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PREDICTING WHICH TEAMS WILL MAKE THE NBA PLAYOFFS

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Abstract. *The National Basketball Association (NBA) is the premier men's professional basketball league in the world. Thirty teams play during the regular season for the sixteen playoff spots and the opportunity to compete for the Larry O'Brien NBA Finals Championship Trophy. In this paper, we introduce a logistic regression model that can be used to predict which teams will make the playoffs at any point in the NBA season. In addition, we discuss potential applications of this ranking scheme that can be used by an NBA front office, "arm-chair" GMs playing fantasy sports, and professional/non-professional gamblers. More importantly, we move beyond the rankings that are commonly seen on the popular websites by providing a measure of uncertainty associated with our predictions. Finally, we introduce an R package (ballr) that can be used to access data from basketball-reference.com.*

Keywords: *NBA, Logistic regression, Predictive analytics.*

1. INTRODUCTION

The National Basketball Association (NBA) is the premier professional basketball league in North America and arguably the world (see NBA (2015) for additional information). The NBA, or often simply referred to as "The League", consists of thirty teams, twenty nine of which are located throughout the United States and one in Toronto, Canada. There are fifteen teams in each of the two conferences, the Eastern and Western conferences. Teams are further divided into one of three divisions within the conferences. In the West, you have the Northwest, Pacific, and Southwest divisions, and the Atlantic, Central, and Southeast in the East.

The ultimate goal for each team in the NBA is to win the Larry O'Brien Championship Trophy, annually awarded to the winner of the NBA Finals series. The Finals are played by the two teams representing their respective Conference Playoffs; eight teams per conference qualify for this post-season tournament. During the 2014-2015 season, the Golden State Warriors won the Larry O'Brien tro-

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phy as league champions, and the Cleveland Cavaliers were the runners-up. The remaining playoff teams from the Eastern conference were the Atlanta Hawks, Chicago Bulls, Toronto Raptors, Washington Wizards, Milwaukee Bucks, Boston Celtics, and Brooklyn Nets, and the Houston Rockets, Los Angeles Clippers, Portland Trail Blazers, Memphis Grizzlies, San Antonio Spurs, Dallas Mavericks, and New Orleans Pelicans from the Western conference.

To say that the NBA is a big business is an understatement. As of early 2015, the average team valuation is more than \$1 Billion (Badenhausen, 2015). And the league as a whole is the third most profitable (per team) among North American professional sports leagues behind the National Football League and Major League Baseball. In addition, a team that makes the playoffs is guaranteed more revenue in the form of ticket sales, concessions, merchandise, etc., and players are further compensated the deeper their team goes in the postseason. While the financial incentive for making the playoffs varies by individual players, it is certainly non-trivial for the organization as a whole. Therefore, planning for playoff expectations as early as possible seems beneficial from an organizational perspective.

The quantitative analysis of basketball, in general, is relatively nascent compared to that of baseball. The seminal work in this area came in the form of the text *Basketball on Paper*, Oliver (2004), followed by an academic summary in Kubatko et al. (2007). Loeffelholz et al. (2009) and Teramoto and Cross (2010) looked at predicting individual game outcomes and how teams play in the playoffs versus the regular season, respectively. More recently, some analyses have focused on spatial patterns and potential applications via player tracking software, see for example Shortridge et al. (2014) and Cervone et al. (2014).

Predicting which teams will make the playoffs on a game-by-game or week-by-week basis has largely been a media curiousity rather than an academic endeavor. Specifically, ESPN provides a weekly power ranking in their Basketball Power Index (Alamar, 2015) and NBA Playoff Odds by John Hollinger (Hollinger, 2015). Similarly, FiveThirtyEight provides Elo-based weekly rankings (Wikipedia, 2017) and simulation-based predictions of each team making the playoffs, as well as their probability of winning the title. See Boice et al. (2017) and Boice (2015) for additional details. And, although they are transparent with respect to their methodology, it is not clear how well the playoff predictions actually perform. In other words, should they be trusted?

In this paper, we take a look at the playoff prediction problem that is familiar to readers of ESPN and FiveThirtyEight, with the following additional information. That is, we ask (and answer) can we predict the playoff teams at any point during the NBA season, quantify the uncertainty in these predictions, *and* backtest the methodology against historical data? The remainder of this paper is outlined as follows. We introduce our statistical methodology in Section 2. We discuss the model fitting, validation, comparisons to FiveThirtyEight, and potential applications in Section 3. In Section 4, we provide an R package (ballr) for scraping data from basketball-reference.com and, finally, we summarize our findings and discuss future possibilities in Section 5.

2. STATISTICAL METHODS

2.1. DATA

The primary source of data for this analysis is derived from data tables that are easily accessible at basketball-reference.com (BBR), Sports Reference LLC (2015). Given the relatively structured makeup of the various pages at this site, we could easily scrape fourteen seasons of team results (2002 - 2015) resulting in a total of 417 team-seasons. Note that the first three seasons in this time period only had 29 teams before the Charlotte Bobcats joined the NBA in the 2005 - 2006 season. An example website from the 2015 season is `http://www.basketball-reference.com/teams/DEN/2015.html`. In addition, we compiled a spreadsheet from the same source on whether or not the teams made the playoffs in the current and prior year. In the ballr section, we describe an R package that we developed for accessing data at BBR.

2.2. STATISTICAL MODEL

Our fundamental goal of this research was to develop a model that can be used to predict whether an NBA team will make the playoffs, given their attributes after a fixed number of games, *e.g.* $n = 20$ games. Note that the methodology is not constrained by this number and, hence, we present the subsequent development for a general $n = 3, 4, \ldots, 81$ number of games. Note that n does not include $1, 2$, or 82 because there is no data at $n = 1$ (aside from prior year's success), only partially complete at $n = 2$, and the season is finished at $n = 82$ games.

Our dependent variable of interest is a binary indicator: 1 if the team made the playoffs and zero otherwise. The following attributes make up our set of predictor variables.

- X_1 = a binary variable indicating whether a team made the prior year's playoffs. This serves as a measure for "organizational stability." Teams that perform well (or not) in one year tend to do the same in the following year, *e.g.* the San Antonio Spurs during the time period under study. (Previous)

- $X_2^{(n)}$ = the cumulative number of wins minus losses after n games. (Record)
- $X_3^{(n)}$ = the average point differential after n games. Suppose team A usually wins by a large margin and tends to keep their losses close and team B often wins by a small margin and is blown out in losses. Then we might expect team A to be better than team B and, hence, a more likely candidate for making the playoffs. (AvgDiff)
- $X_4^{(n)}$ = the number of away games after n games. (Away)
- $X_5^{(n)}$ = the number of back-to-back games after n games. (BackToBack)
- $X_6^{(n)}$ = the cumulative number of wins minus loses for all of the team's opponents to date. (Opponents)

The last three variables serve as proxies, in a sense, to a team's strength of schedule to date, or after n games. Of course, additional variables might serve as better predictor variables or more useful proxies. However, we settled on the set given above due to the fact that they are all available, or easily derived, from the information given on the team pages at BBR. We discuss several of these variables that were not considered in the discussion section.

In order to estimate the probability of a team making the playoffs, we employ the following formulation. Let $Y_{ij} = 1$ if the i^{th} team in year j made the playoffs and zero otherwise, for $i \in \{\text{Atlanta}, \ldots, \text{Washington}\}$ and $j = 2002, 2003, \ldots, 2015$. The probabilities $\pi_{ij}^{(n)} = P(Y_{ij} = 1 | \boldsymbol{X}_{ij}^{(n)} = \boldsymbol{x}_{ij}^{(n)})$ are estimated using the logistic regression model

$$\text{logit}(\pi_{ij}^{(n)}) = \log\left(\frac{\pi_{ij}^{(n)}}{1-\pi_{ij}^{(n)}}\right) = \beta_0^{(n)} + \beta_1^{(n)} X_{1,ij} + \beta_2^{(n)} X_{2,ij}^{(n)} + \ldots + \beta_6^{(n)} X_{6,ij}^{(n)} \quad (1)$$

for all combinations of i and j, *and* after any number of games $n = 3, \ldots, 81$. We will refer to the model in Equation (1) as the full model.

Once estimates for the $\beta^{(n)}$ parameters are obtained, we can estimate the individual probabilities of making the playoffs using the inverse logit function:

$$\hat{\pi}_{ij}^{(n)} = \frac{\exp(\hat{\beta}_0^{(n)} + \hat{\beta}_1^{(n)} X_{1,ij}^{(n)} + \ldots + \hat{\beta}_6^{(n)} X_{6,ij}^{(n)})}{1 + \exp(\hat{\beta}_0^{(n)} + \hat{\beta}_1^{(n)} X_{1,ij}^{(n)} + \ldots + \hat{\beta}_6^{(n)} X_{6,ij}^{(n)})}. \tag{2}$$

As noted above, this formulation is defined for any n. At any point in the season, *i.e.*, after a team has played n games, we can compute their probability of making the playoffs.

A soft classification of making the playoffs or not can be constructed based on the resulting estimated probabilities. An explanation of using soft classification from the results of logistic regression can be found in Friedman et al. (2001). The obvious drawback to a soft classification is that our probability model in Equation (2) does not take into account conference and division membership. That is, there is nothing to prevent the model from classifying, for example, ten teams from the Western Conference as playoff teams when, in fact, only eight teams per conference can make the playoffs.

As of September 8, 2015, the NBA announced that playoff teams would be seeded $1-8$ in each conference based on their final records (NBA 2015). This is a departure from previous years in which the three division winners in each conference were guaranteed to be among the top four seeds in their respective conference. Therefore, we propose to use the eight highest ranked teams from each conference as the playoff teams.

3. RESULTS

3.1 MODEL FITTING

We fit the model for all $n = 3, 4, \ldots, 81$ games in order to provide a basis for comparing teams at any given point in the season. As an example, consider November 17, 2015 as a reference date. At that (or any) point in the season, teams have played a varying number of games due to the logistics of NBA game scheduling. In particular, the Washington Wizards had played ten games whereas three teams, the Atlanta Hawks, Golden State Warriors, and the Portland Trail Blazers, had played fifteen. Therefore, it makes sense to compute the probability of making the playoffs on November 17, 2015 using a model based on $n = 10$ games for the Wizards and $n = 15$ games for the other three teams.

The resulting p-values associated with each of the 79 models ($n = 3, 4, \ldots, 81$) are displayed in Figure 1. From this figure, it is obvious that our "strength of schedule" proxies are not that useful for predicting whether or not a team will make the playoffs. Hence, we decided to drop the following variables from the model for

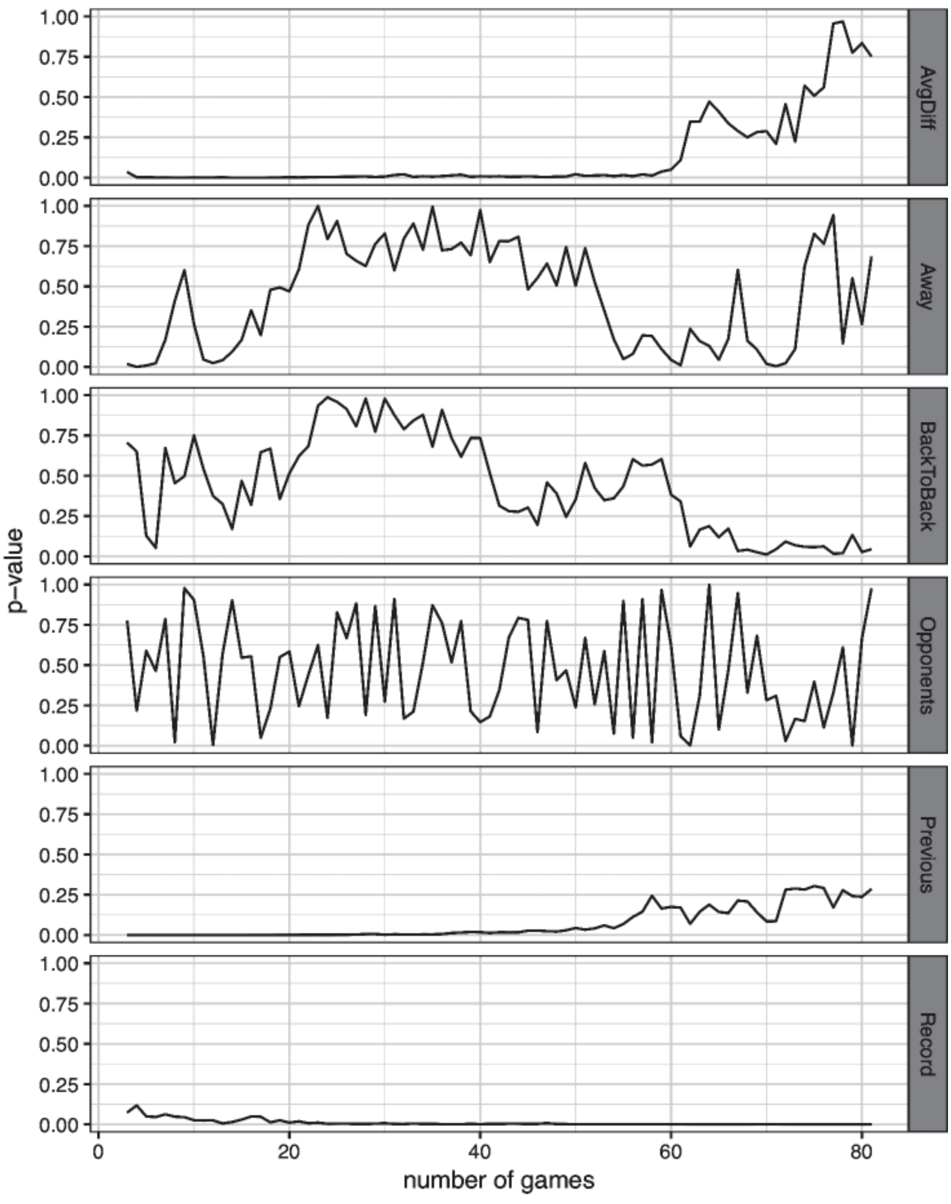

Fig. 1: The p-values for each coefficient associated with all $N = 79$ full model fits.

the subsequent analysis: the number of away games (X_4), the number of back-to-back games (X_5), and the cumulative number of wins minus loses for all of the team's opponents to date (X_6). The final, "reduced" model is then

$$\text{logit}(\pi_{ij}^{(n)}) = \log\left(\frac{\pi_{ij}^{(n)}}{1-\pi_{ij}^{(n)}}\right) = \beta_0^{(n)} + \beta_1^{(n)} X_{1,ij}^{(n)} + \beta_2^{(n)} X_{2,ij}^{(n)} + \beta_3^{(n)} X_{3,ij}^{(n)}, \tag{3}$$

for all combinations of i and j, *and* after any number of games $n = 3, 4, \ldots, 81$. The p-values for the coefficients in the reduced model are given in Figure 2.

As you can see in Figure 2, a team's prior year success (Previous), as measured by making the playoffs in that year, tends to be highly significant in predicting the current year's success early on in the season. In addition, the average point differential (AvgDiff) tends to follow a similar pattern in that its effect on success tails off towards the end of the season. After about 40 and 60 games, Previous and AvgDiff (resp.) are not much use as predictors for NBA team success. On the other hand, a team's record (Record) becomes significant at around 20 games and remains significant throughout the remainder of the season, giving weight to the notion that "you are who you are" at 20 games into the season.

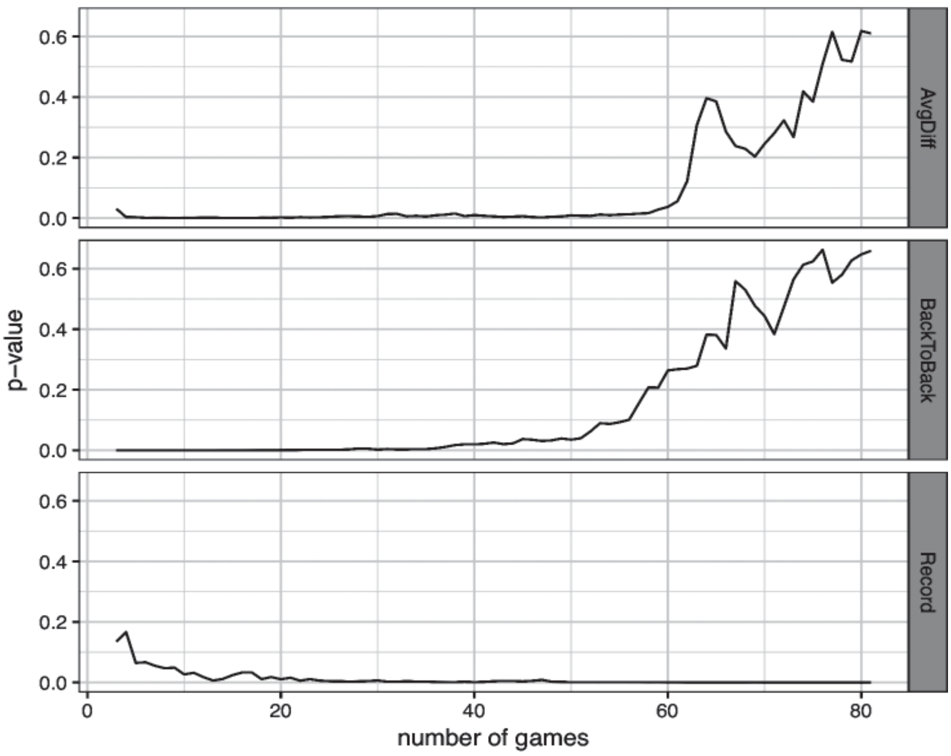

Fig. 2: The p-values for each coefficient associated with all N = 79 reduced model fits.

3.2 MODEL VALIDATION

In order to assess the predictive accuracy of the reduced logistic regression model, we performed a Monte Carlo study. The details are as follows. First, we randomly divided the 417 team-seasons into 300 "training" and 117 "test" observations and fit the model given in Equation (3) at $n = 10, 20, \ldots, 60$ games with the 300 training observations. Using the individual models at the six different game points, we predicted whether or not the remaining 117 teams made the playoffs using a reduced version of Equation (2) and the soft classification procedure that was discussed in Section 2.2. The percentage of correct classifications is recorded for the collection of 117 teams. We repeated the process of randomly dividing our data set and fitting/validating the model 1000 times and the proportion of correct predictions was tabulated.

The results of this Monte Carlo validation experiment are presented in Figure 3. Each boxplot represents (roughly) the distribution of correct predictions based on 1000 replications of predicting the playoffs for each team in the 117 "test" team-seasons. As mentioned previously, the soft classification approach does not take into account the actual constraints involved in making the playoffs, *e.g.* only eight teams from each conference make the playoffs. We are classifying a team as making the playoffs if their estimated probability from Equation (2) is greater than 0.5, without concern for conference/division membership, for example. Unfortunately, accounting for the various constraints is impossible in this sort of experiment and our estimated probabilities could easily be argued as lower bounds for the actual probabilities of correct classification. In addition, we added the results of predicting a team making the playoffs as asterisks based on the overall NBA standings on the date after which the Denver Nuggets played $n = 10, 20, \ldots, 60$ games. In other words, we treated each respective date as the end of the season and classified according to these hypothetical "final" rankings. As a concrete example, the asterisk at 60 games indicates that roughly 90% of the teams that were in position to make the playoffs at 60 games subsequently made the playoffs. The various playoff constraints are satisfied in making the playoff predictions under this scenario.

How do we interpret the results of this validation study? First, the model is much more accurate than simply looking at the standings at or before 10 games (see the left-most boxplot). The mean proportion of correct responses at 10 games is 0.799, whereas the proportion of correct predictions based on the standings is 0.715. This evens out to 0.814 and 0.813 for our model-based predictions and the predictions from the standings after 20 games, respectively. Basically, at 40 games and beyond, you will do as well or better at predicting who will make the playoffs using the current standings as you will if using this reduced model.

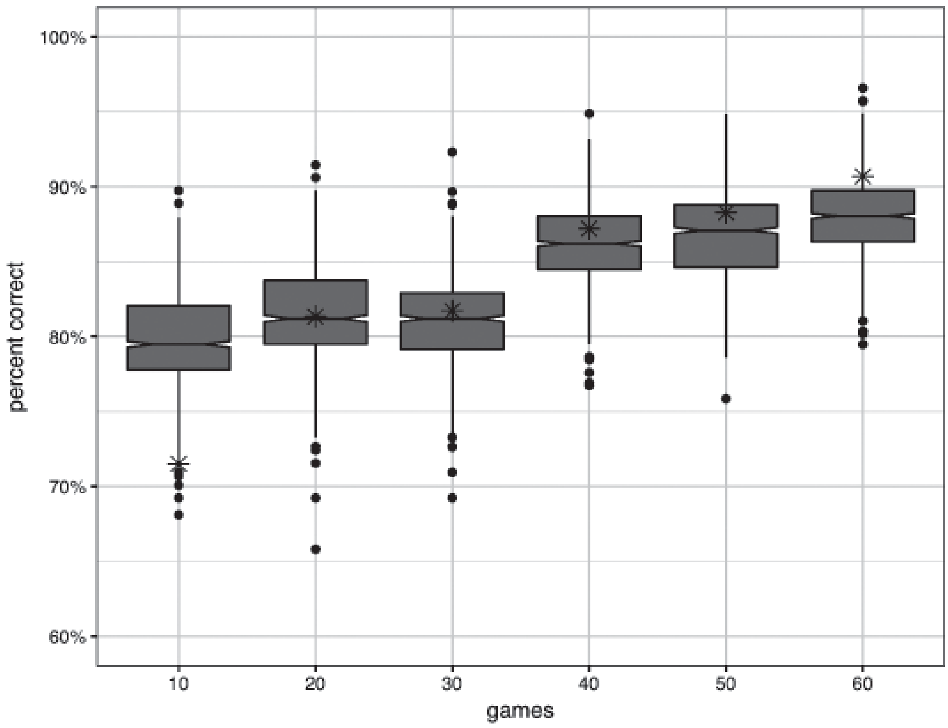

Fig. 3: The boxplots represent the results of the reduced model validation study. The asterisks are the proportion of teams that made the playoffs based on their standings after the various number of games. As an example, the asterisk at 60 games indicates that roughly 90% of the teams that were in position to make the playoffs at 60 games subsequently made the playoffs.

For completeness, the proportion of correct predictions at 30, 40, 50, and 60 games based on the standings is 0.817, 0.872, 0.883, and 0.907 and 0.812, 0.860, 0.868, and 0.881 based on the reduced logit model. This is, of course, not terribly surprising in light of the results shown in Figure 2. The p-values would suggest that the model is dominated by a team's current record at about the 40 game mark.

3.3 APPLICATIONS

There are several applications of this work that anyone from an NBA team's front office to a professional gambler might find useful. These applications could assist with decision making in terms of trade deadline strategy, whether or not to fire a coach after a poor start (ESPN.com news services (2015)), which team to bet on, among other decisions. First, we are able to provide a team-by-team ranking, along with the confidence intervals of these ranks, at any date throughout the NBA season.

Figure 4 shows these ranks at the end of the 2015-6 season. Note that the 95% confidence intervals in this figure are based on an inverting the logit of the ranking $\pm$ 1.96 · (standard error of ranking).

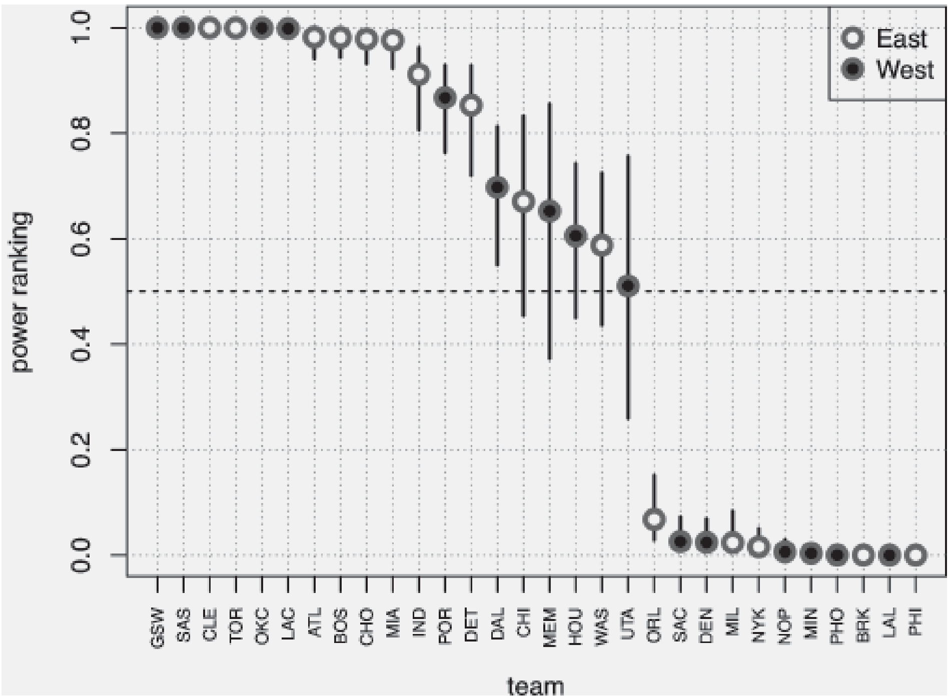

Fig. 4: The end-of-season power rankings for all NBA teams.

Just as easily, we can provide a "power ranking" trajectory for each team, defined as each team's respective probability of making the playoffs. The trajectories illustrate how each team is doing over time, by their number of games played. These curves are shown for each team in the Eastern and Western Conferences in Figures 5 and 6, respectively. From these figures, we can likely conclude that the Cavaliers in the East and the Spurs and Warriors in the West will make the playoffs due to their rankings tending close to one *and* their rankings having very low variability. Several other teams, *e.g.* the Charlotte Hornets are heading in the right direction, but their rankings have a large variation. Overall, these trajectories provide a pretty good indication of which teams are trending in the positive and negative directions.

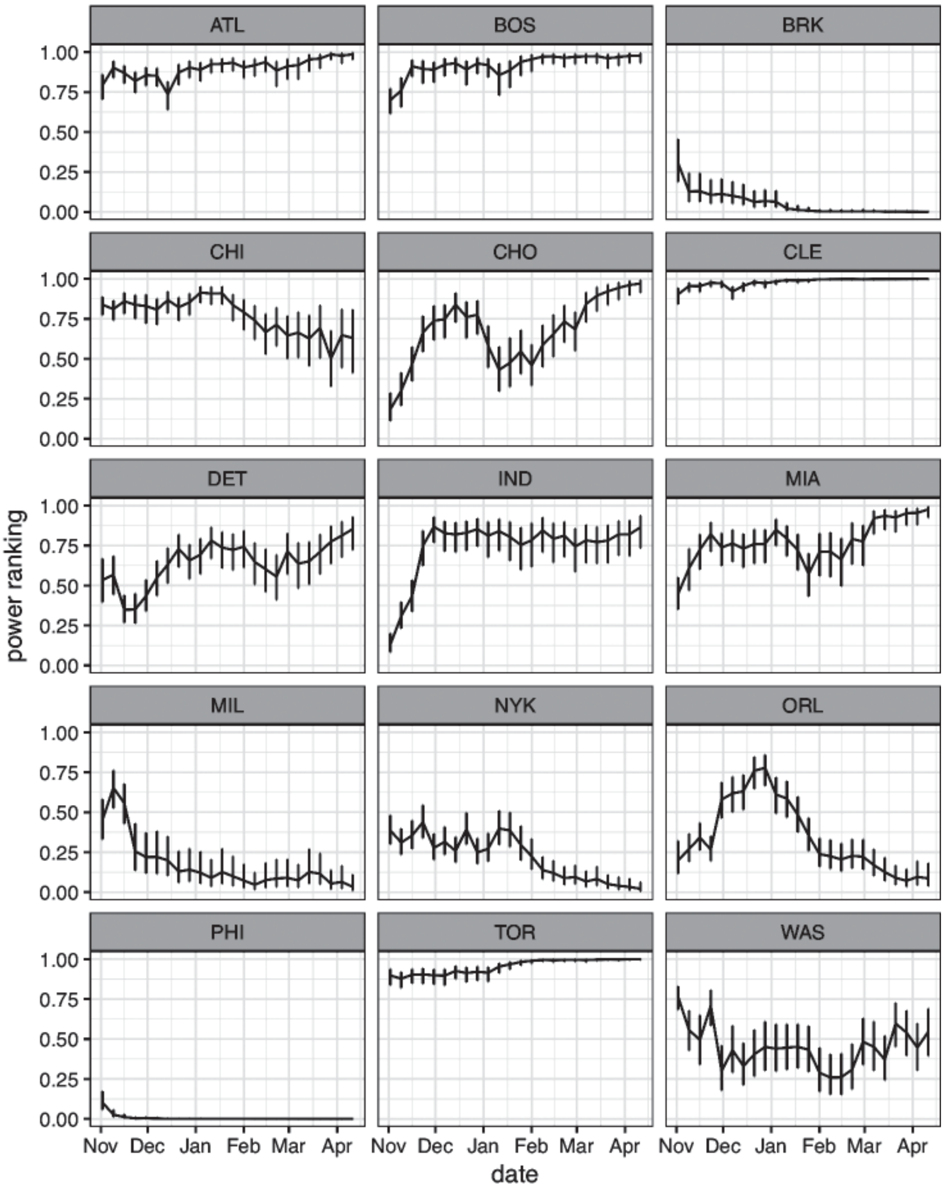

Fig. 5: The complete-season power rankings for all Eastern Conference teams.

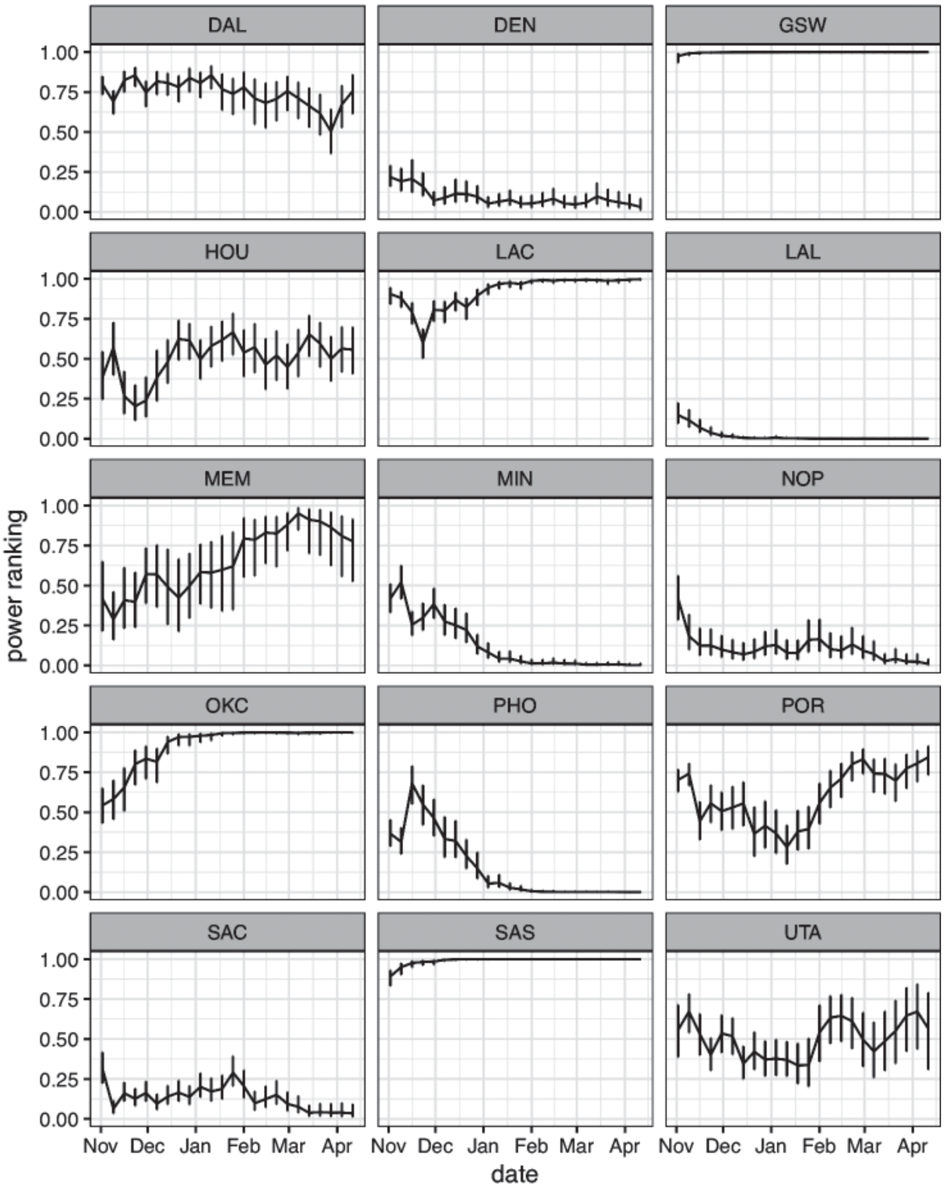

Fig. 6: The complete-season power rankings for all Western Conference teams.

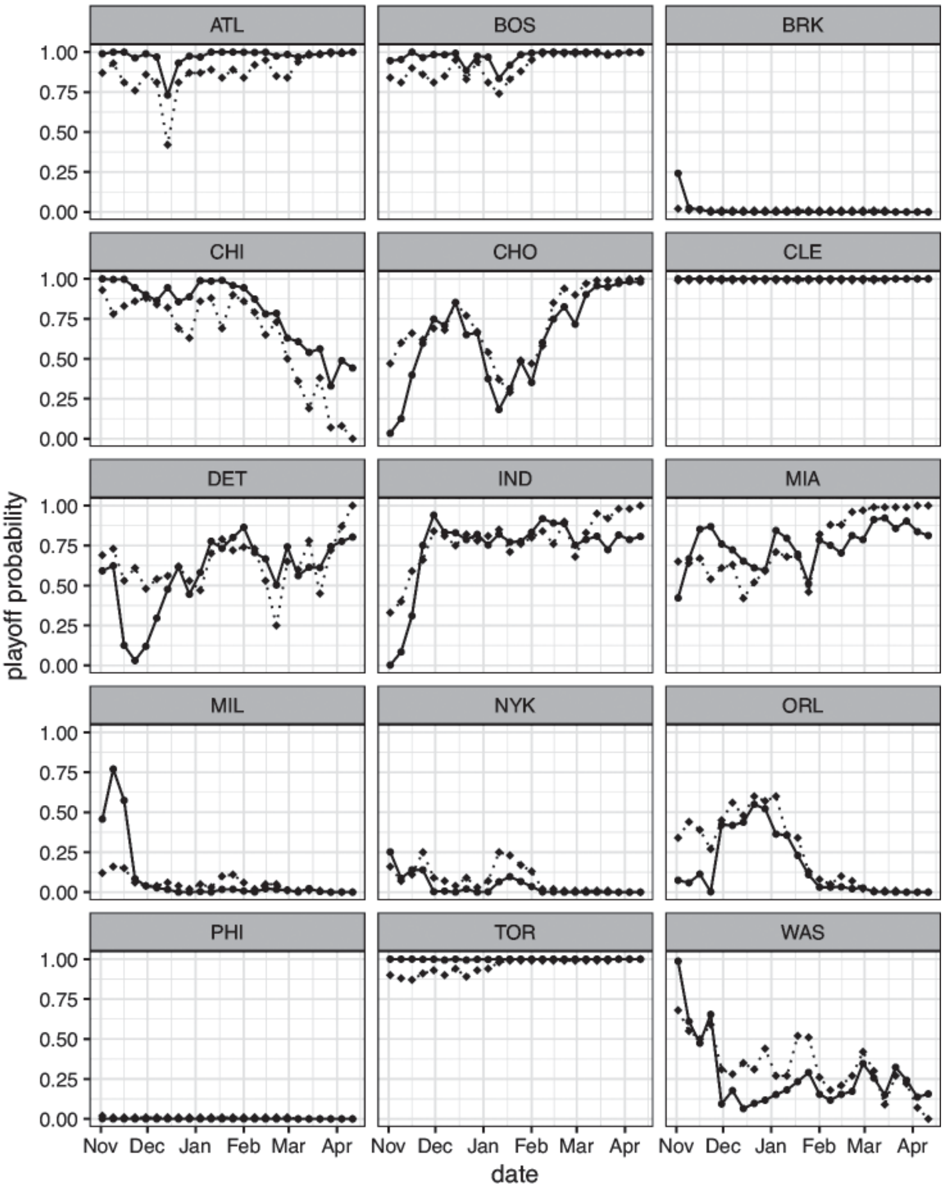

Fig. 7: The complete-season playoff probabilities for all Eastern Conference teams. The black points (solid line) represents the playoff probabilities as pro- posed in this paper whereas the dark grey diamonds (dotted line) are from FiveThir- tyEight.com.

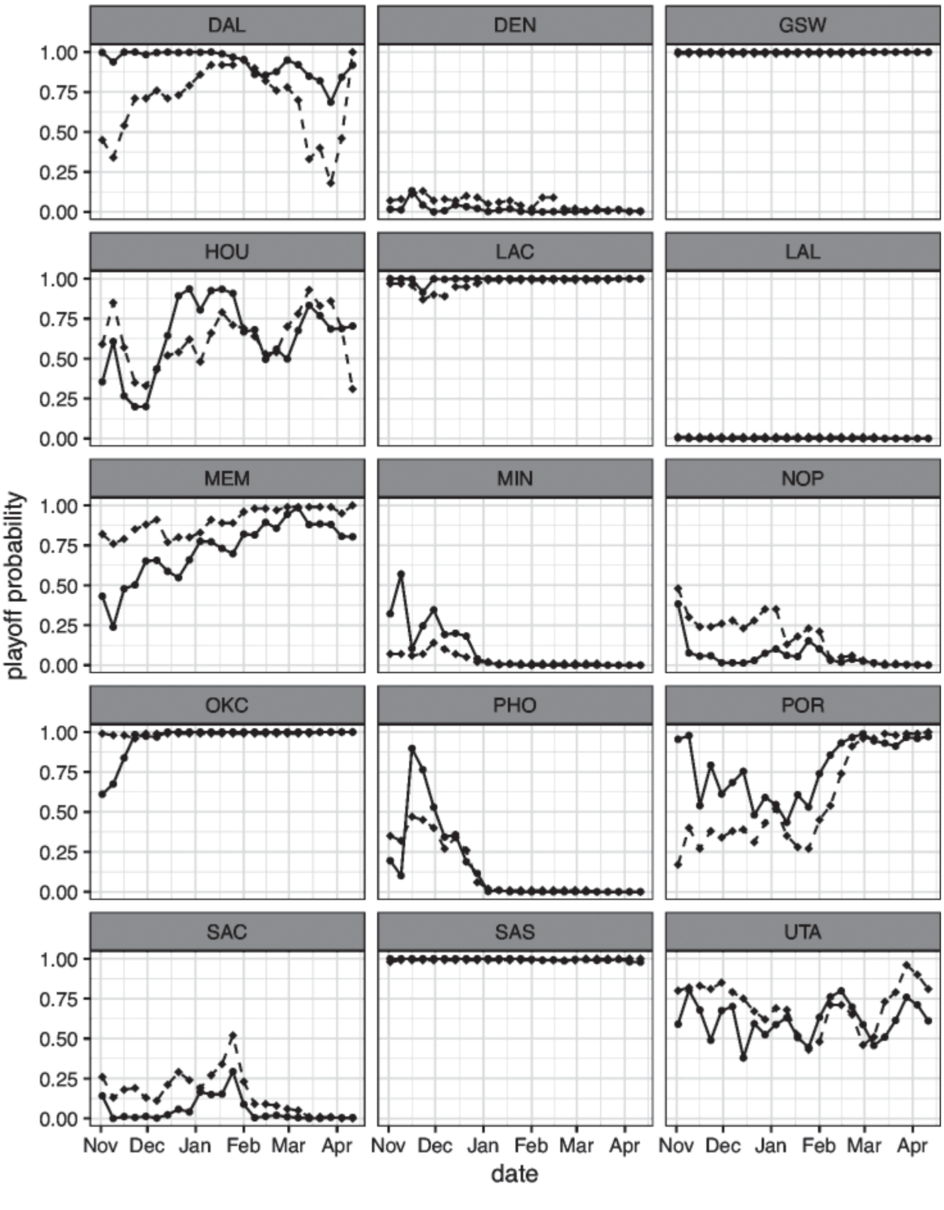

Fig. 8: The complete-season playoff probabilities for all Western Conference teams. The black points (solid line) represents the playoff probabilities as pro- posed in this paper whereas the dark grey diamonds (dotted line) are from FiveThir- tyEight.com.

Furthermore, it is relatively easy to the simulate whether each team is going to make the playoffs or not based on these power rankings. For example, one can easily generate a uniform random variate between each team's estimated lower and upper bounds of their respective power ranking at a given point in the season. This can serve as each team's estimated finishing position and, hence, whether or not they make the playoffs is determined by their respective ranking. Figures 7 and 8 show the results of $N = 1000$ simulated final standings for each week in the 2015-6 season beginning on November 2, 2015 (black line). As a comparison, we added the FiveThirtyEight projections (Boice et al., 2017) as the grey line. Overall, the predictions are quite similar with respect to which teams should make the playoffs at various points in the season. One notable exception is that our predicted probability of the Houston Rockets making the playoffs in the last week was significantly higher than that of the Utah Jazz, and the Rockets made the playoffs. FiveThirtyEight had Utah making the playoffs. We do note, however, that FiveThirtyEight was more bullish on the Detroit Pistons making the playoffs in the final week than we were, though, our model still had them making the playoffs. Our key advantage over ESPN, FiveThirtyEight, and the like is that that we demonstrate the efficacy of our projections in Section 3.2 using the large-scale Monte Carlo study and provide a comprehensive, transparent, and reproducible methodology for estimating playoff probabilites in this paper.

4. BALLR

In order to perform the analyses given in this paper, we relied heavily on the R Software (R Core Team, 2015) and the use of data given on BBR. In order to streamline the data acquisition and data cleaning processes, we developed an R package that serves as an API to BBR. You will need to run the following commands within R in order to install the "ballr" package.

```
> install.packages("devtools")
> install_github("rtelmore/ballr")
```

Please refer to the package's vignette for how to use the various functions contained in the package. This can be done by issuing the following command after installation of the package.

```
> vignette("ballr", package = "ballr")
```

6. DISCUSSION

At almost any point in the NBA season, it is easy to find a "power ranking" or a prediction for the likelihood of any team making the playoffs, see *e.g.* ESPN's Basketball Power Index (Alamar, 2015), John Hollinger's NBA Playoff Odds (Hollinger, 2015), or the FiveThirtyEight projections (Boice et al., 2017). A major shortcoming of the various predictions is that they rarely, if ever, provide a measure of uncertainty surrounding their predictions or results. Further, it is not clear whether their respective methodologies have been tested against historical data. In this paper, we introduced a logistic regression modeling framework for estimating the probability of making the NBA playoffs after n games have been played. We illustrated the framework's utitity by ranking the NBA teams at any point in a season, provided a statistically valid measure of uncertainty surrounding these rankings, *and* backtested the proposed methods. We stress the importance of this uncertainty measure and echo the sentiments given in Section 4.10 of Severini (2014) where he comments

> "… concepts such as the margin of error are still useful for understanding the role of randomness in sports statistics."

As we discussed, there are two primary applications for this work. First, at any date throughout the NBA season, teams will have played a varying number of games. By creating individual models at $n = 2, 3, \ldots, 81$ games, we can assess the entire NBA in terms of whether or not they are likely to make the playoffs. Second, the methods allow anybody to track the progress of each individual team as the season progresses. This is illustrated in Figures 5 and 6.

In addition to what is described above, we introduced a new R package that either "arm chair", or real, NBA front office folks can use to more easily access the treasure trove of data available at Basketball-Reference.com for use in the R statistical software. The package, ballr, provides an R API to BBR as well as several functions to clean the various data tables. We encourage users to contribute to the ballr package as they see fit through the issue tracker, writing code, etc.

We feel that we should address what some people might consider two potential shortcomings of our proposed work: (1) the effect of off-season free agency and (2) strength of schedule. First, there is no straightforward way to incorporate off-season movement into the regression model using BBR data. Obviously, if a team acquires a big-name free agent in the off season, it is quite likely that their probability for making the playoffs will increase. A good example of this phenomenon is when Lebron James signed with the Cavaliers prior to the 2014-2015 season. The Cavaliers went from only winning 33 games and missed the playoffs to winning the Eastern Conference, and subsequently losing to the Golden State Warriors in the NBA Finals. A possible remedy in this situation would be to include a team's salary information year-over-year; however, this is would only be a proxy at best.

Second, we need a better way to assess a team's strength of schedule. We saw in Figure 1 that our original SOS variables are highly insignificant in this context. A possible solution would be to compute the mileage flown between games, particularly for the back-to-back games. It is no secret that it is much easier to play a back-to-back contest as a home team versus an away team. In addition, for strictly away teams, a back-to-back against the Knicks and Nets is much easier than playing against the Lakers followed by the Nuggets. At this point, we have no way to account for these (possibly) important differences.

In addition, it is worth noting that there is a growing sense among the basketball analytics academic community, as well as players in the NBA themselves, that the NBA season is too long. For example, Lopez (2016) compares the rela- tive lenghts of the four major sports leagues (NBA, NFL, MLB, and NHL) and concludes that the NBA could "lose over three-fourths of its season" and retain a comparable regular season length as the other leagues. Kahn (2014) discusses comments by LeBron James on the NBA season being too long and Haberstroh and Knox (2016) discuss, among other topics, about how NBA coaches are resting players at a more frequent rate and, hence, we see an increasing number of DNP-Rests. Their principal argument is that a shorter NBA season would lead to a decrease in the DNP-Rests.

The research presented above seems to support this assertion that the length of the regular season could be shortened. Figure 3 indicates that we essentially know, with a high degree of certainty, which teams will make the playoffs by about the forty game mark of the season. This is supported by the modeling results as well as just simply looking at the regular season standings. Of course, we do not see the NBA shortening the season any time soon given the seemingly large amounts of money that various involved parties might stand to lose.

Finally, we mention that the methods presented in this article are not specific to the game of basketball, or professional basketball specifically. That is, we could easily apply this ranking scheme to teams in the National Hockey League, NCAA men's or women's basketball, among other teams, sports, and leagues.

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APPENDIX

Figures 9 and 10 show the estimated standardized regression coefficients for the models defined in Equations (3) and (1), respectively.

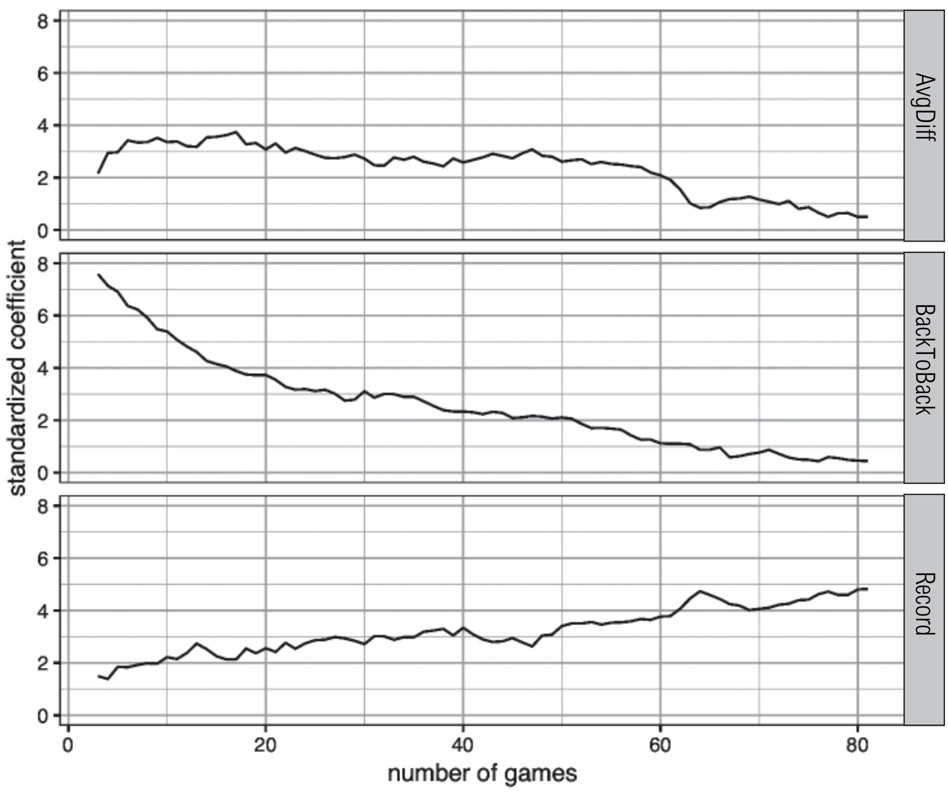

Fig. 9: The standardized regression coefficients for each independent variable associated with all N = 79 reduced model fits

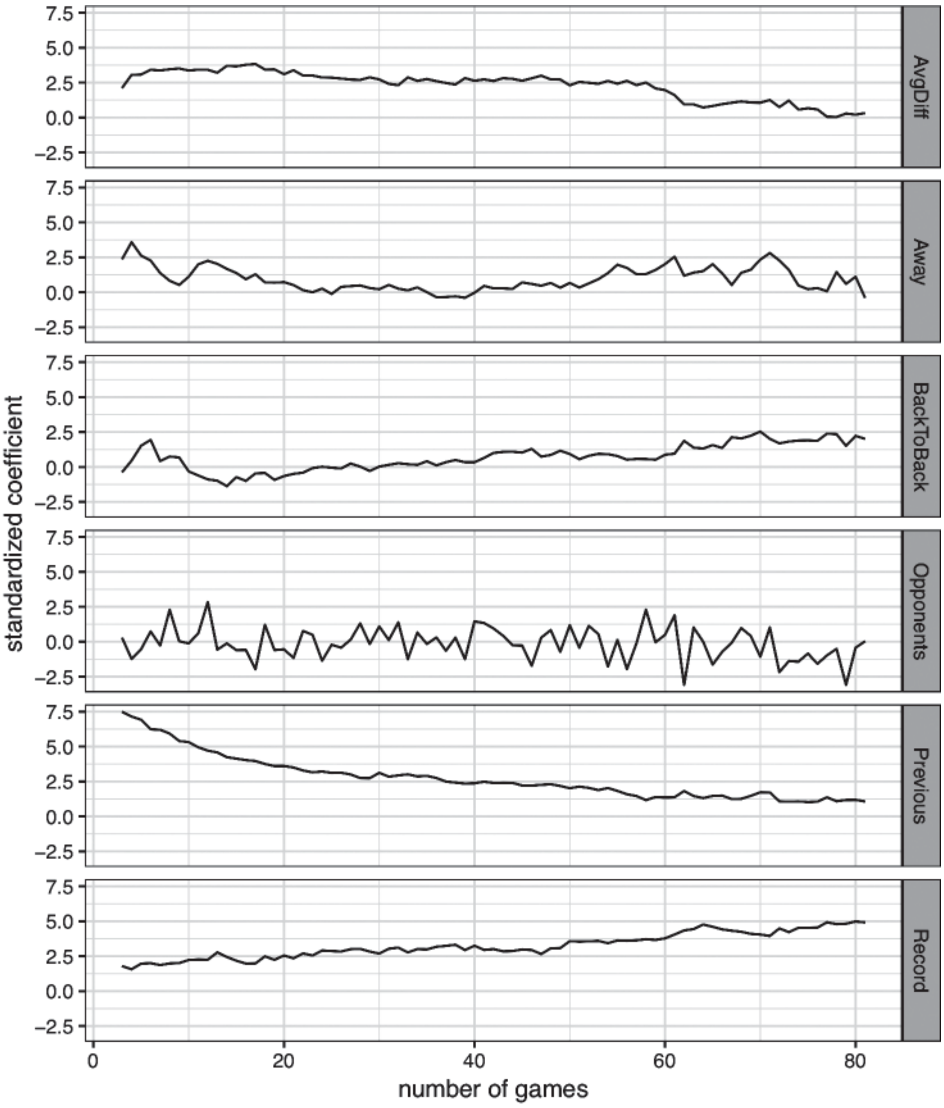

Fig. 10: The standardized regression coefficients for each independent variable associated with all *N* = 79 full model fits

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