Final Report

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Introduction

Basketball has come a long way since James Naismith threw a soccer ball through a peach basket. Webster's dictionary defines basketball as...

The Data

Total number of passes per season were manually downloaded from `https://stats.nba.com/teams/passing/` and concatenated into a "long" dataset. These data were relatively well-organized to begin with and required minimal cleaning, but unfortunately only go back as far as 2013.

Traditional statistics, such as points, rebounds, etc. going back to the beginning of the NBA and ABA were downloaded using an HTML scraping tool developed for this project (see Appendix for code). These data were also relatively clean, but teams that moved or changed names were assigned a unique three letter code corresponding to their current location (e.g. observations from the New Orleans Jazz were given the code "UTA" in order to group them with the rest of the Jazz data). Also, seasons were designated using the numeric year of the first game of the season, (e.g. 2018 for the 2018-2019 season) in order to treat time as a continuous variable. There were no missing or excluded observations in these data, and counting statistics such as points, turnovers, etc. were converted to per-game measures in order to account for shortened seasons in 1998 and 2011. For these analyses I considered only data from after the ABA and NBA merger in 1976.

Passing

Mixed Model Selection

Prior to modeling the number of passes over time, I created a spaghetti plot with a line for each team (see Figure A1). There did not appear to be much of an overall trend. The total number of passes in a season appears to follow a normal distribution (Figure A2), so this outcome was modeled using a simple linear mixed model.

In order to test for a fixed effect of season on total number of passes made, I compared four linear mixed models. In the following models i indexes team, j indexes season, and x represents the season variable.

Model 1: Random Intercept Only

$$Y_{ij} = \beta_0 + \beta_1 x_{ij} + b_{0i} + \epsilon_{ij}$$

$$b_{0i} \sim N(0, \sigma_T^2) \text{ and } \epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$$

Model 2: Random Intercept and AR(1) Structure for Repeated Measures

$$Y_{ij} = \beta_0 + \beta_1 x_{ij} + b_{0i} + \epsilon_{ij}$$

$$b_{0i} \sim N(0, \sigma_T^2) \text{ and } \epsilon_i \sim \text{iid } N(0, R_i)$$

$$R_i = \sigma_\epsilon^2 \begin{bmatrix} 1 & \phi & \phi^2 & \phi^3 & \dots \\ \phi & 1 & \phi & \phi^2 & \\ \phi^2 & \phi & 1 & \phi & \\ \phi^3 & \phi^2 & \phi & 1 & \\ \vdots & & & & \ddots \end{bmatrix}$$

Models 3 & 4: Random Slope for Season

The last two models are the same as models 1 and 2, but with the addition of a random slope, so the random effects are:

$$b_{0i} + b_{1i}x_{ij}$$

with

$$b_{0i} \sim N(0, \sigma_T^2) \text{ and } b_{1i} \sim N(0, \sigma_S^2)$$

The model with random intercept and random slope did not converge without the AR(1) structure for repeated measures, and the model with random intercept and AR(1) structure was the best by the Akaike information criterion (AIC) (Table A1).

Using loess smoothing to plot total number of passes made suggested a potential cubic trend in the data. So once the final model was selected, I also tested the polynomial effects of season up to a quadratic term:

$$Y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij}^2 + \beta_3 x_{ij}^3 + \beta_4 x_{ij}^4 + b_{0i} + \epsilon_{ij}$$

$$b_{0i} \sim N(0, \sigma_T^2) \text{ and } \epsilon_{ij} \sim N(0, R_i)$$

Piecewise Model

In addition to a linear mixed model, I also tried a linear spline model with a knot at 2015, including random intercept and AR(1) structure for repeated measures:

$$Y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 max(x_{ij} - 2015, 0) + b_{0i} + \epsilon_{ij}$$

$$b_{0i} \sim N(0, \sigma_T^2) \text{ and } \epsilon_{ij} \sim N(0, R_i)$$

The year 2015 was chosen based on the estimated break point according to Muggeo's method [1] and implemented using his R package "segmented" [2] (see Appendix for code).

Results

Table 1: The Effect of Time on Total Passes Made

	Value	Std.Error	DF	t-value	p-value
(Intercept)	24349.989	235.835	146	103.250	<1e-04
Season	-40.362	2004.510	146	-0.020	0.984
Seasonˆ2	-1941.549	1404.499	146	-1.382	0.169
Seasonˆ3	360.020	1088.741	146	0.331	0.741
Seasonˆ4	-465.829	925.730	146	-0.503	0.616

According to the linear mixed model, passing has not changed significantly since 2013.

Table 2: Change in Total Passes Made After the 2015 Season

	Value	Std.Error	DF	t-value	p-value
(Intercept)	164836.019	213588.290	148	0.772	0.441
Season	-69.854	106.029	148	-0.659	0.511
Change in Slope	0.181	0.154	148	1.178	0.241

Passing appears to increase slightly after 2015 according to the linear spline model, but the change in slope is not statistically significant ($p = 0.24$).

Assists

Model Selection

Winning percentage appears to be reasonably normally distributed (Figure A3), so I used normal theory linear mixed models to determine whether increasing the percentage of baskets assisted results in more wins. Model selection for this question followed a similar process to the passing question. I compared models with random intercept for team to models with random intercept for team and random slope, both with and without an AR(1) structure for repeated measures. However, in these models the outcome was regular season win percentage and the fixed effects were percetange of baskets assisted ("AST%"); average team age ("Age"); average team height ("Ht."); average team weight ("Wt."); team field goal percentage ("FG%"); and steals ("SPG"), blocks ("BPG"), points ("PPG"), and turnovers ("TPG") per game. Once again, the model with random intercept for team and AR(1) structure for repeated measures was the best by AIC (Table A2).

However, during model selection, I realized that there was a significant positive association between percentage of baskets assisted and winning percentage, but that this effect goes away when adjusting for field goal percentage (Table A3). So, I conducted a mediation analysis (see Appendix for code) to try and determine whether field goal percentage mediates the effect of assists on winning [2]. The "mediation" package in R requires models without the AR(1) structure for repeated measures, so the mediation analysis was conducted using only a random intercept for team.

Results

Table 3: The Effect of Assists per Game on Winning Percentage

Table 3: Fixed Effects

	Value	Std.Error	DF	t-value	p-value
(Intercept)	-277.331	44.178	1110	-6.278	<1e-04
AST%	0.372	0.085	1110	4.397	<1e-04
Age	3.878	0.222	1110	17.471	<1e-04
Ht.	0.508	0.566	1110	0.898	0.369
Wt.	0.338	0.062	1110	5.440	<1e-04
SPG	2.349	0.345	1110	6.804	<1e-04
BPG	3.766	0.350	1110	10.763	<1e-04
TPG	-2.280	0.216	1110	-10.568	<1e-04
PPG	0.847	0.052	1110	16.396	<1e-04

Without adjusting for FG%, increasing the number of baskets assisted by 10 percentage points can lead to a statistically significant (p = <1e-04) increase in winning of 3.72 percentage points on the season (or about 3.1 games). After adjustment for FG%, this effect is no longer significant (Table A3).

Mediation Analysis

There is a significant ($p < 0.0001$) mediation effect of FG% on the relationship between AST% and winning percentage. Field goal percentage accounts for approximately 67.5% of the association, meaning that on average a 10 point increase in AST% directly results in closer to a 1.217 point increase in winning percentage (about 1 game) on the season.

Discussion

Passing hasn't changed, but assists help thorugh increasing FG%. Weird that height wasn't a significant factor in winning. Mediation was done using a very simple Baron and Kenny approach, which may not be right.

References

1. Muggeo, V.M.R. (2003) Estimating regression models with unknown break-points. Statistics in Medicine 22, 3055–3071.
2. Vito M. R. Muggeo (2008). segmented: an R Package to Fit Regression Models with Broken-Line Relationships. R News, 8/1, 20-25. URL https://cran.r-project.org/doc/Rnews/.
3. Tingley D, Yamamoto T, Hirose K, Keele L, Imai K. mediation: R package for causal mediation analysis. UCLA Stat Stat Assoc. August 2014. https://dspace.mit.edu/handle/1721.1/91154. Accessed December 2, 2019.

Appendix

Figure A1: Total Passes by Season

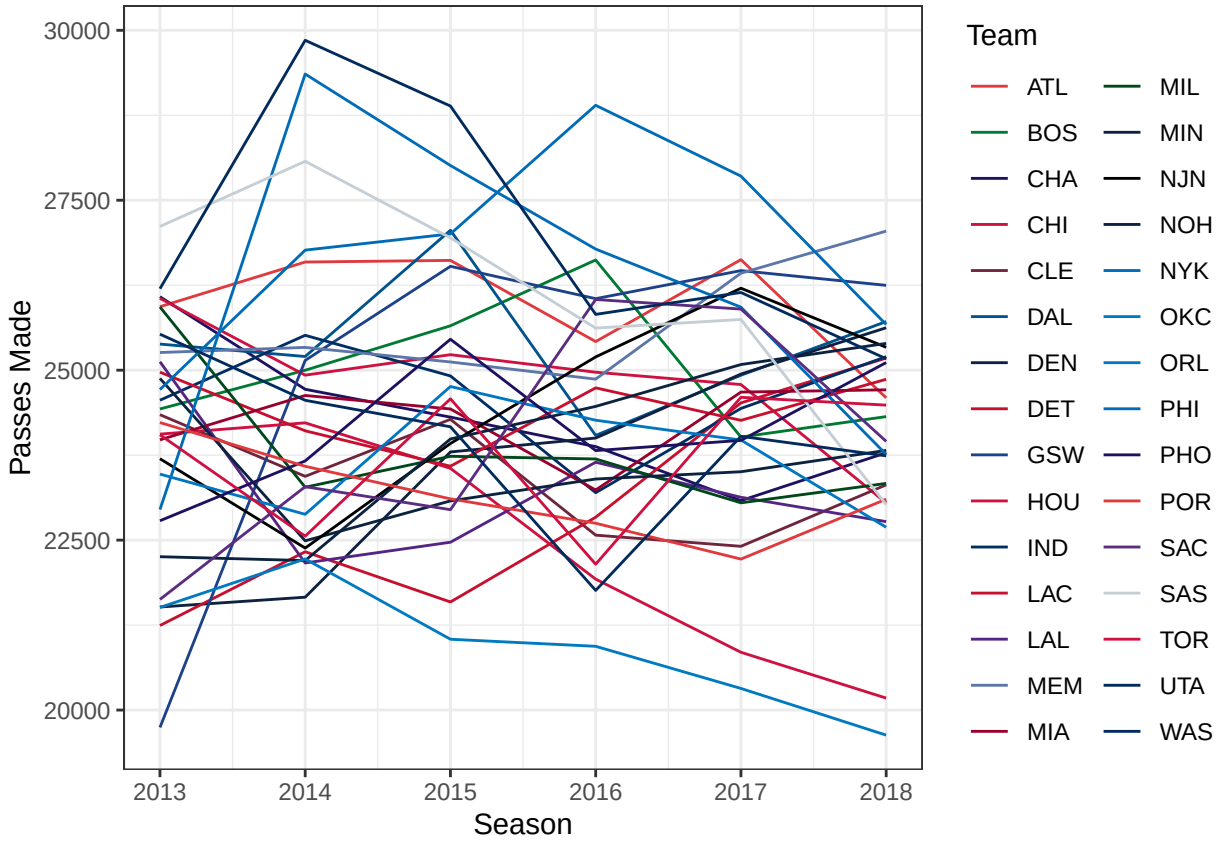


Figure A2: Distribution of Total Passes

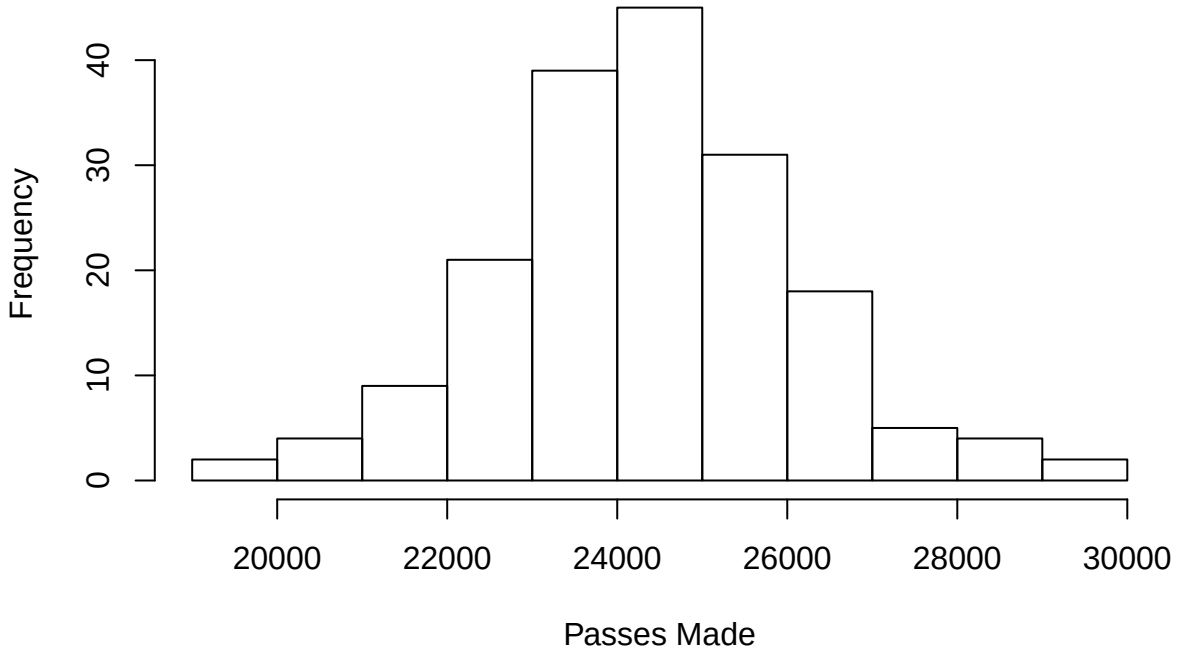


Table A1: AIC of Passes Made Models

All models fit using ML estimation.

	df	AIC
RI Only	4	3159.781
RI and AR(1)	5	3120.225
RI, RS, and AR(1)	7	3124.225

Figure A3: Distribution of Win Percentage

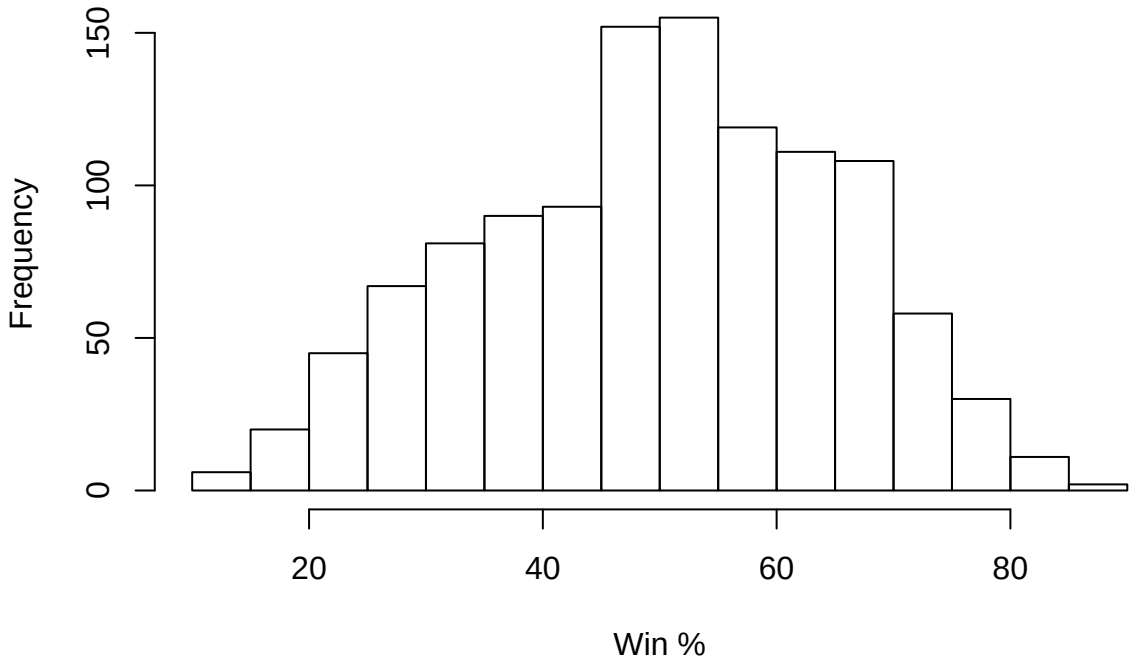


Table A2: AIC of Win Percentage Models

All models fit using ML estimation.

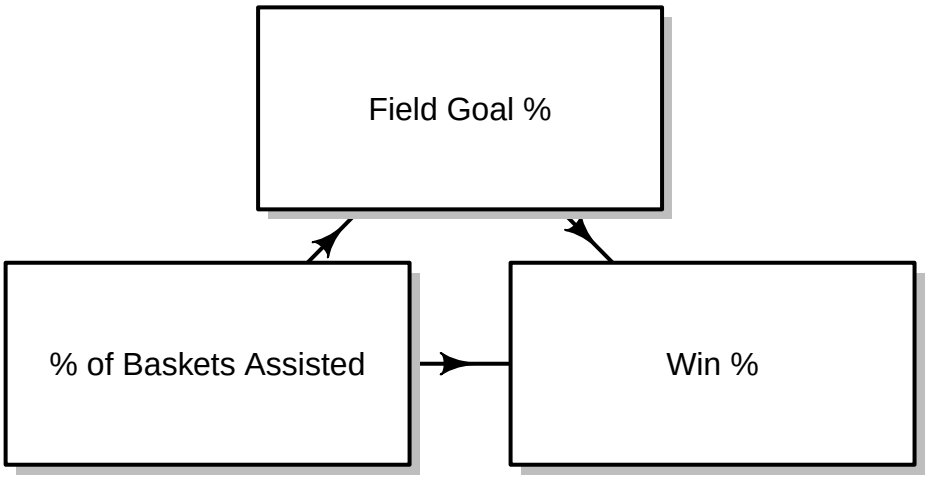
	df	AIC
RI Only	12	8495.325
RI and RS	14	8499.289
RI and AR(1)	13	8264.485
RI, RS, and AR(1)	15	8268.486

Table A3: Effect of Assists on Win Percentage, Adjusted for FG%

Table 6: Fixed Effects

	Value	Std.Error	DF	t-value	p-value
(Intercept)	-288.599	40.557	1109	-7.116	<1e-04
AST%	0.122	0.079	1109	1.530	0.126
Age	3.203	0.209	1109	15.331	<1e-04
Ht.	-0.195	0.521	1109	-0.373	0.709
Wt.	0.436	0.058	1109	7.588	<1e-04
SPG	2.937	0.319	1109	9.192	<1e-04
BPG	3.447	0.322	1109	10.707	<1e-04
TPG	-2.983	0.204	1109	-14.635	<1e-04
PPG	0.099	0.070	1109	1.427	0.154
FG%	351.702	24.059	1109	14.618	<1e-04

Figure A4: Mediation Diagram



Code

HTML Scraping Tool

```
library(rvest)
library(tidyverse)
teams <- c("ATL","BOS","NJN","CHA","CHI","CLE","DAL","DEN","DET","GSW","HOU",
           "IND","LAC","LAL","MEM","MIA","MIL","MIN","NOH","NYK","OKC","ORL",
           "PHI","PHO","POR","SAC","SAS","TOR","UTA","WAS")
# Scrape each team page
all_seasons <- data.frame()
for (team in teams) {
  url <- paste0("https://www.basketball-reference.com/teams/",team,"/stats_basic_totals.html")
  table <- url %>%
    read_html() %>%
    html_nodes("table") %>%
    html_table()
  df <- as.data.frame(table[[1]])
  df <- df[colnames(df) != ""] %>%
    filter(Season != "Season",Season != "2019-20")
  df[df == ""] <- NA
  df <- as.data.frame(lapply(df, as.character))
  colnames(df) <- c("Season","Lg","Tm","W","L","Finish","Age","Ht.","Wt.",
                    "G","MP","FG","FGA","FG%","3P","3PA",
                    "3P%","2P","2PA","2P%","FT","FTA","FT%","ORB","DRB","TRB",
                    "AST","STL","BLK","TOV","PF","PTS")
  df$Team <- team
  all_seasons <- rbind.data.frame(all_seasons,df)
}
```

Break Point

```
linmod <- lm(Passes.Made ~ Season,data = passing)
segmented(linmod)
```

```
## Call: segmented.lm(obj = linmod)
##
## Meaningful coefficients of the linear terms:
## (Intercept)       Season    U1.Season
##   -547034.4        283.7       -421.6
##
## Estimated Break-Point(s):
## psi1.Season
##        2015
```

Mediation

```
# Mediation with FGP as mediator
mod.y <- lmer(w_perc ~ AST_perc + Age + Ht. + Wt. + STL_game + BLK_game + TOV_game +
                PTS_game + FGP + (1|Team),data = post_merger)
mod.m <- lmer(FGP ~ AST_perc + Age + Ht. + Wt. + STL_game + BLK_game + TOV_game +
                PTS_game + (1|Team),data = post_merger)
med_fgp <- mediate(mod.m,mod.y,treat = "AST_perc",mediator = "FGP")
# Mediation with AST as mediator
```

```r
mod.m <- lmer(AST_perc ~ FGP + Age + Ht. + Wt. + STL_game + BLK_game + TOV_game +
                PTS_game + (1|Team),data = post_merger)
med_ast <- mediate(mod.m,mod.y,treat = "FGP",mediator = "AST_perc")
# Mediation summary
summary(med_fgp)
```

```
##
## Causal Mediation Analysis
##
## Quasi-Bayesian Confidence Intervals
##
## Mediator Groups: Team
##
## Outcome Groups: Team
##
## Output Based on Overall Averages Across Groups
##
##                Estimate 95% CI Lower 95% CI Upper p-value
## ACME             0.2511       0.1814         0.32  <2e-16 ***
## ADE              0.1233      -0.0263         0.28    0.13
## Total Effect     0.3745       0.2145         0.54  <2e-16 ***
## Prop. Mediated   0.6723       0.4352         1.12  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 1148
##
##
## Simulations: 1000
```

```r
summary(med_ast)
```

```
##
## Causal Mediation Analysis
##
## Quasi-Bayesian Confidence Intervals
##
## Mediator Groups: Team
##
## Outcome Groups: Team
##
## Output Based on Overall Averages Across Groups
##
##                 Estimate 95% CI Lower 95% CI Upper p-value
## ACME             8.01620     -1.90359        18.56     0.1
## ADE            352.30354    304.62696       396.34  <2e-16 ***
## Total Effect   360.31974    314.36760       403.02  <2e-16 ***
## Prop. Mediated   0.02203     -0.00511         0.05     0.1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 1148
##
##
```

```
## Simulations: 1000
```