Final Project Part 3

Hannah Rosenbaum

Background

Fifty years after the passage of the Title IX Amendment, collegial sports equity has shown relatively minimal change. Allocations of sports budgets often highlight pay discrepancies in participants being "spent [on] $4,285 per men's participant versus $2,588 per women's participant." (Feinberg, D., & Hunzinger, E) With these vast differences in individual spending by gender, we see this phenomenon only heightened in the NCAA with women's basketball. Women's basketball not only fares having lower budgets from the NCAA but also, per an ESPN report, "is underpaying the NCAA for the tournament rights for 29 championships causing the association to lose out on substantial and crucial revenue... denoting that the current budget of $81 million to $112 million multiples more than what the network currently gives." (Zimmbalist) Thus, there is not only a discrepancy in budget allocations among the participants by gender but also amongst large broadcast networks.

Significant systemic issues occur within the gendered branding of 'March Madness.' This can be seen with differentiated treatment of male versus female brackets due to the lack of general awareness of when the women's bracket games even occur. Largely the inequity of the 'March Madness' tournament derives from a differentiation from the NCAA in "distribution agreements, corporate sponsorships, distribution of revenue, organizational structure and culture all to prioritize Division I men's basketball over everything else... to perpetuate gender inequities." (Blinder) Likewise, this institutional creation of a high investment in TV rights for men's basketball and minimal airtime for the women's bracket has led to smaller budgeting and fewer avenues to earn revenue. This has led women's teams to be "starved of a starring role in the national discourse." (Blinder) Thus, it creates a circular effect in women's basketball, deriding fewer resources even within facilities at the NCAA tournament in 2021 and in general awareness of TV times.

I am primarily interested in discussing sports equity in women's basketball due to my own personal experience at UF of wanting to watch NCAA basketball for women but having no general knowledge of when women play. I believe that the discussion of equity in sports for women is essential because of the common dismissal of watching women's sports as a pastime.

Research Questions

1. Does the rate of female enrollment in post-secondary education institutions impact the level of female participation in collegiate sports?
2. What is the relationship between total expenditures on collegiate basketball compared to the total ratio of female athletes in college basketball programs?
3. What is the relationship between total revenue allocation in NCAA basketball by gender and the total ratio of females playing college basketball?

Hypothesis

1. Higher rates of female enrollment at post-secondary institutions do not directly affect female participation in college sports. This hypothesis is because there is no direct correlation between registration and participation in sports, as participation in NCAA sports reflects a small sample size.
2. There is a high correlation between expenditure on university sports programs and the percentage of females in university basketball programs by gender. This notion reflects an increased differentiation in total aggregate costs, higher for male than female basketball athletes.
3. There is a high correlation between revenue on university sports programs and the percentage of females in university basketball programs by gender. This notion reflects an increased differentiation in total aggregate revenue, higher for male than female basketball athletes. Thus contemplating the idea that 'March Madness' drives profits for male athletes compared to female athletes.

Descriptive Statistics

The Equity in Athletics Disclosures Act requires the full financial disclosure of total expenditures, revenue, staffing, and recruiting efforts by men's and women's athletic programs (Mock, J.T.). Data provided by the Equity in Sports project is from all post secondary programs that receive government funding from Title IV funding and is an online database of funding expenses from 2015-2019.

There are 132,327 rows and a total of 28 columns.

Feedback from Part 1

To measure female participation, I will create a model with `sum_partic_women` as the dependent variable and `ef_female_count` as the explanatory variable.

The null data in the `data` matrix exist because a given entry has no male or female participation. The columns with null data are `rev_men`, `rev_women`, `exp_men`, `exp_women`.

Feedback from Part 2

Hypothesis test 1:

- DV: participation of females in sports, basketball -
- Key IV: Ratio of participation of females in sports of female students in attendance -
- Control: percentage of males in sports, basketball -

Hypothesis test 2:

- DV: percentage of females in sports, basketball - I chose this as my dependent variable due to my study wanting to reflect the effect of basketball participation on the total money the university gives to sports.
- Key IV: expenditure of female sport, basketball. This was my independent variable to measure the total effect of expenses on March Madness.
- Control: revenue of female sport, expenditure of male sport, percentage of males, sport type. I used the following as controls due to needing to cross-compare how many males played basketball, and total funding for men for basketball to see the overall effect when using my dependent and independent variablese.

Hypothesis test 3:

- DV: percentage of females in sports
- Key IV: revenue of female sport, basketball
- Control: expenditure of female sport, revenue of male sport, percentage of males, sport type

Read in Sports Equity data-set

```
sports <- readr::read_csv('https://raw.githubusercontent.com/rfordatascience/tidytuesday/m
```

```
Rows: 132327 Columns: 28
-- Column specification --------------------------------------------------------
Delimiter: ","
chr  (8): institution_name, city_txt, state_cd, zip_text, classification_nam...
dbl (20): year, unitid, classification_code, ef_male_count, ef_female_count,...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
library(dplyr)
```

```
Attaching package: 'dplyr'


The following objects are masked from 'package:stats':

    filter, lag


The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union
```

```r
library(wesanderson)
library(ggplot2)
```

Removing 'Ottawa University-Pheonix' due to having zero total male and female attendance

```r
sports = filter(sports, institution_name != "Ottawa University-Phoenix")
```

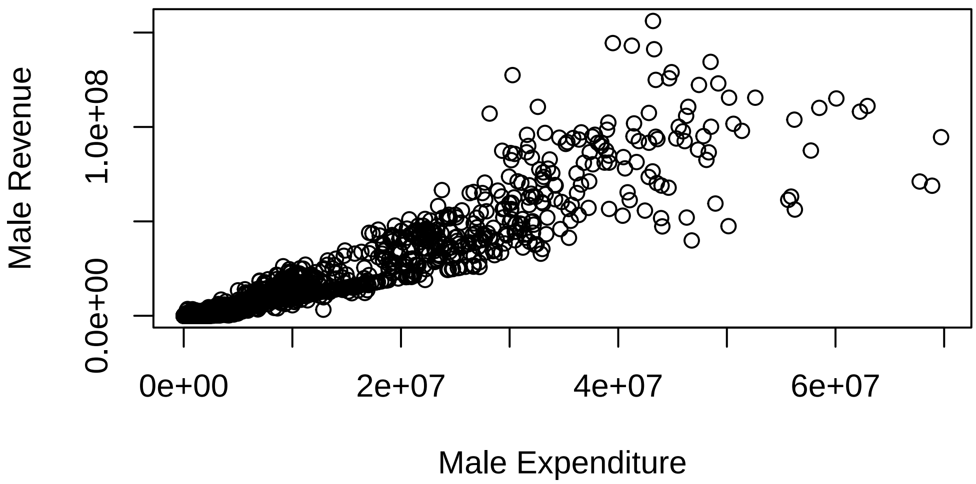
Create data-frames: Critical dimensions, Attendance specific, Basketball specific

```r
data <- as.data.frame(sports[, c("year", "institution_name", "sports", "ef_male_count", "e

attendance_data <- data[,c("institution_name", "sports", "ef_male_count", "ef_female_count

basketball <- as.data.frame(sports[, c("year", "institution_name", "sports", "ef_male_coun
basketball <- filter(basketball, sports=='Basketball')
```

```r
institute_lbl <- distinct(as.data.frame(data[, c("institution_name")]))
sport_lbl <- distinct(as.data.frame(data[, c("sports")]))
```

Scatter plots comparing Expenditures against Revenue by Gender

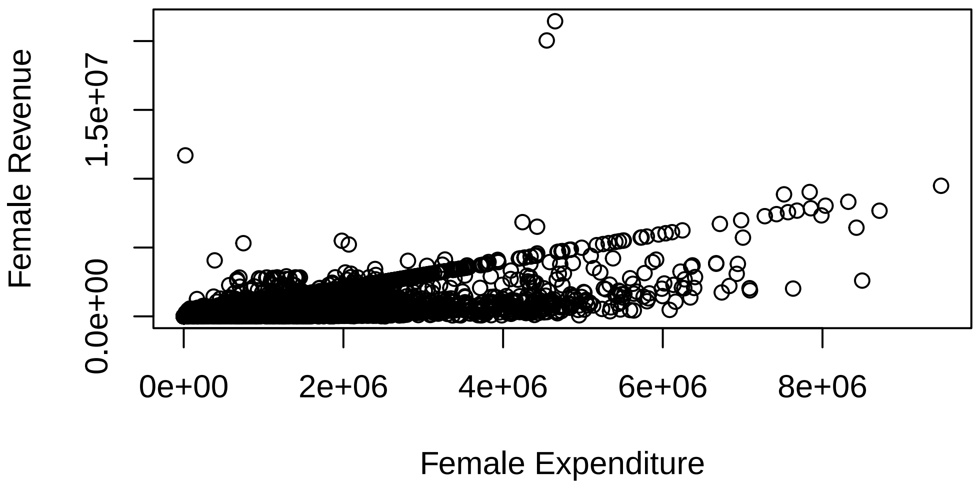
```
#data[is.na(data)] <- 0
plot(data$exp_men, data$rev_men, xlab="Male Expenditure", ylab="Male Revenue")
```




```
#ggplot(data = data, aes(x=exp_men, y=rev_men), fill = institute_lbl) +
#geom_point() +
#scale_fill_manual(values = wes_palette(length(institute_lbl), name = "GrandBudapest1", ty
```

We can see a relationship between revenue and expenditures for men

```
plot(data$exp_women, data$rev_women, xlab="Female Expenditure", ylab="Female Revenue")
```



Similarly, we see a sparser relationship between revenue and expenditures for women.

Descriptive Statistics

```
glimpse(data)
```

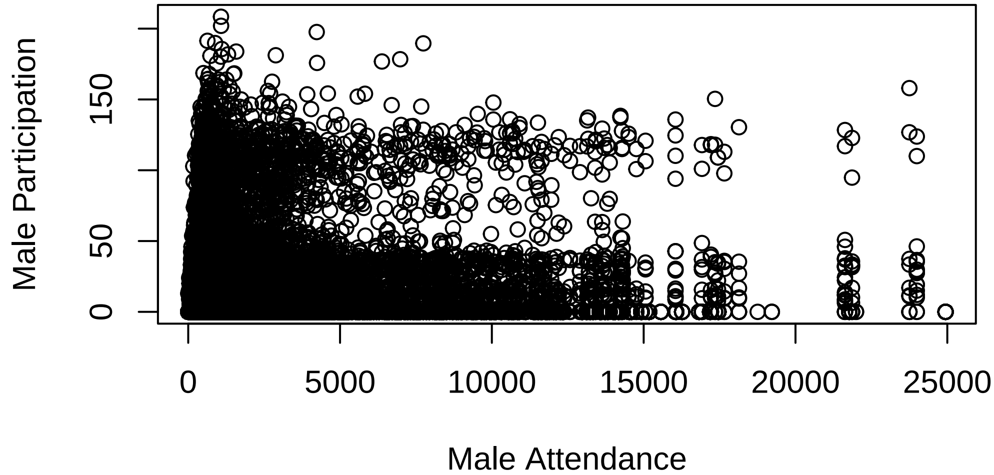
```
Rows: 132,317
Columns: 11
$ year              <dbl> 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015,~
$ institution_name  <chr> "Alabama A & M University", "Alabama A & M University~
$ sports            <chr> "Baseball", "Basketball", "All Track Combined", "Foot~
$ ef_male_count     <dbl> 1923, 1923, 1923, 1923, 1923, 1923, 1923, 1923, 1923,~
$ ef_female_count   <dbl> 2300, 2300, 2300, 2300, 2300, 2300, 2300, 2300, 2300,~
$ sum_partic_men    <dbl> 31, 19, 61, 99, 9, 0, 0, 7, 0, 0, 32, 13, 0, 10, 2, 3~
$ sum_partic_women  <dbl> 0, 16, 46, 0, 0, 21, 25, 10, 16, 9, 0, 20, 68, 7, 10,~
$ rev_men           <dbl> 345592, 1211095, 183333, 2808949, 78270, NA, NA, 7827~
$ rev_women         <dbl> NA, 748833, 315574, NA, NA, 410717, 298164, 131145, 3~
$ exp_men           <dbl> 397818, 817868, 246949, 3059353, 83913, NA, NA, 99612~
$ exp_women         <dbl> NA, 742460, 251184, NA, NA, 432648, 340259, 113886, 3~
```

```r
summary(data)
```

```
     year      institution_name      sports          ef_male_count
 Min.   :2015   Length:132317      Length:132317      Min.   :    0
 1st Qu.:2016   Class :character   Class :character   1st Qu.:  514
 Median :2018   Mode  :character   Mode  :character   Median :  986
 Mean   :2018                                         Mean   : 2126
 3rd Qu.:2019                                         3rd Qu.: 2385
 Max.   :2019                                         Max.   :35954

 ef_female_count sum_partic_men   sum_partic_women    rev_men
 Min.   :    0   Min.   :  0.00   Min.   :  0.00   Min.   :       65
 1st Qu.:  652   1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:    63406
 Median : 1249   Median :  0.00   Median :  6.00   Median :   158069
 Mean   : 2496   Mean   : 14.49   Mean   : 10.86   Mean   :   809028
 3rd Qu.: 2860   3rd Qu.: 20.00   3rd Qu.: 17.00   3rd Qu.:   400383
 Max.   :30325   Max.   :331.00   Max.   :327.00   Max.   :156147208
                                                   NA's   :70460
   rev_women            exp_men             exp_women
 Min.   :       0   Min.   :      65   Min.   :     65
 1st Qu.:   58742   1st Qu.:   63049   1st Qu.:  59294
 Median :  138292   Median :  159649   Median : 141780
 Mean   :  279332   Mean   :  662384   Mean   : 331585
 3rd Qu.:  331034   3rd Qu.:  423980   3rd Qu.: 361817
 Max.   :21440365   Max.   :69718059   Max.   :9485162
 NA's   :63441      NA's   :70460      NA's   :63439
```

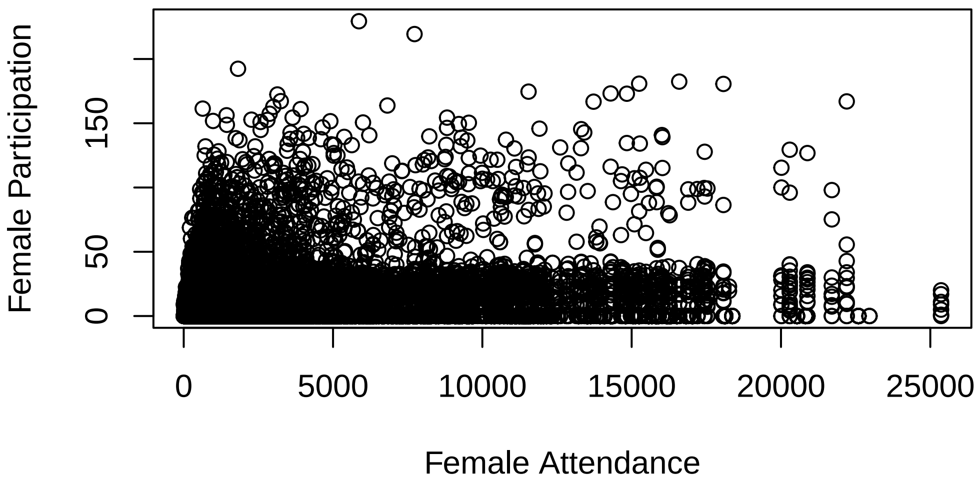
Scatter plots comparing Institution Attendance against Participation by Gender

```r
plot(attendance_data$ef_male_count, attendance_data$sum_partic_men, xlab="Male Attendance"
```



We can see there is ahigh concentration of schools with male attendance between 0 and 5000, as attendance gets higher the distribution stays consistent.

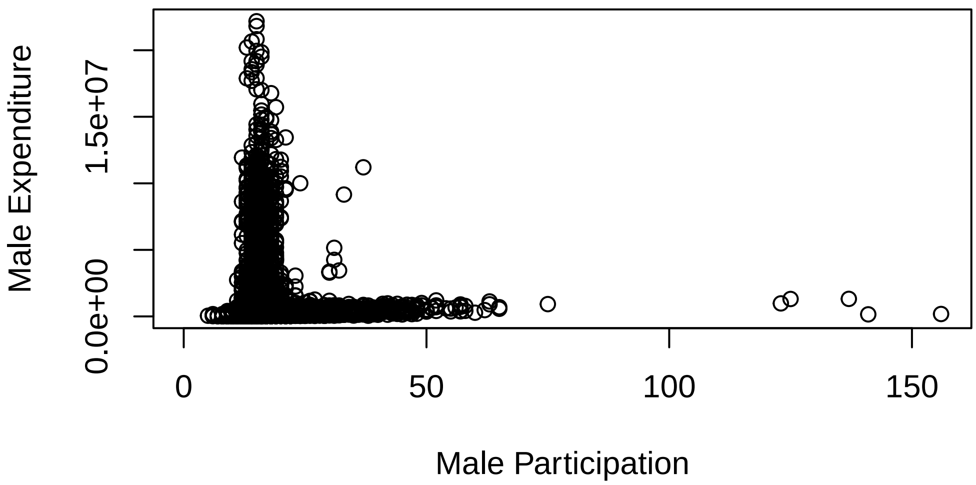
```
plot(attendance_data$ef_female_count, attendance_data$sum_partic_women, xlab="Female Atten
```



Women generally have a lower participation.

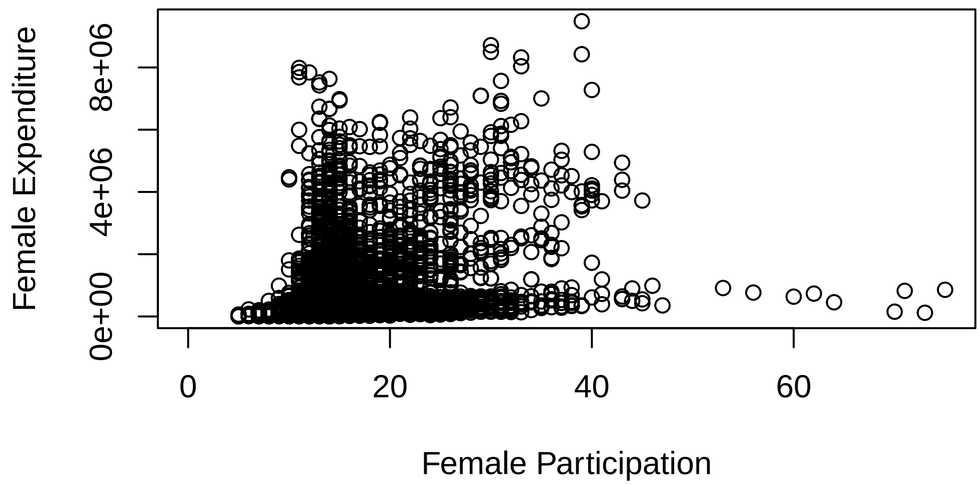
Scatter plots comparing basketball Participation against Expenditures by Gender

```
plot(basketball$sum_partic_men, basketball$exp_men, xlab="Male Participation", ylab="Male
```



There is a high concentration of expenditures within schools where team size is smaller.

```
plot(basketball$sum_partic_women, basketball$exp_women, xlab="Female Participation", ylab=
```



There is no real trend between female expenditures and participation.

```
For the dataset, I could extrapolate my variables of interest as seen here: <https://github.
```

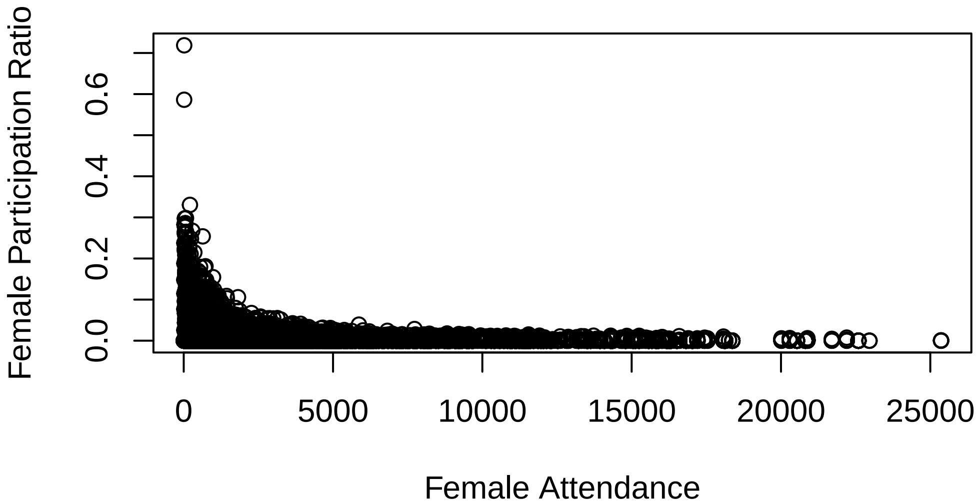
Hypothesis Test 1

Response variable: sum_partic_women

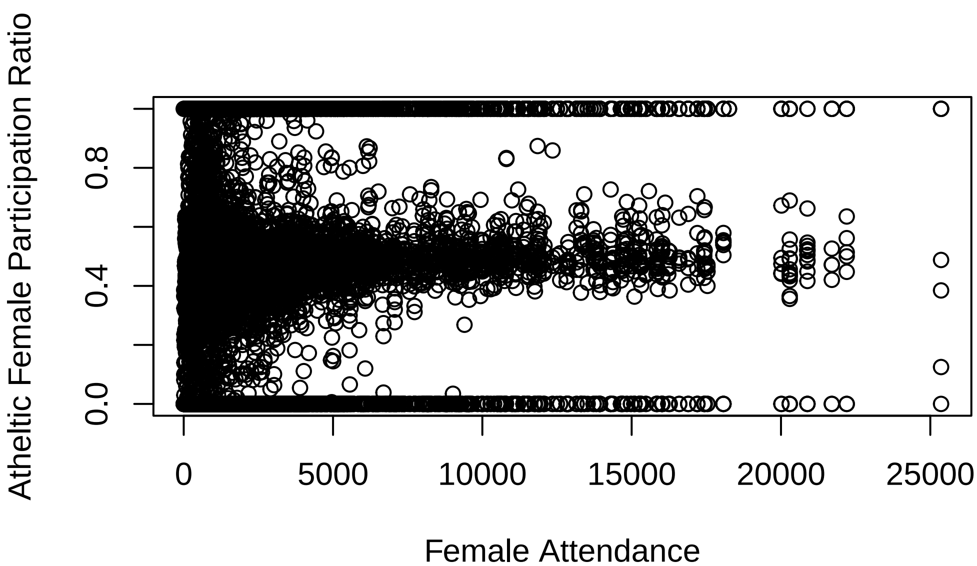
Explanatory variable: sum_partic_women / ef_female_count

Control variable: sum_partic_men

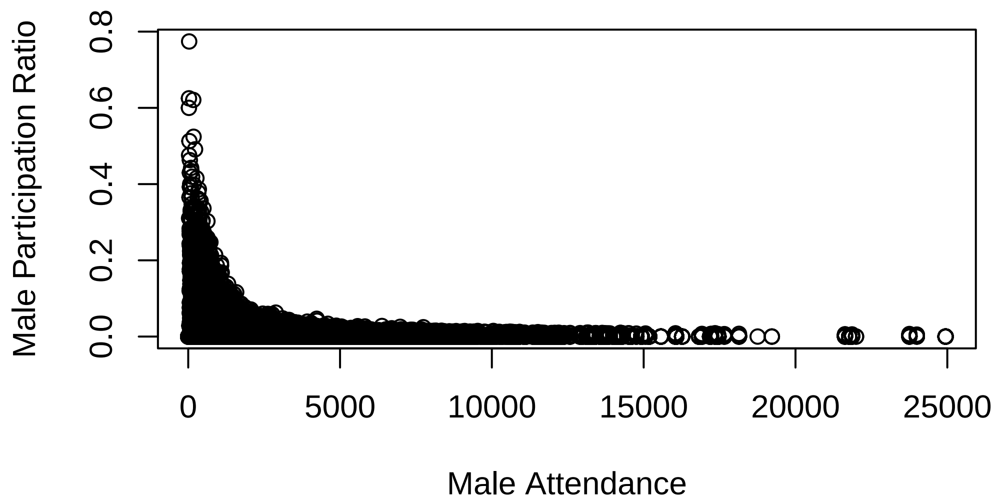
```
attendance_data$female_participation_ratio <- attendance_data$sum_partic_women / attendanc
attendance_data$female_athlete_participation_ratio <- attendance_data$sum_partic_women / (
attendance_data$male_participation_ratio <- attendance_data$sum_partic_men / attendance_da

#ggplot(data = attendance_data, aes(x=ef_female_count, y=female_participation_ratio)) + ge
plot(attendance_data$ef_female_count, attendance_data$female_participation_ratio, xlab="Fe
```




```
plot(attendance_data$ef_female_count, attendance_data$female_athlete_participation_ratio,
```

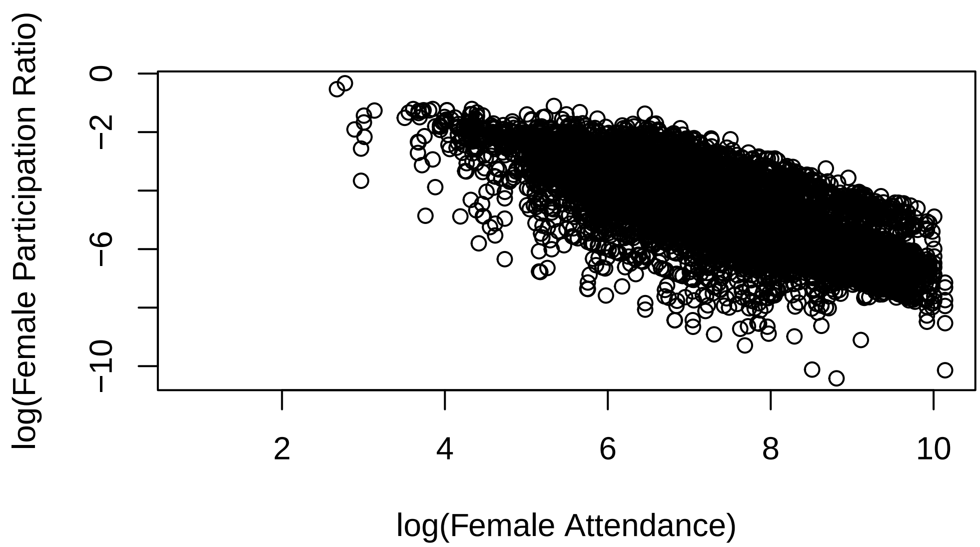


```
plot(attendance_data$ef_male_count, attendance_data$male_participation_ratio, xlab="Male A
```

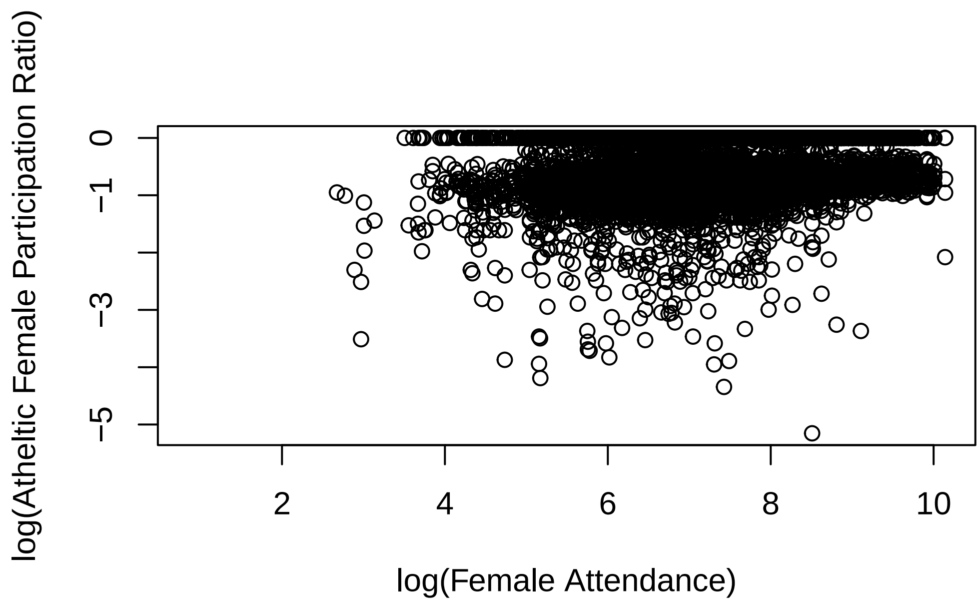


Both plots showing the male/female participation ratio against attendance show a logarithmic pattern.

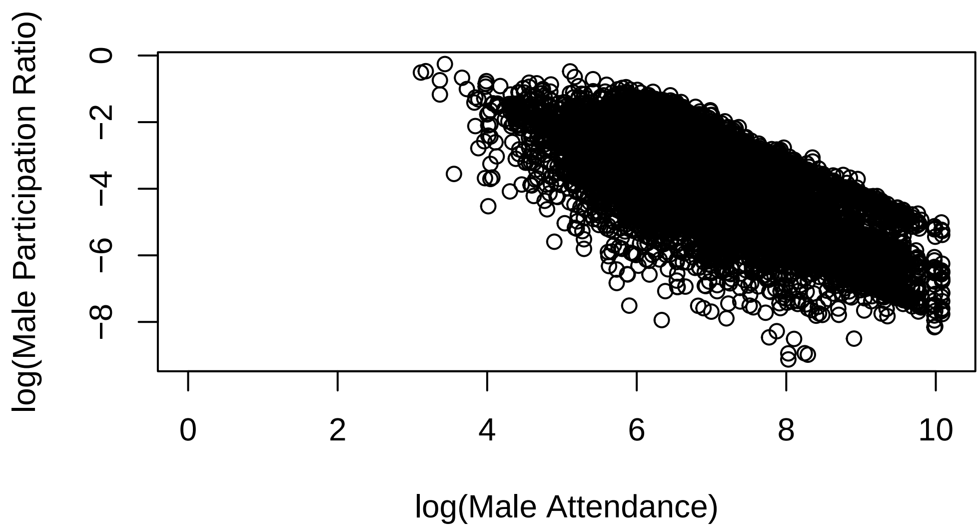
```
plot(log(attendance_data$ef_female_count), log(attendance_data$female_participation_ratio)
```




```
plot(log(attendance_data$ef_female_count), log(attendance_data$female_athlete_participatio
```



```r
plot(log(attendance_data$ef_male_count), log(attendance_data$male_participation_ratio), xl
```




```r
hyp_1_fit_1 <- lm(female_participation_ratio ~ ef_female_count, data = filter(attendance_d
hyp_1_fit_2 <- lm(female_participation_ratio ~ ef_female_count, data = filter(attendance_d
hyp_1_fit_3 <- lm(female_athlete_participation_ratio ~ ef_female_count, data = filter(atte
summary(hyp_1_fit_1)
```

```
Call:
lm(formula = female_participation_ratio ~ ef_female_count, data = filter(attendance_data,
    female_participation_ratio != Inf))

Residuals:
     Min       1Q   Median       3Q      Max
-0.00673 -0.00621 -0.00547 -0.00002  0.71203

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      6.728e-03  7.947e-05   84.66   <2e-16 ***
ef_female_count -6.975e-07  2.044e-08  -34.13   <2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01605 on 63166 degrees of freedom
Multiple R-squared:  0.01811,   Adjusted R-squared:  0.01809
F-statistic:  1165 on 1 and 63166 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_1_fit_2)
```

```
Call:
lm(formula = female_participation_ratio ~ ef_female_count, data = filter(attendance_data,
    female_participation_ratio != Inf & sum_partic_women > 0))

Residuals:
     Min       1Q   Median       3Q      Max
-0.02575 -0.01313 -0.00782  0.00427  0.69150

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      2.729e-02  2.515e-04  108.52   <2e-16 ***
ef_female_count -2.868e-06  6.068e-08  -47.26   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02531 on 16114 degrees of freedom
Multiple R-squared:  0.1218,    Adjusted R-squared:  0.1217
F-statistic:  2234 on 1 and 16114 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_1_fit_3)
```

```
Call:
lm(formula = female_athlete_participation_ratio ~ ef_female_count,
    data = filter(attendance_data, female_athlete_participation_ratio !=
        Inf & sum_partic_women > 0))

Residuals:
    Min      1Q  Median      3Q     Max
-0.7416 -0.1988 -0.1326  0.3447  0.3774
```

```
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     6.226e-01  2.643e-03  235.54   <2e-16 ***
ef_female_count 9.622e-06  6.378e-07   15.09   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.266 on 16115 degrees of freedom
Multiple R-squared:  0.01393,	Adjusted R-squared:  0.01387
F-statistic: 227.6 on 1 and 16115 DF,  p-value: < 2.2e-16
```

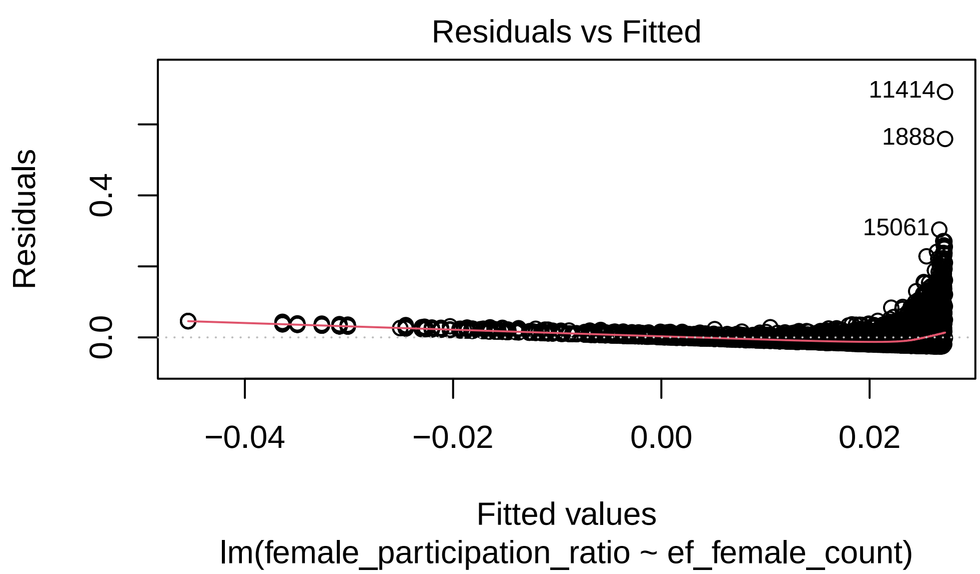
```r
AIC(hyp_1_fit_2)
```

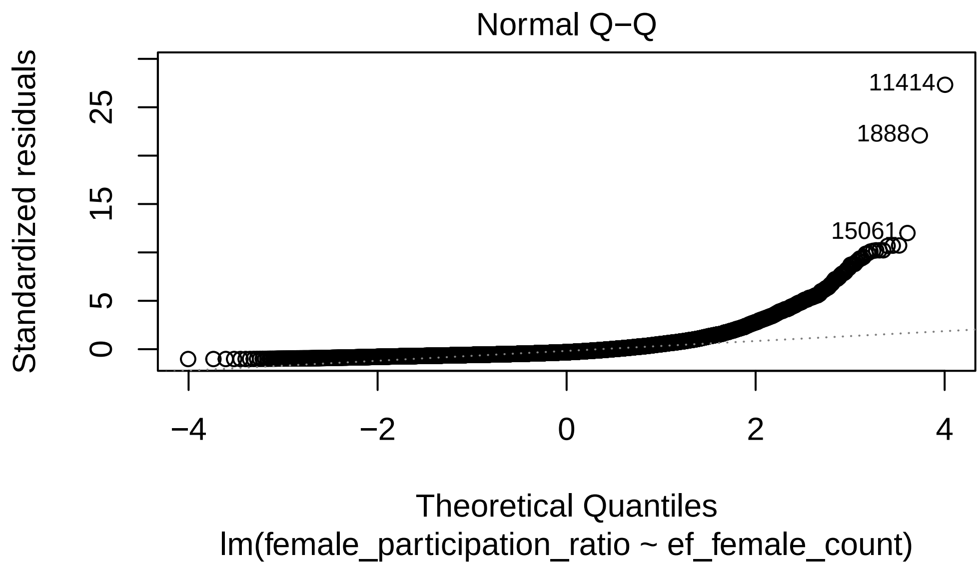
```
[1] -72766.08
```

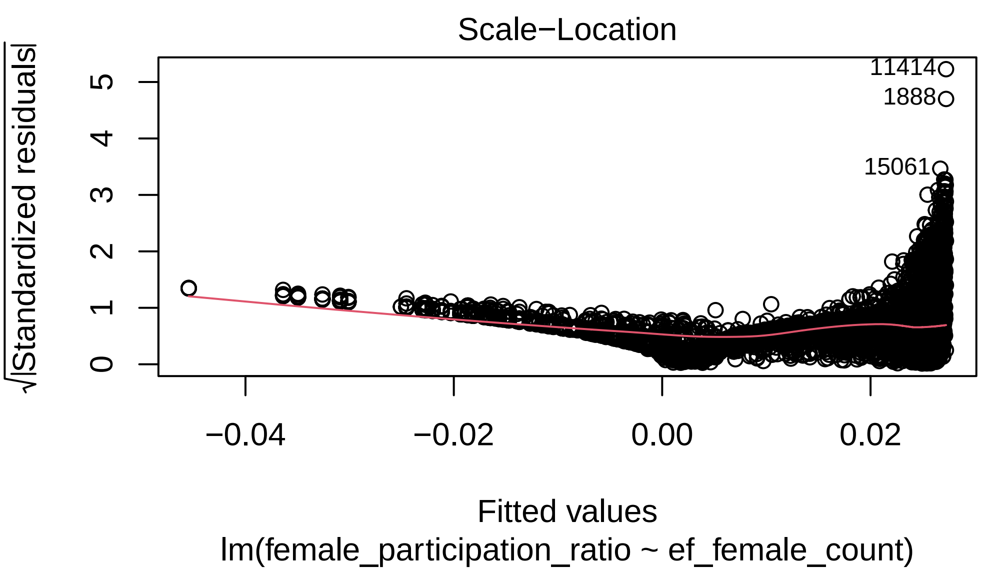
```r
BIC(hyp_1_fit_2)
```

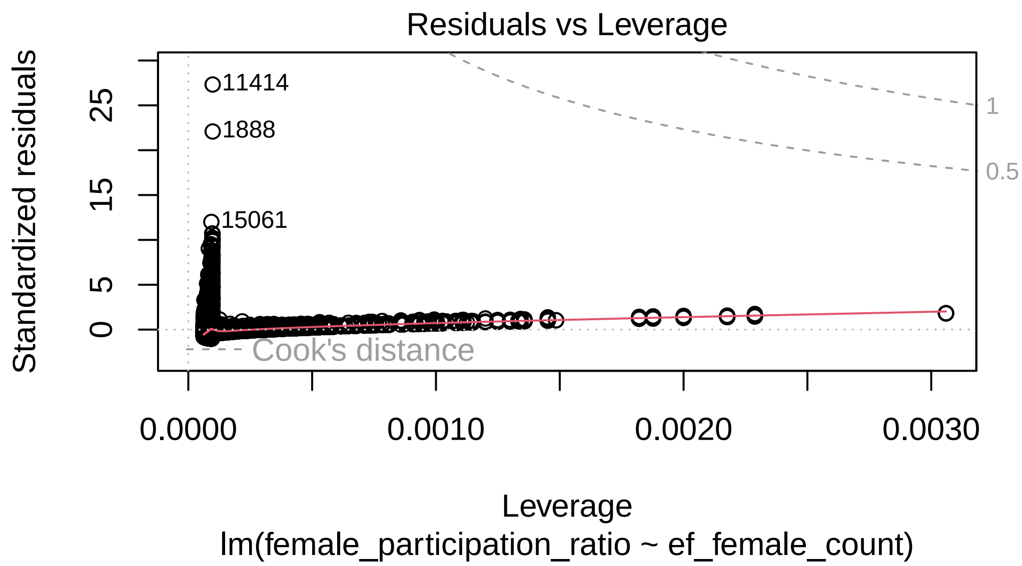
```
[1] -72743.02
```

```r
plot(hyp_1_fit_2)
```




Normal Q−Q
Standardized residuals
0
5
15
25
11414
1888
15061
−4
−2
0
2
4
Theoretical Quantiles
lm(female_participation_ratio ~ ef_female_count)


Scale−Location
√|Standardized residuals|
0
1
2
3
4
5
11414
1888
15061
−0.04
−0.02
0.00
0.02
Fitted values
lm(female_participation_ratio ~ ef_female_count)




```r
hyp_1_fit_4 <- lm(log(female_participation_ratio) ~ log(ef_female_count), data = filter(at
hyp_1_fit_5 <- lm(log(female_athlete_participation_ratio) ~ log(ef_female_count), data = f

summary(hyp_1_fit_4)
```

```
Call:
lm(formula = log(female_participation_ratio) ~ log(ef_female_count),
    data = filter(attendance_data, female_participation_ratio !=
        Inf & sum_partic_women > 0 & ef_female_count > 0))

Residuals:
    Min      1Q  Median      3Q     Max
-4.5862 -0.3587  0.0456  0.3977  2.4977

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           1.523962   0.037858   40.25   <2e-16 ***
log(ef_female_count) -0.835062   0.005171 -161.48   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.7151 on 16114 degrees of freedom
Multiple R-squared:  0.6181,	Adjusted R-squared:  0.618 
F-statistic: 2.608e+04 on 1 and 16114 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_1_fit_5)
```

```

Call:
lm(formula = log(female_athlete_participation_ratio) ~ log(ef_female_count), 
    data = filter(attendance_data, female_athlete_participation_ratio != 
        Inf & female_athlete_participation_ratio > 0 & ef_female_count > 
        0))

Residuals:
    Min      1Q  Median      3Q     Max 
-4.7085 -0.2825 -0.1368  0.4709  0.7736 

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          -1.004208   0.023609  -42.54   <2e-16 ***
log(ef_female_count)  0.065751   0.003225   20.39   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4459 on 16114 degrees of freedom
Multiple R-squared:  0.02515,	Adjusted R-squared:  0.02509 
F-statistic: 415.7 on 1 and 16114 DF,  p-value: < 2.2e-16
```

```r
AIC(hyp_1_fit_4)
```

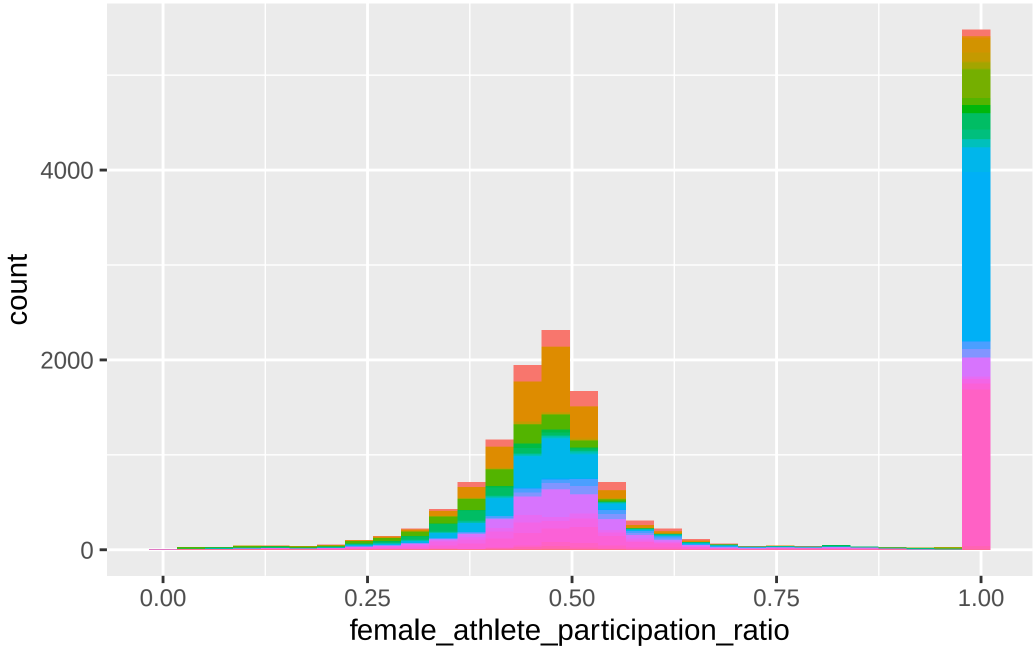
```
[1] 34930.1
```

```r
BIC(hyp_1_fit_4)
```

```
[1] 34953.16
```

```r
#hist(filter(attendance_data, female_athlete_participation_ratio != Inf & sum_partic_women

ggplot(data = filter(attendance_data, female_athlete_participation_ratio != Inf & sum_part
```

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



Female athletic participation has a normal distribution with an outlying spike on the right end.

Hypothesis Test 2

Response variable: exp_women

Explanatory variable: sum_partic_women / ef_female_count

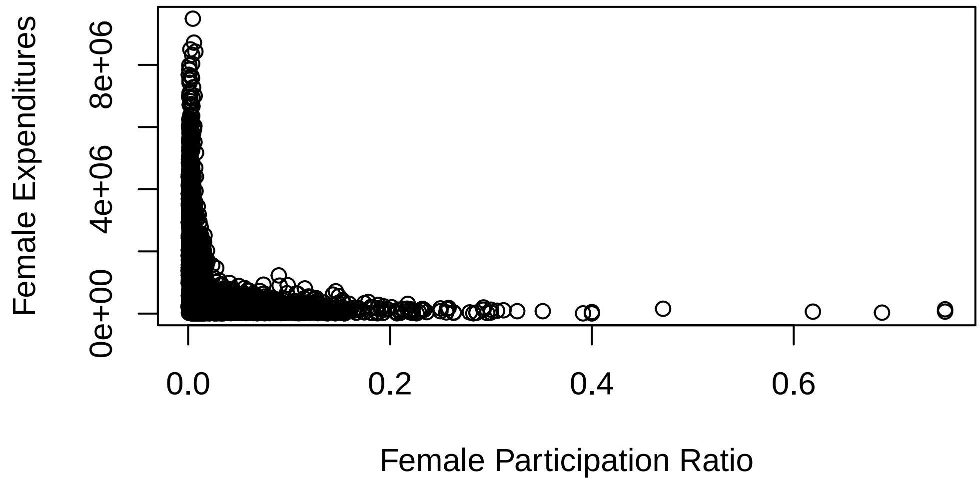
Control variable: exp_men

```r
basketball$female_participation_ratio <- basketball$sum_partic_women / basketball$ef_femal
basketball$female_athlete_participation_ratio <- basketball$sum_partic_women / (basketball

basketball$male_participation_ratio <- basketball$sum_partic_men / basketball$ef_male_coun
```

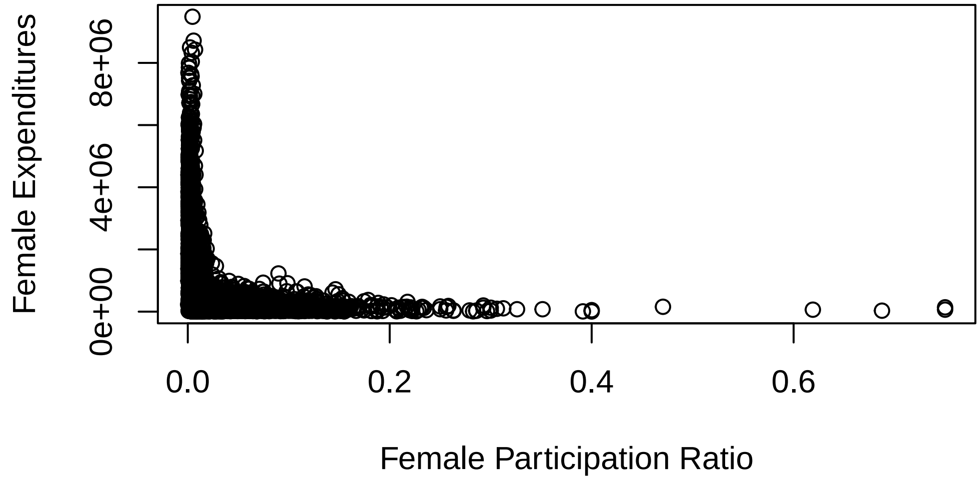
Transform basketball table to separate men and women by column

```
female <- as.data.frame(basketball[, c("year", "institution_name", "sports", "ef_female_co
female$gender <- "Female"
female <- female %>% rename("ef_count"="ef_female_count", "sum_partic"="sum_partic_women",

male <- as.data.frame(basketball[, c("year", "institution_name", "sports", "ef_male_count"
male$gender <- "Male"
male <- male %>% rename("ef_count"="ef_male_count", "sum_partic"="sum_partic_men", "rev"="
basketball_hist <- rbind(male, female)
basketball_hist <- filter(basketball_hist, sum_partic > 0)
```

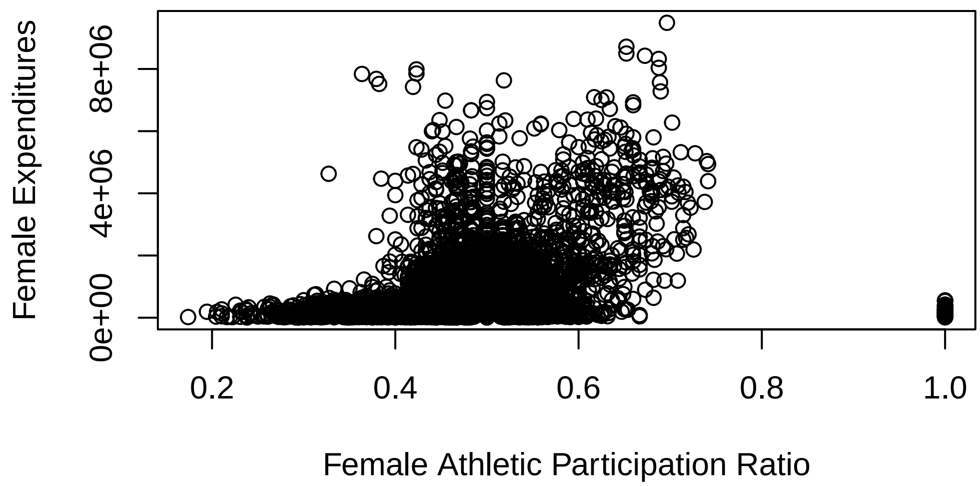
```
plot(basketball$female_participation_ratio, basketball$exp_women, xlab="Female Participati
```



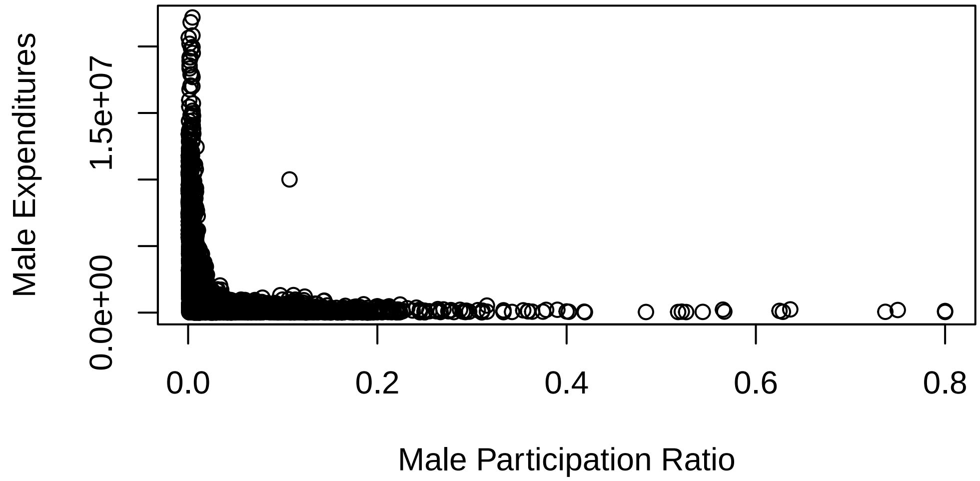

```
plot(filter(basketball, sum_partic_women > 0)$female_participation_ratio, filter(basketbal
```




```
plot(filter(basketball, sum_partic_women > 0)$female_athlete_participation_ratio, filter(b
```

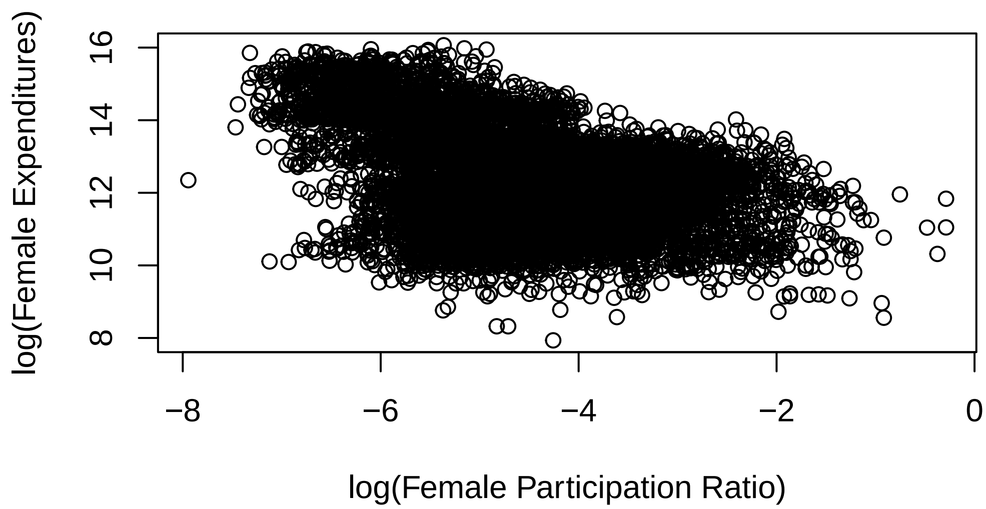


```
plot(basketball$male_participation_ratio, basketball$exp_men, xlab="Male Participation Rat
```

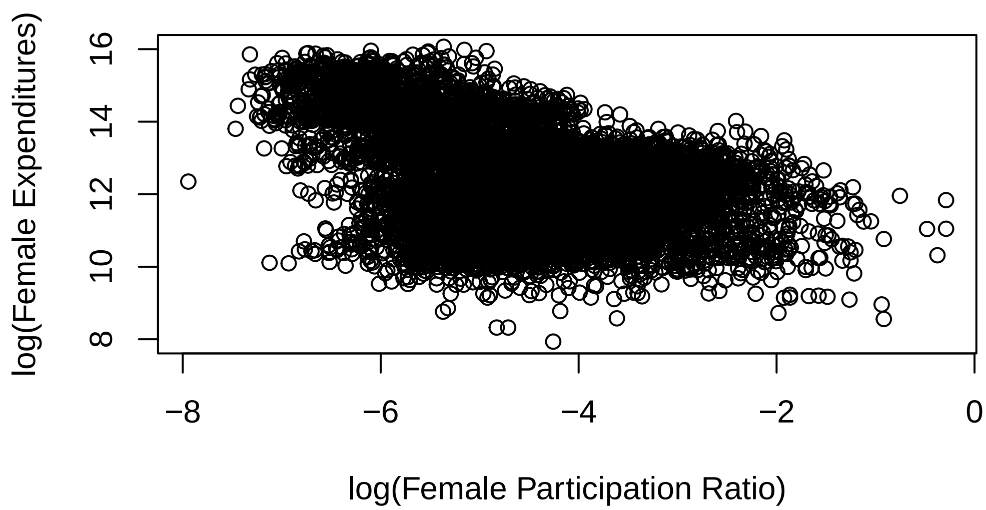


The plot showing female athlete participation against expenditures has a very slight trend, but the other three plots show a strong logarithmic pattern.

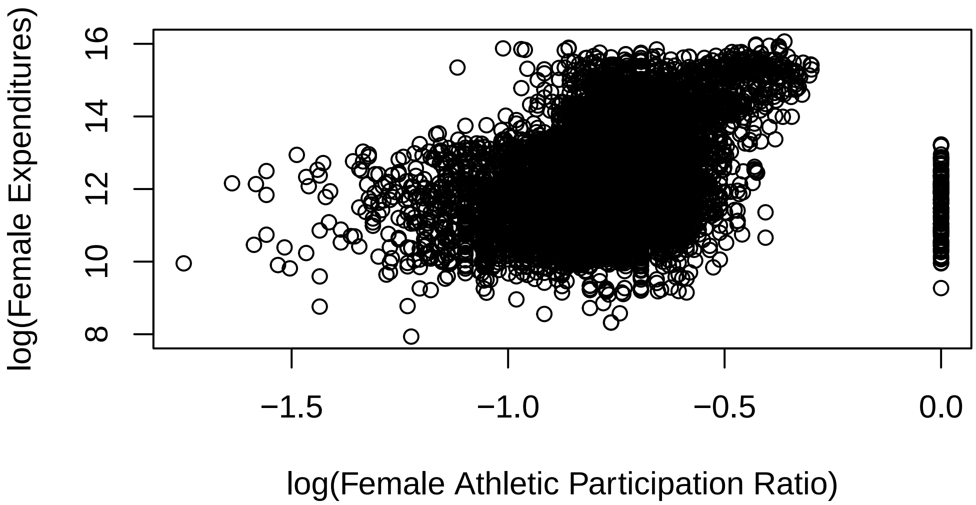
```
plot(log(basketball$female_participation_ratio), log(basketball$exp_women), xlab="log(Fema
```



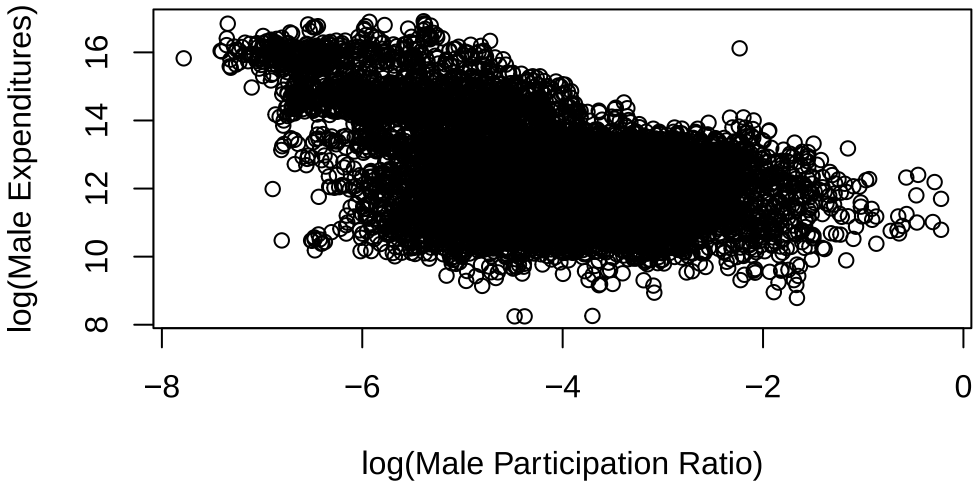

```
plot(log(filter(basketball, sum_partic_women > 0)$female_participation_ratio), log(filter(
```



```r
plot(log(filter(basketball, sum_partic_women > 0)$female_athlete_participation_ratio), log
```




```r
plot(log(basketball$male_participation_ratio), log(basketball$exp_men), xlab="log(Male Par
```




```
hyp_2_fit_1 <- lm(exp_women ~ female_participation_ratio, data = filter(basketball, female
hyp_2_fit_2 <- lm(exp_women ~ female_participation_ratio, data = filter(basketball, female
hyp_2_fit_3 <- lm(exp_women ~ female_athlete_participation_ratio, data = filter(basketball
summary(hyp_2_fit_1)
```

```
Call:
lm(formula = exp_women ~ female_participation_ratio, data = filter(basketball,
    female_participation_ratio != Inf))

Residuals:
    Min      1Q  Median      3Q     Max
-669197 -493134 -320286   10208 8815838

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                  697788      11619   60.06   <2e-16 ***
female_participation_ratio -6077440     300720  -20.21   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 958400 on 9552 degrees of freedom
```

```
  (439 observations deleted due to missingness)
Multiple R-squared:  0.04101,   Adjusted R-squared:  0.0409
F-statistic: 408.4 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_2_fit_2)
```

```
Call:
lm(formula = exp_women ~ female_participation_ratio, data = filter(basketball,
    female_participation_ratio != Inf & sum_partic_women > 0))

Residuals:
    Min      1Q  Median      3Q     Max
-669197 -493134 -320286   10208 8815838

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                  697788      11619   60.06   <2e-16 ***
female_participation_ratio -6077440     300720  -20.21   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 958400 on 9552 degrees of freedom
Multiple R-squared:  0.04101,   Adjusted R-squared:  0.0409
F-statistic: 408.4 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_2_fit_3)
```

```
Call:
lm(formula = exp_women ~ female_athlete_participation_ratio,
    data = filter(basketball, female_participation_ratio != Inf &
        sum_partic_women > 0))

Residuals:
     Min       1Q   Median       3Q      Max
-2056112  -437273  -268066    15346  8284247

Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)                          -785373      53101  -14.79   <2e-16 ***
female_athlete_participation_ratio  2852106     109722   25.99   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 945800 on 9552 degrees of freedom
Multiple R-squared:  0.06606,   Adjusted R-squared:  0.06597
F-statistic: 675.7 on 1 and 9552 DF,  p-value: < 2.2e-16
```

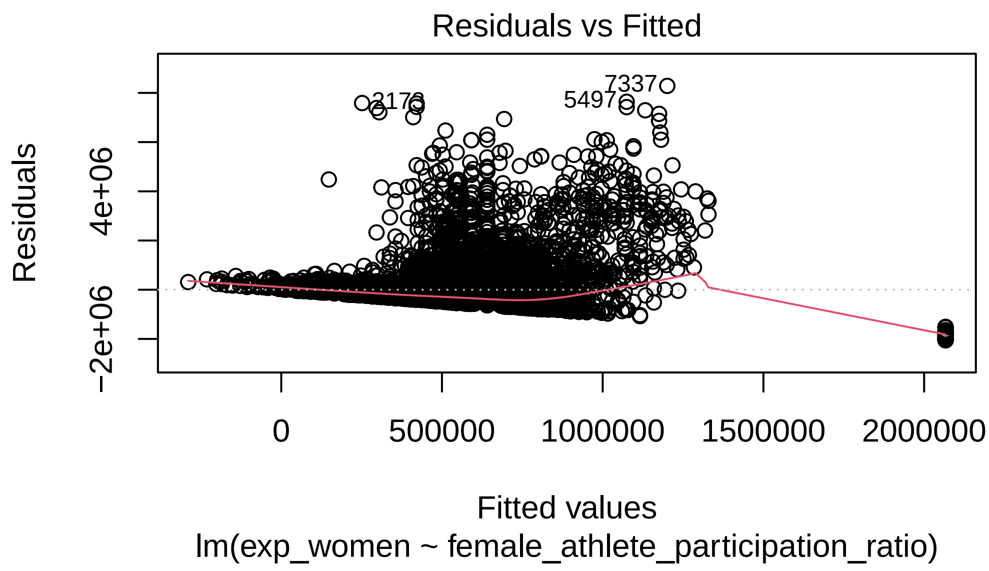
```r
AIC(hyp_2_fit_3)
```

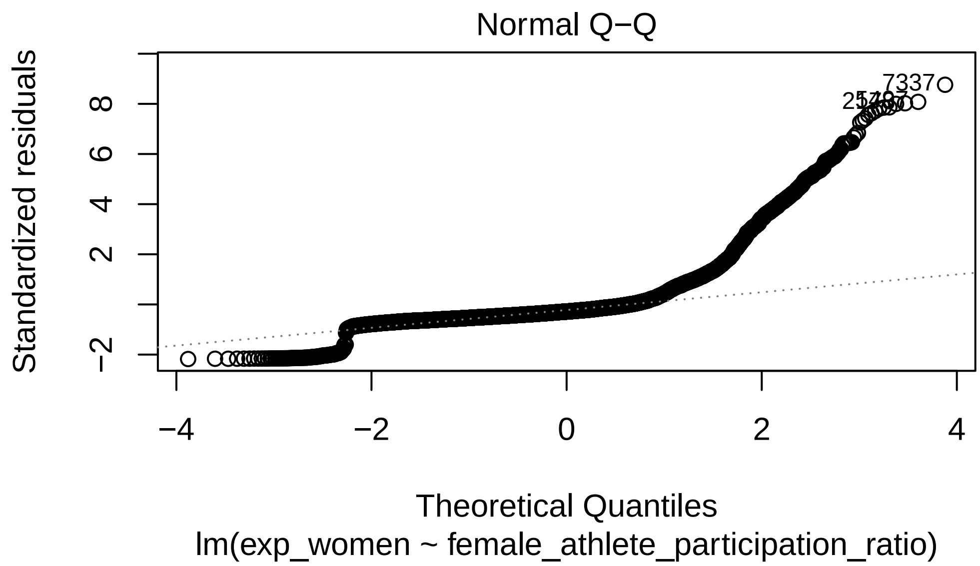
```
[1] 290039
```

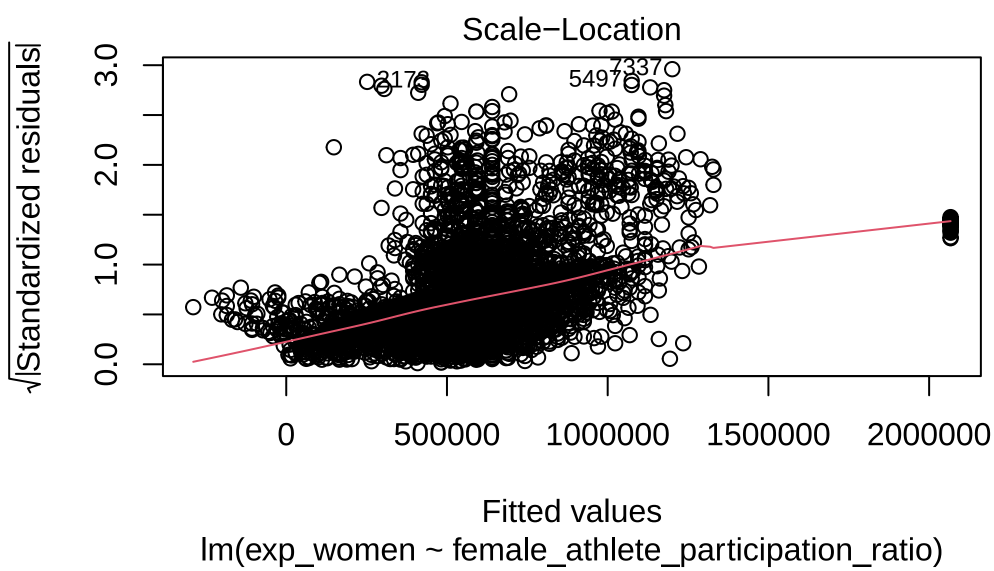
```r
BIC(hyp_2_fit_3)
```

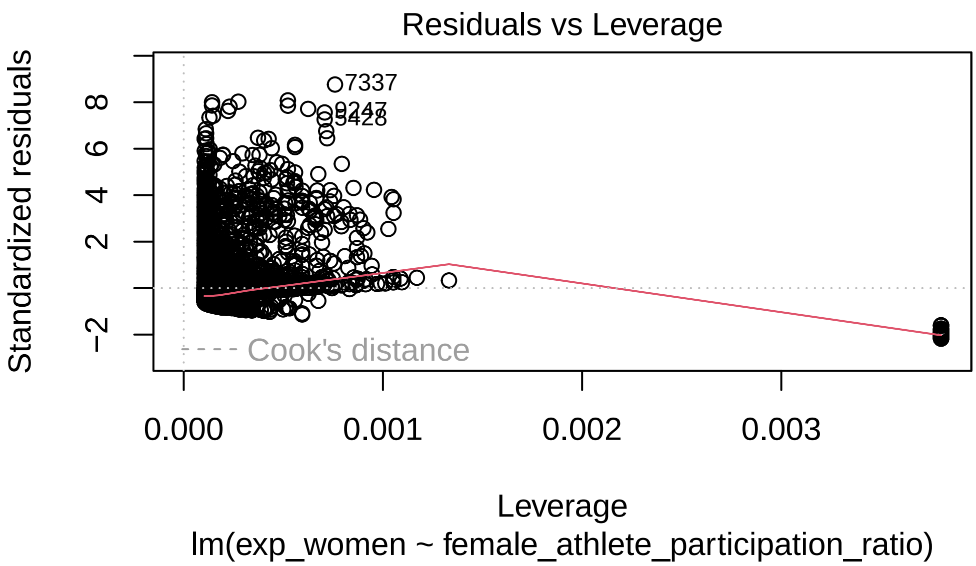
```
[1] 290060.5
```

```r
plot(hyp_2_fit_3)
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(exp_women ~ female_athlete_participation_ratio)
7337


Scale−Location
√|Standardized residuals|
Fitted values
lm(exp_women ~ female_athlete_participation_ratio)
7337
5497




```r
# Controls
hyp_2_fit_c1 <- lm(exp_women ~ rev_women, data = filter(basketball, female_participation_r
hyp_2_fit_c2 <- lm(exp_women ~ exp_men, data = filter(basketball, female_participation_rat
hyp_2_fit_c3 <- lm(exp_women ~ sum_partic_men, data = filter(basketball, female_participat

summary(hyp_2_fit_c1)
```

```
Call:
lm(formula = exp_women ~ rev_women, data = filter(basketball,
    female_participation_ratio != Inf))

Residuals:
      Min        1Q    Median        3Q       Max
-16165268   -106752   -102785    -91699   5879334

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.084e+05  7.487e+03   14.48   <2e-16 ***
rev_women   9.658e-01  8.169e-03  118.23   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 623500 on 9552 degrees of freedom
  (439 observations deleted due to missingness)
Multiple R-squared:  0.5941,	Adjusted R-squared:  0.594 
F-statistic: 1.398e+04 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_2_fit_c2)
```

```

Call:
lm(formula = exp_women ~ exp_men, data = filter(basketball, female_participation_ratio !=
    Inf))

Residuals:
     Min       1Q   Median       3Q      Max 
-5084097  -131233   -77806    69567  5039235 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 1.715e+05  4.216e+03   40.67   <2e-16 ***
exp_men     4.335e-01  1.836e-03  236.13   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 374200 on 9439 degrees of freedom
  (552 observations deleted due to missingness)
Multiple R-squared:  0.8552,	Adjusted R-squared:  0.8552 
F-statistic: 5.576e+04 on 1 and 9439 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_2_fit_c3)
```

```

Call:
lm(formula = exp_women ~ sum_partic_men, data = filter(basketball,
    female_participation_ratio != Inf))

Residuals:
    Min      1Q  Median      3Q     Max 
-638434 -478799 -364507  -39436 8914009 
```

```
Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)      649055      27559  23.552  < 2e-16 ***
sum_partic_men    -4582       1523  -3.008  0.00264 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 978200 on 9552 degrees of freedom
  (439 observations deleted due to missingness)
Multiple R-squared:  0.0009464, Adjusted R-squared:  0.0008418
F-statistic: 9.049 on 1 and 9552 DF,  p-value: 0.002635
```

```
# Logarithmic
hyp_2_fit_4 <- lm(log(exp_women) ~ log(female_participation_ratio), data = filter(basketba
hyp_2_fit_5 <- lm(log(exp_women) ~ log(female_athlete_participation_ratio), data = filter(
summary(hyp_2_fit_4)
```

```
Call:
lm(formula = log(exp_women) ~ log(female_participation_ratio),
    data = filter(basketball, female_participation_ratio != Inf &
        sum_partic_women > 0 & exp_women > 0))

Residuals:
    Min      1Q  Median      3Q     Max
-4.3169 -0.8131  0.0467  0.9068  3.3624

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                     10.14651    0.05119  198.21   <2e-16 ***
log(female_participation_ratio) -0.49438    0.01107  -44.65   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.187 on 9552 degrees of freedom
Multiple R-squared:  0.1726,    Adjusted R-squared:  0.1726
F-statistic:  1993 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```
summary(hyp_2_fit_5)
```

```
Call:
lm(formula = log(exp_women) ~ log(female_athlete_participation_ratio),
    data = filter(basketball, female_participation_ratio != Inf &
        sum_partic_women > 0 & exp_women > 0))

Residuals:
    Min      1Q  Median      3Q     Max
-4.8916 -0.8459 -0.0923  0.8256  4.1097

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                             14.16222    0.05788   244.7   <2e-16
log(female_athlete_participation_ratio)  2.36977    0.07452    31.8   <2e-16

(Intercept)                             ***
log(female_athlete_participation_ratio) ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.241 on 9552 degrees of freedom
Multiple R-squared:  0.09572,   Adjusted R-squared:  0.09563
F-statistic:  1011 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```r
AIC(hyp_2_fit_4)
```

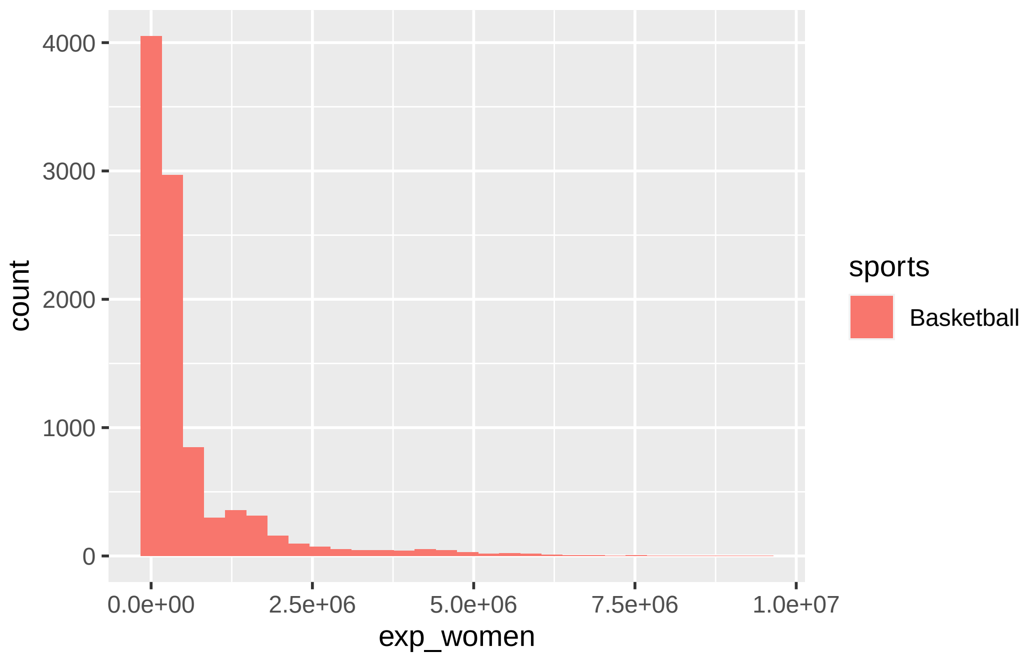
```
[1] 30396.6
```

```r
BIC(hyp_2_fit_4)
```

```
[1] 30418.09
```

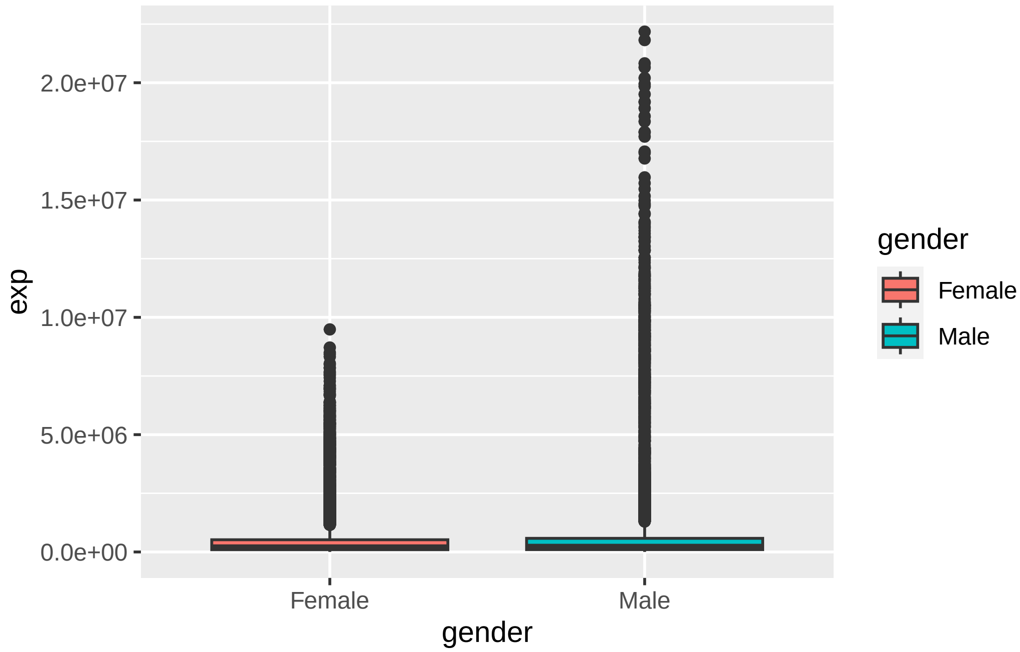
```r
#hist(filter(basketball, female_athlete_participation_ratio != Inf & sum_partic_women > 0)

ggplot(data=filter(basketball, female_athlete_participation_ratio != Inf & sum_partic_wome
```

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



The female participation histogram within basketball has a heavy concentration toward lower values.

```
#boxplot(exp ~ gender, data=basketball_hist, ylab="Expenditures")

ggplot(data=basketball_hist, aes(x=gender, y=exp, fill=gender)) + geom_boxplot()
```



Within basketball women and men have a similar mean expenditure, but at a height men receive nearly twice the funds as women.

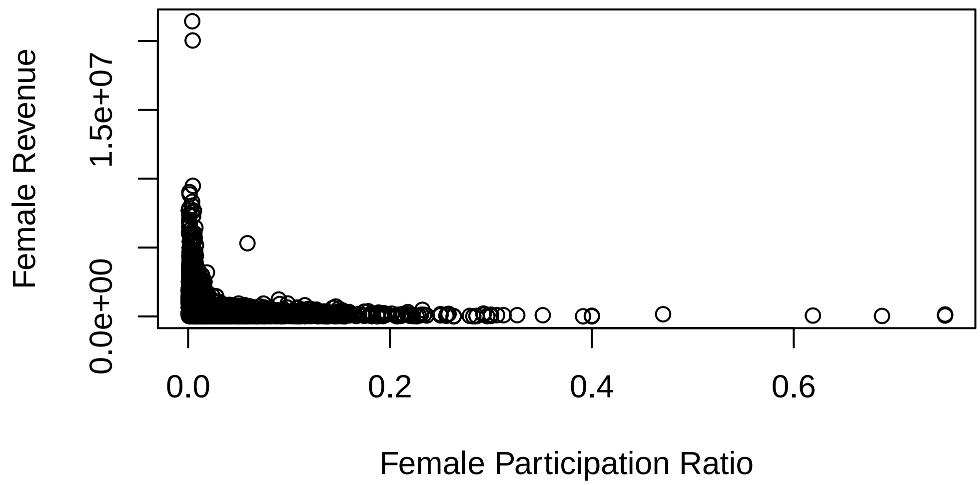
Hypothesis Test 3

Response variable: rev_women

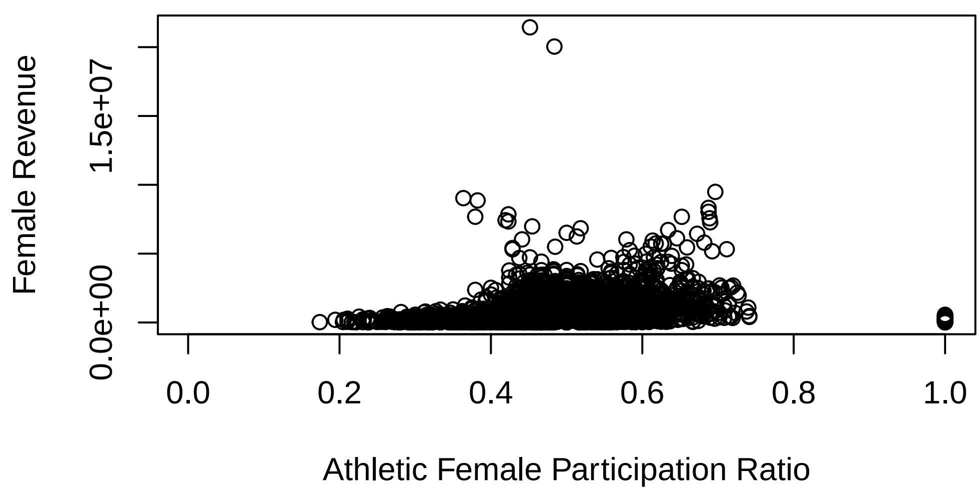
Explanatory variable: sum_partic_women / ef_female_count

Control variable: rev_men

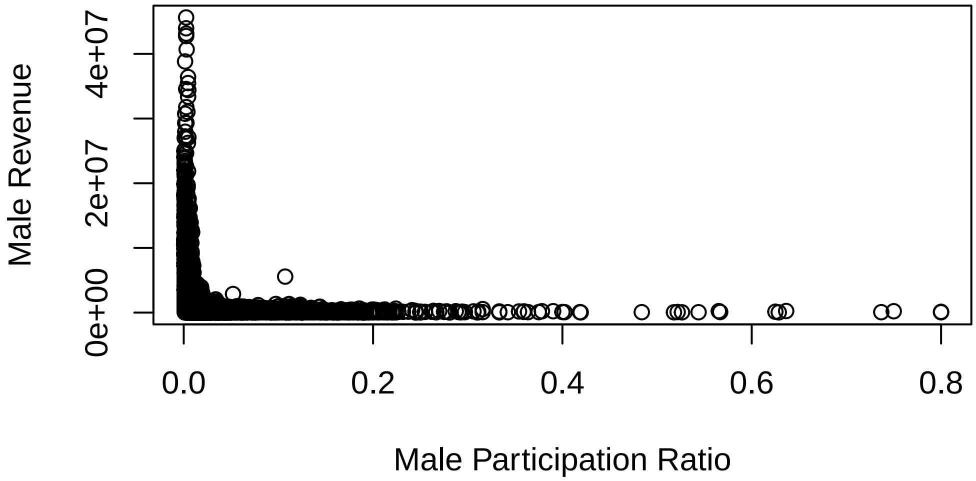
```
plot(basketball$female_participation_ratio, basketball$rev_women, xlab="Female Participati
```




```
plot(basketball$female_athlete_participation_ratio, basketball$rev_women, xlab="Athletic F
```

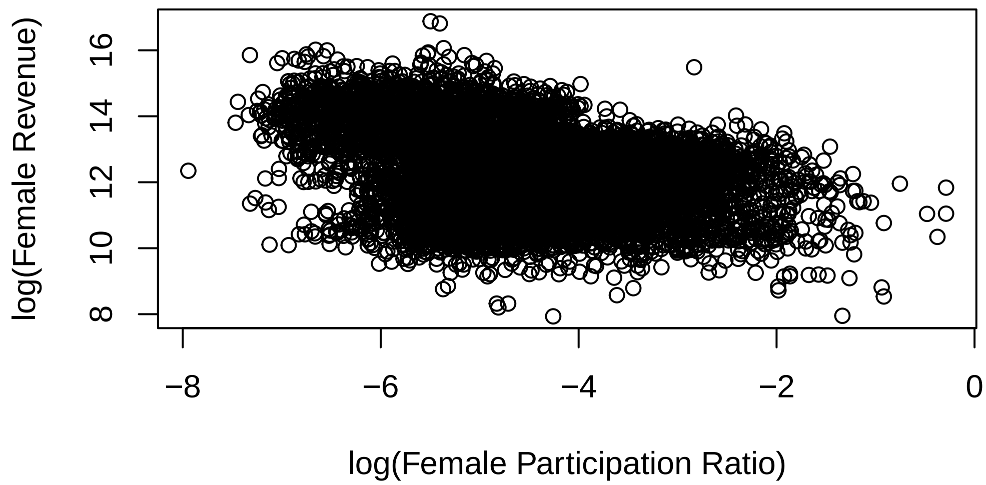


```
plot(basketball$male_participation_ratio, basketball$rev_men, xlab="Male Participation Rat
```

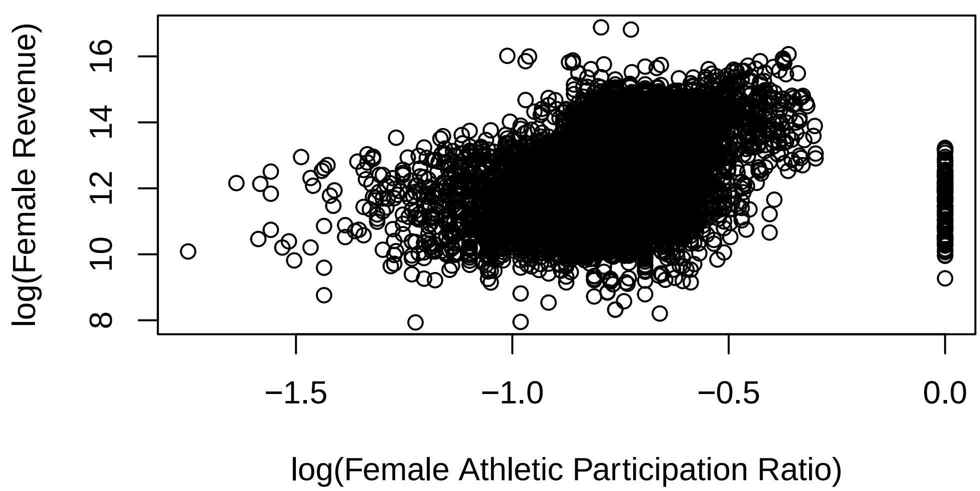


Similar to the plots in hypothesis tests one and two, female athletic participation plotted against revenue has a very light trend; but revenue against female participation/female attendance shows a strong logarithmic pattern.

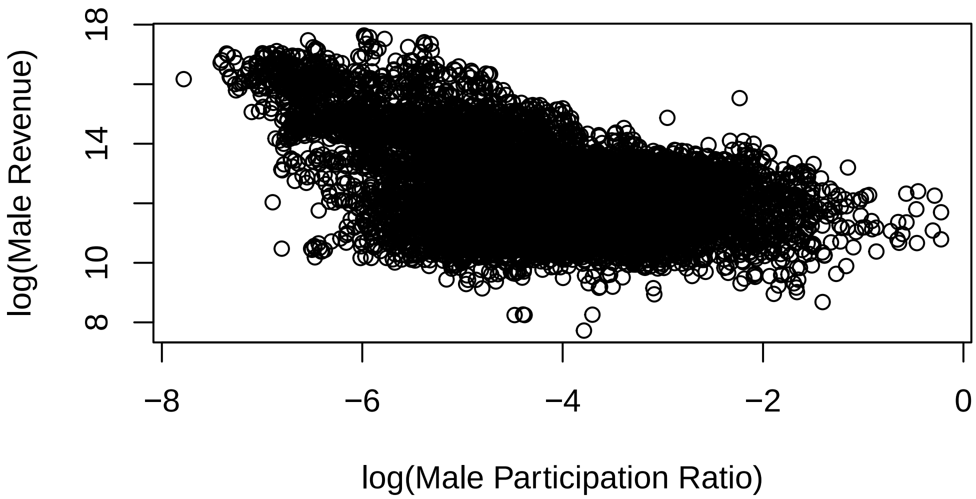
```
plot(log(basketball$female_participation_ratio), log(basketball$rev_women), xlab="log(Fema
```




```
plot(log(basketball$female_athlete_participation_ratio), log(basketball$rev_women), xlab="
```



```r
plot(log(basketball$male_participation_ratio), log(basketball$rev_men), xlab="log(Male Par
```




```r
hyp_3_fit_1 <- lm(rev_women ~ female_participation_ratio, data = filter(basketball, female
hyp_3_fit_2 <- lm(rev_women ~ female_participation_ratio, data = filter(basketball, female
hyp_3_fit_3 <- lm(rev_women ~ female_athlete_participation_ratio, data = filter(basketball
summary(hyp_3_fit_1)
```

```
Call:
lm(formula = rev_women ~ female_participation_ratio, data = filter(basketball,
    female_participation_ratio != Inf))

Residuals:
     Min       1Q   Median       3Q      Max
 -546362  -388437  -240863    59195 20887546

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                  570845       9308   61.33   <2e-16 ***
female_participation_ratio -4393071     240902  -18.24   <2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 767800 on 9552 degrees of freedom
  (439 observations deleted due to missingness)
Multiple R-squared:  0.03364,   Adjusted R-squared:  0.03354
F-statistic: 332.5 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_3_fit_2)
```

```
Call:
lm(formula = rev_women ~ female_participation_ratio, data = filter(basketball,
    female_participation_ratio != Inf & sum_partic_women > 0))

Residuals:
     Min       1Q   Median       3Q      Max
 -546362  -388437  -240863    59195 20887546

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                  570845       9308   61.33   <2e-16 ***
female_participation_ratio -4393071     240902  -18.24   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 767800 on 9552 degrees of freedom
Multiple R-squared:  0.03364,   Adjusted R-squared:  0.03354
F-statistic: 332.5 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_3_fit_3)
```

```
Call:
lm(formula = rev_women ~ female_athlete_participation_ratio,
    data = filter(basketball, female_participation_ratio != Inf))

Residuals:
     Min       1Q   Median       3Q      Max
-1407754  -348702  -220354    43044 21003989
```

```
Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)                         -372330      42943   -8.67   <2e-16 ***
female_athlete_participation_ratio  1790705      88733   20.18   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 764900 on 9552 degrees of freedom
  (439 observations deleted due to missingness)
Multiple R-squared:  0.04089,	Adjusted R-squared:  0.04079 
F-statistic: 407.3 on 1 and 9552 DF,  p-value: < 2.2e-16
```

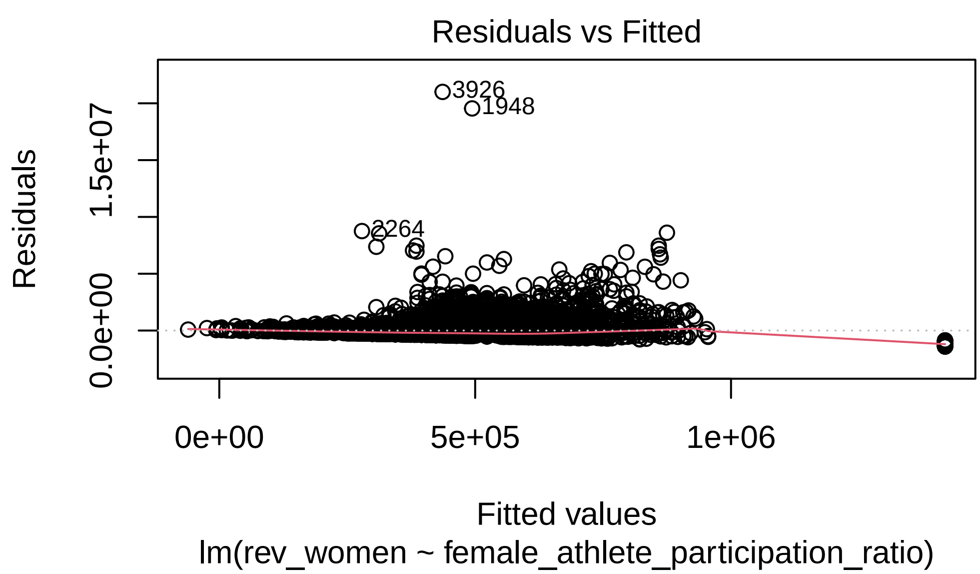
```r
AIC(hyp_3_fit_3)
```

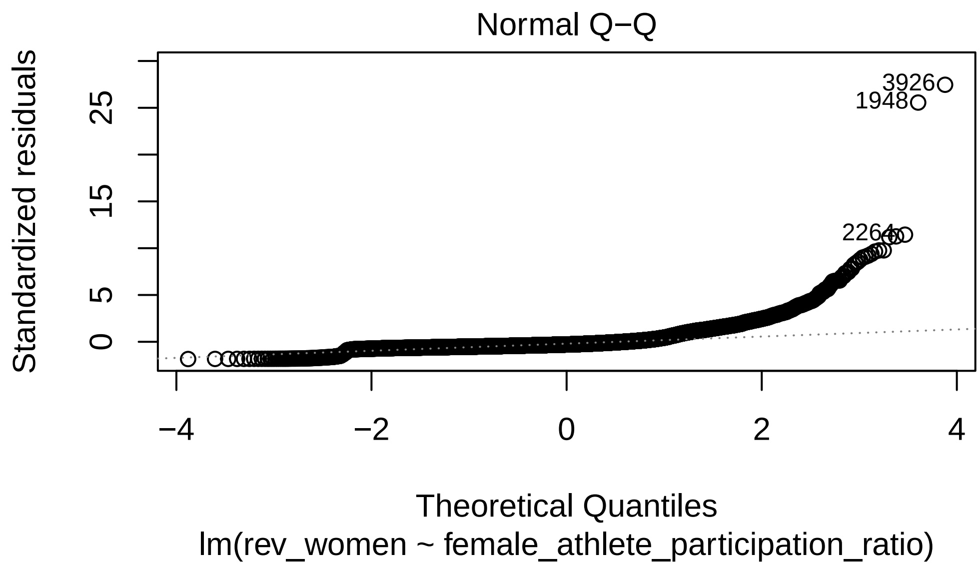
```
[1] 285982.1
```

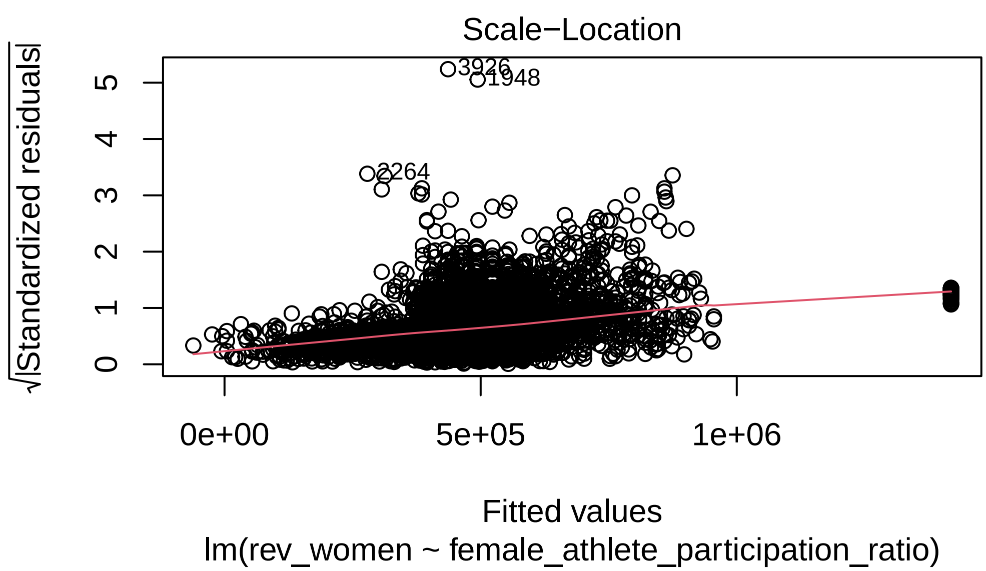
```r
BIC(hyp_3_fit_3)
```

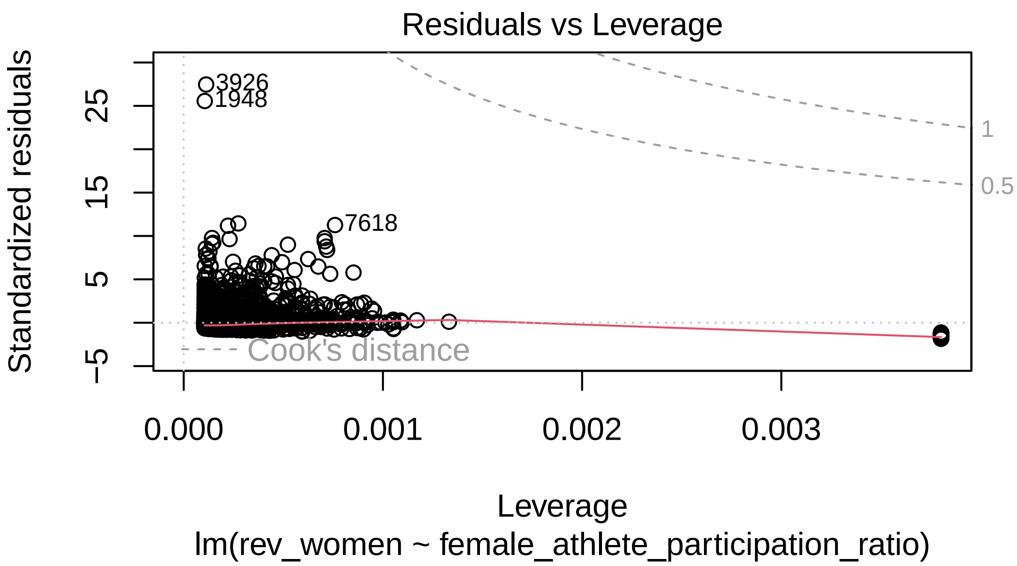
```
[1] 286003.6
```

```r
plot(hyp_3_fit_3)
```




Normal Q−Q
Standardized residuals
0
5
15
25
3926
1948
2264
−4
−2
0
2
4
Theoretical Quantiles
lm(rev_women ~ female_athlete_participation_ratio)


Scale−Location
√|Standardized residuals|
0
1
2
3
4
5
3926
1948
2264
0e+00
5e+05
1e+06
Fitted values
lm(rev_women ~ female_athlete_participation_ratio)




```
# Controls
hyp_3_fit_c1 <- lm(rev_women ~ exp_women, data = filter(basketball, female_participation_r
hyp_3_fit_c2 <- lm(rev_women ~ rev_men, data = filter(basketball, female_participation_rat
hyp_3_fit_c3 <- lm(rev_women ~ sum_partic_men, data = filter(basketball, female_participat

summary(hyp_3_fit_c1)
```

```
Call:
lm(formula = rev_women ~ exp_women, data = filter(basketball,
    female_participation_ratio != Inf))

Residuals:
     Min       1Q   Median       3Q      Max
-3402605   -94839   -54643    56058 18451560

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.281e+05  5.896e+03   21.72   <2e-16 ***
exp_women   6.151e-01  5.202e-03  118.23   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 497600 on 9552 degrees of freedom
  (439 observations deleted due to missingness)
Multiple R-squared:  0.5941,    Adjusted R-squared:  0.594
F-statistic: 1.398e+04 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_3_fit_c2)
```

```

Call:
lm(formula = rev_women ~ rev_men, data = filter(basketball, female_participation_ratio !=
    Inf))

Residuals:
     Min       1Q   Median       3Q      Max
-5310089  -259684  -173394    73537 20160179

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.337e+05  7.284e+03   45.81   <2e-16 ***
rev_men     1.358e-01  2.239e-03   60.63   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 665700 on 9439 degrees of freedom
  (552 observations deleted due to missingness)
Multiple R-squared:  0.2803,    Adjusted R-squared:  0.2802
F-statistic:  3676 on 1 and 9439 DF,  p-value: < 2.2e-16
```

```r
summary(hyp_3_fit_c3)
```

```

Call:
lm(formula = rev_women ~ sum_partic_men, data = filter(basketball,
    female_participation_ratio != Inf))

Residuals:
     Min       1Q   Median       3Q      Max
 -507695  -384110  -274416    32257 20960910
```

```
Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)      518316      21999   23.56   <2e-16 ***
sum_partic_men    -2286       1216   -1.88   0.0602 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 780900 on 9552 degrees of freedom
  (439 observations deleted due to missingness)
Multiple R-squared:  0.0003698,	Adjusted R-squared:  0.0002652 
F-statistic: 3.534 on 1 and 9552 DF,  p-value: 0.06016
```

```
hyp_3_fit_4 <- lm(log(rev_women) ~ log(female_participation_ratio), data = filter(basketba
hyp_3_fit_5 <- lm(log(rev_women) ~ log(female_athlete_participation_ratio), data = filter(
summary(hyp_3_fit_4)
```

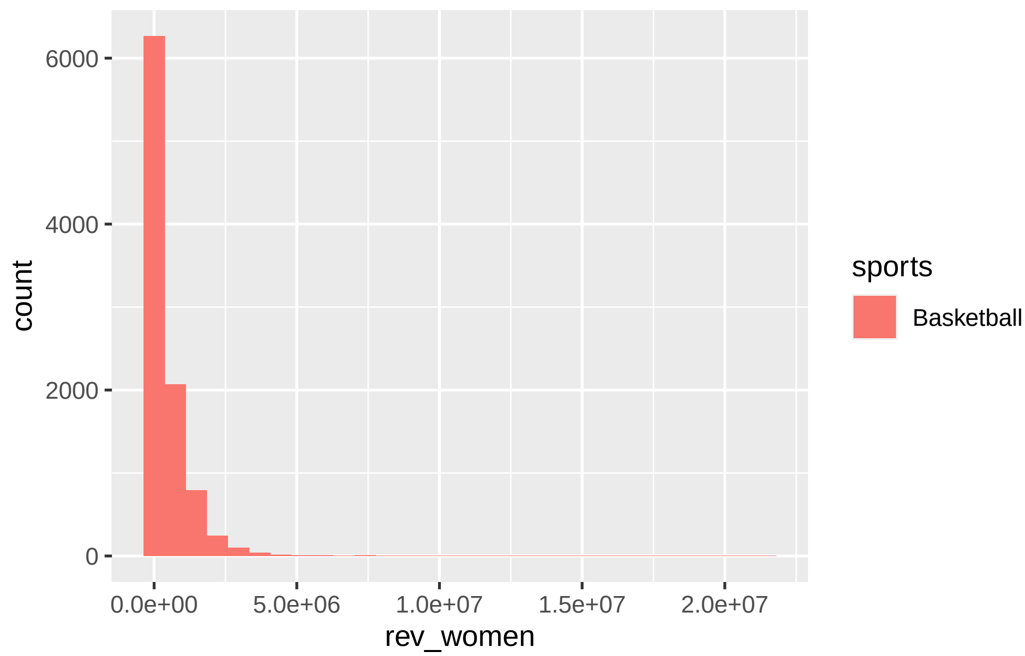
```
Call:
lm(formula = log(rev_women) ~ log(female_participation_ratio), 
    data = filter(basketball, female_participation_ratio != Inf & 
        sum_partic_women > 0 & rev_women > 0))

Residuals:
    Min      1Q  Median      3Q     Max 
-4.2932 -0.7712  0.0441  0.8770  4.1381 

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)    
(Intercept)                     10.45678    0.04920  212.54   <2e-16 ***
log(female_participation_ratio) -0.41592    0.01064  -39.08   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.141 on 9552 degrees of freedom
Multiple R-squared:  0.1379,	Adjusted R-squared:  0.1378 
F-statistic:  1527 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```
summary(hyp_3_fit_5)
```

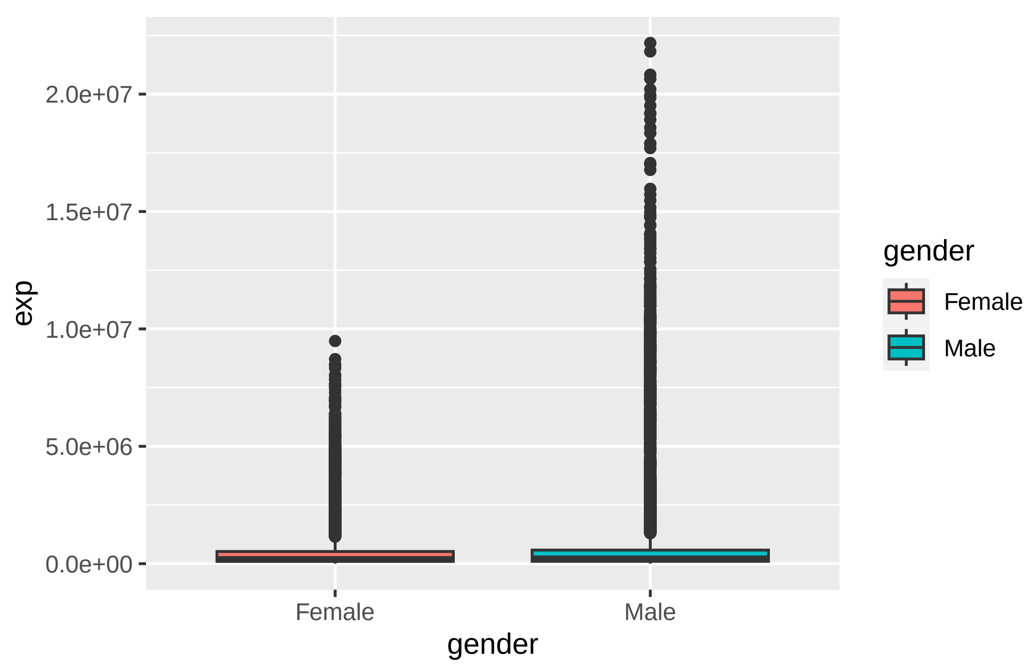
```
Call:
lm(formula = log(rev_women) ~ log(female_athlete_participation_ratio),
    data = filter(basketball, female_participation_ratio != Inf &
        rev_women > 0))

Residuals:
    Min      1Q  Median      3Q     Max
-4.6351 -0.7967 -0.0590  0.8164  4.6339

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                             13.90566    0.05485  253.53   <2e-16
log(female_athlete_participation_ratio)  2.08667    0.07063   29.55   <2e-16

(Intercept)                             ***
log(female_athlete_participation_ratio) ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.176 on 9552 degrees of freedom
Multiple R-squared:  0.08373,   Adjusted R-squared:  0.08364
F-statistic: 872.9 on 1 and 9552 DF,  p-value: < 2.2e-16
```

```
#hist(filter(basketball, female_athlete_participation_ratio != Inf & sum_partic_women > 0)

ggplot(filter(basketball, female_athlete_participation_ratio != Inf & sum_partic_women > 0
```

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




```
#boxplot(rev ~ gender, data=basketball_hist, ylab="Revenue")
ggplot(data=basketball_hist, aes(x=gender, y=exp, fill=gender)) + geom_boxplot()
```



Women receive nearly a third the revenue men do at top values.

My critical variables of interest are the following items:

- year: Period year
- institution name: School name
- sports: Sport name
- ef_male_count: Total male population
- ef_female_count: Total female population
- sum_partic_men: Total male participation
- sum_partic_women: Total female participation
- rev_men: Revenue in USD for men
- rev_women: Revenue in USD for women
- exp_men: Expenditures in USD for men
- exp_women: Expenditures in USD for women

Analysis:

For hypothesis 1, I added these new columns to the `attendance_data` data set:

1. female_participation_ratio
2. female_athlete_participation_ratio
3. male_participation_ratio

I used these metrics to test different approaches to measuring female participation at the collegial level to compare against males.

For hypotheses 2 & 3, I transformed the `basketball` data set to separate men and women by a new column `gender`, and also de-gendered the metrics to accommodate. The main reason was to use a histogram to better view data and compare gendered differences.

Model Comparisons and Diagnostics

Hypothesis 1 Models:

a. The first model used the female participation ratio as the dependent and effective female count as the explanatory variable. The regression yielded .01809 for an R-Squared, denoting a low correlation between female participation to effective female count, thus indicating a failed hypothesis test.

b. The second model filters female participation greater the participation an 0. The R-Squared is at .1217, ; this a slight performance improvement but still is statistically insignificant. Thus, the hypothesis still fails on this test. However, in comparison to .013807 and .01809 the best performing model is in the second test and is what is chosen to represent the data set.

c. The third model is female athlete participation ratio (female participation divided by female and male participation) explained by ef_female_count. The third hypothesis 1 model shows slightly better performance at .013807 but still fails the hypothesis test.

Adding logs

a. The first model applies a natural log to the second model from above. This sees a significant improvement in performance with an adjusted r-squared of 0.618.

b. The second model is similar to the third model above but applying logs. This too sees a great increase in accuracy, but still falls short at 0.02509.

Hypothesis 2 Models:

a. The second model measures the expenditure as a dependent and female participation as an explanatory. The R-Squared is .0409.

b. We see the same R-Squared in a and b due to the filter not removing the used observations.

c. I then use expenditures by the female athlete participation ratio ; we the R-Squared at .0657. Due to .0657 still being higher than the other R-Squared, , we use this as the model comparisons. However, we still reject this hypothesis.

Testing Controls

a. Modeling female expenditures explained by female revenue shows a strong correlation, with an adjsted r-squared of 0.594.

b. The second model has female expenditures explained by male expenditures results in a significant 0.8552 adjusted r-squared value.

c. The first model shows female expenditures by male participation has a lacking result of 0.0008418 as an adjusted r-squared.

Applying Logs

a. The first model shows a log based female expenditures explaine dby a log based female participation ratio. This resulted in a solid 0.1726 adjusted r-squared.

b. The second model shows a log based female expenditure explaing by log(female athletic participation ratio). The model produced a smaller 0.09563 adjusted r-squared.

Hypothesis 3 Models:

a. The third model measures the revenue as a dependent and female participation as an explanatory. The R-Squared is 0.03354.

b. We see the same R-Squared in a and b due to the filter not removing the used observations.

c. I then use revenue by the female athlete participation ratio; we the R-Squared at 0.04079. Due to 0.04079 still being higher than the other R-Squared, we use this as the model comparison. However, we still reject this hypothesis.

Testing Controls

a. Modeling female revenue explained by female revenue shows a strong correlation, with an adjusted r-squared of 0.594.

b. The second model has female revenue explained by male expenditures results in a significant 0.2802 adjusted r-squared value.

c. The first model shows female revenue by male participation has a lacking result of 0.0002652 as an adjusted r-squared.

Applying Logs

a. The first model shows a log based female revenue explained by a log based female participation ratio. This resulted in a solid 0.1378 adjusted r-squared.

b. The second model shows a log based female revenue explaing by log(female athletic participation ratio). The model produced a smaller 0.08364 adjusted r-squared.

Interesting Plot Takeaways

For the boxplot comparing gender to revenue, we see that at the maximum, women make a quarter of the revenue. For the boxplot comparing gender to expenditures, we see that women are given half as much in funding for basketball.

Conclusion:

Through testing, I showed all hypotheses passed by having an adjusted r-squared value greater than 10%. Hypothesis 1 proved as female enrollment at schools increases, participation in sports does not necessarily increase, and tends to decrease. Hypothesis 2 shows there is a correlalation between expenditures toward sports and the participation of each gender in that respective sport. I also show that Men have a significatly higher expenditure rate, indicating schools promote mens sports at a higher rate. Hypothesis 3 shows there is a high correlation between revenue on university sports and the participation of each gender in each sport. As shown through these tests, schools promote men's sports at higher rates. THis contributes to the idea that 'March Madness' drives higher profits for mens sports.

References

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