Effect of rest on soccer and tennis match outcomes

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1 Introduction

Many factors influence athletic performance in competitions. Most models preicting results focus on the strength of the team and location of the competition, but other factors that players and teams can control could have an impact. In this paper we will look at how rest and tiredness impact the performance of soccer teams and tennis players.

1.1 Question

We aim to quantify the effect of rest on Football match outcomes. We ask two questions looking at short and long term rest levels of a team:

1. How does the number of days since a previous match impact the performance of a team?
2. How the the game load of a team in the past month, 2 month, and 3 month impact the performance of a team?

For tennis we look at the effect of the previous match attributes on match outcomes. We ask the quest

1. How does length of the previous match impact performance?

We will look at different models in which performance will either be the probability of winning, drawing, and losing or the expected number of goals scored.

1.2 English Football

Before explaining our motivation we will first given an overview of the English and European soccer system so that the reader may better understand our motivation.

English soccer is comprised of multiple competitions.

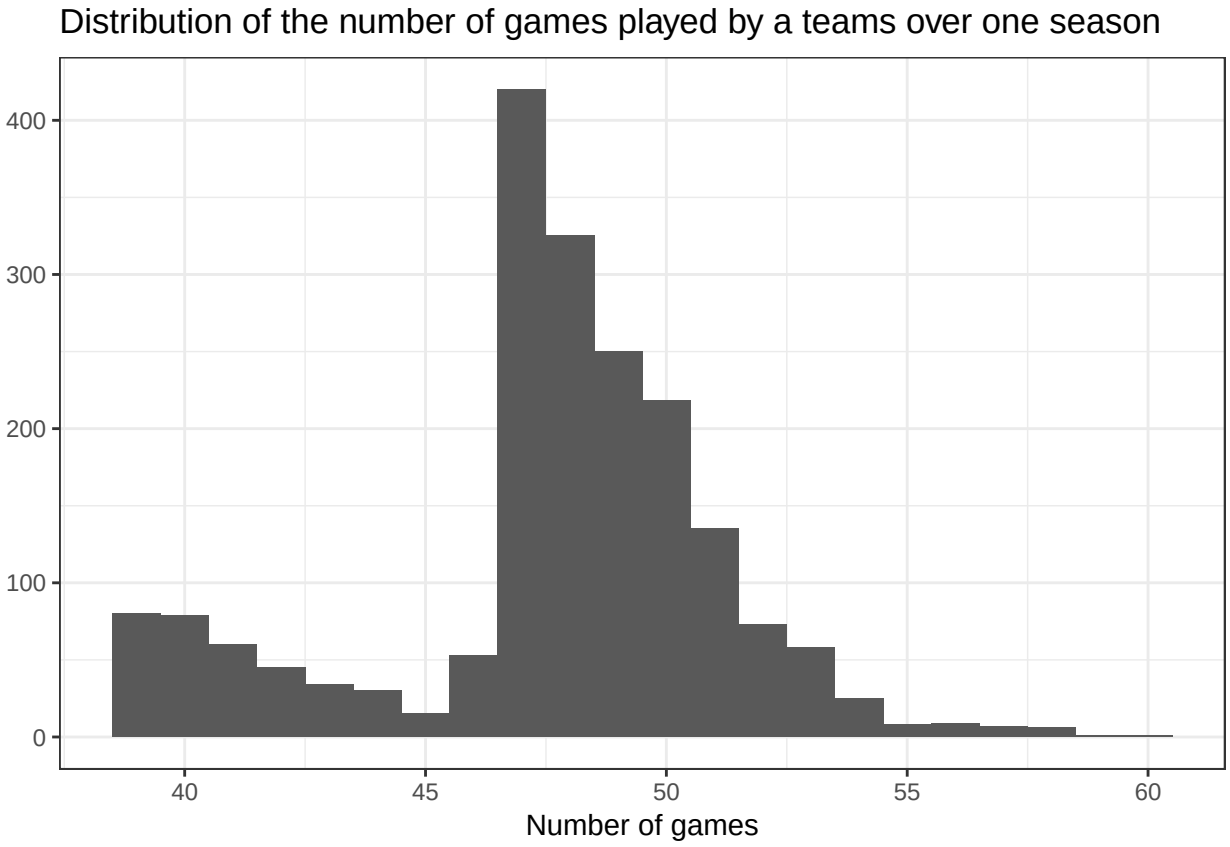
- The top 20 teams in England play in the **Premier League**. They will play each other time once at home and once away resultung in 380 games played each season. Each match earns teams points; a win will get a team 3 points, a draw one point, and loss 0 points. The team with the most points win. The bottom two teams will be relegated to the EFL Championship. The top two teams from EFL Championship will advance to the Premier league. The third to last team in the Premier league and third team in the EFL Championship will play off to play in the Premier league. [**?**]
- The **FA cup** is a knockout tournament open to teams in 10 levels of English football, this a knockout tournament. Teams enter the tournament at different times depending on the level they play in. Teams that play in the Premier league will enter the 3rd round in January with the hope of making it to the final played in May. [**?**]
- The **EFL cup** is a tournament similar to the FA cup but open only to levels 1 through 4. Premier league teams will enter in August. Matches continue until the final in February. Teams playing in European competitions do not play in this cup [**?**]

There are two European competitions which are played with teams from different European leagues:

- The top teams play in the **Champions League**. It starts with a group stage of 32 teams in which mini round robins are run in each group to determine which 16 teams go on to the tournament. Teams not advancing to the tournament are transferred to the Europa league. In the tournament stage teams meet twice: once home and once away. Since only one team can move forward to the next round, the return leg can go overtime to decide who win. The final is played in one match in a location determined ahead of time. [**?**] In England the top three premier league teams automatically qualify for the Champions league. The fourth place team qualifies for a play-off round. [**?**]
- The **Europa league** is similar to the Champions league in format but played with the top teams not qualifying for the champions league. Depending on how a team qualifies it will enter the competition at different rounds. [**?**] The 5th place Premier league team qualifies for the group stage, with the winners of the FA cup and EFL cup qualifying for earlier rounds. [**?**]

Depending on the year, the schedule will be inter-spaced with 2-week **international breaks**, in which players are called to represent their national team in international friendlies or qualifying matches for continent or world cups.

The wide variety of competition that a team could play in means that teams can have different schedule load as shown in the following figure.



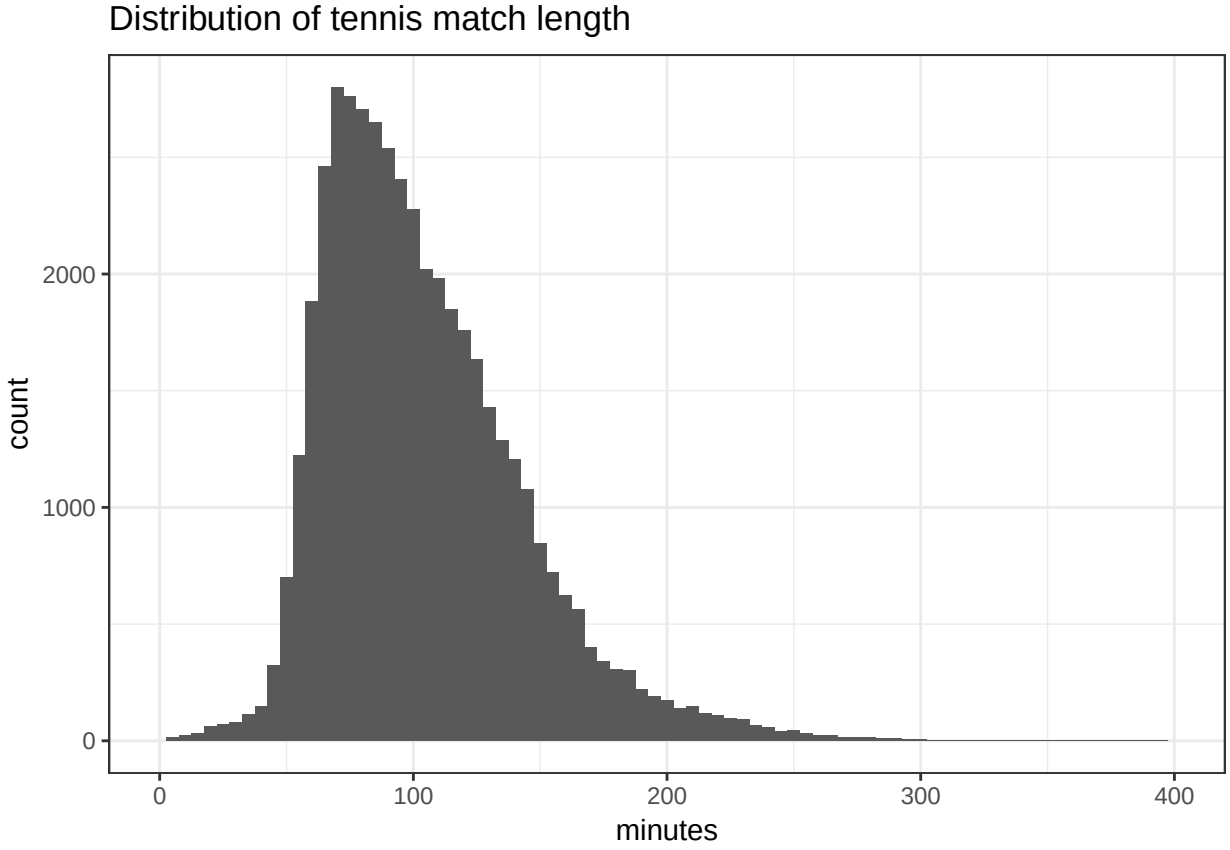
1.3 Men's professional tennis

Throughout the season players will play in a variety of tournaments. Performance in the tournament will determine the number of points earned towards the players' world rankiings. Tournaments have difference importances which influences how many points they grant players.

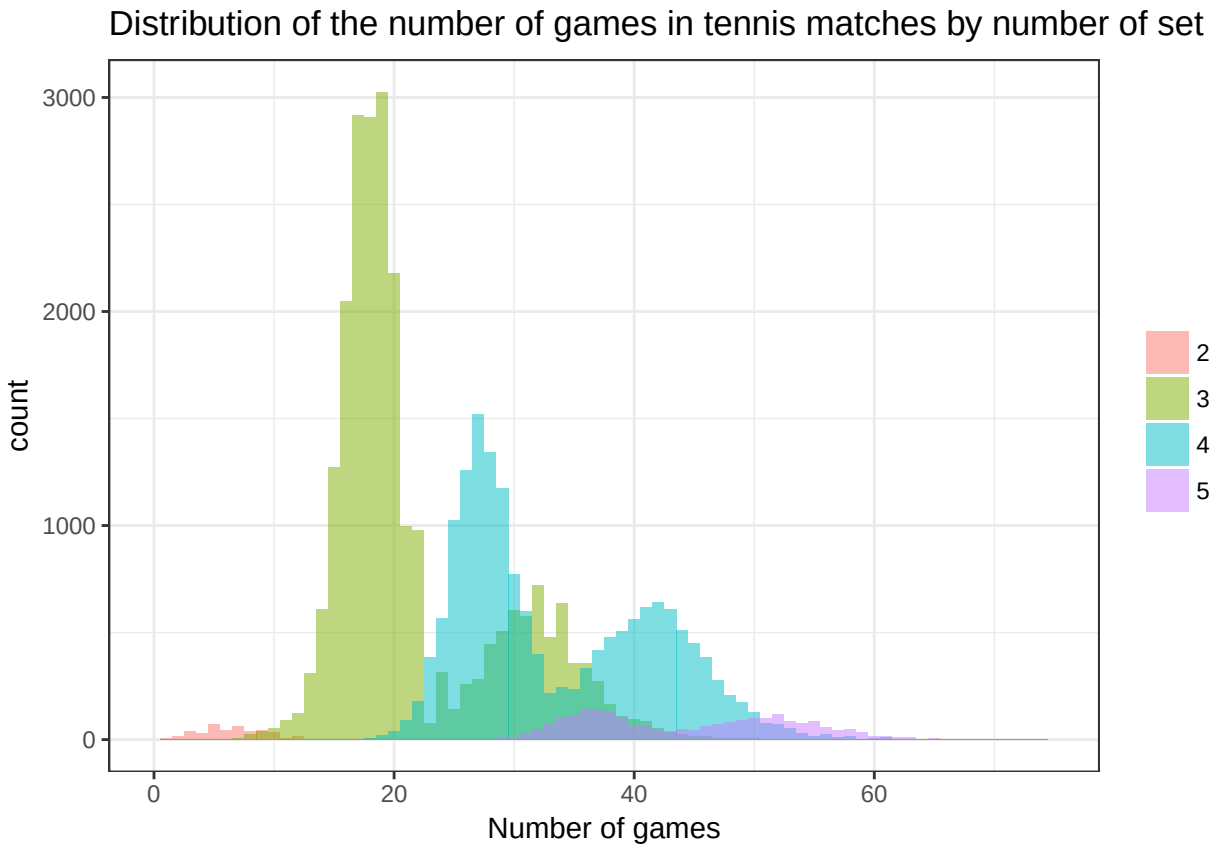
A player's ranking influences the players seeding in individual tournaments which is designed to have top players face each other in the semis and finals.

Professional tennis is played in matchs of 3 or 5 sets. The four main tournaments: Australlian Open, Rolland Garros, Wimbledon, and US open are played in 5 sets, which the rest of tournaments are played in 3 sets. The first player to win 2 or three sets wins.

The winning mechanism allows for games of different time length the distribution of which is shown bellow.



As set is won by obtaining at least 6 points and a 2 point lead resulting in games of different intensities; A game could be won 6-1, of 10-8. The distribution of the number of games is shown bellow along.



1.4 Relevance

Football game scheduling varies from league to league. In particular, some leagues take a winter break while others do not. Some speculate that this winter break influences performance in inter-league competitions such as the Champions and Europa league by allowing teams that have the break to be more refreshed. [**?**]

Further Champions and Europa league games are played Tuesday through Thursday, while club games are played Friday through Mondays, leading to a variety of rest days going into Champions and Europa league games. (NEED CITATION) Some leagues are more willing to accommodate teams playing in European competitions than others by letting them schedule their games earlier in the weekend.

An effect of previous matches on present matches could have an effect on how matches are played. If player's know that long matches hurt them in the long run, they might work harder to win quickly. Of course, we also need to measure the LR effect of working harder before making such a suggestion.

1.5 Approach

While we would ideally want to look at how rest affects performance in european competitions doing so is difficult because the teams that play each other in European competitions do not do so enough for us to calculate and control for team ability on an even scale. We will instead model the outcome of Premier League matches, which are set up such that we can easily control for team ability. We will evaluate how matches in competitions other than the premier league influence premier league matches.

This approach assumes that European competition games are similar Premier League games. This is mostly true except for the fact that European competition games can result in overtime and are higher stakes; a loss

results in elimination. We assume that if we see rest impact outcomes in premier league games, rest is likely to have an impact in European games.

For tennis we measure the effects of previous match attributes on the next match. We look at how these effects differ by surface and whether the match is best of 3 or best of 5.

1.6 Literature review

1.6.1 Rest time

Most of research on impacts of game scheduling focuses on injury and measures of certain activities in games (distance ran, number of sprints, etc.), but not on overall game outcomes.

Over the past decades, Carlos Lago Penas conducted a series of study looking at how physical behaviors of players such as distance run at certain speeds evolve over a series of consecutive games with small rest periods and found minor to no differences in physical behaviors across games. [**?**, **?**]

In 2010, Dupont et al. found a higher injury rates for football players who played two matches a week compared to players playing 1 match a week.

1.6.2 Modeling match outcomes

In 1982, M. J. Maher introduced 2 independent Poisson distributions as a way to model soccer scores. He proposed using a team's attacking strength and its oponent's defensive weakness as predictors of number of goals scores. Maher also found that using a Bivariate Poisson distribution with a correlation of 0.2 improved his model's fit. [**?**]

In 2003, Karlis and Ntzoufras proposed a diagonal inflated bivariate Poisson model in which the probabilities of draws are increased. [**?**] They also created an R package to fit biavariate Poisson GLMs which we will utilize. [**?**]

1.7 Data

1.7.1 Tennis

1.7.1.1 Data set

The data was obtained from Kaggle and contains outcomes and attributes of ATP Mens tennis matches between 2000 and 2017. We split each game into two rows one for each player.

1.7.1.2 Response variable

The response variable is whether or not a player won a game. As players have to either win or lose, the response variable is distributed 50-50 win-lose.

1.7.1.3 Predictors

The predictor is the length of the prior match played by the player in minutes. Three quarters of the games are less than 2 hours long, but games can go on for many more hours. In fact, about five percent of games go on for more than 3 hours.

1.7.1.4 Control variables

We control for player ability by looking at the player's rank at the beggining of the tournament as well as the number of points earned in order to achieve the ranking. Both came out to be important in predicting winners. They differ slightly in that the player ranked number 1 could be leading by a few points or hundreds of point. The broader scale of ranking points provides a better proxy for underlying player ability.

We control also control for whether or not a player is seeded. Seeded players tend to be the top ___ players in the tournement and do not have to play as many early rounds.

We also look at whether or not the effects differ by surface, the number of sets needed to win, and the round of the match.

1.7.1.4.1 Surface

Tennis is either played on Carpet, Clay, Grass, or Hard. Players will have preference for different surfaces and some surfaces are often cited as causes for injuries. The distribution of surfaces is shown bellow.

Table 1: Distribution of matches by surface

	Var1	Freq
1	Carpet	1,489
2	Clay	15,456
3	Grass	4,466
4	Hard	23,876

1.7.1.4.2 Sets needed to win

Most men's tennis matches are won by a player winning 2 sets. The four major tournaments: Rolland Garros, Wimbledon, US Open, and Australian open require 3 sets to be won in order to win

1.7.1.5 Games looked at

We look at all matches for which both players played their previous match in the same tournament. This allows us to make sure that the previous match happened within a reasonable number of days.

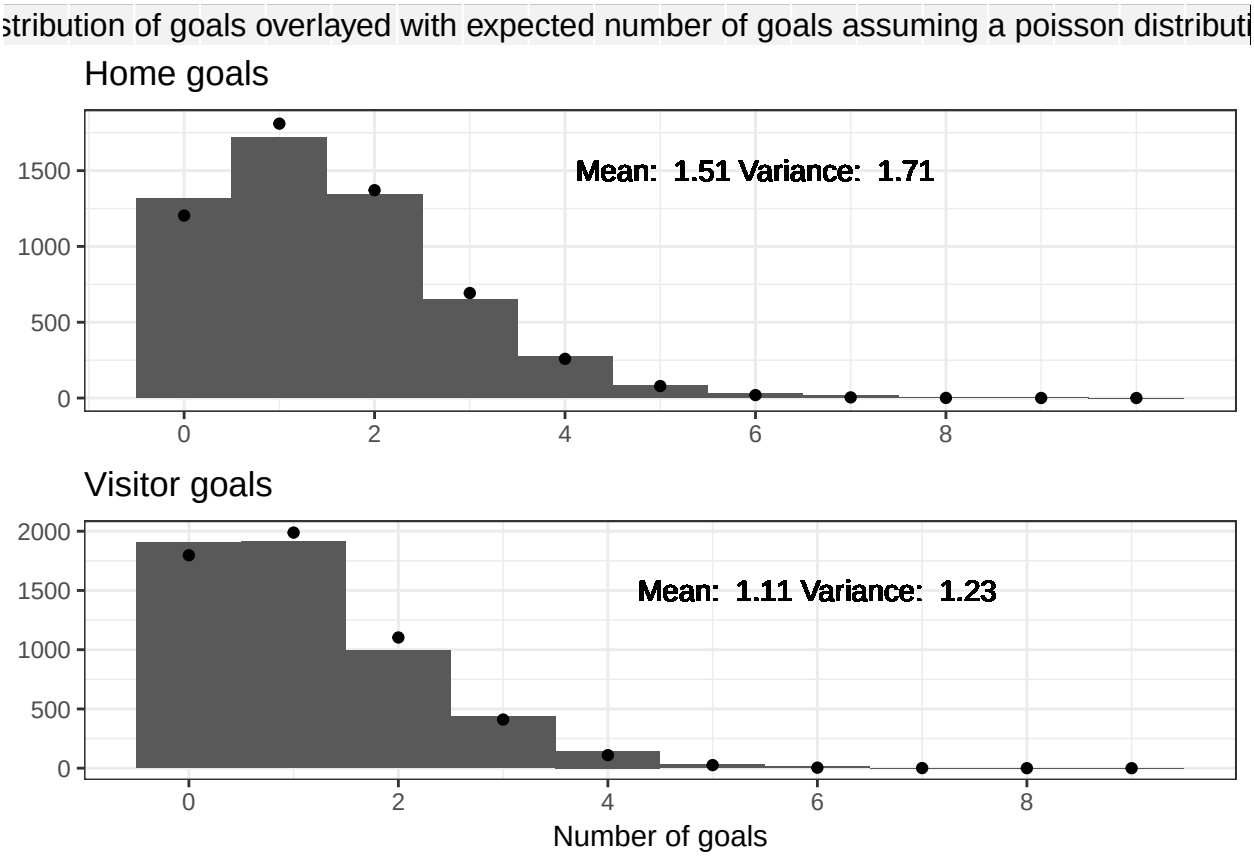
1.7.2 Soccer

1.7.2.1 Data set

The R package "engsoccerdata" provides us with scores from matches in England as well as European competition matches. [**?**] We limit ourselves to matches occurring in seasons 1995 through 2015. The design of English Football stays consistent throughout this time range and the data set is complete for these years.

1.7.2.2 Response variable

We use two different response variables: 1. The number of home and away goals and 2. Weather the a team won, tied, or lost. The distribution of home and away goals is shown bellow.



Most models for the number of goals by team in a game assume he number of home and away goals follow a poisson distribution. We see that this approximately true. There tends more games than expected with zero goals and the variance is slightly larger than the mean number of goals.

A game is a home win if the number of home goals exceeds the number of visitor goals, tied if both teams score the same number of goals, and a visitor win if the number of visitor goals exceeds the number of home goals. The distribution of outcomes is shown below.

Table 2: Distribution of game outcomes

Outcome	Number of games	Share of games
Home win	1,966	0.458
Tie	1,143	0.266
Visitor win	1,187	0.276

1.7.2.3 Predictors

Using this data set we calculate the number of days since the previous game. Before performing out analysis on the effect of rest time we remove games in which either of the team's previous game was over 8 days ago. If team's last non-international game was more than 8 days prior, it is possible that an international break previous happened which we have no way of controlling for.

The distribution of rest time for the home and away team is shown below.

Table 3: Distribution of rest time (in days) for home and away teams

		Visitor						
		2	3	4	5	6	7	8
	2	128	9	1	0	3	0	1
	3	12	343	155	22	38	121	7
	4	0	165	238	43	38	91	61
Home	5	1	26	50	63	31	90	31
	6	3	22	34	42	110	278	41
	7	0	118	74	93	302	798	110
	8	1	3	47	42	32	106	272

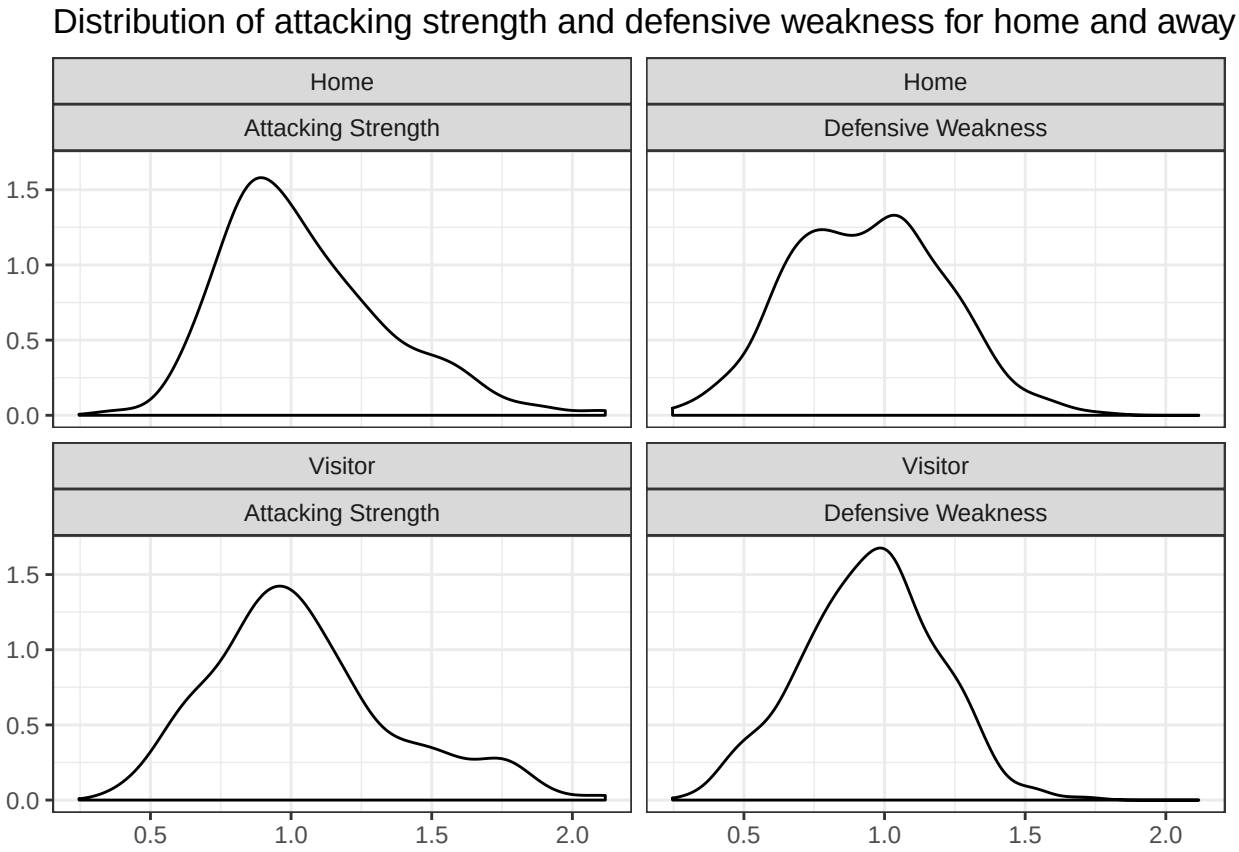
We also create a binary variable for weather or not a team is "more" (6-8 days) or "less" (1-5 days) rested and find the following distribution of rest.

Table 4: Distribution of rest time for home and away teams

		Away	
		1-5 days	6-8 days
Away	1-5 days	1,256	512
	6-8 days	479	2,049

1.7.2.4 Control variables

Using Premier games we calculate a teams attacking and defensive weakness. [**?**] The attacking strength is the ratio of the average number of goals score by a team in a season to the average number of goals scored in the league that season. The defensive weakness is the ratio of the average number of goal conceded by a team in a season to the average number of goals conceded in the league that season. For each team the attacking strength and defensive weakness are computed for home and away games. The better a team the higher its attacking strength and the lower its defensive weakness strength will be. We will use the previous years attacking and defensive weakness to control for a team's ability. We exclude recently promoted teams from our analysis as we cannot use their previous season to calculate such strengths. The distribution of attacking and defensive strengths is shown below.



We also control for the number of games a team plays each season. Better teams will last longer in in playoff competitions (FA Cup, Europa/Champions League, etc.) that happen concurrently with premier league games. These teams will play more games per season and thus on average have lower rest times. In particular, the design of the premier league in which each pair of teams plays each other once at each team's home stadium allows to easily calculate attacking strength and defensive weakness.

1.7.2.5 Matches looked at

As described in the previous subsections there are two points at which we remove premier league games from our data set.

1. Matches with recently promoted teams. Since we use the previous premier league season to calculate the team's attacking strength and defensive weakness we cannot calculate these quantities for recently promote teams. Removing these matches removes 2540 out of 7980 matches (32%).
2. Matches with over 8 days of rest. It is likely that an international match happened during the break which we do not have in our data. Leaving these matches in would lead to low rest matches presenting themselves as high rest matches. Removing these matches removes 1144 out of 5440 matches (21%).

2 Methods

2.1 Poisson model

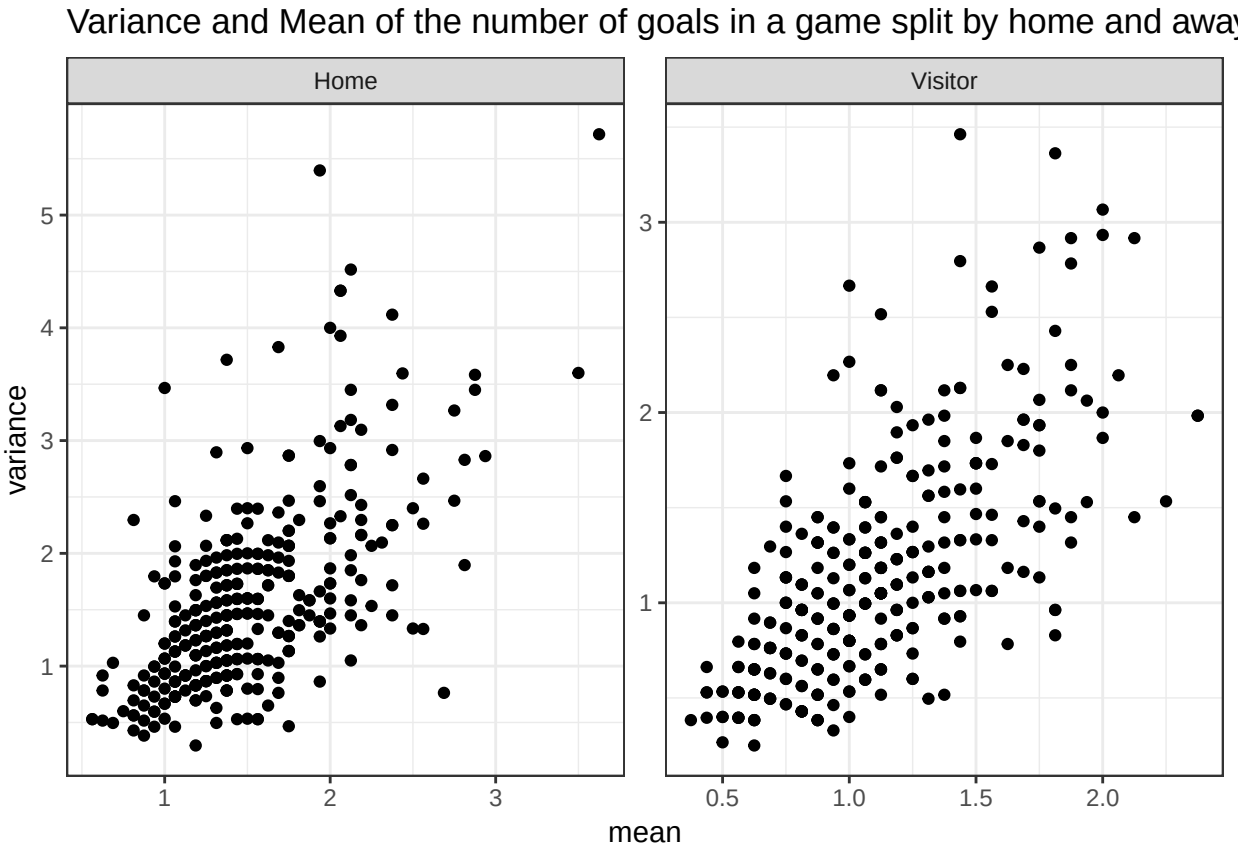
The Poisson model is most commonly used to model soccer scores. It assumes that the number of goals scored by a team in a soccer game follows a Poisson distribution of some parameter. We will use a GLM with a poisson link to predict the parameter.

2.1.1 Model

- Let $j = h, a$ be an indicator for whether we are modeling home or away games.
- Let $G_{j,i}$ be the number of home or away goals in game i.
- Let x_i be the predictors for game i.
- Assume that $G_j \sim Poisson(\lambda_j)$. $P_P(G_{j,i} = g_{j,i}) = \frac{\lambda_j^{g_{j,i}} e^{\lambda_{j,i}}}{g_{j,i}!}$
- The parameter λ_j is a linear combination of the predictors X_j: $\lambda_j = X_j \beta_j$

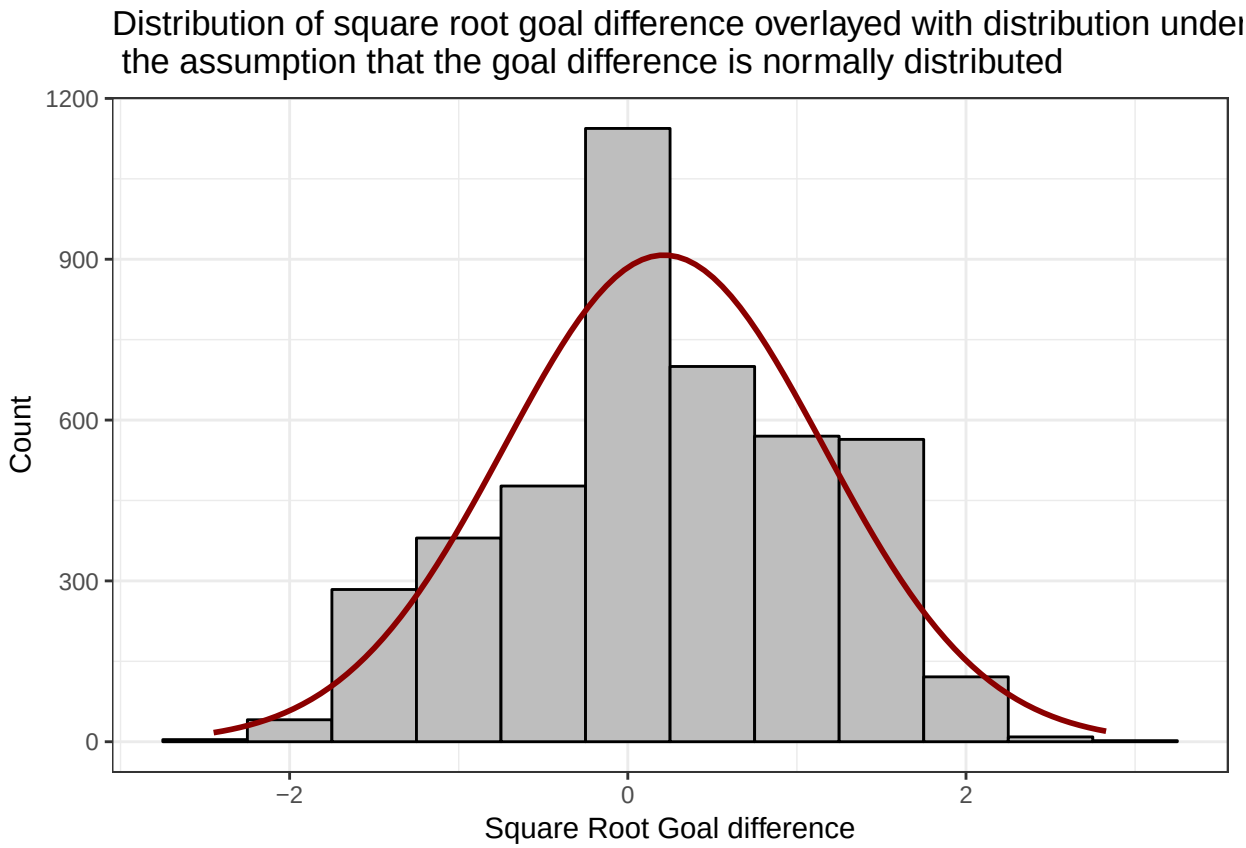
2.1.2 Verifying the Poisson assumption under the null

One of the defining features of the Poisson model is the fact that the mean of a Poisson distribution equals it's variance. As the figure below shows for most teams this equality holds.



2.2 Linear model for goal difference

The square root of a poisson distribution can be approximated by a nornal distribution (cite). We can therefore approximate the difference in square root goals as the difference of two normal distributions, which is itself a normal distribution. This allows us to fit a normal model to the transformed goal difference. The figure below shows the distribution of normal goal difference and its approximation as a normal distribution.



Our model aims to find a linear combination of our predictors that best approximates the square root goal difference

$\sqrt{G_{h,i}} - \sqrt{G_{v,i}} = X_j\beta_j$

In this model we could use difference in the number of rest days as a predictor instead of number of rest days for the home team and number of rest days for the away team. Using the difference in rest as a predictor is equivalent to using the the rest days for the home team and away teams and forcing their coefficients in the model to be the opposite. We chose to not add this constraints and allow home and away rest to vary freely.

2.3 Proportional odds cummulative logit model

We have 3 possible outcomes: home win, tie, or visitor win. Each outcome has a probability π_i of happening. The probabilities of the three outcomes sum to 1 as no other outcome is possible. $\pi_h + \pi_t + \pi_v = 1$

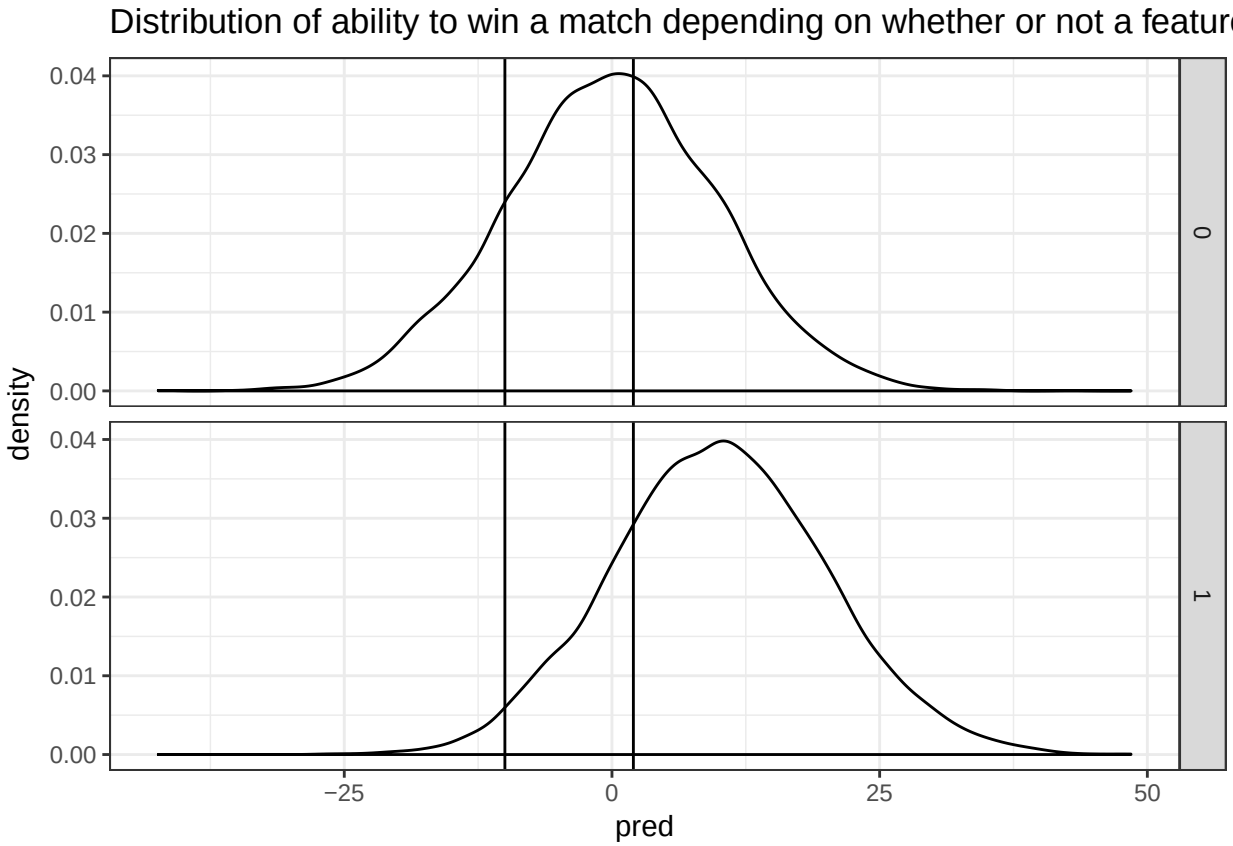
The probability that home loses is $1 - \pi_h - \pi_t = \pi_v$ and it's log odds are $L_v = \log\left(\frac{\pi_v}{\pi_h + \pi_t}\right)$

The probability that home loses or ties is $1 - \pi_h = \pi_v + \pi_t$ and it's log odds are $L_t = \log\left(\frac{\pi_v + \pi_t}{\pi_h}\right)$

The log odds of these two events are assumed to be a linear combination of the predictors; $L_v = \alpha_v + X\beta_v$ and $L_t = \alpha_t + X\beta_t$.

In the proportional odds model we require the coefficients β_v and β_t to be the same; $L_v = \alpha_v + X\beta$ and $L_t = \alpha_t + X\beta$.

The underlying assumption is that there is an unobserved variable which determines match outcomes. Here this variable is the ability of a home team to win against a given openent. The predictors X change our belief as to how this ability is distributed.



α_v can be though of as the threshold in ability to go from a tie or home win to a visitor win and α_t as the threshold to go from a home win to a tie or visitor win or tie. Depending on the distribution of underlying ability, the probability of each outcome changes. In the figure above if the feature is matched, the probability of a win is 78% but if the feature is not matched the probability of a win is 42%.

The 2 outcome case of this model is known as logistic regression. We will use it to model the outcome of tennis matches.

2.4 Logistic regression

Logistic regression assumes that the log odds of the probability of an event in this case a win are given by a linear combination of the predictors. The model can be written as $\log\left(\frac{p}{1-p}\right) = X\beta$ where the first column of X is filled with ones for the intercept.

3 Results

3.1 Simple Poisson GLM

Table **??** summarizes the GLM models for the number of home and away goals. Rest comes in the model either as number of days since the previous game (1) and (3) or as whether or not the team had more than 6 days of rest (2) and (4). In neither of the 4 models do we see rest as having an effect on the number of goals scored.

The strongest effects come from the attacking strength of the home team and defensive weakness of the visitor team. This not to surprising as most models looking to predict soccer outcomes use the product of these two

quantities as the expected number of goals. A team with a high attacking strength should score more since it has in the past, and a team with a high defensive weakness should take in more goals as it has in the past.

We also see an effect from the game load of a team. Game load also measure the quality of a team. Better teams will qualify for more games and thus have a higher game load. We expect to see an increase in a team's game load increase its predicted number of goals and an increase in its opponent's game load decrease a team's predicted number of goal; which is what we see.

Table 5: Generalized Linear Models with Poisson link

	Dependent variable:			
	hgoal		vgoal	
	(1)	(2)	(3)	(4)
Team_rest	−0.004		−0.007	
	(0.009)		(0.011)	
Opp_rest	−0.001		0.005	
	(0.009)		(0.011)	
Team_rest_bin		0.047		−0.044
		(0.031)		(0.036)
Opp_rest_bin		−0.052*		0.043
		(0.031)		(0.037)
Team_att_str	0.371***	0.377***	0.427***	0.425***
	(0.050)	(0.050)	(0.053)	(0.053)
Opp_def_weak	0.274***	0.280***	0.238***	0.239***
	(0.061)	(0.061)	(0.061)	(0.061)
Team_load	0.015***	0.017***	0.011***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Opp_load	−0.020***	−0.021***	−0.024***	−0.023***
	(0.003)	(0.003)	(0.004)	(0.004)
Constant	−0.036	−0.077	−0.025	−0.041
	(0.205)	(0.199)	(0.231)	(0.223)
Observations	4,296	4,296	4,296	4,296
Log Likelihood	−6,597.132	−6,595.641	−5,804.871	−5,804.193
Akaike Inf. Crit.	13,208.260	13,205.280	11,623.740	11,622.390
Note:				*p<0.1; **p<0.05; ***p<0.01

3.2 Linear model for goal difference

Table 6 summarizes the model for the square root goal difference. We find that the rest of the home and away team have no significant impact on the goal difference. Predictors highlighting the strength of the teams involved are most important.

Table 6: Linear model for the difference in goals scored

	Dependent variable:
	goal_diff
h_rest	−0.005
	(0.010)
v_rest	−0.003
	(0.010)
h_att_str	0.399***
	(0.057)
h_def_weak	−0.277***
	(0.057)
v_att_str	−0.380***
	(0.050)
v_def_weak	0.364***
	(0.066)
h_load	0.019***
	(0.003)
v_load	−0.015***
	(0.003)
Constant	−0.037
	(0.246)
Observations	4,296
R^2	0.138
Adjusted R^2	0.136
Residual Std. Error	0.878 (df = 4287)
F Statistic	85.434*** (df = 8; 4287)
Note:	*p<0.1; **p<0.05; ***p<0.01

3.3 Proportional odds cummulative logit model

The odds of moving from a visitor win to a tie or a tie to a home win increase when the home team's attacking strength, home team's game load, or visitor's team team defensive weakness increases. The opposite happens when the team's are reversed. The directionality of these findings agrees with the other models. The proportional odds cummulative logit model does not find any effect of rest, whether measured in days or as a binary variable.

Table 7: Ordered logistic model

	Dependent variable:	
	outcome	
	(1)	(2)
Team_rest	−0.016	
	(0.022)	
Opp_rest	0.006	
	(0.022)	
Team_rest_bin		−0.002
		(0.074)
Opp_rest_bin		−0.039
		(0.074)
Team_att_str	0.864***	0.870***
	(0.130)	(0.130)
Opp_def_weak	0.700***	0.707***
	(0.145)	(0.145)
Opp_att_str	−0.717***	−0.722***
	(0.111)	(0.111)
Team_def_weak	−0.490***	−0.490***
	(0.125)	(0.125)
Team_load	0.042***	0.043***
	(0.008)	(0.008)
Opp_load	−0.034***	−0.035***
	(0.008)	(0.008)
Observations	4,296	4,296
Note:	*p<0.1; **p<0.05; ***p<0.01	

3.4 Logistic GLM

In the simplest model looking at how the difference in minutes of the previous matches affects the probability fo winning we see that having played a longer previous match than one's oponent increases the probabibility of winning. However when we control for the difference in ranking points between the two players the effect dissapears.

When we look at the effect by best of quantity we find a positive effect on winning probability for best of three matches and a negative effect on winning probability for best of five matches.

We then look at how surface plays a role and find no significant effect except prior match length increasing probability of winning for clay surfaces.

We then split the surface effects by best of quantity and see that clay only increases probability of winning on best of three matches. We also see some effects for grass and hard surfaces. As previously seen the effects are positive for best of three matches and negative for best of five matches.

Table 8:

	Dependent variable:				
	won				
	(1)	(2)	(3)	(4)	(5)
delta_minutes	0.0004***	0.0002			
	(0.0001)	(0.0001)			
delta_rank_pts		0.0005***	0.0005***	0.0005***	0.000
		(0.00001)	(0.00001)	(0.00001)	(0.000
delta_minutes:as.factor(best_of)3			0.001***		
			(0.0002)		
delta_minutes:as.factor(best_of)5			−0.002***		
			(0.0003)		
delta_minutes:surfaceCarpet				−0.0003	
				(0.001)	
delta_minutes:surfaceClay				0.001***	
				(0.0002)	
delta_minutes:surfaceGrass				−0.001	
				(0.0004)	
delta_minutes:surfaceHard				0.00003	
				(0.0002)	
delta_minutes:as.factor(best_of)3:surfaceCarpet					−0.0
					(0.0
delta_minutes:as.factor(best_of)5:surfaceCarpet					−0.0
					(0.0
delta_minutes:as.factor(best_of)3:surfaceClay					0.001
					(0.00
delta_minutes:as.factor(best_of)5:surfaceClay					−0.0
					(0.0
delta_minutes:as.factor(best_of)3:surfaceGrass					0.001
					(0.0
delta_minutes:as.factor(best_of)5:surfaceGrass					−0.00
					(0.0
delta_minutes:as.factor(best_of)3:surfaceHard					0.000
					(0.00
delta_minutes:as.factor(best_of)5:surfaceHard					−0.00
					(0.00
Constant	0.000	−0.000	−0.000	−0.000	−0.0
	(0.007)	(0.007)	(0.007)	(0.007)	(0.0
Observations	90,574	90,574	90,574	90,574	90,5
Log Likelihood	−62,775.010	−57,235.310	−57,213.680	−57,230.860	−57,20

4 Discusion

4.1 Importance of game load

5 Conclusion

6 Appendix

7 References

8 Notes

- in 1.1 Do we still care about long term?
- 2.1.2 Remake the figure