Interpretability of Head Coaching Impact Using Advanced NBA Statistics

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Executive Summary

In basketball, it is common knowledge that there can be a variety of members that can influence the team and its success. Coaches are widely seen to be considered as great contributing factors to teams, but can this be measured or is there significant influence at the highest level? This project explores the influence of first-year head coaches on NBA teams. It compares rookie coaches, veteran coaches on new teams and returning coaches to determine if there is a significant statistical difference. The analysis applies statistical methods, including linear and lasso regression, alongside k-fold cross-validation, to assess the coaches' impact. By integrating diverse data sources, such as sports betting records and advanced basketball statistics, the project attempts to offer an analysis of how new head coaches affect success can be interpreted for the highest level of basketball. Additionally, the analysis attempts to measure to what extent coaches are measurable when they are an unexplainable variable. The results indicate largely varying levels of predictability dependent on the coaching experience. None of the final models performed traditionally well, by metrics of RMSE and R^2, but by subsetting the data interesting insights can be extracted. These poorly performing results are likely correlated with the variety of changing variables associated with basketball teams such as team personnel, rule changes, and coaching. The largest predictability belongs to the subset of data including all coaches. The least predictability in coaching belongs to coaches who have previously coached on one team but are coaching for the first time on a new team. Potential improvements for the project include more factors for incorporating player-specific data as well as a stronger focus on causality utilizing causal diagrams.

Project Topic and Problem Statement

Within the National Basketball Association (NBA) there has long been debate regarding what factors determine team success the most. For this analysis, team success is assumed to be a team's regular season wins. Although, a similar exercise can be completed using regular season win percentage. The two largest variables to influence winning are players and their coaches. Players have the most obvious impact, as their statistics are directly caused by them and can be quantifiably recorded. Additionally, when a player is missing, their minutes are allocated elsewhere and their mean statistical presence is missed. Coaches on the other hand, influence the players and their capabilities, but there are difficulties in determining how much a coach can impact. One way to differentiate coaches is their years of experience. Doing so does not intrinsically mean that more experience is equivalent to better coaching. Recent anecdotal evidence has raised interest in the idea of a first year head coach performing better. Within the past few years, several first year head coaches have been highlighted for their team success. Some strong examples include, Nick Nurse and the Toronto Raptors winning the NBA Championship in 2019, Ime Udoka and the Boston Celtics making the NBA Finals in 2022, Joe Mazzulla and the Boston Celtics making the Conference Finals in 2023. Critics to the idea of crediting a coach with large amounts of success would note that in Joe Mazzulla's example, the team before was a championship level team, and the success Mazzulla's team saw was more an indicator of team talent as opposed to coaching skill. Thus, head coaching success should not simply be defined as how far a team makes in the playoffs.

Other potential indicators of a first year head coach creating impact would be an increase in wins during the season in comparison to the year before. Darvin Hamm and the 2023 Los Angeles Lakers improved 10 wins from the 2022 season, resulting in a Conference Finals appearance. Critics would point to the fact that the Lakers had key personnel changes, as well as an additional 16 games of Anthony Davis, leading to a more favorable outcome for Hamm and his team. This scenario lends itself to the idea that coaching and players likely have an intertwined effect on the performance on the team.

There is also a notable difference between first year head coaches and a coaches first year with a team. A key example is Mike Brown and the 2023 Sacramento Kings who improved 18 games from the 2022 season with a new coach. Although, it should be noted that Mike Brown has coached before, and that the Sacramento Kings made key additions to their player roster that likely would have positively influenced their wins regardless of coach. That leads to the issue regarding interpretability of a situation where a historically successful coach is hired to coach a successful team, the odds would likely be in their favor. With all of these considerations in mind, this analysis hopes to consider the question: **can the success of a team with a first-year head coach be substantially determined through advanced data?** Were this question to be answered, there would be numerous sources of value added to front offices around the NBA. Depending on the predictability of a first year head coach, there may be less or more risk associated with the hiring of an unproven one. Hiring a coach with different levels of prestige can have millions of dollars in financial impact. Additionally, NBA fans and media may come to realize whether optimism or skepticism is reasonable to have for an incoming head coach. Impacting such perceptions can somewhat impact markets such as sports betting where team success is predicted and monetary stakes are used. Lastly, this exercise serves as an interesting look into the predictability of innovative coaching schemes in the NBA. Were first year head coaches to be more predictable, or around the same level of predictability as all regular coaches, there would be argument to be made that being a first year head coach with new ideas has less influence on the overall success of a team.

Dataset and Attributes

One of the primary focuses of the analysis was to determine what the predictive variable should be to represent team success. The attention was originally aimed at betting odds to determine which teams that held first year head coaches had outperformed their betting odds. To do this, web scraping was utilized from an archived sports betting database: https://www.sportsoddshistory.com/nba-odds/. The earliest available data was 1993 so the parameters of this project is from the 1994 season to the 2023 season. The metric obtained from this data would be to use the difference between estimated wins and actual team wins. Unfortunately, there were large amounts of missing values, enough to where removing missing values would not be a reliable problem-solving method. Due to the missing data concerns, the next metric decided upon was a win percentage difference. Win percentage difference would be calculated as the net difference in win percentage between the year of prediction and the year before. Later, it would be determined that this metric unfairly penalizes teams that maintain the status quo even with a new coach. Thus, games won in a season were chosen as the final predictor. Since games are won by the same teams in name, every year, the data necessary for this analysis will be time series. The nature of time series regression becomes much more difficult and will be discussed in the next section.

The data necessary to predict the number of games won as well as the remaining variables utilized in this project were web scraped from https://www.basketball-reference.com/ with information coming from teams' advanced statistics as well as general coaching data. Although our dataset originally included as many as 69 variables, many were removed over the course of the analysis. Some variables, such as *season, team_name,* and *Coach_name* are categorical sources of data, and thus would not provide much use in predicting whether a first year head coach was more successful. Other statistics were filtered in order to have coaches meet a set of minimum requirements. *Coaches_games_season* was filtered to be at least 30 games. With this limit, coaches would have a noticeable amount of time to implement their own influence onto the team. Other data, such as *Coach_games_career_PO_HC_win* were cut for the sake of eliminating bias when considering that only coaches that had made it to the playoffs in the first place, the hallmark of a successful team, would even have playoff data in the first place.

With the issue of simply predicting a "good" team, the data needed to be engineered to consider the coaching data of a previous year in association with the current year. Doing so would allow results to be drawn about the impact of a first year head coach based on a previous year's success. After adding the previous years data to be associated with the next season, nearly all current years data was removed, except for *Coach_seasons_team* and *HC_seasons_total*. Logically, when a team is making predictions about the success of their roster, they will not have any access to the upcoming years data, because it will not have happened yet.

There was another statistic added named *roster_continuity* which aimed to determine how many minutes from the previous year belonged to the same players. This strategy would attempt to have the model take into consideration that there were large changes in roster construction, meaning there could be more variance in the team from a players perspective. For the sake of avoiding data noise, the statistic was ultimately removed, as there was not a feasible way to measure how much value had been added or lost through the scope of this project. Although, this could be done by multiplying a chosen player's advanced statistic with the amount of minutes said player accrued in a season. These values could then be summed together for comparison against other seasons to determine a change in value of the roster. Such a topic would be worth further research given the resources.

Problem Solving Methodologies

The intent of this analysis is to answer the problem statement while utilizing machine learning algorithms associated with linear regression and data science techniques. The tools used to attempt this goal were R and Python. The steps taken within this project include: data cleaning and engineering, exploratory data analysis, spliting testing and training data for modeling, modeling, drawing conclusions, and a write-up.

When considering predicting team success, regression for prediction was suggested as the primary methodology for solving this issue. When comparing the number of wins in a season and the number of seasons being a head coach, there is not a clear trend, as pictured in Figure 1. Linear regression methods were selected for the sake of better learning the methodology associated with linear regression as well as the consideration that a non-linear regression methodology may not fit the data as well.

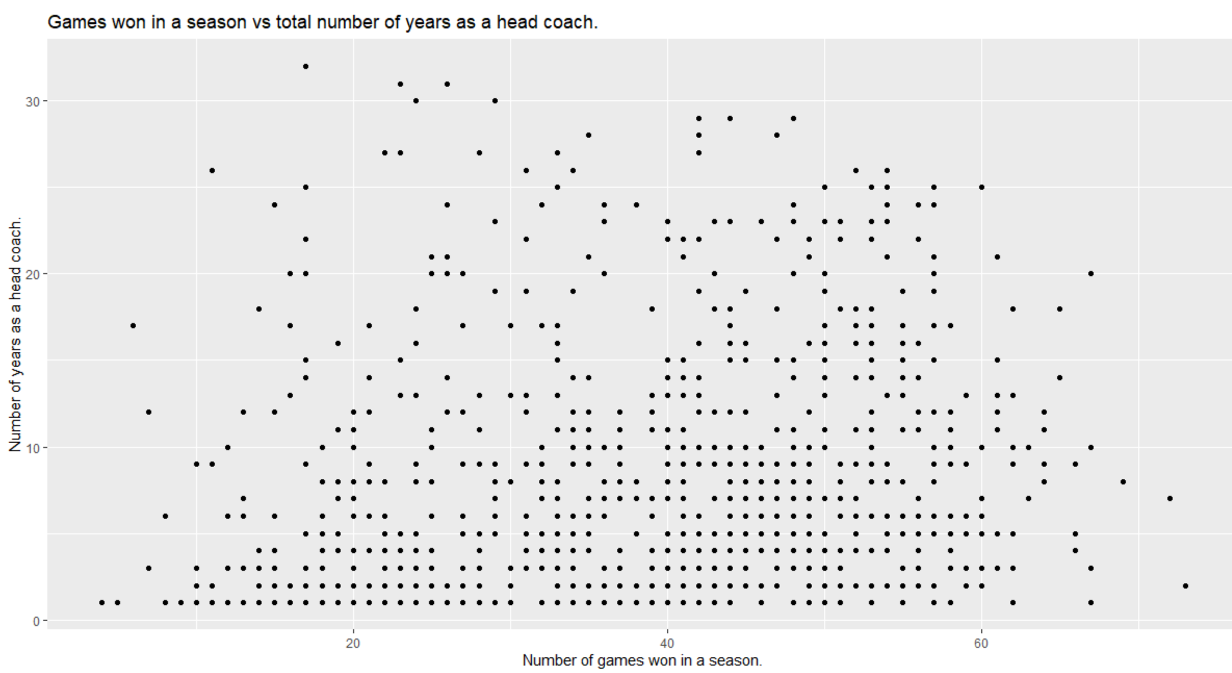


Figure 1: Games won in a season vs. total number of years as a head coach.

When considering doing a regression analysis on time series data, there were a number of assumptions to consider:

1. Stationarity - assumes that over time mean and variance do not change. This assumption holds true based on Figure 2 and 3.

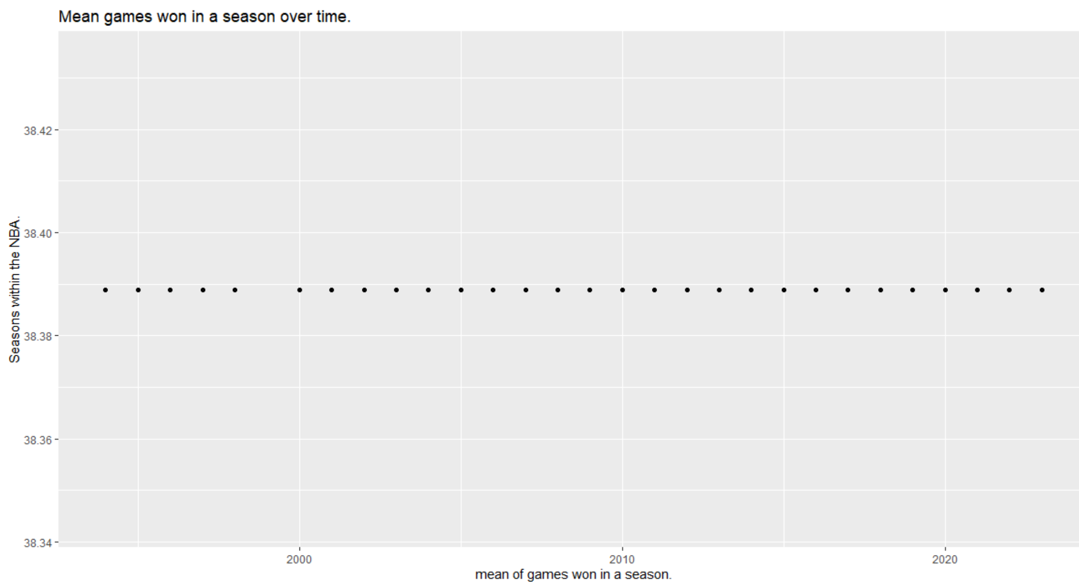


Figure 2: Mean games won in a season over time.

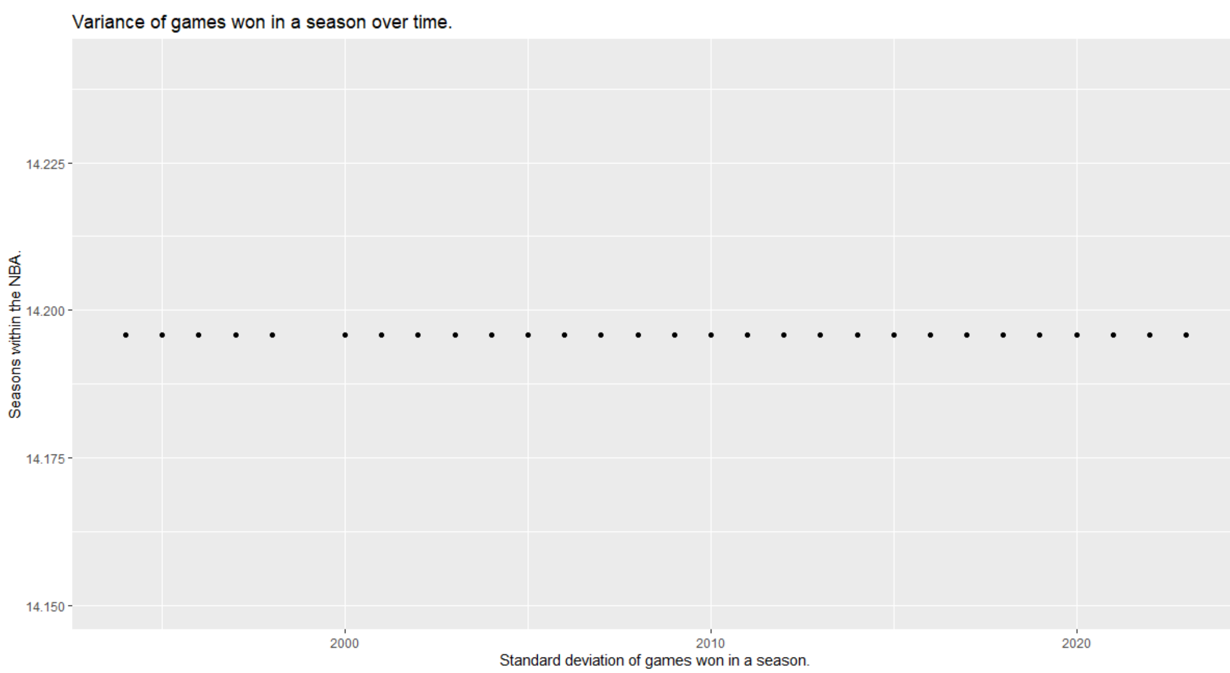


Figure 3: Variance of games won in a season over time.

2. Linear Relationship - assumes that there is a linear relationship between the target variable and features. Lasso regression helps with this assumption by removing variables that are less useful when modeling the predictor variable. The variables included in the modeling process and their correlation to games won in a season are in Appendix Figure 1.
3. Independence of residuals - assumes that residuals are independent of each other. Tests for measuring the independence of residuals *include* the Durbin-Watson test, which measures autocorrelation. To measure for all of our features, we fit a basic linear model. Using a lasso model would not be sufficient due to the tendency for lasso to shrink and eliminate coefficients. The model outputs can be seen in Figure 4. The model itself and its methodology can be seen in Appendix Figure 2. Regarding the results of Figure 4, there is likely autocollinearity because the p value is less than .05, the null hypothesis is rejected and one can conclude that the residuals in this simple linear regression model are autocorrelated. Additionally, autocorrelation can be seen as present in the comparison between previous years win percentage and current year win percentage with an R^2 of .622. Such a strong correlation between the same metrics but of different years indicate that there are large amounts of autocorrelation present inherently within the time series data. This relationship is present in the plot of Figure 5.

```
Warning: prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases lag Autocorrelation D-W Statistic p-value
   1       0.1562494      1.687344       0
 Alternative hypothesis: rho != 0
```

Figure 4: Results of Durbin-Watson test on simple linear model.

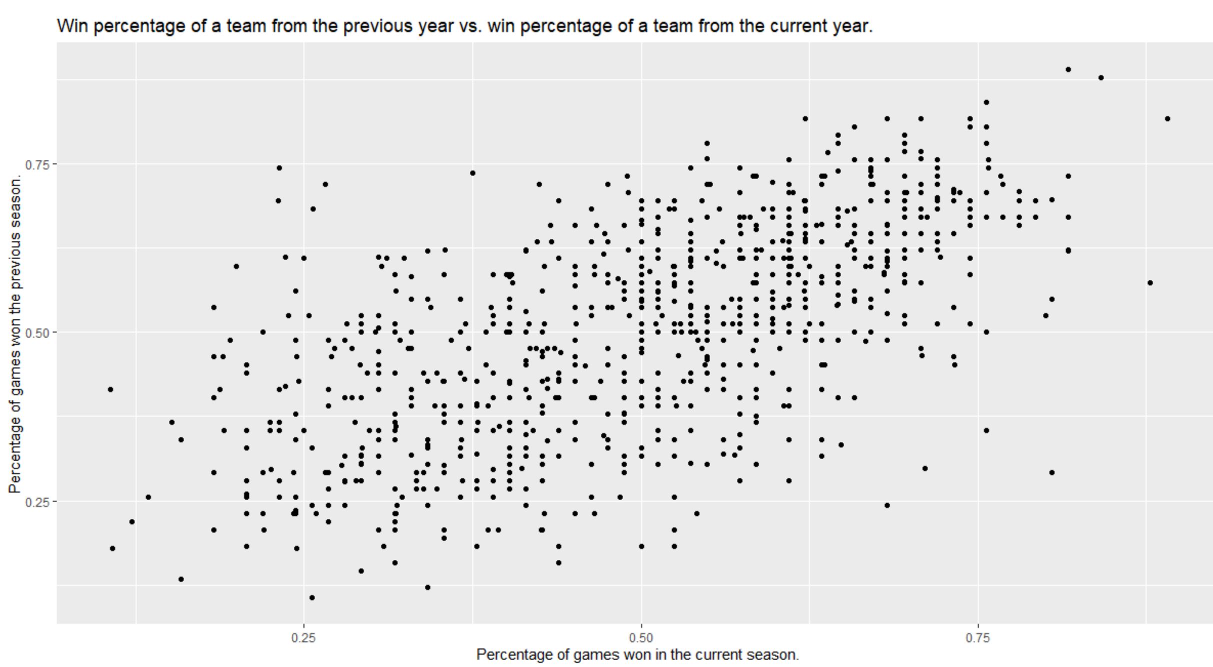


Figure 5: Win percentage of a team from the previous year vs. win percentage of a team from the current year.

With such high autocorrelation, the key ways to mitigate it are to use lasso regression and cross validation. To assist with over or under fitting, this data was put through k-fold cross validation with ten folds. This method was especially useful for the dataset as our number of observations could be less than 100 depending on the filtering of first year head coaches. The rationale behind using ten folds specifically was to find a reasonable balance between reducing the variance found within the dataset and managing computational intensity. Were this data to include even more variables of previous data or more years of information, more intensive computation would be required and less folds may be necessary. Additionally, using ten folds assists with increasing our training set, which is especially useful in cases where the training set is small. Theoretically, to have a higher number of folds, i.e. 10, the prediction error would be minimized as the models see more of the predictive data. Taking the average from ten folds can assist with any variation and make the created model more reliable to assist with mitigating the lack of independence of residuals.

Analysis and Results

Coaching as a metric can be extremely difficult to predict. Not only can the value of a coach be rather qualitative, there can be a good amount of difficulty in separating the success of players and the success of the coach's system. This analysis utilizes lasso regression on data with different filters to compare results with each other. Types of regression utilized began with simple linear, evolved to elastic net regression, and eventually devolved back to Lasso regression to receive the best advantages from the modeling techniques and mitigate the shortcomings of the data. The benefits of landing on lasso regression would be to avoid overutilization of the variables that hold large amounts of multicollinearity. When modeling, the outcomes with the least error were considered those with the lowest mean-squared error (MSE). The amount of lasso penalty weights associated with a specific model are reflected through a lambda value. The optimal log of lambda for the least amount of MSE was selected.

The first set of results are scenarios where there was not a first year head coach of any type. These results can be found in the figure below. The lowest amount of MSE found was 138.09. To put these values into perspective, Root Mean-Squared Error (RMSE) was also calculated and can be considered the amount of error expected, in units of games, with any specific prediction. The RMSE would end up coming out to be 11.75 and although that value may seem low, the important consideration is that the value is scaled relative to the dependent variable. One can think of this value as there being an up to 12 game variation between predicted and actual values. This difference is not insignificant as 12 games can make a huge difference in the outcome of whether a team makes the playoffs or not. Figure 6 displays the output of the model with all coaching data included. Before mentioning a second metric, it is important to highlight potential falterings with relying on RMSE. RMSE is sensitive to outliers. In smaller datasets, as noted in the later models, a few substantial outliers have the potential to skew the RMSE and not accurately predict the model performance. To counterbalance some of the RMSE issues, R^2 was determined and analyzed. For this model, the R^2 of .347 indicates some level of predictability for wins in the next season based on the previous years data. Appendix Figure 3 displays the output of the model and which variables were most utilized. As with RMSE, there are several issues with R^2 as a metric. By itself, this value does not directly capture the causal relationship between the features of a particular model. Without proper context inclusion, and the use of a different measurement, conclusions could not in good faith be drawn.

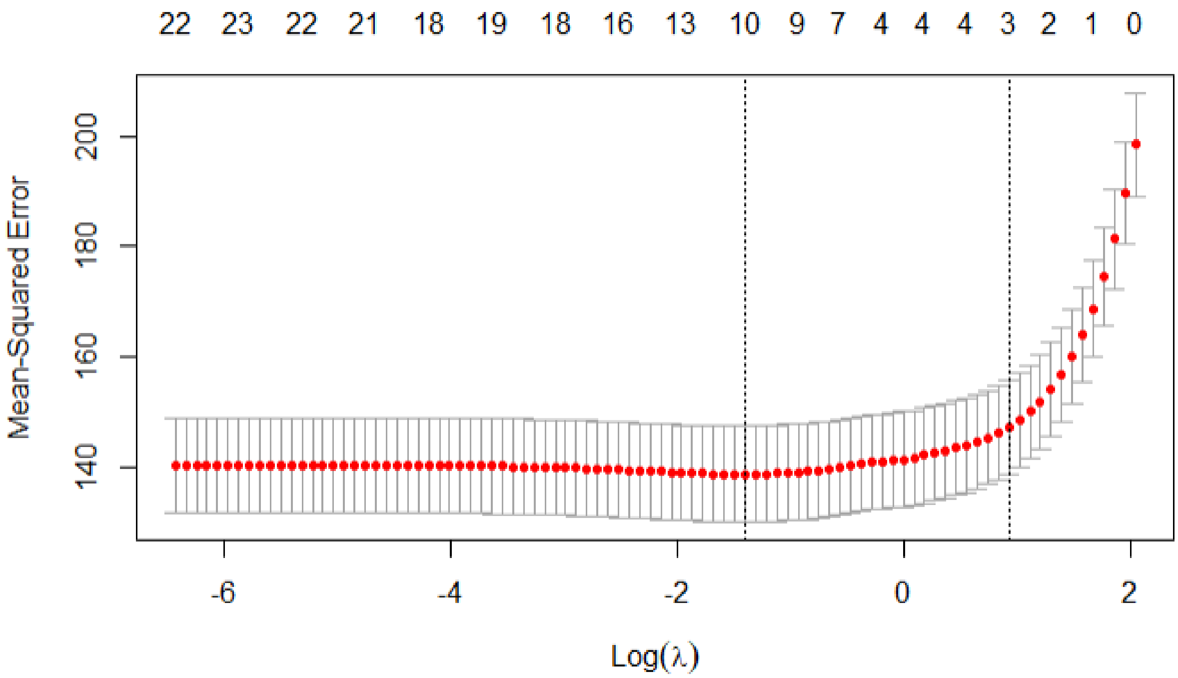


Figure 6: Log of lambda values vs. mean-squared error plot for model including all coaches.

When considering the concerns of the validity of the outcomes from the independent residuals requirement, the residuals were plotted to attempt to determine independence. Figure 7 demonstrates the residuals of the lasso model with all coaches included and there does not appear to be any correlation between them. This lack of trend holds true for the other two models and can be seen in Appendix Figures 4 and 5. The testing set utilized to create this residual plot is 172 observations.

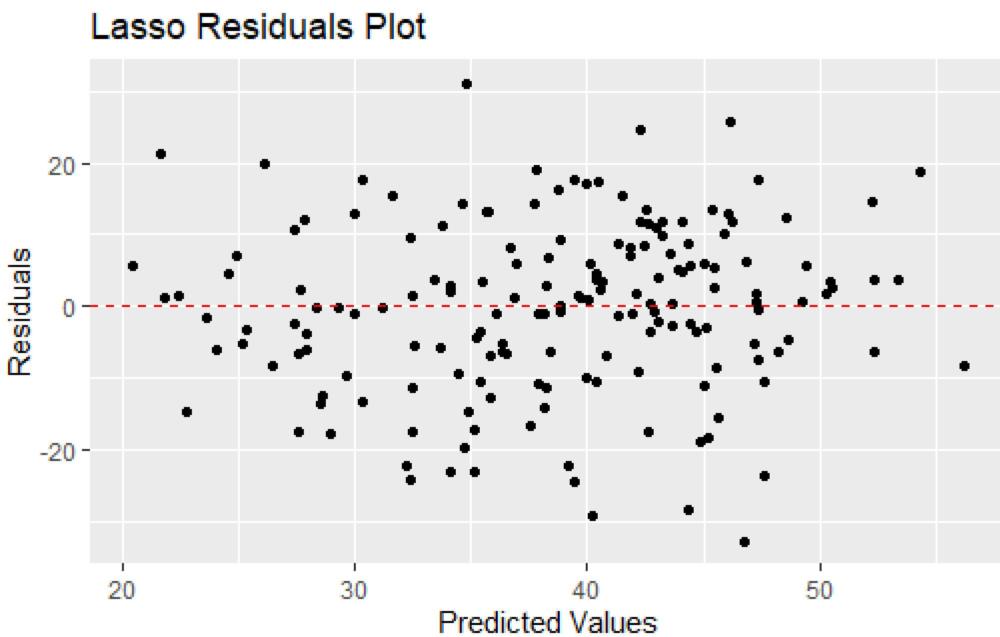


Figure 7: Predicted values vs. residuals plot where the units are games won in a season for the predicted values.

The second set of results are scenarios where there was a first year head coach with a team, but it may not have been their first time head-coaching in the NBA. These results are noticeably worse. They have a worse optimal RMSE at 14.455, meaning there is a larger amount of error when comparing predicted vs. actual values. What is also of note is the nearly 40% decrease in r-squared to -.028, indicating a nearly zero correlation between the selected features with weights and wins in a season. The MSE vs. log of lambda plot can be viewed in Appendix Figure 6. The selected coefficients can be viewed in Appendix Figure 7. For reference, the testing data for this set of predictions were a set of 50 observations, meaning a significant decrease in test size from the data filter of all coaches. This trend is further exacerbated for “true” first year head coaches leading to concern that the testing data is large enough to analyze the validity of the model.

The third set of results were the coaches who had never been a head coach with an NBA team before. The RMSE improves in comparison to the model with first year head coaches for a specific team to a value of 12.26. Additionally, the R^2 improves in comparison to the same model to a value of .098. While still having more error and less explainability than the first model with all coaches, this model holds a noticeable amount of more predictive power than the model for first year head coaches with a specific team. What is of concern is the accuracy of this noted improvement. The set of observations for this model are as low as 34. What is slightly reassuring is that when increasing the testing data to withhold 30% of the data instead of 20% for the other models, this model behaves to a high degree of similarity with or without the added 10%.

Conclusion

The results of the models included in this analysis indicate different levels of variance between all coaches, and those who are a first year head coach for the first time in their careers or with a team. There is difficulty in outlining exactly what is causing this variance in success. But, when player impact has been accounted for, the remaining large external factor is coaching. This analysis does not wish to suggest that the nearly 40% variance in r-squared is solely because of first-year coaching. But, there is an argument to be made that these unexplained and correlated differences have coaching type as a similarity. Although these results do not directly scream that coaching is the rationale behind these variances, our process of elimination for the factors of basketball success along with our subject knowledge indicates that coaching does have some effect. Within this technical write-up, there have been mentions of an unwillingness to say that variances in models are directly caused by coaches. Some of this hesitation stems from the lack of an objective equation for all things that impact a basketball game, and the coefficients that coincide with coaching in that equation. Were causal models, as presented by Judea Pearl and Dana Mackenzie in *The Book of Why: The New Science of Cause and Effect*, used to determine whether coaching is even capable of being controlled for, a more definite conclusion could be made. Other hesitations come from the variance in feature selections in the different coaching types. Since the same exact features weren't selected, comparisons between what features best highlight coaching aren't possible. With that being said, were these conclusions to hold significance, there are still implications to the findings that, when combined with the context of the NBA, can help to paint a better picture as to what may be causing these trends.

Starting with the original model containing all coaches, the large error and low R^2 indicate that the success of a team one year does not directly implicate that team to have similar success the following year, although the correlation is noticeable. This result is especially interesting when considering the willingness of some teams to stay within a status quo, regardless of the lack of a guarantee for a continued success. Still, this continued success is more likely than the potential consequences of bringing in a new coach, veteran or not. The second model, with only veteran coaches, produced the worst-performing model. Using context from the NBA, a potential rationale for this poor performance could be relating to veteran coaches specifically causing organizational-outliers. There is an assumption that a coach who has been hired by two separate teams holds some sort of positive reputation. Or, a reputation that is positive enough to garner a second head coaching job. Fortune 500 companies will often hire CEOs that have been fired or left previous CEO jobs before, partially based on the confidence that the people being hired are fire-tested. These coaches are likely brought in to serve as an outlier performance indicator. Management has no incentive to switch up a large dynamic of the team, unless they had the end goal of changing results drastically. Thus, there may be other noticeable changes that occur in the same years as a head coaching change, leading to an unmeasurable error. One may instead measure the change of a head coach as a management change of strategy, likely instilling other large changes, not measured here. But the question still remains as to why there is a difference between veteran coaches and coaches experiencing their first year ever being a head coach. A possible hypothesis is that true first year head coaches may be put into situations where the change is not expected so drastically, as they aren't battle-tested and may hold the same expectations to completely overhaul an organization. While this theory is purely speculative, it serves as one possible rationale for the slight difference in model performances.

One of the largest concerns when considering the validity of this analysis is the data. The dataset used had 873 entries, including 120 representing true first year head coaches, 137 representing veteran coaches on their first season with new teams, and 616 representing returning coaches. The modeling methods applied cross validation in order to improve the validity of information we could gather from this dataset, but one should note that the size remains small and therefore the results are subject to high variance. The theoretical maximum sample to represent true first year head coaches at this point in time sits at 348 including all of NBA history. Looking back to the NBA-ABA merger, which would represent a more stable dataset for the purposes of this study projecting forward, the dataset could be increased to 1,446 total entries with 263 unique coaches. Regarding the expected growth rate of the dataset, NBA teams have hired first year head coaches at an average rate of 4.6 new coaches per year, and the overall dataset could continue to increase at a rate of 30+ entries per year.

When considering how this project could be made better or present issues with our analysis, there were several concerns highlighted along the way and factors that ought to be mentioned. Regarding improvement and risk control, there are several potential routes. Many of these were either considered in post or deemed infeasible due to the breadth of data required to achieve them.

First is the inclusion of player data as a means to control for roster-related variance. This would require the researcher to collect player data for the length of their sample, including at minimum the team, player ID, player availability, and some measure of player value to estimate the present strength of a team during the coach's season. This could be applied as two new metrics, one indicating the strength of the healthy team (an estimator derived from the one number metrics of the available talent) and an injury coefficient. These would allow for the researcher's regression to control for talent and availability in predicting the upcoming season without informing the estimate with future data.

Furthermore, retaining the same methodology used in this paper a researcher ought to be able to collect a somewhat larger sample of data; our initial analysis related on betting lines for team wins, and restricted our data to periods for which this data was known. When considering overall wins, this restriction is lifted and the new limit is dependent on the historical range of other model features. Such a measure could provide a moderate increase in the size of the dataset if further research is done, supposing the data remains representative in the younger years of the NBA.

Regarding **present issues**, we failed to consider correctly the nature of the data as dependent between features as well as its time-series form. As there are two teams in each game of NBA basketball, it is necessary that for each win in our data there is somewhere a corresponding loss in the same season. Thus, it is the case that the overall trend of average winning percentage in our data should be .500 each season, or 41 wins each season (excluding shortened seasons). This meant that trends could only exist within subgroups (first year head coaches and non-first year head coaches, for example), and even these would be impacted by dependency within the samples. To remove dependency, the same analysis could be performed with respect to each team for all 30 teams, but doing so would limit the sample size by an order of magnitude.

Lastly, a bias within the data should be considered: a heteroskedasticity and survivorship bias. Most coaches do not spend a long time in the league; of those that do, only the best persist to have opportunities. Therefore, there exists a selection process that removes worse coaches and retains good/predictable coaches.

Although this exercise did not provide the kind of meaningful conclusions that would change the framework of coaching within the NBA, the team who conducted this analysis would argue that there was large value gained for the NBA and themselves. For those within the NBA realm, the not so secret conclusion on the difficulty of predicting and understanding the value of coaching remains true. But, the idea that there remains even less predictability in veteran coaches of new teams has generally been an unexplored topic, leading to the potential for more influential risk metrics to be considered when hiring a new coach or considering to stay with an old one. While this analysis is far from perfect, those who conducted said analysis all gained a greater understanding of what is possible from a statistical analysis, and the difficulties in completing one confidently and correctly. The capability to harness and understand the tools of an advanced statistical analysis are valuable to them and their careers within data and they hope to carry the tools from this experience forward with them. Although there are large margins for improvement, there is large value in the direct recognition of where those improvements are, and to what degree they affected this analysis.

Appendix

```
Coach_seasons_team HC_seasons_total previous_season_win_pct previous_avg_age previous_pythagorean_wins previous_pythagorean_losses previous_MOV
         0.2631396        0.1674326               0.5461121        0.2191069                 0.5363534                  -0.5245083      0.558381
previous_Schedule_Strength previous_Simple_Rating_System previous_ORtg previous_DRtg previous_NRtg previous_Pace previous_FTr previous_ThreePAr
                -0.2141463                     0.5569938      0.351938     -0.322598    0.5567197   -0.03511438     0.104922       0.04618703
previous_TS_perc previous_O4F_eFG_perc previous_O4F_TOV_perc previous_O4F_ORB_perc previous_O4F_FT_per_FGA previous_D4F_DRB_perc previous_D4F_TOV_perc
       0.3131342             0.2824543            -0.1025548            0.05355688               0.1319207             0.1011444            0.06904215
previous_D4F_eFG_perc previous_D4F_FT_per_FGA
           -0.2565236              -0.09817654
```

Appendix Figure 1: Correlation between games won in a season and other variables.

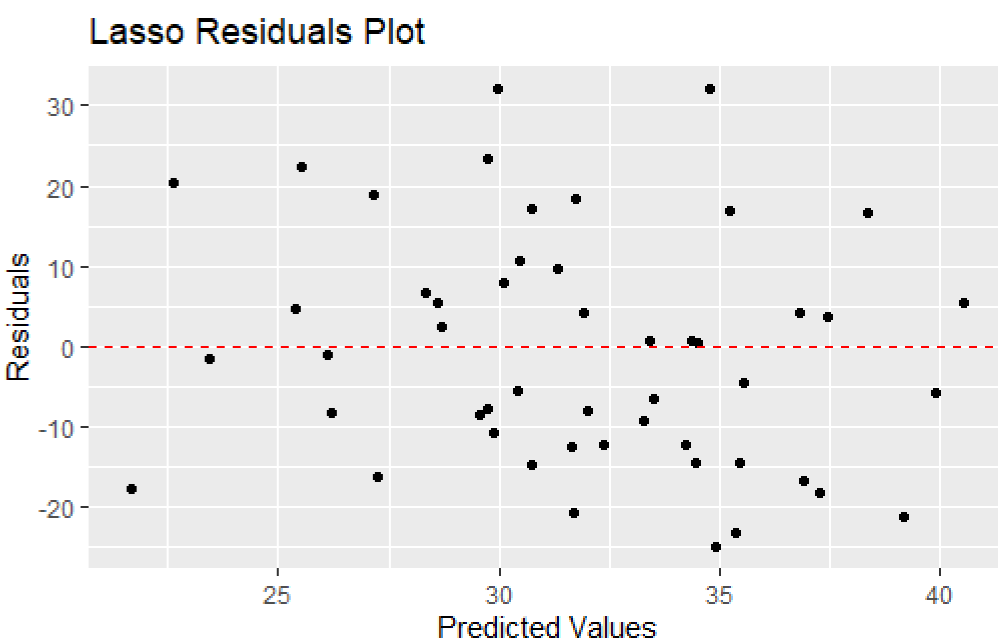
```
```{r}
lm_mid = lm(train_data1$Coach_games_season_win~., data = train_data1)
predictions_lm_mid = predict(lm_mid, newdata = test_data1)
residuals_mid = residuals(lm_mid, newdata = test_data1)
dw_test = durbinWatsonTest(lm_mid)
print(dw_test)

```
```

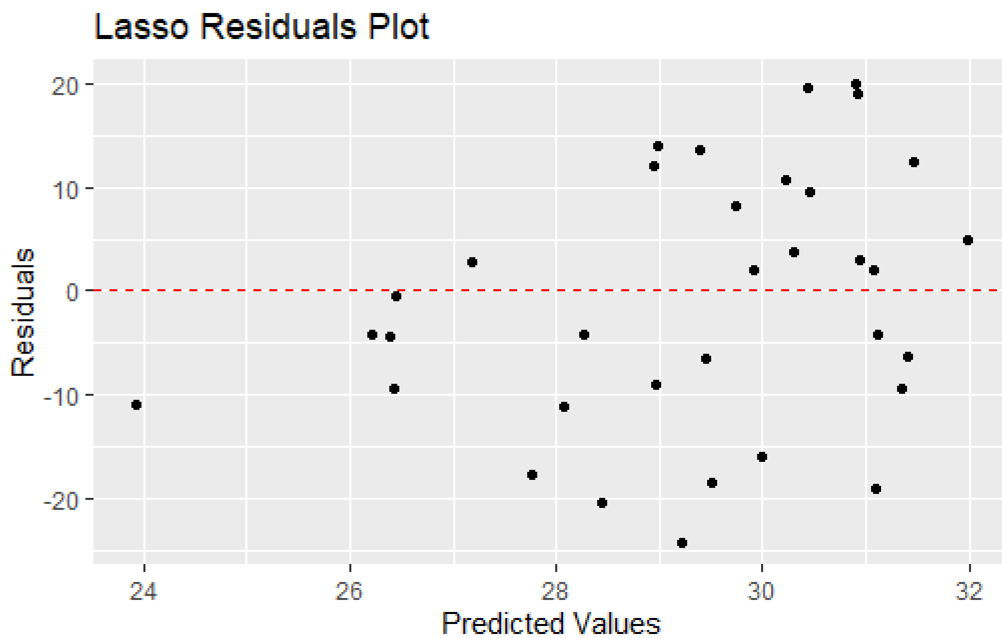
Appendix Figure 2: Simple linear regression model used to determine if autocorrelation was present.

```
                                                    --
(Intercept)                           38.82944642
Coach_seasons_team                     0.34449825
HC_seasons_total                       0.04504771
previous_season_win_pct               13.77439884
previous_avg_age                      -0.77601794
previous_pythagorean_wins              0.01212426
previous_pythagorean_losses            .
previous_MOV                           1.22694892
previous_Schedule_Strength             .
previous_Simple_Rating_System          .
previous_ORtg                          .
previous_DRtg                          .
previous_NRtg                          .
previous_Pace                          .
previous_FTr                           .
previous_ThreePAr                      .
previous_TS_perc                       1.57341525
previous_O4F_eFG_perc                  .
previous_O4F_TOV_perc                  0.91252131
previous_O4F_ORB_perc                  0.04841707
previous_O4F_FT_per_FGA                .
previous_D4F_DRB_perc                  .
previous_D4F_TOV_perc                  .
previous_D4F_eFG_perc                  .
previous_D4F_FT_per_FGA              -14.34151072
```

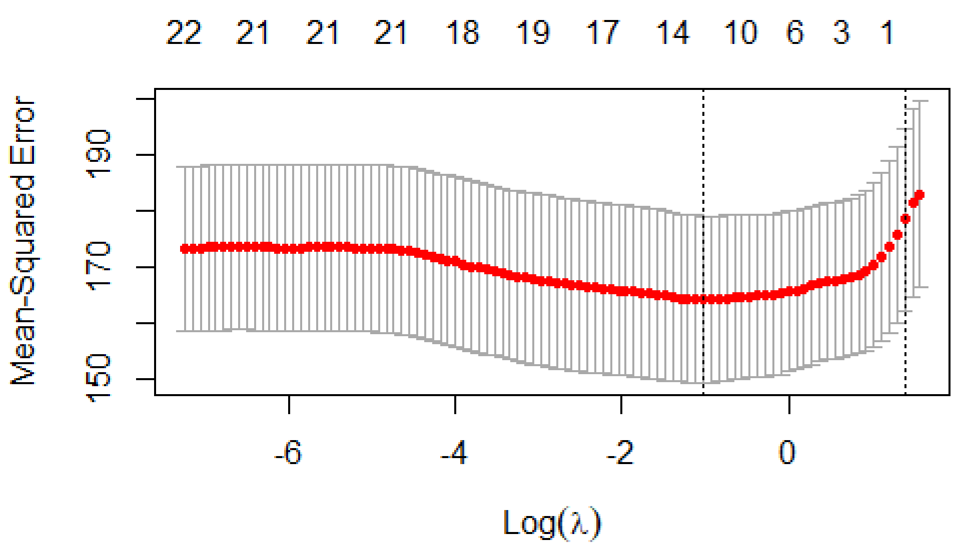
Appendix Figure 3: Coefficients for lasso model with all head coaches included.



Appendix Figure 4: Predicted values vs. residuals plot where the units are games won. Residuals are from the model where a coach is having first year with a team, but not necessarily their first time being a head coach in the NBA.



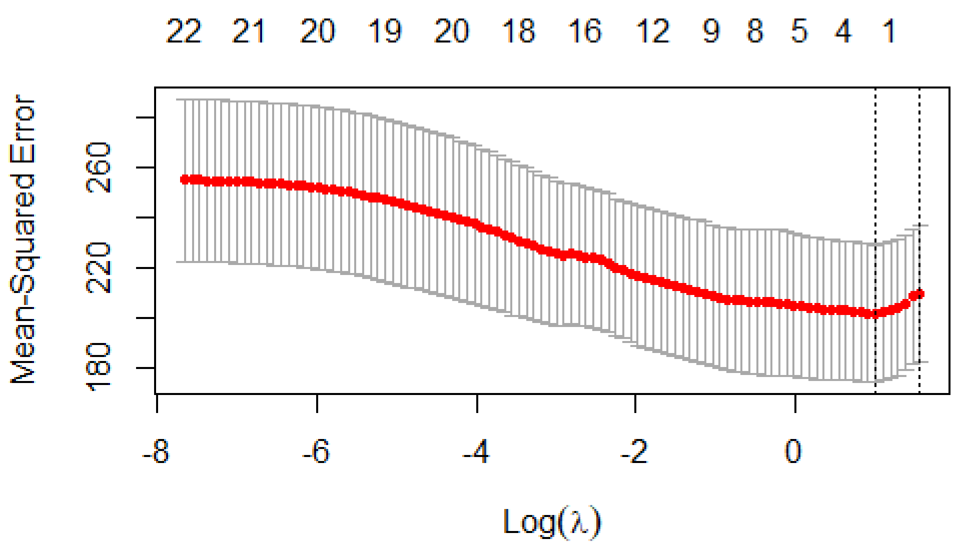
Appendix Figure 5: Predicted values vs. residuals plot where the units are games won. Residuals are from the model where a coach is having their first year with a team and are having their first year as a head coach in the NBA.



Appendix Figure 6: Log of lambda values vs. mean-squared error plot for model including all coaches experiencing their first year as a head coach with a team.

```
(Intercept)                     -57.51123687
Coach_seasons_team                .
HC_seasons_total                  0.22030902
previous_season_win_pct           .
previous_avg_age                  .
previous_pythagorean_wins         0.02246134
previous_pythagorean_losses       .
previous_MOV                      0.69776252
previous_Schedule_Strength       -2.62806231
previous_Simple_Rating_System     .
previous_ORtg                     .
previous_DRtg                     .
previous_NRtg                     .
previous_Pace                     0.29556782
previous_FTr                     38.00099012
previous_ThreePAr                 .
previous_TS_perc                 42.28510785
previous_O4F_eFG_perc             .
previous_O4F_TOV_perc             0.46177310
previous_O4F_ORB_perc             0.16114898
previous_O4F_FT_per_FGA           .
previous_D4F_DRB_perc             0.26982908
previous_D4F_TOV_perc            -0.07265304
previous_D4F_eFG_perc             .
previous_D4F_FT_per_FGA         -11.96745691
```

Appendix Figure 7: Coefficients for lasso model with coaches experiencing their first year as a head coach with a team.



Appendix Figure 8: Log of lambda values vs. mean-squared error plot for model including all coaches experiencing their first year as a head coach with any team.

(Intercept)	30.3268893
Coach_seasons_team	.
HC_seasons_total	.
previous_season_win_pct	.
previous_avg_age	.
previous_pythagorean_wins	.
previous_pythagorean_losses	.
previous_MOV	.
previous_Schedule_Strength	.
previous_Simple_Rating_System	0.4358191
previous_ORtg	.
previous_DRtg	.
previous_NRtg	.
previous_Pace	.
previous_FTr	.
previous_ThreePAr	.
previous_TS_perc	.
previous_O4F_eFG_perc	.
previous_O4F_TOV_perc	.
previous_O4F_ORB_perc	.
previous_O4F_FT_per_FGA	.
previous_D4F_DRB_perc	.
previous_D4F_TOV_perc	.
previous_D4F_eFG_perc	.
previous_D4F_FT_per_FGA	.

Appendix Figure 9: Coefficients for lasso model with coaches experiencing their first year as a head coach with any team.

For any questions or inquiries, please reach out to Peyton Lindogan at peyton2117@gmail.com. Code found to produce this analysis can be found at https://github.com/peytonhl/Head-Coaching-Interpretability-Project.