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

by

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An honors thesis submitted in partial fulfillment of the requirements for the degree of Bachelor of Science

Undergraduate College
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New York University
May 2020

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Acknowledgements

The research done throughout the thesis program would not have been possible without the help, commitment and patience that my thesis advisor, Professor Simonoff, provided. I learnt far more than I could have ever imagined from this endeavor, not just on the research topic, but also about the procedure of research. Many hours were spent peering over models, exploring odd trends in tennis and reading through lengthy drafts; all this effort from Professor Simonoff was invaluable to producing this final paper.

I’d also like to thank Professor Subrahmanyam, the faculty advisor and program coordinator, for providing this excitement opportunity to undergraduate students, organizing the weekly seminars and providing the support throughout the research process.

Lastly, thank you to my friends and family for providing me with unending encouragement throughout the year. I could not have produced this work without your support.
Abstract

The hot hand has been a widely studied phenomenon in the field of sports statistics, specifically in basketball. However, tennis is no stranger to this concept of ‘momentum’. Gilovich, Vallone & Tversky debunked the hot hand in basketball with their paper in 1985, but the belief that a player can ‘get on a roll’ is still widely shared in the tennis community. As a fan, it is difficult to know whether this phenomenon is real or a fallacy. This paper aims to investigate the presence and manifestation of momentum in Grand Slam tennis matches from 2014 to 2019 for men and women.

Specifically, it aims to investigate if there is any carryover effect from the outcome of previous point(s)/game(s)/set(s) to the current one, which cannot be accounted for by metrics measuring player quality, form and fatigue. The primary model, a Generalized Linear Mixed Effect Model, was constructed to fit the data; it helps incorporate the nested structure of a tennis match into a Logistic Regression Model. The primary model’s output would show the effect of factors on the odds of winning a point, game, or set.

On a set level, there is definitely indication there exists positive momentum from winning the previous set, more so for women than for men. Surprisingly, the clay court seems to have the highest degree of momentum, followed by grass and then hard courts.

On a game level, holding one’s serve seems to be paramount for the current serving player, and not doing so in prior games reduces the predicted odds of the winning the current game significantly. Surprisingly, losing a past game can spur positive momentum and is associated with higher predicted odds of winning the next game, which could be explained by players playing harder to get back in the match after losing past games. The momentum effects exhibited are more volatile for men than for women.

On a point level, lagged point outcomes are definitely significant and have a carryover effect on the current point. Winning two or three points in a row is associated with the highest predicted odds of winning the next point, and correspondingly losing two or three points in a row is associated with the lowest predicted odds of winning the next point. It also seems that the momentum effect from winning previous points has a low memory, and Lag 1 point outcomes tend to affect predicted odds more than Lag 2 or Lag 3 point outcomes. Just as in the game level, these momentum effects are more volatile for men than for women.
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Background Information

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 as well stop playing for the rest of the game. According to Craig O’Shannessy, a writer for the Association of Tennis Professionals Tour (ATP Tour), Federer has won 95.8% of these games in all professional tournaments from 2015-2019 (O’Shannessy 2019). Looking at Federer’s caliber, 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 Tennisserver.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?

Rules of Tennis

To the uninitiated, tennis can be a complicated sport to understand. The sport’s basic structural layout has four levels nested within each other:

- **Match:** A match has multiple sets (either 3 or 5 depending on the gender or level of match). To win the match, players must win a majority of the total number of sets. For example, in a 5-set match, a player must win 3 out of 5 sets to win the contest. If the player wins 3 sets before 5 sets are played, the match ends and this player wins.

- **Set:** Each set has multiple games. Players have to win a minimum of 6 games with at least a 2-game advantage. For example, if the player wins 6 games, the other player cannot win more than 4 games if the player wants to win the set. If one player wins 5 games, then the opponent can win the set by winning 7 games. However, if both players win 6 games each, then the set is taken to a tie-breaker.
• **Tiebreaker:** A tie-breaker consists of the two players playing to win points. Winning a rally gives the player a singular point. For a player to win the tie-break (and therefore, the set), they have to win a minimum of 7 points with a 2-point advantage. Until this requirement is achieved, the tie-breaker continues. For example, a player can win a tie-breaker 7-5, but can also win it 10-8.

• **Game and Points:** Each game consists of points, which are collected by winning rallies. Each rally is worth 1 point but points are counted in the following manner: 15, 30, 40. If a player has reached point-40 and they win the point, they win the game. However, if both players are at point-40, the situation is called a deuce. In this case, a player has to win 2 consecutive points to win the game. The first of these points is called the ‘advantage point’, and the second one wins the game (and can be called ‘game point’).

• **Break Point:** If a player who is serving in the game loses the game, the opponent is said to have ‘broken serve’, winning the game on a ‘break point’.

To begin a rally, one player has to serve the ball. Players serve by tossing the ball in the air and hitting into a box on the court called the ‘service box’, such that it bounces towards the general direction of the opponent. One player serves for the whole game, and then the service alternates between the two players.

The two players stand diametrically opposite each other on both sides of the net. The point is won by a player when the opponent cannot hit the ball after the first bounce or if they hit it outside the lines of the opponent’s area of the court.

Players in the ATP Tour (men’s) and WTA (Women’s Tennis Association) Tour (women’s) are ranked based on their performance at tournaments, for which they are given points. More prestigious and challenging tournaments give players the opportunity to gain more points than other contests. Better quality players are usually high-ranking players.

The Grand Slams are the most prestigious tournaments in tennis. The four Grand Slams are the Australian Open, French Open, Wimbledon and US Open. The primary difference between these competitions 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.
Defining Momentum in Tennis

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).

This could be viewed as the player ‘having a good day’ or being ‘top of their game’, since it is a correlation between the outcome of point(s)/game(s)/set(s) and their previous outcomes above what could be expected from their inherent playing skill, athletic ability etc.

Analysis of momentum (which may or may not exist) can be done on and across multiple levels.

- Does winning the previous point/game/set have any influence on the outcome of the next point/game/set? For example, is there a higher tendency for the score to become 30-0 if it is currently 15-0, than for the score to become 15-0 if the score is currently 0-0?
- Do the outcomes of several previous points/games influence the outcome of the next point/game?
- Does momentum manifest itself in different ways in different rounds? For example, later round matches may exhibit more signs of momentum when fatigue becomes a factor.
- Is there any difference in momentum tendencies between men’s and women’s matches?
- Is there any difference in momentum tendencies between different court surfaces? For example, do players tend to win more points in a streak on hard court than on grass or clay?

The quality of players could have a huge effect on the appearance of momentum, and we would have to account for quality differences in the analysis. Better players may simply win more points in a row not because of momentum but simply because they are just far better than their opponents.

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. However, there is also a case to be made that points are independent of each other, and the disparity in player quality leads to streaks of won or lost points.
Research Application

Data analytics and statistics in sports has grown exponentially in recent years. Various tennis-specific metrics to predict wins have been created, and player-by-player optimization and strategies have inundated the sports betting market. Analyzing a factor like momentum can provide valuable insight into all of these spheres — it can help to fine-tune win predictors, help players reassess their strategies in the middle of the game, and add to betting models for sports gamblers and betting agencies.

Data Universe Constraints

The analysis explores only singles matches in Grand Slam tournaments (Australian Open, French Open, Wimbledon and U.S. Open) for both men and women. 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. Looking at both men and women is also important, because analyzing them separately may reveal contrasting trends.

Even though data analysis in tennis has been implemented for quite a few years, point-by-point data is not readily available before 2014, so the analysis will be using Grand Slam matches from 2014 until 2019 only. However, the large number of matches in this range provides a large enough sample set to conduct a meaningful analysis.

A tennis eccentricity needs to be addressed: the deciding set tie-breaker rule. The deciding set in a match (5th set for men and 3rd set for women) has slightly modified rules when compared to other sets for certain Grand Slams. The Australian Open and Wimbledon have historically prohibited the use of a tie-breaker in the deciding set should the set score exceed 6-6; they contend that the players should keep playing until one player takes the lead and wins the set by 2 games. The French Open and US Open have not implemented this rule. However, as a result of prohibiting a fifth set tiebreaker, some matches in the Australian Open and Wimbledon became far too long, disrupting the rest of the tournament schedule (John Isner and Nicholas Mahut played for more than 11 hours at the 2010 Wimbledon). In 2019, both tournaments decided to scrap this rule and implement a ‘super tie-break’ in the deciding set, where a player would win only when they had a minimum of 10 points and a lead of 2 points. Such a change in rules makes it difficult to compare matches before 2019 with non-tie-breaker deciding sets to super tie-breaker matches. Consequently, matches where the deciding set went past a set score of 6-6 were not included in the data universe.
Literature Review

Research in sports (in particular tennis) strategies and data analytics is not a new field of study, and some work has been done in the space of the effects of momentum. One of the early studies into the effect of momentum in sports was Gilovich, Vallone & Tversky (1985), which examined whether the ‘hot-hand’ was a real phenomenon or a fallacy; using Wald-Wolfowitz Runs tests and stationarity tests on Philadelphia 76ers data and a controlled shooting experiment, they found little evidence of the existence of the hot-hand.

In the sport of tennis, Jackson & Mosurski (1997) explored heavy defeats in tennis matches (where the final set score was 2-0 or 3-0) using a generalized linear model on 1987-88 US Open match set scores; they found statistical evidence of some degree of psychological momentum to determine the outcome of the match, but the assumption of independent sets also fit the model equally well. O'Donoghue (2000) also 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. Similarly, Meier, Flepp, Rudisser & Franck (2019) used a linear probability model on US Open and Wimbledon data from 2009 to 2014 to find that personal and contextual factors are more relevant to determine the outcome of points than is psychological momentum. Moss & O'Donoghue (2017) used paired parametric tests to explicitly examine whether outcome of prior points and games affect the outcome of the next one; they found no such effect in the US Open data they used except if the point was a break-point.

Magnus & Klaassen (2001) used a linear probability model with quality variables and dynamic regressors (to measure psychological effects) to determine whether points are identically distributed; they found a small deviation from independence. Pollard, Cross & Meyer (2006) used chi-squared measures on Grand slam matches from 1995 to 2004 to find that sets are not independent and the better players (based on rankings) enjoyed positive momentum if they were leading (because of confidence) or falling back (‘back to the wall’ momentum). Dietl & Nesseler (2017) examined the effect of winning the second-to-last set on the outcome of the last (and deciding) set using logit models; they found that winning the second-to-last set provides positive momentum (a greater chance of winning the final set) but if this set goes to a tie-breaker, there is negative momentum (a smaller chance of winning the final set).

There is also a large number of match outcome prediction models that have been explored. Newton & Aslam (2009), Knottenbelt, Spanias & Madurska (2012), Bevc (2015), Madurska (2012) and Gollub (2017) all used some form of Markov chains to generate probability measures of the outcome of a tennis match. O'Malley (2008), Newton & Keller (2005) and Knight & O'Donoghue (2011) used conditional probability measures. Ingram (2019) developed a Bayesian hierarchical model for tennis match prediction.
Analysis of momentum in other sports also has applicability to our exploration. Burns (2002) explored the effect of adapting the hot hand mindset in a basketball game, and found that scoring actually increased if the hot hand was adapted and the streaky player was given more shots. Sela & Simonoff (2007) explored the presence of momentum in a baseball game using Markov Chains on play-by-play data, and found weak evidence of such momentum. Savage (2012) explored golf to see whether performances on a week-to-week basis in the PGA tour had evidence of psychological momentum; unlike the others, his study found a non-random pattern to performances, and early successes led to more positive outcomes in later weeks.

Connection to Prior Research

The analysis here is similar to the work done in these past papers, and provides findings based on updated and more recent data. However, the analysis does not aim to create a predictive model like a lot of prior research; it seeks to analyze whether the data illustrates any signs of momentum across various levels of the sport and if so the effects such momentum has on the course of the match. There are a few key differences between prior research and this analysis:

- There is an incorporation of control factors like fatigue, which have not been used in past studies. These can have a huge effect on exhaustion being construed as momentum. Prior studies, with few exceptions, have only used player rankings as a control factor to level the ability of players and considered player abilities as static throughout the match.
- Most of the studies have only examined the effect of the previous point/game/set on the current point and gone no further. This study attempts to incorporate more than one lag to detect any sign of momentum.
- Unlike much previous tennis research, this paper attempts to discover if court surfaces influence momentum and if so, why.

Variables

Based on the past research in the space, it is possible to compile a list of variables that can be used to examine momentum on the point-, game- and set-level. Along with these predictive variables, we would also need to incorporate control variables in the model so that we can minimize the effect of other factors creating what appears to be momentum. The measures of these variables will be 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’.
A summary list of the variables is given in Table 1 below.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Level</th>
<th>Source</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Response Variables (with respect to reference player)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Point Winner</td>
<td>Point</td>
<td>-</td>
<td>Binary Variable, where 1 = won and 0 = lost</td>
</tr>
<tr>
<td>Game Winner</td>
<td>Game</td>
<td>-</td>
<td>Binary Variable, where 1 = won and 0 = lost</td>
</tr>
<tr>
<td>Set Winner</td>
<td>Set</td>
<td>-</td>
<td>Binary Variable, where 1 = won and 0 = lost</td>
</tr>
<tr>
<td><strong>Possible Momentum Variables (with respect to reference player)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Point/s Winner/s</td>
<td>Point</td>
<td>Adapted from Gilovich, Vallone &amp; Tversky (1985)</td>
<td>Direct predictor of momentum. Each lag will have binary separate variable, where 1 = previous point/s won and 0 = previous point/s lost</td>
</tr>
<tr>
<td>Lagged Game/s Winner/s</td>
<td>Game</td>
<td>Adapted from Gilovich, Vallone &amp; Tversky (1985)</td>
<td>Direct predictor of momentum. Each lag will have binary separate variable, where 1 = previous game/s won and 0 = previous game/s lost</td>
</tr>
<tr>
<td>Lagged Set Winner</td>
<td>Set</td>
<td>Adapted from Gilovich, Vallone &amp; Tversky (1985)</td>
<td>Direct predictor of momentum. Each lag will have binary separate variable, where 1 = previous set/s won and 0 = previous set/s lost</td>
</tr>
<tr>
<td>Previous Service Game Broken</td>
<td>Game</td>
<td>-</td>
<td>Broken serve puts player one game behind the opponent's tally, which can create further pressure in the next game to hold serve.</td>
</tr>
<tr>
<td>Previous Games Won Spread</td>
<td>Point</td>
<td>Adapted from Dietl &amp; Nesseler (2017)</td>
<td>Measure of intra-set dominance, which is equal to number of games won by player minus number of games won by opponent.</td>
</tr>
<tr>
<td><strong>Control Variables (for each player)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Serving Points Won (%) (from now called PS pct.)</td>
<td>Point, Game &amp; Set</td>
<td>Madurska (2012)</td>
<td>Baseline Scoring Ability on Serve. This value represents the service points won for the player during the course of that year.</td>
</tr>
<tr>
<td>Receiving Points Won (%) (from now called PR pct.)</td>
<td>Point, Game &amp; Set</td>
<td>Madurska (2012)</td>
<td>Baseline Scoring Ability Returning. This value represents the service points won for the player during the course of that year.</td>
</tr>
<tr>
<td>Player Gender</td>
<td>Point, Game &amp; Set</td>
<td>-</td>
<td>Capture difference in momentum effects across gender.</td>
</tr>
<tr>
<td>Player Ranking</td>
<td>Point, Game &amp; Set</td>
<td>Jackson &amp; Mosurski (1997)</td>
<td>Measure of player ability based on ranking by ATP/WTA at that point in time.</td>
</tr>
<tr>
<td>Player Age</td>
<td>Point, Game &amp; Set</td>
<td>-</td>
<td>Athletic and cardiovascular ability can reduce with age</td>
</tr>
<tr>
<td>Number of Sets Played</td>
<td>Point, Game &amp; Set</td>
<td>-</td>
<td>Fatigue factor &amp; time context.</td>
</tr>
<tr>
<td>Number of Games Played</td>
<td>Point, Game &amp; Set</td>
<td>-</td>
<td>Fatigue factor &amp; time context.</td>
</tr>
<tr>
<td>Court Surface</td>
<td>Point, Game &amp; Set</td>
<td>Dietl &amp; Nesseler (2017)</td>
<td>Control speed and bounce of play</td>
</tr>
</tbody>
</table>
A key point has to be made with regards to some of the control variables. Player statistics like serving/returning points won % and ranking change with every tournament played. Player age changes with every year. Since our analysis looks across 6 years of tournaments, these variables have to be dynamic for each player. For example, Nadal has a Serving Points Won pct. of 66.47% at the start of the 2015, but it increased to 67.50% by 2018. To maintain accuracy, our raw data needs to consider such changes in player statistics. However, finding player statistics after each tournament becomes exceedingly difficult given the breadth of players that need to be accounted for. Hence, these player statistics refer to the player’s performance for that year. For example, Nadal will have a 65% serving points won % for all tournaments in 2014. This is definitely not the most accurate method to do this, especially since player performance differs over the course of a year, across different surfaces and different conditions etc. However, the assumption is that over the course of a whole year, there is enough information in the statistic to give an accurate impression of the player’s ability and performance relative to that of other players.

Fundamentally, progression of matches is very different across different tournaments and gender. Not only are there 3 different surfaces that they are played, but they are also subject to different weather conditions. Hence, it is appropriate to analyze these separately, yielding 8 different analyses (4 for men, and 4 for women).

**Data Collection**

Detailed match data that can be used for the purpose of this analysis is difficult to find widely on the internet due to the relative recency in use of advanced software to record tennis matches. Scoreboard.com provides this data on its website, but this is not downloadable. To retrieve such data for the matches we will be examining, data scraping code in Python was written. The primary packages used were BeautifulSoup a Selenium, both of which create links to the website and download the html text. From here, a series of algorithms and calculations were conducted to create the variables that will be used to build the models required. The data, the Python code and the R code will all be at available at github.com/arjungoyal98/grand-slam-data.

Player information, such as age, rankings, serving/returning points won % were retrieved from Jeff Sackmann’s helpful 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. We will discuss these missing data points further when we explore the data analysis.
Set-Level Analysis

Raw Data Analysis

Before exploring any models, we can examine the raw data to see the relationships between the variables we have. Since our main response variable will be the set outcome for a player, we can look at this binary variable using side-by-side box plots against the various predictors.

Figure 1: Player 1 Set Outcome versus Player Ranks

With respect to the rank of player 1, a set win for player 1 has a lower median rank than a set loss. This trend is intuitive, since a lower numerical rank is usually associated with a higher quality player, and it is more likely that these players would win a set.

On the flipside, with respect to the rank of player 2, a set win for player 1 has a higher median rank than a set loss. Again, this trend is intuitive, since a higher numerical rank generally indicates a lower quality player, making it more likely that player 1 would win a set against such a player.

It is also interesting to note that the plots are quite similar across all the tournaments, even though court surface plays a huge role in how a match plays out.
Looking at player age, the boxplots do not indicate any meaningful trend between age and set outcome.
If player 1 had a higher service or returning points won %, they won more sets, which is expected considering that those with higher service points won % are usually better players. Conversely, if player 2 had a higher service or returning points won %, player 1 would win fewer sets since their opponent is of high quality. It’s interesting that the difference in service points won % is quite even across the tournaments, especially considering how important the serve to a surface like grass.

Since tennis is a zero-sum game, the boxplots for the set outcome for player 2 would simply be the reverse of these. This is true for the Game-Level and Point-Level raw data as well.

Now that we have explored these relationships, models can be constructed to fit the dataset.
Model Selection

The simplest way to examine momentum on a set level would be a generalized linear model with a logit function \( \ell(X) \) (GLM), which has the form:

\[
\ell(X) \equiv \log \left[ \frac{\pi(X)}{1 - \pi(X)} \right] = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p = X_i \beta
\]

In this model the probability of winning a set is related to a linear function of the predictors (the so-called linear predictor) through the logit link function, and the observed outcome (0 or 1, corresponding to losing or winning the set) follows a Bernoulli distribution (the random component). The interpretation of the \( \beta \)'s are:

- \( \beta_0 \) is the log odds of winning a set if all predictors are set to 0
- \( \beta_j \) represents the change in log odds of winning a set associated with a change of 1 in predictor \( x_j \), all other variables constant. More intuitively, \( e^{\beta_j} \) is the multiplicative change to the odds of winning a set (the odds ratio).

A GLM provides the relative effect of predictors like player rank, ability, and outcome of the previous set, but it fails to consider a key structure in the data that can affect the results.

Since each observation (e.g., each set) is nested within a match, some matches have been played under different conditions to others. For example, a match on Day 1 of the Australian Open can be very different from one played on Day 4, simply because there might have been a change in the weather, either or both players may have been fatigued or de-motivated, or the court speed has changed. However, it is almost impossible to collect all these factors to use as predictors in the model. Concurrently, they should not be discounted as having minimal effect. For this reason, the Generalized Linear Mixed Effects model (GLMM) is used, in which the probability of winning a set incorporates an effect corresponding to differences between matches.
Mixed Effects models consider two types of effects: fixed effects and random effects. The model generalizes the logistic regression model above by incorporating a random term representing the differences between matches into the linear predictor:

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

where:

- \( \eta_i \) is the linear predictor value for unit \( i \)
- \( X_i \) are the fixed effect predictors
- \( \beta \) is the fixed effect coefficients
- \( Z_i \) are the random effects predictors
- \( u_i \) are the random effect coefficients, assumed to be normally distributed

Fixed effects would include continuous and categorical predictors such as rank, player statistics, outcome of previous set etc. Random effects account for the fact that the observations have been clustered and nested within different matches, each of which are subject to different (and random) conditions. The mixed effects model used in this analysis uses a match ID dummy variable as the random effect, where each match as a unique ID code. Consequently, GLMM yields random intercepts on a match level along with the fixed effects. Similar forms are used at the game level and at the point level.

**Model Parameters**

The initial model that was fitted, Model 0, is a linear logistic model with player ranks as its predictors. Prior research has indicated that player rankings contain a fair amount of information of player ability; using ranks as predictors in a logistic model would help to verify this claim.

Model 0 does not take the nested structure of the data into account, so as was discussed earlier a Generalized Linear Mixed effects model is appropriate. Model 1 uses players ranks as fixed effects in a GLMM model with random intercepts on a match level, using Match IDs as the random effect variable.
Model 2 builds on this and adds player age, points on serve and returning won percentage for both players, and the round of the match as fixed effects to the GLMM model, while continuing to use random intercepts on a match level using Match IDs. The purpose of this model is to account further for hypothesized control (non-momentum-related) effects. In all versions of the model the Round variable and the player age variables do not capture additional variability in the data (apparently dismissing the potential fatigue effects), and henceforth they omitted from more complex models.

Ideally, Model 3 would add the lag value of the Set Outcome for Player 1, i.e., the outcome of the previous set for Player 1. However, the complexity of the model (particularly the match level random effect) makes it difficult to fit the model (for example, in any two-set women’s match the outcome of the first set perfectly predicts the outcome of the second set, and this is confounded with the match-level random effect). While a GLM is not as appropriate as a GLMM, it can shed light on the effect of the lag variable, which is essentially a sign of some form of momentum. So, Model 3 is run as a GLM with player ranks, lag Set Outcome P1 and points on serve and returning won pct. for both players.

What should be noted here is that introducing a lag variable creates a loss of data. Since there is no lag set outcome variable for the first set of a match, all first sets would be removed from the data frame used in the model. This removes the ability to compare the results of Model 3 to that of the previous models since previous models use the information provided by the first set. However, if the 3 models are fit on a dataset without any missing values and compared, the AIC values yields that Model 3 better fits the data than the others across tournaments and gender, so that is what is done. The AIC values comparing the models is in the Appendix.

Since for some tournaments (namely, the men’s Australian Open, Wimbledon and US Open) the GLMM version of model 3 was estimable, this is Model 4 for these tournaments, where the predictors in Model 3 become the fixed effects of Model 4, with the random intercepts on a match level. Where estimable, Model 4 seems to be preferable to Model 3 since its GLMM structure accounts for the nested nature of a tennis match, and the Pearson Chi-square test comparing these models favors Model 4 to fit the data better.
A summary of each model’s parameters is given below.

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<tr>
<th>Model Type</th>
<th>Model 0</th>
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<td>✔️</td>
<td>✔️*</td>
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<td>✔️</td>
<td>✔️</td>
<td>✔️*</td>
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<td>✔️</td>
<td>✔️</td>
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* for select tournaments only

Model Output

Summary tables of the coefficients of each model are given below, indicating the model type, the coefficients for the predictor/fixed effect used, the z-value of the coefficient hypothesis test in parentheses, as well as the significance of the coefficients using asterisk notation. Each coefficient represents the change in log odds of Player 1 winning a set associated with an increase of 1 in the predictor, all other variables remaining constant.
### Table 3: Set-Level Model Coefficients

#### Australian Open Men

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<td>0.0299 (0.685)</td>
<td>0.045 (0.649)</td>
<td>0.1257 (1.757)</td>
<td>-0.1349 (-1.595)</td>
<td>-0.1182 (-1.169)</td>
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<tr>
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<td>-0.0095*** (-9.728)</td>
<td>-0.0006 (-0.347)</td>
<td>-0.0009 (-0.668)</td>
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<td><strong>P2 Rank</strong></td>
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<td>0.0137*** (10.983)</td>
<td>0.006*** (3.5)</td>
<td>0.0068*** (4.374)</td>
<td>0.0061*** (3.903)</td>
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<td>-0.012 (-0.76)</td>
<td>0.2183*** (7.459)</td>
<td>0.1492*** (6.641)</td>
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<td></td>
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<tr>
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<td>0.0016 (0.883)</td>
<td>0.0005 (0.311)</td>
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<tr>
<td><strong>P1 PR pct.</strong></td>
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</tr>
<tr>
<td><strong>P2 PR pct.</strong></td>
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<td>-0.1037*** (-4.269)</td>
<td>-0.111*** (-4.236)</td>
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<td><strong>Round</strong></td>
<td>0.0232 (0.339)</td>
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#### Australian Open Women

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<td>GLMM</td>
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<td>GLMM</td>
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<tr>
<td><strong>Intercept</strong></td>
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## French Open Men

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## French Open Women

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### WIMBLEDON MEN

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<td>-0.0051**</td>
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<td>0.0918***</td>
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<td>(3.919)</td>
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### WIMBLEDON WOMEN

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<td>0.2058*</td>
<td>0.2197*</td>
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<td>1.0551***</td>
<td>(6.652)</td>
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<td>(5.465)</td>
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<td>0.1918*</td>
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### US Open Men

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<tr>
<td>Intercept</td>
<td>0.0891* (2.059)</td>
<td>0.0926 (1.473)</td>
<td>0.178** (2.799)</td>
<td>-0.1275 (-1.592)</td>
<td>-0.0255 (-0.25)</td>
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<td>P1 Rank</td>
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<td>-0.0145*** (-11.28)</td>
<td>-0.005** (-3.092)</td>
<td>-0.0047** (-3.131)</td>
<td>-0.0049** (-2.953)</td>
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<td>0.0096*** (10.589)</td>
<td>0.0112*** (9.146)</td>
<td>0.0084* (2.498)</td>
<td>0.0042** (2.861)</td>
<td>0.0047** (2.881)</td>
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<td>0.5823*** (5.29)</td>
<td>0.4584*** (3.252)</td>
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<td>-0.0142 (-0.975)</td>
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<td>P2 Age</td>
<td>0.0229 (1.634)</td>
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<tr>
<td>P1 PS pct.</td>
<td>0.1745*** (6.78)</td>
<td>0.1262*** (5.943)</td>
<td>0.1536*** (5.926)</td>
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<tr>
<td>P2 PS pct.</td>
<td>-0.1663*** (-6.231)</td>
<td>-0.1051*** (-4.829)</td>
<td>-0.1252*** (-4.779)</td>
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<tr>
<td>P1 PR pct.</td>
<td>0.1845*** (7.208)</td>
<td>0.1432*** (6.669)</td>
<td>0.1743*** (6.533)</td>
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<tr>
<td>P2 PR pct.</td>
<td>-0.1403*** (-5.099)</td>
<td>-0.1009*** (-4.38)</td>
<td>-0.1205*** (-4.468)</td>
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<td>-0.0497 (-0.749)</td>
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### US Open Women

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<td>GLMM</td>
<td>GLM</td>
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<tr>
<td>Intercept</td>
<td>0.0444 (0.85)</td>
<td>0.0602 (0.833)</td>
<td>0.0807 (1.19)</td>
<td>-0.1368 (-1.272)</td>
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<td>P1 Rank</td>
<td>-0.0048*** (-6.36)</td>
<td>-0.006*** (-5.824)</td>
<td>-0.0005 (-0.47)</td>
<td>-0.0012 (-1.107)</td>
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<tr>
<td>P2 Rank</td>
<td>0.0062*** (6.347)</td>
<td>0.0068*** (5.769)</td>
<td>0.0007 (0.556)</td>
<td>0.0009 (0.645)</td>
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<td>Lag Set Outcome P1</td>
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<td></td>
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<td>0.3562* (2.355)</td>
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<td>0.0007 (0.043)</td>
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<tr>
<td>P2 Age</td>
<td>0.0021 (0.128)</td>
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<td>P1 PS pct.</td>
<td>0.2099*** (7.727)</td>
<td>0.1428*** (5.519)</td>
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<td>P2 PS pct.</td>
<td>-0.2017*** (-6.721)</td>
<td>-0.1711*** (-5.608)</td>
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<td>P1 PR pct.</td>
<td>0.1678*** (5.26)</td>
<td>0.1646*** (4.823)</td>
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<td>P2 PR pct.</td>
<td>-0.1642*** (-4.971)</td>
<td>-0.126*** (-3.611)</td>
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<td>-0.0925 (-1.427)</td>
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Significance codes: ‘***’: 0.001; ‘**’: 0.01; ‘*’: 0.05
The model coefficients can also be written as odds ratio coefficients, which are much more easily interpretable. 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 can be written using the following formula.

\[ e^\beta - 1, \text{ where } \beta \text{ is the unscaled coefficient of the predictor} \]

A summary table of the percentage changes in the odds for each model is given below.

*Table 4: Set-Level Model Effects on Odds*

**Australian Open Men**

<table>
<thead>
<tr>
<th></th>
<th>Model 0</th>
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<th>Model 2</th>
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<td><strong>P1 Rank</strong></td>
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<td>-0.95%</td>
<td>-0.08%</td>
<td>-0.09%</td>
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<tr>
<td><strong>P2 Rank</strong></td>
<td>1.00%</td>
<td>1.38%</td>
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<td>0.68%</td>
<td>0.61%</td>
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<td></td>
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<td>63.59%</td>
<td>56.58%</td>
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<td>16.60%</td>
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<td><strong>P2 PS pct.</strong></td>
<td>-16.60%</td>
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<td><strong>P1 PR pct.</strong></td>
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<td>21.33%</td>
<td>15.83%</td>
<td>16.51%</td>
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<td>-9.85%</td>
<td>-10.51%</td>
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<tr>
<td><strong>Round</strong></td>
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**Australian Open Women**

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<tr>
<td><strong>P1 Rank</strong></td>
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<td>-0.70%</td>
<td>-0.42%</td>
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<td>1.18%</td>
<td>0.16%</td>
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### French Open Men

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### French Open Women

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### Wimbledon Men

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<td>0.86%</td>
<td>1.11%</td>
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<td>14.53%</td>
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<td></td>
</tr>
<tr>
<td>P2 PR pct.</td>
<td></td>
<td></td>
<td>-16.02%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Round</td>
<td></td>
<td></td>
<td>-5.89%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Wimbledon Women
<table>
<thead>
<tr>
<th></th>
<th>Model 0</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
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<tr>
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<td>GLMM</td>
<td>GLMM</td>
<td>GLM</td>
<td>GLMM</td>
</tr>
<tr>
<td><strong>P1 Rank</strong></td>
<td>-0.56%</td>
<td>-0.94%</td>
<td>-0.11%</td>
<td>-0.18%</td>
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</tr>
<tr>
<td><strong>P2 Rank</strong></td>
<td>0.64%</td>
<td>1.16%</td>
<td>0.32%</td>
<td>0.14%</td>
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</tr>
<tr>
<td><strong>Lag Set P1</strong></td>
<td></td>
<td></td>
<td>187.21%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>P1 Age</strong></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>P2 Age</strong></td>
<td></td>
<td></td>
<td>-1.17%</td>
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<td></td>
</tr>
<tr>
<td><strong>P1 PS pct.</strong></td>
<td></td>
<td></td>
<td></td>
<td>26.11%</td>
<td>16.76%</td>
</tr>
<tr>
<td><strong>P2 PS pct.</strong></td>
<td></td>
<td></td>
<td></td>
<td>-20.79%</td>
<td>-9.88%</td>
</tr>
<tr>
<td><strong>P1 PR pct.</strong></td>
<td></td>
<td></td>
<td></td>
<td>18.15%</td>
<td>8.82%</td>
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<tr>
<td><strong>P2 PR pct.</strong></td>
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<td></td>
<td></td>
<td>-22.39%</td>
<td>-12.91%</td>
</tr>
<tr>
<td><strong>Round</strong></td>
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<td></td>
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<td>21.14%</td>
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**US OPEN MEN**

<table>
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<tr>
<th></th>
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<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Type</strong></td>
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<td>GLMM</td>
<td>GLMM</td>
<td>GLM</td>
<td>GLMM</td>
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<tr>
<td><strong>P1 Rank</strong></td>
<td>-1.03%</td>
<td>-1.44%</td>
<td>-0.30%</td>
<td>-0.47%</td>
<td>-0.49%</td>
</tr>
<tr>
<td><strong>P2 Rank</strong></td>
<td>0.97%</td>
<td>1.13%</td>
<td>0.40%</td>
<td>0.42%</td>
<td>0.48%</td>
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<tr>
<td><strong>Lag Set P1</strong></td>
<td></td>
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<td>79.01%</td>
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<tr>
<td><strong>P1 Age</strong></td>
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<tr>
<td><strong>P1 PS pct.</strong></td>
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<td>19.07%</td>
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<tr>
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<td>-9.98%</td>
</tr>
<tr>
<td><strong>P1 PR pct.</strong></td>
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<td>20.26%</td>
<td></td>
<td>15.39%</td>
</tr>
<tr>
<td><strong>P2 PR pct.</strong></td>
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<td>-13.09%</td>
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<td>-9.60%</td>
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<tr>
<td><strong>Round</strong></td>
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<td>-4.85%</td>
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**US OPEN WOMEN**

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<tr>
<th></th>
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<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
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</thead>
<tbody>
<tr>
<td><strong>Type</strong></td>
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<td>GLMM</td>
<td>GLMM</td>
<td>GLM</td>
<td>GLMM</td>
</tr>
<tr>
<td><strong>P1 Rank</strong></td>
<td>-0.48%</td>
<td>-0.60%</td>
<td>-0.05%</td>
<td>-0.12%</td>
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</tr>
<tr>
<td><strong>P2 Rank</strong></td>
<td>0.62%</td>
<td>0.69%</td>
<td>0.07%</td>
<td>0.09%</td>
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</tr>
<tr>
<td><strong>Lag Set P1</strong></td>
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<td></td>
<td>42.79%</td>
<td></td>
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</tr>
<tr>
<td><strong>P1 Age</strong></td>
<td></td>
<td></td>
<td>0.07%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>P2 Age</strong></td>
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<td></td>
<td>0.21%</td>
<td></td>
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</tr>
<tr>
<td><strong>P1 PS pct.</strong></td>
<td></td>
<td></td>
<td>23.35%</td>
<td></td>
<td>15.35%</td>
</tr>
<tr>
<td><strong>P2 PS pct.</strong></td>
<td></td>
<td></td>
<td>-18.27%</td>
<td></td>
<td>-15.73%</td>
</tr>
<tr>
<td><strong>P1 PR pct.</strong></td>
<td></td>
<td></td>
<td>18.27%</td>
<td></td>
<td>17.89%</td>
</tr>
<tr>
<td><strong>P2 PR pct.</strong></td>
<td></td>
<td></td>
<td>-15.14%</td>
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<td>-11.84%</td>
</tr>
<tr>
<td><strong>Round</strong></td>
<td></td>
<td></td>
<td>-8.83%</td>
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<td></td>
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</table>
Overall, these odds ratio slope values from Model 4 (or Model 3 if Model 4 is unavailable) give the following insights.

- **Player Rank and Player Statistics (Points on Serve/Returning Won pct.) coefficients appear to be intuitive in their signs:**
  - P1 Rank, P2 PS pct., P2 PR pct. have negative coefficients and P2 Rank, P1 PS pct., P1 PR pct. have positive coefficients. The rationale behind this is the same as that discussed in the raw data analysis of the box plots. A numerically higher ranked player with lower points won percentage is associated with relatively lower skill. He/she would intuitively be less likely to win a set, all else kept constant.
  - The converse holds the same logic, where a numerically lower ranked player with higher points won percentage is more likely to win a set. Therefore, an increase in rank of player 1 is associated with a decrease in likelihood of player 1 winning a set (negative coefficient), and an increase in rank of player 2 is associated with an increase in likelihood of player 1 winning a set. Similarly, an increase in Player Statistics of player 1 is associated with an increase in likelihood of player 1 winning a set (positive coefficient) and an increase in Player Statistics of player 2 is associated with a decrease in likelihood of player 1 winning a set (negative coefficient).

- **Ranks affect Winning Odds more heavily for men than women**
  - The odds of winning a set change far more drastically for men than for women when a change in player rankings have been made. For example, using Model 3 in the US Open, if ranking of player 1 decreases by 10, then the estimated odds of winning the set increases by 4.7% for men compared to only 1.2% for women. This trend suggests that (perhaps other than a few top players) the women’s field is much more uniform than that of the men.

- **Player Statistics like PS pct. and PR pct. capture variability in data better than do ranks:**
  - Every model with player statistics as predictors, across tournaments and gender, have these variables as significant with high z-values and p-value less than 0.01, which is not always the case for ranks. Further, in every case the magnitudes of the player rank coefficients drops when player statistics are included in the model, reflecting that these more objective measures of player quality account for much of the predictive power on performance originally seen from ranks. The ATP and WTA have complicated point systems to determine the rank of players, which account for not only performance in tournaments but also win trajectories. Thus, players that may be of high
quality could have numerically higher ranks simply because of an occurrence like injury or personal issues. Player statistics are far more straightforward, and are cleaner metrics to judge player ability.

- **Insignificance of Player Age shows that experience is secondary to ability:**
  - Just as the boxplot analysis showed, there doesn’t seem to be much association between Player Age and Set Outcome. Since the information about player ability and athleticism has been captured by the rank and player statistics variables, player age would simply show the experience of the player given those other attributes. Due to the predictor’s insignificance, player experience seems to be secondary to their ability.

- **Round variable is not particularly significant:**
  - The Round variable was used primarily to account for fatigue and injury. However, Grand Slams tournaments are scheduled in such a way that players usually get more than adequate rest between rounds should they progress. Moreover, the random effect on the match level would have already incorporated this fatigue or injury factor, at least at a match level, perhaps rendering the Round variable weak as a predictor as a result.

- **Lag of the Set Outcome variable is highly significant:**
  - Perhaps the most relevant portion of the models to the analysis of momentum is the Lag of Set Outcome for Player 1. The Lag Set Outcome is positive and significant for Model 3 across all tournaments and gender. While this model is a GLM and not a GLMM, it shows that there is definitely some carryover effect from the outcome of the previous set onto the next one, namely a positive one if the previous set is won (again, recall that this effect is after accounting for the relative quality of the players through ranks and player statistics). Furthermore, for the GLMM models that were fitted (albeit only for 3 tournaments for the men) the lag variable continued to be positive and highly significant, bolstering the notion of this carryover effect.
  - The increase in odds of winning a set provided a player won the previous set (given the other variables) is huge. For example, according to Model 3, the increase in odds to winning a set is anywhere from 63% to 108% for men. This positive effect on the odds ratio could be seen as the ‘momentum’ effect. This contradicts the findings of Jackson & Mosurski (1997), where the notion of independent sets fit the model equally well. However, the model used here uses player statistics as control variables rather just ranks, and the analysis looks at all matches as opposed to simply those with ‘heavy defeats’.
Different surfaces present different effects of 'momentum':

- Clay seems to provide the biggest effect of momentum, which is surprising since it is the slowest surface and the match would progress at a slower pace. Not surprisingly, the fast grass courts show relatively high degrees of this carryover effect as well. Hard courts come after clay and grass in this regard.

Residual Analysis

While fitting the models outlined above, any glaring outliers which had material effects on the model output were removed and the models were re-fit on the subset. However, there still remained a few outliers in the final models that could be examined.

Many of these outliers were primarily present because one of the players had a very high rank with respect to the other player and managed to snag a set or two in the match. Examples of these include Lokoli vs. Haider-Maurer (Australian Open 2015), Radwanska vs. Putintseva (Australian Open 2014) and Youzhny vs. Federer (US Open 2017). Others could be upsets, where high seeded players lose a set, which is certainly an anomaly (often these players even go on to win the whole tournament!).

Nevertheless, none of the outliers seem to be out of the ordinary, and removing them did not affect the coefficients by a significant amount.
Game-Level Analysis

Raw Data Analysis

Figure 4: Player 1 Game Outcome (on serve and returning) versus Player Rank

The relationship between player rank and game outcome is very similar to that seen in the set analysis i.e. a higher numerical rank for player 1 corresponds to fewer won games for player 1 and a higher numerical rank for player 2 corresponds to more won games for player 1. Unsurprisingly, this effect appears to be weaker at the game-level; since sets consist of several games, game-to-game variation is smoothed out somewhat at the set-level.
Just as was the case in the set analysis, there is no significant relationship between age and games won.
Looking at when a player is on serve, a higher on serve points won percentage is related more games won. This trend is intuitive because higher on serve points won percentages are associated with better servers, who can comfortably serve out their service games. However, the returning points won percentage of player 1 does not seem to have any significant relationship with the outcome of game. This also makes sense since the ability of a player while returning does not convey much information about how they perform when they are on serve, even though it is true that players who are good returners are usually good on serve as well.
When a player is returning, a higher returning points won percentage is associated with more games won, which is again intuitive. However, such an association does not seem to be as strong as that of the service points won percentage. Perhaps the reason is the degree of advantage that a server has while they are serving, which makes it difficult even for good returners to win games (i.e. break their opponent’s serve). The on serve points won percentage does not seem to have any relationship on the outcome of the game, and the explanation for this association is quite similar to the one made when a player is serving: on serve percentages do not convey any information about how good a player is while they are returning.

Model Selection

As before, GLM and GLMM models are used to conduct this analysis, with two important addition. Firstly, every model attempting to analyze momentum has to include a dummy variable indicating which player is serving; the server always has an advantage over their opponent in the game and that effect has to be accounted for.

Secondly, the change of serve from game-to-game would mean that lagged games might not have the same serve status as the current game. For example, if player 1 is currently serving currently, the lagged game would have player 1 receiving, the effect of winning the lagged game would be very different than if player 1 is currently returning (making the lagged game a service game for player 1). The difference in effect can be accounted for using an interaction variable, which is the product of the current service variable and the lagged game outcome variable. This would be in addition to the standalone service and lagged dummy variables. In its simpler form in a GLM, it would have the following form and interpretation:

Say $x_1$ is the player control variable value and $x_2$ is the indicator of whether the player won the previous game. We ignore the presence of other predictors in the model, but if they are present all interpretations below are interpreted as being when all else in the model is held fixed. Then,

$$
\ell(X) \equiv \log \left[ \frac{\pi(X)}{1 - \pi(X)} \right]_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{1i} x_{2i}
$$
The interpretation of the $\beta$s are:

- $\beta_0$ is the log odds of winning a game if all other predictors are set to 0 and the player lost the previous game.
- $\beta_1$ represents the change in log odds of winning a game associated with predictor $x_{i1}$ changing by 1, given the player lost the previous game.
- $\beta_0 + \beta_2$ represents the log odds of winning a game if all other predictors are set to 0 and the player won the previous game.
- $\beta_1 + \beta_3$ represents the change in log odds of winning a game associated with $x_{i1}$ changing by 1, given the player won the previous game.

In the case of a GLMM, these betas are associated with the corresponding fixed effects and interaction variables.

**Model Parameters**

Because of the importance of the serve in determining the outcome of a game, the initial model (Model 0) was a GLM with only the player 1 serving status as a predictor. This would give a rough insight on the degree to which being on serve would affect the log odds of winning a game versus not being on serve.

While Model 0 provides a vague outline of this effect, control variables are required to account for player ability and form, aspects that player serve would fail to capture. Model 1 uses ranks as this control variable along with the service dummy variable, but unlike in the set-level analysis, simplifies the model by only using the difference in ranks between player 1 and player 2. The fits of using difference in ranks and separate rank variables were roughly the same, and the advantage of using differences is that doing so provides the intuitive result that the predictor equaling zero corresponds to two evenly-matched players playing against each other. Model 2 goes slightly further by adding on the difference in on-serve points won percentage and returning points won percentage as control predictors. To account for the nested nature of tennis matches, Model 3 uses the same parameters as Model 2 but in a GLMM.

The models moving forward examine momentum as far as three games prior to the current one. Of course, these models will have to include an interaction variable with the serve variable, whose interpretation is as mentioned in the model selection portion. First, the effects of lagged game outcomes can be modeled on a standalone basis i.e. models with only lagged game outcome variable: Model 4 uses Lag 1, Model 5 uses Lag 2 and Model 6 uses Lag 3 with respect to the current game. Lagged game winners here do not reset after
change of sets i.e. the lagged outcome of the first game in a new set is the outcome of the last game in the previous set.

Note that Model 5 yielded a singular fit as a GLMM, most probably because Lag 2 would represent the same service status as the current game, and the outcome of the lagged game outcome would overwhelmingly determine the outcome of the current (simply because of being on service status). For that reason, a GLM was fit to observe the effects of the Lag 2 game outcome. Obviously, there would be information loss in the momentum-exploratory models, since the first 1, 2 or 3 games (depending on the degree of the lag) would be have to be omitted due to missing values. However, due to the large number of data points, the loss does not have a significant effect on the information available to examine momentum trends. After this, Model 7 uses both Lag 1 and Lag 2 outcomes to see whether an additional lag captures any variability in the data significantly.

Comparing the various models, Model 7 seems to fit the data best across tournaments and genders. The AIC values indicate that Model 7 is a better fit to the data than the other model despite the information lost from introducing lag variables. As a result, Model 7 will be the model of choice going forward.

A summary of the parameters for the various models is given in the table below.

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Model 0</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
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<tbody>
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<td>✔</td>
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<td>✔</td>
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<tr>
<td>Lag 1 Game P1 x Lag 2 Game P1</td>
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<td>✔</td>
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<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Lag 1 Game P1 x Lag 2 Game P1 x Service P1</td>
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<td>✔</td>
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<td>✔</td>
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<td>✔</td>
</tr>
</tbody>
</table>
Model Output

As before, the coefficients, with their significance and z-values, for all models across tournaments and genders are as follows.

**Table 6: Game-Level Model Coefficients**

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Model 0</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GLM</td>
<td>GLM</td>
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<td>GLMM</td>
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<td>-0.9354***</td>
<td>-0.9345***</td>
<td>-0.94***</td>
<td>-0.191***</td>
<td>-1.323***</td>
<td>-1.0128***</td>
<td>-1.0299***</td>
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<td>(-46.565)</td>
<td>(-44.262)</td>
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<td>(-4.487)</td>
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<td>-0.0805*</td>
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<td>-0.0005</td>
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<td>-0.0005</td>
<td>-0.0005</td>
<td>-0.0005</td>
</tr>
<tr>
<td></td>
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<td>(-1.805)</td>
<td>(-1.738)</td>
<td>(-1.967)</td>
<td>(-2.037)</td>
<td>(-2.147)</td>
<td>(-2.147)</td>
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<td>PS Diff</td>
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<td>0.0557***</td>
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**Australian Open Women**
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### FRENCH OPEN WOMEN

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### Other Models

- Lag 1 Game P1
- Lag 2 Game P1
- Lag 3 Game P1
- Lag 1 Game P1 x Service P1
- Lag 2 Game P1 x Service P1
- Lag 3 Game P1 x Service P1
- Lag 1 Game P1 x Lag 2 Game P1
- Lag 1 Game P1 x Lag 2 Game P1 x Service P1

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### US Open Men

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### US Open Women

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<td>0.0801*** (12.933)</td>
<td>0.0801*** (12.933)</td>
<td>0.068*** (14.001)</td>
<td>0.082*** (14.001)</td>
<td>0.082*** (14.001)</td>
<td>0.0777*** (12.249)</td>
</tr>
<tr>
<td>GLMM</td>
<td>0.0532*** (9.743)</td>
<td>0.0572*** (8.603)</td>
<td>0.0593*** (7.775)</td>
<td>0.0499*** (6.861)</td>
<td>0.0585*** (7.614)</td>
<td>0.0566*** (7.625)</td>
<td>0.0566*** (7.625)</td>
<td>0.0566*** (7.625)</td>
</tr>
<tr>
<td>Service P1</td>
<td>1.1932*** (36.308)</td>
<td>1.2021*** (34.527)</td>
<td>1.2288*** (34.553)</td>
<td>1.2644*** (34.701)</td>
<td>1.2711*** (22.01)</td>
<td>1.2145*** (22.122)</td>
<td>1.1472*** (19.859)</td>
<td>1.3112*** (16.431)</td>
</tr>
<tr>
<td>Lag 1 Game P1</td>
<td>-0.1196* (2.084)</td>
<td>0.0926*** (7.264)</td>
<td>0.0926*** (7.264)</td>
<td>0.0926*** (7.264)</td>
<td>-0.0265 (0.357)</td>
<td>-0.966*** (4.271)</td>
<td>-0.966*** (4.271)</td>
<td>-0.966*** (4.271)</td>
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<td>Lag 2 Game P1</td>
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<td>0.094 (0.51)</td>
<td>-0.1108 (-0.945)</td>
<td>-0.1108 (-0.945)</td>
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<td>-0.3298*** (-2.823)</td>
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</tr>
<tr>
<td>Lag 3 Game P1</td>
<td>0.1036 (1.282)</td>
<td>-0.1518 (-1.308)</td>
<td>-0.1518 (-1.308)</td>
<td>-0.1518 (-1.308)</td>
<td>0.2206 (1.344)</td>
<td>0.2206 (1.344)</td>
<td>0.2206 (1.344)</td>
<td>0.2206 (1.344)</td>
</tr>
</tbody>
</table>

Significance codes - ‘***’: 0.001; ‘**’: 0.01; ‘*’: 0.05
Before analyzing manifestations of momentum, the coefficients shed light on some interesting trends:

- **Service variable is highly significant with large coefficients:**
  - Every model across gender and tournaments have the serve variable being highly significant with a large coefficient, indicating that being on serve changes the odds of winning a game by a huge amount. The estimated coefficient is relatively insensitive to the inclusion of control variables in the model. It indicates that for men, being on serve is associated with multiplying the odds of winning the game by a factor of roughly 6.0 to 7.5, while for women being on serve is associated with multiplying the odds by a factor of roughly 2.7 to 4.5. Further, the odds ratios are highest at Wimbledon (grass court), less high at the Australian and U.S. Opens (hard court), and lowest at the French Open (clay court). These patterns are intuitive, and support widely-held beliefs about the importance of serving on certain types of courts for men versus women.

- **Intercepts are significantly negative:**
  - The intercept in these models represents the log odds of player 1 winning a game if they are ‘average’, receiving, with all other fixed effects being 0. This intercept being negative means that the probability of the player winning a game while receiving is less than 50%. Correspondingly, if the opponent is the server then the probability is more than 50%. Again, the paramount effect of the serve in the outcome of the game is demonstrated here.

- **Player statistics affect game outcomes more than rank:**
  - Across court surfaces and gender, player statistics seem to affect the odds ratio far more sharply than ranks. This seems somewhat intuitive for the same reason outlined in the set-level analysis: rank determination is far more complex than player statistics and can be affected by circumstances that are unrelated to ability.

Since Model 7 is the model of choice, the coefficients can be used to analyze the odds of players winning a game with momentum effects, and the trends these effects follow. For each of the variables in the model, the betas will be defined as follows.
Table 7: Coefficient labels for variables of Model 7

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\beta_0$</td>
</tr>
<tr>
<td>Rank Diff</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td>PS Diff</td>
<td>$\beta_2$</td>
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<td>PR Diff</td>
<td>$\beta_3$</td>
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<tr>
<td>Service P1</td>
<td>$\beta_4$</td>
</tr>
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<td>Lag 1 Game P1</td>
<td>$\beta_5$</td>
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<td>Lag 2 Game P1</td>
<td>$\beta_6$</td>
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<td>Lag 1 Game P1 x Service P1</td>
<td>$\beta_7$</td>
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<tr>
<td>Lag 2 Game P1 x Service P1</td>
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<tr>
<td>Lag 1 Game P1 x Lag 2 Game P1</td>
<td>$\beta_9$</td>
</tr>
<tr>
<td>Lag 1 Game P1 x Lag 2 Game P1 x Service P1</td>
<td>$\beta_{10}$</td>
</tr>
</tbody>
</table>

Since there are three binary variables, all of which can take two values, there are $2^3$ or 8 cases that can be analyzed. These are described as follows:

- 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)
Note that for these cases the reported odds of Player 1 winning the game assume the two players are equally ranked and have equal ability (in terms of PS pct. and PR pct.).

The calculation of the log odds for each of these cases can be summarized as follows:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
<th>Case 6</th>
<th>Case 7</th>
<th>Case 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service P1</td>
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<td>✔</td>
<td>✔</td>
<td>✔</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lag 1 Game P1</td>
<td>✔</td>
<td></td>
<td></td>
<td>✔</td>
<td>✔</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lag 2 Game P1</td>
<td></td>
<td>✔</td>
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<td></td>
<td>✔</td>
<td>✔</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Odds</td>
<td>(\beta_0 + \beta_4) (+ \beta_5 + \beta_7)</td>
<td>(\beta_0 + \beta_4 + \beta_6 + \beta_8)</td>
<td>(\beta_0 + \beta_4 + \beta_5 + \beta_6 + \beta_7 + \beta_8 + \beta_9 + \beta_{10})</td>
<td>(\beta_0)</td>
<td>(\beta_0 + \beta_5)</td>
<td>(\beta_0 + \beta_6)</td>
<td>(\beta_0 + \beta_5 + \beta_6 + \beta_9)</td>
<td></td>
</tr>
</tbody>
</table>

These sums of betas can be exponentiated to give the odds in various cases. These effects are given in the table below. Note that Cases 1 to 4 denote when Player 1 is serving in the current game, and Cases 5 to 8 denote when Player 2 is serving in the current game.

| Cases where the player is serving are in green and cases where the player is returning are in red. The odds are then shaded according to their magnitude, with the highest odds on serve being the greenest, the lowest odds on serve being whitest. For the odds while returning, the lowest odds are reddest, and highest odds are whitest. |

The scenarios presented can be discussed from the perspective of the serving player i.e. Cases 1 to 4, since the scenarios where player 1 is returning are the same serving scenarios for player 2. Cases 5 to 8 are mirror images of Case 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 following observations can be gleaned from the odds above.

- **Momentum effects are more volatile for men than for women**
  - A common thread across the tournaments is that 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.
  - An explanation could be the difference in importance of returning between the two groups. Australian coach Simon Rea states that returning is such an important part of the women’s game and so 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.
  - No such difference trend seems evident across court surfaces.

- **Holding serve in previous games is essential for the serving player:**
  - Case 1 and 2, which has the lowest odds amongst the serving cases, shows that having one’s serve broken two games ago 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. This could be a matter of confidence. Losing the previous service game could make an average player feel shaky with their serve, making it more susceptible for them to be broken in the next service game (as demonstrated in Cases 1 and 2). The corresponding accomplishment for the returner gives the returner a higher chance to win the game (as demonstrated in Cases 7 and 8).
  - 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. The outcome of prior service games is clearly important and creates positive momentum for future service games.
Losing previous games can spur positive momentum

- Surprisingly, 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. 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. The hypothesis here could lie in players trying harder to win the current game after losing the previous game. Both Cases 1 and 7 have the player losing the previous game, which may push them harder to win the current game to get back in the match, translating to higher odds.

- This increased effort rationale could also be the reason why 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 given that the returning player has lost the previous two games. The returner would fight harder to get back into the match making it more difficult for the server to win the game. It may also be true that the serving player could relax their intensity considering they have somewhat of an edge over their opponent in the moment, reducing the odds of winning.

**Residual Analysis**

The residual plots showed no potential outliers that would affect the analysis significantly.
Point-Level Analysis

Raw Data Analysis

Figure 7: Player 1 Point Outcome (on serve and returning) versus Player 1 Rank

Similar to the set- and game-level data, numerically larger ranked players tend to lose more points than numerically smaller ranked players. The intuition continues to remain the same: numerically higher ranked are usually of lower quality when compared to their numerically lower ranked counterparts, and so are less likely to win points. In the same vein, opponents of numerically higher ranks will be associated with more won points due to the lower quality associated with them. This trend is the same irrespective of whether the player is serving or returning. Again unsurprisingly, the effect is weaker at the point level than it is at the game level (since aggregation in games smooths out some of the point-to-point variability).
Player age does not seem to have any correlation with point outcome, just as in the set- and game-level analysis.
Surprisingly, there does not seem to be much correlation between outcome of points and points on serve/returning percentage. Won points on serve and returning are slightly more correlated with higher points on serve won percentage and returning points won percentage respectively, but this relationship does not seem to be meaningful. Perhaps this trend occurs because the shorter duration of points makes them more idiosyncratic than games or sets.
Model Selection

The point-level analysis uses models that are quite similar to the game-level ones in terms of form. The serve is an essential component of the model and the interaction term of the lagged services with lagged point winner variables will be included.

Model Parameters

Just as in the game-level analysis, the initial model (Model 0) is a GLM that only uses serve as a predictor. From here, predictors can be added to capture more of the variability in the data. Model 1 adds the difference in the ranks of the players, and Model 2 further adds difference in percentage of points on serve/returning won. Model 3 incorporates these all these predictors as fixed effects in a GLMM, with random intercepts on a match level.

Model 4 incorporates the lagged point winner, specifically the winner of the previous point and its interaction with the server variable of the previous point i.e. the lag 1 winner of the point and the lag 1 server. Note that the lagged winners of points do not reset over change of games i.e. the lagged outcome in the first point of a new game is the outcome of the last game of the previous game. Model 5 supplements the Model 4 by adding on the lag 2 point winner and lag 2 server, the model also contains an interaction between the lagged point winners and their respective lagged service variable, along with an interaction between the two lag point winners. Here, there could also be an interaction between the two lag service variables, between the lag 1 point winner and lag 2 service, and the lag 2 point winner and lag 1 service. However, this model was far too complex to be estimable with accuracy. This does not seem to be a problem since these interaction coefficients did not seem to be significant in a GLM form, and the rest of the coefficients were not hugely affected by removing these interactions.

Model 6 manages to incorporate the effects of the lag 3 point winner, lag 3 server and their interaction, along with the interaction between Lag 1, Lag 2 and Lag 3 point winners (two-way and three-way). Just as in Model 5, additional interactions between the lag variables were possible but made the model too complex to be accurately estimable, and these variables were not significant and had no real effect on the other coefficients.

At this point, it is worthwhile to explore the effects of the outcome of previous games and sets on odds of winning a point. Model 7 attempts to do this by using differences in ranks and percentage of points on serve/returning won and the service variable along with the difference in sets won between the players, difference in games won in that set, and the difference in total games won in the match (rather than outcomes on previous points), in order to see if there is evidence of carryover effects at a larger “macro” level.
AIC value comparisons on all models reveals that even with the information lost from the introduction of lag variables, Model 6 is the best fit for the data at hand. As a result, Model 6 becomes the model of choice going forward with which the odds will be calculated.

The summary of the model parameters for each model is given in the table below.

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Model 0</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
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<tbody>
<tr>
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</tbody>
</table>

**Model Output**

The coefficients of the models for each tournament and gender is given in the tables below, with their corresponding z-values and significance codes.
## Table 11: Point-Level Model Coefficients

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Model 0</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
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</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.4835*** (66.585)</td>
<td>-0.4885*** (66.019)</td>
<td>-0.4874*** (63.095)</td>
<td>-0.4884*** (52.561)</td>
<td>-0.576*** (51.07)</td>
<td>-0.6025*** (43.613)</td>
<td>-0.5346*** (30.836)</td>
<td>-0.4795*** (46.282)</td>
</tr>
<tr>
<td>Rank Diff</td>
<td>-0.0008*** (-18.743)</td>
<td>-0.0001 (-1.522)</td>
<td>-0.0001 (-1.087)</td>
<td>-0.0001 (-1.134)</td>
<td>-0.0001 (-1.159)</td>
<td>-0.0001 (-1.152)</td>
<td>-0.0001 (-1.02)</td>
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<tr>
<td>PS Diff</td>
<td>0.0263*** (18.08)</td>
<td>0.0278*** (14)</td>
<td>0.0261*** (13.922)</td>
<td>0.0257*** (13.776)</td>
<td>0.0261*** (13.749)</td>
<td>0.0324*** (12.791)</td>
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<td>PR Diff</td>
<td>0.0248*** (15.945)</td>
<td>0.0263*** (12.415)</td>
<td>0.0247*** (12.375)</td>
<td>0.0247*** (12.423)</td>
<td>0.0249*** (12.359)</td>
<td>0.0306*** (11.679)</td>
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<tr>
<td>Service P1</td>
<td>0.8507*** (83.115)</td>
<td>0.8581*** (82.274)</td>
<td>0.8615*** (79.105)</td>
<td>0.8685*** (79.385)</td>
<td>0.8906*** (61.395)</td>
<td>0.8999*** (60.762)</td>
<td>0.8878*** (59.26)</td>
<td>0.8564*** (77.575)</td>
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<td>Lag 1 Service P1</td>
<td>-0.0752*** (-4.082)</td>
<td>-0.1043*** (-4.785)</td>
<td>-0.0995*** (-4.546)</td>
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<td>Lag 1 Point P1</td>
<td>0.2120*** (13.325)</td>
<td>0.2567*** (13.359)</td>
<td>0.2242*** (9.403)</td>
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<td>Lag 2 Service P1</td>
<td>-0.0184 (-0.984)</td>
<td>0.0037 (0.169)</td>
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<td>Lag 2 Point P1</td>
<td>0.0401* (2.147)</td>
<td>-0.033 (-1.386)</td>
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<td>Lag 3 Service P1</td>
<td>-0.0467* (-2.468)</td>
<td>-0.1442*** (-6.233)</td>
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<td>Lag 3 Point P1</td>
<td>0.0352 (1.757)</td>
<td>0.0354 (1.573)</td>
<td>0.0291 (1.288)</td>
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<td>Lag 1 Point P1 x Lag 1 Service P1</td>
<td>0.0394*** (4.419)</td>
<td>0.0849*** (3.717)</td>
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<td>Lag 1 Point P1 x Lag 2 Service P1</td>
<td>-0.094*** (-4.248)</td>
<td>0.0116 (0.373)</td>
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<td>Lag 1 Point P1 x Lag 3 Service P1</td>
<td>0.0796* (2.509)</td>
<td>0.1646*** (5.297)</td>
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<td>Lag 1 Point P1 x Lag 2 Point P1</td>
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<td>Lag 2 Point P1 x Lag 3 Point P1</td>
<td>-0.2157*** (-4.882)</td>
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<td>Sets Won Diff</td>
<td>-0.0161 (1.203)</td>
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<td>Games Won Diff</td>
<td>-0.0292*** (4.985)</td>
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<td>Cumulative Games Won Diff</td>
<td>0.0101* (2.037)</td>
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<tr>
<td>Intercept</td>
<td>-0.3421*** (37.532)</td>
<td>-0.3545*** (37.232)</td>
<td>-0.3573*** (37.381)</td>
<td>-0.3597*** (36.622)</td>
<td>-0.4442*** (30.821)</td>
<td>-0.4999*** (28.26)</td>
<td>-0.437*** (19.841)</td>
<td>-0.359*** (30.051)</td>
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<td>Rank Diff</td>
<td>-0.0014*** (4.883)</td>
<td>-0.0005*** (4.883)</td>
<td>-0.0005*** (4.883)</td>
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<td>-0.0004*** (3.493)</td>
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<td>-0.0005*** (3.373)</td>
<td>-0.0005*** (3.565)</td>
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<td>PS Diff</td>
<td>0.0263*** (16.066)</td>
<td>0.0281*** (12.262)</td>
<td>0.0268*** (12.246)</td>
<td>0.0268*** (12.246)</td>
<td>0.0262*** (12.211)</td>
<td>0.0262*** (12.132)</td>
<td>0.0265*** (12.132)</td>
<td>0.0287*** (11.276)</td>
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<td>PR Diff</td>
<td>0.0186*** (9.264)</td>
<td>0.0204*** (7.221)</td>
<td>0.0198*** (7.334)</td>
<td>0.0198*** (7.334)</td>
<td>0.0193*** (7.248)</td>
<td>0.0193*** (7.286)</td>
<td>0.0196*** (7.286)</td>
<td>0.0209*** (6.982)</td>
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<td>Service P1</td>
<td>0.5175*** (40.308)</td>
<td>0.5343*** (39.85)</td>
<td>0.5383*** (40.008)</td>
<td>0.546*** (40.322)</td>
<td>0.5712*** (30.362)</td>
<td>0.5816*** (30.366)</td>
<td>0.5735*** (29.485)</td>
<td>0.5456*** (40.194)</td>
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<td>-0.0484* (2.089)</td>
<td>-0.0691* (2.468)</td>
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<td>0.1971*** (10.041)</td>
<td>0.2732*** (11.612)</td>
<td>0.2136*** (7.253)</td>
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<td>-0.0213 (0.907)</td>
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<td>0.1099*** (4.742)</td>
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<td>0.0535 (1.822)</td>
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<td>-1.338*** (4.629)</td>
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<td>Lag 1 Point P1 x Lag 1 Service P1</td>
<td>0.001 (0.038)</td>
<td>0.0049 (0.179)</td>
<td>0.0068 (0.240)</td>
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<td>0.0724** (2.62)</td>
<td>0.067* (2.412)</td>
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<td>0.6772** (2.776)</td>
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<td>-0.1592*** (5.81)</td>
<td>-0.0718 (1.873)</td>
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<td>0.1251** (3.263)</td>
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<td>0.1252** (3.263)</td>
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<td>-0.1797*** (3.263)</td>
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<td>0.0539* (2.189)</td>
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<td>0.0118 (1.413)</td>
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<td>-0.0157 (1.889)</td>
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<tr>
<td>Intercept</td>
<td>-0.4489*** (-61.154)</td>
<td>-0.4517*** (-60.728)</td>
<td>-0.4639*** (-59.674)</td>
<td>-0.553*** (-48.025)</td>
<td>-0.6012*** (-42.901)</td>
<td>-0.5246*** (-30.006)</td>
<td>-0.4645*** (-48.12)</td>
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<tr>
<td>Rank Diff</td>
<td>-0.0013*** (-23.561)</td>
<td>-0.0006*** (-5.179)</td>
<td>-0.0006*** (-3.616)</td>
<td>-0.0005*** (-3.555)</td>
<td>-0.0005*** (-3.427)</td>
<td>-0.0005*** (-3.386)</td>
<td>-0.0005*** (-3.231)</td>
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<tr>
<td>PS Diff</td>
<td>0.0218*** (13.939)</td>
<td>0.0232*** (10.594)</td>
<td>0.022*** (10.6)</td>
<td>0.0216*** (10.631)</td>
<td>0.022*** (10.666)</td>
<td>0.022** (10.666)</td>
<td>0.0242*** (10.231)</td>
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<tr>
<td>PR Diff</td>
<td>0.0276*** (16.551)</td>
<td>0.0294*** (12.651)</td>
<td>0.0279*** (12.645)</td>
<td>0.0275*** (12.72)</td>
<td>0.028*** (12.735)</td>
<td>0.0364*** (11.901)</td>
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<tr>
<td>Service P1</td>
<td>0.7708*** (74.664)</td>
<td>0.7772*** (74.281)</td>
<td>0.7972*** (72.89)</td>
<td>0.8054*** (73.289)</td>
<td>0.8201*** (55.657)</td>
<td>0.8336*** (55.389)</td>
<td>0.8233*** (53.943)</td>
<td>0.8004*** (72.458)</td>
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<td>Lag 1 Service P1</td>
<td>-0.0599** (-3.229)</td>
<td>-0.0741*** (-3.344)</td>
<td>-0.0705** (-3.172)</td>
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<td>Lag 1 Point P1</td>
<td>0.1985*** (12.366)</td>
<td>0.252*** (13.137)</td>
<td>0.1939*** (8.069)</td>
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<td>Lag 2 Service P1</td>
<td>-0.0568** (-3.012)</td>
<td>-0.0452* (-2.029)</td>
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<td>Lag 2 Point P1</td>
<td>0.0951*** (5.066)</td>
<td>0.0339 (1.425)</td>
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<tr>
<td>Lag 3 Service P1</td>
<td>-0.0415* (-2.174)</td>
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<td>Lag 3 Point P1</td>
<td>-0.1725*** (-7.391)</td>
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<td>Lag 1 Point P1 x Lag 1 Service P1</td>
<td>0.0428 (1.913)</td>
<td>0.0421 (1.869)</td>
<td>0.0406 (1.794)</td>
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<td>Lag 2 Point P1 x Lag 2 Service P1</td>
<td>0.117*** (5.153)</td>
<td>0.1169*** (4.852)</td>
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<td>Lag 3 Point P1 x Lag 3 Service P1</td>
<td>0.0675** (2.947)</td>
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<td>Lag 1 Point P1 x Lag 2 Point P1</td>
<td>-0.1149*** (-5.162)</td>
<td>-0.0218 (0.699)</td>
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<td>Lag 1 Point P1 x Lag 3 Point P1</td>
<td>0.1308*** (4.198)</td>
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<td>Lag 2 Point P1 x Lag 3 Point P1</td>
<td>0.1403*** (4.492)</td>
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<td>Lag 1 Point P1 x Lag 2 Point P1 x Lag 3 Point P1</td>
<td>-0.1946*** (-4.373)</td>
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<td>Games Won Diff</td>
<td>-0.0077 (-1.365)</td>
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<td>Cumulative Games Won Diff</td>
<td>-0.0113* (-2.368)</td>
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<tr>
<td>Intercept</td>
<td>-0.283*** (31.44)</td>
<td>-0.2876*** (30.731)</td>
<td>-0.2894*** (30.731)</td>
<td>-0.2903*** (25.596)</td>
<td>-0.373*** (26.337)</td>
<td>-0.4512*** (25.743)</td>
<td>-0.373*** (25.743)</td>
<td>-0.4512*** (25.743)</td>
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<td>Rank Diff</td>
<td>-0.0011*** (-15.303)</td>
<td>-0.0002* (-2.182)</td>
<td>-0.0002 (-1.691)</td>
<td>-0.0002 (-1.651)</td>
<td>-0.0002 (-1.708)</td>
<td>-0.0002 (-1.752)</td>
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<td>-0.0002 (-1.752)</td>
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<td>PS Diff</td>
<td>0.0218*** (13.448)</td>
<td>0.0236*** (10.689)</td>
<td>0.0224*** (10.606)</td>
<td>0.0217*** (10.517)</td>
<td>0.0215*** (10.423)</td>
<td>0.0221*** (9.938)</td>
<td>0.0221*** (9.938)</td>
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<td>PR Diff</td>
<td>0.0238*** (12.214)</td>
<td>0.0252*** (9.567)</td>
<td>0.0241*** (9.523)</td>
<td>0.0237*** (9.605)</td>
<td>0.0236*** (9.572)</td>
<td>0.0239*** (9.141)</td>
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<td>0.0239*** (9.141)</td>
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<tr>
<td>Service P1</td>
<td>0.4091*** (32.252)</td>
<td>0.4191*** (31.766)</td>
<td>0.4221*** (31.787)</td>
<td>0.427*** (31.983)</td>
<td>0.4384*** (23.609)</td>
<td>0.4469*** (23.649)</td>
<td>0.4454*** (23.208)</td>
<td>0.4482*** (32.042)</td>
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<td>Lag 1 Service P1</td>
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<td>-0.0417 (-1.507)</td>
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## Model Types

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Before examining this output for trends in momentum, the following observations can be made.

• **Service variable is highly significant, but less so than at the game level:**
  
  o Every model across gender and tournaments have the serve variable being highly significant, indicating that being on serve changes the odds of winning a point by a large amount. The estimated coefficient is relatively insensitive to the inclusion of control variables in the model. It indicates that for men, being on serve is associated with multiplying the odds of winning the point by a factor of roughly 2.2 to 2.5, while for women being on serve is associated with multiplying the odds by a factor of roughly 1.5 to 1.9. Further, the odds ratios are again highest at Wimbledon (grass court), less high at the Australian and U.S. Opens (hard court), and lowest at the French Open (clay court), following the expected patterns.

• **Difference in player rank is significant for women but not for men:**
  
  o With each successive model getting more complex, difference in player ranks does not seem to be able to capture any significant additional variability in the men’s data. This trend appears when the control variables of PS pct. and PR pct. are introduced. However, in the women’s data it continues to be a key indicator across tournaments even with these player ability variables being significant.
  
  o This result would suggest that the rank is a better indicator of player ability for women than it is for men, and that it conveys some information in addition to just player ability for women (perhaps experience or playing form), although it is not apparent why that would be the case at the level of points but not at the level of sets or games.

• **Momentum on a point level exists due to significance of lag variable**
  
  o While not all lag variables and their interactions are not significant, a majority of the lagged point outcomes are significant indicating that there is definitely some carryover effect from the previous point. This trend is consistent for men and women.
  
  o Interestingly, this significance is true for lag 3 as well, meaning that the outcome of 3 points ago could have a significant effect on the outcome of the current point. One would not necessarily anticipate this relationship, but due to the short duration of points the trend is not completely unexpected.
• **Carryover effect of winning previous point on serve is no different from winning it while returning**:
  
  - The interaction variable between the lag 1 point outcome and the lag 1 service variable is generally insignificant.
  - Intuitively, one might imagine there to be a greater carryover effect if the previous point was won while returning but the insignificance of the interaction variable indicates that this is not the case. This makes the outcome of the previous point quite an important variable to estimate the outcome of the current point in all scenarios.

• **Outcomes of previous games and sets explain some of the variability in the data but not as much as lagged variables**:
  
  - Difference in sets and games won seem to be significant variables in Model 7, indicating that they can explain the variability of point outcomes. However, a chi-square test between Model 7 and Model 6 (for which the output is in the appendix) indicates that lagged point outcomes are better indicators of current point outcomes by a significant degree. This is intuitive, since the outcome of previous points are far more recent than the outcome of games and sets played throughout the match so far.

Looking at the odds of winning points to analyze momentum effects is a more complicated situation on a point level than the game level. With 6 different lag variables to consider, there could be $2^6$ or 64 different cases each for a serving or returning player that could be examined, making a total of 128 cases. It is far too convoluted to describe them individually.

However, these cases can be split into 16 different groups of cases, or blocks as used here, based on the outcome of the previous points and current service status (each block has 8 different combinations of lag service variables). Blocks 1-8 are as follow:

- **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, lost 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 detailed breakdown of each case is in the table below.

**Table 12: Summary of scenarios with corresponding dummy variables**

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

**Notes:**
- Block 1
- Block 2
- Block 3
- Block 4
To summarize the sum of coefficients for odds calculations, the betas of Model 6 need to be labeled. These are presented in the table below.

<table>
<thead>
<tr>
<th>Coefficient Label</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\beta_0$</td>
</tr>
<tr>
<td>Rank Diff</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td>PS Diff</td>
<td>$\beta_2$</td>
</tr>
<tr>
<td>PR Diff</td>
<td>$\beta_3$</td>
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<tr>
<td>Service P1</td>
<td>$\beta_4$</td>
</tr>
<tr>
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<td>Lag 2 Service P1</td>
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<tr>
<td>Lag 2 Point P1</td>
<td>$\beta_8$</td>
</tr>
<tr>
<td>Lag 3 Service P1</td>
<td>$\beta_9$</td>
</tr>
<tr>
<td>Lag 3 Point P1</td>
<td>$\beta_{10}$</td>
</tr>
<tr>
<td>Lag 1 Point P1 x Lag 1 Service P1</td>
<td>$\beta_{11}$</td>
</tr>
<tr>
<td>Lag 2 Point P1 x Lag 2 Service P1</td>
<td>$\beta_{12}$</td>
</tr>
<tr>
<td>Lag 3 Point P1 x Lag 3 Service P1</td>
<td>$\beta_{13}$</td>
</tr>
<tr>
<td>Lag 1 Point P1 x Lag 2 Point P1</td>
<td>$\beta_{14}$</td>
</tr>
<tr>
<td>Lag 1 Point P1 x Lag 3 Point P1</td>
<td>$\beta_{15}$</td>
</tr>
<tr>
<td>Lag 2 Point P1 x Lag 3 Point P1</td>
<td>$\beta_{16}$</td>
</tr>
<tr>
<td>Lag 1 Point P1 x Lag 2 Point P1 x Lag 3 Point P1</td>
<td>$\beta_{17}$</td>
</tr>
<tr>
<td>Sets Won Diff</td>
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<tr>
<td>Games Won Diff</td>
<td>$\beta_{19}$</td>
</tr>
<tr>
<td>Cumulative Games Won Diff</td>
<td>$\beta_{20}$</td>
</tr>
</tbody>
</table>

The calculation of the log odds for each of the cases will be denoted as the following summation:

$$\sum_{i \in A_x} \beta_i \text{ where } A_x \text{ is a set with coefficient labels present Case } x$$
These coefficient label sets are given in the table below.

<table>
<thead>
<tr>
<th>Case</th>
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<th>$\Delta_{a}$</th>
</tr>
</thead>
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<td></td>
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</tbody>
</table>
The odds of winning the point in each case can be summarized in the tables below. Note that these assume that all other fixed predictors are 0 i.e. the players are evenly matched in rank, PS pct. and PR pct.

![Figure 10: Point-Level Momentum Effects across cases](image)

The color shading of the odds is identical as in the game-level analysis: green if the player is serving and red if the player is returning. On serve, the highest odds are greenest and lowest odds are whitest, and while returning, the highest odds are whitest and lowest odds are reddest.

Just as in the game-level analysis, the discussion of these odds can be done with respect to the serving player i.e. Blocks 1-8. Blocks 9-16 are simply the same effects but flipped since Player 2 is serving. Here, Block 1 for the server corresponds to Block 16 for the returner, Block for the server corresponds to Block 15 for the returner, and so on.
The following observations can be made from the odds of winning a point.

- **Momentum effects are more volatile for men than for women:**
  - Overall, the odds of winning a point seem to be more extreme for men than for women, indicating that the men’s game is more sensitive to momentum effect. This is very similar to the trend observed in the game-level analysis.

- **Winning/losing previous two or three points creates higher positive/negative momentum:**
  - 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 (as per Blocks 9 and 12). Block 8, where the server wins the last three points, shows the highest odds of winning for the server, and so Block 9 shows the lowest odds of winning for the returner.
  - Similarly, losing the last two or three points leads to 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.
  - This trend is intuitive since winning two or three points in a row would increase the confidence of the player in question, leading to a high positive momentum effect, and losing two or three points in a row would reduce confidence, leading to high negative momentum effect.

- **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.
  - Interestingly, 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 than Blocks 2 and 6. There is a similar trend for the returner, where Blocks 13 and 14 show higher odds of winning than 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.
Residual Analysis

Residual plots in the final model showed no potential outliers that would affect the coefficients significantly.
Conclusion

Contrary to previous research done in the field of momentum, this analysis demonstrates a significant carryover effect between sets, games and points. There is plenty of evidence to show that points, games and sets are not independent and identically distributed.

The set analysis shows that winning the previous set has a huge positive effect on the odds of winning the next set, for both men and women. The singularity of the women’s model indicates that the outcome of the previous set almost always determines the outcome of the next one. Additionally, these effects are different for each surface, with the clay court showing the greatest effects.

The game analysis also showed significant carryover effects, where the odds of winning a game were analyzed using different cases. The analysis indicates that holding serve in previous service games is very important for the current serving player. Most interestingly, losing previous games is associated with higher predicted odds of winning the next game, perhaps because this loss motivates players to fight harder to win the next game and come back in the match. These effects are more volatile 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 predicted odds of winning the next point. Conversely, losing two or three points in a row is associated with much lower predicted odds of winning the next point. Interestingly, the momentum effect from prior points seems to have a short memory, with the most recent point having a greater effect on the predicted 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.

However, it cannot be said with certainty that these carryover effects from previous outcomes are momentum. With the addition of control variables, it seems exceedingly likely that the significance of previous outcomes is due to some psychological factor, perhaps a change in confidence. Whether this change in mindset translates to psychosomatic effects, and hence changes to the odds of winning, is not determinable. Either way, the data provides strong indication that momentum in tennis may not be a fallacy after all.
Appendix

Data Scaling

Since the variables are on very different scales, some variables like Player Rank with standard deviations of 25 and some variables like Returning Points Won % with standard deviations with standard deviations of 0.1, optimizers in R find it difficult to fit models with such differently scaled parameters. For that reason, all continuous variables used in models are scaled according to their standard deviations, essentially yielding their z-scores. For example, the men’s Australian Open set level data is scaled with the following R code:

```r
> apply(aus.sbs.men[,c(6,9:16)], 2, function(x) sd(x, na.rm=TRUE))
```

All datasets are scaled in this way. The coefficients given in the main analysis have been unscaled by dividing by the standard deviation, and so can be interpreted.

Set Level R Output

Model Output

**Model 0**

```r
> summary(aus.model0m)
```

Call:
```
glm(formula = P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank, family = "binomial", data = aus.sbs.scaled.men, na.action = na.exclude)
```

Deviance Residuals:
```
Min       1Q   Median       3Q      Max
-2.9397  -1.0875   0.3423   1.1094   3.6104
```

Coefficients:
```
Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.02988    0.04361   0.685    0.493
P1.Rank     -0.64143    0.05993 -10.703   <2e-16 ***
P2.Rank      0.69395    0.05491  12.639   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 3391.8  on 2446  degrees of freedom
Residual deviance: 3086.3  on 2444  degrees of freedom
> summary(aus.model0f)
Call:
Deviance Residuals:
         Min       1Q   Median       3Q      Max
-2.4999  -1.0877  -0.4322   1.0814   2.2267
Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.05658    0.05520  -1.025    0.305
P1.Rank      -0.65253    0.06884  -9.478  < 2e-16 ***
P2.Rank       0.49529    0.06609   7.494 6.69e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 2068.9  on 1492  degrees of freedom
Residual deviance: 1902.4  on 1490  degrees of freedom
(133 observations deleted due to missingness)
AIC: 1908.4
Number of Fisher Scoring iterations: 4

> summary(fo.model0m)
Call:
Deviance Residuals:

Min  1Q Median  3Q Max
-2.5556 -1.0693 0.3798 1.0534 3.4952

Coefficients:

Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.03379 0.04413 0.766 0.444
P1.Rank -0.75441 0.06159 -12.249 <2e-16 ***
P2.Rank 0.71213 0.05350 13.311 <2e-16 ***

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 3499.2 on 2524 degrees of freedom
Residual deviance: 3092.0 on 2522 degrees of freedom
(58 observations deleted due to missingness)
AIC: 3098

Number of Fisher Scoring iterations: 4

> summary(fo.model0f)

Call:
glm(formula = P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank, family = "binomial", data = fo.sbs.scaled.women, na.action = na.exclude)

Deviance Residuals:

Min  1Q Median  3Q Max
-2.5612 -1.0837 -0.5363 1.1424 1.8147

Coefficients:

Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.01094 0.05329 0.205 0.837
P1.Rank -0.31305 0.05607 -5.583 2.36e-08 ***
P2.Rank 0.53890 0.06443 8.365 < 2e-16 ***

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2141.8 on 1544 degrees of freedom
Residual deviance: 2017.9 on 1542 degrees of freedom
(121 observations deleted due to missingness)
AIC: 2023.9

Number of Fisher Scoring iterations: 4
> summary(w.model0m)
Call:
glm(formula = P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank, family = "binomial", data = w.sbs.scaled.men, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-2.7623  -1.0975   0.3079   1.0596   3.1098
Coefficients:
            Estimate  Std. Error   z value  Pr(>|z|)
(Intercept)  0.009172   0.043227   0.212    0.832
P1.Rank     -0.740445   0.059192 -12.509   <2e-16 ***
P2.Rank      0.597774   0.053303  11.215   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 3504.3  on 2527  degrees of freedom
Residual deviance: 3158.2  on 2525  degrees of freedom
   (46 observations deleted due to missingness)
AIC: 3164.2
Number of Fisher Scoring iterations: 4

> summary(w.model0f)
Call:
glm(formula = P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank, family = "binomial", data = w.sbs.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-2.1923  -1.1462   0.7335   1.0877   2.0052
Coefficients:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | 0.13625  | 0.05421    | 2.514   | 0.012    * |
| P1.Rank        | -0.38013 | 0.05872    | -6.474  | 9.54e-11 *** |
| P2.Rank        | 0.44100  | 0.06276    | 7.026   | 2.12e-12 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2058.9  on 1488  degrees of freedom
Residual deviance: 1951.3  on 1486  degrees of freedom
(153 observations deleted due to missingness)
AIC: 1957.3
Number of Fisher Scoring iterations: 4

---

> summary(uso.model0m)

Call:
glm(formula = P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank, family = "binomial", data = uso.sbs.scaled.men, na.action = na.exclude)

Deviance Residuals:

Min      1Q  Median      3Q     Max
-2.883  -1.104   0.623   1.038   3.878

Coefficients:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | 0.08909  | 0.04327    | 2.059   | 0.0395   * |
| P1.Rank        | -0.77662 | 0.06542    | -11.872 | <2e-16   *** |
| P2.Rank        | 0.57002  | 0.05383    | 10.589  | <2e-16   *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 3479.0  on 2513  degrees of freedom
Residual deviance: 3164.4 on 2511 degrees of freedom
   (74 observations deleted due to missingness)
AIC: 3170.4
Number of Fisher Scoring iterations: 4

> summary(uso.model0f)
Call:
  glm(formula = P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank, family = "binomial",
      data = uso.sbs.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-2.1347  -1.1488   0.6549   1.1259   2.0551
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.04437    0.05219   0.850    0.395
P1.Rank     -0.36308    0.05709  -6.360 2.02e-10 ***
P2.Rank      0.36501    0.05751   6.347 2.20e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 2163.3 on 1560 degrees of freedom
  Residual deviance: 2075.1 on 1558 degrees of freedom
  (190 observations deleted due to missingness)
AIC: 2081.1
Number of Fisher Scoring iterations: 4

Standardized Residuals (Male)

Standardized Residuals (Female)
Model 1

> summary(aus.model1m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )
Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
  Data: aus.sbs.scaled.men.sub1

AIC      BIC   logLik deviance df.resid
2967.6   2990.8  -1479.8   2959.6     2439

Scaled residuals:
  Min      1Q  Median      3Q     Max
-4.0234 -0.6597  0.1376  0.6611  6.1467

Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 1.399    1.183
  Number of obs: 2443, groups:  Match.ID, 668

Fixed effects:
  Estimate Std. Error z value Pr(>|z|)
  (Intercept)  0.04499    0.06927   0.649    0.516
  P1.Rank     -0.88328    0.09080  -9.728   <2e-16 ***
  P2.Rank      0.96101    0.08750  10.983   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
   (Intr) P1.Rnk
P1.Rank  0.048
P2.Rank  0.076 -0.306

> summary(aus.model1f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )
Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
  Data: aus.sbs.scaled.women.sub1

AIC      BIC   logLik deviance df.resid
1861.0   1882.2   -926.5   1853.0     1489

Scaled residuals:
  Min      1Q  Median      3Q     Max
-2.5820 -0.6134 -0.1745  0.6079  2.4875

Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 2.078    1.441
  Number of obs: 1493, groups:  Match.ID, 652
Fixed effects:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.08538 | 0.08869    | -0.963  | 0.336    |
| P1.Rank        | -0.95062 | 0.12093    | -7.861  | 3.81e-15 *** |
| P2.Rank        | 0.69380  | 0.10520    | 6.595   | 4.25e-11 *** |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<tr>
<th></th>
<th>(Intr)</th>
<th>P1.Rnk</th>
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<tbody>
<tr>
<td>P1.Rank</td>
<td>0.090</td>
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<tr>
<td>P2.Rank</td>
<td>-0.007</td>
<td>-0.312</td>
</tr>
</tbody>
</table>

> summary(fo.model1m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)

Data: fo.sbs.scaled.men.sub1

AIC      BIC   logLik deviance df.resid
2964.9   2988.2  -1478.5   2956.9     2519

Scaled residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
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<td>-4.2967</td>
<td>-0.6019</td>
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<td>3.1731</td>
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Random effects:

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<th>Std.Dev.</th>
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<tr>
<td>Match.ID</td>
<td>(Intercept)</td>
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<td>1.361</td>
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Number of obs: 2523, groups: Match.ID, 702
Fixed effects:

|                  | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------|----------|------------|---------|----------|
| (Intercept)      | 0.05220  | 0.07486    | 0.697   | 0.486    |
| P1.Rank          | -0.98820 | 0.09510    | -10.391 | <2e-16 *** |
| P2.Rank          | 0.96790  | 0.08923    | 10.847  | <2e-16 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ’ 0.1 ’ ’ 1

Correlation of Fixed Effects:

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<tr>
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<th>(Intr)</th>
<th>P1.Rnk</th>
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<tr>
<td>P1.Rnk</td>
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<tr>
<td>P2.Rank</td>
<td>-0.190</td>
<td></td>
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</table>

> summary(fo.model1f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit )

Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)

Data: fo.sbs.scaled.women.sub1

AIC  BIC  logLik  deviance  df.resid
1975.4  1996.8  -983.7  1967.4  1541

Scaled residuals:

Min 1Q Median 3Q Max
-4.2748 -0.6140 -0.2367 0.6480 1.9318

Random effects:

Groups Name      Variance  Std.Dev.  
Match.ID (Intercept) 1.977    1.406

Number of obs: 1545, groups: Match.ID, 671

Fixed effects:

|                  | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------|----------|------------|---------|----------|
| (Intercept)      | 0.0001629| 0.0848049  | 0.002   | 0.998    |
| P1.Rank          | -0.4464120| 0.0902699  | -4.945  | 7.60e-07 *** |
| P2.Rank          | 0.7627291| 0.1050638  | 7.260   | 3.88e-13 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ’ 0.1 ’ ’ 1

Correlation of Fixed Effects:

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<tr>
<td>P1.Rnk</td>
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<tr>
<td>P2.Rank</td>
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</tbody>
</table>

75
> summary(w.model1m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)

Data: w.sbs.scaled.men.sub1

AIC      BIC   logLik deviance df.resid
3049.5   3072.8  -1520.8   3041.5     2522

Scaled residuals:
Min      1Q  Median      3Q     Max
-3.4859 -0.6423  0.1945  0.6331  3.9732

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 1.544    1.243

Number of obs: 2526, groups: Match.ID, 693

Fixed effects:

Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.01031    0.07019   0.147    0.883
P1.Rank     -1.01538    0.09654 -10.518   <2e-16 ***
P2.Rank      0.76994    0.08079   9.530   <2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

(Intr) P1.Rnk
P1.Rank 0.079
P2.Rank 0.043 -0.180
> summary(w.model1f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
   Data: w.sbs.scaled.women.sub1

AIC      BIC   logLik deviance df.resid
1893.0   1914.2   -942.5   1885.0     1485
Scaled residuals:
       Min      1Q  Median      3Q     Max
-2.6162 -0.5846  0.3261  0.5614  2.2498
Random effects:
   Groups   Name        Variance Std.Dev.
   Match.ID (Intercept) 2.655    1.63
Number of obs: 1489, groups:  Match.ID, 652
Fixed effects:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.20583    0.09544   2.157    0.031 *
P1.Rank      -0.60041    0.10598  -5.665 1.47e-08 ***
P2.Rank       0.67856    0.11208   6.054 1.41e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:
             (Intr) P1.Rnk
P1.Rank      -0.035
P2.Rank      0.108 -0.117

![Standardized Residuals (Male)](image)

![Standardized Residuals (Female)](image)
> summary(uso.model1m)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  (logit )
Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
  Data: uso.sbs.scaled.men.sub1
      AIC   BIC logLik deviance df.resid
3067.6 3090.9  -1529.8  3059.6     2507
Scaled residuals:
  Min      1Q  Median      3Q     Max
-4.6081 -0.7032  0.3617  0.6774  6.5068
Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 1.006    1.003
Number of obs: 2511, groups: Match.ID, 680
Fixed effects:
  Estimate Std. Error    z value  Pr(>|z|)
(Intercept)  0.09262    0.06289   1.473    0.141
P1.Rank     -1.08295    0.09601 -11.280   <2e-16 ***
P2.Rank      0.66426    0.07263   9.146   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:
   (Intr) P1.Rnk
P1.Rank  0.102
P2.Rank  0.073 -0.162

> summary(uso.model1f)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  (logit )
Formula: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
  Data: uso.sbs.scaled.women.sub1
      AIC   BIC logLik deviance df.resid
2054.8 2076.3  -1023.4  2046.8     1557
Scaled residuals:
  Min      1Q  Median      3Q     Max
-1.9765 -0.7520  0.3761  0.7091  2.4510
Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 1.135    1.065
Number of obs: 1561, groups: Match.ID, 666
Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | 0.06024 | 0.07235 | 0.833 | 0.405 |
| P1.Rank | -0.46468 | 0.07979 | -5.824 | 5.76e-09 *** |
| P2.Rank | 0.45698 | 0.07921 | 5.769 | 7.96e-09 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

(Intr) P1.Rnk
P1.Rank -0.003
P2.Rank  0.041 -0.136

---

Model 2

> summary(aus.model2m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )


Data: aus.sbs.scaled.men.sub2

Control: glmerControl(optimizer = "bobyqa")

AIC      BIC   logLik deviance df.resid
2631.3   2694.2  -1304.6   2609.3     2253

Scaled residuals:

Min     1Q Median     3Q    Max
-3.4050 -0.6721  0.2174  0.6632  3.5157

---

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Random effects:
Groups    Name (Intercept) Variance Std.Dev.
Match.ID  (Intercept) 0.8868  0.9417
Number of obs: 2264, groups:  Match.ID, 618
Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|---------|
| (Intercept) | 0.12569    | 0.07152 | 1.757   | 0.078855 |
| P1.Rank    | -0.05203   | 0.14986 | -0.347  | 0.728425 |
| P2.Rank    | 0.42286    | 0.12083 | 3.500   | 0.000466 *** |
| P1.Age     | -0.06211   | 0.06737 | -0.922  | 0.356545 |
| P2.Age     | -0.05181   | 0.06818 | -0.760  | 0.447328 |
| P1.PS.pct  | 0.72950    | 0.09780 | 7.459   | 8.71e-14 *** |
| P2.PS.pct  | -0.65069   | 0.09905 | -6.569  | 5.05e-11 *** |
| P1.PR.pct  | 0.61392    | 0.09378 | 6.546   | 5.91e-11 *** |
| P2.PR.pct  | -0.44846   | 0.08798 | -5.098  | 3.44e-07 *** |
| Round      | 0.02974    | 0.08768 | 0.339   | 0.734486 |

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:

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<td>P1.Rank</td>
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<tr>
<td>P1.Age</td>
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<td>-0.021</td>
<td>-0.128</td>
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<tr>
<td>P2.Age</td>
<td></td>
<td></td>
<td></td>
<td>-0.019</td>
<td>-0.128</td>
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<tr>
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<td>0.075</td>
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<td>P2.PS.pct</td>
<td>0.136</td>
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<td>0.537</td>
<td>-0.023</td>
<td>-0.124</td>
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<tr>
<td>P1.PR.pct</td>
<td>0.247</td>
<td>0.510</td>
<td>0.076</td>
<td>-0.161</td>
<td>-0.007</td>
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<tr>
<td>P2.PR.pct</td>
<td>0.113</td>
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<td>-0.015</td>
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<tr>
<td>Round</td>
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<td>-0.019</td>
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</table>

> summary(aus.model2f)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Data: aus.sbs.scaled.women.sub2
Control: glmerControl(optimizer = "bobyqa")
AIC          BIC          logLik     deviance   df.resid
1687.1   1745.5      -832.6        1665.1     1477
Scaled residuals:
Min      1Q  Median      3Q     Max
-3.0215 -0.6092 -0.1007  0.6455  3.1101

Random effects:  
Groups   Name        Variance Std.Dev.  
Match.ID (Intercept) 1.169    1.081  
Number of obs: 1488, groups: Match.ID, 650  
Fixed effects:  
  Estimate Std. Error z value Pr(>|z|)  
(Intercept) -0.0970259  0.0806294 -1.203 0.228838  
P1.Rank     -0.4246027  0.1122799 -3.782 0.000156 ***  
P2.Rank      0.0932258  0.1055228  0.883 0.376985  
P1.Age       0.0009705  0.0837313  0.012 0.990752  
P2.Age      -0.1053596  0.0852511 -1.236 0.216506  
P1.PS.pct    0.7103358  0.1134791  6.260 3.86e-10 ***  
P2.PS.pct   -0.9324580  0.1187370 -7.853 4.06e-15 ***  
P1.PR.pct    0.5400179  0.1134791  4.860 8.84e-07 ***  
P2.PR.pct   -0.3856852  0.1187370 -3.228 7.08e-04 ***  
Round       0.0665013  0.1022126  0.652 0.515293  
---  
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1  
Correlation of Fixed Effects:  
P1.Rank   0.047  
P2.Rank  0.012 -0.028  
P1.Age   0.025 0.164 0.017  
P2.Age   0.013 0.000 0.184 0.031  
P1.PS.pct -0.056 0.164 -0.025 0.046 0.007  
P2.PS.pct 0.200 0.128 0.268 -0.068 0.034 -0.217  
P1.PR.pct -0.051 0.219 0.005 -0.047 0.032 0.181 -0.088  
P2.PR.pct -0.002 0.018 0.250 0.022 0.071 -0.085 0.164 -0.133  
Round   0.005 0.092 0.104 -0.033 -0.098 -0.275 -0.267 -0.180 -0.227  

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> summary(fo.model2m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )


Data: fo.sbs.scaled.men.sub2

Control: glmerControl(optimizer = "bobyqa")

AIC      BIC   logLik deviance df.resid
2612.5   2675.8  -1295.2   2590.5     2319

Scaled residuals:
Min      1Q  Median      3Q     Max
-3.8695 -0.6197  0.1781  0.6184  3.6411

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 1.047    1.023

Number of obs: 2330, groups:  Match.ID, 647

Fixed effects:

                   Estimate Std. Error   z value Pr(>|z|)
(Intercept)         0.03843    0.07365   0.522 0.601828
P1.Rank            -0.48467    0.15876  -3.053 0.002266 **
P2.Rank             0.42165    0.12423   3.394 0.000689 ***
P1.Age              0.03258    0.06947   0.469 0.639129
P2.Age             -0.02152    0.07056  -0.305 0.760425
P1.PS.pct           0.54955    0.10686   5.143 2.71e-07 ***
P2.PS.pct          -0.54556    0.09858  -5.534 3.12e-08 ***
P1.PR.pct           0.65473    0.10127   6.465 1.01e-10 ***
P2.PR.pct         -0.60366    0.09505  -6.351 2.14e-10 ***
Round               0.05576    0.09646   0.578 0.563228

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:

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<tr>
<td>P2.Rank</td>
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<td>P1.Age</td>
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> summary(fo.model2f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Data: fo.sbs.scaled.women.sub2
Control: glmerControl(optimizer = "bobyqa")
AIC      BIC   logLik deviance df.resid
1791.3   1849.9   -884.6   1769.3     1517
Scaled residuals:
          Min       1Q   Median       3Q      Max
-3.2906 -0.6205  -0.0081  0.6484  3.2062
Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 1.158     1.076
Number of obs: 1528, groups:  Match.ID, 664
Fixed effects:
  Estimate Std. Error  z value Pr(>|z|)
(Intercept)  0.02735   0.07803   0.350   0.72596
P1.Rank      0.01292   0.09688   0.133   0.89395
P2.Rank      0.24809   0.10518   2.359   0.01834 *
P1.Age       -0.15508   0.08268  -1.876   0.06071 .
P2.Age       -0.22469   0.08141  -2.760   0.00578 **
P1.PS.pct    0.69476   0.10443   6.653  2.88e-11 ***
P2.PS.pct    -0.69570   0.11050  -6.296  3.06e-10 ***
P1.PR.pct    0.52014   0.09585   5.427  5.74e-08 ***
P2.PR.pct    -0.63354   0.10626  -5.962  2.49e-09 ***
Round        0.11034   0.09546   1.156   0.24771
---
Correlation of Fixed Effects:

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> summary(w.model2m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit )


Data: w.sbs.scaled.men.sub2

Control: glmerControl(optimizer = "bobyqa")

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Scaled residuals:

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Random effects:

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</table>

Number of obs: 2344, groups: Match.ID, 641

Fixed effects:
|                  | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------|----------|------------|---------|----------|
| (Intercept)      | -0.005876 | 0.068134   | -0.086  | 0.93128  |
| P1.Rank          | -0.348878 | 0.128129   | -2.723  | 0.00647  **|
| P2.Rank          | 0.012019  | 0.121825   | 0.099   | 0.92141  |
| P1.Age           | 0.084528  | 0.066374   | 1.274   | 0.20283  |
| P2.Age           | -0.074795 | 0.066357   | -1.127  | 0.25967  |
| P1.PS.pct        | 0.727424  | 0.100351   | 7.249   | 4.20e-13 ***|
| P2.PS.pct        | -0.952462 | 0.103325   | -9.218  | < 2e-16 ***|
| P1.PR.pct        | 0.408650  | 0.086249   | 4.738   | 2.16e-06 ***|
| P2.PR.pct        | -0.537400 | 0.089765   | -6.021  | 1.73e-09 ***|
| Round            | -0.063897 | 0.089768   | -0.712  | 0.47659  |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<tr>
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<td>0.052</td>
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> summary(w.model2f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']


Family: binomial  ( logit )

Control: glmerControl(optimizer = "bobyqa")

AIC  BIC  logLik deviance df.resid
1740.7 1799.0  -859.3 1718.7     1472

Scaled residuals:

       Min     1Q Median     3Q    Max
-2.8098 -0.6116  0.2248  0.5736  2.1592

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 1.721    1.312

Number of obs: 1483, groups: Match.ID, 649

Fixed effects:

Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.21973    0.08770   2.506   0.0122 *  
P1.Rank     -0.07271    0.10563  -0.688   0.4912  
P2.Rank      0.19104    0.10972   1.741   0.0817 .  
P1.Age      -0.01332    0.09423  -0.141   0.8876  
P2.Age      -0.04864    0.08945  -0.544   0.5866  
P1.PS.pct    0.75152    0.11406   6.589 4.43e-11 ***  
P2.PS.pct   -0.71590    0.11699  -6.119 9.40e-10 ***  
P1.PR.pct    0.44195    0.10341   4.274 1.92e-05 ***  
P2.PR.pct   -0.65866    0.11345  -5.806 6.41e-09 ***  
Round       0.24282    0.11011   2.205   0.0274 *  

---  
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:  
P1.Rank  0.017   
P2.Rank  0.048  0.050   
P1.Age   0.020  0.254  0.062   
P2.Age   0.006 -0.003  0.196  0.002   
P1.PS.pct 0.095  0.185  0.025 -0.016 -0.007   
P2.PS.pct -0.074 -0.036  0.221 -0.012 -0.016 -0.098   
P1.PR.pct 0.070  0.270 -0.037 -0.022  0.004  0.300 -0.030   
P2.PR.pct -0.072 -0.009  0.250  0.072 -0.033 -0.091  0.368 -0.163   
Round  -0.016  0.145  0.092 -0.050 -0.013 -0.256 -0.394 -0.178 -0.295   

> summary(uso.model2m)  
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial (logit)


Data: uso.sbs.scaled.men.sub2

Control: glmerControl(optimizer = "bobyqa")

AIC      BIC   logLik deviance df.resid
2832.2   2895.7  -1405.1   2810.2     2378

Scaled residuals:
Min      1Q  Median      3Q     Max
-3.2698 -0.6957  0.2998  0.6790  3.0969

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.7723   0.8788

Number of obs: 2389, groups:  Match.ID, 646

Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|---------|
| (Intercept) | 0.17799 | 0.06360 | 2.799 | 0.00513 ** |
| P1.Rank | -0.37796 | 0.12222 | -3.092 | 0.00199 ** |
| P2.Rank | 0.23762 | 0.09511 | 2.498 | 0.01247 * |
| P1.Age | -0.06106 | 0.06263 | -0.975 | 0.32963 |
| P2.Age | 0.10164 | 0.06221 | 1.634 | 0.10228 |
| P1.PS.pct | 0.62441 | 0.09209 | 6.780 | 1.20e-11 *** |
| P2.PS.pct | -0.53779 | 0.08631 | -6.231 | 4.63e-10 *** |
| P1.PR.pct | 0.58540 | 0.08122 | 7.208 | 5.69e-13 *** |
| P2.PR.pct | -0.39278 | 0.07702 | -5.099 | 3.41e-07 *** |
| Round | -0.06373 | 0.08511 | -0.749 | 0.45397 |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<td>0.038</td>
<td>0.108</td>
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> summary(uso.model2f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial (logit)

Data: uso.sbs.scaled.women.sub2

Control: glmerControl(optimizer = "bobyqa")

AIC BIC logLik deviance df.resid
1874.0 1932.8  -926.0   1852.0     1532

Scaled residuals:
  Min    1Q  Median    3Q   Max
-2.6979 -0.7556  0.1934  0.7159  2.4231

Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.604    0.7772

Number of obs: 1543, groups:  Match.ID, 658

Fixed effects:
                     Estimate Std. Error z value  Pr(>|z|)
(Intercept)     0.080674   0.067811   1.190 0.234
P1.Rank         -0.037850   0.080484  -0.470 0.638
P2.Rank          0.046059   0.082879   0.556 0.578
P1.Age           0.003118   0.072959   0.043 0.966
P2.Age           0.008886   0.069334   0.128 0.898
P1.PS.pct       0.709475   0.091816   7.727 1.10e-14 ***
P2.PS.pct      -0.608426   0.090528  -6.721 1.81e-11 ***
P1.PR.pct       0.437727   0.083224   5.260 1.44e-07 ***
P2.PR.pct      -0.397778   0.080025  -4.971 6.67e-07 ***
Round        -0.115848   0.081182  -1.427 0.154

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
P1.Rank       0.011
P2.Rank       0.020 -0.005
P1.Age        0.027 0.196 0.069
P2.Age        0.022 0.058 0.185 -0.048
P1.PS.pct     0.048 0.239 -0.046 -0.054 0.025
P2.PS.pct    -0.044 -0.049  0.307  0.023 -0.005 -0.123
P1.PR.pct     0.016 0.258 -0.070 -0.113 -0.005  0.256 -0.076
P2.PR.pct    -0.051  0.009  0.242  0.068 -0.015 -0.074  0.288 -0.077
Round    -0.053  0.077  0.080 -0.036 -0.027 -0.377 -0.257 -0.220 -0.178
Model 3

```r
> summary(aus.model3m)
Call:
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4234  -0.9862   0.3964   0.9600   2.3527
Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                  -0.13487    0.08453  -1.595    0.111
P1.Rank                      -0.08432    0.12624  -0.668    0.504
P2.Rank                      0.47264    0.10805   4.374 1.22e-05 ***
Lag.Set.P1                   0.49221    0.11432   4.305 1.67e-05 ***
P1.PS.pct                    0.49855    0.07507   6.641 3.12e-11 ***
P2.PS.pct                    -0.40659    0.07761  -5.239 1.61e-07 ***
P1.PR.pct                    0.46667    0.07172   6.507 7.68e-11 ***
P2.PR.pct                    -0.30831    0.07222  -4.269 1.96e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 2280.3  on 1645  degrees of freedom
    Residual deviance: 1909.9  on 1638  degrees of freedom
    (938 observations deleted due to missingness)
AIC: 1925.9
```

![Standardized Residuals (Male)](image1)

![Standardized Residuals (Female)](image2)
Number of Fisher Scoring iterations: 4

> summary(aus.model3f)

Call:

Deviance Residuals:
  Min       1Q   Median       3Q      Max
-2.1988  -0.9489  -0.2297   0.9807   2.2916

Coefficients:
  Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.44482    0.11189  -3.976 7.02e-05 ***
P1.Rank      -0.25326    0.10559  -2.398   0.0165 *
P2.Rank      0.03129    0.10057   0.311   0.7557
Lag.Set.P1   0.76294    0.16111   4.735 2.19e-06 ***
P1.PS.pct    0.53869    0.10183   5.290 1.22e-07 ***
P2.PS.pct   -0.64969    0.10456  -6.214 5.17e-10 ***
P1.PR.pct    0.39784    0.10173   3.911 9.20e-05 ***
P2.PR.pct   -0.23233    0.09312  -2.495   0.0126 *

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

  Null deviance:  1161.33  on 837  degrees of freedom
  Residual deviance:  945.16  on 830  degrees of freedom

(787 observations deleted due to missingness)

AIC: 961.16

Number of Fisher Scoring iterations: 4
> summary(fo.model3m)

Call:

Deviance Residuals:
          Min       1Q   Median       3Q      Max
-2.1513   -0.9207   0.3365   0.8857   2.3995

Coefficients:
                     Estimate  Std. Error z value Pr(>|z|)
(Intercept)          -0.33470    0.08515  -3.931  8.47e-05 ***
P1.Rank               -0.42140    0.13724  -3.070  0.00214 **
P2.Rank                0.30512    0.10337   2.952  0.00316 **
Lag.Set.P1            0.73538    0.11632   6.322  2.58e-10 ***
P1.PS.pct             0.42467    0.08407   5.051  4.39e-07 ***
P2.PS.pct             -0.44631    0.07590  -5.880  4.11e-09 ***
P1.PR.pct             0.51132    0.08001   6.391  1.65e-10 ***
P2.PR.pct             -0.39047    0.07384  -5.288  1.24e-07 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2329.0  on 1680  degrees of freedom
Residual deviance: 1843.9  on 1673  degrees of freedom
(900 observations deleted due to missingness)
AIC: 1859.9
Number of Fisher Scoring iterations: 4

> summary(fo.model3f)

Call:

Deviance Residuals:
          Min       1Q   Median       3Q      Max
-2.4008   -0.9137   0.1525   0.9240   2.2396

Coefficients:
                     Estimate  Std. Error z value Pr(>|z|)
(Intercept)          -0.50167    0.11150  -4.499  6.82e-06 ***
P1.Rank               0.10318    0.09355   1.103  0.270062
P2.Rank                0.10994    0.10156   1.082  0.279049
Lag.Set.P1            1.03691    0.15841   6.546  5.92e-11 ***
P1.PS.pct             0.58681    0.09764   6.010  1.85e-09 ***
P2.PS.pct             -0.34228    0.09936  -3.445  6.000000e-05 ***
P1.PR.pct             0.56868    0.09278   6.129  8.84e-10 ***
P2.PR.pct             -0.38620    0.09853  -3.920  8.87e-05 ***
---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1197.7  on 863  degrees of freedom
Residual deviance:  968.8  on 856  degrees of freedom

(800 observations deleted due to missingness)

AIC: 984.8

Number of Fisher Scoring iterations: 4

> summary(w.model3m)

Call:

Deviance Residuals:

  Min       1Q   Median       3Q      Max
-2.3130  -0.9413   0.3031   0.9360   2.2581

Coefficients:

  Estimate Std. Error     z value  Pr(>|z|)
(Intercept)  -0.33357    0.08184  -4.076 4.58e-05 ***
P1.Rank      -0.25520    0.10926  -2.336   0.0195 *
P2.Rank      -0.01353    0.10409  -0.130   0.8966
Lag.Set.P1   0.61337    0.11380   5.390 7.05e-08 ***
P1.PS.pct    0.55073    0.07837   7.027 2.11e-12 ***
P2.PS.pct   -0.74458    0.08178  -9.105  < 2e-16 ***
P1.PR.pct    0.27648    0.07450   3.707  0.00021 ***
P2.PR.pct   -0.44275    0.07430  -5.959 2.54e-09 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 2362.2 on 1703 degrees of freedom
Residual deviance: 1936.5 on 1696 degrees of freedom
(869 observations deleted due to missingness)
AIC: 1952.5
Number of Fisher Scoring iterations: 4

> summary(w.model3f)
Call:
glm(formula = P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + Lag.Set.P1 + P1.PS.pct + P2.PS.pct +
P1.PR.pct + P2.PR.pct, family = binomial, data = w.sbs.scaled.women.sub3, na.action = na.exclude)
Deviance Residuals:
Min      1Q  Median      3Q     Max
-2.1577  -0.9591   0.4548   0.9249   2.1775
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.39559    0.11283  -3.506 0.000455 ***
P1.Rank      -0.11555    0.08923  -1.295 0.195344
P2.Rank       0.08151    0.09674   0.843 0.399484
Lag.Set.P1   1.05505    0.15860   6.652 2.88e-11 ***
P1.PS.pct    0.50205    0.09187   5.465 4.64e-08 ***
P2.PS.pct   -0.31959    0.09054  -3.530 0.000416 ***
P1.PR.pct    0.22382    0.08853   2.528 0.011463 *
P2.PR.pct   -0.35917    0.09294  -3.865 0.000111 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 1153.4 on 833 degrees of freedom
Residual deviance:  965.0  on 826 degrees of freedom
(808 observations deleted due to missingness)
AIC: 981
Number of Fisher Scoring iterations: 4
```r
> summary(uso.model3m)

Call:

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1446  -0.9740   0.4928   0.9534   2.1046

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.12753    0.08011  -1.592  0.11140
P1.Rank      -0.35474    0.11331  -3.131  0.00174 **
P2.Rank       0.24772    0.08658   2.861  0.00422 **
Lag.Set.P1    0.58226    0.11006   5.290 1.22e-07 ***
P1.PS.pct     0.45147    0.07596   5.943 2.80e-09 ***
P2.PS.pct    -0.33998    0.07040  -4.829 1.37e-06 ***
P1.PR.pct     0.45430    0.06812   6.669 2.58e-11 ***
P2.PR.pct    -0.28253    0.06451  -4.380 1.19e-05 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2400.9  on 1738  degrees of freedom
Residual deviance: 2031.6  on 1731  degrees of freedom

(842 observations deleted due to missingness)

AIC: 2047.6
Number of Fisher Scoring iterations: 4
```

**Diagram**

Standardized Residuals (Male)

-3 -2 -1 0 1 2 3

Index

Standardized Residuals (Female)

-3 -2 -1 0 1 2 3

Index

---

**Signif. codes:**  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2400.9  on 1738  degrees of freedom
Residual deviance: 2031.6  on 1731  degrees of freedom

(842 observations deleted due to missingness)

AIC: 2047.6
Number of Fisher Scoring iterations: 4
> summary(uso.model3f)

Call:

Deviance Residuals:
               Min        1Q   Median        3Q       Max
-2.1376     -1.0301   0.2899     1.0090     2.0253

Coefficients:
                     Estimate  Std. Error z value Pr(>|z|)
(Intercept)       -0.13675    0.10749  -1.272 0.203301
P1.Rank            -0.09482    0.08566  -1.107 0.268337
P2.Rank             0.05889    0.09128   0.645 0.518779
Lag.Set.P1         0.35617    0.15125   2.355 0.018533 *
P1.PS.pct          0.48282    0.08749   5.519 3.42e-08 ***
P2.PS.pct          -0.51614    0.09204  -5.608 2.05e-08 ***
P1.PR.pct           0.42940    0.09204   4.823 1.41e-06 ***
P2.PR.pct          -0.30527    0.08454  -3.611 0.000305 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1225.4  on 883  degrees of freedom
Residual deviance: 1063.3  on 876  degrees of freedom

(865 observations deleted due to missingness)

AIC: 1079.3

Number of Fisher Scoring iterations: 4

Model 4
> summary(aus.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

  Family: binomial  ( logit )


  Data: aus.sbs.scaled.men

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

  AIC      BIC   logLik deviance df.resid
  1935.3   1984.0   -958.7   1917.3     1638

Scaled residuals:

  Min      1Q  Median      3Q     Max
  -6.1811 -0.7765  0.2755  0.7648  3.8005

Random effects:

  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.07511  0.2741

Number of obs: 1647, groups:  Match.ID, 618

Fixed effects:

  Estimate Std. Error z value  Pr(>|z|)
 (Intercept)  -0.11816    0.10106  -1.169   0.2423
  P1.Rank      -0.07666    0.12973  -0.591   0.5546
  P2.Rank      0.42898    0.10990   3.903 9.49e-05 ***
  Lag.Set.P1   0.44842    0.14831   3.024   0.0025 **
  P1.PS.pct    0.51328    0.08514   6.029 1.65e-09 ***
  P2.PS.pct   -0.44085    0.08797  -5.011 5.41e-07 ***
  P1.PR.pct    0.48518    0.08234   5.892 3.81e-09 ***
  P2.PR.pct   -0.33006    0.07791  -4.236 2.27e-05 ***

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

  (Intr) P1.Rnk P2.Rnk L.S.P1 P1.PS. P2.PS. P1.PR.
P1.Rank      0.184
P2.Rank      0.235 -0.027
Lag.Set.P1   -0.787  0.030 -0.128
P1.PS.pct    0.427  0.535  0.117 -0.357
P2.PS.pct   -0.208  0.066  0.456  0.352 -0.260
P1.PR.pct    0.402  0.458  0.108 -0.360  0.531 -0.216
P2.PR.pct   -0.145 -0.006  0.467  0.258 -0.213  0.510 -0.238
> summary(w.model4m)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Data: w.sbs.scaled.men.sub4

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC     BIC   logLik deviance df.resid
1952.7   2001.6   -967.3   1934.7     1695

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6941 -0.7152  0.1945  0.7043  3.4076

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.2184   0.4673
Number of obs: 1704, groups:  Match.ID, 641

Fixed effects:
                Estimate Std. Error  z value Pr(>|z|)
(Intercept)  -0.28099    0.09597  -2.928  0.003412 **
P1.Rank     -0.27592    0.11927  -2.313  0.020701 *
P2.Rank     -0.01730    0.11292  -0.153  0.878242  
Lag.Set.P1    0.50372    0.14571   3.457  0.000546 ***
P1.PS.pct    0.59879    0.09311   6.431  1.27e-10 ***
P2.PS.pct   -0.81520    0.10485  -7.775  7.54e-15 ***
P1.PR.pct   -0.48315    0.08641  -5.602  2.25e-08 ***
P2.PR.pct   -0.48315    0.08641  -5.602  2.25e-08 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<tr>
<th></th>
<th>(Intr)</th>
<th>P1.Rnk</th>
<th>P2.Rnk</th>
<th>L.S.P1</th>
<th>P1.PS.</th>
<th>P2.PS.</th>
<th>P1.PR.</th>
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<td>P1.Rank</td>
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<td>P2.Rank</td>
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<td>Lag.Set.P1</td>
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<td>0.016</td>
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<td>P1.PS.pct</td>
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<td>-0.010</td>
<td>-0.326</td>
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<tr>
<td>P2.PS.pct</td>
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<td>0.530</td>
<td>0.426</td>
<td>-0.369</td>
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<tr>
<td>P1.PR.pct</td>
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<td>0.020</td>
<td>-0.221</td>
<td>0.509</td>
<td>-0.210</td>
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<tr>
<td>P2.PR.pct</td>
<td>-0.115</td>
<td>0.063</td>
<td>0.550</td>
<td>0.292</td>
<td>-0.225</td>
<td>0.601</td>
<td>-0.148</td>
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</tbody>
</table>

> summary(uso.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )


Data: uso.sbs.scaled.men.sub4

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
2015.0   2064.1   -998.5   1997.0     1723

Scaled residuals:

<table>
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<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
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<td>-2.7537</td>
<td>-0.7371</td>
<td>0.3083</td>
<td>0.7131</td>
<td>2.7609</td>
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Random effects:

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<th>Std.Dev.</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Match.ID (Intercept)</td>
<td>0.2744</td>
<td>0.5239</td>
</tr>
</tbody>
</table>

Number of obs: 1732, groups: Match.ID, 646

Fixed effects:

|                    | Estimate | Std. Error | z value | Pr(>|z|) |
|--------------------|----------|------------|---------|---------|
| (Intercept)        | -0.02549 | 0.10204    | -0.250  | 0.80271 |
P1.Rank  -0.36958  0.12514  -2.953  0.00314  **  
P2.Rank  0.28163  0.09776   2.881  0.00397  **  
Lag.Set.P1  0.45840  0.14098   3.252  0.00115  **  
P1.PS.pct  0.54956  0.09273   5.926 3.10e-09  ***  
P2.PS.pct  -0.40499  0.08475  -4.779 1.77e-06  ***  
P1.PR.pct  0.55304  0.07547   6.533 7.89e-11  ***  
P2.PR.pct  -0.33721  0.07547  -4.468 7.89e-06  ***  
---  
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
   (Intr) P1.Rnk P2.Rnk L.S.P1 P1.PS. P2.PS. P1.PR.
P1.Rank  0.080  
P2.Rank  0.199  0.016  
Lag.Set.P1  -0.780  0.094 -0.125  
P1.PS.pct  0.396  0.519  0.144 -0.306  
P2.PS.pct  -0.211  0.111  0.462  0.290 -0.171  
P1.PR.pct  0.390  0.366  0.144 -0.321  0.590 -0.191  
P2.PR.pct  -0.168  0.107  0.398  0.235 -0.106  0.492 -0.201

Goodness-of-Fit Tests (Chi-Square)

**Australian Open**

> anova(pure.aus.model1m, pure.aus.model0m)

Data: pure.aus.sbs.scaled.men

Models:
pure.aus.model0m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank
pure.aus.model1m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
### Model Comparison

#### Models:

- **pure.aus.model0m**: \( P1..\text{Set.Winner}..SBS. \sim P1.Rank + P2.Rank \)
- **pure.aus.model1m**: \( P1..\text{Set.Winner}..SBS. \sim P1.Rank + P2.Rank + (1 | \text{Match.ID}) \)
- **pure.aus.model2m**: \( P1..\text{Set.Winner}..SBS. \sim P1.Rank + P2.Rank + P1.Age + P2.Age + P1.PS.pct \)

#### Parameters:

- **AIC**
- **BIC**
- **logLik**
- **deviance**
- **Chisq**
- **Chi Df**
- **Pr(>Chisq)**

#### Results:

- **pure.aus.model0m**
  - AIC: 2062.8
  - BIC: 2079.0
  - logLik: -1028.4
  - deviance: 2056.8
- **pure.aus.model1m**
  - AIC: 2049.1
  - BIC: 2070.7
  - logLik: -1020.5
  - deviance: 2041.1
  - Chisq: 15.742
  - Chi Df: 1
  - Pr(>Chisq): 7.26e-05

#### Significance Codes:

- \('***'\): 0.001
- \('**'\): 0.01
- \('*'\): 0.05
- \('.\'\): 0.1
- \(' '\): 1

### ANOVA Comparisons

- **anova(pure.aus.model2m, pure.aus.model1m)**
  - Data: pure.aus.sbs.scaled.men
  - Models:
    - **pure.aus.model1m**: \( P1..\text{Set.Winner}..SBS. \sim P1.Rank + P2.Rank + (1 | \text{Match.ID}) \)
    - **pure.aus.model2m**: \( P1..\text{Set.Winner}..SBS. \sim P1.Rank + P2.Rank + P1.Age + P2.Age + P1.PS.pct \)
  - Df: 4
  - AIC: 2049.1
  - BIC: 2070.7
  - logLik: -1020.54
  - deviance: 2041.1
  - Chisq: 117.34
  - Chi Df: 7
  - Pr(>Chisq): < 2.2e-16

### Additional Models

- **pure.aus.model3m**
  - AIC: 1933.5
  - BIC: 1976.8
  - logLik: -958.78
  - deviance: 1917.5

- **pure.aus.model2f**
  - AIC: 1094
  - BIC: 1112.9
  - logLik: -542.99
  - deviance: 1086
  - Chisq: 0.0315
  - Chi Df: 1
  - Pr(>Chisq): 0.8592

### Further Comparisons

- **anova(pure.aus.model1f, pure.aus.model0f)**
  - Data: pure.aus.sbs.scaled.women
  - Models:
    - **pure.aus.model0f**: \( P1..\text{Set.Winner}..SBS. \sim P1.Rank + P2.Rank \)
    - **pure.aus.model1f**: \( P1..\text{Set.Winner}..SBS. \sim P1.Rank + P2.Rank + (1 | \text{Match.ID}) \)
  - Df: 3
  - AIC: 1092
  - BIC: 1106.2
  - logLik: -543.00
  - deviance: 1086

- **anova(pure.aus.model2f, pure.aus.model1f)**
  - Data: pure.aus.sbs.scaled.women
  - Models:
pure.aus.model1f: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
pure.aus.model2f: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 | Match.ID)

Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
pure.aus.model1f  4 1093.98 1112.9 -542.99  1085.98
pure.aus.model2f 11  995.11 1047.2 -486.56   973.11 112.86      7 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model2f, pure.aus.model3f)
Data: pure.aus.sbs.scaled.women
Models:
pure.aus.model3f: P2.PS.pct + P1.PR.pct + P2.PR.pct
pure.aus.model2f: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 | Match.ID)

Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
pure.aus.model3f  8 967.57 1005.4 -475.79   951.57
pure.aus.model2f 11  995.11 1047.2 -486.56   973.11     0      3          1

French Open

> anova(pure.fo.model1m, pure.fo.model0m)
Data: pure.fo.sbs.scaled.men
Models:
pure.fo.model0m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank
pure.fo.model1m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)

Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model0m  3 2008.4 2024.7 -1001.18   2002.4
pure.fo.model1m  4 1989.3 2011.0  -990.66   1981.3 21.034      1  4.512e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model2m, pure.fo.model1m)
Data: pure.fo.sbs.scaled.men
Models:
pure.fo.model1m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
pure.fo.model2m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + P1.Age + P2.Age +
pure.fo.model2m: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 | Match.ID)

Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
> anova(pure.fo.model2m, pure.fo.model3m)
Data: pure.fo.sbs.scaled.men
Models:
pure.fo.model3m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + Lag.Set.P1 + P1.PS.pct + 
pure.fo.model3m: P2.PS.pct + P1.PR.pct + P2.PR.pct
pure.fo.model2m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + P1.Age + P2.Age + 
pure.fo.model2m: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 | 
pure.fo.model2m: Match.ID)
Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model3m  8 1871.6 1915.0 -927.79   1855.6
pure.fo.model2m 11 1903.8 1963.5 -940.92   1881.8     0      3          1

> anova(pure.fo.model1f, pure.fo.model0f)
Data: pure.fo.sbs.scaled.women
Models:
pure.fo.model0f: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank
pure.fo.model1f: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model0f  3 1149.4 1163.7 -571.71   1143.4
pure.fo.model1f  4 1149.0 1168.1 -570.50   1141.0 2.4131      1     0.1203

> anova(pure.fo.model2f, pure.fo.model1f)
Data: pure.fo.sbs.scaled.women
Models:
pure.fo.model1f: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
pure.fo.model2f: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 | 
pure.fo.model2f: Match.ID)
Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model1f  4 1149.0 1168.1 -570.50   1141.0
pure.fo.model2f 11 1033.7 1086.1 -505.86   1011.7 129.28      7  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model2f, pure.fo.model3f)
Data: pure.fo.sbs.scaled.women
Models:

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
pure.fo.model3f: P2.PS.pct + P1.PR.pct + P2.PR.pct
pure.fo.model2f: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 |
pure.fo.model2f: Match.ID)

Df AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.fo.model3f  8  996.94 1035.1 -490.47   980.94
pure.fo.model2f 11 1033.72 1086.1 -505.86  1011.72     0      3          1

**Wimbledon**

> anova(pure.w.model1m, pure.w.model0m)
Data: pure.w.sbs.scaled.men
Models:
pure.w.model0m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank
pure.w.model1m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)

Df AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.w.model0m  3 2150.5 2166.8 -1072.3   2144.5
pure.w.model1m  4 2120.3 2142.1 -1056.2   2112.3 32.22      1  1.377e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model2m, pure.w.model1m)
Data: pure.w.sbs.scaled.men
Models:
pure.w.model1m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
pure.w.model2m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + P1.Age + P2.Age +
pure.w.model2m: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 |
pure.w.model2m: Match.ID)

Df AIC   BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model1m  4 2120.3 2142.1 -1056.16   2112.3 
pure.w.model2m 11 1972.5 2032.3  -975.25   1950.5 161.81      7  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model2m, pure.w.model3m)
Data: pure.w.sbs.scaled.men
Models:
pure.w.model3m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + Lag.Set.P1 + P1.PS.pct +
pure.w.model3m: P2.PS.pct + P1.PR.pct + P2.PR.pct
pure.w.model2m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + P1.Age + P2.Age +
pure.w.model2m: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 |
> anova(pure.w.model1f, pure.w.model0f)
> anova(pure.w.model2f, pure.w.model1f)
> anova(pure.w.model2f, pure.w.model0f)
> anova(pure.w.model2f, pure.w.model3f)
US Open

> anova(pure.uso.model1m, pure.uso.model0m)
Data: pure.uso.sbs.scaled.men
Models:
pure.uso.model0m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank
pure.uso.model1m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)

Df  AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.uso.model0m  3 2206.0 2222.4 -1100.0   2200.0
pure.uso.model1m  4 2189.6 2211.4 -1090.8   2181.6 18.387      1  1.803e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model2m, pure.uso.model1m)
Data: pure.uso.sbs.scaled.men
Models:
pure.uso.model1m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + (1 | Match.ID)
   P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 |
   Match.ID)

Df  AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.uso.model1m  4 2189.6 2211.4 -1090.8   2181.6
pure.uso.model2m 11 2098.6 2158.7 -1038.3   2076.6 104.97      7  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model3m, pure.uso.model2m)
Data: pure.uso.sbs.scaled.men
Models:
   P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct
pure.uso.model3m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + Lag.Set.P1 + P1.PS.pct +
   P2.PS.pct + P1.PR.pct + P2.PR.pct

Df  AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.uso.model2m 11 2098.6 2158.7 -1038.3   2076.6
pure.uso.model3m  8  981.0 1018.8 -482.5    965.0

105
pure.uso.model2m: P1.PS.pct + P2.PS.pct + P1.PR.pct + P2.PR.pct + Round + (1 | Match.ID)

<table>
<thead>
<tr>
<th>Df</th>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pure.uso.model3m</td>
<td>8 2084.1  2127.9</td>
<td>-1034.1</td>
<td>2068.1</td>
<td>pure.uso.model2m</td>
<td>11 2098.6  2158.7</td>
<td>-1038.3</td>
<td>2076.6  0  3  1</td>
</tr>
</tbody>
</table>

> anova(pure.uso.model4m, pure.uso.model3m)

Data: pure.uso.sbs.scaled.men

Models:

pure.uso.model3m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + Lag.Set.P1 + P1.PS.pct +
pure.uso.model3m: P2.PS.pct + P1.PR.pct + P2.PR.pct
pure.uso.model4m: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank + Lag.Set.P1 + P1.PS.pct +
pure.uso.model4m: P2.PS.pct + P1.PR.pct + P2.PR.pct + (1 | Match.ID)

<table>
<thead>
<tr>
<th>Df</th>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pure.uso.model3m</td>
<td>8 2084.1  2127.9</td>
<td>-1034.1</td>
<td>2068.1</td>
<td>pure.uso.model4m</td>
<td>9 2085.0  2134.1</td>
<td>-1033.5</td>
<td>2067.0  1 0.2773</td>
</tr>
</tbody>
</table>

# on subset data, model 1 & 2 were singular for females

> anova(pure.uso.model3f, pure.uso.model0f)

Analysis of Deviance Table

P2.PS.pct + P1.PR.pct + P2.PR.pct
Model 2: P1..Set.Winner..SBS. ~ P1.Rank + P2.Rank

<table>
<thead>
<tr>
<th>Resid. Df</th>
<th>Resid. Dev</th>
<th>Df</th>
<th>Deviance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>878</td>
<td>874</td>
<td>1074.0</td>
</tr>
<tr>
<td>2</td>
<td>883</td>
<td>882</td>
<td>1176.6</td>
</tr>
</tbody>
</table>

Game Level R Output

Model Output

Model 0

> summary(aus.model0m)

Call:

glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
data = aus.gbg.scaled.men, na.action = na.exclude)

Deviance Residuals:

<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.6049</td>
<td>-0.8190</td>
<td>0.8035</td>
<td>0.8035</td>
<td>1.5847</td>
</tr>
</tbody>
</table>

Coefficients:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -0.92025   | 0.01962 | -46.91   | <2e-16 *** |
P1..Service..GBG.  1.88520    0.02788   67.61   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 35353  on 25502 degrees of freedom
Residual deviance: 30261  on 25501 degrees of freedom
AIC: 30265
Number of Fisher Scoring iterations: 4

> summary(aus.model0f)
Call:
glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
data = aus.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
Min       1Q   Median       3Q      Max
-1.4431  -0.9352   0.9332   0.9332   1.4407
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.60044    0.02408  -24.94   <2e-16 ***
P1..Service..GBG.  1.20619    0.03409   35.38   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 20871  on 15054 degrees of freedom
Residual deviance: 19562  on 15053 degrees of freedom
AIC: 19566
Number of Fisher Scoring iterations: 4
> summary(fo.model0m)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
      data = fo.gbg.scaled.men, na.action = na.exclude)
Deviance Residuals:
       Min        1Q   Median        3Q       Max
  -1.5664    -0.8448    0.8331    0.8331    1.5515
Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.84680    0.01960   -43.2   <2e-16 ***
P1..Service..GBG.  1.72664    0.02785    62.0   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 34266  on 24717  degrees of freedom
  Residual deviance: 30056  on 24716  degrees of freedom
  AIC: 30060
Number of Fisher Scoring iterations: 4

> summary(fo.model0f)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
      data = fo.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
       Min        1Q   Median        3Q       Max
  -1.3934    -0.9799    0.9758    0.9758    1.3887
Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.48424    0.02359  -20.53   <2e-16 ***
P1..Service..GBG.  0.97902    0.03335   29.37   <2e-16 ***
---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 21188  on 15283 degrees of freedom
Residual deviance: 20299  on 15282 degrees of freedom
AIC: 20303

Number of Fisher Scoring iterations: 4

> summary(w.model0m)

Call:
glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
data = w.gbg.scaled.men, na.action = na.exclude)

Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.6107  -0.8078   0.7990   0.7990   1.5992

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.95252    0.01968  -48.40   <2e-16 ***
P1..Service..GBG.  1.93056    0.02793   69.11   <2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 35577  on 25663 degrees of freedom
Residual deviance: 30230  on 25662 degrees of freedom
AIC: 30234
Number of Fisher Scoring iterations: 4

> summary(w.model0f)
Call:
glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
    data = w.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
        Min       1Q   Median       3Q      Max
  -1.5033  -0.9066   0.8834   0.8834   1.4749
Coefficients:
             Estimate Std. Error z value  Pr(>|z|)
(Intercept)  -0.67669    0.02407  -28.11   <2e-16 ***
P1..Service..GBG.  1.41646    0.03423   41.38   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 21403  on 15440  degrees of freedom
    Residual deviance: 19582  on 15439  degrees of freedom
    AIC: 19586
Number of Fisher Scoring iterations: 4

> summary(uso.model0m)
Call:
glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
    data = uso.gbg.scaled.men, na.action = na.exclude)
Deviance Residuals:
        Min       1Q   Median       3Q      Max
  -1.5959  -0.8369   0.8103   0.8103   1.5615
Coefficients:
             Estimate Std. Error z value  Pr(>|z|)
(Intercept)       -0.86889    0.01949  -44.58   <2e-16 ***
P1..Service..GBG.  1.81406    0.02779   65.27   <2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 35042 on 25281 degrees of freedom
Residual deviance: 30334 on 25280 degrees of freedom
AIC: 30338
Number of Fisher Scoring iterations: 4

> summary(uso.model0f)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ P1..Service..GBG., family = "binomial",
      data = uso.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.4509  -0.9468   0.9266   0.9266   1.4270
Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)                -0.56991    0.02312  -24.65   <2e-16 ***
P1..Service..GBG.          1.19322    0.03286   36.31   <2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 22423 on 16175 degrees of freedom
Residual deviance: 21045 on 16174 degrees of freedom
AIC: 21049
Number of Fisher Scoring iterations: 4
Model 1

> summary(aus.model1m)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.,
  family = "binomial", data = aus.gbg.scaled.men, na.action = na.exclude)
Deviance Residuals:
  Min       1Q   Median       3Q      Max
-2.1577  -0.8309   0.5839   0.8147   2.3834
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.93543    0.02011  -46.51   <2e-16 ***
Rank.diff    -0.23643    0.01497  -15.80   <2e-16 ***
P1..Service..GBG.  1.91233    0.02865   66.76   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 34180  on 24656  degrees of freedom
  Residual deviance: 28968  on 24654  degrees of freedom
  (846 observations deleted due to missingness)
  AIC: 28974
Number of Fisher Scoring iterations: 4

> summary(aus.model1f)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.,
  family = "binomial", data = aus.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
  Min       1Q   Median       3Q      Max
-2.0432  -0.9743  -0.5282   0.9776   2.1062
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.63356    0.02538  -24.96   <2e-16 ***
Rank.diff    -0.29150    0.01887  -15.44   <2e-16 ***
P1..Service..GBG.  1.25643    0.03596   34.94   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 19297  on 13919  degrees of freedom
  Residual deviance: 17782  on 13917  degrees of freedom
  (1135 observations deleted due to missingness)
  AIC: 17788
Number of Fisher Scoring iterations: 4
> summary(fo.model1m)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.,
     family = "binomial", data = fo.gbg.scaled.men, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-2.3504  -0.8699   0.5995   0.8527   2.3289

Coefficients:
            Estimate Std. Error  z value Pr(>|z|)
(Intercept)  -0.86157    0.02003  -43.01   <2e-16 ***
  Rank.diff    -0.29073    0.01502  -19.36   <2e-16 ***
P1..Service..GBG.  1.75728    0.02854   61.58   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 33540  on 24194  degrees of freedom
Residual deviance: 29014  on 24192  degrees of freedom
(523 observations deleted due to missingness)
AIC: 29020
Number of Fisher Scoring iterations: 4

> summary(fo.model1f)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.,
     family = "binomial", data = fo.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-2.3504  -0.8699   0.5995   0.8527   2.3289

Coefficients:
            Estimate Std. Error  z value Pr(>|z|)
(Intercept)  -0.86157    0.02003  -43.01   <2e-16 ***
  Rank.diff    -0.29073    0.01502  -19.36   <2e-16 ***
P1..Service..GBG.  1.75728    0.02854   61.58   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 33540  on 24194  degrees of freedom
Residual deviance: 29014  on 24192  degrees of freedom
(523 observations deleted due to missingness)
AIC: 29020
Number of Fisher Scoring iterations: 4
Coefficients:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -0.49758 | 0.02468 | -20.16   | <2e-16 *** |
| Rank.diff | -0.23893 | 0.01791 | -13.34   | <2e-16 *** |
| P1..Service..GBG. | 1.00682 | 0.03490 | 28.85    | <2e-16 *** |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 19671 on 14189 degrees of freedom
Residual deviance: 18637 on 14187 degrees of freedom

(1094 observations deleted due to missingness)

AIC: 18643
Number of Fisher Scoring iterations: 4

---

> summary(w.model1m)

Call:

`glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG., family = "binomial", data = w.gbg.scaled.men, na.action = na.exclude)`

Deviance Residuals:

<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.1412</td>
<td>-0.8255</td>
<td>0.4888</td>
<td>0.8177</td>
<td>2.1521</td>
</tr>
</tbody>
</table>

Coefficients:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -0.97127 | 0.02004 | -48.45   | <2e-16 *** |
| Rank.diff | -0.25884 | 0.01474 | -17.57   | <2e-16 *** |
| P1..Service..GBG. | 1.96563 | 0.02853 | 68.91    | <2e-16 *** |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 35009 on 25253 degrees of freedom
Residual deviance: 29388 on 25251 degrees of freedom
   (410 observations deleted due to missingness)
AIC: 29394
Number of Fisher Scoring iterations: 4

> summary(w.model1f)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.,
     family = "binomial", data = w.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.9100  -0.9412   0.7100   0.9195   1.8872

Coefficients:
                Estimate Std. Error  z value Pr(>|z|)
(Intercept)      -0.67613    0.02535  -26.67   <2e-16 ***
Rank.diff       -0.23559    0.01843  -12.78   <2e-16 ***
P1..Service..GBG. 1.44125    0.03619   39.83   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 19521  on 14084 degrees of freedom
Residual deviance: 17675  on 14082 degrees of freedom
   (1356 observations deleted due to missingness)
AIC: 17681
Number of Fisher Scoring iterations: 4

> summary(uso.model1m)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.,
    family = "binomial", data = uso.gbg.scaled.men, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-2.4021  -0.8509   0.6680   0.8242   2.2705
Coefficients:
                           Estimate Std. Error z value  Pr(>|z|)
(Intercept)                -0.88059    0.01987  -44.33   <2e-16 ***
Rank.diff                 -0.23055    0.01512  -15.25   <2e-16 ***
P1..Service..GBG.         1.84707    0.02841   65.02   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 34226  on 24693  degrees of freedom
Residual deviance: 29310  on 24691  degrees of freedom
   (588 observations deleted due to missingness)
AIC: 29316
Number of Fisher Scoring iterations: 4

> summary(uso.model1f)
Call:
  glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.,
      family = "binomial", data = uso.gbg.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.8259  -0.9821   0.7224   0.9723   1.8504
Coefficients:
                          Estimate Std. Error z value  Pr(>|z|)
(Intercept)                -0.58278    0.02450  -23.78   <2e-16 ***
Rank.diff                 -0.21717    0.01778  -12.21   <2e-16 ***
P1..Service..GBG.         1.20207    0.03482   34.53   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 20247  on 14605  degrees of freedom
Residual deviance: 18857  on 14603  degrees of freedom
   (1570 observations deleted due to missingness)
AIC: 18863
Number of Fisher Scoring iterations: 4
Model 2

> summary(aus.model2m)

Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG., family = "binomial", data = aus.gbg.scaled.men,
na.action = na.exclude)

Deviance Residuals:
Min       1Q   Median       3Q      Max
-2.2694  -0.8607   0.5565   0.8468   2.0417

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.93455    0.02111 -44.262   <2e-16 ***
Rank.diff         -0.06087    0.02971  -2.048   0.0405 *
PS.pct.diff        0.25559    0.01839  13.895   <2e-16 ***
PR.pct.diff        0.21288    0.01768  12.043   <2e-16 ***
P1..Service..GBG.  1.92136    0.03016  63.705   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 31526  on 22742  degrees of freedom
Residual deviance: 26491  on 22738  degrees of freedom
(2760 observations deleted due to missingness)
AIC: 26501

Number of Fisher Scoring iterations: 4
> summary(aus.model2f)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + 
    PR.pct.diff + P1..Service..GBG., family = "binomial", data = aus.gbg.scaled.women,
    na.action = na.exclude)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1752  -1.0101  -0.4611   1.0033   2.2573

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.64753    0.02576 -25.139  < 2e-16 ***
Rank.diff         -0.10337    0.02184  -4.733 2.21e-06 ***
PS.pct.diff        0.29413    0.02049  14.356  < 2e-16 ***
PR.pct.diff        0.17343    0.02059   8.424  < 2e-16 ***
P1..Service..GBG.  1.28183    0.03655  35.066  < 2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 19239  on 13877  degrees of freedom
Residual deviance: 17424  on 13873  degrees of freedom

(1177 observations deleted due to missingness)
AIC: 17434
Number of Fisher Scoring iterations: 4

> summary(fo.model2m)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + 
    PR.pct.diff + P1..Service..GBG., family = "binomial", data = fo.gbg.scaled.men.sub2,
    na.action = na.exclude)

Standardized Residuals (Male)

Standardized Residuals (Female)
Deviance Residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-2.1307</td>
<td>-0.8939</td>
<td></td>
<td>0.5160</td>
<td>0.8793</td>
</tr>
</tbody>
</table>

Coefficients:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|---------|
| (Intercept)    | -0.89693 | 0.02123    | -42.24  | <2e-16  *** |
| Rank.diff      | -0.12327 | 0.02971    | -4.15   | 3.33e-05 *** |
| PS.pct.diff    | 0.24180  | 0.02039    | 11.86   | <2e-16  *** |
| PR.pct.diff    | 0.27460  | 0.01863    | 14.74   | <2e-16  *** |
| P1..Service..GBG. | 1.82589 | 0.03035    | 60.15   | <2e-16  *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 30898 on 22288 degrees of freedom
Residual deviance: 26186 on 22284 degrees of freedom
(2425 observations deleted due to missingness)
AIC: 26196

Number of Fisher Scoring iterations: 4
> summary(w.model2m)

Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + 
PR.pct.diff + P1..Service..GBG., family = "binomial", data = w.gbg.scaled.men.sub2, 
n.a.action = na.exclude)

Deviance Residuals:
  Min       1Q   Median       3Q      Max
-2.0509  -0.8596   0.5129   0.8427   2.0516

Coefficients:
            Estimate Std. Error  z value Pr(>|z|)
(Intercept)   -0.97318    0.02090  -46.564   <2e-16 ***
Rank.diff     -0.02760    0.02622   -1.052    0.293
PS.pct.diff    0.28734    0.01934  14.859   <2e-16 ***
PR.pct.diff    0.19642    0.01762  11.147   <2e-16 ***
P1..Service..GBG.  1.97091    0.02982  66.098   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 32571  on 23494  degrees of freedom
Residual deviance: 27183  on 23490  degrees of freedom

(2169 observations deleted due to missingness)

AIC: 27193

Number of Fisher Scoring iterations: 4

> summary(w.model2f)

Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + 
PR.pct.diff + P1..Service..GBG., family = "binomial", data = w.gbg.scaled.women.sub2, 
n.a.action = na.exclude)

Deviance Residuals:
<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.1180</td>
<td>-0.9629</td>
<td>0.6241</td>
<td>0.9497</td>
<td>1.8982</td>
</tr>
</tbody>
</table>

Coefficients:

|                      | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------------|----------|------------|---------|---------|
| (Intercept)          | -0.68818 | 0.02569    | -26.788 | < 2e-16 *** |
| Rank.diff            | -0.06616 | 0.02137    | -3.095  | 0.00197 **  |
| PS.pct.diff          | 0.26339  | 0.01985    | 13.269  | < 2e-16 *** |
| PR.pct.diff          | 0.19259  | 0.02037    | 9.453   | < 2e-16 *** |
| P1..Service..GBG.    | 1.47467  | 0.03676    | 40.112  | < 2e-16 *** |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 19445 on 14030 degrees of freedom
Residual deviance: 17345 on 14026 degrees of freedom

(1406 observations deleted due to missingness)

AIC: 17355

Number of Fisher Scoring iterations: 4

> summary(uso.model2m)

Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + P1..Service..GBG., family = "binomial", data = uso.gbg.scaled.men,
    na.action = na.exclude)

Deviance Residuals:

<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.1108</td>
<td>-0.8715</td>
<td>0.5821</td>
<td>0.8500</td>
<td>1.9926</td>
</tr>
</tbody>
</table>

Coefficients:

|                      | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------------|----------|------------|---------|---------|
| (Intercept)          | -0.89105 | 0.02056    | -43.331 | < 2e-16 *** |
| Rank.diff            | -0.10277 | 0.02706    | -3.798  | 0.000146 *** |
| PS.pct.diff          | 0.22523  | 0.01838    | 12.252  | < 2e-16 *** |
| PR.pct.diff          | 0.20555  | 0.01650    | 12.457  | < 2e-16 *** |
> summary(uso.model2f)

Call:
  glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
      PR.pct.diff + P1..Service..GBG., family = "binomial", data = uso.gbg.scaled.women,
      na.action = na.exclude)

Deviance Residuals:
  Min       1Q   Median       3Q      Max
-2.0084  -1.0162   0.5623   1.0094   2.0671

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.59619    0.02497 -23.874   <2e-16 ***
Rank.diff     -0.02272    0.02115  -1.074    0.283
PS.pct.diff    0.30906    0.01999  15.460   <2e-16 ***
PR.pct.diff    0.18785    0.01928   9.743   <2e-16 ***
P1..Service..GBG. 1.22803    0.03554  34.553   <2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

  Null deviance: 20005  on 14430 degrees of freedom
  Residual deviance: 18315  on 14426 degrees of freedom
  (1745 observations deleted due to missingness)
AIC: 18325

Number of Fisher Scoring iterations: 4
Model 3

> summary(aus.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: aus.gbg.scaled.men

AIC      BIC   logLik deviance df.resid
26486.8  26535.0 -13237.4  26474.8    22737

Scaled residuals:

          Min      1Q  Median      3Q     Max
-3.6733 -0.6688  0.3971  0.6557  2.7170

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.03895  0.1974

Number of obs: 22743, groups:  Match.ID, 628

Fixed effects:

                     Estimate Std. Error z value  Pr(>|z|)
(Intercept)          -0.94005    0.02275  -41.322 <2e-16 ***
Rank.diff            -0.06117    0.03389  -1.805   0.0711 .
PS.pct.diff          0.26489    0.02098  12.623   <2e-16 ***
PR.pct.diff          0.22082    0.02012  10.976   <2e-16 ***
P1..Service..GBG.    1.93713    0.03060  63.303   <2e-16 ***
> summary(aus.model3f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: aus.gbg.scaled.women

AIC      BIC   logLik deviance df.resid
17375.4  17420.6  -8681.7  17363.4    13872

Scaled residuals:
Min      1Q  Median      3Q     Max
-3.1036 -0.7976 -0.3479  0.7968  3.3692

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.1316   0.3628

Number of obs: 13878, groups:  Match.ID, 657

Fixed effects:

                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.66426    0.03001 -22.138  < 2e-16 ***
Rank.diff        -0.11004    0.02795  -3.937 8.25e-05 ***
PS.pct.diff       0.31398    0.02611  12.027  < 2e-16 ***
PR.pct.diff       0.18746    0.02627   7.136 9.62e-13 ***
P1..Service..GBG. 1.31589    0.03743  35.154  < 2e-16 ***

---

Signif. codes:  0 ‘****’ 0.001 ‘***’ 0.01 ‘**’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

       (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff    0.066
PS.pct.diff -0.022  0.566
PR.pct.diff -0.020  0.515  0.345
P1..S..GBG. -0.661 -0.012  0.089  0.079

---

Signif. codes:  0 ‘****’ 0.001 ‘***’ 0.01 ‘**’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

       (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff    0.008
PS.pct.diff -0.046  0.331
PR.pct.diff -0.029  0.359 -0.080
P1..S..GBG. -0.624 -0.025  0.070  0.042

---
> summary(fo.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit)

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: fo.gbg.scaled.men.sub3

AIC      BIC   logLik deviance df.resid
26156.1  26204.2 -13072.0  26144.1    22285

Scaled residuals:
Min      1Q  Median      3Q     Max
-2.8326 -0.6903  0.3716  0.6860  2.9864

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.07592  0.2755

Number of obs: 22291, groups: Match.ID, 646

Fixed effects:

                   Estimate Std. Error   z value Pr(>|z|)
(Intercept)     -0.90852    0.02419  -37.562  < 2e-16 ***
Rank.diff       -0.12446    0.03678   -3.384  0.000714 ***
PS.pct.diff      0.25333    0.02534    9.998  < 2e-16 ***
PR.pct.diff      0.28905    0.02308   12.522  < 2e-16 ***
P1..Service..GBG. 1.85376    0.03096   59.882  < 2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

             (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff    0.036
PS.pct.diff  -0.024  0.665
PR.pct.diff  -0.038  0.571  0.435
P1..S..GBG. -0.633 -0.020  0.066  0.083
> summary(fo.model3f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: fo.gbg.scaled.women.sub3

AIC      BIC   logLik deviance df.resid
18118.2  18163.5  -9053.1  18106.2    14060

Scaled residuals:

Min      1Q  Median      3Q     Max
-2.9311 -0.8667  0.3412  0.8655  2.5975

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.1379   0.3714

Number of obs: 14066, groups:  Match.ID, 666

Fixed effects:

Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.52113    0.02948 -17.676   <2e-16 ***
Rank.diff         -0.02819    0.02797  -1.008    0.313
PS.pct.diff        0.28134    0.02671  10.535   <2e-16 ***
PR.pct.diff        0.25344    0.02619   9.678   <2e-16 ***
P1..Service..GBG.  1.05639    0.03629  29.111   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ’ 0.1 ’ 1

Correlation of Fixed Effects:

(Intr) Rnk.df PS.pc. PR.pc.
Rank.diff  0.000
PS.pct.diff -0.029  0.386
PR.pct.diff -0.024  0.354  0.034
P1..S..GBG. -0.616 -0.004  0.052  0.048
> summary(w.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: w.gbg.scaled.men

AIC      BIC   logLik deviance df.resid
27192.4  27240.8 -13590.2  27180.4    23489

Scaled residuals:
Min      1Q  Median      3Q     Max
-2.7130 -0.6619  0.3718  0.6517  2.6589

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.01583  0.1258

Number of obs: 23495, groups:  Match.ID, 642

Fixed effects:

Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.97695    0.02166 -45.104   <2e-16 ***
Rank.diff      -0.02813    0.02776  -1.013    0.311
PS.pct.diff     0.29201    0.02057  14.193   <2e-16 ***
PR.pct.diff     0.19937    0.01868  10.673   <2e-16 ***
P1..Service..GBG. 1.97764    0.03014  65.623   <2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

(Intr) Rnk.df PS.pc. PR.pc.
Rank.diff    -0.021
PS.pct.diff  -0.090  0.616
PR.pct.diff  -0.071  0.522  0.427
P1..S..GBG. -0.692 -0.010  0.103  0.079
> summary(w.model3f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: w.gbg.scaled.women

AIC      BIC   logLik deviance df.resid
17319.2  17364.4  -8653.6  17307.2    14029

Scaled residuals:
          Min      1Q  Median      3Q     Max
-2.9257 -0.7663  0.4292  0.7432  2.8983

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.1269   0.3563

Number of obs: 14035, groups:  Match.ID, 653

Fixed effects:

             Estimate Std. Error z value  Pr(>|z|)
(Intercept)  -0.70420    0.02980 -23.627  < 2e-16 ***
Rank.diff    -0.07157    0.02724  -2.627  0.00861 **
PS.pct.diff   0.28259    0.02513  11.244  < 2e-16 ***
PR.pct.diff   0.20139    0.02583   7.796  6.4e-15 ***
P1..Service..GBG.  1.51021    0.03773  40.032  < 2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

             (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff    0.019
PS.pct.diff  -0.046  0.326
PR.pct.diff  -0.028  0.401  0.072
P1..S..GBG.  -0.622 -0.018  0.078  0.055
> summary(uso.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: uso.gbg.scaled.men

AIC      BIC   logLik deviance df.resid
27474.8  27523.2 -13731.4  27462.8    23422

Scaled residuals:
Min      1Q  Median      3Q     Max
-2.8151 -0.6820  0.4292  0.6564  2.6273

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.05109  0.226

Number of obs: 23428, groups:  Match.ID, 647

Fixed effects:

                     Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.89795    0.02264 -39.657  < 2e-16 ***
Rank.diff         -0.10798    0.03224  -3.349  0.00081 ***
PS.pct.diff        0.23563    0.02173  10.844  < 2e-16 ***
PR.pct.diff        0.21515    0.01946  11.055  < 2e-16 ***
P1..Service..GBG.  1.90143    0.03003  63.311  < 2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

    (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff      0.022
PS.pct.diff   -0.041  0.580
PR.pct.diff   -0.045  0.430  0.359
P1..S..GBG.   -0.645 -0.025  0.073  0.077
> summary(uso.model3f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

Data: uso.gbg.scaled.women

AIC      BIC   logLik deviance df.resid
18258.5  18303.9  -9123.2  18246.5    14425

Scaled residuals:
Min      1Q  Median      3Q     Max
-2.7980 -0.8104  0.3907  0.8133  3.0704

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.1411   0.3756

Number of obs: 14431, groups: Match.ID, 666

Fixed effects:

             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.61208    0.02951 -20.743  < 2e-16 ***
Rank.diff    -0.02786    0.02780  -1.002    0.316
PS.pct.diff  0.33923    0.02623  12.933  < 2e-16 ***
PR.pct.diff  0.20197    0.02515   8.030 9.78e-16 ***
P1..Service..GBG.  1.26440    0.03644  34.701  < 2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

              (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff    -0.001
PS.pct.diff  -0.046  0.398
PR.pct.diff  -0.032  0.338  0.072
P1..S..GBG.  -0.612 -0.007  0.076  0.045

![Standardized Residuals (Male)](image1)

![Standardized Residuals (Female)](image2)
Model 4

> summary(aus.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Data: aus.gbg.scaled.men.sub4

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC   BIC   logLik deviance df.resid
24719.7 24783.7 -12351.8 24703.7    22079

Scaled residuals:
          Min     1Q Median     3Q    Max
-3.0615 -0.6629  0.2863  0.6585  3.0486

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.1884   0.4341

Number of obs: 22087, groups:  Match.ID, 628

Fixed effects:

                 Estimate Std. Error z value Pr(>|z|)
(Intercept)         -0.1917    0.04273  -4.487 7.23e-06 ***
Rank.diff          -0.0818    0.04705  -1.738   0.0822 .
PS.pct.diff         0.3704    0.02906  12.747  < 2e-16 ***
PR.pct.diff         0.3198    0.02780  11.503  < 2e-16 ***
P1..Service..GBG.   1.6120    0.04800  33.583  < 2e-16 ***
Lag1.Game.P1        -1.1209    0.04929 -22.742  < 2e-16 ***
P1..Service..GBG.:Lag1.Game.P1 -0.0778    0.06813  -1.142   0.2533

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

                 (Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L1.G.P
Rank.diff         0.039
PS.pct.diff       0.067  0.567
PR.pct.diff       0.051  0.514  0.338
P1..Sr..GBG.     -0.717 -0.001  0.030  0.038
Lag1.Game.P1     -0.745  0.012 -0.096 -0.074  0.611
P1..S..GBG.:Lag1.Game.P1 -0.683

> summary(aus.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Data: aus.gbg.scaled.women.sub4

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Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

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Number of obs: 13217, groups: Match.ID, 657

Fixed effects:

|                     | Estimate | Std. Error | z value | Pr(>|z|) |
|---------------------|----------|------------|---------|---------|
| (Intercept)         | -0.59413 | 0.04924    | -12.066 | < 2e-16 *** |
| Rank.diff           | -0.11092 | 0.02985    | -3.716  | 0.000203 *** |
| PS.pct.diff         | 0.33853  | 0.02817    | 12.019  | < 2e-16 *** |
| PR.pct.diff         | 0.19806  | 0.02815    | 7.036   | 1.98e-12 *** |
| P1..Service..GBG.   | 1.31637  | 0.05689    | 23.139  | < 2e-16 *** |
| Lag1.Game.P1        | -0.12062 | 0.05894    | -2.046  | 0.040717 * |
| P1..Service..GBG.:Lag1.Game.P1 | -0.10360 | 0.08069    | -1.284  | 0.199165 |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

```
     (Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L1.G.P
Rank.diff    -0.013
PS.pct.diff  0.039  0.323
PR.pct.diff  0.027  0.355 -0.068
P1..Sr..GBG. -0.750 -0.015  0.027  0.013
Lag1.Game.P1 -0.766  0.022 -0.092 -0.060  0.621
P1..S..GBG.:  0.538  0.013 -0.005  0.000 -0.713 -0.681
```
> summary(fo.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lagl.Game.P1) + (1 | Match.ID)

Data: fo.gbg.scaled.men.sub4

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
25032.5  25096.3 -12508.2  25016.5    21626

Scaled residuals:
                      Min      1Q  Median      3Q     Max
-3.0327 -0.6901  0.3037  0.6890  2.9982

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.1732   0.4162

Number of obs: 21634, groups:  Match.ID, 646

Fixed effects:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.44515 | 0.04285    | -10.389 | < 2e-16 *** |
| Rank.diff      | -0.14250 | 0.04457    | -3.197  | 0.00139 ** |
| PS.pct.diff    | 0.30569  | 0.03083    | 9.916   | < 2e-16 ***|
| PR.pct.diff    | 0.35313  | 0.02808    | 12.577  | < 2e-16 ***|
| P1..Service..GBG. | 1.64039 | 0.04778    | 34.335  | < 2e-16 ***|
| Lagl.Game.P1   | -0.69313 | 0.04932    | -14.055 | < 2e-16 ***|
| P1..Service..GBG.:Lagl.Game.P1 | -0.05531 | 0.06799 | -0.814 | 0.41588 |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

(Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L1.G.P
Rank.diff 0.003
PS.pct.diff 0.036 0.662
PR.pct.diff 0.039 0.567 0.432
P1..Sr..GBG. -0.742 0.000 0.025 0.034
Lagl.Game.P1 -0.762 0.026 -0.063 -0.076 0.637
P1..S..GBG.: 0.542 -0.008 -0.006 -0.013 -0.717 -0.685

133
> summary(fo.model4f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit)

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +  
          (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Data: fo.gbg.scaled.women.sub4

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
17280    17340    -8632    17264    13392

Scaled residuals:
        Min      1Q  Median      3Q     Max
-2.8734 -0.8629  0.2053  0.8689  2.7362

Random effects:

Groups   Name        Variance  Std.Dev.
Match.ID (Intercept)   0.1442    0.3797

Number of obs: 13400, groups: Match.ID, 666

Fixed effects:

             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.49426    0.04622 -10.693   <2e-16 ***
Rank.diff    -0.03221    0.02867  -1.124    0.261
PS.pct.diff  0.27400    0.02756   9.943   <2e-16 ***
PR.pct.diff  0.25926    0.02702   9.596   <2e-16 ***
P1..Service..GBG.  1.03252    0.05432  19.009   <2e-16 ***
Lag1.Game.P1   -0.04234    0.05637  -0.751    0.453
P1..Service..GBG.:Lag1.Game.P1  0.02291    0.07717   0.297    0.767

---

Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Correlation of Fixed Effects:

                        (Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L1.G.P
Rank.diff         -0.007
PS.pct.diff      0.044  0.382
PR.pct.diff      0.043  0.350 -0.021
P1..Sr..GBG.    -0.739 -0.001  0.016  0.010
Lag1.Game.P1     -0.757  0.012 -0.084 -0.077  0.605
P1..S..GBG.:     0.530 -0.003 -0.001  0.006 -0.711 -0.686
> summary(w.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
Data: w.gbg.scaled.men.sub4
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
24112.8  24177.1 -12048.4  24096.8    22747
Scaled residuals:
          Min      1Q  Median      3Q     Max
-3.2278 -0.6118  0.2152  0.6073  3.2011
Random effects:
  Groups   Name        Variance Std.Dev.
    Match.ID (Intercept) 0.2622   0.512
Number of obs: 22755, groups:  Match.ID, 642

Fixed effects:
                                 Estimate  Std. Error t value Pr(>|z|)
(Intercept)                           0.05271     0.04378  1.2044    0.229
Rank.diff                           -0.04618     0.04606  -1.0030    0.316
PS.pct.diff                         -0.04618     0.04606  -1.0030    0.316
PR.pct.diff                         -0.04618     0.04606  -1.0030    0.316
P1..Service..GBG.                  -0.34545     0.03383  -10.2620   <2e-16 ***
Lag1.Game.P1                       -1.57835     0.04868 -32.4250   <2e-16 ***
P1..Service..GBG.:Lag1.Game.P1       0.34545     0.03383  -10.2620   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:

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> summary(w.model4f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Data: w.gbg.scaled.women.sub4

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC    BIC   logLik deviance df.resid
16482  16542    -8233    16466    13373

Scaled residuals:

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Random effects:

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<td>Match.ID</td>
<td>(Intercept)</td>
<td>0.1708</td>
<td>0.4133</td>
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</table>

Number of obs: 13381, groups: Match.ID, 653

Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|---------|
| (Intercept) | -0.55724 | 0.05103 | -10.920 | < 2e-16 *** |
| Rank.diff | -0.07431 | 0.02941 | -2.527  | 0.011515 * |
| PS.pct.diff | 0.30168 | 0.02728 | 11.057  | < 2e-16 *** |
| PR.pct.diff | 0.21760 | 0.02798 | 7.778   | 7.4e-15 *** |
| P1..Service..GBG. | 1.42946 | 0.05827 | 24.533  | < 2e-16 *** |
| Lag1.Game.P1 | -0.23245 | 0.06026 | -3.858  | 0.000115 *** |
| P1..Service..GBG.:Lag1.Game.P1 | 0.05515 | 0.08223 | 0.671   | 0.502465 |

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

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summary(uso.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
Data: uso.gbg.scaled.men.sub4
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
26193.3  26257.6 -13088.6  26177.3    22755

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.0176 -0.6727  0.3514  0.6709  2.9879

Random effects:
  Groups   Name        Variance Std.Dev.
         Match.ID (Intercept) 0.1496   0.3867
Number of obs: 22763, groups:  Match.ID, 647

Fixed effects:
  Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.325033   0.041301 -7.870 3.55e-15 ***
Rank.diff      -0.136581   0.040743  -3.352 0.000802 ***
PS.pct.diff     0.295728   0.027324  10.823  < 2e-16 ***
PR.pct.diff     0.275578   0.024393  11.297  < 2e-16 ***
P1..Service..GBG. 1.617840   0.046773  34.589  < 2e-16 ***
Lag1.Game.P1   -0.830858   0.047634  -17.442  < 2e-16 ***
P1..Service..GBG.:Lag1.Game.P1 -0.008966   0.066090  -0.136  0.892089

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:

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<tr>
<th></th>
<th>(Intr)</th>
<th>Rank.diff</th>
<th>PS.pct.diff</th>
<th>PR.pct.diff</th>
<th>P1..Sr..GBG.</th>
<th>L1.G.P</th>
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<tbody>
<tr>
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<td>PR.pct.diff</td>
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<td>P1..Sr..GBG.</td>
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<tr>
<td>Lag1.Game.P1</td>
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<td>-0.082</td>
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<tr>
<td>P1..S..GBG.:</td>
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<td>0.001</td>
<td>0.004</td>
<td>0.003</td>
<td>-0.723</td>
<td>-0.688</td>
</tr>
</tbody>
</table>

> summary(uso.model4f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Data: uso.gbg.scaled.women.sub4

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
17448.5  17508.8  -8716.3  17432.5    13757

Scaled residuals:

<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.8525</td>
<td>-0.8176</td>
<td>0.3855</td>
<td>0.8155</td>
<td>2.9830</td>
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Random effects:

<table>
<thead>
<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
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</thead>
<tbody>
<tr>
<td>Match.ID (Intercept)</td>
<td>0.1793</td>
<td>0.4234</td>
<td></td>
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</tbody>
</table>

Number of obs: 13765, groups: Match.ID, 666

Fixed effects:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|---------|
| (Intercept)    | -0.528440| 0.048285   | -10.944 | < 2e-16 *** |
| Rank.diff      | -0.030724| 0.029694   | -1.035  | 0.3008   |
| PS.pct.diff    | 0.348340 | 0.028280   | 12.317  | < 2e-16 *** |
| PR.pct.diff    | 0.209644 | 0.026963   | 7.775   | 7.53e-15 *** |
| P1..Service..GBG. | 1.217078 | 0.055297   | 22.010  | < 2e-16 *** |
| Lag1.Game.P1   | -0.119610| 0.057399   | -2.084  | 0.0372 *  |
| P1..Service..GBG.:Lag1.Game.P1 | 0.004034 | 0.078519   | 0.051   | 0.9590   |

---

Signif. codes:  0 ‘***’ 0.001 ‘***’ 0.01 ‘**’ 0.05 ‘*’ 0.1 ‘.’ 1

Correlation of Fixed Effects:

<table>
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<tr>
<th></th>
<th>(Intr)</th>
<th>Rank.diff</th>
<th>PS.pct.diff</th>
<th>PR.pct.diff</th>
<th>P1..Sr..GBG.</th>
<th>L1.G.P</th>
</tr>
</thead>
<tbody>
<tr>
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<td>PS.pct.diff</td>
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<td>PR.pct.diff</td>
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<td>0.336</td>
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</table>
Model 5

> summary(aus.model5m)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
data = aus.gbg.scaled.men.sub5, na.action = na.exclude)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1221  -0.7801   0.5108   0.7950   2.1402

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)            -1.32297    0.02844 -46.512   <2e-16 ***
Rank.diff             -0.06174    0.03139  -1.967   0.0492 *
PS.pct.diff            0.21150    0.01952  10.835   <2e-16 ***
PR.pct.diff            0.18033    0.01882   9.584   <2e-16 ***
P1..Service..GBG.      1.53308    0.04661  32.894   <2e-16 ***
Lag2.Game.P1           1.22219    0.04583  26.666   <2e-16 ***
P1..Service..GBG.:Lag2.Game.P1 -0.10391    0.06512  -1.596   0.1105

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 29780  on 21483  degrees of freedom
Residual deviance: 23931  on 21477  degrees of freedom
(4016 observations deleted due to missingness)
AIC: 23945

Number of Fisher Scoring iterations: 4
> summary(aus.model5f)

Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
data = aus.gbg.scaled.women.sub5, na.action = na.exclude)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1127  -1.0040  -0.4698   1.0094   2.1410

Coefficients:
                               Estimate Std. Error z value Pr(>|z|)
(Intercept)                    -0.78584    0.03442 -22.832  < 2e-16 ***
Rank.diff                      -0.08500    0.02299  -3.697 0.000219 ***
PS.pct.diff                     0.29293    0.02180  13.438  < 2e-16 ***
PR.pct.diff                     0.16426    0.02177   7.544 4.55e-14 ***
P1..Service..GBG.              1.23413    0.05615  21.980  < 2e-16 ***
Lag2.Game.P1                   0.40075    0.05610   7.144 9.09e-13 ***
P1..Service..GBG.:Lag2.Game.P1 -0.13423    0.07883  -1.703 0.088626 .

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 17413  on 12560  degrees of freedom
(2491 observations deleted due to missingness)
Residual deviance: 15725  on 12554  degrees of freedom
AIC: 15739
Number of Fisher Scoring iterations: 4
> summary(fo.model5m)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
    data = fo.gbg.scaled.men.sub5, na.action = na.exclude)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
  -2.1352  -0.8626   0.4989   0.8754   2.1124
Coefficients:
                           Estimate Std. Error z value Pr(>|z|)
(Intercept)                  -1.16397    0.02777 -41.915  < 2e-16 ***
Rank.diff                     -0.11061    0.03113  -3.553 0.000381 ***
PS.pct.diff                    0.20571    0.02135   9.633  < 2e-16 ***
PR.pct.diff                    0.23992    0.01957  12.262  < 2e-16 ***
P1..Service..GBG.             1.57094    0.04661  33.705  < 2e-16 ***
Lag2.Game.P1                   0.84284    0.04589  18.366  < 2e-16 ***
P1..Service..GBG.:Lag2.Game.P1 -0.08343    0.06504  -1.283 0.199583
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 29103  on 20993 degrees of freedom
Residual deviance: 24148  on 20987 degrees of freedom
(3717 observations deleted due to missingness)
AIC: 24162
Number of Fisher Scoring iterations: 4

> summary(fo.model5f)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
    data = fo.gbg.scaled.women.sub5, na.action = na.exclude)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
  -2.0638  -1.0702   0.5453  1.0634  2.0581
Coefficients:
                           Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -0.63025    0.03407  -18.498  < 2e-16 ***
Rank.diff                    -0.02437    0.02244   -1.086  0.277
PS.pct.diff                  0.22991    0.02165   10.621  < 2e-16 ***
PR.pct.diff                  0.22451    0.02138   10.499  < 2e-16 ***
P1..Service..GBG.               0.96652    0.05399 17.903 < 2e-16 ***
Lag2.Game.P1                    0.33787    0.05398  6.259 3.87e-10 ***
P1..Service..GBG.:Lag2.Game.P1 -0.04597    0.07600  -0.605    0.545
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘1’ 1

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 17654  on 12734 degrees of freedom
Residual deviance: 16423  on 12728 degrees of freedom
(2548 observations deleted due to missingness)
AIC: 16437
Number of Fisher Scoring iterations: 4

> summary(w.model5m)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
     PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
     data = w.gbg.scaled.men.sub5, na.action = na.exclude)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1436  -0.7154   0.4507   0.7228   2.1225
Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                   -1.48435    0.02905 -51.100   <2e-16 ***
Rank.diff                     -0.01720    0.02838  -0.606   0.5444
PS.pct.diff                    0.23482    0.02104  11.163   <2e-16 ***
PR.pct.diff                    0.15844    0.01913   8.284   <2e-16 ***
P1..Service..GBG.             1.47909    0.04675  31.635   <2e-16 ***
Lag2.Game.P1                   1.59192    0.04624  34.431   <2e-16 ***
P1..Service..GBG.:Lag2.Game.P1 -0.13553    0.06546  -2.070    0.0384 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘ 0.1 ’ 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 30781  on 22203  degrees of freedom
Residual deviance: 23749  on 22197  degrees of freedom
(3453 observations deleted due to missingness)
AIC: 23763

Number of Fisher Scoring iterations: 4

> summary(w.model5f)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
   PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
data = w.gbg.scaled.women.sub5, na.action = na.exclude)
Deviance Residuals:
       Min        1Q       Median        3Q       Max
-2.1224    -0.9637     0.5999     0.9529     1.9412
Coefficients:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.84711    0.03414 -24.816  < 2e-16 ***
Rank.diff          -0.05208    0.02252  -2.313   0.0207 *
PS.pct.diff         0.25212    0.02103  11.987  < 2e-16 ***
PR.pct.diff         0.18172    0.02153   8.439  < 2e-16 ***
P1..Service..GBG.   1.36628    0.05750  23.759  < 2e-16 ***
Lag2.Game.P1        0.45232    0.05608   8.066 7.27e-16 ***
P1..Service..GBG.:Lag2.Game.P1 -0.07169    0.07993  -0.897   0.3697

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘ 0.1 ’ 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 17638  on 12725  degrees of freedom
Residual deviance: 15652  on 12719  degrees of freedom
(2712 observations deleted due to missingness)
AIC: 15666

Number of Fisher Scoring iterations: 4
> summary(uso.model5m)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
       PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
data = uso.gbg.scaled.men.sub5, na.action = na.exclude)
Deviance Residuals:
    Min      1Q  Median      3Q     Max
-2.1378  -0.8304   0.5651   0.8413   2.0574
Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.18055    0.02703 -43.682  < 2e-16 ***
Rank.diff      -0.09306    0.02816  -3.305  0.000951 ***
PS.pct.diff      0.18949    0.01922   9.858  < 2e-16 ***
PR.pct.diff      0.17405    0.01724  10.095  < 2e-16 ***
P1..Service..GBG. 1.58279    0.04577  34.583  < 2e-16 ***
Lag2.Game.P1    0.92825    0.04439  20.912  < 2e-16 ***
P1..Service..GBG.:Lag2.Game.P1 -0.10681    0.06353  -1.681  0.092690 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 30676  on 22133  degrees of freedom
Residual deviance: 25416  on 22127  degrees of freedom
   (3148 observations deleted due to missingness)
AIC: 25430
Number of Fisher Scoring iterations: 4

> summary(uso.model5f)
Call:
glm(formula = P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff +
       PR.pct.diff + (P1..Service..GBG. * Lag2.Game.P1), family = "binomial",
data = uso.gbg.scaled.women.sub5, na.action = na.exclude)
Deviance Residuals:

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<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.0567</td>
<td>-1.0324</td>
<td>0.5681</td>
<td>1.0153</td>
<td>2.0890</td>
</tr>
</tbody>
</table>

Coefficients:

|                      | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------------|----------|------------|---------|----------|
| (Intercept)          | -0.72532 | 0.03337    | -21.735 | < 2e-16 *** |
| Rank.diff            | -0.01577 | 0.02220    | -0.710  | 0.4774   |
| PS.pct.diff          | 0.29588  | 0.02113    | 14.001  | < 2e-16 *** |
| PR.pct.diff          | 0.17640  | 0.02032    | 8.681   | < 2e-16 *** |
| P1..Service..GBG.    | 1.21455  | 0.05490    | 22.122  | < 2e-16 *** |
| Lag2.Game.P1         | 0.39259  | 0.05404    | 7.264   | 3.75e-13 *** |
| P1..Service..GBG.:Lag2.Game.P1 | -0.19636 | 0.07663 | -2.563 | 0.0104 * |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 18159  on 13098 degrees of freedom
Residual deviance: 16619  on 13092 degrees of freedom

(3077 observations deleted due to missingness)

AIC: 16633

Number of Fisher Scoring iterations: 4

---

Model 6

> summary(aus.model6m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)

Data: aus.gbg.scaled.men.sub6

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC  BIC  logLik deviance df.resid
23408.2 23471.8 -11696.1 23392.2 20830

Scaled residuals:
Min 1Q Median 3Q Max
-3.0475 -0.6714 0.2888 0.6659 3.0456

Random effects:
Groups Name Variance Std.Dev.
Match.ID (Intercept) 0.1828 0.4276
Number of obs: 20838, groups: Match.ID, 628

Fixed effects:

|                   | Estimate | Std. Error | z value | Pr(>|z|) |
|-------------------|----------|------------|---------|----------|
| (Intercept)       | -0.12781 | 0.04299    | -2.973  | 0.00295  **|
| Rank.diff         | -0.09629 | 0.04728    | -2.037  | 0.04169  *|
| PS.pct.diff       | 0.36491  | 0.02925    | 12.475  | < 2e-16 ***|
| PR.pct.diff       | 0.31076  | 0.02798    | 11.108  | < 2e-16 ***|
| P1..Service..GBG. | 1.55902  | 0.04906    | 31.776  | < 2e-16 ***|
| Lag3.Game.P1      | -1.17979 | 0.05018    | -23.511 | < 2e-16 ***|
| P1..Service..GBG.:Lag3.Game.P1 | -0.10391 | 0.06966 | -1.492  | 0.13579 |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

(Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L3.G.P
Rank.diff 0.040
PS.pct.diff 0.068 0.565
PR.pct.diff 0.051 0.513 0.339
P1..Sr..GBG. -0.713 -0.004 0.032 0.039
Lag3.Gam.P1 -0.742 0.012 -0.097 -0.073 0.600
P1..S..GBG.: 0.529 0.000 -0.002 -0.018 -0.725 -0.683

> summary(aus.model6f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
Data: aus.gbg.scaled.women.sub6
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC  BIC  logLik deviance df.resid
14961.4  15020.5   -7472.7  14945.4    11896

Scaled residuals:
Min 1Q Median 3Q Max
-2.9794 -0.7952 -0.3611 0.8026 2.8945

Random effects:

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
<th>Std.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Match.ID (Intercept)</td>
<td>0.1527</td>
<td>0.3908</td>
</tr>
</tbody>
</table>

Number of obs: 11904, groups: Match.ID, 657

Fixed effects:
```
|                  | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------|----------|------------|---------|----------|
| (Intercept)      | -0.55219 | 0.05042    | -10.951 | < 2e-16  ***|
| Rank.diff        | -0.09982 | 0.03031    | -3.293  | 0.000992 ***|
| PS.pct.diff      | 0.35204  | 0.02877    | 12.236  | < 2e-16  ***|
| PR.pct.diff      | 0.19995  | 0.02871    | 6.965   | 3.29e-12 ***|
| P1..Service..GBG.| 1.25372  | 0.05921    | 21.174  | < 2e-16  ***|
| Lag3.Game.P1     | -0.16340 | 0.06121    | -2.669  | 0.007597 **|
| P1..Service..GBG.:Lag3.Game.P1 | -0.06346 | 0.08446    | -0.751  | 0.452441  |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<th></th>
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<th>PR.pc.</th>
<th>P1..Sr..GBG.</th>
<th>L3.G.P</th>
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<tr>
<td>PS.pct.diff</td>
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<tr>
<td>PR.pct.diff</td>
<td>0.026</td>
<td>0.351</td>
<td>-0.059</td>
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<tr>
<td>P1..Sr..GBG.</td>
<td>-0.752</td>
<td>-0.015</td>
<td>0.033</td>
<td>0.015</td>
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<tr>
<td>Lag3.Game.P1</td>
<td>-0.764</td>
<td>0.020</td>
<td>-0.094</td>
<td>-0.061</td>
<td>0.613</td>
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<tr>
<td>P1..S..GBG. :</td>
<td>0.537</td>
<td>0.014</td>
<td>-0.008</td>
<td>-0.001</td>
<td>-0.709</td>
<td>-0.682</td>
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</tbody>
</table>

> summary(fo.model6m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)

Data: fo.gbg.scaled.men.sub6
```
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
23538.1  23601.4 -11761.0  23522.1    20331

Scaled residuals:
  Min      1Q  Median      3Q     Max
-3.0200 -0.6935  0.3155  0.6933  3.0414

Random effects:
  Groups   Name        Variance Std.Dev.
     Match.ID (Intercept) 0.1758   0.4193

Number of obs: 20339, groups:  Match.ID, 646

Fixed effects:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)         -0.37495    0.04335 -8.649  < 2e-16 ***
Rank.diff          -0.14410    0.04551  -3.166  0.00154 **
PS.pct.diff         0.30570    0.03147   9.714  < 2e-16 ***
PR.pct.diff         0.36110    0.02870  12.583  < 2e-16 ***
P1..Service..GBG.   1.59112    0.04885  32.569  < 2e-16 ***
Lag3.Game.P1        -0.77814    0.05037 -15.448  < 2e-16 ***
P1..Service..GBG.:Lag3.Game.P1 -0.02809    0.06977  -0.403  0.68723

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
                  (Intr) Rnk.df PS.pct PR.pct. P1..Sr..GBG. L3.G.P
Rank.diff       0.005
PS.pct.diff     0.038  0.661
PR.pct.diff     0.042  0.565  0.434
P1..Sr..GBG.    -0.735 -0.003  0.025  0.034
Lag3.Game.P1    -0.756  0.023 -0.066 -0.081  0.624
P1..S..GBG.:     0.537 -0.004 -0.005 -0.010 -0.716 -0.684

> summary(fo.model6f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
         (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
Data: fo.gbg.scaled.women.sub6
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
23538.1  23601.4 -11761.0  23522.1    20331
15571.9 15631.1 -7777.9 15555.9 12060

Scaled residuals:
  Min     1Q  Median     3Q    Max
-2.6063 -0.8645  0.1902  0.8663  2.7294

Random effects:
  Groups Name        Variance  Std.Dev.
  Match.ID (Intercept) 0.1802   0.4246

Number of obs: 12068, groups: Match.ID, 666

Fixed effects:

  Estimate  Std. Error   z value  Pr(>|z|)
(Intercept)                    -0.43177    0.04857  -8.889   <2e-16 ***
Rank.diff                      -0.02171    0.03106  -0.699   0.4845
PS.pct.diff                     0.28730    0.02994   9.596   <2e-16 ***
PR.pct.diff                     0.27148    0.02933   9.255   <2e-16 ***
P1..Service..GBG.              1.00776    0.05713  17.641   <2e-16 ***
Lag3.Game.P1                   -0.14161    0.05909  -2.397   0.0165 *
P1..Service..GBG.:Lag3.Game.P1  0.01501    0.08140   0.184   0.8537

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

     (Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L3.G.P
Rank.diff    -0.005
PS.pct.diff  0.042  0.383
PR.pct.diff  0.044  0.351 -0.002
P1..Sr..GBG. -0.730 -0.002  0.018  0.008
Lag3.Game.P1 -0.745  0.009 -0.082 -0.080  0.598
P1..S..GBG.:  0.523  0.001 -0.001  0.011 -0.710       -0.688

> summary(w.model6m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial (logit)

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)

Data: w.gbg.scaled.men.sub6

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
22843.7  22907.5 -11413.8  22827.7    21472

Scaled residuals:
Min      1Q  Median      3Q     Max
-3.2031 -0.6160  0.2090  0.6145  3.2396

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.2739   0.5233

Number of obs: 21480, groups:  Match.ID, 642

Fixed effects:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | 0.143595 | 0.044593   | 3.220   | 0.00128 **|
| Rank.diff      | -0.054171| 0.047224   | -1.147  | 0.25133 |
| PS.pct.diff    | 0.494170 | 0.034702   | 14.240  | < 2e-16 ***|
| PR.pct.diff    | 0.338577 | 0.031457   | 10.763  | < 2e-16 ***|
| P1..Service..GBG. | 1.467867| 0.049772   | 29.492  | < 2e-16 ***|
| Lag3.Game.P1   | -1.734492| 0.051973   | -33.373 | < 2e-16 ***|
| P1..Service..GBG.:Lag3.Game.P1 | 0.006683| 0.071648   | 0.093   | 0.92568 |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<th>PS.pct.df</th>
<th>PR.pct.df</th>
<th>P1..Service..GBG.</th>
<th>L3.G.P</th>
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<td>0.517</td>
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<td>0.034</td>
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<td>Lag3.Game.P1</td>
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<td>-0.125</td>
<td>-0.077</td>
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<td>P1..Service..GBG.:Lag3.Game.P1</td>
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<td>0.017</td>
<td>-0.010</td>
<td>-0.724</td>
<td>-0.680</td>
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</table>

> summary(w.model6f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [\'glmerMod\']

Family: binomial (logit)

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)

Data: w.gbg.scaled.women.sub6

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))
AIC  BIC  logLik  deviance  df.resid
14929.8  14989.0  -7456.9  14913.8  12067

Scaled residuals:
Min    1Q  Median    3Q   Max
-2.9889 -0.7712  0.4091  0.7594  2.9231

Random effects:
Groups    Name        Variance Std.Dev.
Match.ID  (Intercept)  0.2019   0.4493

Number of obs: 12075, groups:  Match.ID, 653

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.52922    0.05361  -9.872  < 2e-16 ***
Rank.diff    -0.06857    0.03144  -2.181   0.0292 *
PS.pct.diff  0.31613    0.02929  10.795  < 2e-16 ***
PR.pct.diff  0.22310    0.02995   7.449 9.38e-14 ***
P1..Service..GBG.  1.40459    0.06124  22.934  < 2e-16 ***
Lag3.Game.P1 -0.24654    0.06308  -3.908 9.29e-05 ***
P1..Service..GBG.:Lag3.Game.P1  0.01619    0.08640   0.187   0.8514

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
             (Intr) Rnk.df PS.pct PR.pct. P1..Sr..GBG. L3.G.P
Rank.diff  -0.006
PS.pct.diff  0.046  0.321
PR.pct.diff  0.037  0.397  0.084
P1..Sr..GBG. -0.756 -0.003  0.021  0.011
Lag3.Game.P1 -0.778  0.022 -0.095 -0.068  0.640
P1..Sr..GBG.:  0.552 -0.003  0.010  0.009 -0.717 -0.692
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial (logit)


Data: uso.gbg.scaled.men.sub6

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC BIC logLik deviance df.resid
24812.0 24875.8 -12398.0 24796.0 21468

Scaled residuals:
Min 1Q Median 3Q Max
-3.0187 -0.6807 0.3465 0.6778 2.9781

Random effects:
Groups Name Variance Std.Dev.
Match.ID (Intercept) 0.1618 0.4022

Number of obs: 21476, groups: Match.ID, 647

Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -0.262528 | 0.042092 | -6.237 4.46e-10 *** |
| Rank.diff | -0.131745 | 0.042124 | -3.128 0.00176 ** |
| PS.pct.diff | 0.301094 | 0.028289 | 10.644 < 2e-16 *** |
| PR.pct.diff | 0.280210 | 0.025252 | 11.097 < 2e-16 *** |
| P1..Service..GBG. | 1.554882 | 0.047853 | 32.493 < 2e-16 *** |
| Lag3.Game.P1 | 0.001538 | 0.067762 | 0.023 0.98189 |
| P1..Service..GBG..Lag3.Game.P1 | 0.001538 | 0.067762 | 0.023 0.98189 |

---

Signif. codes: 0 *** 0.001 *** 0.01 ** 0.05 * 0.1 . 1

Correlation of Fixed Effects:

(Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L3.G.P
Rank.diff    -0.003
PS.pct.diff  0.039  0.582
PR.pct.diff  0.040  0.430  0.359
P1..Sr..GBG. -0.733 -0.007  0.021  0.020
Lag3.Gam.P1  -0.761  0.020 -0.080 -0.084  0.629
P1..S..GBG.:  0.541  0.001  0.003  0.005 -0.724 -0.691

> summary(uso.model6f)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)

Data: uso.gbg.scaled.women.sub6
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
15808.7  15868.2  -7896.4  15792.7    12424

Scaled residuals:

    Min      1Q  Median      3Q     Max
-2.8268 -0.8202  0.3922  0.8238  2.4254

Random effects:

Groups     Name        Variance Std.Dev.
Match.ID   (Intercept) 0.1682   0.4101

Number of obs: 12432, groups:  Match.ID, 666

Fixed effects:

                     Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.49635    0.04991 -9.945  < 2e-16 ***
Rank.diff          -0.01730    0.03018  -0.573    0.566
PS.pct.diff        0.35791    0.02899  12.344  < 2e-16 ***
PR.pct.diff        0.20671    0.02751   7.514 5.72e-14 ***
P1..Service..GBG.   1.14720    0.05777  19.859  < 2e-16 ***
Lag3.Game.P1       -0.14722    0.05988  -2.459    0.014 *
P1..Service..GBG.:Lag3.Game.P1 0.10564    0.08240   1.282    0.200

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

       (Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. L3.G.P
Rank.diff   -0.009
PS.pct.diff  0.061  0.391
PR.pct.diff  0.029  0.336  0.090
P1..Sr..GBG. -0.750 -0.002  0.011  0.012
Lag3.Gam.P1  -0.768  0.011 -0.120 -0.064  0.624
P1..S..GBG.:  0.540  0.001  0.023  0.002 -0.710 -0.689

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Model 7

> summary(aus.model7m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
           (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Data: aus.gbg.scaled.men.sub7

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
23120.8  23216.5 -11548.4  23096.8    21457

Scaled residuals:

           Min      1Q  Median      3Q     Max
-2.9969 -0.5937  0.3120  0.5938  2.9958

Random effects:

  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.06274  0.2505

Number of obs: 21469, groups:  Match.ID, 628

Fixed effects:

                          Estimate Std. Error z value Pr(>|z|)
(Intercept)               -1.02987    0.05950 -17.307  < 2e-16 ***
Rank.diff                 -0.08220    0.03828  -2.147   0.0318 *
PS.pct.diff               0.29918    0.02415  12.388  < 2e-16 ***
PR.pct.diff               0.25626    0.02310  11.094  < 2e-16 ***
P1..Service..GBG.        1.98752    0.07870  25.254  < 2e-16 ***
Lag1.Game.P1              -0.39967    0.06824  -5.857 4.72e-09 ***
Lag2.Game.P1              1.72783    0.08391  20.593  < 2e-16 ***
P1..Service..GBG.:Lag1.Game.P1 -1.12228    0.10353 -10.840  < 2e-16 ***
P1..Service..GBG.:Lag2.Game.P1 -1.21722    0.10455 -11.642  < 2e-16 ***
Lag1.Game.P1:Lag2.Game.P1                -1.06949    0.10282 -10.401  < 2e-16 ***
P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1 2.10921  0.14434  14.613  < 2e-16 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

(Intr) Rnk.df PS.pct. PR.pct. P1..Sr..GBG. Lg1.G.P1 L2.G.P P1..Sr..GBG.:L1.G.P1
P1..S..GBG.:L2 L1.G.P1:
Rank.diff             0.009
PS.pct.diff           0.064  0.551
PR.pct.diff           0.060  0.502  0.363
P1..Sr..GBG.         -0.696 -0.005  0.048  0.045
Lag1.Game.P1          -0.857  0.022 -0.079 -0.070  0.599
Lag2.Game.P1          -0.684  0.015 -0.010 -0.031  0.497  0.600
P1..Sr..GBG.:L1.G.P1  0.533  0.010 -0.012 -0.028 -0.759 -0.619 -0.362
P1..S..GBG.:L2        0.530 -0.001 -0.027 -0.007 -0.749 -0.457 -0.794  0.553
L1.G.P1:L2            0.541 -0.013 -0.036 -0.014 -0.417 -0.627 -0.806  0.408  0.650
P1..S..GBG.:L1.G.P1:  -0.380 -0.010  0.023  0.018  0.547  0.439  0.561 -0.708 -0.715 -0.703

> summary(aus.model7f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )
Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1 + Lag2.Game.P1) + (1 | Match.ID)
Data: aus.gbg.scaled.women.sub7

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
15708.2  15797.4  -7842.1  15684.2    12548

Scaled residuals:
    Min     1Q    Median     3Q    Max
-2.7573 -0.8027 -0.3466  0.7987  2.9472

Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.1083   0.3291

Number of obs: 12560, groups:  Match.ID, 657

Fixed effects:
(Intercept)     -0.73254    0.06239 -11.741  < 2e-16 ***
Rank.diff      -0.09607    0.02811  -3.418  0.000631 ***
PS.pct.diff     0.32547    0.02701  12.050  < 2e-16 ***
PR.pct.diff     0.18534    0.02670   6.942  3.86e-12 ***
P1..Service..GBG. 1.36740    0.08163 16.752  < 2e-16 ***
Lag1.Game.P1    -0.85701    0.07571 -11.342  < 2e-16 ***
Lag2.Game.P1                               0.37236  0.09743  3.822 0.000132 ***
P1..Service..GBG.:Lag1.Game.P1             -0.28982  0.11983 -2.419 0.015577 *
P1..Service..GBG.:Lag2.Game.P1             -0.28542  0.11938 -2.391 0.016809 *
Lag1.Game.P1:Lag2.Game.P1                  -0.08195  0.11948 -0.686 0.492767
P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1 0.37634  0.16858  2.232 0.025584 *
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<td>0.651</td>
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<tr>
<td>P1..S..GBG.:L1.G.P1</td>
<td>-0.334</td>
<td>-0.011</td>
<td>0.006</td>
<td>0.009</td>
<td>0.487</td>
<td>0.420</td>
<td>0.558</td>
<td>-0.707</td>
<td>-0.704</td>
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> summary(fo.model7m)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)
Data: fo.gbg.scaled.men.sub7
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))
AIC      BIC   logLik deviance df.resid
23772.6  23868.0 -11874.3  23748.6    20980
Scaled residuals:
  Min     1Q   Median     3Q    Max
 0.0000  0.0000  0.0000  0.0000  0.0000
> summary(fo.model7f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Data: fo.gbg.scaled.women.sub7

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
---
(Intercept)                                  -1.00357    0.05666 -17.711 < 2e-16 ***
Rank.diff                                   -0.12949    0.03873  -3.344 0.000827 ***
PS.pct.diff                                  0.25852    0.02687   9.623 < 2e-16 ***
PR.pct.diff                                  0.30171    0.02465  12.242 < 2e-16 ***
P1..Service..GBG.                            1.92216    0.07371  26.076 < 2e-16 ***
Lag1.Game.P1                                  -0.21975    0.06537  -3.362 0.000775 ***
Lag2.Game.P1                                  1.28367    0.08311  15.446 < 2e-16 ***
P1..Service..GBG.:Lag1.Game.P1               -0.94392    0.10202  -9.253 < 2e-16 ***
P1..Service..GBG.:Lag2.Game.P1               -0.96186    0.10185  -9.443 < 2e-16 ***
Lag1.Game.P1:Lag2.Game.P1                    -0.84226    0.10102  -8.337 < 2e-16 ***
P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1  1.75701    0.14241  12.338 < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

  (Intr) Rnk.df PS.pc. PR.pc. P1..Sr..GBG. Lg1.G.P1 L2.G.P P1..Sr..GBG.:L1.G.P1
Rank.diff            -
PS.pct.dif           0.053  0.654
PR.pct.dif           0.053  0.554  0.450
P1..Sr..GBG.        -0.698 -0.009  0.036  0.046
Lag1.Game.P1        -0.844  0.025 -0.062 -0.067  0.597
Lag2.Game.P1        -0.649  0.002 -0.032 -0.029  0.478  0.568
P1..Sr..GBG.:L1.G.P1 0.512 -0.005 -0.023 -0.026 -0.721 -0.604 -0.331
P1..Sr..GBG.:L2     0.509  0.009 -0.008 -0.010 -0.720 -0.435 -0.807  0.503
L1.G.P1:L2         -0.516 -0.003 -0.004 -0.022 -0.405 -0.608 -0.812  0.385  0.666
P1..Sr..GBG.:L1.G.P1: -0.362 -0.003  0.019  0.023  0.519  0.425  0.563 -0.706 -0.705 -0.701

>
16405.2 16494.7 -8190.6 16381.2 12723

Scaled residuals:
  Min     1Q  Median     3Q    Max
-2.8605 -0.8717  0.3686  0.8655  2.7239

Random effects:
Groups  Name        Variance Std.Dev.  
Match.ID  (Intercept) 0.106    0.3256  
Number of obs: 12735, groups: Match.ID, 666

Fixed effects:
                     Estimate   Std. Error  t value  Pr(>|t|)
(Intercept)        -0.615305    0.059232 -10.388   < 2e-16 ***
Rank.diff          -0.027138    0.027582  -0.984 0.325165
PS.pct.diff        0.256121     0.026880   9.528  < 2e-16 ***
PR.pct.diff        0.241958     0.026280   9.207  < 2e-16 ***
P1..Service..GBG.  1.069694     0.077408  13.819  < 2e-16 ***
Lag1.Game.P1        0.004123     0.073482   0.056 0.955259
Lag2.Game.P1        0.303428     0.092061   3.296 0.000981 ***
P1..Service..GBG.:Lag1.Game.P1  -0.167254    0.113747  -1.470 0.141451
P1..Service..GBG.:Lag2.Game.P1  -0.192292    0.114106  -1.685 0.091948 .
Lag1.Game.P1:Lag2.Game.P1       -0.066441    0.114127  -0.582 0.560454
P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1  0.352686     0.160842   2.193 0.028325 *

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

  (Intr)  Rnk.df PS.pc. PR.pc. P1..Sr..GBG. Lg1.G.P1 L2.G.P P1..Sr..GBG.:L1.G.P1
P1..S..GBG.:L2  L1.G.P1:Rank.diff       -0.015
P1..S..GBG.:L2  L1.G.P1:PS.pct.diff      0.073 0.375
P1..S..GBG.:L2  L1.G.P1:PR.pct.diff      0.058 0.346 0.001
P1..S..GBG.:L2  L1.G.P1:P1..Sr..GBG.     -0.675 0.001 0.036 0.032
P1..S..GBG.:L2  L1.G.P1:Lag1.Game.P1    -0.780 0.017 -0.077 -0.063 0.542
P1..S..GBG.:L2  L1.G.P1:Lag2.Game.P1    -0.616 0.012 -0.052 -0.027 0.435 0.504
P1..S..GBG.:L2  L1.G.P1:P1..Sr..GBG.:L1.G.P1 0.472 -0.007 -0.016 -0.001 -0.681
P1..S..GBG.:L2  L1.G.P1:P1..Sr..GBG.:L2  0.467 -0.004 -0.011 -0.019 -0.678
P1..S..GBG.:L2  L1.G.P1:L2:  0.471 -0.010 -0.004 -0.021 -0.361 -0.612 -0.788 0.392 0.635
P1..S..GBG.:L1.G.P1:  0.334 0.008 0.018 0.014 0.485 0.433 0.556 -0.704 0.706
P1..S..GBG.:L1.G.P1:  0.706 0.707
> summary(w.model7m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
          (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Data: w.gbg.scaled.men.sub7

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
22313.9  22410.0 -11144.9  22289.9    22152

Scaled residuals:

    Min      1Q  Median      3Q     Max
-3.1540 -0.5365  0.2394  0.5342  3.1172

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.06771  0.2602

Number of obs: 22164, groups:  Match.ID, 642

Fixed effects:

                Estimate Std. Error z value Pr(>|z|)
(Intercept)    -1.05540    0.06254 -16.876   <2e-16 ***
Rank.diff      -0.01832    0.03504  -0.523    0.601
PS.pct.diff    0.38502    0.02647  14.543   <2e-16 ***
PR.pct.diff    0.26667    0.02382  11.196   <2e-16 ***
P1..Service..GBG.  2.08671    0.08248  25.299   <2e-16 ***
Lag1.Game.P1   -0.60770    0.07185  -8.458   <2e-16 ***
Lag2.Game.P1   2.10630    0.08591  24.518   <2e-16 ***
P1..Service..GBG.:Lag1.Game.P1  -1.39649    0.10724 -13.022   <2e-16 ***
P1..Service..GBG.:Lag2.Game.P1  -1.51060    0.10737 -14.069   <2e-16 ***
Lag1.Game.P1:Lag2.Game.P1     -1.27731    0.10613 -12.035   <2e-16 ***
P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1  2.62222    0.14913  17.584   <2e-16 ***

---

Signif. codes:  0 ‘***' 0.001 ‘**' 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ' 1
Correlation of Fixed Effects:

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<td>Lag2.Game.P1</td>
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<td>P1..Sr..GBG.:L1.G.P1</td>
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<td>-0.018</td>
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<td>-0.024</td>
<td>-0.013</td>
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> summary(w.model7f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit)

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Data: w.gbg.scaled.women.sub7

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
15633.7  15723.1  -7804.8  15609.7    12714

Scaled residuals:

  Min      1Q  Median      3Q     Max
-2.9422 -0.7624  0.4153  0.7526  2.4972

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.1241   0.3523

Number of obs: 12726, groups: Match.ID, 653

Fixed effects:

            Estimate Std. Error  z value  Pr(>|z|)
(Intercept) -0.77548    0.06533 -11.8700  < 2e-16 ***
Rank.diff   -0.05962    0.02815  -2.1180   0.0342 *
PS.pct.diff  0.28858    0.02661  10.8460  < 2e-16 ***
PR.pct.diff  0.20738    0.02705   7.6670 1.76e-14 ***
P1..Service..GBG. 1.45618    0.08538  17.0550  < 2e-16 ***
Lag1.Game.P1 -0.09353    0.07764  -1.2050   0.2284
Lag2.Game.P1  0.53740    0.10212   5.2630 1.42e-07 ***
P1..Service..GBG.:Lag1.Game.P1 -0.13249    0.12380  -1.0700   0.2845
P1..Service..GBG.:Lag2.Game.P1 \quad -0.28313 \quad 0.12441 \quad -2.276 \quad 0.0229 *
Lag1.Game.P1:Lag2.Game.P1 \quad -0.24224 \quad 0.12266 \quad -1.975 \quad 0.0483 *
P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1 \quad 0.33221 \quad 0.17320 \quad 1.918 \quad 0.0551 .
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Signif. codes: 0 "****" 0.001 "***" 0.01 "**" 0.05 "*" 0.1 "." 1

Correlation of Fixed Effects:

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<th>Rnk.df</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
<th>P1..Sr..GBG.</th>
<th>Lg1.G.P1</th>
<th>L2.G.P</th>
<th>P1..Sr..GBG.:L1.G.P1</th>
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<td>Lag1.Gam.P1</td>
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<td>L1.G.P1:L2</td>
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> summary(uso.model7m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Data: uso.gbg.scaled.men.sub7

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC  BIC  logLik deviance df.resid
24855.9 24951.9 -12415.9 24831.9 22113

Scaled residuals:

Min  1Q Median  3Q  Max
-2.9485 -0.6312  0.3641  0.6268  2.8642

Random effects:

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<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
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<tr>
<td>Match.ID</td>
<td>(Intercept)</td>
<td>0.06908</td>
<td>0.2628</td>
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Number of obs: 22125, groups: Match.ID, 647

Fixed effects:

| Estimate  | Std. Error | z value | Pr(>|z|) |
|-----------|------------|---------|----------|
| (Intercept) | -0.98629   | 0.05646 | -17.468  | < 2e-16 *** |
| Rank.diff  | -0.11446   | 0.03518 | -3.254   | 0.00114 **  |
| PS.pct.diff | 0.25354    | 0.02401 | 10.561   | < 2e-16 *** |
| PR.pct.diff | 0.23314    | 0.02148 | 10.853   | < 2e-16 *** |
| P1..Service..GBG. | 1.98407   | 0.07509 | 26.421   | < 2e-16 *** |
| Lag1.Game.P1 | -0.26229   | 0.06455 | -4.063   | 4.84e-05 *** |
| Lag2.Game.P1 | 1.45364    | 0.08119 | 17.904   | < 2e-16 *** |
| P1..Service..GBG.:Lag1.Game.P1 | -0.99599 | 0.10044 | -9.917   | < 2e-16 *** |
| P1..Service..GBG.:Lag2.Game.P1 | -1.13089 | 0.10111 | -11.184  | < 2e-16 *** |
| Lag1.Game.P1:Lag2.Game.P1 | -0.99753 | 0.09893 | -10.083  | < 2e-16 *** |
| P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1 | 1.93931 | 0.13923 | 13.929   | < 2e-16 *** |

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<td>Lag1.Game.P1</td>
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<td>0.515</td>
<td>0.003</td>
<td>-0.018</td>
<td>-0.027</td>
<td>-0.740</td>
<td>-0.444</td>
<td>-0.794</td>
<td>0.536</td>
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<tr>
<td>L1.G.P1:L2.</td>
<td>0.531</td>
<td>0.005</td>
<td>-0.003</td>
<td>-0.026</td>
<td>-0.406</td>
<td>-0.619</td>
<td>-0.812</td>
<td>0.392</td>
<td>0.654</td>
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<tr>
<td>P1..S..GBG.:L1.G.P1</td>
<td>-0.371</td>
<td>-0.001</td>
<td>0.023</td>
<td>0.028</td>
<td>0.541</td>
<td>0.432</td>
<td>0.564</td>
<td>-0.711</td>
<td>-0.717</td>
<td>-0.701</td>
</tr>
</tbody>
</table>

> summary(uso.model7f)

Generalized linear mixed model fit by maximum likelihood [Laplace Approximation] ['glmerMod']

Family: binomial ( logit )

Formula: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Data: uso.gbg.scaled.women.sub7

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC  16598.0
BIC  16687.7
logLik deviance df.resid
16574.0  3287.0  16574.0   13086

162
Scaled residuals:

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<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
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<tr>
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<td>-2.9204</td>
<td>-0.8253</td>
<td>0.3930</td>
<td>0.8130</td>
<td>2.4859</td>
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Random effects:

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<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
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<tbody>
<tr>
<td>Match.ID</td>
<td>(Intercept)</td>
<td>0.1314</td>
<td>0.3625</td>
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<td></td>
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<tr>
<td>Number of obs: 13098, groups: Match.ID, 666</td>
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<td></td>
</tr>
</tbody>
</table>

Fixed effects:

|                      | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------------|----------|------------|---------|---------|
| (Intercept)          | -0.69218 | 0.06153    | -11.250 | < 2e-16 *** |
| Rank.diff            | -0.02077 | 0.02831    | -0.734  | 0.46300 |
| PS.pct.diff          | 0.33814  | 0.02761    | 12.249  | < 2e-16 *** |
| PR.pct.diff          | 0.19767  | 0.02592    | 7.625   | 2.43e-14 *** |
| P1..Service..GBG.    | 1.31120  | 0.07980    | 16.431  | < 2e-16 *** |
| Lag1.Game.P1         | -0.02647 | 0.07422    | -0.357  | 0.72139 |
| Lag2.Game.P1         | 0.40602  | 0.09507    | 4.271   | 1.95e-05 *** |
| P1..Service..GBG.:Lag1.Game.P1 | -0.11082 | 0.11733    | -0.945  | 0.34487 |
| P1..Service..GBG.:Lag2.Game.P1 | -0.32983 | 0.11685    | -2.823  | 0.00476 ** |
| Lag1.Game.P1:Lag2.Game.P1 | -0.15176 | 0.11605    | -1.308  | 0.19094 |
| P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1 | 0.22055 | 0.16410    | 1.344   | 0.17893 |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<td>Rank.diff</td>
<td>-0.007</td>
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<td>PS.pct.diff</td>
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<tr>
<td>PR.pct.diff</td>
<td>0.051</td>
<td>0.332</td>
<td>0.107</td>
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<tr>
<td>P1..Service..GBG.</td>
<td>-0.667</td>
<td>-0.007</td>
<td>0.039</td>
<td>0.026</td>
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<tr>
<td>Lag1.Game.P1</td>
<td>-0.799</td>
<td>0.002</td>
<td>-0.121</td>
<td>-0.061</td>
<td>0.548</td>
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<tr>
<td>Lag2.Game.P1</td>
<td>-0.611</td>
<td>0.001</td>
<td>-0.064</td>
<td>-0.029</td>
<td>0.433</td>
<td>-0.515</td>
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<tr>
<td>P1..Service..GBG.:Lag1.Game.P1</td>
<td>0.472</td>
<td>0.005</td>
<td>0.016</td>
<td>0.002</td>
<td>-0.677</td>
<td>-0.597</td>
<td>-0.295</td>
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<tr>
<td>P1..Service..GBG.:Lag2.Game.P1</td>
<td>0.463</td>
<td>0.003</td>
<td>-0.014</td>
<td>-0.011</td>
<td>-0.683</td>
<td>-0.378</td>
<td>-0.795</td>
<td>0.453</td>
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<tr>
<td>Lag1.Game.P1:Lag2.Game.P1</td>
<td>0.474</td>
<td>0.010</td>
<td>0.007</td>
<td>-0.010</td>
<td>-0.365</td>
<td>-0.600</td>
<td>-0.801</td>
<td>0.375</td>
<td>0.650</td>
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<tr>
<td>P1..Service..GBG.:Lag1.Game.P1:Lag2.Game.P1</td>
<td>0.336</td>
<td>-0.003</td>
<td>0.007</td>
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<td>0.563</td>
<td>-0.710</td>
<td>0.710</td>
<td>0.707</td>
<td>-0.704</td>
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</table>
Goodness of Fit Tests (Chi-Square)

**Australian Open**

```r
> anova(pure.aus.model0m, pure.aus.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
   Resid. Df Resid. Dev Df Deviance
1     20857      25152
2     20856      24877  1   274.55

> anova(pure.aus.model2m, pure.aus.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
   Resid. Df Resid. Dev Df Deviance
1     20854      24656
2     20856      24877 -2  -221.72

> anova(pure.aus.model3m, pure.aus.model2m)
Data: pure.aus.gbg.scaled.men
Models:
pure.aus.model2m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG.
pure.aus.model3m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
> anova(pure.aus.model4m, pure.aus.model3m)

> anova(pure.aus.model6m, pure.aus.model5m)

> anova(pure.aus.model7m, pure.aus.model6m)
Data: pure.aus.gbg.scaled.men

Models:

pure.aus.model6m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model6m: (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
pure.aus.model7m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model7m: (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 |
pure.aus.model7m: Match.ID)

Df   AIC   BIC  logLik  deviance  Chisq Chi Df Pr(>Chisq)

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.aus.model6f, pure.aus.model1f)
Analysis of Deviance Table

Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.

Resid. Df Resid. Dev Df Deviance
1     11905      15501
2     11904      15302  1   198.94

> anova(pure.aus.model2f, pure.aus.model1f)
Analysis of Deviance Table

Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.

Resid. Df Resid. Dev Df Deviance
1     11902      15019
2     11904      15302 -2  -283.07

> anova(pure.aus.model3f, pure.aus.model2f)
Analysis of Deviance Table

Data: pure.aus.gbg.scaled.women

Models:

pure.aus.model2f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model2f: P1..Service..GBG.
pure.aus.model3f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model3f: P1..Service..GBG. + (1 | Match.ID)

Df   AIC   BIC  logLik  deviance  Chisq Chi Df Pr(>Chisq)

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model4f, pure.aus.model3f)
Data: pure.aus.gbg.scaled.women
Models:
pure.aus.model3f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model3f:     P1..Service..GBG. + (1 | Match.ID)
pure.aus.model4f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model4f:     (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
              Df  AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model3f  6 14992 15036 -7490.1    14980
pure.aus.model4f  8 14982 15041 -7483.2    14966  13.826    2  0.0009949 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model4f, pure.aus.model5f)
Data: pure.aus.gbg.scaled.women
Models:
pure.aus.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model5f:     (P1..Service..GBG. * Lag2.Game.P1)
pure.aus.model4f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model4f:     (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
              Df  AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model5f  7 14962 15014 -7474.2    14948
pure.aus.model4f  8 14982 15041 -7483.2    14966     0      1          1

> anova(pure.aus.model6f, pure.aus.model5f)
Data: pure.aus.gbg.scaled.women
Models:
pure.aus.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model5f:     (P1..Service..GBG. * Lag2.Game.P1)
pure.aus.model6f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model6f:     (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
              Df  AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model5f  7 14962 15014 -7474.2    14948
pure.aus.model6f  8 14977 15036 -7480.4    14961     0      1          1

> anova(pure.aus.model7f, pure.aus.model6f)
Data: pure.aus.gbg.scaled.women
Models:
pure.aus.model6f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model6f:     (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
pure.aus.model7f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model7f: (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model6f  8 14977 15036 -7480.4    14961
pure.aus.model7f 12 14945 15034 -7460.6    14921 39.464      4  5.587e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

French Open

> anova(pure.fo.model0m, pure.fo.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
   Resid. Df Resid. Dev Df Deviance
1     20353      24787
2     20352      24331  1   456.22

> anova(pure.fo.model2m, pure.fo.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
        P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
   Resid. Df Resid. Dev Df Deviance
1     20350      24096
2     20352      24331 -2   -234.6

> anova(pure.fo.model3m, pure.fo.model2m)
Data: pure.fo.gbg.scaled.men
Models:
  pure.fo.model2m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.fo.model2m:     P1..Service..GBG.
  pure.fo.model3m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.fo.model3m:     P1..Service..GBG. + (1 | Match.ID)
Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model2m  5 24106 24146 -12048    24096
pure.fo.model3m  6 24070 24118 -12029    24058 37.932      1  7.327e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model4m, pure.fo.model3m)
Data: pure.fo.gbg.scaled.men
Models:
pure.fo.model3m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model3m: P1..Service..GBG. + (1 | Match.ID)
pure.fo.model4m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model4m: (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
<table>
<thead>
<tr>
<th>Df</th>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
</tr>
</thead>
</table>
pure.fo.model3m 6 24070 24118 -12029 24058
pure.fo.model4m 8 23662 23726 -11823 23646 411.91 2 < 2.2e-16 ***
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model4m, pure.fo.model5m)
Data: pure.fo.gbg.scaled.men
Models:
pure.fo.model5m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model5m: (P1..Service..GBG. * Lag2.Game.P1)
pure.fo.model4m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model4m: (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
<table>
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<tr>
<th>Df</th>
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<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
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</table>
pure.fo.model5m 7 23504 23559 -11745 23490
pure.fo.model4m 8 23662 23726 -11823 23646 0 1 1

> anova(pure.fo.model6m, pure.fo.model5m)
Data: pure.fo.gbg.scaled.men
Models:
pure.fo.model5m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model5m: (P1..Service..GBG. * Lag2.Game.P1)
pure.fo.model6m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model6m: (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
<table>
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<th>Df</th>
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<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
</tr>
</thead>
</table>
pure.fo.model5m 7 23504 23559 -11745 23490
pure.fo.model6m 8 23618 23682 -11801 23602 0 1 1

> anova(pure.fo.model7m, pure.fo.model6m)
Data: pure.fo.gbg.scaled.men
Models:
pure.fo.model6m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model6m: (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
pure.fo.model7m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model7m: (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 |
pure.fo.model7m: Match.ID)
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<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
</tr>
</thead>
</table>
pure.fo.model6m 8 23618 23682 -11801 23602
> anova(pure.fo.model0f, pure.fo.model1f)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
  Resid. Df Resid. Dev Df Deviance
1     12068      16031
2     12067      15901  1   129.66

> anova(pure.fo.model2f, pure.fo.model1f)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
  Resid. Df Resid. Dev Df Deviance
1     12065      15641
2     12067      15901 -2  -260.16

> anova(pure.fo.model3f, pure.fo.model2f)
Data: pure.fo.gbg.scaled.women
Models:  
  pure.fo.model2f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.fo.model2f:     P1..Service..GBG.
  pure.fo.model3f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.fo.model3f:     P1..Service..GBG. + (1 | Match.ID)
  Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model2f  5 15651 15688 -7820.5    15641
pure.fo.model3f  6 15587 15632 -7787.7    15575 65.764      1  5.082e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model4f, pure.fo.model3f)
Data: pure.fo.gbg.scaled.women
Models:  
  pure.fo.model3f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.fo.model3f:     P1..Service..GBG. + (1 | Match.ID)
  pure.fo.model4f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.fo.model4f:     (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
  Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model3f  6 15587 15632 -7787.7    15575
> anova(pure.fo.model4f, pure.fo.model5f)
Data: pure.fo.gbg.scaled.women
Models:
pure.fo.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model5f:     (P1..Service..GBG. * Lag2.Game.P1)
pure.fo.model4f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model4f:     (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
   Df  AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model5f  7 15588 15639 -7786.8    15574
pure.fo.model4f  8 15591 15650 -7787.5    15575     0      1          1

> anova(pure.fo.model6f, pure.fo.model5f)
Data: pure.fo.gbg.scaled.women
Models:
pure.fo.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model5f:     (P1..Service..GBG. * Lag2.Game.P1)
pure.fo.model6f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model6f:     (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
   Df  AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model5f  7 15588 15639 -7786.8    15574
pure.fo.model6f  8 15582 15641 -7782.9    15566 7.7712      1 0.005309 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model7f, pure.fo.model6f)
Data: pure.fo.gbg.scaled.women
Models:
pure.fo.model6f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model6f:     (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
pure.fo.model7f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model7f:     (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 |
pure.fo.model7f:     Match.ID)

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### Wimbledon

```R
> anova(pure.w.model0m, pure.w.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
   Resid. Df Resid. Dev Df Deviance
1     21567      25871
2     21566      25622  1   248.56
> anova(pure.w.model2m, pure.w.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
   P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
   Resid. Df Resid. Dev Df Deviance
1     21564      25398
2     21566      25622 -2  -223.86
> anova(pure.w.model3m, pure.w.model2m)
Data: pure.w.gbg.scaled.men
Models:
pure.w.model2m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model2m:   P1..Service..GBG.
pure.w.model3m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model3m:   P1..Service..GBG. + (1 | Match.ID)
   Df   AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.w.model2m  5 25408 25448 -12699    25398
pure.w.model3m  6 25409 25457 -12698    25397  1.53      1     0.2161
> anova(pure.w.model4m, pure.w.model3m)
Data: pure.w.gbg.scaled.men
Models:
pure.w.model3m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model3m:   (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
```

> anova(pure.w.model4m, pure.w.model5m)
Data: pure.w.gbg.scaled.men
Models:
pure.w.model5m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
   (P1..Service..GBG. * Lag2.Game.P1)
pure.w.model4m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
   (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
Df   AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.w.model5m  7 23188 23244 -11587    23174
pure.w.model4m  8 23424 23488 -11704    23408     0      1          1

> anova(pure.w.model6m, pure.w.model5m)
Data: pure.w.gbg.scaled.men
Models:
pure.w.model5m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
   (P1..Service..GBG. * Lag2.Game.P1)
pure.w.model6m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
   (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
Df   AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.w.model5m  7 23188 23244 -11587    23174
pure.w.model6m  8 23312 23376 -11648    23296     0      1          1

> anova(pure.w.model7m, pure.w.model6m)
Data: pure.w.gbg.scaled.men
Models:
pure.w.model6m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
   (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)
pure.w.model7m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model7m:  (P1..Service..GBG. + Lag1.Game.P1 + Lag2.Game.P1) + (1 | Match.ID)

pure.w.model7m:  (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

   Df   AIC   BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model6m  8 23312 23376 -11648    23296
pure.w.model7m 12 21972 22068 -10974    21948 1347.9      4  < 2.2e-16 *** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model0f, pure.w.model1f)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.

   Resid. Df Resid. Dev Df Deviance
1     12074      15362
2     12073      15232  1    130.2

> anova(pure.w.model2f, pure.w.model1f)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.

   Resid. Df Resid. Dev Df Deviance
1     12071      15009
2     12073      15232 -2  -222.73

> anova(pure.w.model3f, pure.w.model2f)
Data: pure.w.gbg.scaled.women
Models:
   pure.w.model2f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG.
   pure.w.model3f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)

   Df   AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model2f  5 15019 15056 -7504.4    15009
pure.w.model3f  6 14958 15002 -7473.1    14946 62.656      1  2.462e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model4f, pure.w.model3f)
Data: pure.w.gbg.scaled.women
Models:
   pure.w.model3f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG. + (1 | Match.ID)
pure.w.model4f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model4f: (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Df  AIC  BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model3f  6 14958 15002 -7473.1    14946
pure.w.model4f  8 14936 14996 -7460.2    14920 25.751      2   2.56e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model4f, pure.w.model5f)
Data: pure.w.gbg.scaled.women
Models:
pure.w.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model5f: (P1..Service..GBG. * Lag2.Game.P1)
pure.w.model4f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model4f: (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Df  AIC  BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model5f  7 14909 14961 -7447.6    14895
pure.w.model4f  8 14936 14996 -7460.2    14920     0      1          1

> anova(pure.w.model6f, pure.w.model5f)
Data: pure.w.gbg.scaled.women
Models:
pure.w.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model5f: (P1..Service..GBG. * Lag2.Game.P1)
pure.w.model6f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model6f: (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)

Df  AIC  BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model5f  7 14909 14961 -7447.6    14895
pure.w.model6f  8 14935 14994 -7459.5    14919     0      1          1

> anova(pure.w.model7f, pure.w.model6f)
Data: pure.w.gbg.scaled.women
Models:
pure.w.model6f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model6f: (P1..Service..GBG. * Lag3.Game.P1)
pure.w.model7f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model7f: (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Df  AIC  BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model6f  8 14935 14994 -7459.5    14919
pure.w.model7f 12 14880 14969 -7428.1    14856 62.815      4  7.423e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> anova(pure.uso.model0m, pure.uso.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
 Resid. Df Resid. Dev Df Deviance
1  21485  25980
2  21484  25724  1  255.66

> anova(pure.uso.model2m, pure.uso.model1m)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
     P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.
 Resid. Df Resid. Dev Df Deviance
1  21482  25521
2  21484  25724 -2  -203.64

> anova(pure.uso.model3m, pure.uso.model2m)
Data: pure.uso.gbg.scaled.men
Models:
 pure.uso.model2m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
     P1..Service..GBG.
pure.uso.model3m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
     (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
 Df AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.uso.model2m  5 25531 25570 -12760    25521 
pure.uso.model3m  6 25507 25555 -12747    25495 25.77      1  3.847e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.uso.model4m, pure.uso.model3m)
Data: pure.uso.gbg.scaled.men
Models:
 pure.uso.model3m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
     (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
pure.uso.model4m:   (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)
 Df AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.uso.model3m  6 25507 25555 -12747    25495 
pure.uso.model4m  8 24922 24986 -12453    24906 589.04      2 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model4m, pure.uso.model5m)
Data: pure.uso.gbg.scaled.men
Models:
pure.uso.model5m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model5m:  (P1..Service..GBG. * Lag2.Game.P1)
pure.uso.model4m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model4m:  (P1..Service..GBG. * Lag1.Game.P1) + (1 | Match.ID)

Df   AIC   BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.uso.model5m  7 24778 24834 -12382    24764
pure.uso.model4m  8 24922 24986 -12453    24906     0      1          1

> anova(pure.uso.model6m, pure.uso.model5m)
Data: pure.uso.gbg.scaled.men
Models:
pure.uso.model5m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model5m:  (P1..Service..GBG. * Lag2.Game.P1)
pure.uso.model6m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model6m:  (P1..Service..GBG. * Lag3.Game.P1) + (1 | Match.ID)

Df   AIC   BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model5m  7 24778 24834 -12382    24764
pure.uso.model6m  8 24867 24931 -12426    24851     0      1          1

> anova(pure.uso.model7m, pure.uso.model6m)
Data: pure.uso.gbg.scaled.men
Models:
pure.uso.model6m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model6m:  (P1..Service..GBG. * Lag3.Game.P1)
pure.uso.model7m: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model7m:  (P1..Service..GBG. * Lag1.Game.P1 * Lag2.Game.P1) + (1 | Match.ID)

Df   AIC   BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model6m  8 24867 24931 -12426    24851
pure.uso.model7m 12 24256 24351 -12116    24232 619.51      4  < 2.2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model0f, pure.uso.model1f)
Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.

<table>
<thead>
<tr>
<th>Resid. Df</th>
<th>Resid. Dev</th>
<th>Dev Df</th>
<th>Deviance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>16253</td>
<td>111.97</td>
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<tr>
<td>2</td>
<td>12430</td>
<td>16141</td>
<td>1</td>
</tr>
</tbody>
</table>

> anova(pure.uso.model2f, pure.uso.model1f)

Analysis of Deviance Table
Model 1: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..GBG.
Model 2: P1..Game.Winner..GBG. ~ Rank.diff + P1..Service..GBG.

<table>
<thead>
<tr>
<th>Resid. Df</th>
<th>Resid. Dev</th>
<th>Dev Df</th>
<th>Deviance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12428</td>
<td>15862</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>12430</td>
<td>16141</td>
<td>-2</td>
</tr>
</tbody>
</table>

> anova(pure.uso.model3f, pure.uso.model2f)

Data: pure.uso.gbg.scaled.women
Models:

<table>
<thead>
<tr>
<th>Df</th>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pure.uso.model2f</td>
<td>5</td>
<td>15872</td>
<td>15909</td>
<td>-7931.1</td>
<td>15862</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pure.uso.model3f</td>
<td>6</td>
<td>15816</td>
<td>15860</td>
<td>-7902.0</td>
<td>15804</td>
<td>58.149</td>
<td>1</td>
</tr>
</tbody>
</table>

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.uso.model4f, pure.uso.model3f)

Data: pure.uso.gbg.scaled.women
Models:

<table>
<thead>
<tr>
<th>Df</th>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pure.uso.model3f</td>
<td>6</td>
<td>15816</td>
<td>15860</td>
<td>-7902.0</td>
<td>15804</td>
<td>9.6292</td>
<td>2</td>
</tr>
</tbody>
</table>

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.uso.model4f, pure.uso.model5f)
Data: pure.uso.gbg.scaled.women

Models:

pure.uso.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model5f: (P1..Service..GBG. * Lag2.Game.P1)

data.frames: pure.uso.model5f 7 15813 15865 -7899.5    15799
pure.uso.model5f 8 15810 15870 -7897.2    15794 4.7234      1    0.02975 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model6f, pure.uso.model5f)

Data: pure.uso.gbg.scaled.women

Models:

pure.uso.model5f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model5f: (P1..Service..GBG. * Lag2.Game.P1)

data.frames: pure.uso.model5f 7 15813 15865 -7899.5    15799
pure.uso.model6f 8 15814 15873 -7898.8    15798 1.5227      1     0.2172

> anova(pure.uso.model7f, pure.uso.model6f)

Data: pure.uso.gbg.scaled.women

Models:

pure.uso.model6f: P1..Game.Winner..GBG. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model6f: (P1..Service..GBG. * Lag3.Game.P1) + (L | Match.ID)

data.frames: pure.uso.model6f 8 15814 15873 -7898.8    15798 1.5227      1     0.2172

Point Level R Output

Model Output
Model 0

> summary(aus.model0m)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
      data = aus.pbp.scaled.men, na.action = na.exclude)
Deviance Residuals:
       Min       1Q   Median       3Q      Max
-1.3368  -0.9801  -0.9801   1.0260   1.3884
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.483544   0.007262  -66.58   <2e-16 ***
P1..Service..PBP.  0.850670   0.010235   83.11   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 221518  on 159887  degrees of freedom
  Residual deviance: 214453  on 159886  degrees of freedom
  AIC: 214457
Number of Fisher Scoring iterations: 4

> summary(aus.model0f)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
      data = aus.pbp.scaled.women, na.action = na.exclude)
Deviance Residuals:
       Min       1Q   Median       3Q      Max
-1.253  -1.036  -1.036   1.104   1.326
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.342098   0.009115  -37.53   <2e-16 ***
P1..Service..PBP.  0.517520   0.012839   40.31   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 136891  on 98867  degrees of freedom
  Residual deviance: 135253  on 98866  degrees of freedom
  AIC: 135257
Number of Fisher Scoring iterations: 4
> summary(fo.model0m)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
     data = fo.ppb.scaled.men, na.action = na.exclude)

Deviance Residuals:

     Min       1Q   Median       3Q      Max
-1.3168  -0.9937  -0.9937   1.0441   1.3730

Coefficients:

                      Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.448910   0.007341  -61.15   <2e-16 ***
P1..Service..PBP.  0.770767   0.010323   74.66   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 216040  on 155945  degrees of freedom
Residual deviance: 210361  on 155944  degrees of freedom
AIC: 210365
Number of Fisher Scoring iterations: 4

> summary(fo.model0f)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
     data = fo.ppb.scaled.women, na.action = na.exclude)

Deviance Residuals:

     Min       1Q   Median       3Q      Max
-1.231   -1.060  -1.060   1.124   1.300

---
Coefficients:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.28296 | 0.00900    | -31.44  | <2e-16 *** |
| P1..Service..PBP. | 0.40907  | 0.01268    | 32.25   | <2e-16 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 139384  on 100653  degrees of freedom
Residual deviance: 138338  on 100652  degrees of freedom
AIC: 138342

Number of Fisher Scoring iterations: 3

> summary(w.model0m)

Call:
glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
data = w.pbp.scaled.men, na.action = na.exclude)

Deviance Residuals:
Min       1Q   Median       3Q      Max
-1.3508  -0.9718  -0.9718  1.0134  1.3980

Coefficients:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.504972 | 0.007317   | -69.01  | <2e-16 *** |
| P1..Service..PBP. | 0.903797  | 0.010322   | 87.56   | <2e-16 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 219042  on 158086  degrees of freedom
Residual deviance: 211179  on 158085  degrees of freedom
AIC: 211183

Number of Fisher Scoring iterations: 4
> summary(w.model0f)
Call:
glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
data = w.pbp.scaled.women, na.action = na.exclude)
Deviance Residuals:
    Min      1Q  Median      3Q     Max
-1.284  -1.023  -1.023   1.074   1.340
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.37486  0.009047  -41.44   <2e-16 ***
P1..Service..PBP.  0.62234  0.012787   48.67   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 139012  on 100351  degrees of freedom
Residual deviance: 136614  on 100350  degrees of freedom
AIC: 136618
Number of Fisher Scoring iterations: 4

> summary(uso.model0m)
Call:
glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
data = uso.pbp.scaled.men, na.action = na.exclude)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3312  -0.9906  -0.9906   1.0310   1.3765
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.45675  0.007256  -62.94   <2e-16 ***
P1..Service..PBP.  0.81134  0.010236   79.27   <2e-16 ***
Null deviance: 220576  on 159186  degrees of freedom
Residual deviance: 214163  on 159185  degrees of freedom
AIC: 214167
Number of Fisher Scoring iterations: 4

> summary(uso.model0f)
Call:
glm(formula = P1..Point.Winner..PBP. ~ P1..Service..PBP., family = "binomial",
data = uso.pbp.scaled.women, na.action = na.exclude)
Deviance Residuals:
        Min       1Q   Median       3Q      Max
-1.25900 -1.04473 -1.04473  1.09782  1.31553
Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)           -0.318598   0.008732  -36.49   <2e-16 ***
P1..Service..PBP.     0.507782   0.012378   41.02   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 147155  on 106235  degrees of freedom
Residual deviance: 145459  on 106234  degrees of freedom
AIC: 145463
Number of Fisher Scoring iterations: 4
Model 1

> summary(aus.model1m)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
      family = "binomial", data = aus.pbp.scaled.men, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.5732  -1.0021  -0.9203   1.0448   1.7398
Coefficients:
                Estimate  Std. Error z value Pr(>|z|)
(Intercept)    -0.488453   0.007399  -66.02   <2e-16 ***
Rank.diff       0.099220   0.005294   18.74   <2e-16 ***
P1..Service..PBP.  0.858108   0.010430   82.27   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 214113  on 154546  degrees of freedom
  Residual deviance: 206884  on 154544  degrees of freedom
  (5341 observations deleted due to missingness)
AIC: 206890
Number of Fisher Scoring iterations: 4

> summary(aus.model1f)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
      family = "binomial", data = aus.pbp.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.4872  -1.0816  -0.9776   1.1363   1.6141
Coefficients:
                Estimate  Std. Error z value Pr(>|z|)
(Intercept)    -0.354470   0.009521  -37.23   <2e-16 ***
Rank.diff       0.115357   0.006766   17.05   <2e-16 ***
P1..Service..PBP.  0.533997   0.013400   39.85   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
  Null deviance: 126292  on 91221  degrees of freedom
  Residual deviance: 124421  on 91219  degrees of freedom
  (7646 observations deleted due to missingness)
AIC: 124427
Number of Fisher Scoring iterations: 4
> summary(fo.model1m)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
     family = "binomial", data = fo.pbp.scaled.men, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.6676  -1.0339  -0.9136   1.0726   1.7204
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.451684   0.007438  -60.73   <2e-16 ***
Rank.diff      -0.125369   0.005321  -23.56   <2e-16 ***
P1..Service..PBP.  0.777191   0.010463   74.28   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 211373  on 152574  degrees of freedom
Residual deviance: 205249  on 152572  degrees of freedom
(3371 observations deleted due to missingness)
AIC: 205255
Number of Fisher Scoring iterations: 4

> summary(fo.model1f)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
     family = "binomial", data = fo.pbp.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.4490  -1.1114  -0.9991  1.1593  1.4726
Coefficients:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.287631| 0.009360   | -30.73  | <2e-16   ***|
| Rank.diff      | -0.101474| 0.006631   | -15.30  | <2e-16   ***|
| P1..Service..PBP. | 0.419116| 0.013194   | 31.77   | <2e-16   ***|

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 129252  on 93335 degrees of freedom
Residual deviance: 128015  on 93333 degrees of freedom
(7318 observations deleted due to missingness)
AIC: 128021
Number of Fisher Scoring iterations: 4

> summary(w.model1m)

Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
    family = "binomial", data = w.pbp.scaled.men, na.action = na.exclude)

Deviance Residuals:

Min       1Q   Median       3Q      Max
-1.5936  -1.0033  -0.9055   1.0391   1.8054

Coefficients:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.510204| 0.007392   | -69.02  | <2e-16   ***|
| Rank.diff      | -0.116746| 0.005279   | -22.11  | <2e-16   ***|
| P1..Service..PBP. | 0.913240| 0.010432   | 87.54   | <2e-16   ***|

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
Null deviance: 215596  on 155600  degrees of freedom
Residual deviance: 207325  on 155598  degrees of freedom
(2486 observations deleted due to missingness)
AIC: 207331

Number of Fisher Scoring iterations: 4

> summary(w.model1f)

Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
    family = "binomial", data = w.pbp.scaled.women, na.action = na.exclude)

Deviance Residuals:
          Min        1Q   Median       3Q      Max
-1.4916   -1.0625  -0.9625   1.1027   1.5037

Coefficients:
                     Estimate  Std. Error   z value  Pr(>|z|)
(Intercept)          -0.37426      0.00948  -39.47   <2e-16 ***
Rank.diff            -0.09429      0.00673  -14.01   <2e-16 ***
P1..Service..PBP.    0.63167       0.01341   47.09   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 126734  on 91477  degrees of freedom
Residual deviance: 124309  on 91475  degrees of freedom
(8874 observations deleted due to missingness)
AIC: 124315
Number of Fisher Scoring iterations: 4
> summary(uso.model1m)
Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
    family = "binomial", data = uso.pbp.scaled.men, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.6871  -1.0143  -0.9411   1.0488   1.6847
Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.4618    0.007355   -62.76   <2e-16 ***
Rank.diff           -0.0093    0.000507    -18.42   <2e-16 ***
P1..Service..PBP.    0.8206    0.010378     79.07   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 215305  on 155376  degrees of freedom
Residual deviance: 208607  on 155374  degrees of freedom
(3810 observations deleted due to missingness)
AIC: 208613
Number of Fisher Scoring iterations: 4

> summary(uso.model1f)
Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.,
    family = "binomial", data = uso.pbp.scaled.women, na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.4180  -1.0851  -0.9922   1.1306   1.4880
Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.3177    0.009211   -34.49   <2e-16 ***
Rank.diff           -0.0087    0.000639    -13.61   <2e-16 ***
P1..Service..PBP.    0.5097    0.013042     39.08   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 132829  on 95900  degrees of freedom
Residual deviance: 131112  on 95898  degrees of freedom
(10335 observations deleted due to missingness)
AIC: 131118
Number of Fisher Scoring iterations: 4
Model 2

> summary(aus.model2m)

Call:

  glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
      PR.pct.diff + P1..Service..PBP., family = "binomial", data = aus.pbp.scaled.men,
      na.action = na.exclude)

Deviance Residuals:

       Min        1Q      Median        3Q       Max  
-1.6496    -1.0424    -0.8723     1.0755    1.6446  

Coefficients:

                                Estimate Std. Error      z value Pr(>|z|)
(Intercept)               -0.487365   0.007724  -63.095   <2e-16 ***
Rank.diff                -0.016383   0.010766   -1.522    0.128
PS.pct.diff               0.120262   0.006652   18.080   <2e-16 ***
PR.pct.diff               0.101641   0.006375   15.945   <2e-16 ***
P1..Service..PBP.        0.861529   0.010891   79.105   <2e-16 ***

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 197527  on 142565 degrees of freedom
Residual deviance: 190404  on 142561 degrees of freedom

   (17322 observations deleted due to missingness)

AIC: 190414

Number of Fisher Scoring iterations: 4
> summary(aus.model2f)
Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + P1..Service..PBP., family = "binomial", data = aus.pbp.scaled.women,
    na.action = na.exclude)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
  -1.5484  -1.1093  -0.9349   1.1572   1.6602
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.35728  0.009558 -37.381  < 2e-16 ***
 Rank.diff  -0.03888  0.007961  -4.883 1.04e-06 ***
PS.pct.diff  0.11905  0.007410  16.066  < 2e-16 ***
 PR.pct.diff  0.06952  0.007504   9.264  < 2e-16 ***
P1..Service..PBP  0.53829  0.013455  40.008  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 125894  on 90935  degrees of freedom
Residual deviance: 123654  on 90931  degrees of freedom
(7932 observations deleted due to missingness)
AIC: 123664
Number of Fisher Scoring iterations: 4
> summary(fo.model2m)
Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + P1..Service..PBP., family = "binomial", data = fo.pbp.scaled.men,
    na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.6009  -1.0609  -0.8739   1.0976   1.6459
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.463942   0.007775 -59.674  < 2e-16 ***
Rank.diff    -0.055655   0.010746  -5.179 2.23e-07 ***
PS.pct.diff   0.102609   0.007361  13.939  < 2e-16 ***
PR.pct.diff   0.111319   0.006726  16.551  < 2e-16 ***
P1..Service..PBP.  0.797164   0.010936  72.890  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 194802  on 140617  degrees of freedom
Residual deviance: 188452  on 140613  degrees of freedom
(15328 observations deleted due to missingness)
AIC: 188462
Number of Fisher Scoring iterations: 4

> summary(fo.model2f)
Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + P1..Service..PBP., family = "binomial", data = fo.pbp.scaled.women,
    na.action = na.exclude)
Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.7111  -1.1285  -0.9678   1.1782   1.6833
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.289373   0.009416 -30.731   <2e-16 ***
Rank.diff    -0.017334   0.007944  -2.182   0.0291 *
PS.pct.diff   0.100320   0.007460  13.448   <2e-16 ***
PR.pct.diff   0.089976   0.007366  12.214   <2e-16 ***
P1..Service..PBP.  0.422149   0.013281  31.787   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 128103  on 92506  degrees of freedom
Residual deviance: 126540  on 92502  degrees of freedom
(8147 observations deleted due to missingness)
AIC: 126550
Number of Fisher Scoring iterations: 4

> summary(w.model2m)
Call:
  glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
      PR.pct.diff + P1..Service..PBP., family = "binomial", data = w.pbp.scaled.men,
      na.action = na.exclude)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
  -1.5698  -1.0301  -0.8593   1.0608   1.6197
Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.510878   0.007679 -66.526   <2e-16 ***
Rank.diff         -0.007230   0.009589  -0.754    0.451
PS.pct.diff        0.139938   0.007003  19.983   <2e-16 ***
PR.pct.diff        0.095709   0.006426  14.895   <2e-16 ***
P1..Service..PBP.  0.914788   0.010838  84.408   <2e-16 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 200638  on 144804  degrees of freedom
Residual deviance: 192578  on 144800  degrees of freedom
(13282 observations deleted due to missingness)
AIC: 192588
Number of Fisher Scoring iterations: 4

> summary(w.model2f)

Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
     PR.pct.diff + P1..Service..PBP., family = "binomial", data = w.pbp.scaled.women,
     na.action = na.exclude)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
  -1.5636  -1.0921  -0.9295   1.1231   1.6291

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.376683   0.009521 -39.565  < 2e-16 ***
Rank.diff   -0.026480   0.007852  -3.373 0.000745 ***
PS.pct.diff  0.108069   0.007186  15.040  < 2e-16 ***
PR.pct.diff  0.072038   0.007409   9.722  < 2e-16 ***
P1..Service..PBP.  0.638735   0.013468  47.424  < 2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 126250  on 91125  degrees of freedom
Residual deviance: 123525  on 91121  degrees of freedom
  (9226 observations deleted due to missingness)
AIC: 123535

Number of Fisher Scoring iterations: 4
> summary(uso.model2m)

Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + P1..Service..PBP., family = "binomial", data = uso.pbp.scaled.men,
    na.action = na.exclude)

Deviance Residuals:
    Min      1Q  Median      3Q     Max
-1.563  -1.045  -0.887   1.077   1.568

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -4.693e-01  7.590e-03 -61.830  < 2e-16 ***
PS.pct.diff               2.107e+00  1.389e-01  15.164  < 2e-16 ***
PR.pct.diff               2.316e+00  1.482e-01  15.625  < 2e-16 ***
P1..Service..PBP.       8.311e-01  1.069e-02  77.770  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 204083 on 147271 degrees of freedom
Residual deviance: 197239 on 147267 degrees of freedom
(11915 observations deleted due to missingness)
AIC: 197249

Number of Fisher Scoring iterations: 4

> summary(uso.model2f)

Call:
glm(formula = P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff +
    PR.pct.diff + P1..Service..PBP., family = "binomial", data = uso.pbp.scaled.women,
    na.action = na.exclude)

Deviance Residuals:
    Min      1Q  Median      3Q     Max
-1.7131  -1.1167  -0.9443   1.1583   1.5830

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -3.286e-01  9.325e-03 -35.242   <2e-16 ***
Rank.diff                  -8.154e-05  7.636e-05  -1.068    0.286
PS.pct.diff               3.032e+00  1.680e-01  18.047   <2e-16 ***
PR.pct.diff               2.113e+00  2.009e-01  10.517   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 204083 on 147271 degrees of freedom
Residual deviance: 197239 on 147267 degrees of freedom
(11915 observations deleted due to missingness)
AIC: 197249

Number of Fisher Scoring iterations: 4
Model 3

> summary(aus.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + (1 | Match.ID)

Data: aus.pbp.scaled.men

AIC      BIC   logLik deviance df.resid
190297.6 190356.8 -95142.8 190285.6   142560

Scaled residuals:
       Min      1Q  Median      3Q     Max
-1.7230  -0.8588  -0.6654  0.8931  1.6459

Random effects:
  Groups   Name        Variance Std.Dev.
          Match.ID (Intercept) 0.01587  0.126

Number of obs: 142566, groups:  Match.ID, 628

Number of Fisher Scoring iterations: 4

Fixed effects:
   Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.488401  0.009292  -52.561 <2e-16 ***
Rank.diff    -0.016139  0.014850   -1.087 0.277
PS.pct.diff   0.127032  0.009074   14.000 <2e-16 ***
PR.pct.diff  0.107673  0.008673  12.415   <2e-16 ***
P1..Service..PBP.  0.868541  0.010941  79.385   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr) Rnk.df PS.pc. PR.pc.
Rank.diff  0.062
PS.pct.diff  0.017  0.577
PR.pct.diff  0.015  0.520  0.322
P1..S..PBP. -0.591  0.002  0.035  0.030

> summary(aus.model3f)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  (logit )
Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + (1 | Match.ID)
Data: aus.pbp.scaled.women
AIC      BIC   logLik deviance df.resid
123518.0 123574.5 -61753.0 123506.0    90930
Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.5570 -0.9287 -0.7140  0.9867  1.7634
Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.02889  0.17
Number of obs: 90936, groups:  Match.ID, 657
Fixed effects:
  Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.35972   0.01175  -30.622  < 2e-16 ***
Rank.diff    -0.04030   0.01127   -3.577  0.000348 ***
PS.pct.diff   0.12735   0.01039    12.262  < 2e-16 ***
PR.pct.diff   0.07617   0.01055    7.221  5.17e-13 ***
P1..Service..PBP.  0.54603   0.01354   40.322  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:

(Intr) Rnk.df PS.pc. PR.pc.
Rank.diff -0.005
PS.pct.diff -0.016   0.338
PR.pct.diff -0.010  0.372 -0.109
P1..S..PBP. -0.581 -0.010  0.020  0.011
> summary(fo.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + (1 | Match.ID)
  Data: fo.pbp.scaled.men

AIC      BIC   logLik deviance df.resid
188313.1 188372.2 -94150.5 188301.1   140612

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.6567 -0.8823 -0.6715  0.9214  1.6869

Random effects:
  Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.01868  0.1367
Number of obs: 140618, groups:  Match.ID, 646

Fixed effects:

  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.466040   0.009526 -48.921  < 2e-16 ***
Rank.diff         -0.054388   0.015039  -3.616 0.000299 ***
PS.pct.diff        0.109453   0.010331  10.594  < 2e-16 ***
PR.pct.diff        0.118762   0.009388  12.651  < 2e-16 ***
P1..Service..PBP.  0.805432   0.010990  73.289  < 2e-16 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

                                        (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff          0.029
PS.pct.diff       -0.006  0.668
PR.pct.diff       -0.001  0.580  0.421
P1..S..PBP.       -0.583 -0.006  0.019  0.025
> summary(fo.model3f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + 
(1 | Match.ID)

Data: fo.pbp.scaled.women

AIC      BIC   logLik deviance df.resid
126429.8 126486.4 -63208.9 126417.8    92501

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.8365 -0.9449 -0.7535  1.0052  1.6924

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.02516  0.1586

Number of obs: 92507, groups:  Match.ID, 666

Fixed effects:
  Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.290330   0.011343 -25.596   <2e-16 ***
Rank.diff    -0.018444   0.010909  -1.691   0.0909 .
PS.pct.diff  0.108542   0.010154  10.689   <2e-16 ***
PR.pct.diff  0.095414   0.009974   9.567   <2e-16 ***
P1..Service..PBP.  0.426969   0.013350  31.983   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

  (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff   -0.002
PS.pct.diff -0.008  0.383
PR.pct.diff -0.012  0.349 -0.088
P1..S..PBP. -0.591 -0.004  0.013  0.016

Standardized Residuals (Male)

Standardized Residuals (Female)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + (1 | Match.ID)

Data: w.pbp.scaled.men

AIC      BIC   logLik deviance df.resid
192503.8 192563.1  -96245.9 192491.8   144799

Scaled residuals:
       Min      1Q  Median      3Q     Max
-1.5865 -0.8412 -0.6551  0.8732  1.6622

Random effects:
   Groups   Name        Variance Std.Dev.
    Match.ID (Intercept) 0.01251  0.1118

Number of obs: 144805, groups:  Match.ID, 642

Fixed effects:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.513723   0.008916  -57.62   <2e-16 ***
Rank.diff         -0.007340   0.012450   -0.59    0.555
PS.pct.diff       0.146881   0.009009   16.30   <2e-16 ***
PR.pct.diff       0.099566   0.008256   12.06   <2e-16 ***
P1..Service..PBP.  0.921160   0.010883   84.64   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ’ 0.1’  ’ 1

Correlation of Fixed Effects:
                     (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff           -0.031
PS.pct.diff         0.043  0.622
PR.pct.diff         -0.036  0.524  0.401
P1..S..PBP.        -0.613  0.000  0.036  0.031

> summary(w.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + (1 | Match.ID)

Data: w.pbp.scaled.men

AIC      BIC   logLik deviance df.resid
192503.8 192563.1  -96245.9 192491.8   144799

Scaled residuals:
       Min      1Q  Median      3Q     Max
-1.5865 -0.8412 -0.6551  0.8732  1.6622

Random effects:
   Groups   Name        Variance Std.Dev.
    Match.ID (Intercept) 0.01251  0.1118

Number of obs: 144805, groups:  Match.ID, 642

Fixed effects:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.513723   0.008916  -57.62   <2e-16 ***
Rank.diff         -0.007340   0.012450   -0.59    0.555
PS.pct.diff       0.146881   0.009009   16.30   <2e-16 ***
PR.pct.diff       0.099566   0.008256   12.06   <2e-16 ***
P1..Service..PBP.  0.921160   0.010883   84.64   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ’ 0.1’  ’ 1

Correlation of Fixed Effects:
                     (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff           -0.031
PS.pct.diff         0.043  0.622
PR.pct.diff         -0.036  0.524  0.401
P1..S..PBP.        -0.613  0.000  0.036  0.031

> summary(w.model3f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + (1 | Match.ID)

Data: w.pbp.scaled.women

AIC      BIC   logLik deviance df.resid
123404.7 123461.2  -61696.3 123392.7    91120

Scaled residuals:
       Min      1Q  Median      3Q     Max
-1.5094 -0.9126 -0.7113  0.9529  1.5998

Random effects:
   Groups   Name        Variance Std.Dev.
    Match.ID (Intercept) 0.01085  0.1043

Number of obs: 91120, groups:  Match.ID, 280

Fixed effects:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.507379   0.008900  -57.56   <2e-16 ***
Rank.diff         -0.007341   0.012451   -0.59    0.555
PS.pct.diff       0.146883   0.009001   16.31   <2e-16 ***
PR.pct.diff       0.099564   0.008253   12.06   <2e-16 ***
P1..Service..PBP.  0.921159   0.010876   84.64   <2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ’ 0.1’  ’ 1

Correlation of Fixed Effects:
                     (Intr) Rnk.df PS.pc. PR.pc.
Rank.diff           -0.031
PS.pct.diff         0.043  0.622
PR.pct.diff         -0.036  0.524  0.401
P1..S..PBP.        -0.613  0.000  0.036  0.031

> summary(w.model3f)
Random effects:

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<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Match.ID</td>
<td>(Intercept)</td>
<td>0.02734</td>
<td>0.1653</td>
</tr>
</tbody>
</table>

Number of obs: 91126, groups: Match.ID, 653

Fixed effects:

|             | Estimate | Std. Error | z value | Pr(>|z|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | -0.381305| 0.011625   | -32.800 | < 2e-16 *** |
| Rank.diff   | -0.028834| 0.011004   | -2.620  | 0.00878 **  |
| PS.pct.diff | 0.117926  | 0.009955   | 11.846  | < 2e-16 *** |
| PR.pct.diff | 0.077598  | 0.010311   | 7.526   | 5.25e-14 *** |
| P1..Service..PBP. | 0.649075 | 0.013566 | 47.847 | < 2e-16 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<thead>
<tr>
<th></th>
<th>(Intr)</th>
<th>Rnk.df</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
<th>P1)..Service..PBP.</th>
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<td>Rank.diff</td>
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<td>PS.pct.diff</td>
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<tr>
<td>PR.pct.diff</td>
<td>-0.006</td>
<td>0.408</td>
<td>0.049</td>
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<tr>
<td>P1..Service..PBP.</td>
<td>-0.584</td>
<td>-0.006</td>
<td>0.025</td>
<td>0.015</td>
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> summary(uso.model3m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit)

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + (1 | Match.ID)

Data: uso.pbp.scaled.men

AIC   BIC logLik deviance df.resid
197148.8  197208.2  -98568.4    197136.8    147266

Scaled residuals:

<table>
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<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1.6050</td>
<td>-0.8624</td>
<td>-0.6819</td>
<td>0.8895</td>
<td>1.5899</td>
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</table>
Random effects:

<table>
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<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
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</thead>
<tbody>
<tr>
<td>Match.ID</td>
<td>(Intercept)</td>
<td>0.01416</td>
<td>0.119</td>
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</tbody>
</table>

Number of obs: 147272, groups: Match.ID, 647

Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -0.463045 | 0.008959 | -51.687  < 2e-16 *** |
| Rank.diff | -0.043900 | 0.013446 | -3.265  0.00109 ** |
| PS.pct.diff | 0.107517 | 0.008908 | 12.069 < 2e-16 *** |
| PR.pct.diff | 0.098764 | 0.007958 | 12.410 < 2e-16 *** |
| P1..Service..PBP. | 0.837394 | 0.010731 | 78.038 < 2e-16 *** |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

<table>
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<tr>
<th></th>
<th>(Intr)</th>
<th>Rnk.df</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
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</thead>
<tbody>
<tr>
<td>Rank.diff</td>
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<tr>
<td>PS.pct.diff</td>
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<tr>
<td>PR.pct.diff</td>
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<tr>
<td>P1..Service..PBP.</td>
<td>-0.600</td>
<td>-0.004</td>
<td>0.024</td>
<td>0.027</td>
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:

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<tr>
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<th>(Intr)</th>
<th>Rnk.diff</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
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</thead>
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<tr>
<td>Rnk.diff</td>
<td>-0.004</td>
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<tr>
<td>PS.pct.diff</td>
<td>-0.018</td>
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<td>PR.pct.diff</td>
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<tr>
<td>P1..S..PBP.</td>
<td>-0.579</td>
<td>-0.004</td>
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<td>0.010</td>
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</table>

Model 4

> summary(aus.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )
Data: aus.pbp.scaled.men.sub4
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
189092.3 189181.1 -94537.2 189074.3   141929
Scaled residuals:
        Min      1Q  Median      3Q     Max
-1.8196  -0.8672  -0.6541  0.9039  1.7685
Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.01186  0.1089

Number of obs: 141938, groups:  Match.ID, 628

Fixed effects:

|            | Estimate | Std. Error | z value | Pr(>|z|) |
|------------|----------|------------|---------|----------|
| (Intercept)| -0.576047| 0.011280   | -51.070 | < 2e-16  *** |
| Rank.diff  | -0.015842| 0.013976   | -1.134  | 0.257    |
PS.pct.diff 0.119319 0.008570 13.922 < 2e-16 ***
PR.pct.diff 0.101393 0.008194 12.375 < 2e-16 ***
P1..Service..PBP. 0.890569 0.014506 61.395 < 2e-16 ***
Lag1.Service.P1 -0.075245 0.018432 -4.082 4.46e-05 ***
Lag1.Point.P1 0.212860 0.015975 13.325 < 2e-16 ***
Lag1.Service.P1:Lag1.Point.P1 0.035218 0.022359 1.575 0.115
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

<table>
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<tr>
<th></th>
<th>(Intr)</th>
<th>Rnk.df</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
<th>P1..S.</th>
<th>Lg1.S.P1</th>
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<tr>
<td>PS.pct.diff</td>
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<tr>
<td>PR.pct.diff</td>
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<tr>
<td>P1..S..PBP.</td>
<td>-0.267</td>
<td>0.001</td>
<td>0.019</td>
<td>0.015</td>
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<tr>
<td>Lg1.Srvc.P1</td>
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<td>0.000</td>
<td>0.016</td>
<td>0.009</td>
<td>-0.533</td>
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<tr>
<td>Lg1.Pnt.P1</td>
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<td>0.001</td>
<td>-0.026</td>
<td>-0.029</td>
<td>0.069</td>
<td>0.294</td>
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<tr>
<td>L1.S.P1:L1.</td>
<td>0.385</td>
<td>0.002</td>
<td>-0.003</td>
<td>0.006</td>
<td>0.016</td>
<td>-0.598</td>
<td>-0.706</td>
</tr>
</tbody>
</table>

> summary(aus.model4f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  (logit )
Data: aus.pbp.scaled.women.sub4
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC       BIC      logLik deviance df.resid
122419.2  122503.9 -61200.6  122401.2    90270
Scaled residuals:
Min      1Q  Median      3Q     Max
-1.6263 -0.9276 -0.7056  0.9888  1.8567
Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.02303  0.1518
Number of obs: 90279, groups:  Match.ID, 657
Fixed effects:

|                | Estimate  | Std. Error  | z value | Pr(>|z|) |
|----------------|-----------|-------------|---------|---------|
| (Intercept)    | -0.444227 | 0.014413    | -30.821 | < 2e-16 *** |
| Rank.diff      | -0.037441 | 0.010720    | -3.493  | 0.000478 *** |
| PS.pct.diff    | 0.121403  | 0.009914    | 12.246  | < 2e-16 *** |
| PR.pct.diff    | 0.073767  | 0.010058    | 7.334   | 2.23e-13 *** |
| P1..Service..PBP. | 0.571183 | 0.015975    | 30.362  | < 2e-16 *** |
| Lag1.Service.P1| -0.048418 | 0.023174    | -2.089  | 0.036674 *  |
| Lag1.Point.P1  | 0.197093  | 0.019628    | 10.041  | < 2e-16 *** |
Lag1.Service.P1:Lag1.Point.P1  0.001046   0.027372   0.038 0.969531
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:

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<th>Rnk.df</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
<th>P1..S.</th>
<th>Lg1.S.P1</th>
<th>L1.P.P</th>
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> summary(fo.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  (logit)
Data: fo.pbp.scaled.men.sub4
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC  BIC  logLik deviance df.resid
187065.7 187154.3 -93523.8 187047.7  139963
Scaled residuals:
  Min  1Q Median  3Q  Max
-1.7227 -0.8879 -0.6584  0.9272  1.7718
Random effects:
  Groups   Name        Variance Std.Dev.
          Match.ID (Intercept) 0.0144 0.12
Number of obs: 139972, groups: Match.ID, 646
Fixed effects:

Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.553036  0.011516  -48.025  < 2e-16 ***
Rank.diff -0.051215  0.014225  -3.600  0.000318 ***
PS.pct.diff 0.103616  0.009775  10.600  < 2e-16 ***
PR.pct.diff 0.112459  0.008893  12.645  < 2e-16 ***
P1..Service..PBP. 0.820089  0.014735  55.657  < 2e-16 ***
Lag1.Service.P1 -0.059931  0.018560  -3.229  0.001243 **
Lag1.Point.P1 0.198486  0.016051  12.366  < 2e-16 ***
Lag1.Service.P1:Lag1.Point.P1 0.042842  0.022392  1.913  0.055715 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

 (Intr) Rnk.df PS.pc. PR.pc. P1..S. Lg1.S.P1 L1.P.P
Rank.diff 0.021
PS.pct.diff 0.016 0.668
PR.pct.diff 0.013 0.579 0.424
P1..S..PBP. -0.259 -0.003 0.011 0.013
Lg1.Srvc.P1 -0.329 -0.005 0.007 0.009 -0.542
Lag1.Pnt.P1 -0.563 0.003 -0.023 -0.028 0.066 0.298
L1.S.P1:L1. 0.386 0.003 0.001 0.003 0.013 -0.591 -0.708

> summary(fo.model4f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. + 
(Lag1.Service.P1 * Lag1.Point.P1) + (1 | 
Match.ID)
Data: fo.pbp.scaled.women.sub4
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000)

AIC   BIC   logLik deviance df.resid
125347.5  125432.3  -62664.7  125329.5    91832
Scaled residuals:
Min      1Q  Median      3Q     Max
-1.8976 -0.9427 -0.7437  1.0026  1.7634
Random effects:
 Groups   Name        Variance Std.Dev.
 Match.ID (Intercept) 0.02  0.1414
 Number of obs: 91841, groups:  Match.ID, 666
Fixed effects:

   Estimate Std. Error t value Pr(>|z|)
 (Intercept) -0.373044  0.014164 -26.337  <2e-16 ***
 Rank.diff   -0.017191  0.010411  -1.651  0.0987 .
 PS.pct.diff  0.103071  0.009718  10.606  <2e-16 ***
 PR.pct.diff  0.090897  0.009545   9.523  <2e-16 ***
P1..Service..PBP. 0.438411  0.018570  23.609  <2e-16 ***
summary(w.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial (logit)
Data: w.pbp.scaled.men

Control: glmerControl(optCtrl = list(maxfun = 2e+05))

AIC    BIC   logLik deviance df.resid
191269.9 191358.8 -95625.9 191251.9   144154

Scaled residuals:
Min 1Q Median 3Q Max
-1.6509 -0.8515 -0.6467 0.8894 1.7919

Random effects:
Groups Name Variance Std.Dev.
Match.ID (Intercept) 0.008841 0.09403

Number of obs: 144163, groups: Match.ID, 642
Fixed effects:  

|             | Estimate | Std. Error | z value | Pr(>|z|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | -0.588543| 0.010935   | -53.820 | < 2e-16  *** |
| Rank.diff   | -0.006771| 0.011727   | -0.577  | 0.564    |
| PS.pct.diff | 0.137458 | 0.008523   | 16.128  | < 2e-16  *** |
| PR.pct.diff | 0.094385 | 0.007802   | 12.097  | < 2e-16  *** |
| P1..Service..PBP. | 0.948562 | 0.014297 | 66.346  | < 2e-16  *** |
| Lag1.Service.P1 | -0.113614| 0.018266 | -6.220  | 4.97e-10 *** |
| Lag1.Point.P1 | 0.186736 | 0.015922 | 11.729  | < 2e-16  *** |
| Lag1.Service.P1:Lag1.Point.P1 | 0.090826 | 0.022296 | 4.074  | 4.63e-05 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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> summary(w.model4f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit )


Data: w.pbp.scaled.women

Control: glmerControl(optCtrl = list(maxfun = 2e+05))

AIC  BIC  logLik  deviance  df.resid
122342.0 122426.7 -61162.0 122324.0    90464

Scaled residuals:

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<th>1Q</th>
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Random effects:

Groups | Name         | Variance | Std.Dev.
Match.ID | (Intercept) | 0.02199 | 0.1483

Number of obs: 90473, groups: Match.ID, 653

Fixed effects:

|             | Estimate | Std. Error | z value | Pr(>|z|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | -0.454389| 0.014257   | -31.871 | < 2e-16  *** |
| Rank.diff   | -0.027641| 0.010501   | -2.632  | 0.008485 ** |
| PS.pct.diff | 0.111858 | 0.009533   | 11.734  | < 2e-16  *** |
summary(uso.model4m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )


Data: uso.pbp.scaled.men

Control: glmerControl(optCtrl = list(maxfun = 2e+05))

AIC BIC logLik deviance df.resid
195839.3 195928.4 -97910.7 195821.3 146616

Scaled residuals:
   Min 1Q Median 3Q Max
-1.6773 -0.8764 -0.6641 0.9028 1.6738

Random effects:
   Groups   Name        Variance Std.Dev.

Match.ID (Intercept)  0.01036  0.1018
Number of obs: 146625, groups:  Match.ID, 647
Fixed effects:

                         Estimate Std. Error  z value   Pr(>|z|)  
(Intercept)                      -0.567450  0.010992 -51.623  < 2e-16 ***  
Rank.diff                       -0.042907  0.012631  -3.397 0.000682 ***  
PS.pct.diff                     0.100227   0.008406  11.924  < 2e-16 ***  
PR.pct.diff                     0.092456   0.007515  12.302  < 2e-16 ***  
P1..Service..PBP.              0.849141   0.014347  59.187  < 2e-16 ***  
Lag1.Service.P1                -0.036312   0.018205  -1.995 0.046091 *  
Lag1.Point.P1                  0.239667   0.015622  15.341  < 2e-16 ***  
Lag1.Service.P1:Lag1.Point.P1 -0.006451   0.021912  -0.294 0.768444  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:

                        (Intr) Rnk.df PS.pc. PR.pc. P1..S. Lg1.S.P1 L1.P.P
Rank.diff               0.001
PS.pct.diff             -0.001  0.586
PR.pct.diff             -0.003  0.434  0.349
P1..S..PBP.             -0.264 -0.002  0.013  0.013
Lag1.Srvc.P1            -0.334 -0.002  0.013  0.014 -0.539
Lag1.Pnt.P1             -0.577  0.006 -0.021 -0.022  0.067  0.297
L1.S.P1:L1.             0.393  0.000 -0.006 -0.004  0.016 -0.598 -0.705

> summary(uso.model4f)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Data: uso.pbp.scaled.women
Control: glmerControl(optCtrl = list(maxfun = 2e+05))
AIC   BIC logLik deviance df.resid
127846.9 127931.9 -63914.4 127828.9    94060
Scaled residuals:
     Min      1Q  Median      3Q     Max
-1.8382 -0.9358 -0.7213  0.9921  1.6848
Random effects:
 Groups   Name       Variance Std.Dev.  
Match.ID (Intercept)  0.02088  0.1445
Number of obs: 94069, groups:  Match.ID, 666
Fixed effects:

                         Estimate Std. Error  z value   Pr(>|z|)  
(Intercept)                      -0.415452  0.014003 -29.669 < 2e-16 ***
Model 5

> summary(aus.model5m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial (logit )


Data: aus.pbp.scaled.men

AIC      BIC   logLik deviance df.resid
188266.7 188394.9 -94120.4 188240.7   141297

Scaled residuals:
     Min      1Q  Median      3Q     Max

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

     (Intr) Rnk.df PS.pct. PR.pct. P1..S. Lg1.S.F1 L1.P.P
Rank.diff   -0.005
PS.pct.diff  0.005  0.402
PR.pct.diff -0.001  0.339  0.049
P1..S..PBP. -0.230 -0.002  0.009  0.004
Lg1.Srvc.P1 -0.347 -0.002  0.012  0.005 -0.571
Lag1.Pnt.P1 -0.586  0.005 -0.034 -0.019  0.043  0.325
L1.S.F1:L1.  0.403  0.000 -0.005 -0.001  0.018 -0.581 -0.702

Standardized Residuals (Male)

Index

-3.0  -2.5  -2.0  -1.5  -1.0  -0.5   0.0   0.5   1.0

Stand Residual

0 5000 10000 15000

Standardized Residuals (Female)

Index

-3.0  -2.5  -2.0  -1.5  -1.0  -0.5   0.0   0.5   1.0

Stand Residual

0 5000 10000 15000

211
Random effects:

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Number of obs: 141310, groups: Match.ID, 628

Fixed effects:

|             | Estimate | Std. Error | z value | Pr(>|z|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | -0.602461 | 0.013814   | -43.613 | < 2e-16 *** |
| Rank.diff   | -0.016096 | 0.013889   | -1.159  | 0.2465   |
| PS.pct.diff | 0.117493  | 0.008529   | 13.776  | < 2e-16 *** |
| PR.pct.diff | 0.101286  | 0.008153   | 12.423  | < 2e-16 *** |
| P1..Service..PB.. | 0.899897  | 0.014810   | 60.762  | < 2e-16 *** |
| Lag1.Service.P1 | -0.104305 | 0.021799   | -4.785  | 1.71e-06 *** |
| Lag1.Point.P1 | 0.256692  | 0.019072   | 13.459  | < 2e-16 *** |
| Lag2.Service.P1| -0.018400 | 0.018700   | -0.984  | 0.3251   |
| Lag2.Point.P1 | 0.040111  | 0.018680   | 2.147   | 0.0318 *  |
| Lag1.Service.P1:Lag1.Point.P1 | 0.035352  | 0.022483   | 1.572   | 0.1159   |
| Lag2.Service.P1:Lag2.Point.P1 | 0.094145  | 0.022691   | 4.149   | 3.34e-05 *** |
| Lag1.Point.P1:Lag2.Point.P1 | -0.094050 | 0.022142   | -4.248  | 2.16e-05 *** |

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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> summary(aus.model5f)

Generalized linear mixed model fit by maximum likelihood ('Laplace Approximation') ['glmerMod']

Family: binomial (logit)

Data: aus.pbp.scaled.women

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Scaled residuals:

- Min: -1.6354
- 1Q: -0.9257
- Median: -0.6951
- 3Q: 0.9891
- Max: 1.9245

Random effects:

- Groups: Name Variance Std.Dev.
- Match.ID (Intercept) 0.02118 0.1455

Number of obs: 89622, groups: Match.ID, 657

Fixed effects:

|                       | Estimate | Std. Error | z value | Pr(>|z|) |
|-----------------------|----------|------------|---------|----------|
| (Intercept)           | -0.499884| 0.017688   | -28.260 | < 2e-16 *** |
| Rank.diff             | -0.036800| 0.010558   | -3.486  | 0.000491 *** |
| PS.pct.diff           | 0.118466 | 0.009781   | 12.112  | < 2e-16 *** |
| PR.pct.diff           | 0.071880 | 0.009781   | 7.248   | < 2e-16 *** |
| P1..Service..PBP.     | 0.581640 | 0.019155   | 30.366  | < 2e-16 *** |
| Lag1.Service.P1       | -0.069054| 0.027985   | -2.468  | 0.013605 * |
| Lag1.Point.P1         | 0.273246 | 0.023531   | 11.612  | < 2e-16 *** |
| Lag2.Service.P1       | -0.021252| 0.023435   | -0.907  | 0.364497 |
| Lag2.Point.P1         | 0.109929 | 0.023184   | 4.742   | < 2e-16 *** |
| Lag1.Point.P1:Lag1.Point.P1 | 0.004936| 0.023531   | 11.612  | < 2e-16 *** |
| Lag2.Service.P1:Lag2.Point.P1 | 0.072404| 0.027633   | 2.620   | 0.008787 ** |
| Lag1.Point.P1:Lag2.Point.P1 | -0.159225| 0.027404   | -5.810  | 6.24e-09 *** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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> summary(fo.model5m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )


Data: fo.pbp.scaled.men

AIC      BIC   logLik deviance df.resid
186091.2 186219.2 -93032.6 186065.2   139313

Scaled residuals:
 Min  1Q  Median    3Q   Max
-1.7370 -0.8900 -0.6490  0.9279  1.8675

Random effects:
 Groups   Name        Variance Std.Dev.
 Match.ID (Intercept) 0.01279  0.1131

Number of obs: 139326, groups: Match.ID, 646

Fixed effects:

                                Estimate Std. Error z value Pr(>|z|)
(Intercept)                    -0.601198   0.014014 -42.901  < 2e-16 ***
Rank.diff                     -0.049456   0.013913  -3.555 0.000379 ***
PS.pct.diff                    0.101708   0.009567  10.631  < 2e-16 ***
PR.pct.diff                    0.110801   0.008711  12.720  < 2e-16 ***
P1..Service..PBP.              0.833616   0.015050  55.389  < 2e-16 ***
Lag1.Service.P1               -0.074051   0.022144  -3.344 0.000826 ***
Lag1.Point.P1                  0.252009   0.019183  13.137  < 2e-16 ***
Lag2.Service.P1               -0.056780   0.018850  -3.012 0.002593 **
Lag2.Point.P1                  0.095055   0.018764   5.066 4.07e-07 ***
Lag1.Service.P1:Lag1.Point.P1  0.042111   0.022529  1.869 0.061596 .
Lag2.Service.P1:Lag2.Point.P1  0.117010   0.022709  5.153 2.57e-07 ***
> summary(fo.model5f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit)

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. +

Data: fo.pbp.scaled.women

AIC      BIC   logLik deviance df.resid
124370.2 124492.6 -62172.1 124344.2    91162

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.9006 -0.9405 -0.7297  1.0039  1.8167

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.01709  0.1307
Number of obs: 91175, groups:  Match.ID, 666

Fixed effects:

                      Estimate Std. Error  z value  Pr(>|z|)
(Intercept)           -0.451220  0.017528   -25.74   <2e-16 ***
Rank.diff             -0.017299  0.010128    -1.71     0.0876 .
PS.pct.diff           0.099652  0.009476    10.52   <2e-16 ***
PR.pct.diff           0.089396  0.009307     9.54   <2e-16 ***
P1..Service..PBP.     0.446818  0.018887    23.65   <2e-16 ***
Lag1.Service.P1       -0.041692  0.027668    -1.50     0.1318
Lag1.Point.P1         0.255760  0.023168    11.04   <2e-16 ***
Lag2.Service.P1       0.012949  0.023128     0.05     0.9589

> summary(w.model5m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
          P1..Service..PBP. +

Data: w.pbp.scaled.men

AIC       BIC   logLik deviance df.resid
190377.1  190505.5 -95175.5 190351.1   143508

Scaled residuals:

Standardized Residuals (Female)
Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.008362 0.09144
Number of obs: 143521, groups:  Match.ID, 642

Fixed effects:

Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.624382 0.013516 -46.197  < 2e-16 ***
Rank.diff   -0.006641 0.011642  -0.570   0.56837
PS.pct.diff  0.135718 0.008477  16.010  < 2e-16 ***
PR.pct.diff  0.092980 0.007756  11.989  < 2e-16 ***
P1..Service..PBP. 0.962434 0.014616  65.846  < 2e-16 ***
Lag1.Service.P1 0.146868 0.021494   6.833 8.31e-12 ***
Lag1.Point.P1   0.239699 0.018980  12.629  < 2e-16 ***
Lag2.Service.P1 0.013915 0.018540  -0.751  0.45293
Lag2.Point.P1   0.051191 0.018567   2.757  0.00583 **
Lag1.Service.P1:Lag1.Point.P1 0.089229 0.022446  3.975  0.00016 ***
Lag2.Service.P1:Lag2.Point.P1 0.097662 0.021494  4.506 1.86e-05 ***
Lag1.Point.P1:Lag2.Point.P1 0.0106615 0.022037 -4.838 1.31e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

                       (Intr) Rnk.df PS.pct. PR.pct. P1..S. Lg1.S.P1 Lg1.P.P1 Lg2.S.P1 L2.P.P L1.S.P1: L2.S.P1:
Rank.diff   -0.020
PS.pct.diff  -0.005  0.523
PR.pct.diff  -0.005  0.523  0.407
P1..S..PBP.  -0.283  0.001  0.019  0.016
Lg1.Service.P1 0.105 0.000  0.010  0.004 -0.533
Lag1.Point.P1 -0.543 -0.002 -0.023 -0.020  0.061  0.196
Lag2.Service.P1 0.266 0.000  0.020  0.013  0.125 -0.438 -0.058
Lag2.Point.P1  -0.537 -0.001 -0.026 -0.022  0.027 -0.012  0.237  0.219
L1.S.P1:L1.L.  0.277 0.000  0.007  0.001  0.016 -0.522 -0.571  0.060  0.067
L2.S.P1:L2.   0.242 0.000 -0.007  0.001  0.022  0.042  0.109 -0.601 -0.544 -0.079
L1.P.P1:L2.   0.314 0.004  0.002  0.001 -0.002  0.020 -0.540  0.067 -0.505 -0.042 -0.119

> summary(w.model5f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. +
Data: w.pbp.scaled.women

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Scaled residuals:

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Random effects:

- Groups Name Variance Std.Dev.
- Match.ID (Intercept) 0.01964 0.1402

Number of obs: 89820, groups: Match.ID, 653

Fixed effects:

|                                | Estimate | Std. Error | z value | Pr(>|z|) |
|--------------------------------|----------|------------|---------|----------|
| (Intercept)                    | -0.5324855 | 0.0175524 | -30.337 | < 2e-16 *** |
| Rank.diff                      | -0.0270783 | 0.0102861 | -2.633  | 0.00848 ** |
| PS.pct.diff                    | 0.1091894 | 0.0093597 | 11.666  | < 2e-16 *** |
| PR.pct.diff                    | 0.0738881 | 0.0096645 | 7.645   | 2.08e-14 *** |
| P1..Service..PBP.              | 0.7020752 | 0.0190853 | 36.786  | < 2e-16 *** |
| Lag1.Service.P1                | -0.1148922 | 0.0280466 | -4.096  | 4.19e-05 *** |
| Lag1.Point.P1                  | 0.2456204 | 0.0235079 | 10.448  | < 2e-16 *** |
| Lag2.Service.P1                | 0.0277061 | 0.0235761 | 1.175   | 0.23992  |
| Lag2.Point.P1                  | 0.1574011 | 0.0231138 | 6.810   | 9.77e-12 *** |
| Lag1.Service.P1:Lag1.Point.P1  | 0.0279877 | 0.0276327 | 1.013   | 0.31113  |
| Lag2.Service.P1:Lag2.Point.P1  | -0.0003637 | 0.0277575 | -0.013  | 0.98955  |
| Lag1.Point.P1:Lag2.Point.P1    | -0.1470561 | 0.0274352 | -5.360  | 8.32e-08 *** |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

(Inter) Rnk.df PS.pc. PR.pc. P1..S. Lg1.S.P1 Lg1.P.P1 Lg2.S.P1 L2.P.P L1.S.P1: L2.S.P1:

|                                | Estimate | Std. Error | z value | Pr(>|z|) |
|--------------------------------|----------|------------|---------|----------|
| Rank.diff                      | 0.004    |            |         |          |
| PS.pct.diff                    | 0.015    | 0.326      |         |          |
| PR.pct.diff                    | 0.011    | 0.405      | 0.055   |          |
| P1..Service..PBP.              | -0.240   | -0.003     | 0.012   | 0.006    |
| Lag1.Service.P1                | -0.116   | -0.002     | 0.005   | 0.003    | 0.559  |
| Lag1.Point.P1                  | -0.554   | 0.003      | -0.026  | -0.014   | 0.043  | 0.209|
| Lag2.Service.P1                | -0.274   | -0.004     | 0.013   | 0.008    | 0.124  | -0.457| -0.042 |
| Lag2.Point.P1                  | -0.554   | 0.003      | -0.027  | -0.015   | 0.023  | -0.003 | 0.270 | 0.238 |
| L1.S.P1:L1.                   | 0.297    | 0.002      | -0.001  | -0.001   | 0.022  | -0.501 | -0.568 | 0.038 | 0.037 |
| L2.S.P1:L2.                   | 0.274    | 0.003      | -0.002  | -0.001   | 0.018  | 0.021  | 0.070  | -0.583 | -0.548 | -0.035 |
| L1.P.P1:L2.                   | 0.314    | 0.002      | -0.001  | -0.004   | -0.006 | 0.015  | -0.548 | 0.052 | -0.525 | -0.034 | -0.088 |
> summary(uso.model5m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )
Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. +
Data: uso.pbp.scaled.men

AIC      BIC   logLik deviance df.resid
194915.1 195043.7 -97444.6 194889.1   145965

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.6699 -0.8773 -0.6550  0.9039  1.7446

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.009401 0.09696
Number of obs: 145978, groups:  Match.ID, 647

Fixed effects:

Estimate Std. Error    z value  Pr(>|z|)
(Intercept) -0.623284  0.013517  -46.112 < 2e-16 ***
Rank.diff -0.041259  0.012427   -3.320  0.000900 ***
PS.pct.diff  0.098340  0.008286    11.868 < 2e-16 ***
PR.pct.diff  0.091799  0.007411    12.387 < 2e-16 ***
P1..Service..PBP.  0.866557  0.014658   59.120 < 2e-16 ***
Lag1.Service.P1 -0.077373  0.021578   -3.586  0.000336 ***
Lag1.Point.P1   0.287398  0.018721    15.351 < 2e-16 ***
Lag2.Service.P1  0.102392  0.018325    5.587  2.30e-08 ***
Lag2.Point.P1   0.103699  0.021745    4.769  1.85e-06 ***
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Correlation of Fixed Effects:

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<td>0.004</td>
<td>-0.002</td>
<td>0.000</td>
<td>-0.006</td>
<td>0.019</td>
<td>-0.546</td>
<td>0.069</td>
<td>-0.513</td>
<td>-0.038</td>
<td>-0.114</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

> summary(uso.model5f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )


Data: uso.pbp.scaled.women

AIC      BIC   logLik deviance df.resid
126902.1 127024.9 -63438.0 126876.1    93390

Scaled residuals:

Min   1Q Median   3Q  Max
-1.8537 -0.9336 -0.7113  0.9921  1.7318

Random effects:

Groups Name             Variance Std.Dev.   
Match.ID (Intercept) 0.01948  0.1396

Number of obs: 93403, groups: Match.ID, 666

Fixed effects:

    Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.474216   0.017285 -27.435  < 2e-16 ***
Rank.diff  -0.011237   0.010288  -1.092   0.2747
PS.pct.diff  0.031607   0.009539  13.796  < 2e-16 ***
PR.pct.diff  0.074121   0.009206   8.052 8.17e-16 ***
P1..Service..PBP.  0.534194   0.018682  28.594  < 2e-16 ***
Lag1.Service.P1 -0.063180   0.027436  -2.303   0.0213 *
Lag1.Point.P1   0.243399   0.022916  10.621  < 2e-16 ***
Lag2.Service.P1  0.021080   0.022977   0.917   0.3589
Lag2.Point.P1   0.117154   0.022549   5.196 2.04e-07 ***
Lag1.Service.P1:Lag1.Point.P1  0.038370   0.026892  1.427   0.1536
Lag2.Service.P1:Lag2.Point.P1  0.013495   0.026990   0.500   0.6171
Lag1.Point.P1:Lag2.Point.P1   -0.117088   0.026780  -4.372  1.23e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:
  (Intr) Rnk.df P5.pct. PR.pct. P1..S. Lg1.S.P1 Lg1.P.P1 Lg2.S.P1 L2.P.P L1.S.P1: L2.S.P1:
Rank.diff   -0.006
PS.pct.diff  0.019  0.400
PR.pct.diff  0.008  0.339  0.052
P1..S..PBP. -0.229 -0.002  0.007  0.003
Lg1.Srvc.P1 -0.126 -0.001  0.006  0.002 -0.559
Lag1.Pnt.P1  -0.556  0.003 -0.026 -0.014  0.037  0.223
Lg2.Srvc.P1  -0.280 -0.002  0.012  0.005  0.122 -0.466 -0.043
Lag2.Pnt.P1  -0.556  0.003 -0.027 -0.015  0.018 -0.003  0.272  0.253
L1.S.P1:L1.  0.303  0.000 -0.005  0.000  0.021 -0.497 -0.572  0.043  0.034
L2.S.P1:L2.  0.282  0.000 -0.005 -0.001  0.021  0.021  0.066 -0.577 -0.552 -0.040
L1.P.P1:L2.  0.311  0.002 -0.005 -0.003 -0.006  0.012 -0.551  0.043 -0.529 -0.024 -0.078

Model 6
> summary(aus.model6m)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
  Family: binomial   ( logit )
  Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  Data: aus.pbp.scaled.men
  Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

       AIC    BIC logLik deviance df.resid
   187405.1 187592.3  -93683.5 187367.1   140663
Scaled residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1.8443</td>
<td>-0.8726</td>
<td>-0.6477</td>
<td>0.9060</td>
<td>1.8717</td>
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</tbody>
</table>

Random effects:

<table>
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<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Match.ID</td>
<td>(Intercept)</td>
<td>0.01216</td>
<td>0.1103</td>
</tr>
</tbody>
</table>

Number of obs: 140682, groups: Match.ID, 628

Fixed effects:

|                  | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------|----------|------------|---------|---------|
| (Intercept)      | -0.534567| 0.017336   | -30.836 | < 2e-16 *** |
| Rank.diff        | -0.016221| 0.014087   | -1.152  | 0.249510 |
| PS.pct.diff      | 0.118984 | 0.008654   | 13.749  | < 2e-16 *** |
| PR.pct.diff      | 0.102220 | 0.008271   | 12.359  | < 2e-16 *** |
| P1..Service..PBP.| 0.887818 | 0.014982   | 59.260  | < 2e-16 *** |
| Lag1.Service.P1  | -0.099492| 0.021888   | -4.546  | 5.48e-06 *** |
| Lag1.Point.P1    | 0.224230 | 0.023848   | 9.403   | 0.0165458 |
| Lag2.Service.P1  | 0.003721 | 0.021962   | 0.169   | 0.865458 |
| Lag2.Point.P1    | -0.033013| 0.023818   | -1.386  | 0.165742 |
| Lag3.Service.P1  | 0.046740 | 0.018940   | 2.468   | 0.013596 * |
| Lag3.Point.P1    | -0.144238| 0.023142   | -6.233  | 4.58e-10 *** |
| Lag1.Service.P1:| 0.029071 | 0.022572   | 1.288   | 0.197788 |
| Lag2.Service.P1:| 0.084905 | 0.022842   | 3.717   | 0.000202 *** |
| Lag3.Service.P1:| 0.049833 | 0.022889   | 2.177   | 0.029466 * |
| Lag1.Point.P1:| 0.011579 | 0.031010   | 0.373   | 0.708855 |
| Lag1.Point.P1:| 0.079567 | 0.030974   | 2.569   | 0.010204 * |
| Lag2.Point.P1:| 0.164583 | 0.031074   | 5.297   | 1.18e-07 *** |
| Lag1.Point.P1:| -0.215746| 0.044188   | -4.882  | 1.05e-06 *** |

> summary(aus.model6f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. +


Lag2.Point.P1 *

Lag3.Point.P1) + (1 | Match.ID)

Data: aus.pbp.scaled.women

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC  BIC logLik deviance df.resid

120558.6 120737.1 -60260.3 120520.6 88946

Scaled residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
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<td>-0.9266</td>
<td>-0.6916</td>
<td>0.9894</td>
<td>1.9788</td>
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Random effects:

<table>
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<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Match.ID</td>
<td>(Intercept)</td>
<td>0.022024</td>
<td>0.1484</td>
</tr>
</tbody>
</table>

Number of obs: 88965, groups: Match.ID, 657

Fixed effects:

|                | Estimate  | Std. Error | z value |   Pr(>|z|) |
|----------------|-----------|------------|---------|-----------|
| (Intercept)    | -0.4370085| 0.0220254  | -19.841 | < 2e-16   *** |
| Rank.diff      | -0.0359896| 0.0106709  | -3.373  | 0.000744  *** |
| PS.pct.diff    | 0.1200448 | 0.0098948  | 12.132  | < 2e-16   *** |
| PR.pct.diff    | 0.0730633 | 0.0100273  | 7.286   | 3.18e-13  *** |
| P1..Service..PBP. | 0.5735449 | 0.0194523  | 29.485  | < 2e-16   *** |
| Lag1.Service.P1| -0.0664548| 0.0280507  | -2.369  | 0.017832  * |
| Lag1.Point.P1  | 0.2136032 | 0.0294497  | 7.253   | 4.07e-13  *** |
| Lag2.Service.P1| -0.0007306| 0.0280532  | -0.026  | 0.979222  |
| Lag2.Point.P1  | 0.0535336 | 0.0293770  | 1.822   | 0.068410  . |
| Lag3.Service.P1| -0.0619175| 0.0237652  | -2.605  | 0.009177  ** |
| Lag3.Point.P1  | -0.1338279| 0.0289078  | -4.629  | 3.67e-06  *** |
| Lag1.Service.P1:Lag1.Point.P1 | 0.0068061| 0.0276599  | 0.246   | 0.805634  |
| Lag2.Service.P1:Lag2.Point.P1 | 0.0670307| 0.0277869  | 2.412   | 0.015852  * |
| Lag3.Service.P1:Lag3.Point.P1 | 0.0772220| 0.0278201  | 2.776   | 0.005507  ** |
| Lag1.Point.P1:Lag2.Point.P1  | -0.0718021| 0.0382551  | -1.877  | 0.060528  .|
| Lag1.Point.P1:Lag3.Point.P1  | 0.1250553| 0.0383301  | 3.263   | 0.001104  ** |
| Lag2.Point.P1:Lag3.Point.P1  | 0.1252490| 0.0383819  | 3.263   | 0.001102  ** |
| Lag1.Point.P1:Lag2.Point.P1:Lag3.Point.P1 | -0.1797262| 0.0550463  | -3.265  | 0.001095  ** |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(fo.model6m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Data: fo.pbp.scaled.men

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+06))

AIC      BIC   logLik deviance df.resid
185192.7 185379.6 -92577.3 185154.7   138661

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.7520 -0.8910 -0.6448  0.9284  1.9217

Random effects:
Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.01376  0.1173

Number of obs: 138680, groups:  Match.ID, 646

Fixed effects:

                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -0.524596   0.017483 -30.006  < 2e-16 ***
Rank.diff                -0.048453   0.014140  -3.427 0.000611 ***
PS.pct.diff               0.103752   0.009727  10.666  < 2e-16 ***
PR.pct.diff               0.112798   0.008857  12.735  < 2e-16 ***
P1..Service..PBP.         0.823302   0.015262  53.943  < 2e-16 ***
Lag1.Service.P1          -0.070485   0.022222  -3.172 0.001514 **
Lag1.Point.P1            0.193867   0.024026   8.069 7.09e-16 ***
Lag2.Service.P1          -0.045204   0.022794  -2.029 0.042451 *
Lag2.Point.P1            0.033903   0.023794   1.425 0.154205
Lag3.Service.P1          -0.172486   0.023337  -7.391 1.46e-13 ***
Lag3.Point.P1            -0.181518   0.019094  -9.543  < 2e-16 ***
Lag1.Service.P1:Lag1.Point.P1 -0.040605   0.022634  -1.794 0.072818 .
Lag2.Service.P1:Lag2.Point.P1 0.110873   0.022852   4.852 1.22e-06 ***
Lag3.Service.P1:Lag3.Point.P1 0.067502   0.022902   2.947 0.003204 **
Lag1.Point.P1:Lag2.Point.P1 0.021769   0.031155  -0.699 0.484720
Lag1.Point.P1:Lag3.Point.P1 0.130790   0.031156   4.198 2.69e-05 ***
Lag2.Point.P1:Lag3.Point.P1 0.140342   0.031245   4.492 7.07e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(fo.model6f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )
Data: fo.pbp.scaled.women
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
123444.3 123623.2 -61703.2 123406.3    90490

Scaled residuals:
    Min      1Q  Median      3Q     Max
  -1.9119 -0.9422 -0.7272  1.0044  1.8602

Random effects:
  Groups   Name        Variance Std.Dev.
          Match.ID (Intercept) 0.01676  0.1295
Number of obs: 90509, groups:  Match.ID, 666

Fixed effects:

  Estimate Std. Error z value  Pr(>|z|)
(Intercept)                     -0.417099    0.021827  -19.110  < 2e-16 ***
Rank.diff                      -0.017733    0.010120   -1.752   0.0797 .
PS.pct.diff                    0.098793    0.009479   10.423  < 2e-16 ***
PR.pct.diff                    0.089107    0.009310    9.572  < 2e-16 ***
P1..Service..PBP.             0.445448    0.019194   23.209  < 2e-16 ***
Lag1.Service.P1               -0.037922    0.027716   -1.368   0.1712
Lag1.Point.P1                0.194239    0.029119    6.670  0.0014 ***
Lag2.Service.P1               0.018198    0.027707    0.657   0.5113
Lag2.Point.P1                0.096033    0.028906    3.322  0.0009 ***
Lag3.Service.P1              -0.006133    0.023442   -0.262   0.7936
Lag3.Point.P1                -0.081964    0.028631   -2.863  0.0042 **
Lag1.Service.P1:Lag1.Point.P1   -0.002117    0.027185   -0.078   0.9321
Lag2.Service.P1:Lag2.Point.P1   -0.005060    0.027266   -0.186   0.8527
Lag3.Service.P1:Lag3.Point.P1   -0.000843    0.027295   -0.031   0.9755
Lag1.Point.P1:Lag2.Point.P1    -0.076430    0.037723   -2.026   0.0427 *
Lag1.Point.P1:Lag3.Point.P1    0.138559    0.037807    3.665  0.0002 ***
Lag2.Point.P1:Lag3.Point.P1    0.152220    0.037826    4.024  0.0000 **
Lag1.Point.P1:Lag2.Point.P1:Lag3.Point.P1 -0.170654    0.054199   -3.149  0.0016 **

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(w.model6m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit)


Data: w.pbp.scaled.men

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+06))

AIC      BIC   logLik deviance df.resid
189517.7 189705.2 -94739.8 189479.7   142860

Scaled residuals:

Min      1Q  Median      3Q     Max
-1.7008 -0.8568 -0.6399  0.8887  1.9016

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.009525 0.0976

Number of obs: 142879, groups: Match.ID, 642

Fixed effects:

                         Estimate Std. Error  z value Pr(>|z|)
(Intercept)              -0.547664   0.017104 -32.020  < 2e-16 ***
Rank.diff                -0.006995   0.011910  -0.587 0.556977
PS.pct.diff              0.138054   0.008674  15.916  < 2e-16 ***
PR.pct.diff              0.094986   0.007932  11.974  < 2e-16 ***
P1..Service..PBP.       0.950721   0.014790  64.279  < 2e-16 ***
Lag1.Service.P1         -0.145480   0.021608  -6.733 1.67e-11 ***
Lag1.Point.P1           0.197702   0.023801   8.307  < 2e-16 ***
Lag2.Service.P1         -0.011128   0.021663  -0.514 0.607457
Lag2.Point.P1            0.003223   0.023657   0.136 0.891617
Lag3.Service.P1         -0.012734   0.018766  -0.679 0.497411
| Term                                      | Estimate  | Std. Error | z value  | Pr(>|z|)  |
|-------------------------------------------|-----------|------------|----------|-----------|
| Lag3.Point.P1                             | -0.171154 | 0.023060   | -7.422   | 1.15e-13 *** |
| Lag1.Service.P1:Lag1.Point.P1             | 0.088164  | 0.022569   | 3.906    | 9.37e-05 ***  |
| Lag2.Service.P1:Lag2.Point.P1             | 0.091089  | 0.022857   | 3.985    | 6.75e-05 ***  |
| Lag3.Service.P1:Lag3.Point.P1             | 0.043589  | 0.022895   | 1.904    | 0.056929 .  |
| Lag1.Point.P1:Lag2.Point.P1               | -0.042967 | 0.030871   | -1.392   | 0.163973 .  |
| Lag1.Point.P1:Lag3.Point.P1               | 0.095749  | 0.030843   | 3.104    | 0.001907 **  |
| Lag2.Point.P1:Lag3.Point.P1               | 0.112597  | 0.030905   | 3.643    | 0.000269 *** |
| Lag1.Point.P1:Lag2.Point.P1:Lag3.Point.P1 | -0.139711 | 0.043967   | -3.178   | 0.001485 **  |

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> summary(w.model6f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
Lag2.Point.P1 *
Lag3.Point.P1) + (1 | Match.ID)
Data: w.pbp.scaled.women
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+06))

AIC      BIC   logLik deviance df.resid
120487.9 120666.5 -60225.0 120449.9    89148

Scaled residuals:
       Min      1Q  Median      3Q     Max
-1.5891 -0.9211 -0.6835  0.9605  1.8389

Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.01957  0.1399

Number of obs: 89167, groups:  Match.ID, 653

Fixed effects:
                               Estimate Std. Error z value Pr(>|z|)
(Intercept)                    -0.478600  0.021913 -21.841  < 2e-16 ***
Rank.diff                     -0.027032  0.010304  -2.623  0.008707 **
PS.pct.diff                   0.108285  0.009388  11.534  < 2e-16 ***
PR.pct.diff                   0.074149  0.009686   7.655 1.93e-14 ***
P1..Service..PBP.             0.696332  0.019382  35.928  < 2e-16 ***
Lag1.Service.P1               -0.109062  0.028129  -3.877  0.000106 ***
Lag1.Point.P1                 0.177287   0.029700   5.969  2.38e-09 ***
Lag2.Service.P1               0.028732   0.028131   1.021  0.307097
Lag2.Point.P1                 0.112597   0.030905   3.643  0.000269 ***
Lag3.Service.P1               0.095749   0.030843   3.104  0.001907 **
Lag3.Point.P1                 0.112597   0.030905   3.643  0.000269 ***
Lag1.Point.P1:Lag2.Point.P1   -0.042967  0.030871  -1.392  0.163973 .  
Lag3.Point.P1:Lag1.Point.P1   -0.042967  0.030871  -1.392  0.163973 .  
Lag2.Service.P1:Lag2.Point.P1 0.043589   0.022895   1.904  0.056929 .  
Lag2.Service.P1:Lag3.Point.P1 0.095749   0.030843   3.104  0.001907 **
Lag3.Point.P1:Lag3.Point.P1   -0.125675  0.029024  -4.330  1.49e-05 ***
Lag3.Point.P1:Lag2.Point.P1   -0.139711  0.043967  -3.178  0.001485 **
> summary(uso.model6m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Formula: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP. +
          Lag3.Point.P1) + (1 | Match.ID)

Data: uso.pbp.scaled.men

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC      BIC   logLik deviance df.resid
194038.1 194225.9 -97000.0 194000.1   145312

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.6796 -0.8789 -0.6526  0.9051  1.8069

Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.01005  0.1002

Number of obs: 145331, groups:  Match.ID, 647

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Lag3.Service.Pl:Lag3.Point.Pl  0.038984   0.027973   1.394 0.163431
Lag1.Point.Pl:Lag2.Point.Pl   -0.039444   0.038461  -1.026 0.305093
Lag1.Point.Pl:Lag3.Point.Pl   0.155169   0.038500   4.030 5.57e- 05 ***
Lag2.Point.Pl:Lag3.Point.Pl   0.147637   0.038559   3.829 0.000129 ***

Standardized Residuals (Male)
Fixed effects:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.570340| 0.016989   | -33.571 | < 2e-16 *** |
| Rank.diff      | -0.041624| 0.012597   | -3.304  | 0.000952 *** |
| PS.pct.diff    | 0.099682 | 0.008400   | 11.867  | < 2e-16 *** |
| PR.pct.diff    | 0.092482 | 0.007512   | 12.312  | < 2e-16 *** |
| P1..Service..PBP. | 0.860905| 0.014866   | 57.911  | < 2e-16 *** |
| Lag1.Service.P1| -0.077321| 0.021664   | -3.569  | 0.000358 *** |
| Lag1.Point.P1  | 0.244770 | 0.023513   | 10.410  | < 2e-16 *** |
| Lag2.Service.P1| 0.007326 | 0.023362   | 0.337   | 0.736119  |
| Lag2.Point.P1  | 0.045025 | 0.023362   | 1.927   | 0.053948 . |
| Lag3.Service.P1| 0.009116 | 0.018736   | 0.487   | 0.626590  |
| Lag3.Point.P1  | -0.122562| 0.022792   | -5.377  | 7.56e-08 *** |
| Lag1.Service.P1:Lag1.Point.P1 | -0.003564 | 0.022134 | -0.161 | 0.872082 |
| Lag2.Service.P1:Lag2.Point.P1 | 0.052058 | 0.022379 | 2.326 | 0.020008 * |
| Lag3.Service.P1:Lag3.Point.P1 | -0.006045 | 0.022428 | -0.270 | 0.787536 |
| Lag1.Point.P1:Lag2.Point.P1 | -0.046058 | 0.030524 | 3.235 | 0.001216 ** |
| Lag1.Point.P1:Lag3.Point.P1 | 0.134271 | 0.030620 | 4.385 | 1.16e-05 *** |
| Lag2.Point.P1:Lag3.Point.P1 | 0.098746 | 0.030524 | 3.235 | 0.001216 ** |
| Lag1.Point.P1:Lag2.Point.P1:Lag3.Point.P1 | -0.129731 | 0.043481 | -2.984 | 0.002848 ** |

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> summary(uso.model6f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit )


Data: uso.pbp.scaled.women

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 20000))

AIC  BIC   logLik deviance df.resid
126001.7 126181.0 -62981.9 125963.7    92718

Scaled residuals:
Min     1Q  Median     3Q    Max
-1.8554 -0.9331 -0.7092  0.9914  1.7539

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.01987  0.141

Number of obs: 92737, groups: Match.ID, 666
Fixed effects:  

| Term                  | Estimate | Std. Error | z value | Pr(>|z|) |
|-----------------------|----------|------------|---------|---------|
| (Intercept)           | -0.409282| 0.021585   | -18.961 | < 2e-16 *** |
| Rank.diff             | -0.010503| 0.010354   | -1.014  | 0.310395 |
| PS.pct.diff           | 0.130716 | 0.009614   | 13.597  | < 2e-16 *** |
| PR.pct.diff           | 0.074006 | 0.009269   | 7.985   | 1.41e-15 *** |
| P1..Service..PBP.     | 0.528681 | 0.018974   | 27.863  | < 2e-16 *** |
| Lag1.Service.P1       | -0.062184| 0.027503   | -2.261  | 0.023758 * |
| Lag1.Point.P1         | 0.167967 | 0.028831   | 5.826   | 5.68e-09 *** |
| Lag2.Service.P1       | 0.020030 | 0.027529   | 0.728   | 0.466848 |
| Lag2.Point.P1         | 0.036848 | 0.028686   | 1.285   | 0.198948 |
| Lag3.Service.P1       | -0.017492| 0.023328   | -0.750  | 0.453356 |
| Lag3.Point.P1         | -0.143843| 0.028231   | -5.095  | 3.49e-07 *** |
| Lag1.Service.P1:Lag1.Point.P1 | 0.043395 | 0.027018   | 1.606   | 0.108236 |
| Lag2.Service.P1:Lag2.Point.P1 | 0.034554 | 0.027189   | 1.271   | 0.203758 |
| Lag1.Point.P1:Lag2.Point.P1 | -0.023204| 0.037496   | -0.619  | 0.536023 |
| Lag1.Point.P1:Lag3.Point.P1 | 0.162404| 0.037566   | 4.323   | 1.54e-05 *** |
| Lag2.Point.P1:Lag3.Point.P1 | 0.176578| 0.037591   | 4.697   | 2.64e-06 *** |
| Lag1.Point.P1:Lag2.Point.P1:Lag3.Point.P1 | -0.202382| 0.053784   | -3.763  | 0.000168 *** |

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

---

Model 7

> summary(aus.model7m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )

Data: aus.pbp.scaled.men
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

<table>
<thead>
<tr>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>df.resid</th>
</tr>
</thead>
<tbody>
<tr>
<td>190228.3</td>
<td>190317.1</td>
<td>-95105.1</td>
<td>190210.3</td>
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Scaled residuals:

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<tr>
<th>Min</th>
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<th>Median</th>
<th>3Q</th>
<th>Max</th>
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</thead>
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<tr>
<td>-1.7679</td>
<td>-0.8638</td>
<td>-0.6590</td>
<td>0.8969</td>
<td>1.7589</td>
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Random effects:

Groups Name Variance Std.Dev.

Match.ID (Intercept) 0.02789 0.167

Number of obs: 142566, groups: Match.ID, 628

Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|---------|
| (Intercept) | -0.479505  | 0.010361 | -46.282 | < 2e-16 *** |
| Rank.diff    | -0.017638  | 0.017293 | -1.020  | 0.3077    |
| PS.pct.diff  | 0.148069   | 0.011576 | 12.791  | < 2e-16 *** |
| PR.pct.diff  | 0.125320   | 0.010730 | 11.679  | < 2e-16 *** |
| P1..Service..PBP | 0.856368 | 0.011039 | 77.575  | < 2e-16 *** |
| Set.Won.Diff | 0.016082   | 0.013366 | 1.203   | 0.2289    |
| Game.Won.Diff| -0.029200  | 0.005858 | -4.985  | 6.2e-07 *** |
| Cum.Game.Won.Diff | -0.010084 | 0.004949 | -2.037  | 0.0416 *  |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

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<tr>
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<tr>
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<td>0.000</td>
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<tr>
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<td>0.050</td>
<td>-0.003</td>
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<tr>
<td>Gm.W.D</td>
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<td>-0.008</td>
<td>0.019</td>
<td>0.081</td>
<td>0.641</td>
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<tr>
<td>Cum.Gm.W.D</td>
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<td>-0.243</td>
<td>-0.242</td>
<td>0.020</td>
<td>-0.792</td>
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> summary(aus.model7f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )


(1 | Match.ID)

Data: aus.pbp.scaled.women

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

<table>
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<tr>
<th>AIC</th>
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<th>logLik</th>
<th>deviance</th>
<th>df.resid</th>
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<tbody>
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<td>123603.6</td>
<td>-61750.4</td>
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Scaled residuals:

<p>| | | | | |</p>
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</thead>
<tbody>
<tr>
<td>Min</td>
<td>1Q</td>
<td>Median</td>
<td>3Q</td>
<td>Max</td>
</tr>
<tr>
<td>-1.5656</td>
<td>-0.9285</td>
<td>-0.7156</td>
<td>0.9878</td>
<td>1.7821</td>
</tr>
</tbody>
</table>

Random effects:

Groups     Name        Variance Std.Dev.
Match.ID (Intercept) 0.03178 0.1783

Number of obs: 90936, groups: Match.ID, 657

Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -0.359017 | 0.011947 | -30.051 < 2e-16 *** |
| Rank.diff | -0.041702 | 0.011697 | -3.565 0.000363 *** |
| PS.pct.diff | 0.130080 | 0.011537 | 11.276 < 2e-16 *** |
| PR.pct.diff | 0.077838 | 0.011449 | 6.982 2.92e-12 *** |
| Pl..Service..PBP. | 0.545635 | 0.013575 | 40.194 < 2e-16 *** |
| Set.Won.Diff | 0.053861 | 0.024601 | 2.189 0.028570 * |
| Game.Won.Diff | 0.011805 | 0.008352 | 1.413 0.157554 |
| Cum.Game.Won.Diff | -0.015666 | 0.008295 | -1.889 0.058945 . |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

| (Intercept) Rnk.df PS.pct. PR.pct. Pl..S.. St.W.D Gm.W.D Gm..W.D |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Rank.diff        -0.009         | 0.007           | 0.244           | 0.004           | -0.572          | 0.019           | 0.004           | 0.001           |
| PS.pct.diff      0.004          | 0.316           | -0.004          | 0.004           | 0.004           | 0.019           | 0.043           | 0.026           |
| PR.pct.diff      0.004          | 0.316           | -0.004          | 0.004           | 0.004           | 0.019           | 0.043           | 0.026           |
| Pl..S..PBP.      -0.572         | 0.019           | -0.028          | -0.004          | 0.004           | 0.004           | 0.019           | 0.043           |
| Set.Won.Diff     0.019          | 0.004           | -0.023          | 0.032           | 0.015           | 0.038           | 0.019           | 0.043           |
| Game.Won.Diff    -0.004         | -0.023          | 0.032           | 0.015           | 0.038           | 0.019           | 0.043           | 0.026           |
| Cum.Game.Won.Diff 0.017         | 0.108           | -0.238          | -0.150          | 0.003           | -0.808          | -0.775          | 0.738           |

**Figure: Standardized Residuals**

- **Standardized Residuals (Male)**
  - Index
  - Residual

- **Standardized Residuals (Female)**
  - Index
  - Residual
> summary(fo.model7m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )


   (1 | Match.ID)

Data: fo.pbp.scaled.men

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

AIC   BIC  logLik deviance df.resid
188278.4 188367.1 -94130.2 188260.4   140609

Scaled residuals:
   Min      1Q  Median      3Q     Max
-1.6776 -0.8834 -0.6699  0.9221  1.7160

Random effects:
  Groups   Name        Variance Std.Dev.
    Match.ID (Intercept) 0.01991  0.1411

Number of obs: 140618, groups:  Match.ID, 646

Fixed effects:

   Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.464503  0.009653 -48.120  < 2e-16 ***
Rank.diff    -0.052050  0.015374  -3.386 0.000710 ***
PS.pct.diff  0.114128  0.011155  10.231  < 2e-16 ***
PR.pct.diff  0.122788  0.010317  11.901  < 2e-16 ***
P1..Service..PBP.  0.800371  0.011046  72.458  < 2e-16 ***
Set.Won.Diff   0.053515  0.013783   3.883 0.000103 ***
Game.Won.Diff -0.007662  0.005612  -1.365 0.172212
Cum.Game.Won.Diff -0.011350  0.004793  -2.368 0.017895 *

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

  (Intr) Rnk.df PS.pc. PR.pc. P1..S..St.W.D Gm.W.D
Rank.diff    0.026
PS.pct.diff  0.014  0.593
PR.pct.diff  0.008  0.496  0.494
P1..S..PBP. -0.578 -0.002  0.000  0.002
Set.Won.Diff -0.033  0.028  0.064  0.050  0.000
Game.Wn.Diff -0.063  0.012  0.013  0.000  0.065  0.642
Cum.Gm.Wn.Df  0.024  0.034 -0.225 -0.237  0.010 -0.825 -0.657

233
> summary(fo.model7f)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  ( logit )
Data: fo.pbp.scaled.women
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

AIC      BIC   logLik deviance df.resid
126425.1 126510.0 -63203.6 126407.1    92498

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.8229 -0.9446 -0.7540  1.0066  1.7143

Random effects:
 Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.01889  0.1375

Number of obs: 92507, groups:  Match.ID, 666

Fixed effects:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.291035   0.010919 -26.654   <2e-16 ***
Rank.diff    -0.017142   0.010275  -1.668   0.0953 .
PS.pct.diff   0.101554   0.010198   9.958   <2e-16 ***
PR.pct.diff   0.090239   0.009872   9.141   <2e-16 ***
P1..Service..PBP.  0.428180   0.013363  32.042   <2e-16 ***
Set.Won.Diff  0.060674   0.023993   2.529   0.0114 *
Game.Won.Diff 0.018310   0.008116   2.256   0.0241 *
Cum.Game.Won.Diff -0.009491   0.007660  -1.239   0.2154

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

correlation of fixed effects:

       (Intr) Rnk.df PS.pc. PR.pc. P1..S.. St.W.D Gm.W.D
Rank.diff   -0.003
PS.pct.diff  0.007  0.343
PR.pct.diff  0.003  0.319  0.028
P1..S..PBP. -0.615 -0.003  0.001  0.004
Set.Won.Diff 0.014  0.012  0.015  0.046 -0.001
Game.Wn.Diff -0.005  0.004  0.001  0.007  0.030  0.738
Cum.Gm.Wn.Df -0.027  0.015 -0.176 -0.173  0.005 -0.829 -0.794
> summary(w.model7m)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
  Family: binomial  ( logit )
           (1 | Match.ID)
  Data: w.pbp.scaled.men
  Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

    AIC      BIC   logLik deviance df.resid
 192354.8 192443.7 -96168.4 192336.8   144796

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.6904 -0.8512 -0.6465  0.8801  1.8246

Random effects:
  Groups   Name        Variance Std.Dev.
  Match.ID (Intercept) 0.02591  0.161

Number of obs: 144805, groups:  Match.ID, 642

Fixed effects:

  Estimate Std. Error z value Pr(>|z|)
 (Intercept)  -0.50450    0.01008 -50.062  < 2e-16 *** 
 Rank.diff    -0.00686    0.01490  -0.460  0.64528 
 PS.pct.diff   0.17612    0.01184  14.872  < 2e-16 *** 
 PR.pct.diff   0.11960    0.01035  11.557  < 2e-16 *** 
 P1..Service..PBP. 0.90383    0.01099  82.263  < 2e-16 *** 
 Set.Won.Diff  0.03236    0.01283   2.521  0.01170 *
 Game.Won.Diff -0.04197    0.00606  -6.926 4.34e-12 *** 
 Cum.Game.Won.Diff -0.01535    0.00517  -2.970  0.00298 **

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:

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<td>-0.001</td>
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> summary(w.model7f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial ( logit )


(1 | Match.ID)

Data: w.pbp.scaled.women

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

AIC      BIC   logLik deviance df.resid
123381.3 123466.1 -61681.6 123363.3    91117

Scaled residuals:
Min      1Q  Median      3Q     Max
-1.5106 -0.9163 -0.7093  0.9542  1.6443

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.02425  0.1557

Number of obs: 91126, groups:  Match.ID, 653

Fixed effects:

|                | Estimate | Std. Error | z value | Pr(>|z|) |
|----------------|----------|------------|---------|----------|
| (Intercept)    | -0.382240|  0.011458  | -33.360 | < 2e-16  *** |
| Rank.diff      | -0.029106|  0.010769  | -2.703  |  0.00688  **  |
| PS.pct.diff    |  0.113502|  0.010441  | 10.870  | < 2e-16  *** |
| PR.pct.diff    |  0.074451|  0.010404  |  7.156  |  8.31e-13 *** |
| P1..Service..PBP. |  0.647811|  0.013605  | 47.614  | < 2e-16  *** |
| Set.Won.Diff   |  0.117473|  0.024562  |  4.783  |  1.73e-06 *** |
| Game.Won.Diff  |  0.017594|  0.008526  |  2.063  |  0.03907  *  |
| Cum.Game.Won.Diff | -0.022560|  0.008499  | -2.654  |  0.00795  ** |

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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:

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<th>PR.pc.</th>
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<th>St.W.D</th>
<th>Gm.W.D</th>
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</tr>
<tr>
<td>P1..S..PBP.</td>
<td>-0.596</td>
<td>-0.001</td>
<td>0.006</td>
<td>0.002</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Set.Won.Dff</td>
<td>-0.018</td>
<td>-0.042</td>
<td>0.039</td>
<td>0.026</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Game.Wn.Dff</td>
<td>-0.046</td>
<td>-0.032</td>
<td>0.026</td>
<td>0.016</td>
<td>0.038</td>
<td>0.726</td>
<td></td>
</tr>
<tr>
<td>Cm.Gm.Wn.Df</td>
<td>-0.006</td>
<td>0.086</td>
<td>-0.209</td>
<td>-0.147</td>
<td>0.010</td>
<td>-0.834</td>
<td>-0.793</td>
</tr>
</tbody>
</table>

```r
> summary(uso.model7m)
```

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial (logit)


Data: uso.pbp.scaled.men

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

<table>
<thead>
<tr>
<th></th>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>df.resid</th>
</tr>
</thead>
<tbody>
<tr>
<td>197120.2</td>
<td>197209.3</td>
<td>-98551.1</td>
<td>197102.2</td>
<td>147263</td>
<td></td>
</tr>
</tbody>
</table>

Scaled residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1.6604</td>
<td>-0.8635</td>
<td>-0.6777</td>
<td>0.8931</td>
<td>1.6455</td>
</tr>
</tbody>
</table>

Random effects:

<table>
<thead>
<tr>
<th>Groups Name</th>
<th>Variance</th>
<th>Std.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Match.ID (Intercept)</td>
<td>0.01888</td>
<td>0.1374</td>
</tr>
</tbody>
</table>

Number of obs: 147272, groups: Match.ID, 647
Fixed effects:

|                  | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------|----------|------------|---------|----------|
| (Intercept)      | -0.457838| 0.009449   | -48.453 | < 2e-16 *** |
| Rank.diff        | -0.044610| 0.014471   | -3.083  | 0.00205 **  |
| PS.pct.diff      | 0.117434 | 0.010402   | 11.289  | < 2e-16 *** |
| PR.pct.diff      | 0.107005 | 0.009138   | 11.710  | < 2e-16 *** |
| P1..Service..PBP.| 0.830985 | 0.018089   | 76.882  | < 2e-16 *** |
| Set.Won.Diff     | 0.040197 | 0.013060   | 3.078   | 0.00208 **  |
| Game.Won.Diff    | -0.008373| 0.005616   | -1.491  | 0.13598 |
| Cum.Game.Won.Diff| 0.013205 | 0.004806   | -2.748  | 0.00600 **  |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

<table>
<thead>
<tr>
<th></th>
<th>(Intr)</th>
<th>Rnk.df</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
<th>P1..S.</th>
<th>St.W.D</th>
<th>Gm.W.D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank.diff</td>
<td>-0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PS.pct.diff</td>
<td>0.035</td>
<td>0.515</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PR.pct.diff</td>
<td>0.027</td>
<td>0.384</td>
<td>0.439</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P1..S..PBP.</td>
<td>-0.578</td>
<td>0.000</td>
<td>-0.001</td>
<td>0.003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Set.Won.Diff</td>
<td>0.013</td>
<td>0.032</td>
<td>0.032</td>
<td>0.036</td>
<td>-0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Game.Won.Diff</td>
<td>-0.038</td>
<td>0.024</td>
<td>0.010</td>
<td>0.010</td>
<td>0.077</td>
<td>0.642</td>
<td></td>
</tr>
<tr>
<td>Cum.Game.Won.Diff</td>
<td>-0.061</td>
<td>0.011</td>
<td>-0.245</td>
<td>-0.228</td>
<td>0.010</td>
<td>-0.811</td>
<td>-0.665</td>
</tr>
</tbody>
</table>

> summary(uso.model7f)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']

Family: binomial  (logit)

          (1 | Match.ID)

Data: uso.pbp.scaled.women

Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))

AIC     BIC   logLik deviance df.resid
128985.3 129070.4 -64483.6 128967.3    94726

Scaled residuals:

  Min 1Q Median 3Q  Max
-1.7618 -0.9344 -0.7290 0.9833 1.6170

Random effects:

Groups   Name        Variance Std.Dev.
Match.ID (Intercept) 0.02346 0.1532

Number of obs: 94735, groups: Match.ID, 666
Fixed effects:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -0.329703 | 0.011159 | -29.546  | < 2e-16 *** |
| Rank.diff | -0.011426 | 0.010681 | -1.070   | 0.2847     |
| PS.pct.diff | 0.137996 | 0.011205 | 12.315   | < 2e-16 *** |
| PR.pct.diff | 0.075779 | 0.009980 | 7.593    | 3.13e-14 *** |
| P1..Service..PBP. | 0.522232 | 0.013274 | 39.344   | < 2e-16 *** |
| Set.Won.Diff | 0.027645 | 0.023521 | 1.175    | 0.2399     |
| Game.Won.Diff | 0.016936 | 0.007961 | 2.127    | 0.0334 *   |
| Cum.Game.Won.Diff | -0.007155 | 0.007710 | -0.928   | 0.3534     |

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:

<table>
<thead>
<tr>
<th></th>
<th>(Intr)</th>
<th>Rnk.df</th>
<th>PS.pc.</th>
<th>PR.pc.</th>
<th>P1..S.</th>
<th>St.W.D</th>
<th>Gm.W.D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank.diff</td>
<td>-0.008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PS.pct.diff</td>
<td>0.005</td>
<td>0.316</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PR.pct.diff</td>
<td>-0.001</td>
<td>0.299</td>
<td>0.185</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P1..S..PBP.</td>
<td>-0.594</td>
<td>0.001</td>
<td>-0.005</td>
<td>-0.004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Set.Won.Diff</td>
<td>-0.013</td>
<td>-0.024</td>
<td>0.032</td>
<td>0.024</td>
<td>-0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Game.Won.Diff</td>
<td>-0.038</td>
<td>-0.004</td>
<td>0.027</td>
<td>0.022</td>
<td>0.043</td>
<td>0.736</td>
<td></td>
</tr>
<tr>
<td>Cum.Game.Won.Diff</td>
<td>-0.004</td>
<td>0.055</td>
<td>-0.297</td>
<td>-0.192</td>
<td>0.010</td>
<td>-0.780</td>
<td>-0.758</td>
</tr>
</tbody>
</table>
Goodness of Fit Tests (Chi-Square):

Australian Open

> anova(pure.aus.model0m, pure.aus.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
  Resid. Df Resid. Dev Df Deviance
  1  140680  188877
  2  140679  188444  1   432.86

> anova(pure.aus.model2m, pure.aus.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
  Resid. Df Resid. Dev Df Deviance
  1  140677  188016
  2  140679  188444 -2  -428.07

> anova(pure.aus.model3m, pure.aus.model2m)
Data: pure.aus.pbp.scaled.men
Models:
  pure.aus.model2m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.aus.model2m:   P1..Service..PBP.
  pure.aus.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.aus.model3m:   P1..Service..PBP. + (1 | Match.ID)
  Df    AIC    BIC logLik deviance Chisq Chi Df Pr(>Chisq)
  pure.aus.model2m  5 188026 188076 -94008   188016
  pure.aus.model3m  6 187913 187972 -93950   187901 115.79      1  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model4m, pure.aus.model3m)
Data: pure.aus.pbp.scaled.men
Models:
  pure.aus.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.aus.model3m:   P1..Service..PBP. + (1 | Match.ID)
  pure.aus.model4m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.aus.model4m:   P1..Service..PBP. + (Lag1.Service.P1 * Lag1.Point.P1) + (1 |
  pure.aus.model4m:   Match.ID)
> anova(pure.aus.model5m, pure.aus.model4m)
Data: pure.aus.pbp.scaled.men
Models:
  pure.aus.model4m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.aus.model5m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model4m  9 187505 187594 -93744   187487  413.39      3  < 2.2e-16 ***
pure.aus.model5m 13 187460 187588 -93717   187434  52.913      4  8.886e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model6m, pure.aus.model5m)
Data: pure.aus.pbp.scaled.men
Models:
  pure.aus.model5m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.aus.model6m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model5m 13 187460 187588 -93717   187434
pure.aus.model6m 19 187405 187592 -93684   187367  67.158      6  1.562e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model7m, pure.aus.model6m)
Data: pure.aus.pbp.scaled.men
Models:
  pure.aus.model6m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
                   (1 | Match.ID)
pure.aus.model6m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 

Df | AIC | BIC | logLik | deviance | Chisq | Chi Df | Pr(>Chisq)
--- | --- | --- | ------ | -------- | ------ | ------- | ----------------
pure.aus.model7m 9 187844 187932 -93913 187826
pure.aus.model6m 19 187405 187592 -93684 187367 458.69     10 < 2.2e-16 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.aus.model0f, pure.aus.model1f)
Analysis of Deviance Table

Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.

Resid. Df Resid. Dev Df Deviance
1     88963     121626
2     88962     121344  1   281.38

> anova(pure.aus.model2f, pure.aus.model1f)
Analysis of Deviance Table

Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.

Resid. Df Resid. Dev Df Deviance
1     88960     120967
2     88962     121344 -2  -377.81

> anova(pure.aus.model3f, pure.aus.model2f)
Analysis of Deviance Table

Data: pure.aus.pbp.scaled.women
Models:
pure.aus.model2f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
P1..Service..PBP.
pure.aus.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
P1..Service..PBP. + (1 | Match.ID)

Df | AIC | BIC | logLik | deviance | Chisq | Chi Df | Pr(>Chisq)
--- | --- | --- | ------ | -------- | ------ | ------- | ----------------
pure.aus.model2f 5 120977 121024 -60483 120967
pure.aus.model3f 6 120829 120885 -60408 120817 150.01      1 < 2.2e-16 ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.aus.model4f, pure.aus.model3f)
Data: pure.aus.pbp.scaled.women

Models:

pure.aus.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
pure.aus.model3f: P1..Service..PBP. + (1 | Match.ID)

pure.aus.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
pure.aus.model4f: Match.ID)

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model3f  6 120829 120885 -60408   120817
pure.aus.model4f  9 120630 120714 -60306   120612 204.78      3  < 2.2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model5f, pure.aus.model4f)
Data: pure.aus.pbp.scaled.women

Models:

pure.aus.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
pure.aus.model4f: Match.ID)
pure.aus.model5f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
pure.aus.model5f: Match.ID)

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model4f  9 120630 120714 -60306   120612
pure.aus.model5f 13 120574 120696 -60274   120548 64.033      4  4.113e-13 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.aus.model6f, pure.aus.model5f)
Data: pure.aus.pbp.scaled.women

Models:

pure.aus.model5f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + 
pure.aus.model5f: Match.ID)

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model5f 13 120574 120696 -60274   120548
pure.aus.model6f 19 120559 120737 -60260   120521 27.121      6  0.0001375 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

243
> anova(pure.aus.model7f, pure.aus.model6f)

Data: pure.aus.pbp.scaled.women

Models:

pure.aus.model7f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.aus.model7f: (1 | Match.ID)

pure.aus.model6f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.aus.model7f  9 120830 120915 -60406   120812
pure.aus.model6f 19 120559 120737 -60260   120521 291.66     10  < 2.2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

French Open

> anova(pure.fo.model0m, pure.fo.model1m)

Analysis of Deviance Table

| Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP. |
| Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP. |
| Resid. Df Resid. Dev Df Deviance |
| 1 138678 186924 |
| 2 138677 186208 1 715.74 |

> anova(pure.fo.model2m, pure.fo.model1m)

Analysis of Deviance Table

| Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
P1..Service..PBP. |
| Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP. |
| Resid. Df Resid. Dev Df Deviance |
| 1 138675 185875 |
| 2 138677 186208 -2 -333.35 |

> anova(pure.fo.model3m, pure.fo.model2m)

Data: pure.fo.pbp.scaled.men

Models:

pure.fo.model2m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model2m: P1..Service..PBP. |
pure.fo.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model3m: P1..Service..PBP. + (1 | Match.ID)
> anova(pure.fo.model4m, pure.fo.model3m)
Data: pure.fo.pbp.scaled.men

Models:

pure.fo.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model4m: P1..Service..PBP. + (1 | Match.ID)

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model3m  6 185738 185797 -92863   185726 149.34      1  < 2.2e-16 ***
pure.fo.model4m  9 185360 185449 -92671   185342 383.59      3  < 2.2e-16 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.fo.model5m, pure.fo.model4m)
Data: pure.fo.pbp.scaled.men

Models:

pure.fo.model4m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model5m: (1 | Match.ID)

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model4m  9 185360 185449 -92671   185342
pure.fo.model5m 13 185243 185371 -92609   185217 124.75      4  < 2.2e-16 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.fo.model6m, pure.fo.model5m)
Data: pure.fo.pbp.scaled.men

Models:

pure.fo.model5m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model6m: (1 | Match.ID)

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model5m 13 185243 185371 -92609   185217
pure.fo.model6m 17 185136 185300 -92599   185110 11.46      4  0.1754    1
pure.fo.model6m: \( \text{P1..Service..PBP.} + (\text{Lag1.Service.P1} \times \text{Lag1.Point.P1}) + (\text{Lag2.Service.P1} \times \text{Lag2.Point.P1}) + (\text{Lag3.Service.P1} \times \text{Lag3.Point.P1}) + (\text{Lag1.Point.P1} \times \text{Lag2.Point.P1}) + (\text{Lag1.Point.P1} \times \text{Lag3.Point.P1}) + (1 \mid \text{Match.ID}) \)

\[
\begin{array}{ccccccc}
\text{Df} & \text{AIC} & \text{BIC} & \text{logLik} & \text{deviance} & \text{Chisq} & \text{Chi Df} & \text{Pr(>Chisq)} \\
pure.fo.model5m & 13 & 185243 & 185371 & -92609 & 185217 \\
pure.fo.model6m & 19 & 185193 & 185380 & -92577 & 185155 & 62.742 & 6 & 1.246e-11 ***
\end{array}
\]

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model7m, pure.fo.model6m)

Data: pure.fo.pbp.scaled.men

Models:

\[
\begin{align*}
pure.fo.model7m: \text{P1..Point.Winner..PBP.} & \sim \text{Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP.} \\
pure.fo.model6m: \text{P1..Point.Winner..PBP.} & \sim \text{Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP.}
\end{align*}
\]

\[
\begin{array}{ccccccc}
\text{Df} & \text{AIC} & \text{BIC} & \text{logLik} & \text{deviance} & \text{Chisq} & \text{Chi Df} & \text{Pr(>Chisq)} \\
pure.fo.model7m & 9 & 185703 & 185792 & -92842 & 185685 \\
pure.fo.model6m & 19 & 185193 & 185380 & -92577 & 185155 & 530.32 & 10 & < 2.2e-16 ***
\end{array}
\]

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model0f, pure.fo.model1f)

Analysis of Deviance Table

Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.

\[
\begin{array}{cccc}
\text{Resid. Df} & \text{Resid. Dev} & \text{Df} & \text{Deviance} \\
1 & 90507 & 124361 \\
2 & 90506 & 124148 & 1 & 212.92
\end{array}
\]

> anova(pure.fo.model2f, pure.fo.model1f)

Analysis of Deviance Table

Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.

\[
\begin{array}{cccc}
\text{Resid. Df} & \text{Resid. Dev} & \text{Df} & \text{Deviance} \\
1 & 90504 & 123799 \\
2 & 90506 & 124148 & -2 & -348.93
\end{array}
\]

> anova(pure.fo.model3f, pure.fo.model2f)

Data: pure.fo.pbp.scaled.women
Models:

pure.fo.model2f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model2f: P1..Service..PBP.

pure.fo.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model3f: P1..Service..PBP. + (1 | Match.ID)

Df AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model2f  5 123809 123856 -61899   123799
pure.fo.model3f  6 123694 123751 -61841   123682 116.59      1  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model4f, pure.fo.model3f)
Data: pure.fo.pbp.scaled.women
Models:

pure.fo.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model3f: P1..Service..PBP. + (1 | Match.ID)
pure.fo.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model3f  6 123694 123751 -61841   123682
pure.fo.model4f  9 123524 123609 -61753   123506 176.47      3  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model5f, pure.fo.model4f)
Data: pure.fo.pbp.scaled.women
Models:

pure.fo.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.fo.model5f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.fo.model4f  9 123524 123609 -61753   123506
pure.fo.model5f 13 123455 123577 -61714   123429 76.935      4  7.762e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.fo.model6f, pure.fo.model5f)
Data: pure.fo.pbp.scaled.women
Models:


Df    AIC    BIC logLik   deviance Chisq Chi Df Pr(>Chisq)
pure.fo.model5f 13 123455 123577 -61714   123429
pure.fo.model6f 19 123444 123623 -61703   123406 22.591      6  0.0009456 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.fo.model7f, pure.fo.model6f)
Data: pure.fo.pbp.scaled.women
Models:

Df    AIC    BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.fo.model7f  9 123688 123773 -61835   123670
pure.fo.model6f 19 123444 123623 -61703   123406 264.15     10  < 2.2e-16 ***

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.w.model0m, pure.w.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
Resid. Df Resid. Dev Df Deviance
1    142877     191030
2    142876     190589  1    440.87

> anova(pure.w.model2m, pure.w.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP.

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 '*' 0.05 '.' 0.1 ' ' 1

Wimbledon

> anova(pure.w.model0m, pure.w.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
Resid. Df Resid. Dev Df Deviance
1    142877     191030
2    142876     190589  1    440.87

> anova(pure.w.model2m, pure.w.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff + P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
Resid. Df Resid. Dev Df Deviance
1 142874 190146
2 142876 190589 -2 -442.55

> anova(pure.w.model3m, pure.w.model2m)
Data: pure.w.pbp.scaled.men
Models:
pure.w.model2m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model2m: P1..Service..PBP.
pure.w.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model3m: P1..Service..PBP. + (1 | Match.ID)

Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.w.model2m 5 190156 190206 -95073 190146
pure.w.model3m 6 190076 190135 -95032 190064 82.287 5 9.879e-09 ***
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model4m, pure.w.model3m)
Data: pure.w.pbp.scaled.men
Models:
pure.w.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model3m: P1..Service..PBP. + (1 | Match.ID)
pure.w.model4m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model4m: P1..Service..PBP. + (Lag1.Service.P1 * Lag1.Point.P1) + (1 | Match.ID)

Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.w.model3m 6 190076 190135 -95032 190064
pure.w.model4m 9 189637 189726 -94810 189619 444.57 3 9.879e-16 ***
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model5m, pure.w.model4m)
Data: pure.w.pbp.scaled.men
Models:
pure.w.model4m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model4m: P1..Service..PBP. + (Lag1.Service.P1 * Lag1.Point.P1) + (1 | Match.ID)
pure.w.model5m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)
pure.w.model4m 9 189637 189726 -94810 189619
> anova(pure.w.model6m, pure.w.model5m)
Data: pure.w.pbp.scaled.men
Models:
pure.w.model5m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model5m: P1..Service..PBP. + (Lag1.Service.P1 * Lag1.Point.P1) + (Lag2.Service.P1 *
pure.w.model6m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model5m 13 189581 189709 -94778   189555
pure.w.model6m 19 189518 189705 -94740   189480 75.309      6  3.316e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.w.model7m, pure.w.model6m)
Data: pure.w.pbp.scaled.men
Models:
pure.w.model7m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model7m: P1..Service..PBP. + Set.Won.Diff + Game.Won.Diff + Cum.Game.Won.Diff +
pure.w.model7m: (1 | Match.ID)
pure.w.model6m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model7m  9 189928 190017 -94955   189910
pure.w.model6m 19 189518 189705 -94740   189480 430.69     10  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> anova(pure.w.model0f, pure.w.model1f)

Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
Resid. Df Resid. Dev Df Deviance
1   89165   121350
2   89164   121166  1  184.28
> anova(pure.w.model2f, pure.w.model1f)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
  Resid. Df Resid. Dev Df Deviance
1     89162     120866
2     89164     121166 -2   -299.59

> anova(pure.w.model3f, pure.w.model2f)
Data: pure.w.pbp.scaled.women
Models:
pure.w.model2f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model2f:     P1..Service..PBP.
pure.w.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model3f:     P1..Service..PBP. + (1 | Match.ID)
  Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model2f  5 120876 120923 -60433   120866
pure.w.model3f  6 120750 120806 -60369   120738 128.87      1   < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model4f, pure.w.model3f)
Data: pure.w.pbp.scaled.women
Models:
pure.w.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model3f:     P1..Service..PBP. + (1 | Match.ID)
pure.w.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model4f:     P1..Service..PBP. + (Lag1.Service.P1 * Lag1.Point.P1) + (1 |
pure.w.model4f:     Match.ID)
  Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model3f  6 120750 120806 -60369   120738
pure.w.model4f  9 120571 120655 -60276   120553 184.74      3   < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model5f, pure.w.model4f)
Data: pure.w.pbp.scaled.women
Models:
pure.w.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model5f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model4f  9 120571 120655 -60276   120553
pure.w.model5f 13 120502 120624 -60238   120476  76.765      4  8.434e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model6f, pure.w.model5f)
Data: pure.w.pbp.scaled.women
Models:
pure.w.model5f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model6f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model5f 13 120502 120624 -60238   120476
pure.w.model6f 19 120488 120666 -60225   120450  26.094      6  0.0002138 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.w.model7f, pure.w.model6f)
Data: pure.w.pbp.scaled.women
Models:
pure.w.model6f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.w.model7f:     (1 | Match.ID)
pure.w.model6f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.w.model6f 19 120488 120666 -60225   120450 258.75     10  < 2.2e-16 ***
US Open

> anova(pure.uso.model0m, pure.uso.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
  Resid. Df Resid. Dev Df Deviance
1 145329 195447
2 145328 195040 1 406.96

> anova(pure.uso.model2m, pure.uso.model1m)
Analysis of Deviance Table
Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.
  Resid. Df Resid. Dev Df Deviance
1 145326 194694
2 145328 195040 -2 -346.36

> anova(pure.uso.model3m, pure.uso.model2m)
Data: pure.uso.pbp.scaled.men
Models:
  pure.uso.model2m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.uso.model2m: P1..Service..PBP.
  pure.uso.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.uso.model3m: P1..Service..PBP. + (1 | Match.ID)
             Df  AIC   BIC logLik deviance  Chisq Chi Df     Pr(>Chisq)
pure.uso.model2m 5 194704 194753 -97347   194694
pure.uso.model3m 6 194603 194662 -97295   194591 102.92      1 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model4m, pure.uso.model3m)
Data: pure.uso.pbp.scaled.men
Models:
  pure.uso.model3m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
  pure.uso.model3m: P1..Service..PBP. + (1 | Match.ID)
  pure.uso.model4m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
> anova(pure.uso.model15m, pure.uso.model14m)

Data: pure.uso.pbp.scaled.men
Models:
pure.uso.model15m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model15m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model14m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model14m  9 194151 194240 -97066   194133
pure.uso.model15m 13 194065 194193 -97019   194039 94.09      4  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model16m, pure.uso.model15m)

Data: pure.uso.pbp.scaled.men
Models:
pure.uso.model16m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model15m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model15m 13 194065 194193 -97019   194039
pure.uso.model16m 19 194038 194226 -97000   194000 38.565      6  8.71e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model17m, pure.uso.model16m)

Data: pure.uso.pbp.scaled.men
Models:
pure.uso.model17m: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

pure.uso.model7m: (1 | Match.ID)

pure.uso.model6m: P1..Point Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +


Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)

pure.uso.model7m 9 194573 194662 -97278 194555

pure.uso.model6m 19 194038 194226 -97000 194000 555.13 10 < 2.2e-16 ***

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model0f, pure.uso.model1f)

Analysis of Deviance Table

Model 1: P1..Point.Winner..PBP. ~ P1..Service..PBP.
Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.

Resid. Df Resid. Dev Df Deviance

1 92735 126983
2 92734 126812 1 170.84

> anova(pure.uso.model2f, pure.uso.model1f)

Analysis of Deviance Table

Model 1: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Model 2: P1..Point.Winner..PBP. ~ Rank.diff + P1..Service..PBP.

Resid. Df Resid. Dev Df Deviance

1 92732 126410
2 92734 126812 -2 -402.3

> anova(pure.uso.model3f, pure.uso.model2f)

Data: pure.uso.pbp.scaled.women

Models:

pure.uso.model2f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

pure.uso.model2f: P1..Service..PBP.

pure.uso.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

pure.uso.model3f: P1..Service..PBP. + (1 | Match.ID)

Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)

pure.uso.model2f 5 126420 126467 -63205 -63205 0.0

pure.uso.model2f 5 126420 126467 -63205 126410
> anova(pure.uso.model4f, pure.uso.model3f)
Data: pure.uso.pbp.scaled.women
Models:
pure.uso.model3f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model3f: P1..Service..PBP. + (1 | Match.ID)
pure.uso.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model4f: Match.ID)
Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model3f  6 126290 126346 -63139   126278
pure.uso.model4f  9 126061 126146 -63021   126043 234.99      3  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> anova(pure.uso.model5f, pure.uso.model4f)
Data: pure.uso.pbp.scaled.women
Models:
pure.uso.model4f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model4f: Match.ID)
pure.uso.model5f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model4f  9 126061 126146 -63021   126043
pure.uso.model5f 13 126022 126145 -62998   125996 46.593      4  1.853e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> anova(pure.uso.model6f, pure.uso.model5f)
Data: pure.uso.pbp.scaled.women
Models:
pure.uso.model5f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
\begin{verbatim}
Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model5f 13 126022 126145 -62998   125996
pure.uso.model6f 19 126002 126181 -62982   125964 32.426      6  1.352e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(pure.uso.model7f, pure.uso.model6f)
Data: pure.uso.pbp.scaled.women
Models:
pure.uso.model7f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +
pure.uso.model7f:     (1 | Match.ID)
pure.uso.model6f: P1..Point.Winner..PBP. ~ Rank.diff + PS.pct.diff + PR.pct.diff +

Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
pure.uso.model7f  9 126290 126375 -63136   126272
pure.uso.model6f 19 126002 126181 -62982   125964 308.69     10  < 2.2e-16 ***
\end{verbatim}
Works Cited


Bevc, M. (2015). *Predicting the Outcome of Tennis Matches From Point by Point Data*. Online at www.semanticscholar.org/paper/Predicting-the-Outcome-of-Tennis-Matches-From-Data-Bevc/1cbe1beca36298e4aee813bf967d5aab034c7deb. Date Accessed: October 11, 2019


