Hot Racquet or Not? An Exploration of Momentum in Grand Slam Tennis Matches

Arjun Goyal and Jeffrey S. Simonoff
Leonard N. Stern School of Business, New York, NY, USA

Abstract

The presence of momentum in sports, where the outcome of a previous event affects a following event, is a belief often held by fans, and has been the subject of statistical study for many sports. This paper investigates the presence and manifestation of momentum in Grand Slam tennis matches from 2014 through 2019 for men and women, to see if there is evidence of any carryover effect from the outcome of previous point(s)/game(s)/set(s) to the current one that cannot be accounted for by player quality, fitness or fatigue. Generalized linear mixed effect models (GLMMs) are used to explore the effects of the outcomes of previous sets, games, or points on the odds of winning a set, game, or point, while incorporating control variables that account for differences in player quality and the current status of the match. We find strong evidence of carryover effects at the set, game, and point level. Holding one’s serve in prior service games is strongly related to winning a current game, but losing a past game is associated with higher estimated odds of winning the next game. Winning the previous two or three points in a row is associated with highest estimated odds of winning the next point.

Keywords: Tennis, momentum, generalized linear mixed effects model

1 Corresponding author: Arjun Goyal, New York University, New York, NY 10012, USA. E-mail: ag5574@stern.nyu.edu
1. Introduction

If you have the fortune (or misfortune) of facing Roger Federer on a tennis court as he is serving 15-0 up, you might consider moving on to the next game. According to Craig O’Shannessy, a writer for the Association of Tennis Professionals Tour (ATP Tour), Federer won 95.8% of these games in all professional tournaments from 2015-2019 (O’Shannessy, 2019). Considering the caliber of Federer’s play, this statistic is not surprising. He has won a record 20 Grand Slams, served more than 10,000 aces, and is widely considered the greatest player of all time.

Casual tennis watchers might attribute Federer’s remarkable statistic to ‘momentum’. They might hear commentators utter “His serve is feeling good” and “he’s on a roll” during matches. As evidenced in many blogs and columns, many fans and tennis writers believe such momentum exists in sports, especially in tennis. A blog post at The New York Times was entitled “The Importance of Momentum in Tennis” (MacDonald, 2009). A column on Tenniisserver.com explicitly put forward “In most sports, it is pretty clear when the momentum has shifted from one team or player to another. This is certainly true of the wonderful game of tennis” (Waite, 2014). Does momentum really exhibit itself in tennis?

The possibility of the existence of momentum (and its close cousin, streakiness) in sports has been a subject of study in both the academic literature and popular press for many decades. An early examination of this was Gilovich, Vallone and Tversky (1985), which examined whether the ‘hot hand’ in basketball was a real phenomenon or a fallacy; they found little evidence of the existence of the hot hand.

In the sport of tennis, Jackson and Mosurski (1997) explored Wimbledon and US Open data, and found statistical evidence indicating effects of psychological momentum, although this was mostly concentrated in heavy defeats (where the final set score was 2-0 or 3-0). O’Donoghue (2001) found that there was no significant effect of the scoreboard of a match on the outcome of a point, implying that outcome of previous points have no effect on the outcome of the next. Moss and O’Donoghue (2017) found no momentum effect in the US Open data they examined, unless the point was a break point. O’Donoghue and Brown (2009) found no evidence of momentum in the outcomes of service points when examining data from 13 Grand Slam matches.
Not all studies have shown weak indications of momentum. Klaassen and Magnus (2001) used dynamic regressors to measure psychological momentum and found a small deviation from independence of points. Pollard, Cross and Meyer (2006) analyzed Grand Slam matches from 1995 to 2004, and found that the probability of winning a set is not constant, and the better players (but not the weaker players) were able to change the probability of winning a set both when they were ahead (‘on-a-roll’) and behind (‘trying harder when behind’). Dietl and Nesseler (2017) examined the effect of winning the second-to-last set on the outcome of the last (and deciding) set and they found that winning the second-to-last set provides positive momentum, but if this set goes to a tie-breaker, there is anti-momentum (i.e., successes following failures and failures following successes). Meier et al. (2019) examined US Open and Wimbledon data from 2009 to 2014, focusing on the effects of interruptions after break points, and found that while there is evidence of momentum after break points if play immediately continues, this disappears if there is a break in play because of a scheduled rest period.

There have been studies finding some evidence of momentum in other sports as well. Burns (2004) explored the effect of adapting to a hot hand mindset in a basketball game by giving players on a streak more shots, and found that scoring increased in this case (although he emphasized that the paper is focused on the implications of behaving as if the hot hand exists, as opposed to the validity of the belief itself). Sela and Simonoff (2007) explored the presence of momentum in a baseball game and found weak evidence of such momentum in some circumstances. Savage (2012) explored golf to see whether performances on a week-to-week basis in the PGA tour had evidence of psychological momentum; his study found a non-random pattern to performances, and early successes led to more positive outcomes in later weeks.

In this paper we investigate the possible existence of momentum in professional tennis; specifically, in singles matches in Grand Slam tournaments (Australian Open, French Open, Wimbledon and U.S. Open), which are the most prestigious tournaments of the season, for both men and women. “Momentum” is defined here as being evidence of carryover effects from earlier performance in the match that cannot be accounted for by objective measures of quality difference between the opponents, or other effects like fatigue. While it is possible to speculate about whether such patterns would reflect physical effects, psychological effects, or some combination of the two, it is clearly not possible to know this with any certainty, so we do not hypothesize
about that. Generalized linear mixed effects models are used to model success (winning a point, game, or set) as a function of previous success (or failure), taking into account factors unrelated to those earlier outcomes. Unlike in many other sports contexts, we find strong evidence of momentum at all three (point, game, and set) levels.

2. Data and Methodology

2.1. Rules of Tennis

A tennis match’s basic structural layout has four levels nested within each other, namely matches, sets, games and points. A match has multiple sets (either 3 or 5 depending on the gender of the players or tournament). To win the match, players must win a majority of the total number of sets (three sets in a five-set match, and two sets in a three-set match). To win a set, players have to win a minimum of six games with at least a two-game advantage. Should both players win six games each, the set is taken to a tiebreaker, where players have to win a minimum of seven points with a two-point advantage. Each game consists of points, which are collected by winning rallies. To win a game, players must win at least 4 points, with at least a two-point advantage. The serve, which is when one player tosses the ball and hits it into the ‘service box’ diametrically opposite the player’s position, is alternated between games.

Players in the ATP Tour (men’s) and WTA (Women’s Tennis Association) Tour (women’s) are ranked based on their performance in tournaments, for which they are given points depending on the prestige of the tournament (the Grand Slams are the most prestigious tournaments in tennis). The primary difference between these competitions (apart from location) is the surface of the court: the Australian Open and US Open are played on hard courts, Wimbledon is played on a grass court, and the French Open is played on a clay court.

2.2. Defining Momentum

Defining momentum in tennis can be challenging given the sport’s structural complexity. In a generalized sense, momentum manifests itself when the outcome of prior events influences the outcome of future ones. In tennis, momentum could exhibit itself if a player tends to win a point/game/set more often if they have won the previous point(s)/game(s)/set(s). Momentum factors could be physiological, psychological or a
combination of both. Winning on a big point can improve the mindset of a player by instilling confidence, which in turn may lead to better posture, more positive thinking or even increased shot power.

The quality of players clearly has a very large effect on performance; better players may win more points in a row not because of momentum, but simply because they are just better than their opponents. For this reason, any assessment of potential momentum must account for quality differences between players.

2.3. Data

The analyses presented here are based on point-by-point data for singles play in Grand Slam tournaments from 2014 through 2019 (point-by-point data are not available for tournaments before 2014). Limiting the matches to Grand Slams somewhat controls the ranking and relative skill levels of players (usually all in the top 100) in the matches being analyzed. It also standardizes the number of sets per match in each gender, best of 5 for men and best of 3 for women. More details on data collection can be found in the Supplemental Material.

Some matches that were played during this period have been removed from the data universe due to the differences in rules regarding the tiebreaker in the deciding set of a match (fifth set for men and third set for women). The Australian Open and Wimbledon have prohibited the use of a tiebreaker during these sets, resulting in certain matches becoming anomalously long. To ensure consistency in the matches being analyzed, matches where the deciding set went past a set score of 6-6 were not included in the data universe.

2.4. Predicting Variables

The predicting variables used are a combination of momentum indicators and control variables. The variables are defined with respect to a ‘reference player’; in the case of our analysis, the reference player will be the player whose name appears first in the match on the tournament bracket. This player will be referred to as ‘Player 1’ or ‘P1’, while his or her opponent will be referred to as ‘Player 2’ or ‘P2’.

Depending on the level of a match being analyzed, the response variable is whether the winner of the set, game or point is P1 (1) or P2 (0). The primary momentum indicators used here are the outcomes of the previous (or lagged) set, games or points. Accounting for the amount of time needed to complete a set, game, or point,
the degree of the lag used is different on each level: the set-level uses one lag, the game level uses two lags and the point level uses three lags.

Control variables are used to ensure that player quality and other factors are accounted for and do not appear as indication of momentum. The variables controlling for player quality are percentage of points won on serve (PS pct.), percentage of points won returning (PR pct.), player ranking, player age and player gender. Since the analysis uses matches across six years, the players of a match are assigned the metrics that correspond to them for the year in which the match was played. A key control variable on the game and point level is the indicator of the serving player (which is binary, where 1 represents P1 serving, and 0 represents P1 receiving). Variables that control for fatigue and time are the number of sets and games played in the match. Note that one thing that cannot be accounted for in this analysis is if one particular player’s game is particularly well-suited or poorly-suited to playing against another particular player, since the effects of the control variables are hypothesized to be the same for all players, without any relationship to the specific players in a match.

2.5. Statistical models

Analyses are built around a generalized linear model with a logit function \( \ell(X) \) (logistic regression), which has the form

\[
\ell(X) \equiv \log \left[ \frac{\pi(X)}{1-\pi(X)} \right]_i = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_p x_{pi} = X_i \beta = \eta_i,
\]

where \( \pi(X) \) is the probability of winning a set (for example), and response (0 or 1, corresponding to losing or winning the set) following a Bernoulli distribution. Each observation (each set, game, or point) is nested within a match, and to account for unmodeled heterogeneity between matches, generalized linear mixed effects models (GLMMs) are used, generalizing the logistic regression model to

\[
\eta_i = X_i \beta + Z_i u_i
\]

where the \( Z_i \) are the random effects predictors and the \( u_i \) are the random effect coefficients, assumed to be normally distributed. In this paper the match effect is fit via a random intercept for each match, implying that \( Z_i \) is just a column of ones.
Models including all potential control variables were originally considered as candidate models, with both players having individual and separate control variables. However, when running these models, R was not able to accurately estimate coefficients on the game and point levels due to their complexity, and displayed a convergence error. Therefore, the numbers from the models with all potential control variables cannot be trusted. For this reason, the results reported on in the next section are based on models that do not include predictors that never provide useful predictive power (i.e. player age and game/point number), and use the differences between the two players for the remaining control variables (i.e. Rank, PS pct. and PR pct.), which are all estimable.

3. Results

Broad relationships with the control variables follow the expected patterns. Higher-ranked players (which, of course, somewhat paradoxically corresponds to a lower rank number) are more likely to win a set, a game, or a point. Similarly, players with more effective serve (higher serve percentage) or return (higher return percentage) are more likely to win a set, game, or point. Somewhat surprisingly, the latter effect does not seem to vary much across tournaments, despite the commonly-held view that serve success is more important on grass (Wimbledon) than on hard court (Australian and US Opens), and more important on hard court than on clay (French Open). These quality-related and serve-related effects become progressively stronger moving from point-level to game-level to set-level, presumably reflecting a Central Limit Theorem-type effect of games being the “sum” of several points, and sets being the “sum” of several games.

3.1. Fitted Models

Table 1, Table 2, and Table 3 summarize the results of the fitted models. Game-level and point-level fits include interaction effects between the indicator of whether Player 1 was serving and the momentum variables (outcomes of previous games and points), in order to account for the fact that a player winning the previous game or point when they were serving in that game or point is much less surprising than if they were receiving serve in that game or point. Game-level and point-level analyses are based on generalized linear mixed effects model fits; mixed effects models could not be fit at the set level for some tournaments, so in cases where this happens, generalized linear models are used instead. Such situations are noted in the table. Game and point-
level analyses are based on models using differences between control variable values for the two players, rather than the values themselves, in order to simplify the analysis.

3.2. Set-Level Momentum

Table 4 gives odds ratios for the odds of Player 1 winning the set associated with the model fits. It is clear that the lag of the set outcome variable is highly significant. The Lag Set Outcome slope is positive and statistically significant across all tournaments and both genders. This shows that after accounting for the relative quality of the players through ranks and player statistics, there is a strong positive carryover effect from the outcome of the previous set onto the next one. The increase in odds of winning a set between losing and winning the previous set is very large in a practical sense, being anywhere from 56% to 109% for men, and from 42% to 187% for women.

There also seem to be differences in the magnitude of this carryover effect depending on gender and court surface. Other than for the US Open, women benefit more from winning the previous set than men do. An explanation for this trend could be that since the women’s match is a best-of-three sets match, winning one set would give a player a bigger advantage than in the men’s match, which is a best-of-five sets match. A clay court surface is associated with the largest effect of momentum, which is perhaps surprising, since it is the slowest surface (which results in matches that progress at a slower pace). The fast grass courts show relatively high degrees of this carryover effect as well. Hard courts trail clay and grass in this regard.

Sets in which an apparently much stronger player lost the set do occur, and are identified as outliers relative to the model fit. Omitting these sets does not affect the estimated model parameters in a meaningful way.

3.3. Game-Level Momentum

Game-level momentum effects correspond to an interaction of three binary variables: the server of the current game, the result of the previous game, and the result of the game before that. This results in eight possibilities:

- Case 1: Player 1 is currently on serve and lost the previous two games (player 2 held serve in the previous game, and player 1’s serve was broken two games ago)
• Case 2: Player 1 is currently on serve, won the previous game, and lost the game before that (broke player 2’s serve in the previous game, and was broken two games ago)

• Case 3: Player 1 is currently on serve, lost the previous game, and won the game before that (player 2 held serve in the previous game, and player 1 held serve two games ago)

• Case 4: Player 1 is currently on serve and won the previous two games (broke player 2’s serve in the previous game, and player 1 held serve two games ago)

• Case 5: Player 2 is on serve and player 1 lost the previous two games (player 1’s serve was broken in the previous game, and player 2 held serve two games ago)

• Case 6: Player 2 is on serve, and player 1 won the previous game, and lost the game before that (player 1 held serve in the previous game, and player 2 held serve two games ago)

• Case 7: Player 2 is on serve, and player 1 lost the previous game, and won the game before that (player 1 was broken in the previous game, and broke player 2’s serve two games ago)

• Case 8: Player 2 is on serve, and player 1 won the previous two games (player 1 held serve in the previous game, and broke player 2’s serve two games ago)

Table 5 gives the estimated odds of Player 1 winning the game for each combination, assuming the two players are equally ranked and have equal ability (in terms of serve percentage and return percentage). Details on how these were obtained can be found in the Supplemental Material. Note that Cases 1 to 4 correspond to when Player 1 is serving in the current game, and Cases 5 to 8 correspond to when Player 2 is serving in the current game. Cases where Player 1 is serving are shaded in green and cases where Player 1 is returning are shaded in red. Note that these assume that all other fixed predictors are 0; i.e., the players are evenly matched in rank, serving percentage, and return percentage. The odds are shaded according to their magnitude, with the highest odds on serve being darkest and the lowest odds being lightest. The reverse pattern is used when Player 1 is returning serve. Thus, darker cells correspond to stronger odds in the expected direction of the serving player winning the game. Cases 5 to 8 are mirror images of Cases 1 to 4, with Case 1 corresponding to Case 8, Case 2 to Case 7, Case 3 to Case 6 and Case 4 to Case 5.
The primary observation that can be made from Table 5 is that, as would be expected, the most important factor in who wins a game is who is serving, with the server having a great advantage. Given this, from a momentum point of view holding serve in previous games is very important for the serving player. Cases 1 and 2, which have the lowest odds amongst the serving cases, show that having one’s serve broken two games ago (that is, the previous service game) is associated with a negative effect on the current service game. Correspondingly, these cases’ mirror images, Case 7 and Case 8, show the highest odds amongst the returning cases when he or she had broken serve in the previous return game. Case 3, where the serving player held serve in the previous service, shows the highest odds of winning, and correspondingly Case 6 shows the lowest odds of winning.

Interestingly, losing previous games apparently can spur positive results (that is, anti-momentum). Case 1 shows higher odds of winning than Case 2, even though the serving player has not broken the other player in the previous game (that is, s/he lost the previous game). In a similar fashion, Case 7 shows higher odds of winning than Case 8, even though the returner has lost the previous game in Case 7. Further, Case 4 does not show the highest odds of winning even though the serving player has won the past two games, and Case 5 does not show the lowest odds even though the returning player has lost the previous two games. Thus, there is evidence that a player could recover, at least to some extent, from poor outcomes in the immediate past.

There is little evidence of differences in the carryover effects between different court surfaces. On the other hand, momentum effects are apparently stronger for men than for women. The magnitude of carryover is far larger for men than for women, indicating that the likelihood of streaks of games won is more likely in a men’s match than in a women’s one. A potential explanation of this could be the difference in importance of returning serve between the two groups. Australian coach Simon Rea states that returning serve is such an important part of the women’s game that most players return at an incredibly high level (Trollope 2017), which could make it difficult for players to win multiple games consecutively, diminishing any kind of carryover effect that may occur.
3.4. **Point-Level Momentum**

At the point level, there is evidence of carryover effects going back three previous points. This implies 16 different blocks of cases, based on the outcome of the previous points and current service status (each block further has 8 different combinations of lag service variables that reflect the importance of who is serving). The blocks are as follows:

- **Block 1**: Player 1 is currently serving and has lost the last 3 points
- **Block 2**: Player 1 is currently serving, won the last point and lost 2 points prior to that
- **Block 3**: Player 1 is currently serving, lost the last point, won 2 points ago and lost 3 points ago
- **Block 4**: Player 1 is currently serving, lost the last 2 points but won 3 points ago
- **Block 5**: Player 1 is currently serving, won the last 2 points but lost 3 points ago
- **Block 6**: Player 1 is currently serving, won the last point, lost 2 points ago and won 3 points ago
- **Block 7**: Player 1 is currently serving, lost the last point, won 2 points ago and won 3 points ago
- **Block 8**: Player 1 is currently serving and won the last 3 points

Blocks 9-16 are identical to ones above but with Player 2 serving in the current point (Player 1 returning).

The odds of winning the point in each case are summarized in Table 6 (Blocks 1-8, with Player 1 serving) and Table 7 (Blocks 9-16, with Player 2 serving). Details on how these were obtained can be found in the Supplemental Material. Note that these assume that all other fixed predictors are 0; i.e., the players are evenly matched in rank, serving percentage, and return percentage. The color shading of the odds is identical to that in the game-level analysis: green if the player is serving and red if the player is returning, with darker shades corresponding to greater odds in the expected direction of the server winning the point.

Just as in the game-level analysis, the discussion of these odds can be done with respect to the serving player, as Blocks 9-16 are mirror images of Blocks 1-8. Here, Block 1 for the server corresponds to Block 16 for the returner, Block 2 for the server corresponds to Block 15 for the returner, and so on.

An intuitive trend that can be seen is that winning/losing the previous two or three points is associated with higher positive/negative momentum, respectively. Blocks 5 and 8 show that winning the last two or three
points is associated with higher odds of winning the point for the server, and correspondingly the lowest odds for the returner (Blocks 9 and 12). Block 8, where the server wins the last three points, shows the highest odds of winning for the server, and Block 9 shows the lowest odds of winning for the returner. Similarly, losing the last two or three points is associated with lower odds of winning the current point, as shown in Blocks 1 and 4 for the server. Correspondingly, Blocks 13 and 16 show higher odds of winning for the returner, with the server having lost the last two points.

An interesting implication of Table 6 and Table 7 is that the previous point seems to be more important than Lag 2 and Lag 3 points. Blocks 2 and 6, where the server wins the previous point, also show high odds of winning the point for the server, in spite of the server losing once or twice in the two points before last. Correspondingly, Blocks 11 and 15 show lower odds of winning for the returner. Blocks 3 and 7, where the server lost the previous point but won at least once in the two points before last, show lower odds winning than do Blocks 2 and 6. There is a similar trend for the returner, where Blocks 13 and 14 show higher odds of winning than do Blocks 11 and 15. Essentially, this shows that the outcome of the previous point has a greater effect than the Lag 2 and Lag 3 outcomes, and momentum effects are stronger when the outcome is recent.

Similar to the trend seen in the game-level analysis, momentum effects on the point level are stronger for men than for women.

4. Conclusions

Contrary to much previous research done examining momentum in sports, tennis results demonstrate significant carryover effects between sets, games and points, implying that results for them are not independent of each other. At the set level, winning the previous set has a huge positive effect on the odds of winning the next set, for both men and women. Indeed, for women the outcome of the previous set determines the outcome of the next one a very large proportion of the time. These effects are different for different surfaces, with the clay court showing the greatest effects. At the game level, holding serve in previous service games is very important for the currently-serving player. Interestingly, losing the previous game is associated with higher estimated odds of winning the next game. These effects are stronger for men than women.
Winning previous points also creates positive effects for the next point, and winning two points in a row is associated with very high estimated odds of winning the next point. Conversely, losing two or three points in a row is associated with much lower estimated odds of winning the next point. The momentum effect from prior points seems to have a short memory, with the most recent point having a greater effect on the estimated odds of winning than Lag 2 or Lag 3 points. Just as in the game-level analysis, these effects are stronger for men than they are for women.

As was noted earlier, it cannot be said with certainty that these carryover effects from previous outcomes are momentum. Given the presence of the control variables, it seems reasonable to hypothesize that these effects are due to some psychological factor, perhaps a change in confidence level. This psychological factor was studied by Jones and Harwood (2008), who conducted interviews with soccer players and concluded that there was a wide range of triggers during matches that made players perceive phases of momentum and change their strategies accordingly. This seems particularly plausible in a sport like tennis, which is not only an individual (rather than team) sport, but is one with direct one-on-one competition between players. Whether this change in mindset translates to physical effects and actions (what Mortimer and Burt, 2014, referred to as behavioral momentum), and hence changes to the odds of winning mimicking differences in player quality, is, however, not determinable from the available data.

The data used here, and R code (R Core Team, 2019) to perform all of the analyses, are available at github.com/arjungoyal98/grand-slam-data and github.com/arjungoyal98/hot-racquet, respectively.

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## Tables and Figures

Table 1: Set-Level Coefficients (#: GLMM could not be estimated; GLM output displayed)

|                   | AO Men | AO Women* | FO Men* | FO Women* | WB Men | WB Women* | USO Men | USO Women* |
|-------------------|--------|-----------|---------|-----------|--------|-----------|---------|------------|
| **Intercept**     | -0.1182| -0.4448***| -0.3347***| -0.5017***| -0.281**| -0.3956***| -0.0255| -0.1368    |
|                   | (-1.169)| (-3.976) | (-3.931) | (-4.499)  | (-2.928)| (-3.506)  | (-2.5)  | (-1.272)   |
| **P1 Rank**       | -0.0008| -0.0042* | -0.0056**| 0.0016    | -0.004* | -0.0018   | -0.0049***| -0.0012   |
|                   | (-0.591)| (-2.398) | (-3.07)  | (1.103)   | (-2.313)| (-1.295)  | (-2.953) | (-1.107)   |
| **P2 Rank**       | 0.0061***| 0.0005 | 0.005** | 0.0017 | -0.0002 | 0.0014 | 0.0047***| 0.0009    |
|                   | (3.903) | (0.311) | (2.952)  | (1.082)   | (-0.153)| (0.843)   | (2.881)  | (0.645)    |
| **Lag Set Outcome** |       |       |         |         |       |         |         |            |
| **P1**            | 0.4484**| 0.7629***| 0.7354***| 1.0369***| 0.5037***| 1.0551***| 0.4584**| 0.3566*    |
|                   | (3.024) | (4.735) | (6.322)  | (6.546)   | (3.457) | (6.652)   | (3.252) | (2.355)    |
| **P1 PS pct.**    | 0.1536***| 0.1445***| 0.1215***| 0.1711***| 0.1755***| 0.153*** | 0.1536***| 0.1428***  |
|                   | (6.029) | (5.29)  | (5.051)  | (6.01)    | (6.431) | (5.465)   | (5.926) | (5.519)    |
| **P2 PS pct.**    | -0.123***| -0.1925***| -0.1364***| -0.1014***| -0.2279***| -0.104***| -0.1252***| -0.1711*** |
|                   | (-5.011)| (-6.214)| (-5.88)  | (-3.445)  | (-7.775)| (-3.53)   | (-4.779)| (-5.608)   |
| **P1 PR pct.**    | 0.1528***| 0.1334***| 0.1615***| 0.207***  | 0.1012***| 0.0845*  | 0.1743***| 0.1646***  |
|                   | (5.892) | (3.911) | (6.391)  | (3.634)   | (2.528) | (6.533)  | (4.823) |            |
| **P2 PR pct.**    | -0.111***| -0.091* | -0.1322***| -0.13***  | -0.157***| -0.1382***| -0.1205***| -0.126***  |
|                   | (-4.236)| (-2.495)| (-5.288) | (-3.92)   | (-5.592)| (-3.865) | (-4.468)| (-3.611)   |

Significance codes - ***: 0.001; **: 0.01; *: 0.05

Note: AO: Australian Open, FO: French Open, WB: Wimbledon, USO: US Open
# Table 2: Game-Level Coefficients

|                          | AO Men | AO Women | FO Men | FO Women | WB Men | WB Women | USO Men | USO Women |
|--------------------------|--------|----------|--------|----------|--------|----------|---------|-----------|
| Intercept                | -1.0299*** | -0.7325*** | -1.0036*** | -0.6153*** | -1.0554*** | -0.7755*** | -0.9863*** | -0.6922*** |
|                          | (-17.307) | (-11.741) | (-17.711) | (-10.388) | (-16.876) | (-11.87) | (-17.468) | (-11.25) |
| Rank Diff                | -0.0007*  | -0.0012*** | -0.0013*** | -0.0003  | -0.0002  | -0.0007*  | -0.0011*** | -0.0002  |
|                          | (-2.147)  | (-3.418)  | (-3.344)  | (-0.984)  | (-0.523)  | (-2.118)  | (-3.254)  | (-0.734)  |
| PS Diff                  | 0.0652*** | 0.0716*** | 0.0545*** | 0.0554*** | 0.0821*** | 0.0652*** | 0.0527***  | 0.0777*** |
|                          | (12.388)  | (12.05)   | (9.623)   | (9.528)   | (14.543)  | (10.846)  | (10.561)  | (12.249)  |
| PR Diff                  | 0.0621*** | 0.0498*** | 0.0744*** | 0.0635*** | 0.0635*** | 0.0587*** | 0.0576***  | 0.056***  |
|                          | (11.094)  | (6.942)   | (9.207)   | (11.196)  | (7.667)   | (10.853)  | (7.625)   |          |
| Service                  | 1.9875*** | 1.3674*** | 1.9223*** | 1.0697*** | 2.0867*** | 1.4562*** | 1.9841***  | 1.3112*** |
|                          | (25.254)  | (16.752)  | (26.076)  | (13.819)  | (25.299)  | (17.055)  | (26.421)  | (16.431)  |
| Lag 1 Game               | -0.3997*** | -0.0627  | -0.2198*** | 0.0041   | -0.6077*** | -0.0935  | -0.2623*** | -0.0265  |
|                          | (-5.857)  | (-0.829)  | (-3.362)  | (0.056)   | (-8.458)  | (-1.265)  | (-4.065)  | (-0.357)  |
| Lag 2 Game               | 1.7278*** | 0.3724*** | 1.2837*** | 0.3034*** | 2.1063*** | 0.5374*** | 1.4536***  | 0.406***  |
|                          | (20.939)  | (3.822)   | (15.446)  | (3.296)   | (24.518)  | (5.263)   | (17.904)  | (4.271)   |
| Lag 1 Game x Service     | -1.1223*** | -0.2898*  | -0.9439*** | -0.1673  | -1.3965*** | -0.11325 | -0.996***  | -0.1108  |
|                          | (-10.84)  | (-2.419)  | (-9.253)  | (-1.47)   | (-13.02)  | (-1.07)   | (-9.917)  | (-0.945)  |
| Lag 2 Game x Service     | -1.2172*** | -0.2854*  | -0.9619*** | -0.1923  | -1.5106*** | -0.2831*  | -1.1309*** | -0.3298** |
|                          | (-11.642) | (-2.391)  | (-9.443)  | (-1.685)  | (-14.069) | (-2.276)  | (-11.184) | (-2.823)  |
| Lag 1 Game x Lag 2 Game  | -1.0693*** | -0.082   | -0.8423*** | -0.0664  | -1.2773*** | -0.2422*  | -0.9975*** | -0.1518  |
|                          | (-10.401) | (-0.686)  | (-8.337)  | (-0.582)  | (-12.035) | (-1.975)  | (-10.083) | (-1.308)  |
| Lag 1 Game x Lag 2 Game x Service | 2.1092*** | 0.3763*  | 1.757***  | 0.3277*  | 2.6222*** | 0.3322  | 1.9393***  | 0.2206  |
|                          | (14.613)  | (2.232)   | (12.338)  | (2.193)   | (17.584)  | (1.918)   | (13.929)  | (1.344)   |

Significance codes - ***: 0.001; **: 0.01; *: 0.05

Note: AO: Australian Open, FO: French Open, WB: Wimbledon, USO: US Open
Table 3: Point-Level Coefficients

|                      | AO Men | AO Women | FO Men | FO Women | WB Men | WB Women | USO Men | USO Women |
|----------------------|--------|----------|--------|----------|--------|----------|---------|-----------|
| **Lag 3 Point**      | 0.8878*** | 0.5735*** | 0.8233*** | 0.4445*** | 0.9507*** | 0.6963*** | 0.8609*** | 0.5287*** |
| **Lag 2 Point**      | -0.0995*** | -0.0665* | -0.0705** | -0.0370*** | -0.1455*** | -0.1091*** | -0.0773*** | -0.0622*  |
| **Lag 1 Point**      | 0.2242*** | 0.2136*** | 0.1939*** | 0.1942*** | 0.1977*** | 0.1773*** | 0.2448*** | 0.1686*** |
| **Lag 3 Service**    | -0.0461* | -0.0619** | -0.0415* | -0.0061 | -0.0127 | -0.0230 | 0.0091 | -0.0015 |
| **Lag 2 Service**    | 0.0037 | -0.0007 | -0.0452* | 0.0182 | -0.0111 | 0.0287 | 0.0073 | 0.0020 |
| **Lag 1 Service**    | -0.033 | 0.0535 | 0.0339 | 0.0966*** | 0.0032 | 0.0963** | 0.045 | 0.0368 |
| **Lag 3 Point**      | -0.1442*** | -0.1338*** | -0.1725*** | -0.0820*** | -0.1712*** | -0.1257*** | -0.1226*** | -0.1438*** |
| **Lag 2 Point**      | 0.0849*** | 0.067* | 0.1109*** | -0.0051 | 0.0911*** | -0.0035 | 0.0521* | 0.0094 |
| **Lag 1 Service**    | 0.0498* | 0.0772** | 0.0675** | -0.0008 | 0.0436 | 0.039 | -0.006 | 0.0346 |
| **Lag 3 Point**      | 0.0116 | -0.0718 | -0.0218 | -0.0764* | -0.043 | -0.0394 | -0.0461 | -0.0232 |
| **Lag 2 Point**      | 0.0116 | -0.0718 | -0.0218 | -0.0764* | -0.043 | -0.0394 | -0.0461 | -0.0232 |
| **Lag 3 Point**      | 0.0796* | 0.1251** | 0.1308*** | 0.1386*** | 0.0957** | 0.1552*** | 0.0987*** | 0.1624*** |
| **Lag 2 Point**      | 0.1646*** | 0.1252** | 0.1403*** | 0.1522*** | 0.1126*** | 0.1476*** | 0.1343*** | 0.1766*** |
| **Lag 1 Point**      | -0.2157*** | -0.1797** | -0.1946*** | -0.1707*** | -0.1397** | -0.2348*** | -0.1297*** | -0.2024*** |

Significance codes - ***: 0.001; **: 0.01; *: 0.05

Note: AO: Australian Open, FO: French Open, WB: Wimbledon, USO: US Open
Table 4: Proportional Change to Odds of Winning a Set for unit change in variables (odds ratios)

|                | AO Men | AO Women | FO Men | FO Women | WB Men | WB Women | USO Men | USO Women |
|----------------|--------|----------|--------|----------|--------|----------|---------|-----------|
| **P1 Rank**    | -0.08% | -0.42%   | -0.56% | 0.16%    | -0.40% | -0.18%   | -0.47%  | -0.12%    |
| **P2 Rank**    | 0.61%  | 0.05%    | 0.50%  | 0.17%    | -0.02% | 0.14%    | 0.42%   | 0.09%     |
| **Lag Set**    |        |          |        |          |        |          |         |           |
| **Outcome**    |        |          |        |          |        |          |         |           |
| **P1**         | 56.58% | 114.46%  | 108.63%| 182.05%  | 65.49% | 187.21%  | 79.01%  | 42.79%    |
| **P1 PS pct.** | 16.60% | 15.55%   | 12.92% | 18.66%   | 19.18% | 16.76%   | 13.45%  | 15.35%    |
| **P2 PS pct.** | -11.57%| -17.51%  | -12.75%| -9.64%   | -20.38%| -9.88%   | -9.98%  | -15.73%   |
| **P1 PR pct.** | 16.51% | 14.27%   | 17.52% | 23.00%   | 10.65% | 8.82%    | 15.39%  | 17.89%    |
| **P2 PR pct.** | -10.51%| -8.70%   | -12.39%| -12.19%  | -14.53%| -12.91%  | -9.60%  | -11.84%   |

Note: AO: Australian Open, FO: French Open, WB: Wimbledon, USO: US Open
| Case Number | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|
| AO Men      | 2.606 | 0.569 | 4.342 | 2.681 | 0.357 | 0.239 | 2.010 | 0.462 |
| AO Women    | 1.887 | 1.326 | 2.058 | 1.942 | 0.481 | 0.451 | 0.698 | 0.604 |
| FO Men      | 2.506 | 0.769 | 3.896 | 2.984 | 0.367 | 0.294 | 1.323 | 0.458 |
| FO Women    | 1.575 | 1.338 | 1.760 | 1.991 | 0.540 | 0.543 | 0.732 | 0.688 |
| WB Men      | 2.805 | 0.378 | 5.089 | 2.632 | 0.348 | 0.190 | 2.860 | 0.434 |
| WB Women    | 1.975 | 1.576 | 2.547 | 2.223 | 0.460 | 0.419 | 0.788 | 0.563 |
| USO Men     | 2.712 | 0.771 | 3.745 | 2.729 | 0.373 | 0.287 | 1.596 | 0.453 |
| USO Women   | 1.857 | 1.619 | 2.004 | 1.871 | 0.500 | 0.487 | 0.751 | 0.629 |

Note: AO: Australian Open, FO: French Open, WB: Wimbledon, USO: US Open
Table 6: Odds of Winning a Point for each case (Serving)

| Case Number | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|-------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| AO Men      | 1.42 | 1.29 | 1.43 | 1.36 | 1.36 | 1.23 | 1.29 | 1.23 | 1.78 | 1.66 | 1.79 | 1.70 | 1.71 | 1.58 | 1.67 | 1.59 |
| AO Women    | 1.15 | 1.07 | 1.15 | 1.08 | 1.08 | 1.01 | 1.07 | 1.01 | 1.42 | 1.34 | 1.42 | 1.33 | 1.33 | 1.26 | 1.34 | 1.26 |
| FO Men      | 1.35 | 1.26 | 1.29 | 1.29 | 1.24 | 1.21 | 1.20 | 1.15 | 1.64 | 1.59 | 1.56 | 1.57 | 1.50 | 1.52 | 1.52 | 1.46 |
| FO Women    | 1.03 | 0.99 | 1.05 | 1.02 | 1.04 | 0.98 | 1.01 | 1.00 | 1.25 | 1.20 | 1.27 | 1.24 | 1.26 | 1.19 | 1.22 | 1.21 |
| WB Men      | 1.50 | 1.29 | 1.48 | 1.48 | 1.46 | 1.28 | 1.28 | 1.26 | 1.82 | 1.72 | 1.80 | 1.80 | 1.78 | 1.70 | 1.70 | 1.68 |
| WB Women    | 1.24 | 1.11 | 1.28 | 1.21 | 1.25 | 1.09 | 1.15 | 1.12 | 1.48 | 1.37 | 1.53 | 1.45 | 1.49 | 1.34 | 1.41 | 1.38 |
| USO Men     | 1.34 | 1.24 | 1.35 | 1.35 | 1.36 | 1.25 | 1.25 | 1.26 | 1.71 | 1.58 | 1.72 | 1.72 | 1.74 | 1.59 | 1.59 | 1.60 |
| USO Women   | 1.13 | 1.06 | 1.15 | 1.11 | 1.13 | 1.04 | 1.08 | 1.06 | 1.33 | 1.31 | 1.36 | 1.31 | 1.34 | 1.29 | 1.33 | 1.31 |

Note: AO: Australian Open, FO: French Open, WB: Wimbledon, USO: US Open
Table 7: Odds of Winning a Point for each case (Returning)

| Case Number | Block 9 | Block 10 |
|-------------|---------|----------|
| Block 11    | Block 12 |          |
| Block 13    | Block 14 |          |
| Block 15    | Block 16 |          |

| AO Men | AO Women | FO Men | FO Women | WB Men | WB Women | USO Men | USO Women |
|--------|----------|--------|----------|--------|----------|---------|-----------|
| 0.59   | 0.55     | 0.59   | 0.56     | 0.56   | 0.51     | 0.53    | 0.51      |
| 0.65   | 0.50     | 0.57   | 0.57     | 0.57   | 0.56     | 0.57    | 0.57      |
| 0.59   | 0.55     | 0.57   | 0.54     | 0.53   | 0.53     | 0.72    | 0.70      |
| 0.66   | 0.67     | 0.67   | 0.67     | 0.63   | 0.65     | 0.64    | 0.80      |
| 0.58   | 0.50     | 0.57   | 0.57     | 0.56   | 0.49     | 0.49    | 0.49      |
| 0.62   | 0.56     | 0.64   | 0.61     | 0.62   | 0.54     | 0.57    | 0.56      |
| 0.57   | 0.52     | 0.57   | 0.57     | 0.53   | 0.53     | 0.72    | 0.67      |
| 0.66   | 0.62     | 0.68   | 0.65     | 0.67   | 0.61     | 0.64    | 0.63      |

| AO Men | AO Women | FO Men | FO Women | WB Men | WB Women | USO Men | USO Women |
|--------|----------|--------|----------|--------|----------|---------|-----------|
| 0.57   | 0.51     | 0.54   | 0.54     | 0.51   | 0.51     | 0.51    | 0.51      |
| 0.68   | 0.50     | 0.57   | 0.57     | 0.55   | 0.55     | 0.50    | 0.46      |
| 0.61   | 0.57     | 0.65   | 0.63     | 0.61   | 0.61     | 0.50    | 0.46      |
| 0.73   | 0.70     | 0.73   | 0.72     | 0.69   | 0.69     | 0.61    | 0.58      |
| 0.58   | 0.50     | 0.57   | 0.57     | 0.50   | 0.54     | 0.49    | 0.42      |
| 0.68   | 0.61     | 0.70   | 0.67     | 0.60   | 0.63     | 0.55    | 0.49      |
| 0.59   | 0.55     | 0.63   | 0.60     | 0.55   | 0.58     | 0.50    | 0.46      |
| 0.69   | 0.65     | 0.71   | 0.68     | 0.70   | 0.64     | 0.58    | 0.54      |

| AO Men | AO Women | FO Men | FO Women | WB Men | WB Women | USO Men | USO Women |
|--------|----------|--------|----------|--------|----------|---------|-----------|
| 0.72   | 0.67     | 0.78   | 0.68     | 0.75   | 0.64     | 0.73    | 0.70      |
| 0.79   | 0.74     | 0.84   | 0.74     | 0.79   | 0.70     | 0.79    | 0.74      |
| 0.73   | 0.71     | 0.78   | 0.70     | 0.74   | 0.68     | 0.75    | 0.72      |
| 0.82   | 0.78     | 0.83   | 0.81     | 0.82   | 0.78     | 0.79    | 0.79      |
| 0.68   | 0.64     | 0.73   | 0.67     | 0.72   | 0.63     | 0.69    | 0.68      |
| 0.78   | 0.72     | 0.80   | 0.77     | 0.78   | 0.71     | 0.74    | 0.72      |
| 0.72   | 0.67     | 0.77   | 0.73     | 0.77   | 0.67     | 0.71    | 0.71      |
| 0.80   | 0.78     | 0.82   | 0.78     | 0.81   | 0.77     | 0.80    | 0.79      |

| AO Men | AO Women | FO Men | FO Women | WB Men | WB Women | USO Men | USO Women |
|--------|----------|--------|----------|--------|----------|---------|-----------|
| 0.58   | 0.52     | 0.63   | 0.63     | 0.53   | 0.53     | 0.57    | 0.64      |
| 0.68   | 0.65     | 0.72   | 0.69     | 0.73   | 0.64     | 0.68    | 0.69      |
| 0.59   | 0.55     | 0.63   | 0.61     | 0.65   | 0.57     | 0.59    | 0.61      |
| 0.78   | 0.75     | 0.79   | 0.77     | 0.78   | 0.74     | 0.76    | 0.75      |
| 0.55   | 0.47     | 0.59   | 0.56     | 0.61   | 0.49     | 0.51    | 0.53      |
| 0.70   | 0.63     | 0.72   | 0.71     | 0.73   | 0.64     | 0.64    | 0.65      |
| 0.60   | 0.55     | 0.63   | 0.60     | 0.64   | 0.56     | 0.59    | 0.59      |
| 0.71   | 0.67     | 0.73   | 0.72     | 0.75   | 0.68     | 0.69    | 0.70      |

Note: AO: Australian Open, FO: French Open, WB: Wimbledon, USO: US Open
Supplemental Material

S1. Data Collection

Detailed match data were obtained from the scoreboard.com website. Data scraping code in Python was written to retrieve the data. The primary packages used were BeautifulSoup and Selenium, both of which create links to the website and download the html text. The data, and the Python code and R code used to conduct all of the analyses in the paper are available at https://github.com/arjungoyal98/grand-slam-data and https://github.com/arjungoyal98/hot-racquet, respectively.

Player information, such as age, rankings, and serving/returning points won percentages were retrieved from Jeff Sackmann’s Github page (github.com/JeffSackmann) and ultimatetennisstatistics.com for men, and the WTA website (www.wtatennis.com/stats) for women. While data for most players were available, this is not the case for all players. For these players, the unavailable metrics were left blank. Rather than attempting to infer or impute these missing data points, these observations were left out from the dataset of models that required that specific variable.

S2. Odds Calculations Procedures

The calculations of odds and odds ratios, which are the basis of the momentum exploration in the paper, are calculated in the following ways.

S2.1. Set-Level Odds Ratio calculations

From the coefficients found in Table 1, the proportional change in the odds of a player winning a set associated with a one-unit change in a predictor holding all else in the model fixed is \( e^\beta - 1 \), where \( \beta \) is the slope coefficient of the predictor. The value associated with lagged set outcome predictor is the observable effect of momentum.

S2.2. Game-Level Odds calculations

There are 8 different scenarios being explored, with each scenario having a unique combination of coefficients/betas that can be aggregated to form the log odds of winning a set in that scenario; these are
exponentiated to provide the estimated odds. These combinations are summarized in Table S1 based on the coefficient estimates in Table 2.

S2.3. **Point-Level Odds calculations**

The 128 different scenarios can be summarized using Table S2 and Table S3. For every case, 1 represents the presence of the variable in that scenario and 0 represents its absence. The calculation of the log odds for each of the cases is given by \( \sum_{l \in A_x} \beta_l \), where \( A_x \) is a set with coefficient labels present in Case x. The set \( A_x \) can be found in Table S5, and labels are based on those outlined in Table S4. The estimated coefficients for each variable are found in Table 3. These values are then exponentiated to provide the estimated odds.
## Supplemental Tables and Figures

### Table S1: Odds Calculation on Game-Level

|               | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 | Case 7 | Case 8 |
|---------------|--------|--------|--------|--------|--------|--------|--------|--------|
| Service       | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      |
| Lag 1 Game    | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      |
| Lag 2 Game    | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      | ✔      |

Log Odds

\[
\logit(X) = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7 + \beta_8 + \beta_9 + \beta_{10}
\]

where,

- Intercept: \(\beta_0\)
- Rank Diff: \(\beta_1\)
- PS Diff: \(\beta_2\)
- PR Diff: \(\beta_3\)
- Service: \(\beta_4\)
- Lag 1 Game: \(\beta_5\)
- Lag 2 Game: \(\beta_6\)
- Lag 1 Game x Service: \(\beta_7\)
- Lag 2 Game x Service: \(\beta_8\)
- Lag 1 Game x Lag 2 Game: \(\beta_9\)
- Lag 1 Game x Lag 2 Game x Service: \(\beta_{10}\)
Table S2: Summary of Scenarios on Point-Level (Serving)

| Case Number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|-------------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|
| P1 Service  | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 1 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 1 Point | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| Lag 2 Service | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 2 Point | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| Lag 3 Service | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 3 Point | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |

**Block 1**

| Case Number | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 |
|-------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| P1 Service  | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 1 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 1 Point | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lag 2 Service | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 2 Point | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| Lag 3 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 3 Point | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 |

**Block 2**

| Case Number | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 |
|-------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| P1 Service  | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 1 Service | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 1 Point | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lag 2 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 2 Point | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| Lag 3 Service | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 3 Point | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |

**Block 3**

| Case Number | 49 | 50 | 51 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 |
|-------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| P1 Service  | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 1 Service | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 1 Point | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 2 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 2 Point | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| Lag 3 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 3 Point | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |

**Block 4**

| Case Number | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 |
|-------------|----|----|----|----|----|----|----|----|----|----|
| P1 Service  | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Lag 1 Service | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 1 Point | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lag 2 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lag 2 Point | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| Lag 3 Service | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lag 3 Point | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |

**Block 5**

| Case Number | 63 | 64 |
|-------------|----|----|
| P1 Service  | 1 | 1 |
| Lag 1 Service | 0 | 0 |
| Lag 1 Point | 1 | 1 |
| Lag 2 Service | 1 | 1 |
| Lag 2 Point | 0 | 1 |
| Lag 3 Service | 1 | 1 |
| Lag 3 Point | 0 | 0 |

**Block 6**

| Case Number | 65 | 66 |
|-------------|----|----|
| P1 Service  | 1 | 1 |
| Lag 1 Service | 0 | 0 |
| Lag 1 Point | 1 | 1 |
| Lag 2 Service | 1 | 1 |
| Lag 2 Point | 0 | 1 |
| Lag 3 Service | 1 | 1 |
| Lag 3 Point | 0 | 0 |

**Block 7**

| Case Number | 67 | 68 |
|-------------|----|----|
| P1 Service  | 1 | 1 |
| Lag 1 Service | 0 | 0 |
| Lag 1 Point | 1 | 1 |
| Lag 2 Service | 1 | 1 |
| Lag 2 Point | 0 | 1 |
| Lag 3 Service | 1 | 1 |
| Lag 3 Point | 0 | 0 |

**Block 8**

| Case Number | 69 | 70 |
|-------------|----|----|
| P1 Service  | 1 | 1 |
| Lag 1 Service | 0 | 0 |
| Lag 1 Point | 1 | 1 |
| Lag 2 Service | 1 | 1 |
| Lag 2 Point | 0 | 1 |
| Lag 3 Service | 1 | 1 |
| Lag 3 Point | 0 | 0 |

Note: 1 represents ‘yes’, 0 represents ‘no’
Table S3: Summary of Scenarios on Point-Level (Returning)

| Case Number | 65 | 66 | 67 | 68 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 | 80 |
|-------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| P1 Service  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 1 Service | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  |
| Lag 1 Point | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 1  | 1  | 0  | 0  |
| Lag 2 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  |
| Lag 2 Point | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  |
| Lag 3 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 3 Point | 0  | 0  | 1  | 1  | 1  | 0  | 1  | 1  | 0  | 0  | 1  | 1  | 0  | 1  | 0  | 1  |

| Block 9 | Block 10 |
|---------|---------|
| Case Number | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 |
| P1 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 1 Service | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  |
| Lag 1 Point | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  |
| Lag 2 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  |
| Lag 2 Point | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  |
| Lag 3 Service | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  |
| Lag 3 Point | 0  | 0  | 1  | 1  | 1  | 0  | 1  | 1  | 0  | 0  | 1  | 1  | 0  | 1  | 0  | 1  |

| Block 11 | Block 12 |
|----------|----------|
| Case Number | 97 | 98 | 99 | 100 | 101 | 102 | 103 | 104 | 105 | 106 | 107 | 108 | 109 | 110 | 111 | 112 |
| P1 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 1 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 1 Point | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 0  |
| Lag 2 Service | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 2 Point | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  |
| Lag 3 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  |
| Lag 3 Point | 0  | 0  | 1  | 1  | 1  | 0  | 1  | 1  | 0  | 0  | 1  | 1  | 0  | 1  | 1  | 1  |

| Block 13 | Block 14 |
|----------|----------|
| Case Number | 113 | 114 | 115 | 116 | 117 | 118 | 119 | 120 | 121 | 122 | 123 | 124 | 125 | 126 | 127 | 128 |
| P1 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 1 Service | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 1 Point | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  |
| Lag 2 Service | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 2 Point | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 1  | 0  | 1  | 1  | 1  | 0  | 0  |
| Lag 3 Service | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| Lag 3 Point | 0  | 0  | 1  | 1  | 1  | 0  | 1  | 1  | 0  | 0  | 1  | 1  | 0  | 1  | 1  | 0  |

| Block 15 | Block 16 |
|----------|----------|

Note: 1 represents ‘yes’, 0 represents ‘no’
Table S4: Coefficient Labels for variables of Point-Level model

| Variable                              | Coefficient |
|---------------------------------------|-------------|
| Intercept                             | $\beta_0$   |
| Rank Diff                             | $\beta_1$   |
| PS Diff                               | $\beta_2$   |
| PR Diff                               | $\beta_3$   |
| Service                               | $\beta_4$   |
| Lag 1 Service                         | $\beta_5$   |
| Lag 1 Point                           | $\beta_6$   |
| Lag 2 Service                         | $\beta_7$   |
| Lag 2 Point                           | $\beta_8$   |
| Lag 3 Service                         | $\beta_9$   |
| Lag 3 Point                           | $\beta_{10}$|
| Lag 1 Point x Lag 1 Service           | $\beta_{11}$|
| Lag 2 Point x Lag 2 Service           | $\beta_{12}$|
| Lag 3 Point x Lag 3 Service           | $\beta_{13}$|
| Lag 1 Point x Lag 2 Point             | $\beta_{14}$|
| Lag 1 Point x Lag 3 Point             | $\beta_{15}$|
| Lag 2 Point x Lag 3 Point             | $\beta_{16}$|
| Lag 1 Point x Lag 2 Point x Lag 3 Point| $\beta_{17}$|
| Case 1     | $A_r$          | Case 2     | $A_r$          |
|-----------|----------------|-----------|----------------|
| 1         | [0, 5]         | 12        | [0, 7]         |
| 2         | [0, 4, 5]      | 7         | [0, 7]         |
| 3         | [0, 4, 7]      | 9         | [0, 9]         |
| 4         | [0, 4, 9]      | 6         | [0, 7]         |
| 5         | [0, 4, 7, 9]   | 5         | [0, 5]         |
| 6         | [0, 4, 5, 9]   | 3         | [0, 5, 7, 9]   |
| 7         | [0, 4, 5, 7]   | 8         | [0, 6, 7]      |
| 8         | [0, 4, 5, 7, 9]| 9         | [0, 5, 6, 7, 9, 11] |
| 9         | [0, 4, 6, 7]   | 7         | [0, 5, 6, 7, 9, 11] |
| 10        | [0, 4, 5, 6, 11]| 6         | [0, 6, 7, 9]   |
| 11        | [0, 4, 6, 7]   | 5         | [0, 6, 7, 9]   |
| 12        | [0, 4, 5, 6, 7]| 4         | [0, 6, 7, 9]   |
| 13        | [0, 4, 5, 6, 7, 9]| 3         | [0, 6, 7, 9]   |
| 14        | [0, 4, 6, 9]   | 2         | [0, 6, 7, 9]   |
| 15        | [0, 4, 6, 7, 9, 11]| 1         | [0, 6, 7, 9]   |
| 16        | [0, 4, 6, 6, 9]| 2         | [0, 6, 7, 9]   |
| 17        | [0, 4, 6, 9]   | 1         | [0, 6, 7, 9]   |
| 18        | [0, 4, 5, 8]   | 2         | [0, 6, 7, 9]   |
| 19        | [0, 4, 5, 6, 9, 11]| 1         | [0, 6, 7, 9]   |
| 20        | [0, 4, 6, 9]   | 2         | [0, 6, 7, 9]   |
| 21        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 22        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 23        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 24        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 25        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 26        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 27        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 28        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 29        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 30        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 31        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 32        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 33        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 34        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 35        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 36        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 37        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 38        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 39        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 40        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 41        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 42        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 43        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 44        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 45        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 46        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 47        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 48        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 49        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 50        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 51        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 52        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 53        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 54        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 55        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 56        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 57        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 58        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 59        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 60        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 61        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 62        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 63        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 64        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |
| 65        | [0, 4, 5, 6, 7, 9]| 1         | [0, 6, 7, 9]   |

Table S5: Sets of coefficient labels corresponding to each scenario