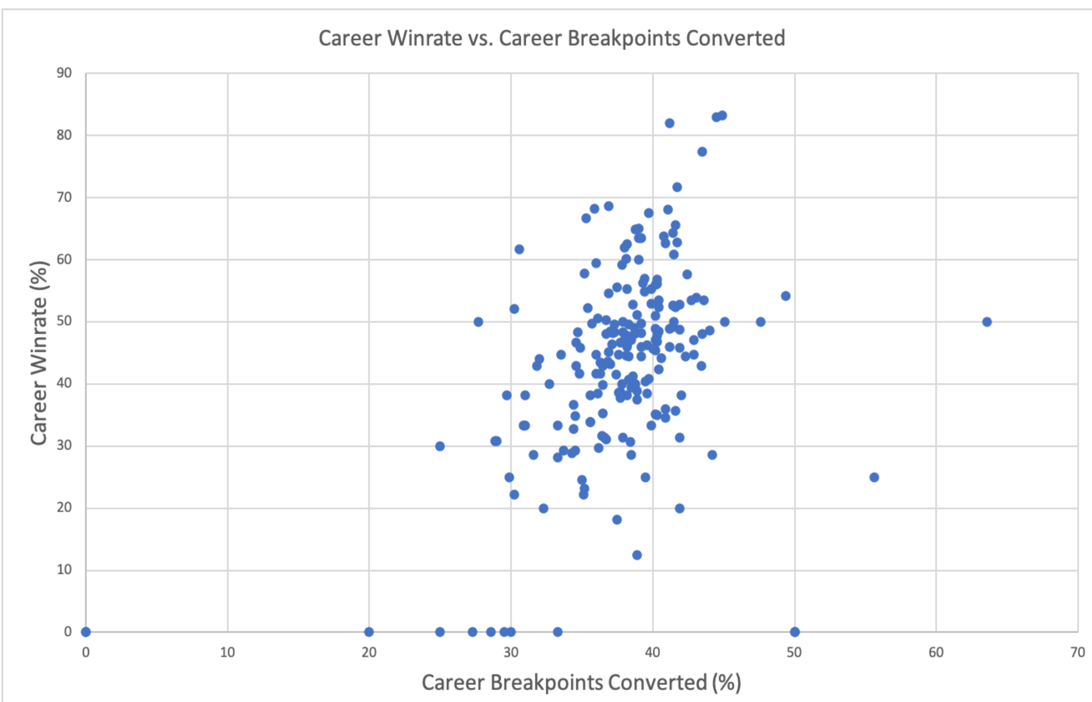

Figure 2: Breakpoints converted (%) vs Winrate (Career)

Section V: Results

The regressions I ran consisted of two different models that differ in the dependent variable being tested. These two variables, *Points* and *Winrate*, are used as indicators of the success levels of the top 200 professional tennis players. Furthermore for each model, I ran a specification that drops the Big Three players Nadal, Djokovic, and Federer. In addition, two simple side regressions of breakpoints converted on points and win rate were performed. The results of the side regressions are presented in Table III. Interestingly, *Breakpoints_converted* and *CBreakpoints_converted* are both statistically significant at the 0.01 level. The R-squared value for *CBreakpoints_converted* is higher however, showing more explanatory power when this performance variable is regressed on *Winrate* as opposed to *Points*. This adds further validity to a stronger relationship between breakpoints converted and win rate, as I explored earlier in the scatterplots.

Table IV details the regression results for the first model. For both specifications with and without the Big Three, the results were very similar. *Breakpoints_converted* and *Tiebreaks_won* were both statistically significant and had a positive relationship with *Points*. *Double_faults* had also had a negative coefficient, as predicted, but was not statistically significant. Table II, which presents summary statistics, shows that the median double fault percentage was 3.6%. Since the occurrence of double faults are fairly low for most players, it could be that players are not as phased by losing a point through double faulting as they are from losing a breakpoint or a tiebreak set. This makes sense, since players have at least four instances to serve in an individual game and losing a point here and there will not matter as much. It would be interesting to see the effect of this variable on points and win rate looking at only players with high double fault percentages (like above 10%).

Surprisingly, all the non-performance related variables were not statistically significant. I suspect that these variables did not follow the expected results because of the small sample size. 200 is a high benchmark to achieve if we consider all the professional men's singles tennis players, which is around 2,000.

The average age of the players as described in Table II is 28. Since players peak around their mid 20s, this may suggest that the declining effects of age on performance are not as severe until much later on. In the top 200, there was only one player in their 40s. If we look at a larger sample of players, the effect of age will likely be more robust.

While the literature found that height did impact the probability of winning positively, there are still reasons why shorter players can still reach high rankings. Shorter players weigh less, meaning that they can move around faster on court. Furthermore, having good baseline groundstrokes can also help make up for the benefits provided by being taller.

For handedness, the regression results show that being left-handed is not a significant predictor of having more points. One explanation for this could be that right-handed players have adapted to playing against the style of a left-handed player since the 20th century when left-handed players dominated. The strength of the back-hand, a counter to lefties, has also developed tremendously over the past few decades.

Nationality is the last non-performance variable that I included in the regression. This dummy variable controlled for the effects of a player coming from the select countries that have historically churned out top talent. This unexpected regression result may indicate that other countries have caught up in their ability to develop top tennis players and that there is a more even playing field now.

The results of the secondary regression shown in Table V that had win rate as the dependent variable were mostly similar to the main regression but with a few key differences. The two performance related variables of break points converted and tiebreaks won were also significant again but this time, *Height* was also significant. This was puzzling since this indicates that taller players do indeed win more, but this success was not reflected in points. A possible reason could be taller players might be more prone to injuries due to the greater force of stress on the body. If they are injured, they cannot play as many tournaments to get more points. This is a topic that can be further explored. Additionally, *Age* was statistically significant in this model, but only when the Big Three was included. The coefficient was also positive when it was expected to be negative. This is likely due to the skew of the Big Three, who are all in their thirties and all boast very high win rates.

Another important distinction in comparing this model to the first is that the R-squared values were drastically higher, with the value being 0.620 including the Big Three and 0.6094 without the Big Three, compared to 0.178 and 0.174 in the previous model. I believe that the core reason for this change might be that win rate is a much better indicator of success in the long term. When looking at the player make-up of my data, I saw that a few players like Richard Gasquet and Andy Murray, who in previous years were top ten players, were dramatically lower in points in 2019. I found out that both were injured that year, and thus were not able to participate as frequently to retain or improve their ranking. Thus, it supports the idea that points do not necessarily reflect ability. Also, it means that win rate does not necessarily reflect the success of a player on the rankings.

Section VI: Conclusion

This paper finds that the percentage of breakpoints converted and the percentage of tiebreaks won are both statistically significant predictors of both points and win rate in professional men's singles tennis. These positive relationships presented in this paper shows that the top players have higher percentages of breakpoints converted and tiebreaks won. This may suggest that breakpoints and tiebreak sets are indeed key moments of a tennis match and that winning them can strongly influence the outcome of a match to victory. In proposing a mechanism for how these statistics are influential, I hypothesized that players who win these critical points or sets are likely to generate a lot of positive psychological momentum. This momentum increases confidence, effort levels, and creates a higher sense of success, which all help to increase the chance of winning a match.

It is difficult to look at the mental side of sports empirically, but my paper attempts this anyway to certain degrees of success. My analysis could have been tremendously improved if I had access to more observations, and consequently the results are not as statistically robust as they could have been. In predicting points and win rate, there are also bound to be other variables that my model was missing since tennis is such a complex and dynamic game.

Table I: Description of Variables

Variable	Unit	Description
Points	Points	Number of points granted by ATP at year-end 2019 used to rank players
Winrate	Percentage	% of matches won out of total matches played in career
Breakpoints_converted	Percentage	% of break points converted out of total break points played in 2019
CBreakpoints_converted	Percentage	% of break points converted out of total break points played in career
Double_faults	Percentage	% of double faults executed out of total service points played in 2019
CDouble_faults	Percentage	% of double faults executed out of total service points played in career
Tiebreaks_won	Percentage	% of tie-break sets won out of total tie-break sets played in 2019
CTiebreaks_won	Percentage	% of tie-break sets won out of total tie-break sets played in career
Age	Years	Current age
Height	Centimeters	Current player height
Nationality	n/a (dummy variable)	1 if player is Australian, German, American, Swedish, or Spanish
Lefthanded	n/a (dummy variable)	1 if player is left-handed

Table II: Summary of Statistics

Variable	Observations	Mean	Median	St. Dev.	Min.	Max.

Points	200	931.725	575.5	1255.36	252	9985
Winrate	200	43.26	45.7	16.01	0	83.2
Breakpoints_converted	200	37.05	37.6	8.87	0	66.7
CBreakpoints_converted	200	37.67	38.2	6.14	0	63.6
Double_faults	200	3.77	3.6	1.54	0	11.4
CDouble_faults	200	3.83	3.7	1.27	.8	11.4
Tiebreaks_won	200	42.48	46.3	23.71	0	100
CTiebreaks_won	200	45.11	48.1	16.23	0	100
Age	200	28.04	28	4.48	19	41
Height	200	186.51	185	7.11	163	211
Nationality	200	.27	n/a	.44	0	1
Lefthanded	200	.13	n/a	.33	0	1

Table III: Side Regressions

	(1)	(2)
DEPENDENT VARIABLE	*Points* (Log)	*Winrate*
Observations	200	200
R-squared	0.054	0.165
Adjusted R-squared	0.048	0.1824
INDEPENDENT VARIABLE		
Breakpoints_converted for (1), *CBreakpoints_converted* for (2)	0.009***	1.08***
	(0.0028)	(0.1616)
Constant	0.0538	2.04
	(0.013)	(6.154)

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table IV: Main Regression

	(1)	(2) - Big Three Omitted
DEPENDENT VARIABLE	*Points* (Log)	*Points* (Log)
Observations	200	200
R-squared	0.178	0.174
Adjusted R-squared	0.148	0.144
INDEPENDENT VARIABLES		
Breakpoints_converted	0.0073***	0.0058**
	(0.0025)	(0.0023)
Double_faults	-0.0045	0.0001
	(0.0145)	(0.0133)
Tiebreaks_won	0.0047***	0.044***
	(0.0009)	(0.0008)
Age	0.0010	-0.0043
	(0.0049)	(0.0045)
Height	0.0036	0.0031
	(0.0031)	(0.0028)
Nationality	-0.0121	-0.0205
	(0.0489)	(0.045)
Lefthanded	0.0361	0.0078
	(0.0649)	(0.0604)
Constant	1.6557***	1.927***
	(0.6106)	(0.56)

Standard errors in parentheses

*** p < 0.01, ** p < 0.05, * p < 0.1

Table V: Secondary Regression

	(1)	(2) - Big Three Omitted
DEPENDENT VARIABLES	*Winrate*	*Winrate*
Observations	200	200
R-squared	0.620	0.6094
Adjusted R-squared	0.606	0.595
INDEPENDENT VARIABLES		
CBreakpoints_converted	0.843***	0.809***
	(0.125)	(0.122)
CDouble_faults	-1.438	-1.237
	(0.593)	(0.580)
CTiebreaks_won	0.550***	0.536***
	(0.046)	(0.045)
Age	0.445***	0.340
	(0.162)	(0.161)
Height	0.510***	0.501***
	(0.104)	(0.101)
Nationality	-1.902	-2.211
	(1.642)	(1.610)
Lefthanded	-0.74	-1.501
	(2.183)	(2.163)
Constant	-114.919	-109.298
	(21.1)	(20.6)

Standard errors in parentheses

*** p < 0.01, ** p < 0.05, * p < 0.1

Works Cited

Cohen-Zada, D., Krumer, A., Rosenboim, M., & Shapir, O. M. (2017). Choking under pressure and gender: Evidence from professional tennis. *Journal of Economic Psychology, 61*, 176-190. doi:10.1016/j.joep.2017.04.005

Iso-Ahola, S. E., & Dotson, C. O. (2016). Psychological Momentum—A Key to Continued Success. *Frontiers in Psychology, 7*. doi:10.3389/fpsyg.2016.01328

Joffe, P. (2020, May 03). Forces behind unforced errors: The problem of choking in tennis. Retrieved May 2, 2022, from https://www.sportsciencesupport.com/forces-behind-unforced-errors-the-problem-of-choking-in-tennis/

Ma, S., Liu, C., Tan, Y., & Ma, S. (2013). Winning matches in Grand Slam men's singles: An analysis of player performance-related variables from 1991 to 2008. *Journal of Sports Sciences, 31*(11), 1147-1155. doi:10.1080/02640414.2013.775472

MouratoMonday, J., & Mourato, J. (n.d.). Why Being Left-Handed is an Advantage in Tennis? Retrieved May 2, 2022, from https://www.oddsmarket.com/tips/tennis/why-being-left-handed-is-an-advantage-in-tennis/89626/

Natu, S. (2013, January 23). Tennis 101: The importance of the serve and the service-break. Retrieved May 2, 2022, from https://www.sportskeeda.com/tennis/tennis-101-the-importance-of-the-serve-and-the-service-break

Ovaska, T., & Sumell, A. J. (2014). Who Has The Advantage? An Economic Exploration of Winning in Men's Professional Tennis. *The American Economist, 59*(1), 34-51. doi:10.1177/056943451405900104

Persaud, R. (2015, September 15). Do Tennis Champions Reveal the Secret to Mental Toughness? Retrieved May 2, 2022, from https://www.psychologytoday.com/gb/blog/slightly-blighty/201509/do-tennis-champions-reveal-the-secret-mental-toughness

Robson, D. (2016, May 31). Being a left-handed tennis player isn't the advantage it once was. Retrieved May 2, 2022, from https://www.washingtonpost.com/sports/tennis/being-a-left-handed-tennis-player-isnt-the-advantage-it-once-was/2016/05/31/fad2abd2-2740-11e6-a3c4-0724e8e24f3f_story.html

Ultimate Tennis Statistics. (n.d.). Retrieved May 2, 2022, from https://www.ultimatetennisstatistics.com/