International Journal of Performance Analysis in Sport
2015, 15, 1007-1021.

Winning in straight sets helps in Grand Slam tennis

Dries R. Goossens[1], Jurgen Kempeneers[2], Ruud H. Koning[3] and Frits C.R. Spieksma[4]

[1] Faculty of Economics and Business Administration, Ghent University, Belgium.
[2] Faculty of Business and Economics, KU Leuven, Belgium.
[3] Faculty of Economics and Business, University of Groningen, The Netherlands.
[4] Center for Operations Research and Business Statistics (ORSTAT), Faculty of Business and Economics, KU Leuven, Belgium.

Abstract

In this contribution, we study whether fatigue resulting from the previous match affects a player's chances of winning his (or her) next match in Grand Slam tennis. We measure relative fatigue levels of two opponents by looking at the difference in number of sets played in their previous match. We develop two approaches to answer this question: the so-called carry-over method and the more common logit model. Both methods differ in the assumptions they make and the type of results they offer. Our results are based on data collected from the 4 Grand Slam tournaments (men and women) from 1992 till 2011, covering 20,320 matches. We find that there is indeed an impact of the relative effort invested in winning a match on the probability of winning the next match in a Grand Slam tournament. For women, having played one set more in the previous match than the opponent in her previous match, leads to a decreased winning probability. For men, this is the case only for a set difference of two. Our results show that this effect is present in each of the grand slam tournaments and does not vary with the surface type.

Keywords: tennis, fatigue, grand slam, performance, advantage

1. Introduction

Perhaps more than for its finals, the 2010 Wimbledon Championships will be remembered for the epic match between John Isner and Nicolas Mahut. This match took 11 hours and 5 minutes, spread over 3 days, making it the longest match in professional tennis history. Eventually, Isner won with a score of 70-68 in the fifth and final set, for a total of 183 games (see also O'Donoghue (2013)). Less well known is that in his next match, Isner was defeated by Thiemo de Bakker in 3 short sets, after a mere 74 minutes of play. Although no-one will question that Isner's swift defeat was due to fatigue resulting from his confrontation with Mahut, we want to study the effect of fatigue caused by the previous match on the outcome of the next match in Grand Slam tennis in general. To what extent does the physical effort invested in winning a match have an effect on the probability of winning the next match? Is it indeed beneficial to close out a match in straight sets in order to be "fully fresh" for the next match? Does an extra day of rest before the final make a difference in the chance of winning the tournament? These questions are subject of debate, and in this contribution, we intend to shed some light on this issue.

Several authors have examined the effects of fatigue on tennis skills. Vergauwen et al. (1998) and Davey et al. (2002) both set up a tennis performance simulation test using a ball machine. Both contributions find only a modest impact of fatigue on groundstroke and service accuracy, although Davey et al. (2002) observed a more dramatic decrease when the players reached volitional exhaustion (which does not seem likely to occur during real match circumstances). Ferrauti et al. (2001) found that running speed and stroke quality during intermittent tennis tests are highly dependent on recovery time, although stroke precision can be maintained for a short period even if the duration of recovery decreases. A more advanced exercise protocol to simulate tennis matchplay has been developed by Davey et al. (2003). Performance deterioration and fatigue have also been studied in more natural settings, such as 1 hour match play simulations (Dawson et al. (1985)), four-set tennis matches involving professional players (Gomes et al. (2011)), and prolonged tennis matches of 4 hours (Struder et al. (1995)). Most studies choose certain tennis skills as performance measure, and find them to deteriorate with progressive fatigue. The effect of the deterioration of these skills on match outcome is however not immediately clear. Furthermore, the experimental setup typically does not include real tournament conditions. Indeed, Hornery et al. (2007) point out that it presents a huge methodological challenge to replicate the demands of actual match play in a scientific field-based experiment.

Tournaments have also been studied from an economic point of view (e.g. Ryvkin (2011)). Indeed, business contracts, tenders, and employee promotions are often awarded through a multistage elimination procedure, not unlike the design of a tennis tournament. This resemblance allows a number of studies to use data from professional tennis to test predictions of economic theory. In such an economic context, the effort invested in a particular stage corresponds to the energy a player allocates in a certain match. For instance, Brown and Milnor (2014) present evidence for the existence of a so-called negative *spillover effect*: past exertion makes current effort more costly and reduces performance (negative spillover might reflect fatigue; positive spillover might reflect momentum). Sunde (2009) finds that the incentive to provide effort is highest in tennis tournaments with homogeneous players (in terms of player strength), and heterogeneity especially impacts the effort choice of the stronger player. One issue that limits the impact on tennis of these studies is the question to what extent a player, in the heat of the match, can strategically allocate his/her effort over time. Interestingly, Varshney (2014) shows that some players in specific situations, do not waste any energy in winning the next point; he also shows that top players play all points indistinguishable.

In this empirical study, we opt for the chance of winning a Grand Slam tennis match as our performance criterion. Indeed, winning is ultimately the goal for any athlete, the stakes are high at these prestigious tournaments, and tournament conditions are by far the most relevant. This choice, however, limits the availability of data describing the conditions of the previous match. Traditional indicators of fatigue as e.g. heart rate, blood lactate, body mass loss or core body temperature are obviously not up for grabs.

Smekal et al. (2001) show that the energy demand of a tennis match is significantly influenced by the duration of the rallies, but as even the total time spent on court is only available for recent Grand Slam matches, this is not an option either. In light of this, we settled for the number of sets played as our measure for the effort a player invests in a match. Apart from the fact that these data are freely available for a period of over 20 years, it also allows for a straightforward way to categorize the relative effort invested, namely the difference between both opponents in number of sets played in their previous match. Alternatively, when considering the number of games (or points) played, we would need to group matches according to boundaries that are rather arbitrary. Notice that we study the effort of the last match, assuming that fatigue or other effects from matches played earlier than the previous one have been digested. Given a proper number of resting days between successive matches, we believe this is a defendable choice.

We want to point out that this topic is also related to the so called *carry-over effect*. Russell (1980) originally defined some player (or team) A to receive a carry-over effect from player B if some player X plays against player B in one round, and against player A in the next round. The carry-over effect is perceived to be particularly relevant in physical, body-contact sports. For instance, if player B is very strong, and tough-playing, one can imagine that his opponent, player X, is weakened by injuries, fatigue or lowered morale, which could be an advantage for its next opponent, player A. Goossens and Spieksma (2012) empirically studied the influence of the carry-over effect on football (soccer) matches, but found no evidence for any meaningful impact on match outcome. Here, we present an empirical study revealing the impact of the effort invested in the previous match on the current match result in Grand-Slam tennis.

2. Methods

We present two methods to measure the effect of a player's previous match on his/her next match. The first method can be seen as an adaptation of a procedure proposed by Goossens and Spieksma (2012), to which we will refer as the carry-over method (Section 2.1). The second method is based on a logit model approach, see e.g. Koning (2011); we refer to this method as the logit model (Section 2.2). We conclude in Section 2.3 with a brief comparison of the assumptions, strengths, and weaknesses of each method.

2.1. The carry-over method

The idea of this approach is to compare the actual result of each match with the result that could be expected when both opponents would have played the same number of sets in their matches in the previous round. From the difference between this expected result and the actual result, we obtain insight in the influence of the previous match on winning probability. First we explain how we arrive at expected match results. Next, we discuss the details of the comparison and the statistical significance test.

We need to determine for each tennis match which result we expect when both players played the same number of sets in their previous match. We assume that the result of a match is determined (only) by the tennis court surface, and the strength and gender of both players. The strength of a player is measured by his/her ATP/WTA world ranking at the start of the tournament; we consider four surface types: grass, clay, acrylic hard court, and synthetic hard court. This is in accordance with e.g. del Corral and Prieto-Rodriguez (2010), who found the (difference in) ATP or WTA rankings to be the most relevant explanatory variable for Grand Slam tennis outcomes, and also found a significant surface effect (for men). Gender has been shown to have an impact on strategy and performance in tennis by several researchers (e.g. O'Donoghue (2002)). More specifically, Du Bois and Heyndels (2007) found differences in competitive balance between men's and women's tennis: lower-ranked men have a better chance of performing well in a tournament than lower-ranked women. Hence, for each gender and surface type, we determine a matrix, which gives the proportion of wins for the stronger player, for matches between opponents belonging to given player strength groups. We define the following 7 strength groups: players ranked 1 to 4, 5 to 8, 9 to 16, 17 to 32, 33 to 64, 65 to 128, and finally players with a world ranking worse than 128. These groups are conveniently in line with Grand Slam tournament design and seeding, and with the fact that world ranking differences become less important as players are lower ranked (del Corral and Prieto-Rodriguez, 2010). Furthermore, using more strength groups would not allow us to have sufficiently many observations for each pair of different strength groups; using fewer groups would not allow an accurate expression of player strength. Ideally, to make sure that our matrix is not influenced by previous-match effects, it should contain only first round matches (ignoring the fact that a minority of the players had already played one or more qualification matches). However, since higher ranked player hardly ever meet in the first round, we also included matches between players that played the same number of sets in their previous match.

Table 1. Win probabilities for Wimbledon (women), depending on their strength groups

Ranking	**1-4**	**5-8**	**9-16**	**17-32**	**33-64**	**65-128**	**>128**
1-4	0.50	0.60	0.81	0.91	0.89	0.95	0.94
5-8	0.40	0.50	0.82	0.70	0.77	0.89	0.97
9-16	0.19	0.18	0.50	0.48	0.71	0.88	0.90
17-32	0.09	0.30	0.52	0.50	0.64	0.73	0.81
33-64	0.11	0.23	0.29	0.36	0.50	0.62	0.73
65-128	0.05	0.11	0.12	0.27	0.38	0.50	0.56
>128	0.06	0.03	0.10	0.19	0.27	0.44	0.50

In order to construct the win probability matrix in Table 1, we collected data from the women's singles matches in the Wimbledon tournaments from 1992 until 2011. Each cell gives the proportion of matches won by the player from the stronger strength group, for matches between players from the corresponding strength groups. The interpretation is that, for instance, if a player's world ranking is between 17 and 32, there is a 9% probability that this player will beat a top-4 player on a grass surface. Cells on the diagonal were set to 50%; each cell *(i,j)* above the diagonal and its counterpart *(j,i)* below the diagonal add up to 1. Ideally, one would expect win proportions to go up when playing against weaker opponents (i.e. non-decreasing in rows and non-increasing in columns). We refer to this condition as the regularity property. Although it turns out that the win probabilities almost satisfy the regularity property, a close inspection of the table reveals some anomalies. For instance, for a player ranked between 5 and 8, a win against a player ranked between 9 and 16 is more likely than a win against a weaker player, ranked between 17 and 32. Since these irregularities may well distort our results and conclusions, we compute minimum adjustments to the matrices, in order to find estimates of the win probabilities, satisfying the regularity properties. This can be done by solving a simple linear optimization model; we refer to Goossens and Spieksma (2012) for more details. The resulting win probabilities for each Grand Slam tournament (for men and women) can be found in the appendix.

The next step is to compare the actual result of a collection of matches with the expected result. In Table 2, as an example, we selected five Wimbledon matches for women where player 1 played one set more than player 2 in her previous match. The actual result is 1 if player 1 won, and 0 if player 2 won; the expected results are based on Table 11 (see Appendix). We find a win probability of 40% for the player having played an extra set in the previous match, while we would expect 46.2%.

Table 2. Example matches where player 1 played 1 set more than player 2 in her previous match

Year	Player 1	Player 2	Rank 1	Rank 2	Actual	Expected
1992	Navratilova, M.	Rittner, B.	4	43	1	0.89
1995	Tauziat, N.	Pierce, M.	35	5	1	0.23
1998	Black, C.	Tanasugarn, T.	189	46	0	0.27
2002	Capriati, J.	Mauresmo, A.	2	9	0	0.81
2009	Vesnina, E.	Dementieva, E.	37	4	0	0.11
Win probability					0.400	0.462

To find out whether the actual results of these matches differ significantly from the expected results, a chi-square test is performed, where the null hypothesis is that there is no difference between actual and expected results. For this particular example (which has too few observations), Table 3 shows that the test results in a *p*-value of 0.78. This does not allow us to conclude that the actual and expected observations originate from a different probability distribution. In other words, the fact that player 1 played an extra set in her previous match didn't have a significant impact on the outcome of the match.

Table 3: Chi-square test for the example in Table 2

	Matches won	Matches lost
Actual number of observations	2.00	3.00
Estimated number of observations	2.31	2.69

$\chi^2 = 0.077$

$\chi^2_{0.95} = 3.84$ (d.f. = 1)

p-value = 0.78

2.2. The logit model

The logit model is a generalization of the linear regression model when the dependent variable is binary (Harrell, 2001). As we use the binary variable ``winning a match'' as the dependent variable, a logit model is well suited. Let's consider two arbitrary tennis players, A and B, and denote by *Pr(A>B)* the probability that A wins against B. The individual characteristics of A and B are represented by vectors x_A and x_B respectively. Koning (2011) stresses that only *differences* in individual characteristics can be entered as covariates, as an increased winning probability for player A should imply a decreased winning probability of player B. Hence, our model is

$$\Pr(A > B) = \frac{1}{1 + \exp(-\beta'(x_A - x_B))},$$

where β is a vector of coefficients to be estimated. The specification is such that if β_k is positive, the probability is increasing with the difference x_{Ak} - x_{Bk}. We consider the following individual characteristics: player strength, number of days elapsed since the previous match, and number of sets played in the previous match. We measure the strength of a player by his/her world (ATP/WTA) ranking at the start of the tournament. As suggested by Klaassen and Magnus (2001, 2014), strength differences between players are included using the difference of log (2 base) world rankings. For the remainder of this text, the *rank* of player A (denoted by r_A) is the $\log_2$ of the world ranking of player A (denoted by WR_A). To find out whether the effect of the difference in sets played in the previous match varies with the surface type or gender, we can include common effects for each surface type (gender), and interaction effects for the surface type (gender) with the difference in sets played in the previous match.

2.3. Comparison

The carry-over method and the more common logit model each have their strengths and weaknesses to tackle the issue of previous match effects in tennis. Contrary to the logit model, the carry-over method does not assume a log-linear relationship between dependent and independent variables. Furthermore, the carry-over method takes into account Grand Slam tournament design with strength groups in accordance with the fact that half of the players are eliminated after each round, and acknowledges that matches featuring stronger players are over-represented in the dataset. On the other hand, the logit model produces more detailed information, allowing for instance to compare the effect of having played one set less than your opponent with the quality of that opponent based on the world ranking. Furthermore, the logit model is more powerful in assessing whether the previous-match effects vary with sex or surface type.

3. Results

We now assess the effect of fatigue resulting from the previous match on the outcome of Grand Slam matches. Our results are based on data from the four Grand Slam tournaments between 1992 and 2011, for a total of 20,320 matches. We collected these data using the TennisNavigator database, and the website tennis-data.co.uk. The carry-over method produces the results in Table 4. Each row in the table corresponds to the difference in sets played in the previous match, for men and women separately. This difference can be at most two for men and one for women, as we removed matches following walk-overs and abandoned matches from our dataset. The table reveals the actual win proportion (w_{act}), the expected win proportion (w_{exp}), and the difference between both (Δw). It also shows the p-value of the chi-square test on the difference between actual and expected results.

Table 4. Analysis of previous-match effect in Grand Slam tennis (carry-over method)

	Men				**Women**			
Δset	w_{exp}	w_{act}	Δw	p	w_{exp}	w_{act}	Δw	p
1	0.465	0.451	-0.014	0.24	0.433	0.388	-0.045	<0.0001
2	0.436	0.387	-0.049	<0.001				

Notice that the actual win proportions are considerably below 0.5 and dropping as the difference in sets played in the previous match increases. From this, however, one cannot conclude that fatigue from the previous match has an impact on match outcome. Indeed, the player that needs fewer sets to win might simply be the better player. Furthermore, the seeding in Grand Slam tournaments favors higher ranked players, offering them an easier way to a win in straight sets. We emphasize however that this effect is taken into account in the expected win proportions, such that the difference Δw gives insight in the decrease in win probability due to previous-match fatigue. We see that for men, having played one additional set in the previous match compared to the opponent does not decrease one's chances: the deviations are small and not significant. However, for a difference of two sets, the more tired player sees his chances decrease by almost 5 percentage points. For women, having played one additional set previously already results in a significantly lowered winning probability.

Results obtained with the logit model are given in Table 5. In this table, the columns labeled $\hat{\beta}$ display point estimates, columns labeled S.E.($\hat{\beta}$) represent the standard errors of those point estimates, and p refers to the p-value resulting from the regression. We estimate the relation between win probability and differences in player rank (Δrank) and difference in number of sets played in the previous match (Δsets). We did not include an intercept, because two players with (hypothetically) equal world ranking and without differences in the other covariates should have an equal probability to win the current match.

Table 5. Analysis of previous-match effect in Grand Slam tennis (logit model)

	Men			**Women**		
	$\hat{\beta}$	S.E.($\hat{\beta}$)	p	$\hat{\beta}$	S.E.($\hat{\beta}$)	p
Δrank	-0.439	0.015	<0.0001	-0.474	0.153	<0.0001
Δsets=1	-0.076	0.051	0.134	-0.286	0.052	<0.0001
Δsets=2	-0.184	0.039	<0.0001			

For men as well as women, the difference in rank is highly significant. The negative sign for the difference in rank is expected: keeping the rank r_B of player B fixed, an increase in the value of the difference means that rank r_A increases, so A becomes a poorer player and naturally, his/her winning probability decreases. Table 5 confirms the results found with the carry-over method: previous-match fatigue kicks in already after a set difference of one for women, whereas a male player is affected only if he played two sets more than his opponent in the previous match.

The results in Table 5 also allow us to compare the impact of player ranking and previous-match fatigue. Consider for instance three female players A, B, and C, with ranks r_A, r_B, and r_C, respectively. In the first setting, A and B both played their previous match on the same day, and won after playing the same number of sets. In this case, the winning probability of A is determined solely by $\beta_{\Delta rank}(r_A - r_B)$. In the second situation, A plays against C, and A won the previous match in one set more than C. The winning probability of A against C depends on $\beta_{\Delta rank}(r_A - r_C) + \beta_{\Delta set=1}$. The winning probability of player A is equal in both cases if

$$\beta_{\Delta rank}(r_A - r_B) = \beta_{\Delta rank}(r_A - r_C) + \beta_{\Delta set=1} \Leftrightarrow r_B = r_C - \frac{\beta_{\Delta set=1}}{\beta_{\Delta rank}}.$$

Because ranks are measured in $\log_2$ of the world ranking, we get

$$WR_B = 2^{-\beta_{\Delta set=1}/\beta_{\Delta rank}} WR_C.$$

This provides a nice interpretation of the previous-match effect. Using the point estimates given in Table 5, the factor $2^{-\beta_{\Delta set=1}/\beta_{\Delta rank}}$ is approximately 0.66. Suppose the world rank of player C is 30. Player A has an equal win probability against player B when player B is ranked 20. In other words, for women, an opponent ranked 30 that played one set less in her previous match is equivalent to an opponent ranked 20, with no difference in sets played in the previous match.

In Table 6, we examine whether the results vary by sex using the logit model. Since the win probability is impacted only if the difference in sets played in the previous match is maximal, we estimate this model with a maximum set difference indicator (which is 1 for males if the set difference is 2, -1 if the set difference is -2, 1 for females if the set difference is 1, and -1 for females if the set difference is -1). The results show that neither the rank effect nor the set difference effect varies by sex.

Table 6. Differences in previous-match effect between men and women (logit model)

	$\hat{\beta}$	$S.E.(\hat{\beta})$	p
Δrank	-0.440	0.015	<0.0001
Δrank x sex=women	-0.033	0.021	0.118
Δsets=max	-0.184	0.039	<0.0001
Δsets=max x sex=women	-0.101	0.064	0.115

Since we only have date of play information for the matches played in 2000-2011, we have used a restricted dataset to measure the impact of rest days on winning probabilities. Our model includes the difference in rest days (Δdays) and combines data from men and women; the results are reported in Table 7.

Table 7. Analysis of the impact of rest days in Grand Slam tennis (logit model)

	$\hat{\beta}$	$S.E.(\hat{\beta})$	p
Δrank	-0.498	0.012	<0.0001
Δsets=max	-0.149	0.042	0.0004
Δdays	-0.065	0.105	0.533

Perhaps surprisingly, the difference in rest days is not significant. A closer look at the data shows that the difference in rest days between both opponents at Grand Slam tournaments is at most one in over 98% of the matches. Apparently, this issue is handled very well by the tournament organizers, such that, in general, it has no impact on match outcome.

Table 8. Comparison of previous-match fatigue for all Grand Slam tournaments (carry-over method)

	Men				**Women**			
	w_{exp}	w_{act}	Δw	p	w_{exp}	w_{act}	Δw	p
***Δset* =1**								
Australian Open	0.469	0.465	-0.004	0.86	0.418	0.378	-0.040	0.06
French Open	0.471	0.446	-0.025	0.24	0.433	0.388	-0.045	0.03
US Open	0.451	0.432	-0.019	0.41	0.431	0.385	-0.046	0.03
Wimbledon	0.467	0.456	-0.011	0.59	0.449	0.399	-0.050	0.02
***Δset* =2**								
Australian Open	0.418	0.370	-0.048	0.10				
French Open	0.428	0.400	-0.028	0.33				
US Open	0.436	0.395	-0.041	0.17				
Wimbledon	0.454	0.386	-0.068	0.02				

In Table 8, we disaggregated the data to find out whether the effect of previous-match fatigue varies with the Grand Slam tournament (and surface type) using the carry-over method, both for men and women. Although the results all point in the same direction - having played relatively more sets in the previous match decreases one's win probability - no effect is found significant within the 1% level. We believe this is due to an insufficiently large dataset for this method. For instance, for women, in less than 44% of the matches the opponents played a different number of sets in their previous match, leaving just a few hundred of matches to work with. Nevertheless, the decrease in win proportion seems slightly more pronounced for Wimbledon. Summers (2011) report that due to the dominance of serve on grass, a Wimbledon tennis match stands a larger chance to feature tie-breaks, and hence has a larger chance of going to five sets. We also observed that almost one out of four matches at Wimbledon features a player who won a five setter whereas his opponent won in straight sets. To check whether Wimbledon is really different from the other Grand Slam tournaments, we estimated a logit model (see Table 9). As none of the interaction effects between tournament and Δset=max are significant, we can claim that the effect of the difference in number of sets played in the previous match does not vary with the surface type.

Table 9. Comparison of previous-match fatigue for all Grand Slam tournaments (logit model). The reference tournament for set difference is the Australian Open

	$\widehat{\beta}$	$S.E.(\widehat{\beta})$	*p*
Δrank	-0.476	0.011	<0.0001
Δset=max	-0.204	0.063	0.0012
Δset=max x tournament=French Open	0.047	0.088	0.5960
Δset=max x tournament=US Open	-0.070	0.090	0.4391
Δset=max x tournament=Wimbledon	-0.045	0.086	0.6000

4. Discussion and conclusion

We considered the question whether the probability of winning a match in a Grand Slam tournament is affected by the relative effort invested in the previous match. We use two different approaches to tackle this issue: the carry-over method and the more common logit model. Both methods support the conclusion that there is indeed an impact of the relative effort invested in winning a match on the winning probability for the next match in a Grand Slam tournament. For women, having played one set more in the previous match than the opponent in her previous match leads to a decreased winning probability. For men, this is the case only for a set difference of two.

Our results refine work by O'Donoghue (2006), who studied the effect of having played fewer sets than the opponent in the previous *two* rounds of Grand Slam tennis tournaments. He found that for women, higher ranked players won a higher proportion of the matches when they had played fewer sets than their opponent, than when they had played the same number or more. For men, on the other hand, differences in the number of sets played did not significantly affect the outcome. It should be noted that the research by O'Donoghue (2006) does not address the gap in ability between player strength (other than higher or lower ranked), nor does it consider the number of rest days; further, the results are based on a data set which includes Grand Slam matches from 2005 only (242 matches). Our results confirm his findings for women, however, here we show that previous match effects do exist for men provided that the difference in sets played in the previous round is two. Furthermore, we managed to quantify this effect, in terms of a decrease in winning probability, as well as in terms of the world ranking of the opponent.

The results presented here confirm results presented by Brown and Milnor (2014), who found that more games played in previous rounds for the stronger player decreases his/her probability of winning the current match, whereas more previous games for the weaker player increases the chance that the stronger player wins. The authors also find that a common proportional increase in the number of games played in all previous rounds decreases the probability that the stronger player wins. An implication of their analysis is that the rank effect wears off if one of the players has played more games. However, we were not able to find a significant interaction effect that would confirm this proposition. Notice though that - contrary to our assumptions - Brown and Milnor (2014) do not work with the *difference* in previous match effort by both players, and use a measure of fatigue which cumulatively builds up over all previous matches.

O'Donoghue and Ingram (2001) show that both the sex of the player and surface of the court have a significant influence on the nature of singles tennis at Grand Slam tournaments. For instance, they find that the length of rallies is significantly longer for women than for men, and that rallies are significantly shorter at Wimbledon and significantly longer at the French Open than at any other tournament. However, our results show that the set difference effect does not vary by sex or surface type. We should keep in mind that the length of rallies is just one aspect of fatigue, which could be compensated by others (e.g. the fact that Wimbledon sets have a larger chance of being decided in tie-breaks).

In conclusion, we find that if a tennis player needs the maximum number of sets to proceed to the next round, he or she will pay a price the next round when matched with an opponent that won in straight sets. Indeed, his/her chances to win this next round will decrease by almost 5 percentage points.

5. Acknowledgements

This work was supported by the Interuniversity Attraction Poles Programme initiated by the Belgian Science Policy Office under Grant P7/36. The authors wish to thank Anne Baeten, Hilde Van Grieken, Maarten Schmook and Anneleen Steurs for their excellent contributions to the master thesis which led to this paper.
This study has been approved by the Ethics Committee of the Faculty of Economics and Business Administration of Ghent University.

6. References

Brown, J. and Minor, D. (2014), Selecting the best? Spillover and shadows in elimination tournaments, **Management Science**, 60(12), 3087-3102.

Davey, P., Thorpe, R. and Williams, C. (2002), Fatigue decreases skilled tennis performance, **Journal of Sport Sciences**, 20, 311-318.

Davey, P., Thorpe, R. and Williams, C. (2003), Simulated tennis matchplay in a controlled environment, **Journal of Sport Sciences**, 21, 456-467.

Dawson, B., Elliot, B., Pyke, F. and Rogers, R. (1985), Physiological and performance responses to playing tennis in a cool environment and similar intervalized treadmill running in a hot climate, **Journal of Human Movement Studies**, 11, 21-34.

del Corral, J. and Prieto-Rodriguez, J. (2010), Are differences in ranks good predictors for grand slam tennis matches? **International Journal of Forecasting**, 26, 551-563.

Du Bois, D. and Heyndels, B. (2007), It's a different game you go to watch: competitive balance in men's and women's tennis, **European Sport Management Quarterly**, 7, 167-185.

Ferrauti, A., Pluim, B. and Weber, K. (2001), The effect of recovery duration on running speed and stroke quality during intermittent training drills in elite tennis players., **Journal of Sports Sciences**, 19, 235-242.

Gomes, R., Coutts, A., Viveiros, L. and Aoki, M. (2011), Physiological demands of match-play in elite tennis: A case study, **European Journal of Sport Science**, 11(2), 105-109.

Goossens, D. and Spieksma, F. (2012), The carryover effect does not influence football results, **Journal of Sports Economics**, 13, 261-278.

Harrell, F. E. (2001). **Regression modelling strategies**. Springer: New York.

Hornery, D., Farrow, D., Mujika, I. and Young, W. (2007), Fatigue in tennis: Mechanisms of fatigue and effect on performance, **Sports Medicine**, 37(3), 199-212.

Klaassen, F. and Magnus, J. (2001), Are points in tennis independent and identically distributed? Evidence from a dynamic binary panel data model, **Journal of the American Statistical Association**, 96(454), 500-509.

Klaassen, F. and Magnus, J. (2014), **Analyzing Wimbledon**. Oxford University Press.

Koning, R. (2011), Home advantage in professional tennis, **Journal of Sports Sciences**, 29(1), 19-27.

O'Donoghue, P. and Ingram, B. (2001), A notational analysis of elite tennis strategy, **Journal of Sports Sciences**, 19, 107-115.

O'Donoghue, P. (2002), Performance models of ladies' and men's singles tennis at the Australian open, **International Journal of Performance Analysis in Sport**, 2, 73-84.

O'Donoghue, P. (2013), Rare events in tennis, **International Journal of Performance Analysis in Sport**, 13, 535-552.

O'Donoghue, P.G. (2006), The advantage of playing fewer sets than the opponent in the previous two rounds of Grand Slam tennis tournaments, **Performance Analysis of Sport** 7 (Edited by Dancs, H., Hughes, M. and O'Donoghue, P.G.), 23rd-26th August 2006, Szombathely, Hungary, Cardiff: CPA UWIC Press, pp. 631-635.

Russell, K. (1980), Balancing carry-over effects in round robin tournaments, **Biometrika** 67(1), 127-131.

Ryvkin, D. (2011), Fatigue in dynamic tournaments, **Journal of Economics and Management Strategy**, 20(4), 1011-1041.

Smekal, G., Von Duvillard, S., C., R., Pokan, R., P., H., Baron, R., Tschan, H. and Bachl, N. (2001), A physiological profile of tennis match play, **Medicine and Science Sports and Exercise**, 33, 999-1005.

Struder, H., Hollman, W., Duperly, J. and Weber, K. (1995), Amino acid metabolism in tennis and its possible influence on the neuroendocrine system, **British Journal of Sports Medicine**, 29(1), 28-30.

Summers, M. (2011). Clay vs. Grass: A statistical comparison of the French Open and Wimbledon, **Biometrika**, 67(1), 127-131.

Sunde, U. (2009), Heterogeneity and performance in tournaments: a test for incentive effects using professional tennis data, **Applied Economics**, 41(25), 3199-3208.

Varshney, K. (2014), An analysis of losing unimportant points in tennis, **KDD Workshop on LargeScale Sports Analytics**.

Vergauwen, L., Spaepen, A., Lefevre, J. and Hespel, P. (1998), Evaluation of stroke performance in tennis, **Medicine and Science in Sports and Exercise**, 30, 1281-1288.

Appendix

Table 10. Win probabilities for Australian Open (women), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.68	0.79	0.92	0.96	0.96	0.96
5-8	0.32	0.50	0.69	0.69	0.88	0.94	0.94
9-16	0.21	0.31	0.50	0.56	0.87	0.90	0.90
17-32	0.08	0.31	0.44	0.50	0.59	0.75	0.75
33-64	0.04	0.12	0.13	0.41	0.50	0.61	0.64
65-128	0.04	0.06	0.10	0.25	0.39	0.50	0.53
>128	0.04	0.06	0.10	0.25	0.36	0.47	0.50

Table 11. Win probabilities for Australian Open (men), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.67	0.67	0.83	0.83	0.96	1.00
5-8	0.33	0.50	0.67	0.76	0.79	0.85	0.96
9-16	0.33	0.33	0.50	0.64	0.79	0.85	0.94
17-32	0.17	0.24	0.36	0.50	0.57	0.70	0.78
33-64	0.17	0.21	0.21	0.43	0.50	0.68	0.71
65-128	0.04	0.15	0.15	0.30	0.32	0.50	0.57
>128	0.00	0.04	0.06	0.22	0.29	0.43	0.50

Table 12. Win probabilities for French Open (women), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.75	0.75	0.83	0.97	0.97	1.00
5-8	0.25	0.50	0.75	0.82	0.83	0.89	0.96
9-16	0.25	0.25	0.50	0.78	0.78	0.87	0.87
17-32	0.17	0.18	0.22	0.50	0.72	0.74	0.75
33-64	0.03	0.18	0.22	0.28	0.50	0.65	0.72
65-128	0.03	0.11	0.13	0.26	0.35	0.50	0.55
>128	0.00	0.04	0.13	0.25	0.28	0.45	0.50

Table 13. Win probabilities for French Open (men), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.57	0.57	0.71	0.88	0.91	0.91
5-8	0.43	0.50	0.57	0.67	0.76	0.84	0.91
9-16	0.43	0.43	0.50	0.67	0.76	0.84	0.91
17-32	0.29	0.33	0.33	0.50	0.62	0.67	0.79
33-64	0.12	0.24	0.24	0.38	0.50	0.59	0.72
65-128	0.09	0.16	0.16	0.33	0.41	0.50	0.50
>128	0.09	0.09	0.09	0.21	0.28	0.50	0.50

Table 14. Win probabilities for Wimbledon (women), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.60	0.81	0.89	0.89	0.95	0.95
5-8	0.40	0.50	0.70	0.70	0.77	0.89	0.95
9-16	0.19	0.30	0.50	0.50	0.71	0.88	0.90
17-32	0.11	0.30	0.50	0.50	0.64	0.73	0.81
33-64	0.11	0.23	0.29	0.36	0.50	0.62	0.73
65-128	0.05	0.11	0.12	0.27	0.38	0.50	0.56
>128	0.05	0.05	0.10	0.19	0.27	0.44	0.50

Table 15: Win probabilities for Wimbledon (men), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.50	0.50	0.86	0.91	0.91	0.91
5-8	0.50	0.50	0.50	0.53	0.74	0.85	0.86
9-16	0.50	0.50	0.50	0.53	0.73	0.76	0.82
17-32	0.14	0.47	0.47	0.50	0.63	0.69	0.79
33-64	0.09	0.26	0.27	0.37	0.50	0.65	0.71
65-128	0.09	0.15	0.24	0.31	0.35	0.50	0.50
>128	0.09	0.14	0.18	0.21	0.29	0.50	0.50

Table 16. Win probabilities for US Open (women), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.75	0.81	0.85	0.97	0.98	0.99
5-8	0.25	0.50	0.50	0.80	0.82	0.96	0.96
9-16	0.19	0.50	0.50	0.65	0.82	0.86	0.90
17-32	0.15	0.20	0.35	0.50	0.73	0.77	0.78
33-64	0.03	0.18	0.18	0.27	0.50	0.67	0.67
65-128	0.02	0.04	0.14	0.23	0.33	0.50	0.59
>128	0.02	0.04	0.10	0.22	0.33	0.41	0.50

Table 17: Win probabilities for US Open (men), depending on their strength groups, after adjusting for the regularity property

Ranking	1-4	5-8	9-16	17-32	33-64	65-128	>128
1-4	0.50	0.50	0.87	0.87	0.88	0.94	0.94
5-8	0.50	0.50	0.50	0.68	0.80	0.88	0.94
9-16	0.13	0.50	0.50	0.68	0.76	0.85	0.85
17-32	0.13	0.32	0.33	0.50	0.57	0.79	0.84
33-64	0.13	0.20	0.24	0.43	0.50	0.62	0.77
65-128	0.06	0.12	0.15	0.21	0.38	0.50	0.56
>128	0.06	0.06	0.15	0.16	0.23	0.44	0.50