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Momentum in tennis: Controlling the match

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Abstract

Although many studies examine if players in sports and especially in tennis benefit from a psychological or physiological boost (momentum) none examine whether the set score as a dependent variable or tournament rounds as independent variables are important determinants when assessing momentum. We empirically investigate whether professional female and male tennis players benefit from momentum. In contrast to previous work, we find players benefit from momentum as long as they control a match. Once players lose control over a match, they have a significantly lower chance to win the next set than their opponent. This loss of control results in what we call anti-momentum.

JEL classification: L83

Keywords: *Momentum, anti-momentum, control theory, tennis*

Introduction

Momentum means that a player benefits from a psychological and/or physiological boost. A psychological boost is a positive change in cognition. Cognition includes changes in self-efficacy, motivation, and attention. A physiological boost is a positive change in behavior. Behavior includes activity level, pace, posture, or frequency. Our definition is in line with previous definitions of momentum in sports (see the multidimensional model of momentum by Taylor & Demick, 1994). Therefore, we use the concept of momentum, which includes both psychological and physiological effects.

In sports psychology, researches examine momentum because they want to know if a player outperforms at one point in a match. If momentum is ascertainable then players, coaches, and managers have a genuine advantage to exploit. Benefiting from momentum could give a player the final component to win a decisive match. In this paper, we empirically investigate when professional female and male tennis players benefit from momentum.

Psychologists use momentum to describe a competitive situation between two individuals (psychological momentum). In such a competitive situation, one person uses psychological warfare to improve his own situation (Iso-Ahola & Mobily, 1980). Psychological momentum is the result of successful psychological warfare. Iso-Ahola and Mobily (1980, p. 391) describe psychological momentum: ” . . . it increases the person’s perceived probability of success by modifying his and the opponent’s perceptions and impressions of one another.” This definition fits perfectly to a sports environment. In sports competition between individuals

or teams is essential. One of the first research papers in psychological momentum by Gilovich, Vallone, and Tversky (1985) received widespread attention. The authors examine the so called "hot hand" for basketball players. They define a hot hand as the "performance of a [basketball] player during a particular period [which] is significantly better than expected on the basis of the player's overall record." (Gilovich et al., 1985, p. 295-296) This means that a player who is significantly better than expected based on his overall record benefits from psychological momentum. In the context of basketball, Gilovich et al. (1985) define momentum by the shooting accuracy of a player. They examine shooting records of the Philadelphia 76ers, free-throw records of the Boston Celtics, and shooting records of varsity players from Cornell University. They empirically examine if a high shooting accuracy is stable throughout a game. They conclude that basketball players do not increase their probability to hit with every consecutive shot.

The hot hand is mainly examined in the context of basketball. The similarity between the hot hand and momentum is that both approaches state that dependencies in future performance rely upon past streaks (Hughes & Franks, 2015). One difference is that the hot hand is mostly, but not exclusively, applied to basketball and momentum to other sports. Additionally, as the hot hand measures shooting accuracy it is more a performance measurement than a measurement for momentum.

Their results initiated widespread discussion among researchers. Wardrop (1995) criticized Gilovich et al.'s research methods. He asserts that Gilovich

et al. (1985) results suffer from the Simpson paradox, which states that if a trend appears in different data groups the trend can disappear when the groups are combined. Wardrop claims that Gilovich et al. (1985) incorrectly combine groups in their analysis, therefore their data analysis yields incorrect results. Burns (2001) argues, that Gilovich et al. (1985) need the performance data of every team player to test for the improved performance of an individual. Gilovich et al. (1985) however, observe only individual performance.

Bar-Eli, Avugos, and Raab (2006) examine how research on the hot hand has evolved and what results it provides. They examine how research regarding the hot hand has evolved in the last twenty years. They find no clear indicator that the hot hand exists. In a recent paper by Csapo, Avugos, Raab, and Bar-Eli (2015) the authors examine that players face increased competition when they outperform. Thus, in order to measure momentum, researchers should correct for the increased amount of competition. These papers show that in team sports and especially in basketball, the existence of psychological momentum is widely disputed.

In contrast to team sports, individual sports (e.g. tennis and racquetball), provide a competitive situation where momentum is more easily visible. In these sports, opponents directly influence each other. Thus, no intermediates (e.g. other team members) bias the results. Tennis is a good individual sport to study because most matches are played one-on-one procedure. This one-on-one situation is especially interesting for research in sports momentum because research in team sports is influenced by several opponents and members from

the own team.

In tennis, momentum is empirically examined by observing if the player who won the second to last set has a significant advantage in the last set. In a best-of-three set match this means that both players have won one set. Researchers then observe who wins the last set. This means that the researcher wants to examine if player has a comeback.

Clearly, the hot hand in basketball is not the same as momentum in tennis. However, both concepts rely on the notion that players have a psychological or physiological advantage at one point in a match.

Several authors have already examined momentum in tennis. Silva, Hardy, and Crace (1986) observe intercollegiate tennis. They do not find evidence for psychological momentum for best-of-three set matches. Thus, Silva et al. observe if the player who was down one set benefits from a comeback. This is also their definition of momentum: Momentum, in their context, means that the player who won the second to last set has an increased probability to win the last set. Weinberg and Jackson (1989) examine a vast dataset of professional and amateur tennis players. They observe the comeback behavior of men and women after losing the first of three sets. They find that men are more likely to win a "comeback game" than women. Burke, Edwards, Weigand, and Weinberg (1997) ask tennis players to assess when they observe momentum. They find that tennis players disagree when a player benefits from momentum. Our analysis differs in two ways from previous work in the area of momentum.

Our first difference is that we examine the set score. We analyze whether

the set score has an effect on momentum. Earlier studies (cf., Silva et al., 1986; Richardson, Adler, & Hanks, 1988; Weinberg & Jackson, 1989) analyze only whether a player wins or loses (i.e. win=1, lose=0) a set. Henceforth, this method is called the binary approach. A drawback to using the binary approach, is that it does not distinguish if a player wins a set 6 - 0 or 7 - 6. Reducing the outcome of a decisive set to a binary variable does not exploit all relevant information within the data, therefore we include the set score in our data analysis.

Our second point of departure is that we check if momentum depends on the rounds in a tournament. We want to analyze whether momentum increases or decreases for a player depending on the round he plays. The message is that players might perform differently in a final round compared to a first round; we might observe different momentum levels. We find that momentum does not depend on the round; no difference exists between a final match or a first round match.

In contrast to earlier studies, our results show that momentum depends on the set score. We find that winning the second to last set with a high margin significantly increases the chances to win the last set. On the other hand, if a player barely wins the second to last set he is likely to lose the last set and, therefore, the entire match. We call this phenomenon anti-momentum. Anti-momentum is the result of a perceived loss of control. A player who barely won the second to last set, after being ahead in the match, feels that he is losing control of the match. Whereas a player who easily won the second to last set

after being behind in the match feels that he has (re-) gained control of the match. Our paper is structured as follows: Section 2 gives a general explanation of tennis rules. Section 3 presents our data. Section 4 evaluates the data and Section 5 is a brief conclusion of our findings.

Tennis rules

Tennis is played in a one on one game (singles) or in a two on two game (doubles). There are tournaments for men's singles, men's doubles, women's singles, women's doubles, and mixed doubles.

Tennis is structured in this way: points form a game, games form a set, and sets form a match. A game is not the same as a match. A player wins a game if he wins at least four points and two more than his opponent. A set is complete if one player wins at least six games and wins two more games than his opponent. In some Grand Slam tournaments a player has to win two more games than his opponent to win the last and/or decisive set. However, in the second to last set a tie break is played. When the score is 6 - 6 a set is decided by a tie break. The outcome of the set is won by the player who has scored at least seven points and two more points than his opponent.

If one player has won five games, then the opponent needs at least seven games to win the set. Matches are played in best-of-three sets or best-of-five sets mode. Women always play best-of-three set matches, men also play best-of-five set matches. The player who wins two (respectively three) sets wins the match.

Tennis tournaments give different amounts of points. Winning the final in the

highest ranked tournament gives 2,000 points (Grand Slam), 1,500 points in the second highest ranked tournament (ATP World Tour Final), and 1,000 points in the third highest ranked tournament (ATP 1,000 Tournaments). Players who do not win a tournament receive a share of the points based on their success in the respective tournament.¹

A player is ranked based on the points he gathers in all ATP or Grand Slam tournaments in the previous twelve months. The ranking ” . . . is the ATP’s historical objective merit-based method used for determining entry and seeding in all tournaments for both singles and doubles, except as modified for the Barclays ATP World Tour Finals.” (Association of Tennis Professionals, 2015)

Method

Data

We use data for all Grand Slam tournaments beginning with 1985 for men and 2003 for women. This is due to the availability of complete data. Otherwise we would have included the same time frame for both men and women. Our analysis includes the Australian Open, Roland Garros, US Open, and Wimbledon. Table 1 gives an overview of all variables. We include only matches played until the last point (we do not include matches where a player resigns). If a male player needs three or four sets to win (respectively, a female player needs two sets to win),

¹For example in a Grand Slam tournament, the runner up receives 1,200 points, a semi-finalist 720 points and so on.

the respective match is omitted from our dataset because we cannot determine a certain set or outcome in these matches to measure momentum. This is only possible for best-of-five-set matches for men and best-of-three-set matches for women. Due to this process a large part of the matches are omitted (we keep approximately 4,200 matches from a total of approximately 19,000 matches.).

[Insert Table 1 near here]

As covariates we include information about the winner and the loser of a match. Because the data provides the nationality of both players, we add a variable to control how players benefit from a home advantage. Therefore, we differentiate between players from Australia, France, United Kingdom, and USA the venues for the Grand Slam tournaments. Similar approaches are applied by Koning (2011) and Krumer, Rosenboim, and Shapir (2016).

Additionally, we add the number of sets a player played in the previous match in the same tournament. For a Grand Slam tournament a previous match has either three, four, or five sets for men and two or three sets for women. The explanation is that a player is tired after playing five sets in the previous round. If a player has not played in the previous match (e.g., in the first round) we categorize the player as not tired.²

We distinguish between the rounds. A Grand Slam tournament has seven stages: 1st round, 2nd round, 3rd round, 4th round, quarterfinal, semifinal, and

²This means a player has a "0" in all previous match categories.

final. The effort level between rounds could vary because players receive a higher compensation the further they advance in a tournament. Players could invest more effort for higher paying tournaments, however, for all tournaments in our data set the players receive the same number of points. Additionally, the effort depends on the quality of the player and his opponents.

[Insert Table 2 near here]

Table 2 provides a concise overview of this data. The table shows the score of the second to last set in every round. For example 68.7% of all players won the match in the first round when they won the second to last set 6-0. Additionally, the tournament type yields information about the playing surface. The surface in Wimbledon is grass; at the French Open clay; and at the Australian and US Open hard court. It is possible that the different surface types influence the results of our analysis. For a more advanced discussion about the impact of the surface in tennis see for example Gilsdorf and Sukhatme(2008) or del Corral (2009). We add tournament type as a dummy variables in the analysis.

We use the points a player has received immediately before the tournament starts. We generate a variable that measures the different accumulated points of the players who face each other. Tennis players are ranked based on the amount of points they gathered in the previous twelve months (as explained in the previous section). We use the log of the rank of the winner of a match minus the log of the rank of the runner-up. For a similar approach see e.g., Koning

(2001) or Krumer, Rosenboim, and Shapir (2016). The difference in points controls for the players skill sets. All variables, except for the log of ranking and the set outcome, are dummy variables.

Data Analysis - Classical binary approach

Table 3 shows the results when using the binary approach. The dependent variable is "1 if the player won both the second to the last and then last set, a 0 represents the case when the player won the second to last set and lost the last set. Throughout this paper we use the same dependent variable. We include all control variables mentioned in the previous section. This approach, except for the introduction of the control variables, is similar to the approach used by Silva et al. (1986), Richardson et al. (1988) and Weinberg and Jackson (1989). In the binary approach a player either wins or loses the second to last set. The set outcome is omitted when using the binary approach. That means a 6 - 0 or a 7 - 6 are both a "1" for the winner and "0" for the runner-up. By using this approach a significant amount of information is lost.

Because the dependent variable is binary, one can also use a logit/probit model; however, the additional value of the logit/probit model in this context is not clear. For a more detailed discussion of the advantages and disadvantages of a probit model see Angrist (2001) or Beck (2011). We performed the same analysis with a probit regression and did not receive statistically significant different results. We use ordinary least squares with robust standard errors. Round 1 and Round 2 are omitted in every regression because of collinearity issues with

Round 3. This means, that the results from round 1, round 2, and round 3 are too similar to include all in our analysis. Accordingly, we omit both round 1 and round 2.

[Insert Table 3 near here]

Table 3 shows that players have a 54.2% chance to win the last set when they win the second to last set (assuming that all variables are "0"). Thus, the constant term states the size of momentum. Rounds, home advantage, gender difference, and previous matches for females have no statistically significant effect on the outcome in both Table 3.

Data Analysis - Set score approach

In Table 4 we analyze the data from a different perspective. To examine the set score of a match we divide every second to last set into its outcome. The dependent variable, set score, shows the results of this approach. Again the variable is binary "1" for win and "0" for runner-up.

[Insert Table 4 near here]

Table 3 and Table 4 show three main results. First we see almost no difference between the rounds. No single round yields a stable statistically significant advantage for a player. For example, on the one hand players have a significant

advantage when they win the second to last set 6 - 2 in round 3, on the other hand players have a significant disadvantage when they win the second to last set 7 - 5 in the final. In addition to these seemingly random results in each round, we do not see any pattern between rounds. Therefore, we conclude that players do not behave differently from round to round.

The second result concerns all set scores except the set score 7 - 6. Figure 1 shows the results from table I and table II. The x-axis displays the chance to win the last set, the y-axis displays three covariates (Ranking, Gender of the player, and home match) and the constant. All set scores, except the set score 7 - 6, yield a higher chance to win the last set. Players have a significant advantage of up to 60% to win the last set after winning the previous set.

[Insert Figure 1 near here]

However, our last result concerns the set score 7 - 6 (i.e. a player wins through a tie break). We see, that if a player won the second to last set in tie break, he faces anti-momentum in the last set. A player only has a 45.8% chance to win the last set when he won the second to last set in tie break. Anti-momentum then means that a player has a lower chance to win the last set even though he won the second to last set. This result is visible in Figure 1. The set score 7 - 6 is a clear outlier in both cases.

Discussion

Table 3 analyzes different rounds with the binary approach. We observe that players have momentum, with a 54.2% chance to win the last set (assuming all control variables are "0"). In the introduction of the paper we explained how momentum was introduced in basketball. In basketball, researchers use the "hot hand" as a synonym for momentum. This means that a player has a high probability to make the consecutive shots he takes. The definition includes the concept that a player benefits from momentum even though he does not hit every shot.

The concept of momentum is misinterpreted in tennis when using the binary approach. Winning a set in tennis has different meanings depending on the winning score (7 - 6 or 6 - 0). An opponent constantly challenged a player if a set is won through e.g. a tie break (thus, winning 7 - 6) or in overtime (viz. 7 - 5). It can be the case, that after winning a game the opponent directly countered the player. Thus, winning a set in such a situation only results in a benefit for the match but it does not give the player momentum. Momentum is applicable only when players benefit from a clear advantage.

The message from Table 3 is straightforward. Players have a 4.2% higher chance to win the last set than their opponents. These results change completely when we include the set score in Table 4. We observe a considerably higher momentum for every set score except for 7 - 6.

When a player wins the second to last set in tie break (winning 7 - 6) he has a significantly lower chance to win the last set than his opponent. Therefore, a player has anti-momentum after winning a set in tie break. One explanation for

this counterintuitive result is that players need control over a match to succeed. Without controlling a match, players are not able to influence the match in their desired direction. Our results support the control theory (Rotter, 1966). Control theory states ” . . . one should expect to succeed to the extent that one feels in control of one’s successes and failures.” (Eccles & Wigfield, 2002, p.111) A player evaluates a tie-breaking win (7 - 6) as a negative outcome. Beating another player in a tie-breaker is the closest possible margin to win a set. Although the player wins the second to the last set, the player loses control over the match. Thus, a player is disappointed that he beat his opponent only in a tie-breaker and not with a higher margin. This loss of control leads to a loss in the player’s success perception; the player has anti-momentum.

We do not find any empirical support for including the variable *rounds*. No round shows a significant advantage or disadvantage for a player. While including rounds makes sense from a theoretical perspective, we do not observe any statistical significance or pattern. However, the same pattern is visible for both home advantage and the gender of the player. Thus, the variable could still have an influence in future research.

Conclusion

We examine in this paper whether tennis players benefit from momentum. First, we analyze our data with the classical binary approach. We find momentum for players; however, we think that set scores are decisive factors when evaluating a match. Thus, limiting a set outcome to win or lose unnecessarily narrows the

dataset. Second, we include set scores and tournament rounds to analyze the data. We do not find any significant effects for the different tournament rounds. However, the set score approach, in contrast to the binary approach, shows a strong momentum for every set-score except for a tie break.

Nonetheless, our analysis is far from complete. Future research could incorporate whether player characteristics (e.g. age, handedness, or effect of a wild card) influence the results of this paper or influence momentum. In an ideal dataset we would be able to include the results of all sets in a match. This follows the result that the outcome of every set is important to assess momentum. We measure tiredness by the amount of sets played in the previous match in the same tournament. A more complete measure could incorporate how many tournaments a player attended in a specific time period. Additionally, an analysis in combination with the betting market could observe if bettors exploit knowledge regarding the set scores or if this information is included in already the odds.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	N
Binary depend variable	0.542	0.498	4366
Log rank difference	-0.356	1.453	4,283
<u>Set outcome in second to last set:</u>			
6 - 0	0.019	0.138	4366
6 - 1	0.059	0.236	4366
6 - 2	0.083	0.275	4366
6 - 3	0.129	0.335	4366
6 - 4	0.116	0.32	4366
6 - 5	0.059	0.235	4366
7 - 6	0.077	0.267	4366
Male - 3 sets previous match	0.146	0.353	4366
Male - 4 sets previous match	0.101	0.302	4366
Male - 5 sets previous match	0.059	0.236	4366
Female - 2 sets previous match	0.062	0.24	4366
Female - 3 sets previous match	0.062	0.24	4366
Male	0.377	0.485	4366
Home advantage	0.096	0.294	4351
Roland Garros	0.25	0.433	4366
US Open	0.242	0.428	4366
Wimbledon	0.26	0.439	4366
Australian Open	0.247	0.432	4366
Round 1	0.511	0.5	4366
Round 2	0.243	0.429	4366
Round 3	0.121	0.326	4366
Round 4	0.066	0.248	4366
Quarterfinal	0.033	0.177	4366
Semifinal	0.018	0.134	4366
Final	0.007	0.085	4366

Table 2: Summary statistics

Set score	6 - 0	6 - 1	6 - 2	6 - 3	6 - 4	6 - 5	7 - 6	N
Round 1	.687	.650	.582	.530	.510	.508	.479	2,233
Round 2	.655	.623	.549	.586	.457	.627	.465	1,063
Round 3	.786	.55	.707	.583	.481	.673	.469	539
Round 4	.5	.423	.547	.562	.603	.558	.471	287
Quarterfinal	.833	.714	.455	.526	142	.471	.461	142
Semifinal	1	.625	.615	.611	.461	.7	.529	80
Final		.75	0	.384	.75	0	.4	32

Table 3: Binary approach

Binary set score	
Round 3	0.0299 (0.0265)
Round 4	0.00102 (0.0335)
Quarterfinal	-0.0247 (0.0450)
Semifinal	0.0428 (0.0580)
Final	-0.119 (0.0910)
Ranking	-0.00106 (0.00526)
3 sets previous match male	0.0185 (0.0264)
4 sets previous match male	0.0104 (0.0295)
5 sets previous match male	0.0130 (0.0356)
2 sets previous match female	-0.0228 (0.0369)
3 sets previous match female	-0.0170 (0.0304)
Female	-0.00919 (0.0221)
Home advantage	-0.0224 (0.0267)
Tournament Dummy	Y
Constant	0.542*** (0.0194)
18	
Observations	4,268
R-squared	0.002

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05

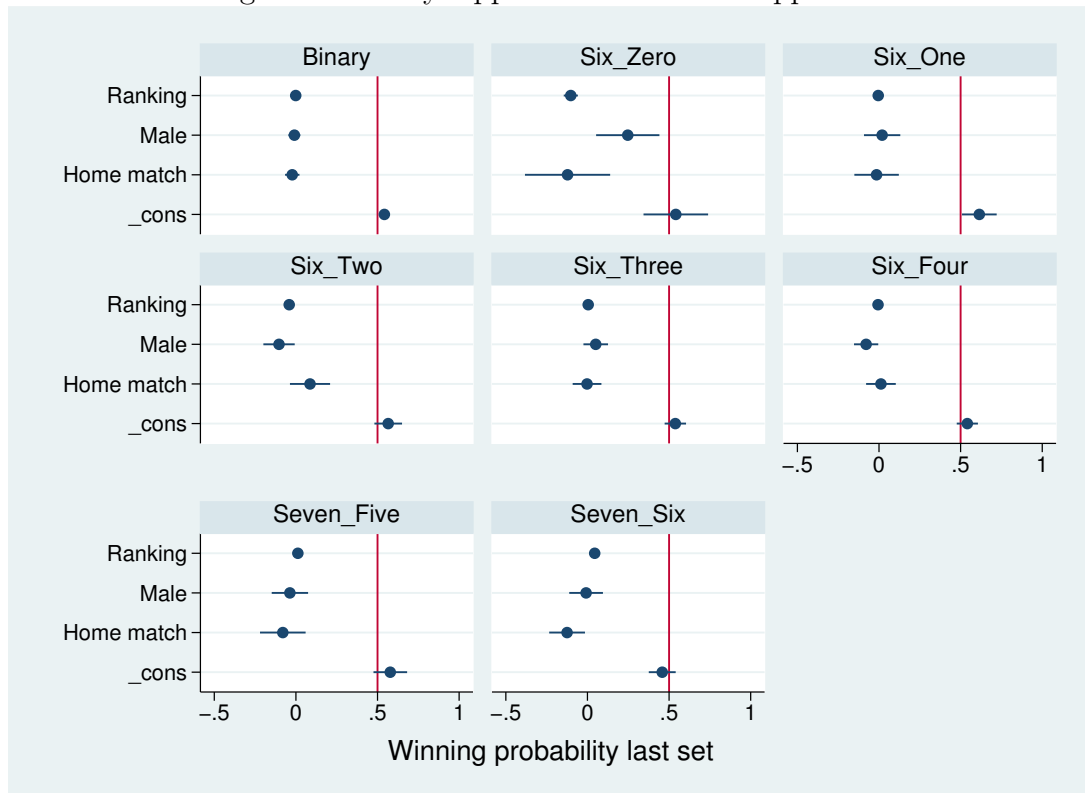
Table 4: Set score approach

Set score	6 - 0	6 - 1	6 - 2	6 - 3	6 - 4	7 - 5	7 - 6
Round 3	0.157 (0.173)	-0.0835 (0.0823)	0.147* (0.0661)	0.000724 (0.0564)	0.0320 (0.0553)	0.0420 (0.0837)	-0.00248 (0.0668)
Round 4	-0.0607 (0.194)	-0.190 (0.115)	0.00598 (0.0874)	-0.00736 (0.0706)	0.135 (0.0729)	-0.0557 (0.0972)	0.00184 (0.0798)
Quarterfinal	0.201 (0.165)	0.0533 (0.189)	0.000514 (0.141)	-0.133 (0.0934)	0.0709 (0.0900)	-0.173 (0.133)	-0.0240 (0.107)
Semifinal	0.499* (0.206)	-0.00781 (0.179)	0.149 (0.145)	0.0116 (0.125)	-0.0205 (0.142)	0.121 (0.169)	0.0372 (0.126)
Final		0.121 (0.234)	-0.514*** (0.0865)	-0.167 (0.147)	0.348 (0.218)	-0.662*** (0.0663)	-0.118 (0.194)
Ranking	-0.102*** (0.0260)	-0.00471 (0.0180)	-0.0409** (0.0133)	0.00470 (0.0112)	-0.00581 (0.0114)	0.0121 (0.0159)	0.0445*** (0.0128)
3 sets previous match male	0.216 (0.126)	0.0288 (0.0851)	-0.00183 (0.0733)	0.0744 (0.0544)	-0.0407 (0.0544)	-0.0106 (0.0855)	0.00705 (0.0618)
4 sets previous match male	0.0604 (0.200)	0.0567 (0.0888)	-0.0829 (0.0803)	0.0745 (0.0602)	-0.101 (0.0655)	0.137 (0.0915)	0.0137 (0.0677)
5 sets previous match male	0.187 (0.217)	-0.124 (0.138)	0.000690 (0.0969)	0.104 (0.0733)	-0.0775 (0.0713)	0.252** (0.0965)	-0.0419 (0.0817)
2 sets previous match female	-0.0624 (0.188)	-0.0438 (0.117)	-0.110 (0.0900)	0.0655 (0.0776)	-0.0614 (0.0785)	0.0105 (0.114)	0.0235 (0.0953)
3 sets previous match female	-0.333* (0.140)	-0.120 (0.0981)	0.0293 (0.0741)	-0.0158 (0.0639)	-0.0549 (0.0655)	0.183* (0.0888)	-0.0288 (0.0892)
Female	0.247* (0.117)	0.0192 (0.0675)	-0.103 (0.0583)	0.0507 (0.0458)	-0.0788 (0.0451)	-0.0367 (0.0676)	-0.00830 (0.0627)
Home Advantage	-0.122 (0.157)	-0.0147 (0.0827)	0.0865 (0.0746)	-0.00253 (0.0535)	0.0120 (0.0552)	-0.0802 (0.0847)	-0.125 (0.0665)
Tournament Dummy	Y	Y	Y	Y	Y	Y	Y
Constant	0.541*** (0.119)	0.615*** (0.0644)	0.566*** (0.0514)	0.538*** (0.0398)	0.541*** (0.0394)	0.578*** (0.0625)	0.458*** (0.0501)
Observations	123	411	606	1,001	985	450	692
R-squared	0.203	0.037	0.048	0.009	0.018	0.047	0.027

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Figure 1: Binary Approach - Set Score Approach.



References

- Angrist, J. D. (2001). Estimation of limited dependent variable models with dummy endogenous regressors, *Journal of Business & Economic Statistics* 19(1).
- Association of Tennis Professionals (2015). What is the emirates atp rankings?, <http://www.atpworldtour.com/Rankings/Rankings-FAQ.aspx>. Retrieved: 2015-08-03.
- Bar-Eli, M., Avugos, S. & Raab, M. (2006). Twenty years of hot hand research: Review and critique, *Psychology of Sport and Exercise* 7(6): 525–553.
- Beck, N. (2011). Is ols with a binary dependent variable really ok?: Estimating (mostly) tscs models with binary dependent variables and fixed effects, *Unpublished working paper, NYU* <http://politics.as.nyu.edu/docs/IO/2576/pgm2011.pdf>. Retrieved: 2015-08-03.
- Burke, K., Edwards, T., Weigand, D., Weinberg, R. et al. (1997). Momentum in sport: a real or illusionary phenomenon for spectators., *International Journal of Sport Psychology* 28(1): 79–96.
- Burns, B. D. (2001). The hot hand in basketball: Fallacy or adaptive thinking, *Proceedings of the Twenty-third Annual Meeting of the Cognitive Science Society*, pp. 152–157.
- Csapo, P., Avugos, S., Raab, M. & Bar-Eli, M. (2014). The effect of perceived streakiness on the shot-taking behaviour of basketball players, *European Journal of Sport Science* (ahead-of-print): 1–8.

- Del Corral, J. (2009). Competitive balance and match uncertainty in grand-slam tennis: effects of seeding system, gender, and court surface, *Journal of Sports Economics* .
- Eccles, J. S. & Wigfield, A. (2002). Motivational beliefs, values, and goals, *Annual Review of Psychology* 53(1): 109–132.
- Gilovich, T., Vallone, R. & Tversky, A. (1985). The hot hand in basketball: On the misperception of random sequences, *Cognitive Psychology* 17(3): 295–314.
- Gilsdorf, F. K. & Sukhatme, V. A. (2008). Tournament incentives and match outcomes in women’s professional tennis, *Applied Economics* 40(18): 2405–2412.
- Hughes, M. & Franks, I. (2015). *Essentials of performance analysis in sport*, Routledge.
- Iso-Ahola, S. E. & Mobily, K. (1980). ” psychological momentum”: A phenomenon and an empirical (unobtrusive) validation of its influence in a competitive sport tournament, *Psychological Reports* 46(2): 391–401.
- Koning, R. H. (2011). Home advantage in professional tennis, *Journal of Sports Sciences* 29(1): 19–27.
- Krumer, A., Rosenboim, M. & Shapir, O. M. (2014). Gender, competitiveness, and physical characteristics evidence from professional tennis, *Journal of Sports Economics* pp. 1–26.
- Krumer, A., Rosenboim, M. & Shapir, O. M. (2016). Gender, competitiveness, and physical characteristics evidence from professional tennis, *Journal of*

- Sports Economics* **17**(3): 234–259.
- Richardson, P. A., Adler, W. & Hanks, D. (1988). Game, set, match: Psychological momentum in tennis, *The Sport Psychologist* 2(1): 69–76.
- Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement., *Psychological Monographs: General and Applied* 80(1): 1.
- Silva, J. M., Hardy, C. J. & Crace, R. K. (1988). Analysis of psychological momentum in intercollegiate tennis, *Journal of Sport and Exercise Psychology* 10(3): 346–354.
- Taylor, J. & Demick, A. (1994). A multidimensional model of momentum in sports, *Journal of Applied Sport Psychology* 6(1): 51–70.
- Wardrop, R. L. (1995). Simpson’s paradox and the hot hand in basketball, *The American Statistician* 49(1): 24–28.
- Weinberg, R. & Jackson, A. (1989). The effects of psychological momentum on male and female tennis players revisited, *Journal of Sport Behavior* 12(3): 167–179.