

# How Diverse Body Shapes in American Football Athletes Address the NFL's 40 Yard Dash

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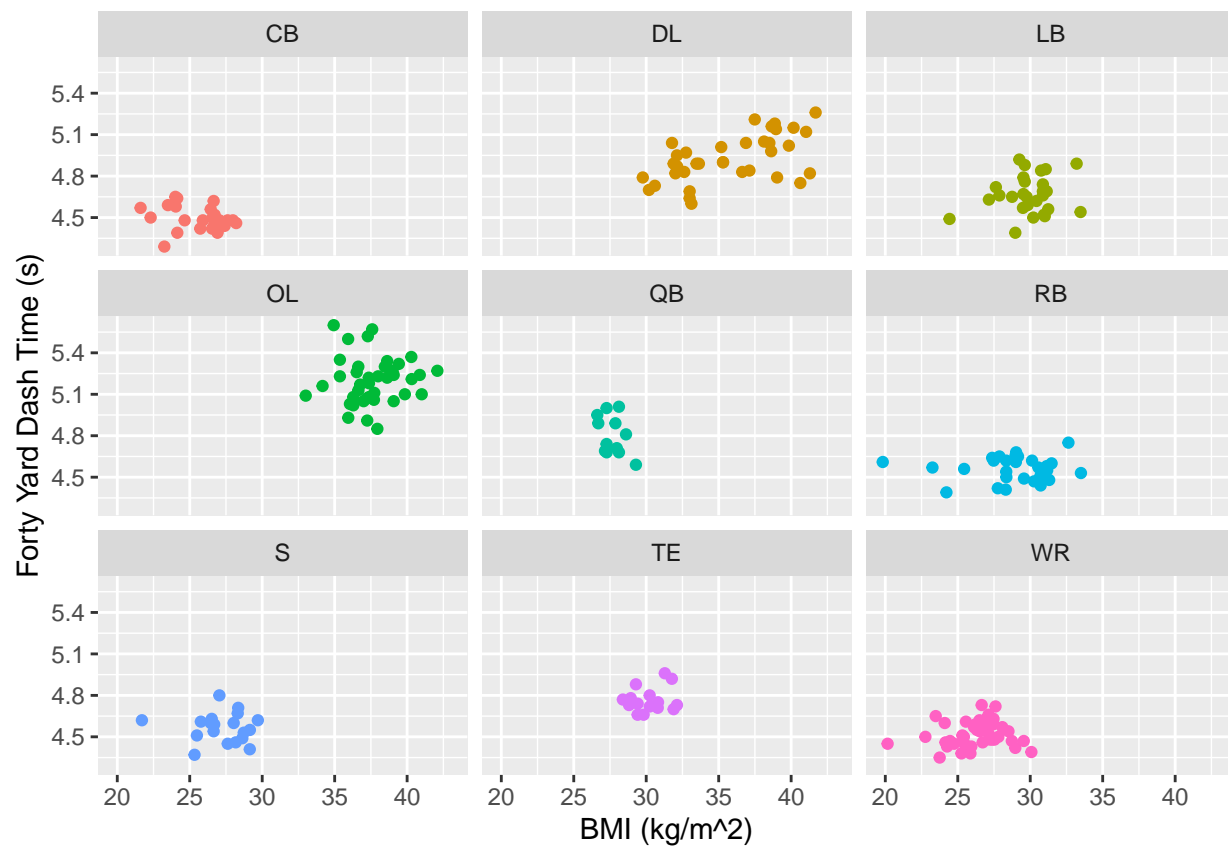
11/08/2020

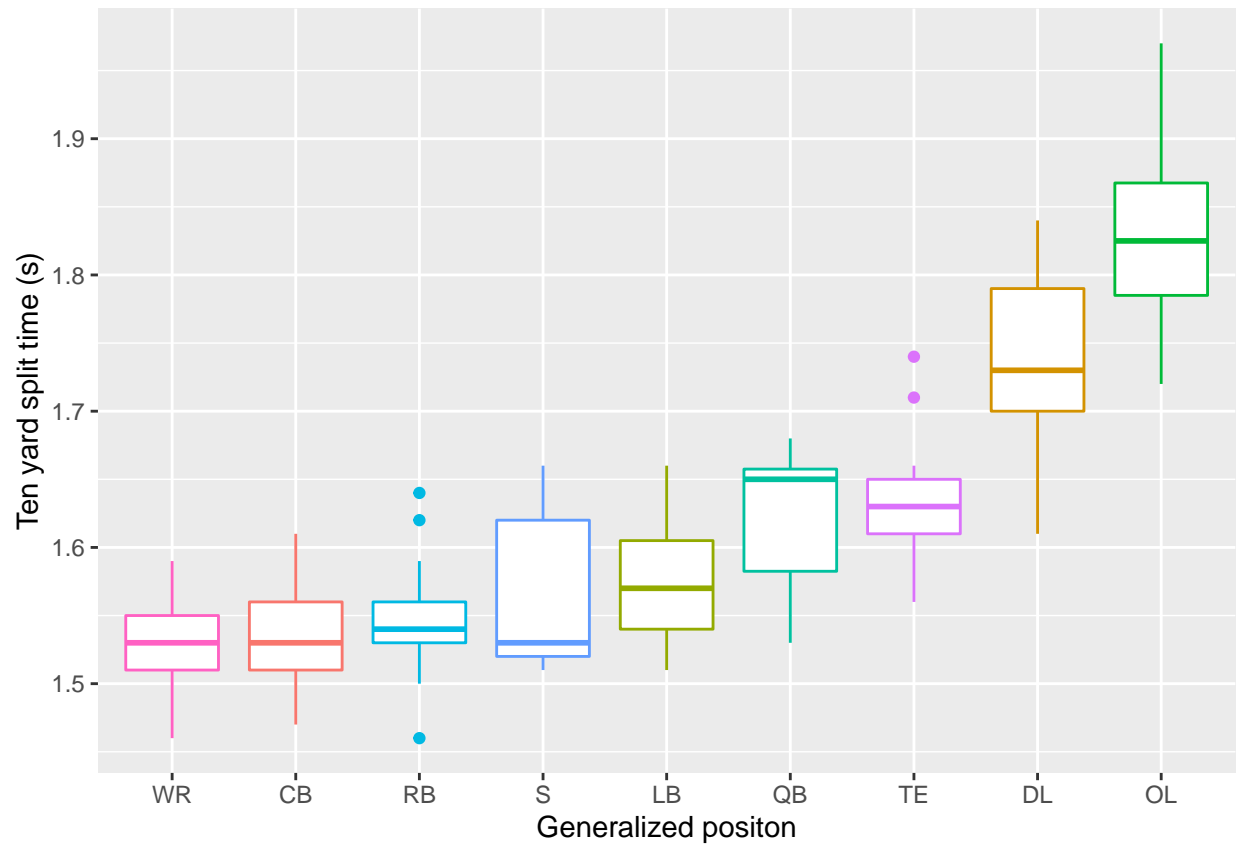
## Introduction

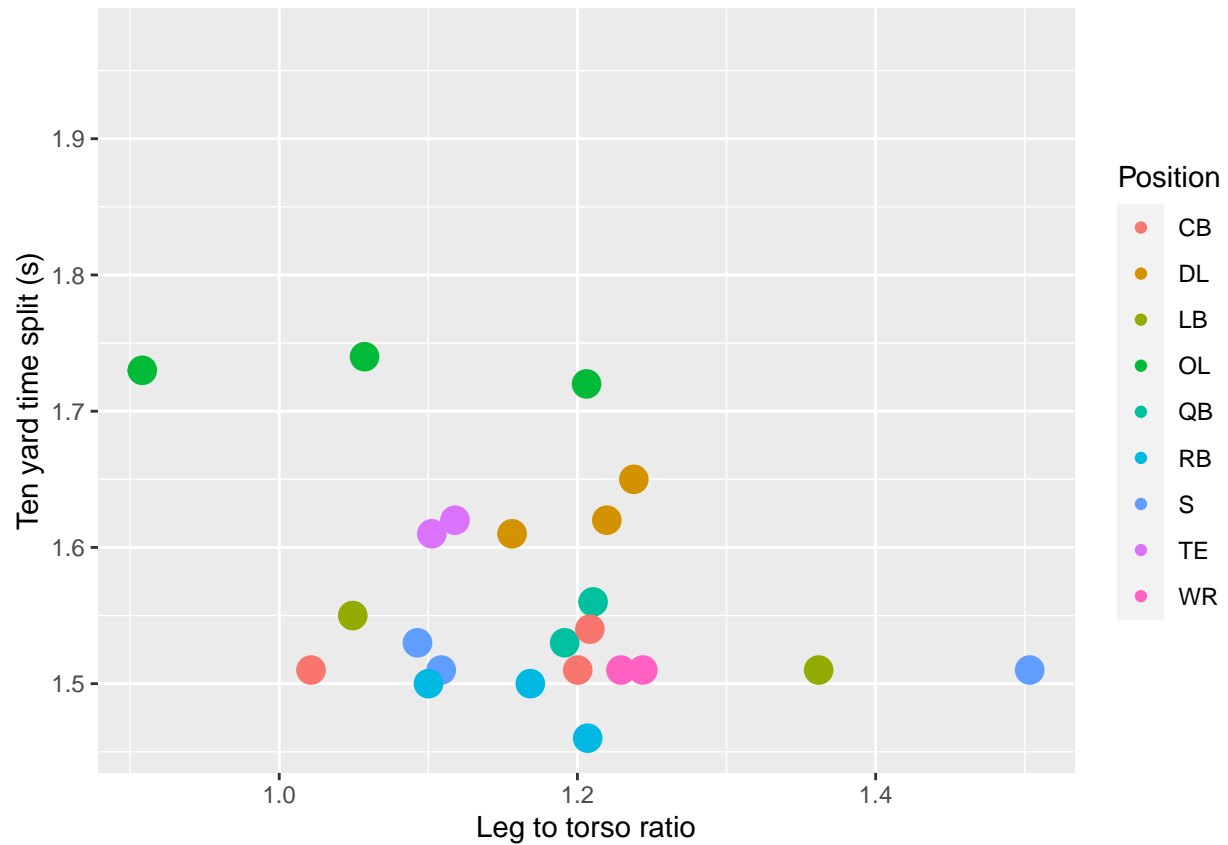
Does body proportions determine position on the field or is it BMI? \* use leg length and BMI: is there is a suggested determinant for how fast the athlete runs the 40? \*\* Does BMI and/or leg length determine how fast the 40 or first ten yard split is ran? \*\*\* Use ovr forty time as a metric the NFL uses to measure athlete speed \*\*\* Use ten split time to determine the explosiveness of the athlete

## Data Plots

```
## Observations: 308
## Variables: 8
## $ name      <chr> "Zuniga, Jabari", "Young, Chase", "Woodward, David", "W...
## $ POS       <chr> "DE", "DE", "OLB", "TE", "DE", "TE", "OT", "DT", "OT", ...
## $ bmi       <dbl> 32.99737, 31.30548, 29.52993, 31.76957, 30.59400, 28.93...
## $ fortyTime <dbl> 4.64, NA, 4.79, 4.92, 4.73, 4.78, 4.85, 4.90, 5.32, 4.6...
## $ tenTimeOvr <dbl> 1.61, NA, 1.62, 1.74, 1.70, 1.63, 1.72, 1.76, 1.87, 1.5...
## $ Height    <dbl> 75, 77, 74, 76, 77, 77, 77, 76, 79, 79, 77, 75, 75, 76,...
## $ legHgtRatio <dbl> 1.156159, NA, NA, NA, NA, NA, 1.206093, NA, NA, NA, NA,...
## $ genPos     <chr> "DL", "DL", "LB", "TE", "DL", "TE", "OL", "DL", "OL", "...
```







## Statistical Analyses

### BMI v Forty Time

$$\alpha = 0.05$$

$H_0$ : BMI and forty time do not have a strong ( $\leq 0.5$ ), postive correlation.

$H_A$ : BMI and forty time do have a strong ( $>0.5$ ), postive correlation.

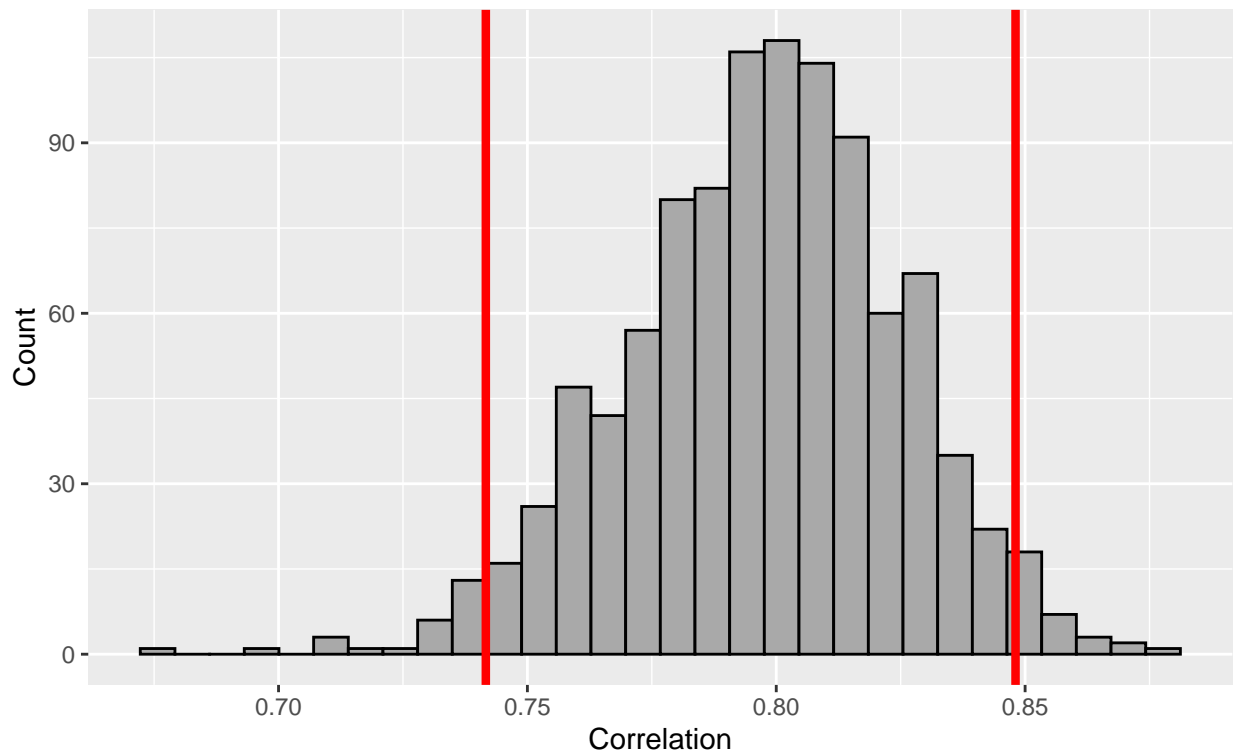
```
## # A tibble: 1 x 2
```

```
##   lower upper
```

```
##   <dbl> <dbl>
```

```
## 1 0.742 0.848
```

### Bootstrap distribution of correlation between BMI and Forty Time with 95% confidence interval



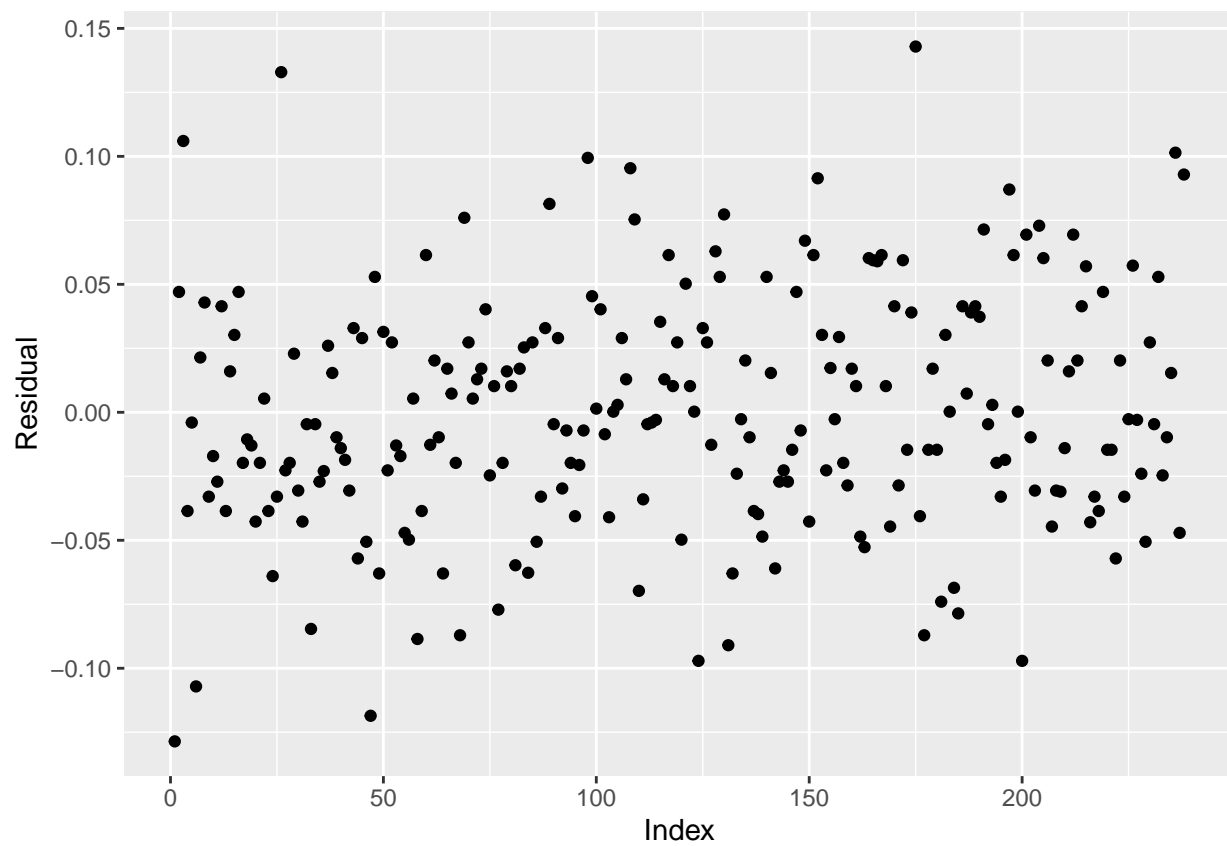
Based on an  $\alpha$  level of 0.05, we are 95% confident that the true population coefficient for BMI and forty times is between (0.7485, 0.8436). There is enough evidence to reject the null hypothesis that there is not a strong, positive correlation between BMI and forty time.

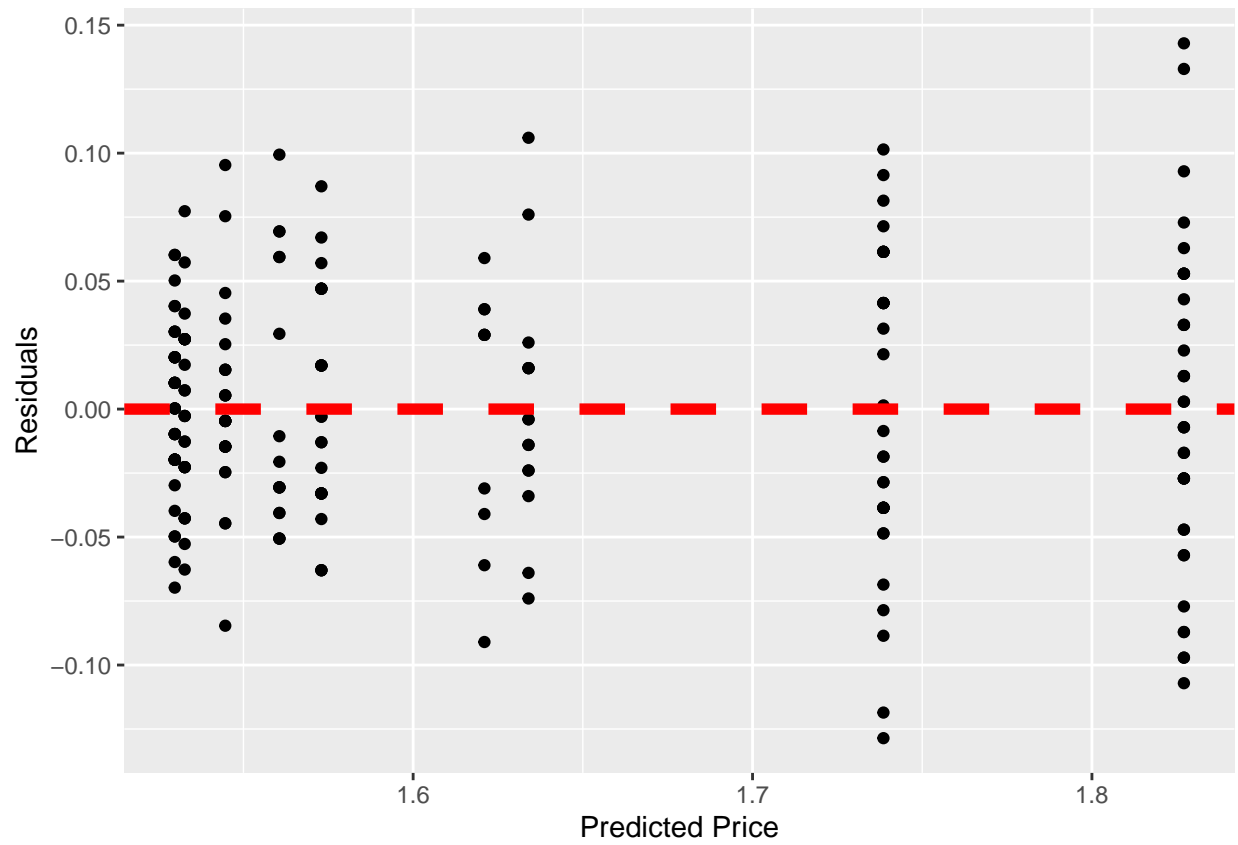
### Position v Ten Time

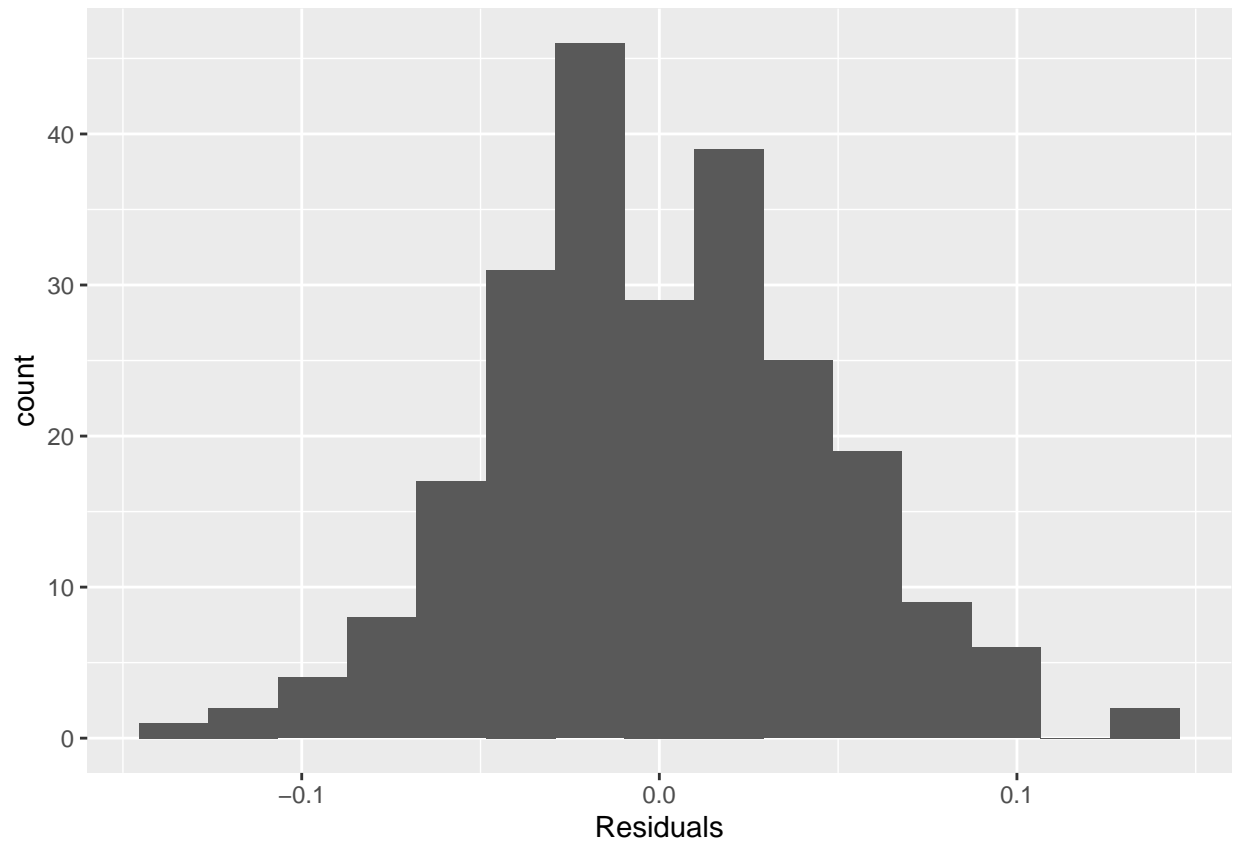
What is the relationship between positions and the first ten yard splits? All conditions met, can use linear inference to determine relationship.

```
## # A tibble: 9 x 5
##   term          estimate std.error statistic  p.value
##   <chr>         <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)  1.53      0.00925   166.    1.85e-240
## 2 genPosDL     0.206     0.0122    16.9    5.09e- 42
## 3 genPosLB     0.0403    0.0130     3.11    2.12e-  3
## 4 genPosOL     0.294     0.0120    24.5    5.16e- 66
```

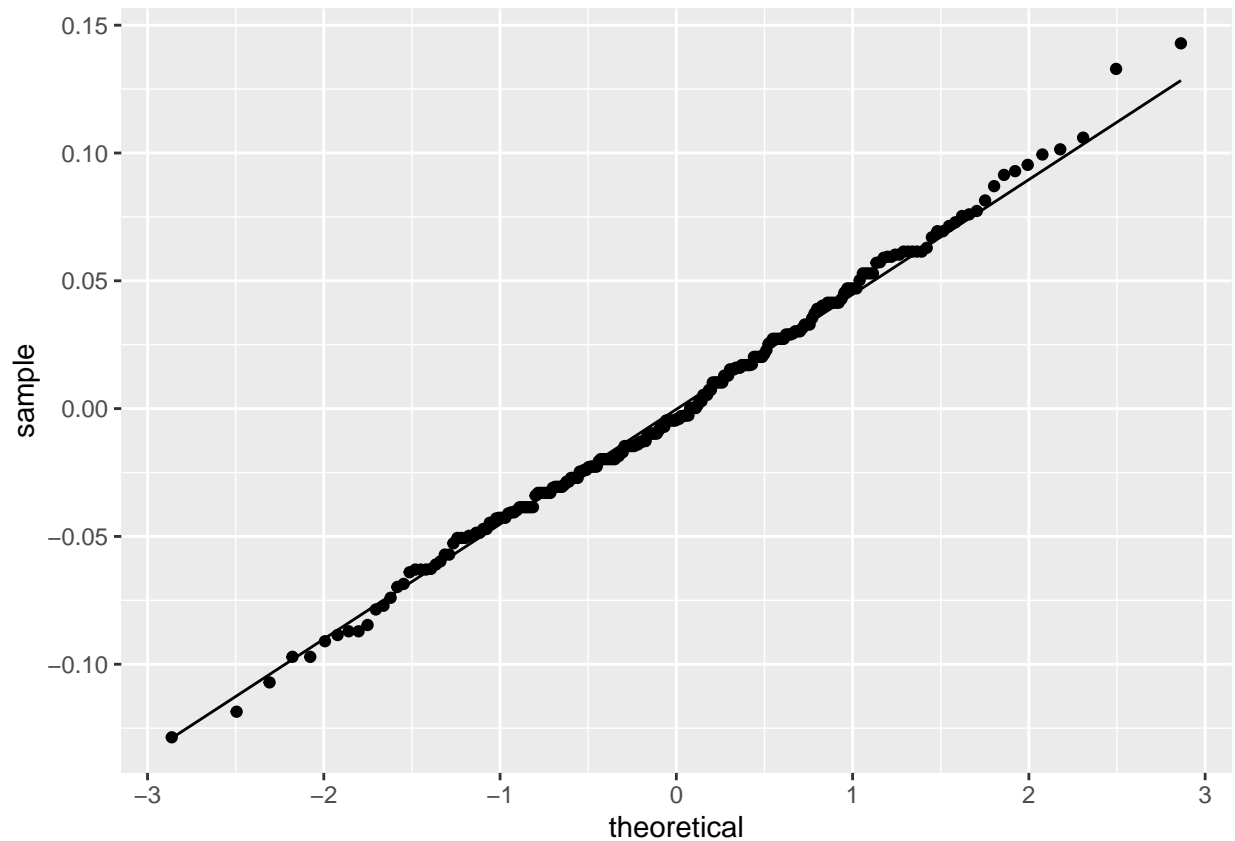
## 5	genPosQB	0.0883	0.0175	5.03	9.78e- 7
## 6	genPosRB	0.0120	0.0128	0.931	3.53e- 1
## 7	genPosS	0.0279	0.0147	1.90	5.91e- 2
## 8	genPosTE	0.101	0.0153	6.63	2.44e- 10
## 9	genPosWR	-0.00293	0.0118	-0.249	8.04e- 1











$$\hat{S}_{split} = 1.533 \text{ (CB)} + 0.206 \text{ (DL)} + 0.040 \text{ (LB)} + 0.294 \text{ (OL)} + 0.088 \text{ (QB)} + 0.012 \text{ (RB)} + 0.028 \text{ (S)} + 0.101 \text{ (TE)} - 0.003 \text{ (WR)}$$

### Leg:Torso and Ten Time Split

```
#obs correlation between BMI and forty time
dimension_analysis = combine2 %>%
  summarize(
    sdTenTime = sd(tenTimeOvr, na.rm=TRUE),
    sdRatio = sd(legHgtRatio, na.rm=TRUE),
    covar = cov(tenTimeOvr, legHgtRatio, use = "complete.obs")
  ) %>%
  mutate(
    sample_correlation = (covar/(sdTenTime*sdRatio))
  ) %>%
```

```

select(sample_correlation)

#simulation based approach for correlation
set.seed(1)
boot_dist2 = numeric(1000)

for(i in 1:1000){
  indices <- sample(1:nrow(combine2), replace = T)
  boot_ten_time <- combine2 %>%
    slice(indices) %>%
    summarize(boot_sd_tenTime = sd(tenTimeOvr), na.rm=TRUE) %>%
    pull()
  boot_ratio <- combine2 %>%
    slice(indices) %>%
    summarize(boot_sd_ratio = sd(logHgtRatio, na.rm=TRUE)) %>%
    pull()
  boot_covar_ratio <- combine2 %>%
    slice(indices) %>%
    summarize(boot_covar = cov(tenTimeOvr, logHgtRatio,
                                use = "complete.obs")) %>%
    pull()
  boot_dist2[i] <- (boot_covar_ratio/(boot_ratio*boot_ten_time))
}
boot_means2 <- tibble(boot_dist2)

boot_means3 = boot_means2 %>%
  summarize(lower = quantile(boot_dist2, 0.025),
            upper = quantile(boot_dist2, 0.975))
boot_means3

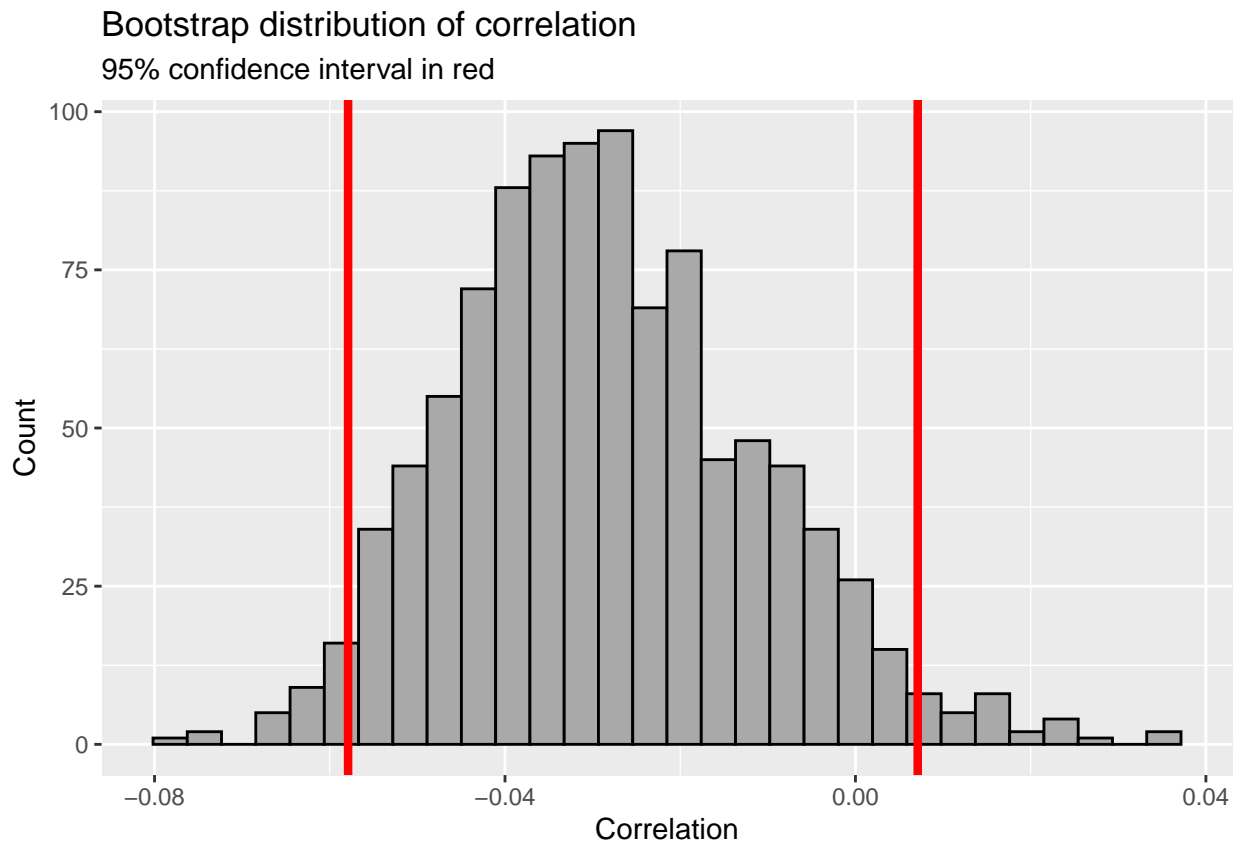
## # A tibble: 1 x 2
##   lower upper
##   <dbl> <dbl>

```

```
## 1 -0.0579 0.00711
```

```
ggplot(data = boot_means2, aes(x = boot_dist2)) +  
  geom_histogram(color = "black",  
                 fill = "darkgrey") +  
  labs(title = "Bootstrap distribution of correlation",  
        subtitle = "95% confidence interval in red",  
        x = "Correlation", y = "Count") +  
  geom_vline(xintercept = c(boot_means3$lower, boot_means3$upper),  
             color = "red", lwd = 1.5)
```

```
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
```



Based on an  $\alpha$  level of 0.05, we are 95% confident that the true population coefficient for leg:torso and ten time splits is between (-0.05468, 0.0006826435).

Can't infer from lm for tentime and leg:torso or fortyTime and leg:torso Not normally distributed

Conclusion: evidence fails to reject the null that there is no correlation between leg:torso and ten time splits