

# Final Report

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## Introduction

I've been watching basketball since 2011 and following the National Basketball Association (NBA) semi-obsessively since 2014. In that time the game has changed enormously with increased focus on the three point shot league-wide, a trend that has been well documented by analyst/journalists like Kirk Goldsberry and is part of a larger movement towards increased efficiency (i.e. taking good shots and avoiding bad ones) [1]. Based purely on the "eye test," it seems that teams across the league are passing the ball more than ever in order to create better shots for their most efficient scorers.

So, this project was split into two distinct questions of interest: 1) Has the total passing rate increased over time? and 2) Do teams that pass more tend to win more (i.e. does passing actually help)?

## The Data

Total number of passes made 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 the American Basketball Association (ABA) were downloaded using an HTML scraping tool written 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 after their move to Salt Lake City). 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 suggested a potential cubic trend in the data (Figure A3). So once the final model was selected, I also tested the polynomial effects of season up to a quadratic term:

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

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

### Piece-wise 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 [2] and implemented using his R package "segmented" [3] (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
Season^2	-1941.549	1404.499	146	-1.382	0.169
Season^3	360.020	1088.741	146	0.331	0.741
Season^4	-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 A4), 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 percentage 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. I chose to use percentage of baskets assisted because it should be a reasonable indicator of how much a team passes compared to others (a team with lower AST% is relying more on isolation plays).

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 AST% 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, Figure A5 for mediation diagram) to try and determine whether field goal percentage mediates the effect of assists on winning [4]. 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

	Value	Std.Error	DF	t-value	p-value
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 AST% by 10 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), although AST% still has a positive effect estimate.

### 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 and Limitations

The passing analysis appears to indicate that the overall passing rate has not increased significantly since 2013. However, it's possible that the trend is more recent and there simply isn't enough data to parse it out yet. Also, it's possible that a subset of the elite teams have increased their passing rate, but this is being averaged out by teams without as many good passers. It would be interesting to look into passing trends among specific teams, rather than at a league-wide level.

As one might expect, the percentage of baskets assisted has a significant positive association with winning percentage. On average a 10 point increase in AST% can lead to an additional 1 - 3 games won per season. This may not sound like a great return on investment but for some teams, particularly in the competitive Western conference, this could be the difference between making the playoffs or not. Playoff games are an enormous source of revenue, with some teams earning as much as \$2 million per game [5]. So those 1-3 extra wins could be worth millions of dollars, although increasing AST% by 10 points may be no easy task (particularly for teams that already have a high AST%).

It's also remarkable that FG% mediates approximately two thirds of the positive effect of AST%. I repeated the mediation analysis with both FG% and AST% as the mediator, and the results suggest that FG% is mediating the positive effect of AST% and not the other way around. This is interesting because it implies in a general way that passing leads to better shooting, which in turn leads to increased wins. This makes some intuitive sense. On the other hand, because the effect of AST% is no longer statistically significant after adjusting for FG%, one could argue that this is a case of complete mediation. This would imply that good shooting far outweighs passing in importance. Determining directionality in mediation analysis is difficult, particularly in the basic Baron and Kenny [6] framework that I used, so this relationship requires additional study. There are more modern methods available but they were beyond the scope of this work.

Finally, there are some general limitations to these analyses that would be important to address in future work. First, NBA teams do not play a balanced schedule, which means that playing bad teams more frequently should increase win percentage. It would have been helpful to adjust for strength of schedule, but these data were unfortunately not available to me. Perhaps most importantly though, looking at trends at a league-wide level probably results in vital information being averaged out. For example, average team height was not associated with increased wins (when we know that height is important in basketball), but this is probably because there isn't much variation in average team height across the whole league. To accurately determine the effects of passing, we really need much more detailed information than is currently available.

## References

1. Goldsberry, Kirk. SPRAWLBALL: a Visual Tour of the New Era of the NBA. Mariner Books, 2020.
2. Muggeo, V.M.R. (2003) Estimating regression models with unknown break-points. *Statistics in Medicine* 22, 3055–3071.
3. 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/>.
4. 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.
5. Dignam, Devin, et al. “The Best NBA Markets of 2012-13.” *The Wages of Wins Journal*, <http://wagesofwins.com/2013/03/28/the-best-nba-markets-of-2012-13/>.
6. Baron, R.M. and D.A. Kenny, The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, 1986. 51(6): p. 1173.

## Appendix

Figure A1: Total Passes by Season

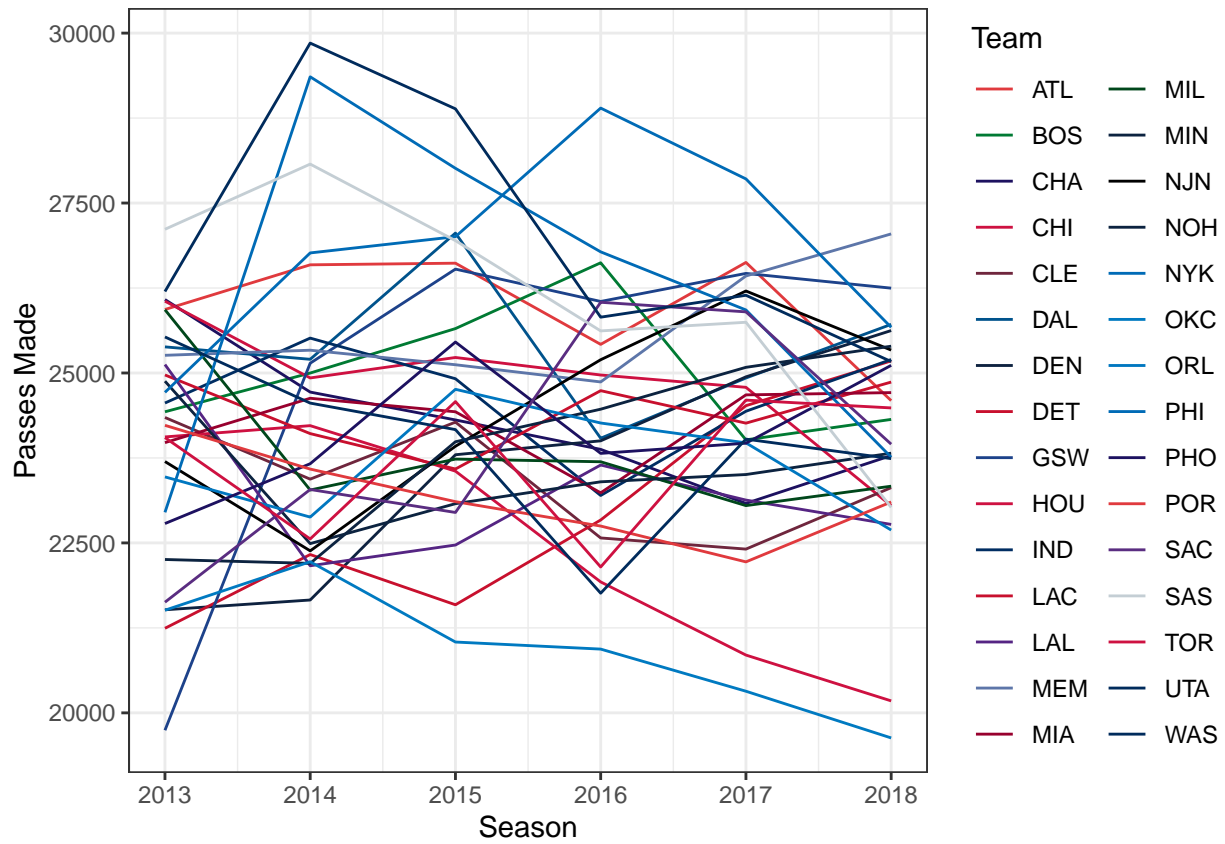
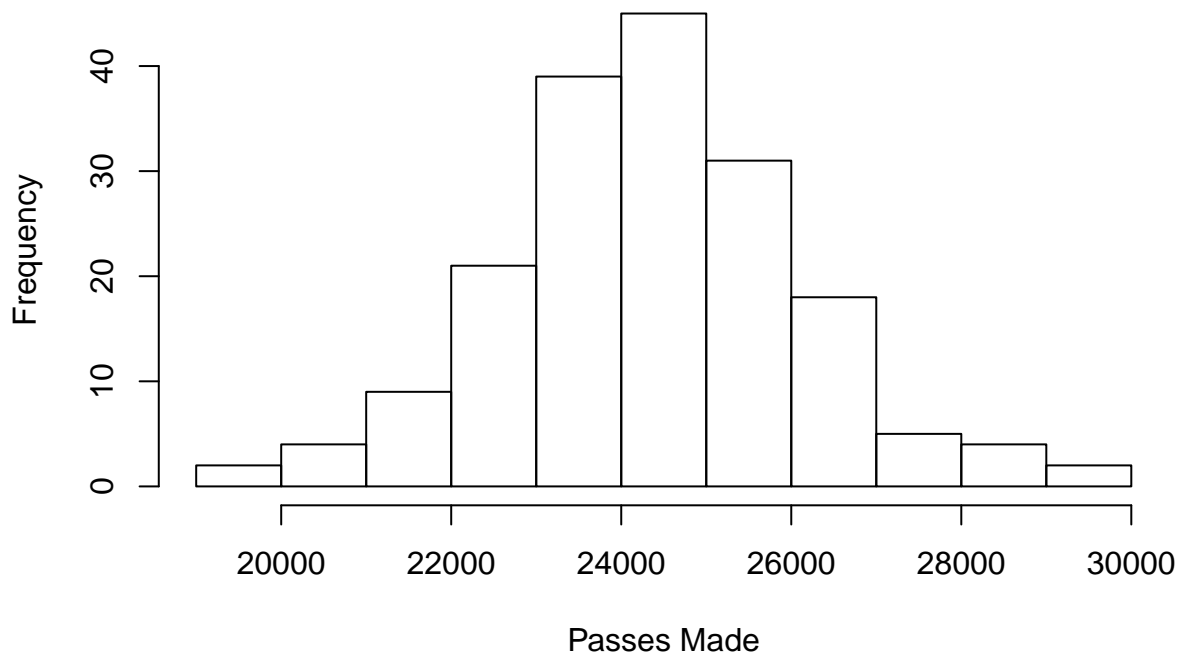


Figure A2: Distribution of Total Passes

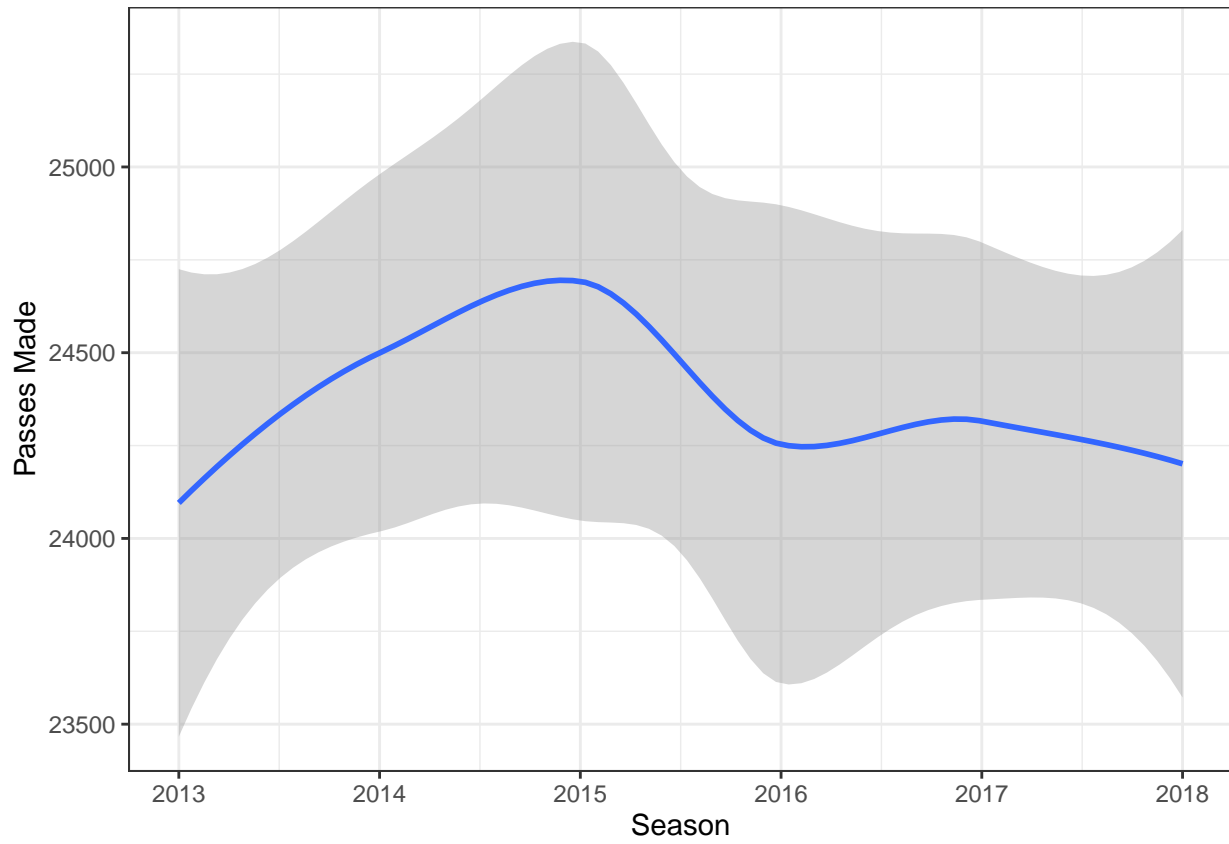


**Table A1: AIC of Passes Made Models**

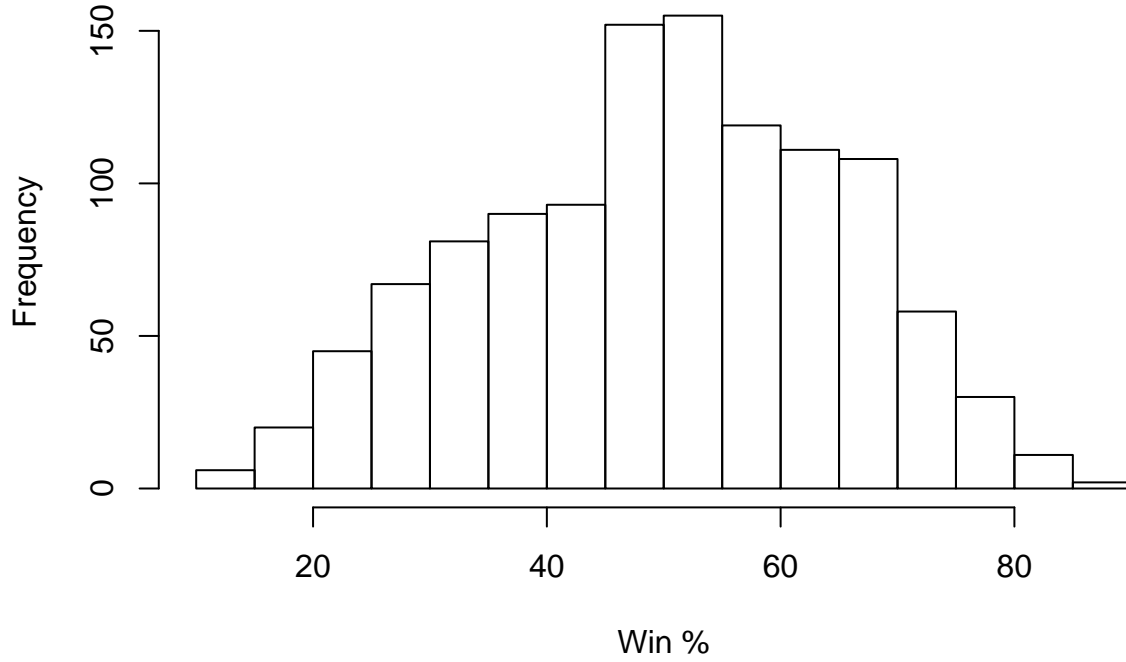
All models fit using ML estimation.

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

**Figure A3: Overall Trend in Total Passes by Season, Loess Smoothing**



**Figure A4: 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

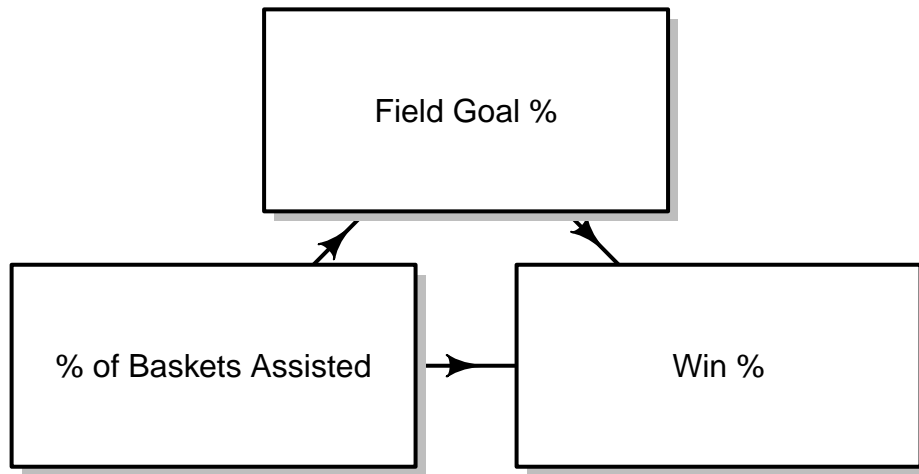
**Table A3: Effect of Assists on Win Percentage, Adjusted for FG%**

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 A5: 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
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(mod.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
```

```
summary(mod_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
```