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Using tennis rankings to predict performance in upcoming tournaments

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Using tennis rankings to predict performance in upcoming tournaments

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27 November 2014

Abstract

We show how to use ATP and WTA rankings to estimate the probability that a player with a certain ranking advances to a specific round (for instance, the quarterfinals) in an upcoming tournament. We use the results from Grand Slam and Olympic tournaments in the period 2004–2014. Pooling the data, which is justified according to our tests, allows us to compute probabilities with relatively small confidence intervals. For instance, the probability of a top 4 tennis player to reach the quarterfinals is 0.722 with a 95% confidence interval of (0.669; 0.771).

This study was motivated by a request from the Dutch Olympic Committee (NOC*NSF). Based on our results, NOC*NSF decides which Dutch single tennis players to invite to participate at the 2016 Olympic Games of Rio de Janeiro.

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1. Introduction

To what extent is the position of a (tennis) player on a world ranking list (ATP for the men, and WTA for the women) related to his/her performance in an upcoming tournament? Can we reliably predict whether or not a (tennis) player makes it to, say, the quarterfinals of a Grand Slam tournament, knowing only his/her ranking on, say, two weeks before that tournament? In this paper, we attempt to answer these questions.

Rankings of tennis players have been intensively used in the literature for predicting outcomes of individual matches. In Del Corral & Prieto-Rodríguez (2010) it is argued that differences between ratings are good predictors for Grand Slam tennis outcomes, and that there are no significant gender differences in this respect. Klaassen & Magnus (2003) use logit models, based on, among other things, a nonlinear difference between two players' rankings, for computing winning probabilities before and during the match. Clarke & Dyte (2000) use a difference between rating points to compute a winning probability for each tournament round, and, by means of these probabilities, the chance to win the tournament is calculated for each player. Other research focuses on the physiology of tennis performance (Kovacs, 2006), and on improvements of the tennis ranking system (Ruiz, Pastor & Pastor, 2013; and Irons, Buckley & Paulden, 2014). However, as far as we know, rankings have not been used to calculate probabilities of reaching tournament rounds. The idea to calculate this connection is already mentioned in Reid & Morris (2013): "Future work should focus on the change in top 100 demographics over time as well as the evaluation of the interaction between rankings and tournament plays". Reid, Morgan, Churchill & Bane (2014) address the first topic, we address the second topic. More specifically, we describe a method that computes a confidence interval, indicating the likelihood that a player with a particular ranking reaches a particular round in an upcoming tournament.

The research of this paper is motivated by a request from the Dutch Olympic Committee (the "*Nederlands Olympisch Comité * Nederlandse Sport Federatie*", or NOC*NSF) to calculate the probability that a player with a certain ATP/WTA ranking reaches the quarterfinals in an upcoming tournament. The NOC*NSF is the main organization for organized sports in The Netherlands with 88 member organizations that account for around 28,000 sport clubs which totals more than five million people involved in organized sports (NOC*NSF, 2014). The NOC*NSF is responsible for designing the process, for setting up the selection criteria, and for the selection of athletes who represent the Netherlands in the Olympic Games. The request of the NOC*NSF was to calculate the probability that a player with a specific position on the ATP and the WTA ranking on a so-called reference date, reaches the quarterfinals of the upcoming Olympic tennis tournament.

The methodology that we use in this paper is not tennis-specific, and is applicable to all sports with world rankings. Of course, the selection criteria itself depend on the sport discipline. For a number of sports (including tennis and badminton) a particular position on the world ranking list can be used as selection criterion: only players that have at least this ranking position on the reference date are selected. The NOC*NSF is entitled to fix both the reference date and the required ranking position.

We use the results of the three most recent Olympic tennis tournaments, as well as the results of all Grand Slam tournaments in the period 2004–2014. We acknowledge the fact that Grand Slam tournaments differ in many ways from Olympic tennis tournaments. However, tests reveal that the differences between the calculated probabilities of the two tournaments are statistically not significant. Also gender differences turn out to be statistically not significant, allowing us to pool male and female tournaments, thereby increasing the precision of the results to an even larger extent.

The main contributions of this paper can be summarized as follow:

(i) For each tennis player on the WTA/ATP ranking, we show how to calculate a probability and an associated confidence interval to reach a specific round at an upcoming tournament. The probability is based on the position of the player on a world tennis ranking with a date prior to the tournament.

(ii) We apply this procedure to compute the probabilities of reaching the quarterfinals of the 2016 Olympic Games.

(iii) We show that, when it comes to the probability of reaching the quarterfinals, statistically there are no differences between men and women, and not between Grand Slam tournaments and Olympic tournaments.

(iv) This method is applicable to other sports using world rankings as well. Following a request by NOC*NSF we have applied a similar method to badminton.

This paper is organized as follows. Section 2 presents the data used in the analysis. Section 3 illustrates our methodology of pooling the results for the Olympic Games of 2004 (Athens), 2008 (Beijing) and 2012 (London), for men and women separately. In Section 4, we extend the analysis by including Grand Slam tournaments. This section presents the pooled estimation results. We also discuss the differences between Grand Slam and Olympic tennis tournaments, and test whether the probabilities of entering the quarterfinals are statistically different between these two tournaments. We also test for differences between court surfaces and for differences between men and women. Section 5 concludes.

2. Data

We consider the period August 2004 until January 2014. In this period 38 Grand Slams and three Olympic tennis tournaments took place (see Table 1). Grand Slam tournaments start with 128 participants and Olympic tennis tournament with 64. The differences between Olympic tennis tournaments and Grand Slam tournaments are extensively discussed in Section 3. Our database contains the names of the 64 players of the three most recent editions of the Olympic tennis tournaments, as well as the names of the 64 players who won the first round in each of the 38 Grand Slam tournaments. So the database has (41x64=) 2,624 observations for both men and women, yielding a total of 5,248 observations. We also have the ranking of each player on the so-called *reference date* prior to a tournament (Stevegtennis, 2014); the (ATP/WTA) ranking on the reference date is used for the calculation of the probabilities of reaching the quarterfinals of the next tournament. Table 1 shows the tournament data, including court surface types and reference dates.

Table 1 – Tournaments in the database.

Tournament	Location and period	Court surface	Reference date
Olympic Games	London 2012 27 July–12 August	grass court	11 June 2012
	Beijing 2008 8 August–24 August	hard court	9 June 2008
	Athens 2004 13 August–29 August	hard court	14 June 2004
Grand Slams	Australian Open 2005–2014 January	hard court	two weeks prior to each tournament
	Roland Garros 2005–2013 May/June	red clay court	two weeks prior to each tournament
	Wimbledon 2005–2013 June/July	grass court	two weeks prior to each tournament
	US Open 2004–2013 August/September	hard court	two weeks prior to each tournament

The reference dates for the Olympic tennis tournaments are fixed by the International Tennis Federation (ITF). For Grand Slam tournaments we use as reference dates the date two weeks before the start of the tournament. The actual selection procedure for Grand Slam tournaments is different: direct acceptances and draws are based on rankings on different dates, and the selection procedure also differs across years. Moreover, tournament organisers have the opportunity to give wildcards, and allow qualifiers to enter the main tournament.

Table 2 shows the distribution of all players (men and women) in the database. For 19% of the players, the rank on the ATP or WTP is 101 or lower. In this paper we have decided to restrict ourselves to top 100 players. In this respect, we may refer to Reid *et al*. (2014): reaching the top 100 can be seen as an important goal with more than just a symbolic value; it may result in an automatic qualification for the next Grand Slam tournament. However, sometimes low ranked or even unranked players perform exceptionally well. In the recent history, two unranked Belgian female players reached the final of a Grand Slam tournament. Both players received a so called wildcard, and made this surprising comeback after two years. These players were Kim Clijsters, who defeated Caroline Wozniacki in the final of the 2009 US Open, and Justin Henin, who lost the final of the Australian Open in 2010 to Serena Williams. Besides these two Belgians, two more unranked players made it to the semi-finals, and nine unranked players qualified for the quarterfinals.

Table 2 – Distribution of the ranks of male and female tennis players (64 players in the first round of an Olympic tennis tournament and the second round of a Grand Slam tournament).

Rank	Women	Men	Total
1 – 10	344	353	697
11 – 20	325	308	633
21 – 30	293	277	570
31 – 40	234	238	472
41 – 50	171	182	353
51 – 60	190	195	385
61 – 70	172	164	336
71 – 80	154	148	302
81 – 90	137	140	277
91 – 100	131	124	255
101+	473	495	968
Total	2624	2624	5248

Table 2 shows that the database contains the most players in the positions 1–10. This can be explained by the idea that a higher ranked player has a higher probability of winning the first round of a Grand Slam tournament than a lower ranked player. This also explains that the number of players with lower rankings is decreasing. Moreover, for the Olympic tournaments, there is a country limit (see next section) which mainly affects the lowest positions on the world rankings.

3. Methodology

In this section, we first sketch a “common-sense” method that yields a point estimate of the probability that a player with a particular position on the ATP ranking or the WTP ranking reaches a specific tournament round. In this illustration we compare top 32 players with players ranked 33 and lower. Next, we introduce the probit model which, in addition to this point estimate, determines the corresponding confidence intervals. These confidence intervals are used to test whether or not the differences between men and women, and between Grand Slams and Olympic tournaments, are statistically significant. The common sense method is applied on the data of the Olympic tennis tournaments in 2005, 2008 and 2012 for men and women.

A total of (3x64=) 192 female tennis players participated in these three Olympic Games. Of these players, 72 were ranked at position 32 or better, and 120 were ranked position 33 or lower. This is shown in the first lines of Figure 1. The graph depicts the number players of both categories that advanced to a next round.

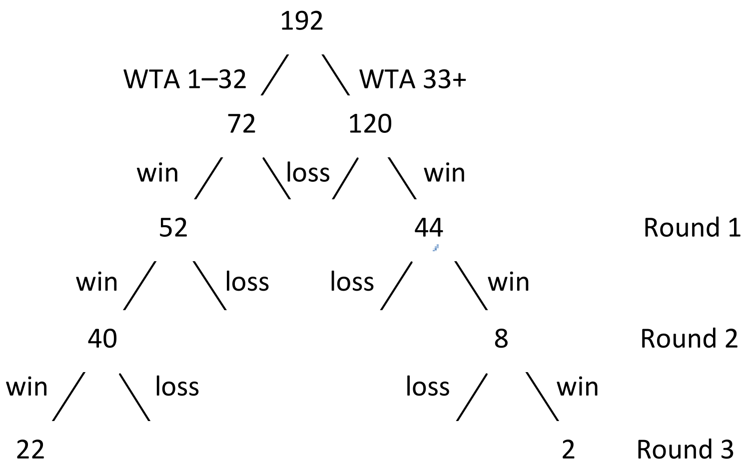

Figure 1 – Performance tree of top 32 and 33+ female tennis players in the three most recent editions

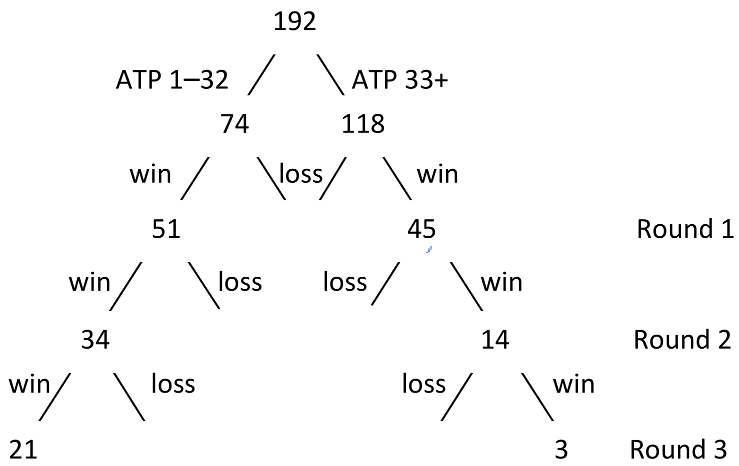

Figure 2 – Performance tree of top 32 and 33+ male tennis players in the three most recent editions of the Olympic tennis tournament.

Figure 1 shows that

- after the first round (3x32=) 96 players proceeded to round 2, of which 52 were from the top 32 on the WTP ranking;
- after the second round (3x16=) 48 players went to round 3, of which 40 were in the top 32;

- 22 players of the top 32 made it to round 3;
- the percentage of top 32 players, that made it to the final eight, is (22/72=) 30.6%;
- the percentage of players ranked 33 or lower (33+), that made it to the final eight is only (2/120=) 1.7%.

Figure 2 shows a similar graph for the male tennis players in our data set. A total of (3x64=) 192 male tennis players participated in the three most recent editions of the Olympic Games. Of these players, 74 were ranked at position 32 or better, and 118 were ranked position 33 or lower. From Figure 2 we conclude that

- out of a total of 192 players 74 are ranked 32 or higher and 118 are ranked lower on the ATP ranking;
- the percentage of top 32 players in the final eight is (21/74=) 28.4%, while (3/118=) 2.5% is ranked 33 or lower.

From this example it should be clear how to extend the procedure to other rounds or other tournaments. However, this procedure falls short in a couple of aspects. Firstly, it is unclear how reliable the probabilities are: there is no way of telling whether the 30.6%, describing the probability that a female top 32 player reaches the quarterfinals, is statistically different from the corresponding 28.4% probability in case of male tennis players. So, we need confidence intervals. Secondly, the two clusters in Figures 1 and 2, namely 'top 32' and '33+', are quite large. We would like to calculate the probabilities for more and smaller clusters, for instance for clusters of size four: clusters of players ranked 1 through 4, 5 through 8, 9 through 12, and so forth.

A common method for the calculation of point estimates and confidence intervals is regression analysis. If the dependent variable y can only take two values the use of a probit model is a popular model. The probit model transforms a nonlinear S-shaped curve to a straight line that can then be analyzed by maximum likelihood. The probit model is defined as follows:

$$P(y = 1|x, \beta) = 1 - \Phi(-x'\beta) = \Phi(x'\beta), \tag{1}$$

where $\Phi(.)$ is the cumulative distribution function of the standard normal distribution, and x are the explanatory variables. The dependent variable y is a vector of 1's and 0's: a '1' means that the corresponding player wins round 3 and advances to the quarterfinal, and a '0' means that the corresponding player did not reach the quarterfinal.

In our application x is a vector of ones denoted as ι (the constant term, or intercept), and hence β is the estimator of the intercept:

$$P(y = 1|\iota, \beta) = \Phi(\beta), \tag{2}$$

With this specification of the probit model we are counting the number of players winning round 3 just as we did above. The advantage is that the probit model also delivers confidence intervals. However, to find precise estimates (that is, narrow confidence intervals), also for clusters containing lower-ranked players, say players ranked 85 through 88, and 89 through 92, we require many observations. The probit model is estimated for different clusters of ranks on both the WTA and the ATP ranking.

Table 3 – Probit estimates of top 32 players that have reached the quarterfinals in one of the three most recent Olympic tennis tournaments.

Dependent variable: (0, 1)-dummy variable: 1 = winning the third round, 0 otherwise.
Sample: Olympic Games of 2004 (Athens), 2008 (Beijing), and 2012 (London).

Women
Observations: 72 (of which 22 with value 1) top 32 players.

					95% Confidence interval	
Variable	Coefficient β	Std. error	z-Statistic	p-Value	Low	High
constant	−0.508	0.155	−3.284	0.001	−0.817	−0.200

Men
Observations: 74 (of which 21 with value 1) top 32 players

					95% Confidence interval	
Variable	Coefficient β	Std. error	z-Statistic	p-Value	Low	High
constant	−0.572	0.155	−3.696	<0.001	−0.880	−0.263

Table 3 shows the probit estimates for all top 32 players advancing to the final eight. In the three Olympic tournaments for women, the number of top 32 players is 72, of which 22 advance to the quarterfinals. The probability is (22/72=) 30.6%, which is also shown in Figure 1. The probability of 0.306 corresponds to the marginal effect of the intercept estimate −0.508 in the probit model, which is found by transforming the corresponding coefficient using the standard normal distribution function, that is $\Phi(-0.508) = 0.306$. The corresponding 95% confidence interval is $(\Phi(-0.817); \Phi(-0.200)) = (0.207; 0.421)$. The interpretation of the 95% confidence interval is that with a probability of 95%, this interval contains the population estimate. For men the estimate is (21/74=) 28.4% with a 95% confidence interval of $(\Phi(-0.880); \Phi(-0.263)) = (0.189; 0.396)$.

4. Pooled results

The method described above is applicable to any round in any tennis tournament, while various sizes of ranking clusters can be used. For small sized clusters and small sized interval estimates, we need to use both Grand Slam tournaments and Olympic tennis tournaments, although these tournaments are not the same. Grand Slam tournaments start with 128 tennis players and Olympic tennis tournament with 64. In order to reach a quarterfinal of a Grand Slam, the first four matches need to be won, while in an Olympic tournament this number is three. We have solved this problem by including only Grand Slam tennis players in our data set that won in the first round. Another difference is that there is a limit of four male and four female players from the same country (see Australian Olympic Committee, 2014). We will return to this point below.

We have tested whether or not the estimates differ between men and women, across court surfaces, and between Olympic Games and Grand Slam tournaments. The results of the tests for five clusters are shown in Appendix A. For the 'lower' clusters the test results are available from the authors. To test for, for instance, gender differences we include a gender dummy M (with a value 1 for men and 0 for women) in the probit model, and test whether the coefficient for the dummy variable deviates significantly from 0 at usual levels of significance. Table A1 shows that, only for cluster 1–4, the estimate for the gender dummy variable M deviates from 0 at a 5% significance level. Since these players will for sure be selected for the Games, these differences can be considered as irrelevant with respect to the purpose of this research. Similar tests reveal that differences between court surfaces for Grand Slam tournaments are small and statistically different for players only in cluster 9–12 and in cluster 41–44. Despite the differences between Olympic and Grand Slam tournaments, Table A3 shows that the probabilities of reaching the quarterfinals are not statistically different for the higher clusters, only for the cluster with players ranked 81–84 the results differ.

We now apply the probit model to all tournaments described in Table 1. The database includes 41 tournaments (3 Olympic Games and 38 Grand Slam tournaments) for men and women, which increases the sample size to a maximum of 5,248 observations. Table 4 presents pooled estimates for clusters of size 4. Table 4 shows the number of observations in each cluster and it also indicates the number of 1's in the sample. The final three columns present the point estimates and the 95% confidence intervals.

Table 4 shows that for a top 4 tennis player the probability of reaching the quarterfinals is 0.722 with a 95% confidence interval of (0.669; 0.771). If the position on the ranking would be irrelevant than the probability of winning three matches in a row would be $0.5^3 = 0.125$, or 12.5%. So, for top 4 players the rank certainly matters because the lower bound of the 95% confidence interval exceeds the value 0.125. Also for cluster 17–20, the 95% confidence interval does not include 0.125. So, the rank is relevant for this cluster as well. Likewise for players in the cluster 25–28 and in lower clusters, the rank matters, because the 95% confidence intervals do not include 0.125. But for these lower clusters the probability of advancing to the quarterfinals is smaller than 12.5%.

Note that for some clusters the probability increases for lower clusters. An example is cluster 41–44; players with these positions seem to have a higher probability of advancing to the quarterfinals than players ranked between 37 and 40. However, the 95% confidence intervals overlap for these clusters, and formal testing shows that the difference is statistically not different from 0 at a 5% significance level.

Table 4 – Probit estimates and 95% confidence intervals for the probability of entering the quarterfinals.

	Number of observations			95% Confidence interval	
Cluster	Total	(of which 1's)	Probability	Low	High
1– 4	299	(216)	0.722	0.669	0.771
5– 8	267	(127)	0.476	0.416	0.536
9– 12	256	(78)	0.305	0.251	0.363
13– 16	263	(45)	0.171	0.129	0.221
17– 20	245	(44)	0.180	0.135	0.232
21– 24	224	(21)	0.094	0.061	0.138
25– 28	231	(16)	0.069	0.042	0.109
29– 32	223	(18)	0.081	0.050	0.123
33– 36	186	(14)	0.075	0.044	0.121
37– 40	178	(4)	0.022	0.008	0.055
41– 44	144	(9)	0.062	0.032	0.113
45– 48	143	(10)	0.070	0.037	0.123
49– 52	153	(4)	0.026	0.009	0.064
53– 56	152	(5)	0.033	0.013	0.073
57– 60	146	(5)	0.034	0.013	0.076
61– 64	130	(3)	0.023	0.007	0.065
65– 68	134	(2)	0.015	0.003	0.052
69– 72	135	(4)	0.030	0.010	0.072
73– 76	123	(2)	0.016	0.004	0.057
77– 80	116	(4)	0.034	0.012	0.084
81– 84	112	(2)	0.018	0.004	0.062
85– 88	106	(2)	0.019	0.004	0.066
89– 92	111	(3)	0.027	0.008	0.075
93– 96	98	(3)	0.031	0.009	0.085
97–100	105	(2)	0.019	0.004	0.066

Finally, one of the differences between Olympic Games and Grand Slam tournaments is the restriction of four male and four female players from the same country for the singles competitions. One could argue that we should take into account this restriction in case of the Grand Slam tournaments by deleting observations. There are three arguments why cleaning up the Grand Slam results in our case is not necessary. Firstly, the probability of winning three rounds is not affected by a players' nationality. What matters is the ATP/WTA rank of the player. Secondly, testing for differences between third round results of Olympic Games and fourth round results of Grand Slam tournaments are statistically not different. Finally, we would lose more than 800 observations, and sacrifice accuracy.

5. Conclusions

Since 2014, the NOC*NSF has changed its qualification model for selecting tennis players for the Olympic Games; the new model needs to be based on the relationship between a players' rank and the probability of advancing to the quarterfinals. The results in this paper will be used by NOC*NSF for the selection of Dutch tennis players for the 2016 Olympic Games.

The database, which we use to find this relationship, contains 41 tournaments for both men and women in the period 2004–2014. We have shown that pooling gender and tournaments is valid, which allowed us to pool the data and to calculate probabilities for small clusters.

The pooled analysis shows that the position on world ranking matters. For a top 4 tennis player the probability of reaching the quarterfinals is 0.722 with a 95% confidence interval of (0.669; 0.771), while for a player ranked between 5 and 8, probability of reaching the quarterfinals drops to 0.476 with a 95% confidence interval (0.416; 0.536). For ranks 1–20, the probability of entering the quarterfinals is larger than 12.5%, while for ranks 25–100, the probability of entering the quarterfinals is smaller than 12.5%.

References

Australian Olympic Committee (2014). Retrieved October 20, 2014 from: http://corporate.olympics.com.au/files/dmfile/Rio2016QualificationSystem-Tennis.pdf

Clarke, S., & Dyte, D. (2000). Using official ratings to simulate major tennis tournaments. *International Transactions in Operations Research,* 7(6), 585–594.

Del Corral, J., & Prieto-Rodríguez, J. (2010). Are differences in ranks good predictors for Grand Slam tennis matches? *International Journal of Forecasting,* 26(3), 551–563.

Irons, D.J., Buckley, S., & Paulden, T. (2014). Developing an improved tennis ranking system. *Journal of Quantitative Analysis in Sports,* 10(2), 109–118.

ITF, Retrieved October 20, 2014 from: http://www.itftennis.com/olympics/players/qualification.aspx

Klaassen, F., & Magnus, J. (2003). Forecasting the winner of a tennis match. *European Journal of Operational Research,* 148(2), 257–267.

Kovacs, M.S. (2006). Applied physiology of tennis performance. *British Journal of Sports Medicine,* 40(5), 381–386.

NOC*NSF (2014). Retrieved October 20, 2014 from: http://www.nocnsf.nl/en

Reid, M., Morgan, S., Churchill, T., & Bane, M.K. (2014). Rankings in professional men's tennis: a rich but underutilized source of information. *Journal of Sports Science,* 32(10), 986–992.

Reid, M., & Morris, C. (2013). Ranking benchmarks of top 100 players in men's professional tennis. *European Journal of Sports Science,* 13(4), 350–355.

Ruiz, J.L., Pastor, D., & Pastor, J.T. (2013). Assessing professional tennis players using data envelopment analysis (DEA). *Journal of Sports Economics,* 14(3), 276–302.

Stevegtennis (2014). Retrieved October 20, 2014 from: http://www.stevegtennis.com

Appendix A – Significance tests

Table A1 - Testing differences between men (M = 1) and women (M = 0).

Cluster	Observations	Constant (se)	M (se)
1– 4	299	0.341	0.545*
		(0.105)	(0.158)
5– 8	267	0.067	−0.252
		(0.110)	(0.154)
9–12	256	−0.502	−0.017
		(0.115)	(0.164)
13–16	263	−0.901	−0.104
		(0.125)	(0.183)
17–20	245	−0.883	−0.068
		(0.131)	(0.187)

* Significantly different from 0 at a 5% significance level.

Table A2 - Testing differences between court surfaces for Grand Slam tournaments: US open (AU = 0, WB = 0, and RG = 0); Australian Open (AU = 1); Wimbledon (WB = 1) and Roland Garros (RG = 1).

Cluster	Observations	Constant (se)	AU (se)	WB (se)	RG (se)
1– 4	281	0.578	0.273	−0.187	−0.031
		(0.158)	(0.228)	(0.222)	(0.228)
5– 8	248	−0.076	0.204	−0.168	0.031
		(0.154)	(0.216)	(0.228)	(0.228)
9–12	239	−0.197	−0.633*	−0.561*	−0.216
		(0.158)	(0.238)	(0.242)	(0.238)
13–16	244	−1.068	0.110	0.076	0.226
		(0.195)	(0.269)	(0.280)	(0.269)
17–20	226	−0.956	−0.470	0.235	0.235
		(0.193)	(0.300)	(0.273)	(0.273)

* Significantly different from 0 at a 5% significance level.

Table A3 - Testing for differences between Olympic Games (OG = 1) and Grand Slam tournaments (OG = 0).

Cluster	Observations	Constant (se)	OG (se)
1– 4	299	0.590	–0.001
		(0.080)	(0.325)
5– 8	267	–0.051	–0.149
		(0.080)	(0.300)
9–12	256	–0.533	0.310
		(0.085)	(0.318)
13–16	263	–0.962	0.157
		(0.095)	(0.338)
17–20	245	–0.944	0.310
		(0.098)	(0.325)

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