Examining the Effect of Age and Contract Year on Baseball Player-Seasons

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Abstract

Within this report, we come to a conclusion on the Analysis of Variance of a baseball player-season's performance based on age and year in contract. After exploring the data with density plots, summary statistics (etc.), we decide to ANOVA methods to come to a conclusion. Testing assumptions we decide to use a parametric shortcut (ANOVA F Test). Through that test we come to the conclusion that a baseball player's age ultimately has a significant and practical effect on their overarching performance. While inversely, a player's contract situation does not, alongside the interaction between year and age combined. Utilizing a traditional two-way ANOVA model, we come to the conclusion, through the evaluation of player-seasons from a random year, that the effect of a player being "Young" (20-29 Years Old) versus "Old" (30-39 Years Old) is much more significant on all levels regardless of the financial contract situation a player may currently be signed under. Through the post-hoc analysis and use of the Tukey to create Simultaneous Confidence Intervals (SCI) to control for Type-I error rates we found that only the comparison of Young versus Old given last year in contract had statistical differences in performance.

Introduction and Background

For some time in American sports, it has been widely stated that players in a "contract-season," specifically an athlete in their final season within their current financial contract, perform significantly better than their counterparts, denominating the terminology known as the "Contract-Year Phenomena." This isn't just specific to baseball, as it is inquired that because a player has a greater financial inventive in their performance, with respect to teammates with >1 years of seasons remaining, that an athlete will perform at a high level in comparison to previous seasons.

To further elaborate, "Contract-Year Phenomena" is defined in Wikipedia as:

> "…to describe the occurrence when athletes perform at a very high level in the season prior to their free agency eligibility. Most often, these athletes have seasons that are statistically better than previous years, but then once they sign their new contract, they return to their previous level of performance."

This psychological analysis is often utilized and stated in the commentary of many sports, as is commonly referenced with respect to professional athletes in Basketball and American Football. While many studies have tried to analyze this specific factor with analysis of niche statistics, such as a basketball players points scored per game or football players rushing yards in a season, we turn to the sport of baseball to examine such in a greater holistic fashion.

Within our report, we will analyze exactly how an athlete is affected by such phenomena, accounting for potential confounding variable of an athletes age, utilizing a baseball players "Wins Above Average", denoted WAA, as the response as a player's performance in a single season. WAA is a subset of the more popular "Wins Above Replacement", or WAR. Wins Above Replacement is illicitly defined within baseball-reference, our trusted baseball statistics database, as:

> "A single number that presents the number of wins the player added to the team above what a replacement player would add."

In further explanation, WAR is essentially how much more valuable a player was to a team over the course of a season, in comparison to a player calculated to be "possible replacement player". The only subset to get WAA is to compare players to a "league average player". Additionally, we will keep our analysis solely to hitters, to avoid any potential calculation inconsistencies between a pitcher's and hitter's contribution.

WAR for hitters, within our report and through baseball-referenced is calculated as such:

1) Find the runs added or lost in comparison to a league-average player. This is done utilizing the formula:

$$Player\ Runs\ over\ Replacement = (Hitter\ Runs - LA\ Hitter\ Runs) + (LA\ Hitter\ Runs - Replacement\ Hitter)$$

2) After finding this Player Runs Added number, then convert Runs Added to Wins Added. This is done with the following simplified subsequent formula:

$$WAR = Log_2(Runs\ per\ Season) + Player\ Runs\ Added\ per\ Season - Player\ Runs\ Subtracted\ per\ Season$$

For more specific calculations, see links here and here.

In conclusion, our report seeks to find the answer to our primary curiosity: "Is the Contract-Year Phenomena fact or fallacy?" By utilizing a traditional two-way ANOVA model to account for potential confounding variables like age, we debunk the notion of the "Contract-Year Fallacy" and claim that any foreseen physiological impact is most likely insignificant.

Study Design and Methods

This is an observational study in order to investigate the research question. The available measurement units, player-seasons, were to be selected as "qualified" players. We defined this to be position players in which, in a given year, played in 120 or more regular season games (out of a 162 game season). In the study, out of the years 2012-2021 (excluding 2020 because of shortened season), a random year was selected to create the sample of players. This range of years were picked because complete, accurate, MLB contract data only goes back to the year 2012. The random year selected was 2015, and this created a sample of 116 player-seasons. It is important to note that because of the nature of how randomization was done this lead to a imbalanced design.

For each case in the data set the Age factor and Contract Year factor was marked. The Age factor is determined "Young" if the player is 20-29 years old, and "Old" if the player is 30-39 years old. The Contract Year factor is determined "First" if the player was in the first year of a multi-year contract, "Middle" if they were in any of the years of a multi-year contract that was not the first or last year, and "Last" if the player was in the last year of a multi-year contract or if they were in a one year contract. This was decided because in context of the "Contract-Year Phenomena", a one year contract would mean they are playing for their next contract, and therefore are in their “Last” contract year. Then the WAA (player-season measure of performance) was measured for each player-season case as the response.

Explicitly our SRQs and Hypotheses are listed below:

-Does the contract year make a difference on WAA of a player-season?

– $H_{1,0}$: There is no statistically significant impact of WAA due to contract year.
– $H_{1,A}$: There is a statistically significant impact of WAA due to contract year.

-Does the age make a difference on WAA of a player-season?

– $H_{2,0}$: There is no statistically significant impact of WAA due to age.
– $H_{2,A}$: There is a statistically significant impact of WAA due to age.

-Does the interaction of contract year and age make a difference on WAA of a player-season?

– $H_{3,0}$: There is no statistically significant interaction effect on WAA between contract year and age.
– $H_{3,A}$: There is a statistically significant interaction effect on WAA between contract year and age.

Exploration of the Data

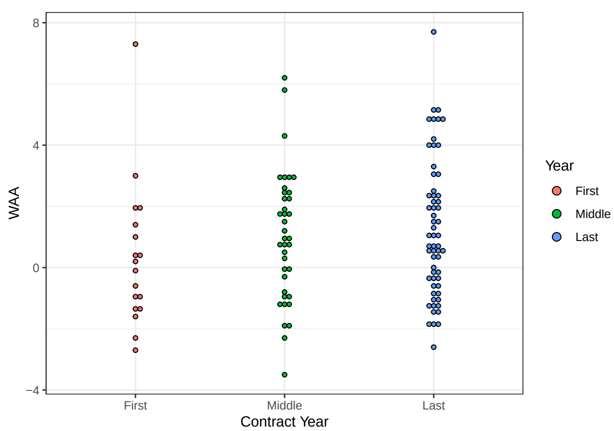


Figure 1: Strip Chart for the Contract Year Study

Figure 1: Strip chart that shows the WAA for each player season separated by contract year. In this chart, it can be seen that for the most part most of the seasons for each of the contract years are similar in value but in the first year of the contract there is only one high point (greater than 4) while the middle and last have a multiple high points.

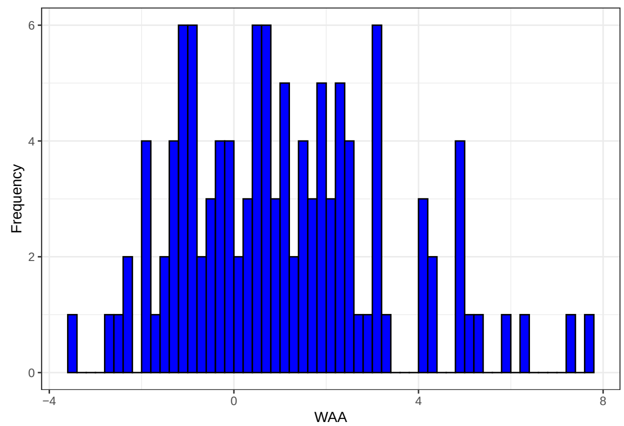
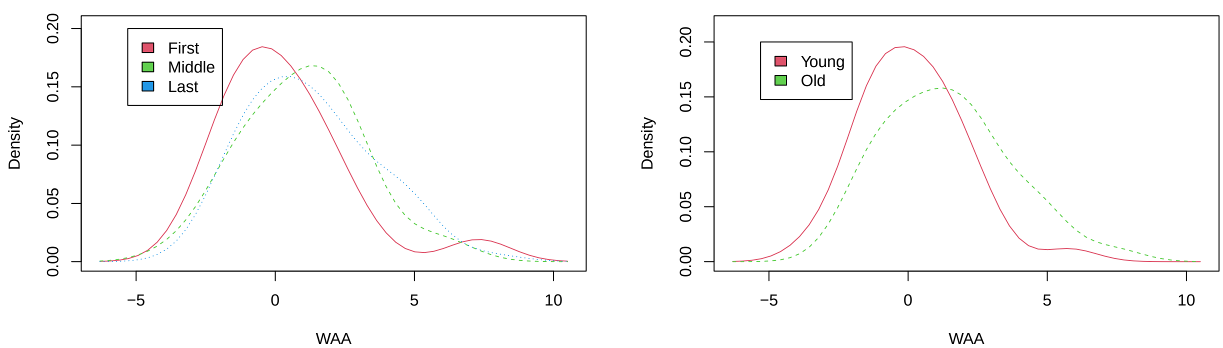


Figure 2: Strip Chart for the Contract Year Study

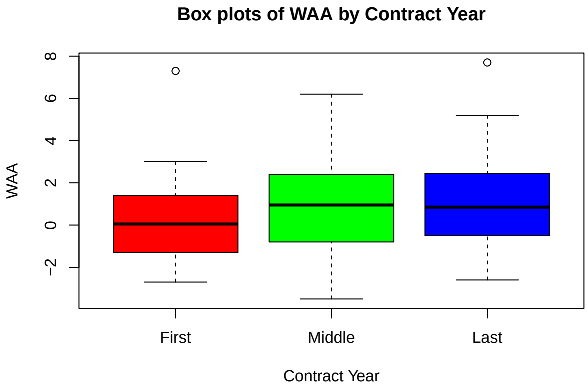
Figure 2: This histogram shows the frequencies of WAA for our entire sample of player-seasons. It shows that the sample that we have gathered tends to show that a good amount of these player seasons are above 0 WAA so a majority of the seasons that are being worked with are above the average season based on this metric. It also shows very few player-season's below -2 WAA while many are above 4, some even close to 8.



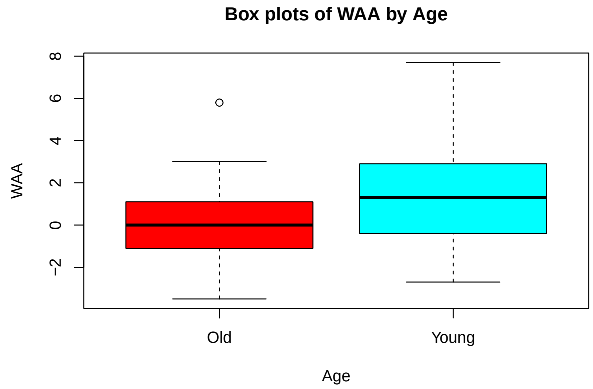
(a) WAA Ditribution by Contract Year

(b) WAA Ditribution by Age

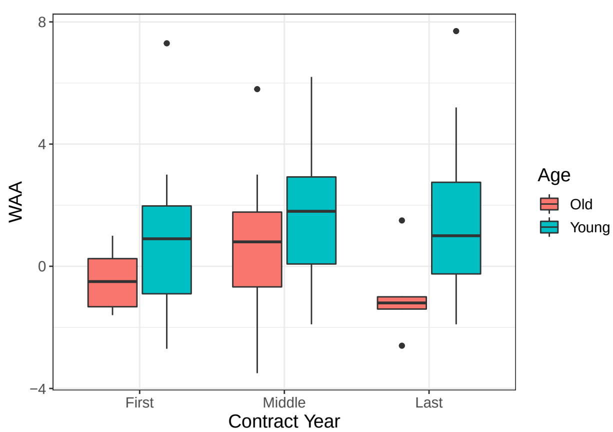
Figure 3: Density Plots for Contract Year Study



(a) WAA Boxplot for Contract Year



(b) WAA Boxplot for Age



(c) WAA Boxplot for Contract Year and Age

Figure 4: WAA Boxplot for Age and Contract Year

Table 1: Summary Statistics for Player-Season WAA

	n	Min	Q1	Median	Q3	Max	MAD	SAM	SASD	Sample Skew	Sample Ex. Kurtosis
First	18	-2.7	-1.225	0.05	1.300	7.3	2.002	0.317	2.331	1.331	1.911
Last	60	-2.6	-0.450	0.85	2.425	7.7	2.150	1.258	2.239	0.550	-0.330
Middle	38	-3.5	-0.675	0.95	2.375	6.2	2.224	1.018	2.127	0.250	-0.115
Old	35	-3.5	-1.100	0.00	1.100	5.8	1.779	0.151	1.841	0.614	0.744
Young	81	-2.7	-0.400	1.30	2.900	7.7	2.520	1.415	2.273	0.494	-0.207
First and Old	8	-1.6	-1.325	-0.50	0.250	1.0	1.260	-0.462	0.965	0.159	-1.802
First and Young	10	-2.7	-0.900	0.90	1.975	7.3	2.520	0.940	2.927	0.697	-0.328
Last and Old	5	-2.6	-1.400	-1.20	-1.000	1.5	0.296	-0.940	1.499	0.584	-1.295
Last and Young	55	-1.9	-0.250	1.00	2.750	7.7	2.076	1.458	2.196	0.544	-0.360
Middle and Old	22	-3.5	-0.675	0.80	1.775	5.8	1.927	0.623	2.022	0.270	0.274
Middle and Young	16	-1.9	0.075	1.80	2.925	6.2	1.779	1.562	2.211	0.135	-0.770

Looking back at the study, we can see from the given distributions that the later in a contract period, on top of the younger an athlete is, the greater the WAA is in aggregate for baseball players. Specifically, we can see that the SAM (Sample Arithmetic Mean) is larger for players in their middle and last year of contract (1.018, 1.258), in comparison to their first (0.317). Further, we determine that the older category of players have in large a lesser SAM WAA (0.151) than the younger players (1.415).

Table 1 shows the values of various descriptive statistics divided by different conditions(contract year or age or both them). Visually, we can see that the variation within each level of contract year appears to be the same. The variation within the old players is less than the young. Visually, we can see this in the box plots of Figure 4. When we look at values of the Sample Arithmetic Mean (SAM), expect for the groups First and Last where the The latter SAM is much larger than the former. And the young group SAM is much larger than the old.

As we can see in the box plots of Figure 4, the median WAA of player-seasons in Last and Old group is the smallest among all groups. In group Last and Old, and group First and Young, there appears to be some outliers which is apparent by the larger skewness values in Table 1 for those groups.

Forming Model

Figure 5 shows the Hasse diagram for the Contract Year study. We know that the response is quantitative (WAA). From the Hasse diagram, we have two factors (Contract Year and Age) which are both categorical and fixed. It can also be seen that we are doing a full factorial structure. Also, since we have positive Degrees of Freedom for each node in the Hasse diagram, we know that we can be able to estimate the two main effects, the interaction, and the residuals.

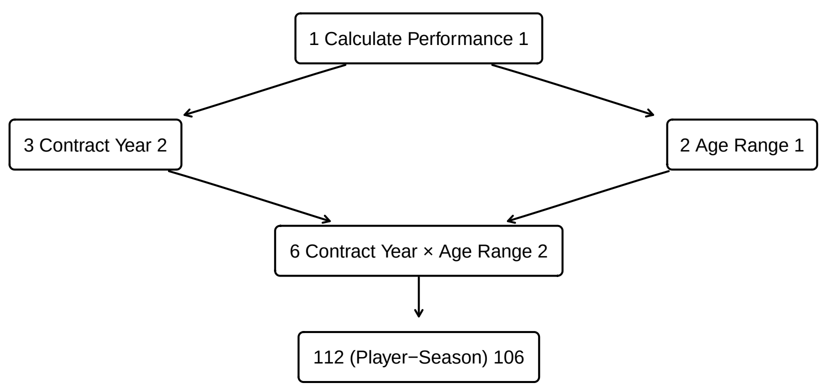


Figure 5: Hasse Diagram for the Contract Year Study

Checking for interactions

From this interaction plot 6 we can see that as the contract moves from “First” to “Middle” to “Last”, we can see that it mainly does not matter whether or not the age range is young or old, the WAA (response), reacts the same way. For the old age group, WAA starts low, goes up, and then goes back down. For the young age group, WAA starts low, goes up, then stays about the same. Therefore, we have very little interaction between the two factors. We will still include the interaction effect in the model, but we will have to keep this in mind.

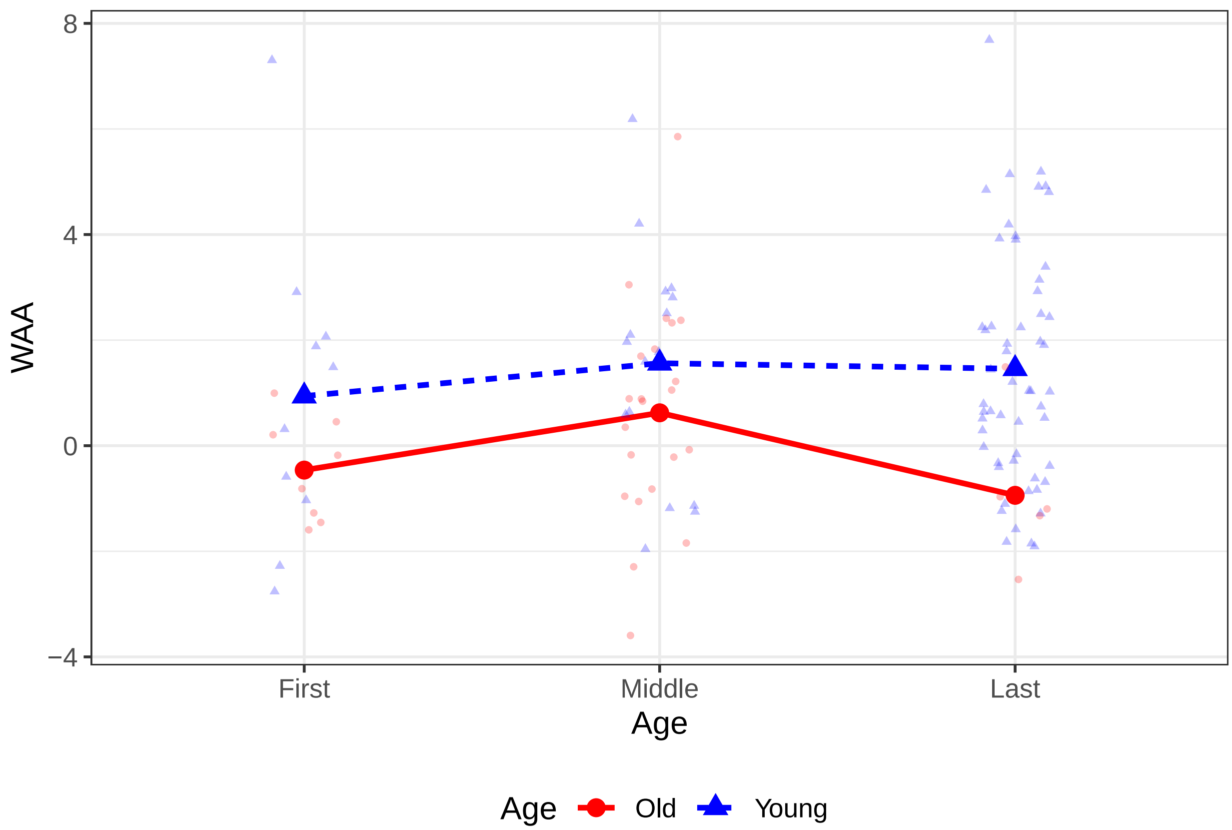


Figure 6: Interaction Plot for the Contract Year Study

Given the model and after checking the interactions we can fit our factorial model. We will control our overall Type I risk at 5%, and we'll use a personal unusualness threshold of 3%. We have an imbalanced model so we will have to choose SSQ, and according to how the SRQs are set up, we will use Type III Sum of Squares in order to test differences amongst factor levels. If needed, we will do Tukey adjustment.

We will fit our model will look this (as seen in the Hasse Diagram):

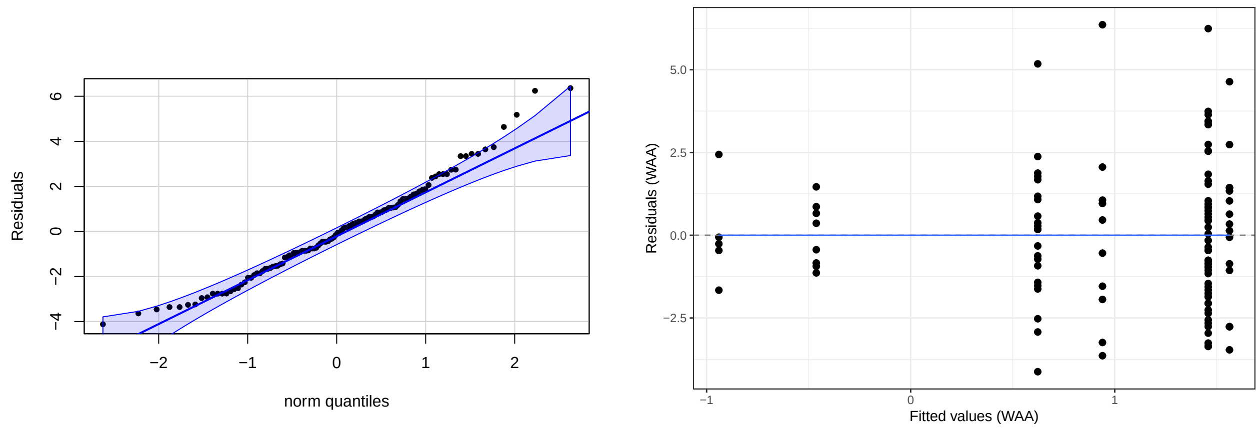
$$y_{ijk} = \mu_{\bullet\bullet\bullet} + \alpha_i + \beta_j + \alpha\beta_{ij} + \epsilon_{ijk}$$

Figure 7: Two-Way ANOVA Model

The y term is the response, the mu term is the grand mean of the data, the alpha is the Contract Year factor, the beta is the Age factor, and the epsilon term is the residuals.

Checking Assumptions

For the parametric shortcut for factorial designs (the ANVOA F test), we have the three assumptions: Gaussian Residuals, Homoscedasticity, and Independence of Observations.



(a) QQ Plot

(b) Tukey-Anscombe Plot

Figure 8: Assessing Assumptions for Contract Year Study

Looking at the Gaussian assumption we can see Figure 8 shows the QQ plot for residuals with a 90% confidence envelope. Only three points (~3%) fall outside the envelope and also from Table ref and there is no apparent pattern, therefore we can say this assumption is satisfied.

Also, in Figure 8 we can look at the Tukey-Anscombe Plot for the homoscedasticity assumption. The only time the homoscedasticity assumption is questionable or violated is if a group's length doubled is lower than the length of another group. Also, it can be violated if there is a pattern. Looking at the chart, we can see that the first two groups are smaller than the other four groups, but because it is only two groups and blue reference line is perfectly horizontal we will say that we will proceed with caution with this assumption.

For the issue of independence of observations, this is an observational study so there is no measurement order. We will look to the nature of the study to prove independence. We can see that we did not choose pitchers, only hitters, also the year from what was chosen was randomized so there is no two player-seasons that are different seasons from the same player. All cases are unique to player and season, and compounded with the randomization of the year of data there is independence of the observations.

Results

DECSISON:

Given that we have a imbalanced design, we will proceed with the parametric two-way ANOVA F test and our planned Type III SSQ.

Omnibus Test

Table 2: ANOVA Table for Contract Year Study-Type III SSQs

	Source	SS	df	MS	F	p-value	Partial Omega Sq.	Partial Eta Sq.	Partial Epsilon Sq.
1	Year	13.0166	2	6.5083	1.3979	0.2515	0.0068	0.0248	0.0071
2	Age	40.7738	1	40.7738	8.7575	0.0038	0.0627	0.0737	0.0653
3	Year:Age	6.5230	2	3.2615	0.7005	0.4985	-0.0052	0.0126	-0.0054
5	Residuals	512.1447	110	4.6559					

As we can see from Table 2, the contract year accounts for 1.3979 times as much variation as the residuals.

Age accounts for 8.7575 times as much variation as the residuals. The interaction term accounts for 0.7005 times as much variation as the residuals.

The probability that we observe our actual output value of the test statistic F or a more extreme output value is 0.2515 when we use the null hypothesis model 1 to form the sampling distribution.
The probability that we observe our actual output value of the test statistic F or a more extreme output value is 0.0038 when we use the null hypothesis model 2 to form the sampling distribution.
The probability that we observe our actual output value of the test statistic F or a more extreme output value is 0.4985 when we use the null hypothesis model 3 to form the sampling distribution.

Looking at the p-value for Age we can see that it is less than our unusualness threshold ($0.0627 < 0.03$), for Contract Year and the interaction term, the p-value is greater than the UT, therefore we will reject the null hypothesis for Age and fail to reject for the other two. We decide to act as if the condition of age is the only factor that has a statistically significant effect on WAA. In particular, that condition accounts for about 6.27% of the variation in the whole model, this is medium according to Field's Suggested Rule of Thumb (omega^2 = 0.0627, eta^2 = 0.0737, epsilon^2 = 0.0653). It is important to note that the effect size is not a unique variation of the response, but a variation of the whole model.

Table 3: Point Estimates from the Contract Year Study

	Estimate
Grand Mean	0.53
First	-0.29
Middle	0.56
Last	-0.27
Old	-0.79
Young	0.79
First x Old	0.09
Middle x Old	0.32
Last x Old	-0.41
First x Young	-0.09
Middle x Young	-0.32
Last x Young	0.41

From Table 3, ignoring all factors, player-seasons performance was 0.53 times as large as the number of player-seasons we tested.

In the first contract year, the player performance was an reduction of 0.29 WAA/player-season from than the common baseline.
In the middle contract year, the player performance was an additional of 0.56 WAA/player-season greater than the common baseline.
In the first contract year, the player performance was an reduction of 0.27 WAA/player-season from than the common baseline.

For old players, the player performance was an reduction of 0.79 WAA/player-season from than the common baseline.
For young players, the player performance was an additional of 0.79 WAA/player-season greater than the common baseline.

Due to the interaction of first contract year and old players, player performance has an additional of 0.09 WAA/player-season.
Due to the interaction of second contract year and old players, player performance has an additional of 0.32

WAA/player-season.
Due to the interaction of third contract year and old players, player performance has an reduction of -0.41 WAA/player-season.
Due to the interaction of first contract year and young players, player performance has an reduction of -0.09 WAA/player-season.
Due to the interaction of second contract year and young players, player performance has an reduction of -0.32 WAA/player-season.
Due to the interaction of third contract year and young players, player performance has an additional of 0.41 WAA/player-season

From this we can see that the largest addition/reduction to the grand mean comes from age of the player which is synonymous with our results from the F test.

Post-Hoc Analysis

After doing the omnibus test we can see that the only factor that rejected the null hypothesis is Age, therefore we will still carry out our conditional pairwise comparisons with Tukey, but only for Age given Contract Year.

Table 4: Marginal Means-Tukey 95% Adjustment

Age	Contract Year	Marginal Mean	SE	DF	Lower Bound	Upper Bound
Old	First	-0.4625	0.7629	110	-1.9743	1.0493
Young	First	0.9400	0.6823	110	-0.4122	2.2922
Old	Middle	0.6227	0.4600	110	-0.2889	1.5344
Young	Middle	1.5625	0.5394	110	0.4935	2.6315
Old	Last	-0.9400	0.9650	110	-2.8523	0.9723
Young	Last	1.4582	0.2910	110	0.8816	2.0348

Table 5: Pairwise Comparisons of Age-Tukey 95% Adjustment

Comparison	Contract Year	Estimate	SE	DF	t Statistic	p-value
Old - Young	First	-1.4025	1.0235	110	-1.3703	0.1734
Old - Young	Middle	-0.9398	0.7090	110	-1.3256	0.1877
Old - Young	Last	-2.3982	1.0079	110	-2.3794	0.0191

In Table 5, we can see the pairwise comparisons for Age, given each Contract Year. This is only one comparison because the factor Age has only two levels. We can see that for the Age comparison given the First and Middle Contract Year, the p-value is higher than the unusualness threshold and therefore we can say this is a typical event under the null hypothesis and that there is no statistical difference between the Age given those Contract Years. For the Age comparison given the Last contract year, we see that the p-value is lower than the UT, so we say there is a statistical difference between Young and Old given that Contract Year. To interpret that p-value we can say that We would only anticipate seeing a difference of at least as large as -2.3982 about 1.91% of the time if there was no difference between these Age groups given Last Contract Year.

Tables 4 and 6, should confirm these findings. We can see in 4, that the largest difference in marginal means between Young and Old for a given Contract Year is with the Last Contract Year. Interpreting these numbers we can say after accounting for the impact of the Last Contract Year, our Young group accumulated a total WAA that was 1.4582 times as large as the size of that group. Accounting for the impact of the Last Contract Year, our Old group accumulated a total WAA that was -0.9400 times as large as the size of that group.

In 6, we should see that the largest absolute value of Cohen's d should be for the Age comparison given Last Contract Year and it is at 1.111. We can interpret this as there are -1.111 standard deviations between the player-seasons of Old versus Young given the Last Contract Year in terms of WAA. Looking at the Probability of Superiority, we can say approximately 21.6% of the time we randomly select a player-season from the Old group and a player-season from the Young group, the player-season from the Old group will have the higher WAA.

Table 6: Effect Sizes for Age Comparisons

Comparison	Contract Year	Cohen's d	Probability of Superiority
(Old - Young)	First	-0.650	0.323
(Old - Young)	Middle	-0.436	0.379
(Old - Young)	Last	-1.111	0.216

Discussion and Limitations

In this report, we explored the SRQs of whether the Age, Contract Year, and/or the interaction term would result in a difference in WAA. From the results of our ANOVA F Test we found that the Age factor is the only factor that has an influence on WAA based on its levels, Young and Old. Though, this effect seems to only apply when comparing young and old given we are in the last year of the contract. This result is synonymous with the begging box plots, we can see that between the conference years there is not much difference in the medians of young and old, but within each contract year, there are significant differences between young and old. The largest difference is when we are in the last contract year which is also synonymous with our results.

There are many things to be considered when thinking about the results and limitations of this study. With baseball data, it is hard and nearly impossible to control for all outside possible attributes. By how we set up the study by defining the population as "qualified" player-seasons, we were able to filter out some attributes that would have caused problems in the study, like the number of games played in a season. If we revisit the introduction, the "Contract-Year Phenomena" was introduced, and it makes sense that we couldn't find performance differences based on a contract year, realistically a player would be trying their hardest every season whether it be for merit or to increase their "stock" (reputation). It also makes sense that we found that there was a statistical difference in performance based on age because it is well known that as a player gets older their performance in general decreases. Also, the result that old vs. young given last year in the contract was statistically significant makes sense because many older players in their last year of contract are thinking about retirement which brings a different dynamic to their game.

As mentioned in the last paragraph the main limitation was not being able to control for certain attributes that exist with baseball data, but on the opposite end of this, we had to limit our population to control for some attributes. Our sample was also limited to only one year due to the fact there would not be independence of observations if a player had multiple player-seasons in the population. There could be other ways to keep the independence of observations and also take data from multiple years such as randomly picking one year for each player, but either way, the population is limited. We also were limited to an imbalanced design, if we forced a balanced design then there would be sample size problems.

References

Contract data was taken from Spotrac, more info here
Other baseball statistics like WAA and age was taken from baseball reference using the stathead feature, the website is linked here
The raw complied data used for the study can be found here

Author Contributions

The authors of this report would like to acknowledge their individual contributions to the report:
- Chris Miller contributed to the analysis of data, Results of SRQ and the writing of the report.
- Tim Chelgren contributed to the analysis of data, exploration and presentation of data and the writing of the report.
- Enhao Yu contributed to the analysis of data, exploration and presentation of data and the writing of the report.
- Ryan Castoral contributed to the analysis of data, presenting of SRQ and the writing of the report.

Code Appendix

```
# Setting Document Options
knitr::opts_chunk$set(
  echo = FALSE,
  warning = FALSE,
  message = FALSE,
  fig.align = "center"
)

# Add additional packages by name to the following list
packages <- c(
  "tidyverse", "knitr", "kableExtra", "readxl","emmeans",
  "psych", "car", "parameters","sm"
  )
lapply(X = packages, FUN = library, character.only = TRUE)

# Loading Helper Files and Setting Global Options
options(knitr.kable.NA = "")
options("contrasts" = c("contr.sum", "contr.poly"))
source("https://raw.github.com/neilhatfield/STAT461/master/rScripts/ANOVATools.R")

source("https://raw.github.com/neilhatfield/STAT461/master/rScripts/shadowgram.R")


Final <- read.csv(
  file =
  "https://raw.githubusercontent.com/christopher-k-miller/STAT461/main/project_data2.csv",
  header = TRUE,
  sep = ","
)


Final$Contract.Year <- factor(
x = Final$Contract.Year,
levels = c("First", "Middle", "Last")
)
Final$Age <- as.factor(Final$Age)
  names(Final) <- c('WAA','Year','Age')
ggplot2::ggplot(
data = Final,
  mapping = aes(x = Year, y = WAA, fill = Year)
) +
ggplot2::geom_dotplot(
binaxis = "y",
binwidth = 0.15,
binpositions = "bygroup",
stackdir = "centerwhole"
) +
ggplot2::theme_bw() +
xlab("Contract Year") +
ylab("WAA")
Final %>%
```

```r
ggplot2::ggplot(
mapping = aes(x = WAA)
) +
ggplot2::geom_histogram(
binwidth = 0.2,
boundary = 0,
closed = "left",
na.rm = TRUE,
col = "black",
fill = "blue"
) +
ggplot2::theme_bw() +
xlab("WAA") +
ylab("Frequency")
attach(Final)
sm.density.compare(WAA,Year)
colfill=c(2:4)
legend(-5.3,0.20,legend=levels(Year),fill=colfill)

age=factor(Age,levels=c("Young","Old"))
sm.density.compare(WAA,Age)
legend(-5.3,0.20,legend=levels(age),fill=c(2:3))

boxplot(WAA~Year,main="Box plots of WAA by Contract Year",
        xlab="Contract Year",ylab="WAA",col=rainbow(3))


boxplot(WAA~Age,main="Box plots of WAA by Age",xlab="Age",
        ylab="WAA",col=rainbow(2))

ggplot(
data = Final,
mapping = aes(
x = Year,
y = WAA,
fill = Age
)
) +
geom_boxplot() +
theme_bw() +
xlab("Contract Year") +
ylab("WAA") +
labs(
fill = "Age"
) +
theme(
legend.position = "right",
text = element_text(size = 14)
)

Stat1=describeBy(x=Final$WAA,group = paste(Final$Year),
           na.rm = TRUE,
           skew = TRUE,
```

```
           ranges = TRUE,
           quant = c(0.25, 0.75),
           IQR = TRUE,
           mat = TRUE,
           digits = 4)
Stat2=describeBy(x=Final$WAA,group = paste(Final$Age),
           na.rm = TRUE,
           skew = TRUE,
           ranges = TRUE,
           quant = c(0.25, 0.75),
           IQR = TRUE,
           mat = TRUE,
           digits = 4)
Stat3=describeBy(x=Final$WAA,group = paste(Final$Year,Final$Age,sep=" and "),
           na.rm = TRUE,
           skew = TRUE,
           ranges = TRUE,
           quant = c(0.25, 0.75),
           IQR = TRUE,
           mat = TRUE,
           digits = 4)
Stat=rbind(Stat1,Stat2)
Stat=rbind(Stat,Stat3)

Stat %>%
tibble::remove_rownames() %>%
tibble::column_to_rownames(
        var = "group1"
) %>%
dplyr::select(
        n, min, Q0.25, median, Q0.75, max, mad, mean, sd, skew, kurtosis
) %>%
knitr::kable(
caption = "Summary Statistics for Player-Season WAA",
digits = 3,
format.args = list(big.mark = ","),
align = rep('c', 11),
col.names = c("n", "Min", "Q1", "Median", "Q3", "Max", "MAD", "SAM", "SASD",
"Sample Skew","Sample Ex. Kurtosis"),
booktabs = TRUE
) %>%
kableExtra::kable_styling(
font_size = 12,
latex_options = c("HOLD_position", "scale_down") )


modelLabels <- c("1 Calculate Performance 1", "3 Contract Year 2",
                 "2 Age Range 1", "6 Contract Year × Age Range 2",
                 "112 (Player-Season) 106")
modelMatrix <- matrix(
  data = c(FALSE, FALSE, FALSE, FALSE, FALSE, TRUE, FALSE, FALSE,
           FALSE, FALSE, TRUE, FALSE, FALSE, FALSE,FALSE,
           TRUE, TRUE, TRUE, FALSE, FALSE, TRUE, TRUE,
```

```
           TRUE, TRUE, FALSE),
  nrow = 5,
  ncol = 5,
  byrow = FALSE
)
hasseDiagram::hasse(
 data = modelMatrix,
 labels = modelLabels
)
ggplot(
data = Final,
mapping = aes(
x = Year,
y = WAA,
shape = Age,
color = Age,
linetype = Age,
group = Age
)
) +
stat_summary(fun = "mean", geom = "point", size = 3) +
stat_summary(fun = "mean", geom = "line", size = 1) +
geom_jitter(width = 0.1, height = 0.1, alpha = 0.25, size = 1) +
ggplot2::theme_bw() +
xlab("Age") +
ylab("WAA") +
labs(
color = " Age",
shape = " Age",
linetype = " Age"
) +
scale_color_manual(values = c("red", "blue")) +
theme(
legend.position = "bottom",
text = element_text(size = 12)
)
finalModel <- aov(
formula = WAA ~ Year*Age,
data = Final
)
car::qqPlot(
x = residuals(finalModel),
distribution = "norm",
envelope = 0.90,
id = FALSE,
pch = 20,
ylab = "Residuals"
)

ggplot(
data = data.frame(
residuals = residuals(finalModel),
fitted = fitted.values(finalModel)
```

```r
),
mapping = aes(x = fitted, y = residuals)
) +
geom_point(size = 2) +
geom_hline( ## Adds reference line at zero
yintercept = 0,
linetype = "dashed",
color = "grey50"
) +
geom_smooth( ## Adds the smoothed line
formula = y ~ x,
method = stats::loess,
method.args = list(degree = 1),
se = FALSE,
size = 0.5
) +
theme_bw() +
xlab("Fitted values (WAA)") +
ylab("Residuals (WAA)")


parameters::model_parameters(
model = finalModel,
omega_squared = "partial",
eta_squared = "partial",
epsilon_squared = "partial",
type = 3, # Type III SSQs
drop = "(Intercept)",
verbose = FALSE
) %>%
dplyr::mutate(
p = ifelse(
test = is.na(p),
yes = NA,
no = pvalRound(p)
)
) %>%
knitr::kable(
digits = 4,
col.names = c("Source", "SS", "df", "MS", "F", "p-value",
"Partial Omega Sq.", "Partial Eta Sq.", "Partial Epsilon Sq."),
caption = "ANOVA Table for Contract Year Study-Type III SSQs",
align = c('l',rep('c',8)),
booktab = TRUE
) %>%
kableExtra::kable_styling(
bootstrap_options = c("striped", "condensed"),
font_size = 12,
latex_options = c("scale_down", "HOLD_position")
)
pointEst <- dummy.coef(finalModel)
pointEst <- unlist(pointEst)
names(pointEst) <- c(
```

```
"Grand Mean",
levels(Final$Year),
levels(Final$Age),
outer(
levels(Final$Year),
levels(Final$Age),
FUN = paste,
sep = " x "
)
)
data.frame("Estimate" = pointEst) %>%
knitr::kable(
digits = 2,
caption = "Point Estimates from the Contract Year Study",
booktabs = TRUE,
align = "c"
) %>%
kableExtra::kable_styling(
font_size = 12,
latex_options = c("HOLD_position")
)
finalMeans <- emmeans::emmeans(
object = finalModel,
# The order of factors does not really matter for this
specs = pairwise ~ Age | Year,
adjust = "tukey", # Where you specify your chosen method
level = 0.95 # 1--Type I Risk
)
as.data.frame(finalMeans$emmeans) %>%
knitr::kable(
digits = 4,
col.names = c("Age", "Contract Year", "Marginal Mean","SE", "DF",
"Lower Bound","Upper Bound"),
caption = "Marginal Means-Tukey 95\\% Adjustment",
align = rep("c", 7),
booktabs = TRUE
) %>%
kableExtra::kable_styling(
bootstrap_options = c("striped", "condensed"),
font_size = 12,
latex_options = c("HOLD_position")
)

finalPH <- emmeans::emmeans(
object = finalModel,
# Order maters for this; comparisons | held constant
specs = pairwise ~ Age | Year,
adjust = "tukey", # Where you specify your chosen method
level = 0.95 # 1--Type I Risk
)
as.data.frame(finalPH$contrasts) %>%
knitr::kable(
digits = 4,
```

```r
col.names = c("Comparison", "Contract Year", "Estimate","SE", "DF",
"t Statistic", "p-value"),
caption = "Pairwise Comparisons of Age-Tukey 95\\% Adjustment",
align = rep("c", 7),
booktabs = TRUE
) %>%
kableExtra::kable_styling(
bootstrap_options = c("striped", "condensed"),
font_size = 12,
latex_options = c("HOLD_position")
)
as.data.frame(
eff_size(
object = finalPH,
sigma = sigma(finalModel),
edf = df.residual(finalModel)
)
) %>%
dplyr::mutate(
ps = probSup(effect.size),
.after = effect.size
) %>%
dplyr::select(contrast, Year, effect.size, ps) %>%
knitr::kable(
digits = 3,
col.names = c("Comparison", "Contract Year", "Cohen's d", "Probability of Superiority"),
align = "lccc",
caption = "Effect Sizes for Age Comparisons",
booktab = TRUE
) %>%
kableExtra::kable_styling(
bootstrap_options = c("striped", "condensed"),
font_size = 12,
latex_options = "HOLD_position"
)
```