The Effect of Pressure on Mixed-Strategy Play in Tennis: The Effect of Court Surface on Service Decisions

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Abstract

This study finds support for mixed strategy play by professional tennis players choosing where to locate their serves. However, we find that servers are less able to adopt optimal strategies when they face more pressure. We use the type of court surface to proxy different levels of stress faced by players serving the ball. Court surfaces that allow more aces put more pressure on the server to hit a good serve, simply because serves are more important on these surfaces. We find that as servers face more pressure, they tend to hit the serve to an opponent's backhand too often.

I. Introduction

Starting with Walker and Wooders (2001), researchers have used professional sports as a natural laboratory for testing the predictions derived from mixed strategy equilibrium play. The researchers have given several reasons for expecting that professional athletes, while playing their sport, are among the people most likely to employ the sophisticated strategies predicted by game theoretic models. First, scholars note that by adopting good strategic play, a player can improve his performance. The gain in performance can result in substantial financial rewards, giving the athlete an incentive to play an efficient strategy. Second, researchers note that athletes often play their game for many years, so they are likely to find it worthwhile to learn how to make good strategic decisions.

Despite a near perfect setting for optimal strategic decision making, the empirical evidence has produced mixed results on whether professional athletes play efficient mixed-strategies. Multiple studies have found professional athletes are playing with optimal strategies. Chiappori, Levitt, and Groseclose (2002), Coloma (2007), and Palacios-Huerta (2003) find that during soccer penalty kicks, when the position player decides where to kick the ball and the goalie decides where to dive, they are making choices that are consistent with mixed strategy play. Other sports provide evidence of optimal strategic play as well. McGarrity and Linnen (2010) find it in play calling in the National Football League. Hsu, Huang, and Tang (2007) find evidence of good strategic play in the choice of whether tennis players serve to an opponent's forehand or backhand. McGarrity (2012) finds evidence of strategic play in baseball.

In contrast, some of the literature suggests that that these professionals are not playing with the optimal strategy as game theory predicts. Walker and Wooders (2001) found that men's pro tennis players did not randomize their serves optimally. They find the players were switching serve direction too often. Kovash and Levitt (2009) find that pitch selection in Major League Baseball and play calling in the National Football League cannot be explained with good strategic play.

Their results state that pitchers appear to throw too many fastballs and football teams pass less than they should. In both sports, Kovash and Levitt find that there is negative serial correlation in the decisions, which is the same result Walker and Wooders (2001) found in tennis. Mitchell (2010) reports similar results in the NFL.

One possible explanation for the mixed results is that stress may determine how well professionals can play their strategy. Most of the literature today has analyzed the impact of stress on performance, but not on strategic choices. For instance, Ariely et al (2009) find that excessive rewards may cause stress and lead to a decline in job performance. Apesteguia and Palacios-Huerta (2010) analyzed penalty kicks in professional soccer leagues. They found the stress of going second in a penalty kick causes a decline in performance. However, Kocher et al (2010) expanded on the data set of Apesteguia and Palacios-Huerta and found that there were no detrimental effects of stress present. Gonzales-Diaz et al (2010) did a similar study in tennis and found that the top players played better during more important points in a match. Only Downey and McGarrity (2012) looked at the impact of stress on the ability to make good strategic choices. They analyzed situations in Major League Baseball when there was a runner on first base. Optimally the pitcher should randomly throw to first base or home plate, so that the base runner cannot detect and exploit a pattern. However, the authors find that when the task of throwing to first base becomes more difficult, or when the base runner is more able (both factors act to increase stress), pitchers are less able to randomize their decision making.

Building on Downey and McGarrity's work, this paper attempts to look at the impact of stress on decision making in professional tennis. Following Walker and Wooders (2001), this paper will examine the service play of professional tennis players. The paper will examine the decision of where to serve the ball and determine if the stress caused by the varying court surfaces influences the ability to adopt optimal strategies. This paper considers three types of court surfaces: grass, clay and hard surface. Grass court surfaces best facilitate ball speed, allowing the server to score many more easy points via an ace (an unreturned serve). This means that the payoff from a good service strategy is greater on the grass surface than on clay or hard court, so there is more pressure on every serve on a grass court.

Our experiment finds that tennis players are able to randomize their service decisions on all three surfaces. However, the players do a poorer job of equalizing the payoffs from both choices as mixed strategy play predicts that they should. As players move to court surfaces that allow more aces, the servers play the ball to an opponent's weak-side (backhand) too often. These results suggest that stress and pressure produce a detrimental effect on the strategic choices of individuals in games and could explain why the literature offers conflicting evidence on whether professionals can play efficient strategies.

II. Predictions of mixed strategy play in tennis serves

To attempt to show the effect of stress on the strategic play of tennis players, this study follows the approach taken by Walker and Wooders (2001). In tennis, one player serves and then both players exchange shots until one player cannot return the ball. The winner of the volley is awarded a point. The points are scored 15, 30, 40, and game -- to the winner of the score after 40, with the qualification that a player has to win by two scores if the score becomes tied at 40. It takes six or seven games to win a set, typically two to three sets to win a match. To begin a point in tennis, one player must serve the tennis ball overhead to the receiving player to begin the exchange of shots. The serving player can choose to serve the ball to the left or right of the receiving player. All else equal, it is advantageous to serve to the backhand (non-dominant) hand of the receiving player because typically the return shot is more difficult. However, it is necessary to mix the serve direction in order to keep the receiving player guessing, so that the serving player might obtain an ace. If a player does not mix his serve directions, then the receiving player will be able to figure out which direction the ball will be coming to, and he will make an adjustment to capitalize on this information. For instance, if the receiving player knows a ball is coming to the backhand (the tougher direction) the receiving player might begin to line up outside to compensate, or he might start to run around the backhand serve to return it with his stronger forehand. If the receiving player knows which way the serve is aimed, an ace is very unlikely and the return shot will be much easier, both of which are disadvantageous to the server and advantageous to the defender.

In the game between a server, who must decide to serve to his opponent's forehand or backhand, and a defender, who must decide which of these types of shots to defend, two predictions emerge: 1) Serves are serially independent.

That is, serve direction for one serve does not depend upon the choice previously made, and 2) The winning percentage for serving to the left of a player in a match should be equal to the winning percentage for serving to the right. For example, if a player is having a lot of success to the right, then the server should play to the right until the receiving player shifts his strategy to account for playing poorly on the right. Eventually, this interaction will equalize the winning percentages of each type of serve.

III. Data & Results

A. Data

In this experiment, the data was obtained by observing matches on Youtube. All of the matches were semifinals or finals of the Grand Slam tournaments, the four major tournaments of the World Tennis Association. The four Grand Slam tournaments are played across all three court surfaces, so it allowed us to access how service decisions are influenced by the effects of stress that varies with court surface. Our data set includes every serve in ten matches for each type of court surface. The matches occurred between 2006 and 2011 and they were picked based on availability on Youtube.

Walker and Wooders (2001) differentiated between serves where the score is tied in a game, at deuce, versus when one player has an advantage in the score. This difference is important because players might play harder when the score is tied versus when they are down significantly in a game. To account for this effect, Walker and Wooders split each player's service game into serves where the score is tied (deuce-court) and serves when one player has a lead (ad-court). This study will do the same.

B. Aces per Serve Data

Table 1 reports the numbers of aces, number of serves, and aces per serve for each player. The information for each court surface is listed separately in these tables. As can be seen in the results, grass courts have the highest probability of an ace with 10.09% of serves resulting in aces; hard courts came in second at 7.01%, with clay-courts following at 6.33 aces per serve. These results confirm conventional wisdom in tennis, which states that grass courts have the highest payoff from good service strategy because on grass, service shots tend to bounce little, allowing them to stay low and fast, a disadvantage for the receiving player. Clay-court and hard- court surfaces tend to allow the ball to bounce much higher, both by slowing down the serve by the time it reaches the receiving player, and by placing the ball at a high location, making the return shot much easier. In terms of pressure, since there is the greatest chance of an ace on grass-court, pressure would be at its highest level on grass courts.

Table 1: Aces per Serve

A: Hard Court Aces per Serve				
Match	**Player**	**Aces**	**Serves**	**Aces/Serve**
09 SF Aust Open	Nadal	12	173	0.06936416
09 SF Aust Open	Verdasco	20	209	0.09569378
08 F US Open	Federer	3	82	0.03658537
08 F US Open	Murray	3	78	0.03846154
08 F Aust Open	Djokovic	11	120	0.09166667
08 F Aust Open	Tsonga	15	134	0.1119403
07 F US Open	Federer	11	102	0.10784314
07 F US Open	Djokovic	5	111	0.04504505
07 F Aust Open	Federer	5	86	0.05813953
07 F Aust Open	Gonzalez	6	130	0.04615385
Avg Aces/Serve: Hard Court				**0.07008934**
B: Clay Court Aces per Serve				
Match	**Player**	**Aces**	**Serves**	**Aces/Serve**
11 SF French Open	Federer	18	140	0.12857143
11 SF French Open	Djokovic	7	168	0.04166667
09 F French Open	Federer	18	78	0.23076923
09 F French Open	Soderling	2	85	0.02352941
11 SF French Open	Nadal	2	115	0.0173913
11 SF French Open	Murray	5	103	0.04854369
11 F French Open	Nadal	4	145	0.02758621
11 F French Open	Federer	11	124	0.08870968
08 F French Open	Nadal	0	66	0
08 F French Open	Federer	2	77	0.02597403
Avg Aces/Serve for Clay Court:				**0.06327416**
C: Grass Court Aces per Serve				
Match	**Player**	**Aces**	**Serves**	**Aces/Serve**
09 F Wimbledon	Federer	50	192	0.26041667
09 F Wimbledon	Roddick	27	235	0.11489362
11 F Wimbledon	Nadal	5	81	0.0617284
11 F Wimbledon	Djokovic	7	100	0.07
06 F Wimbledon	Federer	13	119	0.1092437
06 F Wimbledon	Nadal	9	126	0.07142857
07 F Wimbledon	Federer	24	152	0.15789474
07 F Wimbledon	Nadal	1	168	0.00595238
08 F Wimbledon	Federer	25	192	0.13020833
08 F Wimbledon	Nadal	6	214	0.02803738
Avg Aces/Serve for Grass Court:				**0.10098038**

Statistical tests confirm that ace frequencies vary with court surface. Chi-Square Goodness of Fit Tests was run on data from each pair of surfaces, as well as on all of the surfaces combined. In all cases, we can reject the null hypothesis of equal proportion of aces across all surfaces.[1].

C. Runs Test for Serial Independence

Following Walker and Wooders (2001), Table 2 reports a Runs Test for serial independence. Presented in the table are left serves, right serves, runs (repeated sequences of choices) in the serve directions, the Runs Test estimated number of runs, the Runs Test standard deviation, and the Runs Test Statistic. In tennis, serial independence means that the player's string of serve directions can be considered random and that the player did not begin to either stick with one serve direction for too long or switch between the directions too often. The Runs Test allows you to test a string of choices and analyze the number of runs to see if the choices are random.

[1] For the paired tests, a test statistic greater than 3.84 would reject the null of equality, the results were 109 Grass-Hard, 154 for Grass-Clay, and 92 for Clay-Hard. For the full data set, a test statistic greater than 5.99 will reject, the result was 46.

For example, for the calculations, we might observe a string of serve direction choices that turn out to be LRLLLLR, with L signifying a left serve and R signifying a serve to the right. This data string has four runs in it, with each change in direction beginning a new run. The Runs Test predicts an estimated number of runs that should appear in a randomly generated dataset. The test will then compare the expected runs to the actual runs.

Table 2: Runs Test for Serial Independence

A: Runs Test for Hard Court							
Match	**Player**	**Total L**	**Total R**	**Est. # of Runs**	**σ of Runs**	**# of Runs**	**Runs Test Value**
09 SF Aust Open	Nadal	73	100	85.393	6.397	84	-0.218
09 SF Aust Open	Verdasco	111	98	105.096	7.183	103	-0.292
08 F US Open	Federer	41	41	42.000	4.500	39	-0.667
08 F US Open	Murray	48	30	37.923	4.150	37	-0.222
08 F Aust Open	Djokovic	63	57	60.850	5.440	57	-0.708
08 F Aust Open	Tsonga	65	69	67.940	5.761	69	0.184
07 F US Open	Federer	53	49	51.922	5.017	46	-1.180
07 F US Open	Djokovic	70	41	52.712	4.883	47	-1.170
07 F Aust Open	Federer	55	31	40.651	4.246	40	-0.153
07 F Aust Open	Gonzalez	82	48	61.554	5.287	63	0.274
B: Runs Test for Clay Court							
Match	**Player**	**Total L**	**Total R**	**Est. # of Runs**	**σ of Runs**	**# of Runs**	**Runs Test Value**
11 SF French Open	Federer	79	61	69.843	5.797	71	0.200
11 SF French Open	Djokovic	109	59	77.560	5.886	73	-0.775
09 F French Open	Federer	50	28	36.897	4.034	39	0.521
09 F French Open	Soderling	47	38	43.024	4.530	50	1.540
11 SF French Open	Nadal	53	62	58.148	5.305	54	-0.782
11 SF French Open	Murray	37	66	48.417	4.645	42	-1.382
11 F French Open	Nadal	113	32	50.876	4.114	53	0.516
11 F French Open	Federer	53	71	61.694	5.427	67	0.978
08 F French Open	Nadal	48	18	27.182	3.185	24	-0.999
08 F French Open	Federer	37	40	39.442	4.352	38	-0.331
C: Runs Test for Grass Court							
Match	**Player**	**Total L**	**Total R**	**Est. # of Runs**	**σ of Runs**	**# of Runs**	**Runs Test Value**
09 F Wimbledon	Federer	114	78	93.625	6.666	92	-0.244
09 F Wimbledon	Roddick	145	90	112.064	7.228	125	1.790
11 F Wimbledon	Nadal	42	39	41.444	4.466	40	-0.323
11 F Wimbledon	Djokovic	40	60	49.000	4.774	40	-1.885
06 F Wimbledon	Federer	50	69	58.983	5.292	64	0.948
06 F Wimbledon	Nadal	83	43	57.651	5.022	62	0.866
07 F Wimbledon	Federer	69	83	76.355	6.091	77	0.106
07 F Wimbledon	Nadal	121	47	68.702	5.200	66	-0.520
08 F Wimbledon	Federer	95	97	96.990	6.909	102	0.725
08 F Wimbledon	Nadal	132	82	102.159	6.897	90	-1.763

A value of 1.96 or greater means the play violates the null hypothesis of serial independence at a .05 confidence level

In no case, at conventional levels, can we reject the null hypothesis that serve directions are randomly generated. Based on the results of the test, we can conclude that the tennis players' service games are serially independent. This result suggests that professional players can randomize their decisions on any of the three types of playing surfaces.

D. Pearson Goodness of Fit for Testing the Equality of Payoffs

Table 3 reports the results of the Pearson Goodness of Fit Test used by Walker and Wooders (2001)[2]. The purpose of this test is to examine if the winning percentages for the two strategies, either a left serve or right serve, are equal in each match. Optimal mixed strategy play predicts that the winning percentages for both strategies will be equal. The null hypothesis for this test is that the winning percentages for the service choices are equivalent. Only 11 of 60 matches have winning percentages that are statistically different across service location. This result suggests that, overall, players are mixing their service direction enough so that the expected pay-off from either choice is roughly the same.

Table 3: Pearson Goodness of Fit Test

A: Pearson Goodness of Fit for Hard Court Results

Match	Server	Court	L	R	Total	L%	R%	L Won	R Won	L Win %	R Win %	Pearson	p-value	Sig	B/F
09 SF Aust Open	Nadal	Ad	49	65	114	0.4298	0.5702	31	45	0.6327	0.6923	0.44741	0.5036		
09 SF Aust Open	Nadal	Deuce	24	35	59	0.4068	0.5932	18	26	0.7500	0.7429	0.00383	0.9506		
09 SF Aust Open	Verdasco	Ad	77	54	131	0.5878	0.4122	52	39	0.6753	0.7222	0.32912	0.5662		
09 SF Aust Open	Verdasco	Deuce	34	44	78	0.4359	0.5641	21	27	0.6176	0.6136	0.00130	0.9712		
08 F US Open	Federer	Ad	23	28	51	0.4510	0.5490	14	20	0.6087	0.7143	0.63354	0.4261		
08 F US Open	Federer	Deuce	18	13	31	0.5806	0.4194	12	10	0.6667	0.7692	0.38539	0.5347		
08 F US Open	Murray	Ad	35	14	49	0.7143	0.2857	21	7	0.6000	0.5000	0.40833	0.5228		
08 F US Open	Murray	Deuce	13	16	29	0.4483	0.5517	7	7	0.5385	0.4375	0.29279	0.5883		
08 F Aust Open	Djokovic	Ad	43	32	75	0.5733	0.4267	34	23	0.7907	0.7188	0.52067	0.4706		
08 F Aust Open	Djokovic	Deuce	20	25	45	0.4444	0.5556	15	16	0.7500	0.6400	0.62730	0.4283		
08 F Aust Open	Tsonga	Ad	42	45	87	0.4828	0.5172	25	30	0.5952	0.6667	0.47666	0.4899		
08 F Aust Open	Tsonga	Deuce	23	24	47	0.4894	0.5106	17	16	0.7391	0.6667	0.29487	0.5871		
07 F US Open	Federer	Ad	34	33	67	0.5075	0.4925	26	26	0.7647	0.7879	0.05175	0.82		
07 F US Open	Federer	Deuce	19	16	35	0.5429	0.4571	13	12	0.6842	0.7500	0.18421	0.6678		
07 F US Open	Djokovic	Ad	50	25	75	0.6667	0.3333	32	14	0.6400	0.5600	0.44978	0.5024		
07 F US Open	Djokovic	Deuce	20	16	36	0.5556	0.4444	16	12	0.8000	0.7500	0.12857	0.7199		
07 F Aust Open	Federer	Ad	41	21	62	0.6613	0.3387	32	17	0.7805	0.8095	0.07065	0.7904		
07 F Aust Open	Federer	Deuce	14	10	24	0.5833	0.4167	12	9	0.8571	0.9000	0.09796	0.7543		
07 F Aust Open	Gonzalez	Ad	56	25	81	0.6914	0.3086	26	17	0.4643	0.6800	3.22938	0.0723	*	F
07 F Aust Open	Gonzalez	Deuce	26	23	49	0.5306	0.4694	18	16	0.6923	0.6957	0.00064	0.9798		

B: Pearson Goodness of Fit for Clay Court Results

Match	Server	Court	L	R	Total	L%	R%	L Won	R Won	L Win %	R Win %	Pearson	p-value	Sig	B/F
11 SF French Open	Federer	Ad	50	42	92	0.5435	0.4565	30	34	0.6000	0.8095	4.73299	0.0296	**	F
11 SF French Open	Federer	Deuce	29	19	48	0.6042	0.3958	19	12	0.6552	0.6316	0.02794	0.8673		
11 SF French Open	Djokovic	Ad	78	36	114	0.6842	0.3158	47	19	0.6026	0.5278	0.56515	0.8121		
11 SF French Open	Djokovic	Deuce	31	23	54	0.5741	0.4259	18	14	0.5806	0.6087	0.04303	0.8357		
09 F French Open	Federer	Ad	31	18	49	0.6327	0.3673	26	14	0.8387	0.7778	0.28198	0.5954		
09 F French Open	Federer	Deuce	19	10	29	0.6552	0.3448	17	6	0.8947	0.6000	3.46850	0.0625	*	B
09 F French Open	Soderling	Ad	31	26	57	0.5439	0.4561	20	16	0.6452	0.6154	0.05388	0.8164		
09 F French Open	Soderling	Deuce	16	12	28	0.5714	0.4286	6	7	0.3750	0.5833	1.19658	0.274		
11 SF French Open	Nadal	Ad	32	40	72	0.4444	0.5556	22	26	0.6875	0.6500	0.11250	0.7373		
11 SF French Open	Nadal	Deuce	21	22	43	0.4884	0.5116	6	15	0.2857	0.6818	6.74663	0.0094	***	F
11 SF French Open	Murray	Ad	24	43	67	0.3582	0.6418	9	26	0.3750	0.6047	3.25592	0.01712	**	B(L)
11 SF French Open	Murray	Deuce	13	23	36	0.3611	0.6389	10	15	0.7692	0.6522	0.53633	0.4644		
11 F French Open	Nadal	Ad	77	17	94	0.8191	0.1809	48	11	0.6234	0.6471	0.03342	0.855		
11 F French Open	Nadal	Deuce	36	15	51	0.7059	0.2941	23	8	0.6389	0.5333	0.49492	0.4817		
11 F French Open	Federer	Ad	40	41	81	0.4938	0.5062	24	26	0.6000	0.6341	0.09993	0.7519		
11 F French Open	Federer	Deuce	13	30	43	0.3023	0.6977	9	13	0.6923	0.4333	2.43447	0.1187		
08 F French Open	Nadal	Ad	28	12	40	0.7000	0.3000	22	9	0.7857	0.7500	0.06144	0.8042		
08 F French Open	Nadal	Deuce	20	6	26	0.7692	0.2308	13	2	0.6500	0.3333	1.89616	0.1685		
08 F French Open	Federer	Ad	22	25	47	0.4681	0.5319	9	12	0.4091	0.4800	0.23805	0.6256		
08 F French Open	Federer	Deuce	15	15	30	0.5000	0.5000	7	3	0.4667	0.2000	2.40000	0.1213		

[2] The mechanics for this test are discussed in Mead's (1974) book on statistics, page 449

C: Pearson Goodness of Fit for Grass Court Results															
Match	**Server**	**Court**	**L**	**R**	**Total**	**L%**	**R%**	**L Won**	**R Won**	**L Win %**	**R Win %**	**Pearson**	**p-value**	**Sig**	**B/F**
09 F Wimbledon	Federer	Ad	76	56	132	0.5758	0.4242	59	49	0.7763	0.8750	2.11075	0.1463		
09 F Wimbledon	Federer	Deuce	38	22	60	0.6333	0.3667	31	17	0.8158	0.7727	0.16148	0.6878		
09 F Wimbledon	Roddick	Ad	89	68	157	0.5669	0.4331	70	45	0.7865	0.6618	3.06159	0.0802	*	B
09 F Wimbledon	Roddick	Deuce	56	22	78	0.7179	0.2821	46	15	0.8214	0.6818	1.80618	0.179		
11 F Wimbledon	Nadal	Ad	24	36	60	0.4000	0.6000	18	20	0.7500	0.5556	2.34450	0.1257		
11 F Wimbledon	Nadal	Deuce	18	3	21	0.8571	0.1429	14	1	0.7778	0.3333	2.48889	0.1147		
11 F Wimbledon	Djokovic	Ad	23	39	62	0.3710	0.6290	18	21	0.7826	0.5385	3.69569	0.0546	*	F(L)
11 F Wimbledon	Djokovic	Deuce	17	21	38	0.4474	0.5526	11	15	0.6471	0.7143	0.19651	0.6576		
06 F Wimbledon	Federer	Ad	34	47	81	0.4198	0.5802	29	28	0.8529	0.5957	6.25901	0.0124	**	F(L)
06 F Wimbledon	Federer	Deuce	16	22	38	0.4211	0.5789	13	16	0.8125	0.7273	0.37226	0.5418		
06 F Wimbledon	Nadal	Ad	47	35	82	0.5732	0.4268	31	21	0.6596	0.6000	0.30688	0.5796		
06 F Wimbledon	Nadal	Deuce	36	8	44	0.8182	0.1818	23	3	0.6389	0.3750	1.88557	0.1697		
07 F Wimbledon	Federer	Ad	47	62	109	0.4312	0.5688	32	44	0.6809	0.7097	0.10524	0.7456		
07 F Wimbledon	Federer	Deuce	22	21	43	0.5116	0.4884	15	16	0.6818	0.7619	0.34252	0.5584		
07 F Wimbledon	Nadal	Ad	81	31	112	0.7232	0.2768	55	18	0.6790	0.5806	0.95582	0.3282		
07 F Wimbledon	Nadal	Deuce	40	16	56	0.7143	0.2857	26	11	0.6500	0.6875	0.07169	0.7889		
08 F Wimbledon	Federer	Ad	70	57	127	0.5512	0.4488	55	32	0.7857	0.5614	7.32652	0.0068	***	F(L)
08 F Wimbledon	Federer	Deuce	25	40	65	0.3846	0.6154	15	31	0.6000	0.7750	2.27760	0.1313		
08 F Wimbledon	Nadal	Ad	80	55	135	0.5926	0.4074	52	43	0.6500	0.7818	2.71615	0.0993	*	F
08 F Wimbledon	Nadal	Deuce	52	27	79	0.6582	0.3418	32	22	0.6154	0.8148	3.26770	0.0707	*	F

* significant to the ten percent level, ** significant at the 5% level, and *** significant to the one percent level.
B/F: Whether the non-optimal server was overplaying to the backhand or forehand.
(L) indicates that opponent was left handed

However, there are differences between the results of the three court surfaces. On the hard court, which is the court surface with the lowest probability of attaining an ace and, by association, the lowest amount of service pressure, there was only one case of statistically significant unequal winning percentages across service direction. (This accounts for only five percent of cases). On the clay court surface, with the middle level of service pressure, 20 percent of matches had statistically significant unequal success between the service directions. In contrast, grass courts, the highest pressure surface, resulted in 30 percent of players using non-optimal strategies. These results suggest that increasing the pressure on players decreases the athlete's ability to play a good strategy.

Consider the 11 cases with statistically significant unequal pay-offs to service direction. In eight of these cases, the serve to the forehand had a higher winning percentage than the serve to the backhand. These players would have gained from serving to the forehand more often and the back hand less often. Until the success rates equalized, this change in the choice of service direction would have depressed the success rate of the forehand shots and increased the success of the backhand shots. These results suggest that when the optimal strategy breaks down, players are more likely to overplay the ball to the opponent's weak side.

Serving players are leaving points on the court, particularly on grass courts, where the pressure is the highest. If services strategy was improved by a player on grass courts, a player would be able to get more aces, leading to more games, sets, matches, and winnings from victories. For the receiving player, the implication is that they should switch their strategy to one that exposes the serving player's tendency to go to the backhand too often. Receiving players could switch to a strategy based on lining up outside more often and planning to run around backhand serves to improve their chance at winning because servers are overplaying to the receiver's backhand.

IV. Conclusion

This study finds support for two predictions that emerge from mixed strategy play. First, athletes randomize their tennis serve location. Second, generally tennis players choose a mix of service direction so that the chance of winning the point is the same for each choice. This research suggests that an athlete's response to stress may explain why the literature has often been unable to find evidence of mixed strategy play in professional leagues. This paper finds that as players move to court surfaces that place more pressure on the server, the strategic play of the server gets worse. The pressure causes the server to direct serves to his opponent's backhand too often. The results in this paper are consistent with Downey and McGarrity (2012), who also found that pressure decreased a professional's ability to play optimally strategies.

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