Gina McFarland Final Project - 4442

R Markdown

```
# loads data file
world_happ <- read.csv(file='CombinedDat_WorldHappinessReport.csv')

# variable processing
names(world_happ)[1] <- "country"
names(world_happ)[2] <- "year"
world_happ$year <- as.factor(world_happ$year)
names(world_happ)[4]<- "social.support"
names(world_happ)[5]<- "life.expectancy"
names(world_happ)[6]<- "freedom.choices"
names(world_happ)[7]<- "perceptions.corruption"
world_happ$perceptions.corruption<-
as.numeric(world_happ$perceptions.corruption)

## Warning: NAs introduced by coercion

names(world_happ)[8]<- "generosity"
names(world_happ)[9]<- "overall.rank"
world_happ$overall.rank <- as.numeric(world_happ$overall.rank)
world_happ$overall.rank <- NULL
names(world_happ)[9]<- "score"

sum(is.na(world_happ))

## [1] 1

world_happ[is.na(world_happ$perceptions.corruption),]

##                   country year GDP.per.capita social.support life.expectancy
## 99 United Arab Emirates 2018          2.096          0.776            0.67
##    freedom.choices perceptions.corruption generosity score
## 99           0.284                     NA      0.186 6.774

world_happ <- DropNA(world_happ)

## No Var specified. Dropping all NAs from the data frame.

## 1 rows dropped from the data frame because of missing values.

world_happ[is.na(world_happ$perceptions.corruption),]

## [1] country                year                   GDP.per.capita
## [4] social.support         life.expectancy        freedom.choices
## [7] perceptions.corruption generosity             score
## <0 rows> (or 0-length row.names)
```

The UAE 2018 perceptions.corruption variable was NA in the original data set. Since that data is irretrievable, that row has been removed. That is the only N/A in the data set.

```r
#MultiVar Non-graphical

table(world_happ$country, exclude=FALSE)
```

```
## 
##              Afghanistan                  Albania                  Algeria 
##                        5                        5                        5 
##                   Angola                Argentina                  Armenia 
##                        4                        5                        5 
##                Australia                  Austria               Azerbaijan 
##                        5                        5                        5 
##                  Bahrain               Bangladesh                  Belarus 
##                        5                        5                        5 
##                  Belgium                   Belize                    Benin 
##                        5                        3                        5 
##                   Bhutan                  Bolivia   Bosnia and Herzegovina 
##                        5                        5                        5 
##                 Botswana                   Brazil                 Bulgaria 
##                        5                        5                        5 
##             Burkina Faso                  Burundi                 Cambodia 
##                        5                        5                        5 
##                 Cameroon                   Canada Central African Republic 
##                        5                        5                        4 
##                     Chad                    Chile                    China 
##                        5                        5                        5 
##                 Colombia                  Comoros       Congo (Brazzaville) 
##                        5                        3                        5 
##        Congo (Kinshasa)               Costa Rica                  Croatia 
##                        5                        5                        5 
##                   Cyprus           Czech Republic                  Denmark 
##                        5                        5                        5 
##                 Djibouti       Dominican Republic                  Ecuador 
##                        1                        5                        5 
##                    Egypt              El Salvador                  Estonia 
##                        5                        5                        5 
##                 Ethiopia                  Finland                   France 
##                        5                        5                        5 
##                    Gabon                   Gambia                  Georgia 
##                        5                        1                        5 
##                  Germany                    Ghana                   Greece 
##                        5                        5                        5 
##                Guatemala                   Guinea                    Haiti 
##                        5                        5                        5 
##                 Honduras                Hong Kong  Hong Kong S.A.R., China 
##                        5                        4                        1 
##                  Hungary                  Iceland                    India 
##                        5                        5                        5 
```

```
##                  Indonesia                       Iran                       Iraq 
##                          5                          5                          5 
##                    Ireland                     Israel                      Italy 
##                          5                          5                          5 
##                Ivory Coast                    Jamaica                      Japan 
##                          5                          5                          5 
##                     Jordan                 Kazakhstan                      Kenya 
##                          5                          5                          5 
##                     Kosovo                     Kuwait                 Kyrgyzstan 
##                          5                          5                          5 
##                       Laos                     Latvia                    Lebanon 
##                          4                          5                          5 
##                    Lesotho                    Liberia                      Libya 
##                          4                          5                          5 
##                  Lithuania                 Luxembourg                  Macedonia 
##                          5                          5                          4 
##                 Madagascar                     Malawi                   Malaysia 
##                          5                          5                          5 
##                       Mali                      Malta                 Mauritania 
##                          5                          5                          5 
##                  Mauritius                     Mexico                    Moldova 
##                          5                          5                          5 
##                   Mongolia                 Montenegro                    Morocco 
##                          5                          5                          5 
##                 Mozambique                    Myanmar                    Namibia 
##                          4                          5                          4 
##                      Nepal                Netherlands                New Zealand 
##                          5                          5                          5 
##                  Nicaragua                      Niger                    Nigeria 
##                          5                          5                          5 
##               North Cyprus            North Macedonia            Northern Cyprus 
##                          3                          1                          2 
##                     Norway                       Oman                   Pakistan 
##                          5                          1                          5 
##   Palestinian Territories                     Panama                   Paraguay 
##                          5                          5                          5 
##                       Peru                Philippines                     Poland 
##                          5                          5                          5 
##                   Portugal                Puerto Rico                      Qatar 
##                          5                          1                          5 
##                    Romania                     Russia                     Rwanda 
##                          5                          5                          5 
##               Saudi Arabia                    Senegal                     Serbia 
##                          5                          5                          5 
##               Sierra Leone                  Singapore                   Slovakia 
##                          5                          5                          5 
##                   Slovenia                    Somalia          Somaliland Region 
##                          5                          4                          2 
##               South Africa                South Korea                South Sudan 
##                          5                          5                          4 
```

```
##                   Spain                 Sri Lanka                     Sudan
##                       5                         5                         4
##                Suriname                 Swaziland                    Sweden
##                       2                         2                         5
##             Switzerland                     Syria                    Taiwan
##                       5                         5                         4
## Taiwan Province of China                Tajikistan                  Tanzania
##                       1                         5                         5
##                Thailand                      Togo         Trinidad & Tobago
##                       5                         5                         2
##     Trinidad and Tobago                   Tunisia                    Turkey
##                       3                         5                         5
##            Turkmenistan                    Uganda                   Ukraine
##                       5                         5                         5
##    United Arab Emirates            United Kingdom             United States
##                       4                         5                         5
##                 Uruguay                Uzbekistan                 Venezuela
##                       5                         5                         5
##                 Vietnam                     Yemen                    Zambia
##                       5                         5                         5
##                Zimbabwe
##                       5

(sum(dplyr::count(world_happ,country)==1))

## [1] 7

counts<-(world_happ %>% count(country))

one_country <- counts[counts$n == 1,]

five_country <- counts[counts$n == 5,]

three_country <- counts[counts$n >2,] # 3 or more

four_country <- counts[counts$n > 3,] # 4 or more

# 7 countries with one observation; need to subset data to exclude these
# this is necessary since two points are needed to fit a line, not possible
with 1

world_happ_subset <- filter(world_happ, !(country %in% one_country$country))
(sum(dplyr::count(world_happ_subset,country)==1))  # no remaining issues with
only 1 data point

## [1] 0

counts_subset<-(world_happ_subset %>% count(country))

world_happ_subset_balanced <- filter(world_happ, country %in%
```

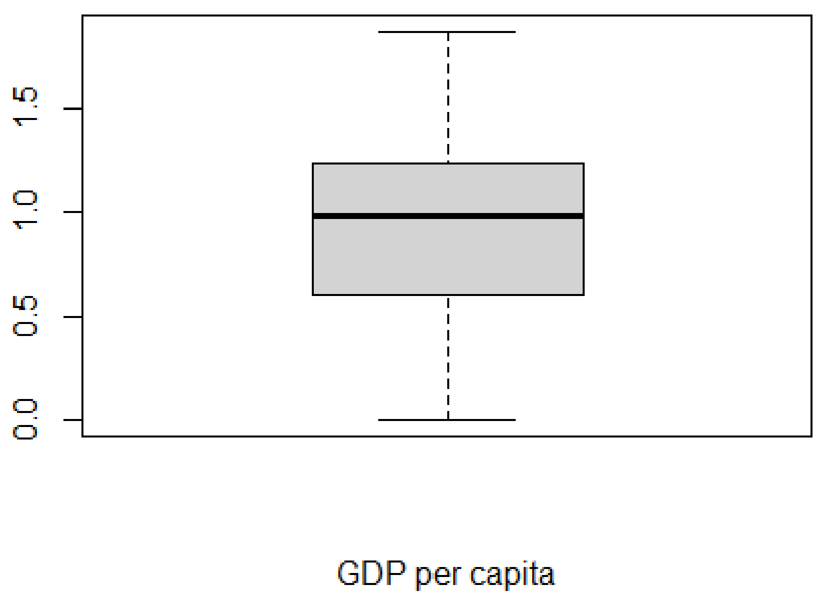
```r
five_country$country)

world_happ_subset_3ormore <- filter(world_happ, country %in%
three_country$country)

world_happ_subset_4ormore <- filter(world_happ, country %in%
four_country$country)

table(world_happ$year, exclude=FALSE)

##
## 2015 2016 2017 2018 2019
##  158  157  155  155  156

table(world_happ_subset$year, exclude = FALSE)

##
## 2015 2016 2017 2018 2019
##  156  156  153  155  154

table(world_happ_subset_3ormore$year)

##
## 2015 2016 2017 2018 2019
##  153  154  153  153  151

table(world_happ_subset_4ormore$year)

##
## 2015 2016 2017 2018 2019
##  150  150  150  152  150

table(world_happ_subset_balanced$year, exclude = FALSE)

##
## 2015 2016 2017 2018 2019
##  140  140  140  140  140
```

While the number of countries varies per year, there are nearly the same number. Also, which countries are represented in the sample varies by year. While some countries, such as Zambia, are in the sample 5 times, others, such Oman are listed only once. These are not balanced, which is acceptable in this model. Data sets were created with countries with all countries, countries with groups greater than 2, countries with groups greater than 3, countries with groups greater than 4, and countries that are present in all 5 waves. This was in an attempt to get the random effects on year along with country.

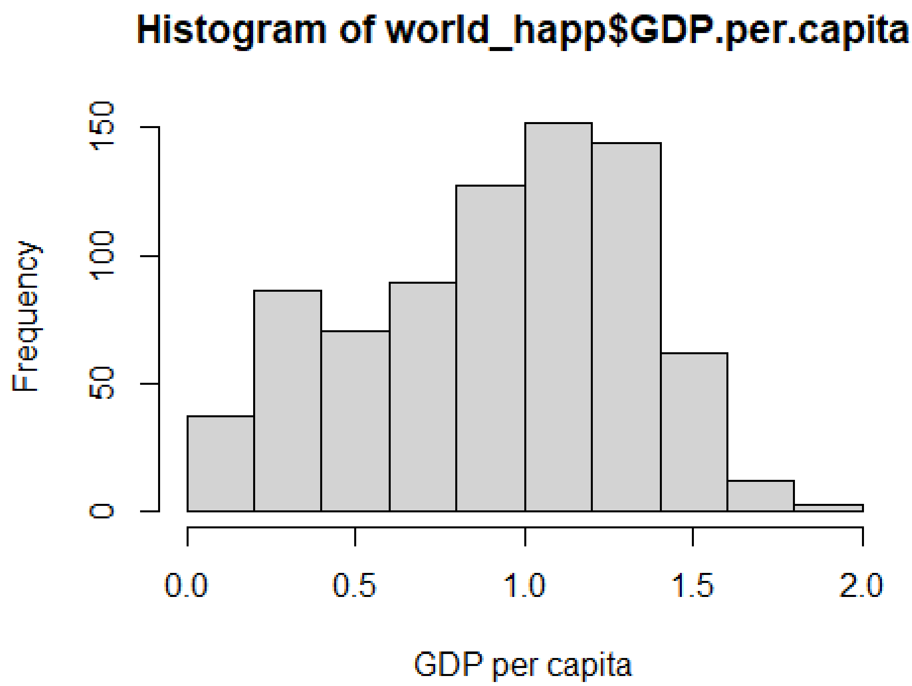
```r
summary(world_happ)

##    country              year     GDP.per.capita   social.support
##  Length:781         2015:158   Min.   :0.0000   Min.   :0.0000
##  Class :character   2016:157   1st Qu.:0.6050   1st Qu.:0.8702
##  Mode  :character   2017:155   Median :0.9820   Median :1.1250
```

```
##                      2018:155   Mean   :0.9145   Mean   :1.0788
##                      2019:156   3rd Qu.:1.2337   3rd Qu.:1.3280
##                                 Max.   :1.8708   Max.   :1.6440
##  life.expectancy  freedom.choices  perceptions.corruption   generosity
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000          Min.   :0.0000
##  1st Qu.:0.4401   1st Qu.:0.3105   1st Qu.:0.0540          1st Qu.:0.1300
##  Median :0.6472   Median :0.4310   Median :0.0910          Median :0.2020
##  Mean   :0.6123   Mean   :0.4113   Mean   :0.1254          Mean   :0.2186
##  3rd Qu.:0.8080   3rd Qu.:0.5310   3rd Qu.:0.1560          3rd Qu.:0.2791
##  Max.   :1.1410   Max.   :0.7240   Max.   :0.5519          Max.   :0.8381
##      score
##  Min.   :2.693
##  1st Qu.:4.509
##  Median :5.321
##  Mean   :5.377
##  3rd Qu.:6.182
##  Max.   :7.769
```

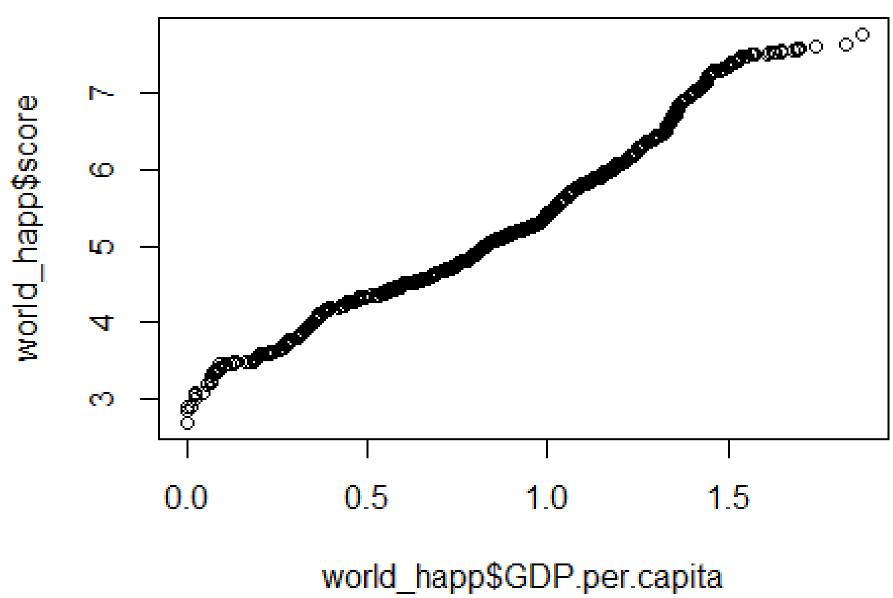
```r
boxplot(world_happ$GDP.per.capita, xlab = "GDP per capita")
```



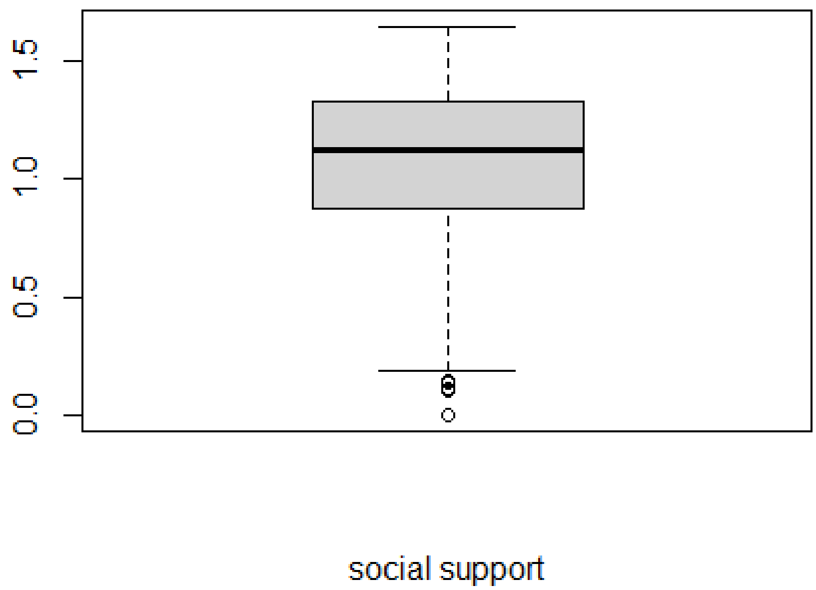

```r
hist(world_happ$GDP.per.capita, xlab = "GDP per capita")
```



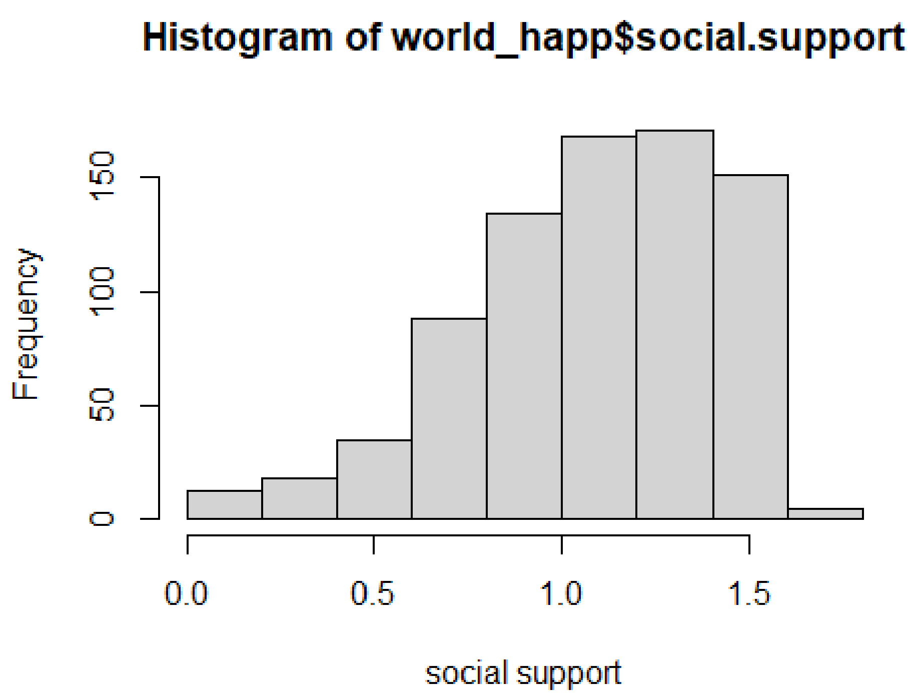

```
qqplot(x = world_happ$GDP.per.capita, y = world_happ$score)
```



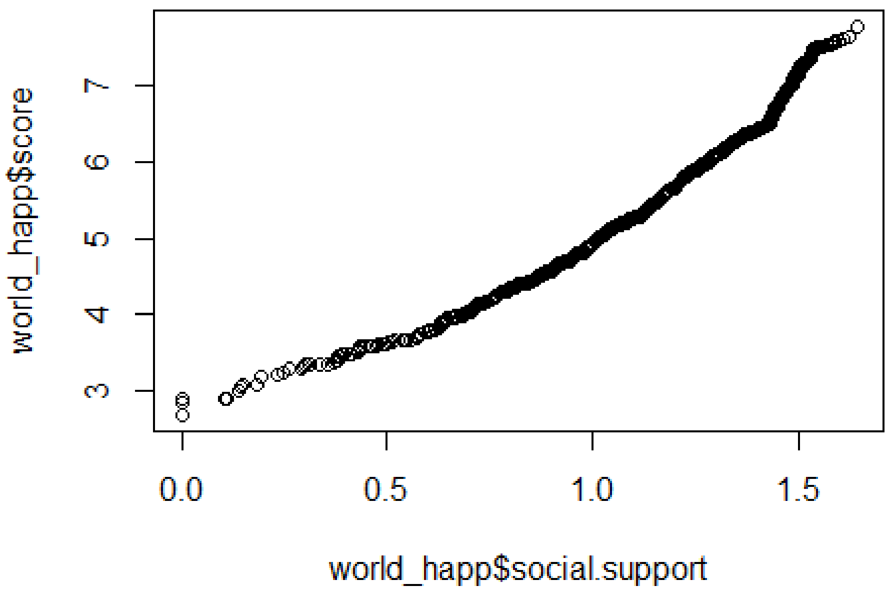

```
boxplot(world_happ$social.support, xlab = 'social support')
```



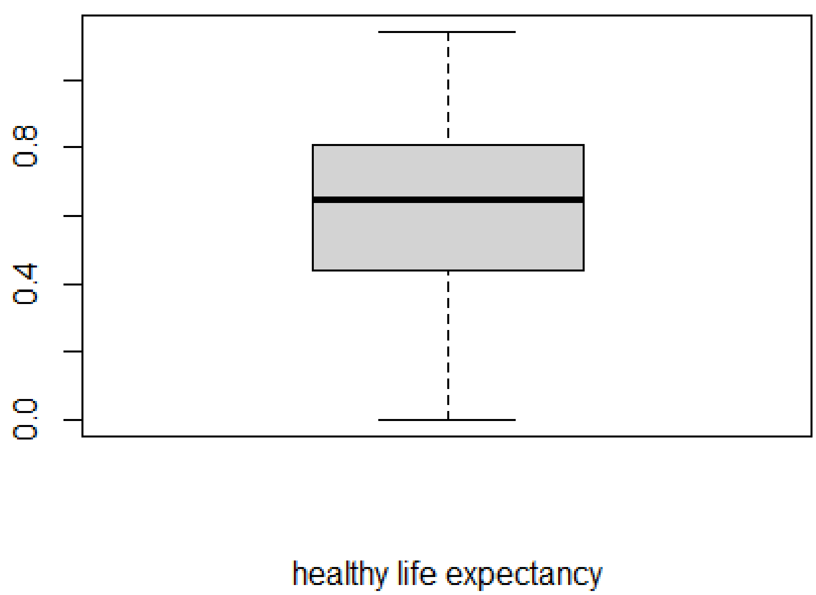

```r
hist(world_happ$social.support, xlab = 'social support')
```



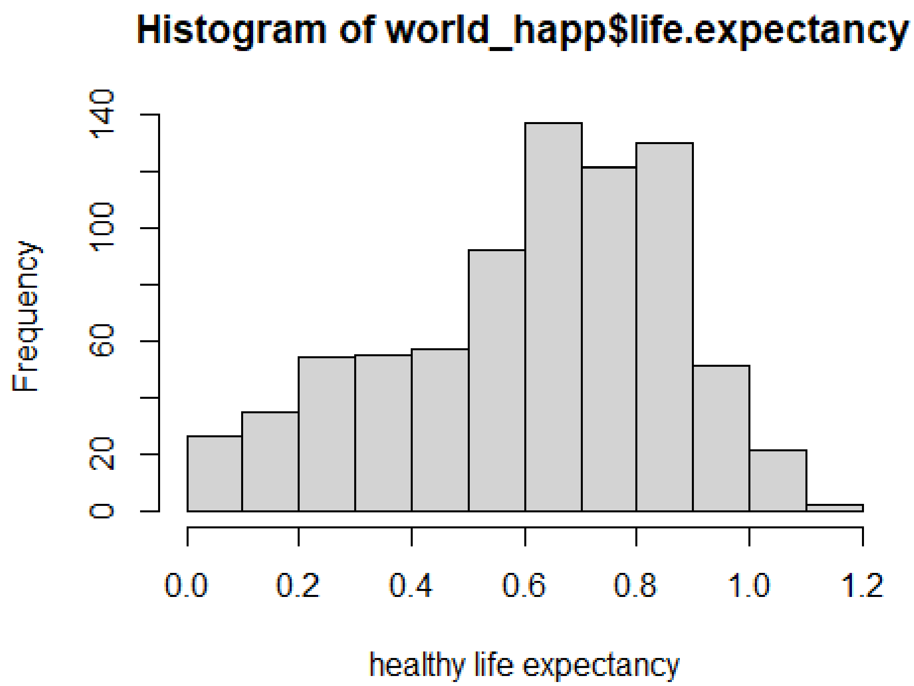

```r
qqplot(world_happ$social.support, y = world_happ$score)
```




```r
boxplot(world_happ$life.expectancy, xlab = 'healthy life expectancy')
```

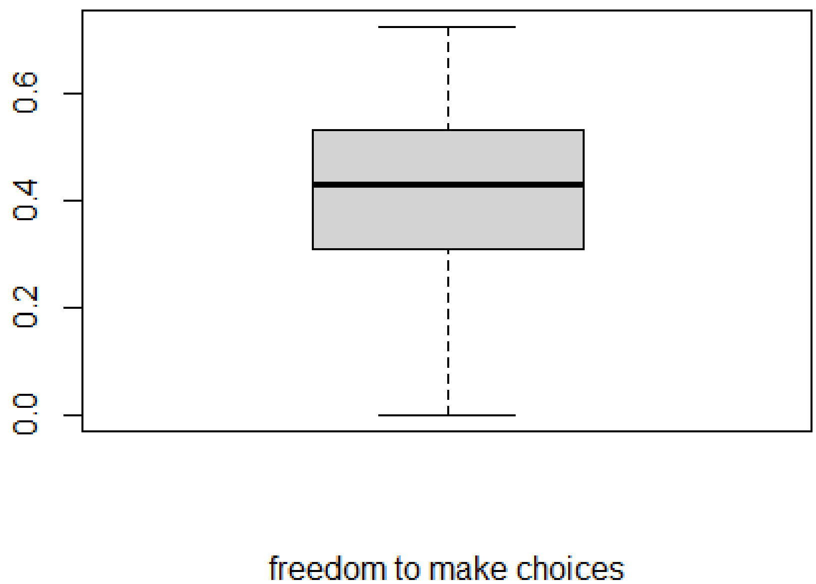



```r
hist(world_happ$life.expectancy, xlab = 'healthy life expectancy')
```

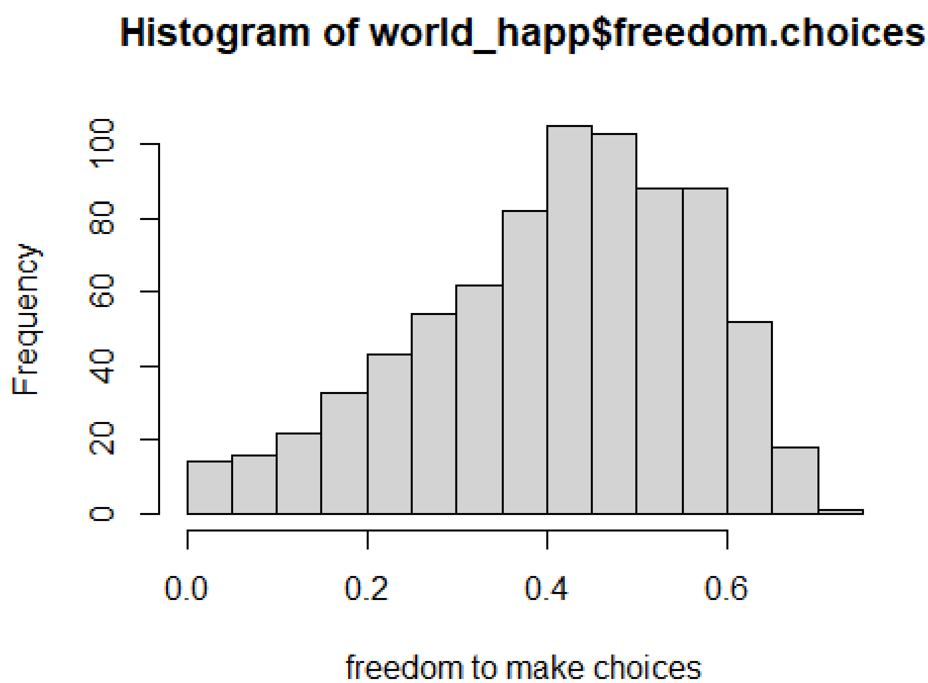



```r
qqplot(world_happ$life.expectancy, y = world_happ$score)
```

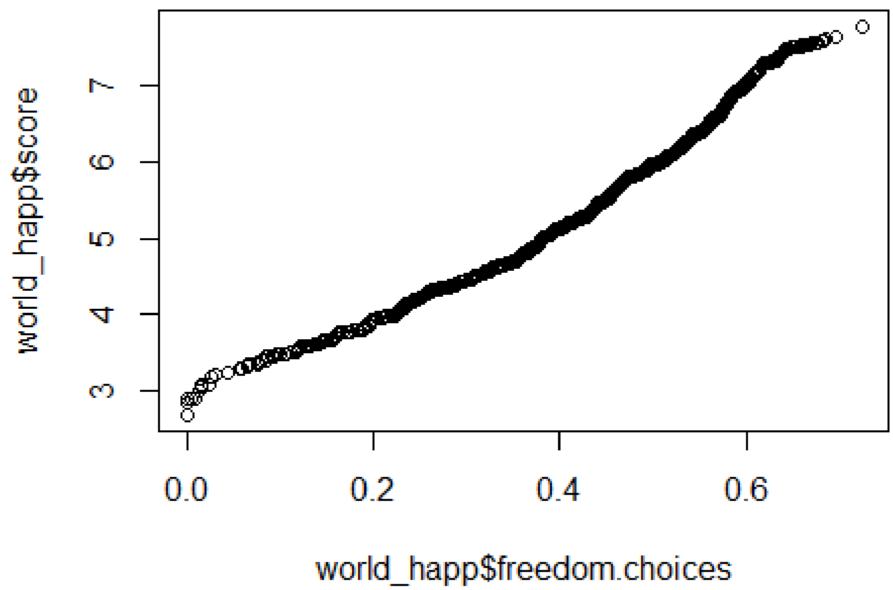

```r
boxplot(world_happ$freedom.choices, xlab = "freedom to make choices")
```



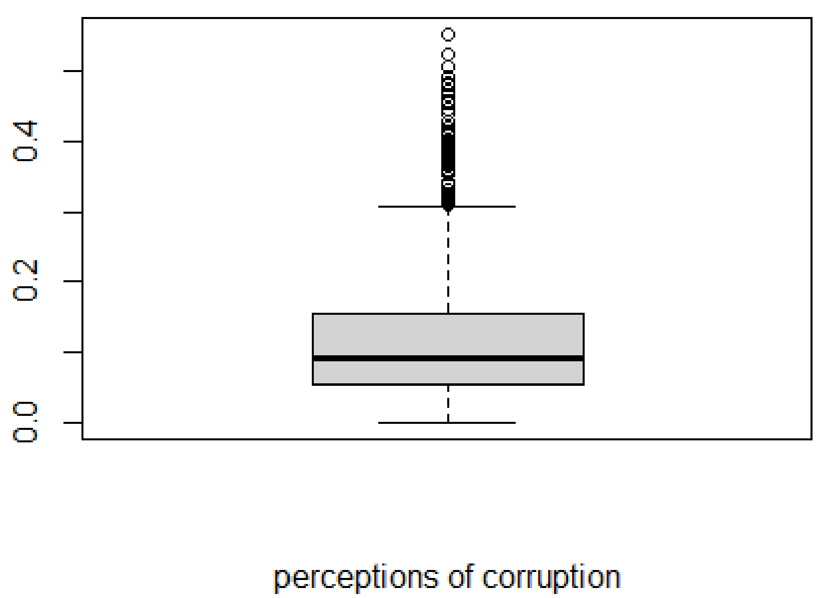

```r
hist(world_happ$freedom.choices, xlab = "freedom to make choices")
```



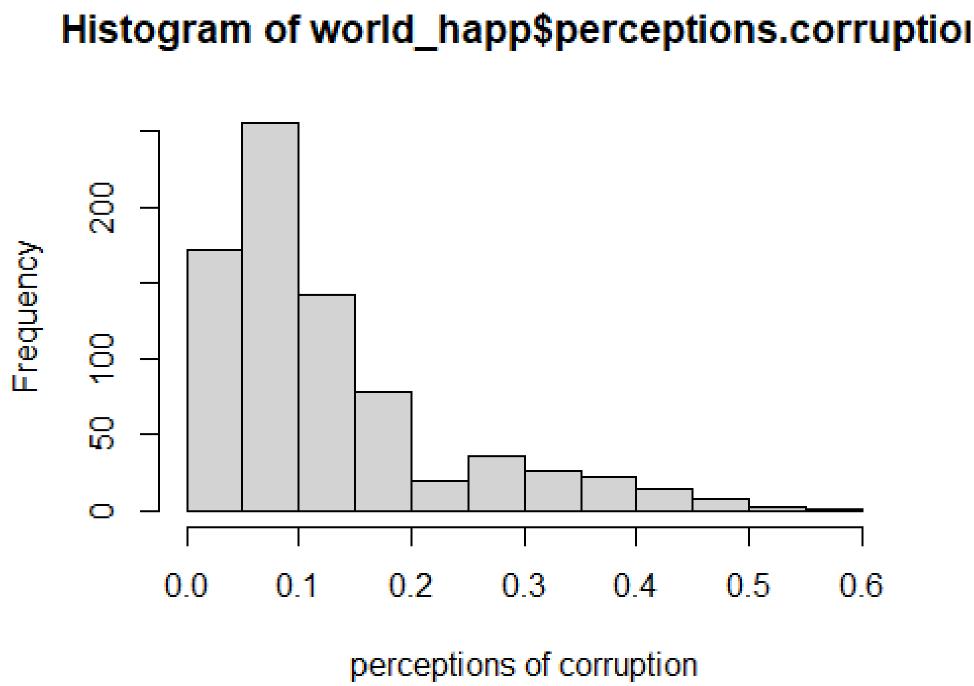

```r
qqplot(world_happ$freedom.choices, y = world_happ$score)
```



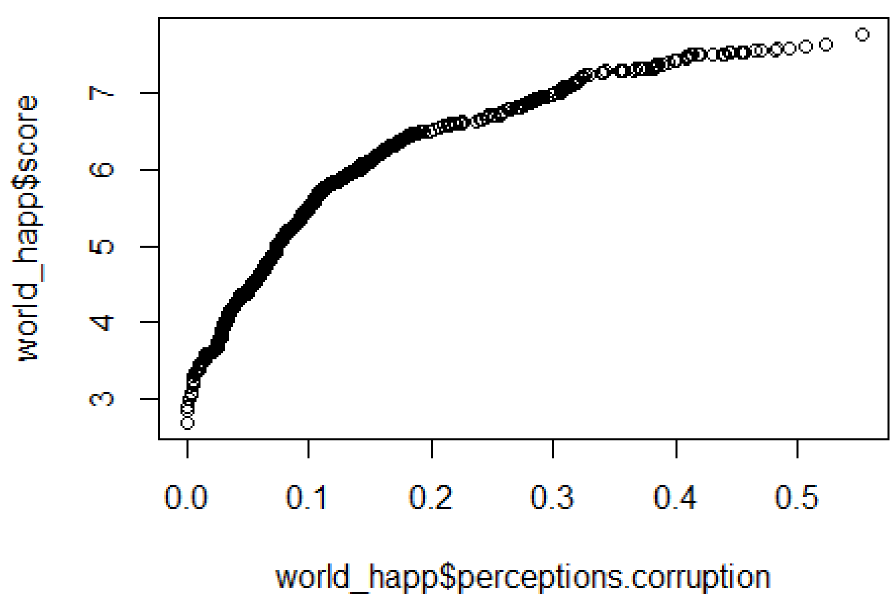

```r
boxplot(world_happ$perceptions.corruption,xlab = "perceptions of corruption")
```



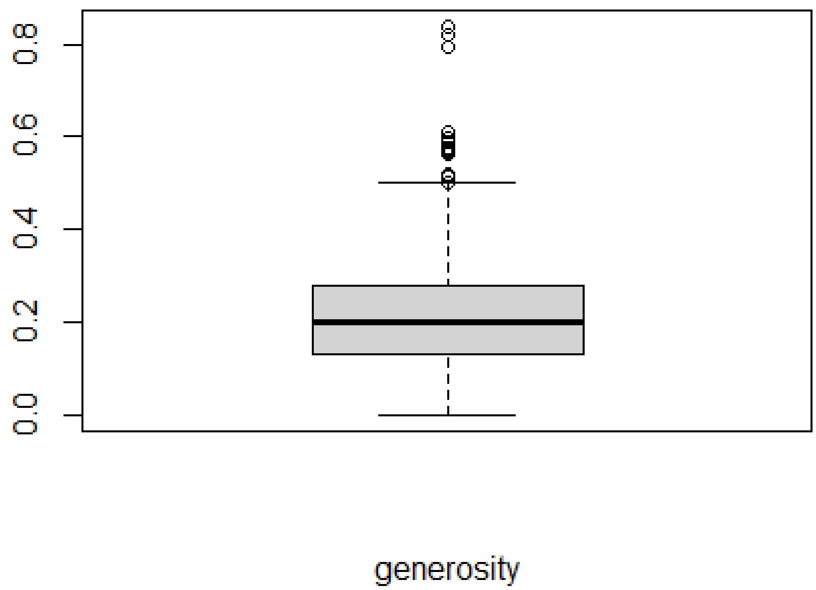

```r
hist(world_happ$perceptions.corruption,xlab = "perceptions of corruption")
```



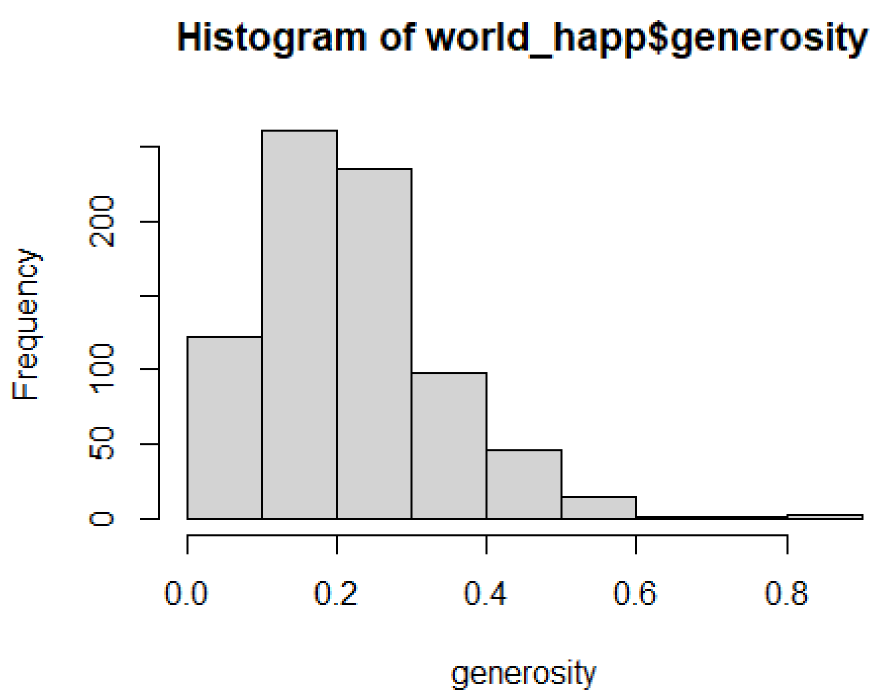

```
qqplot(world_happ$perceptions.corruption, y = world_happ$score)
```



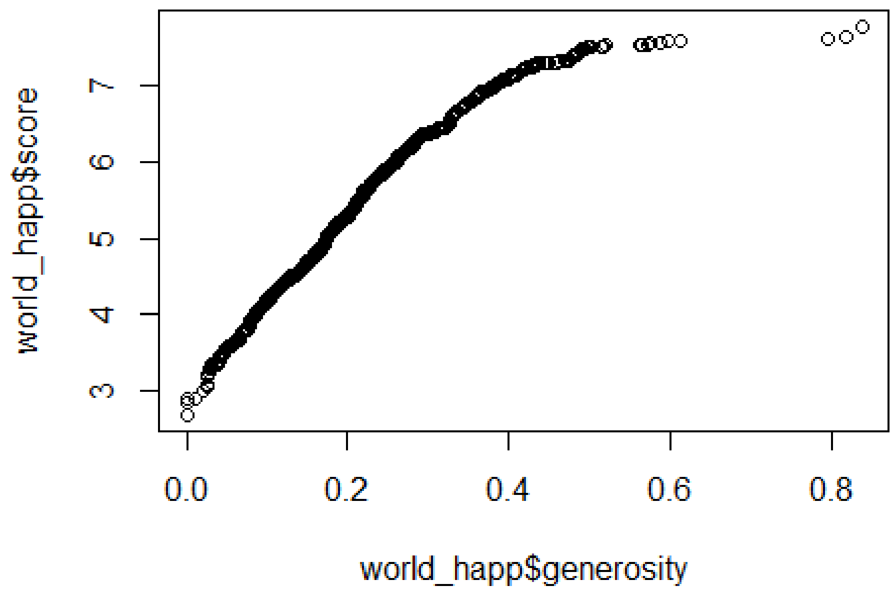

```
boxplot(world_happ$generosity,xlab = "generosity")
```



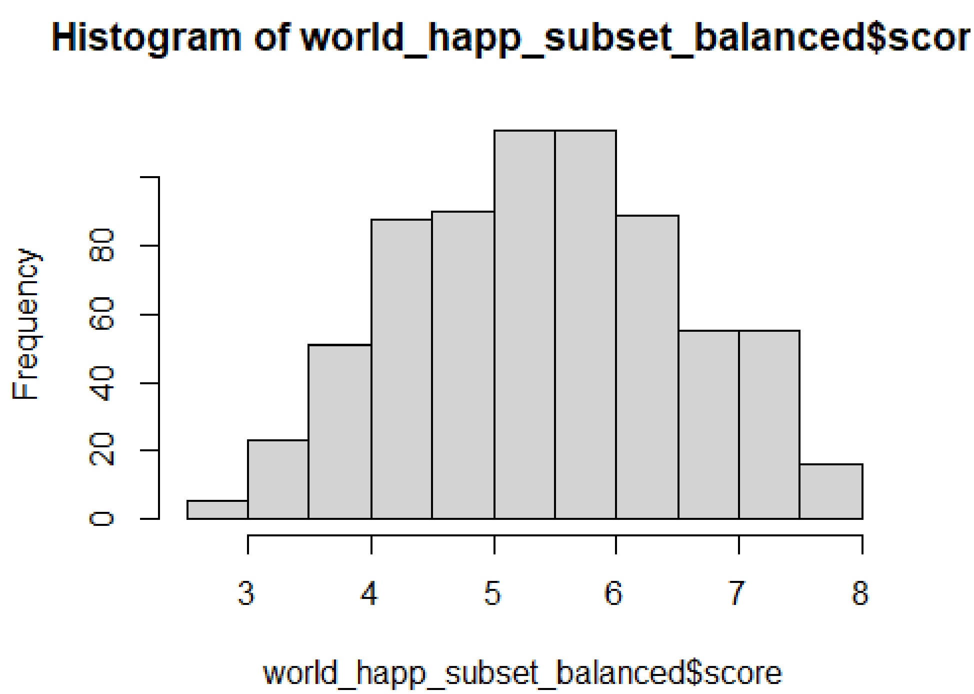

```r
hist(world_happ$generosity,xlab = "generosity")
```



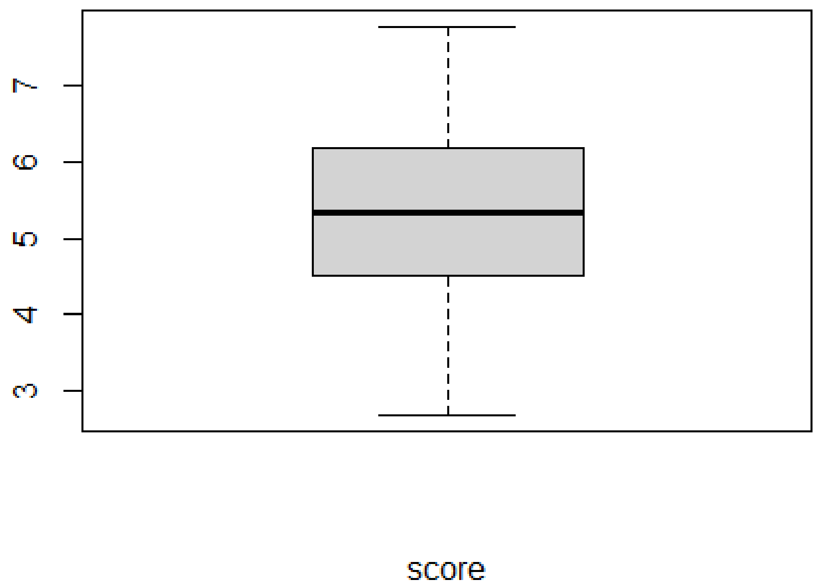

```r
qqplot(world_happ$generosity, y = world_happ$score)
```



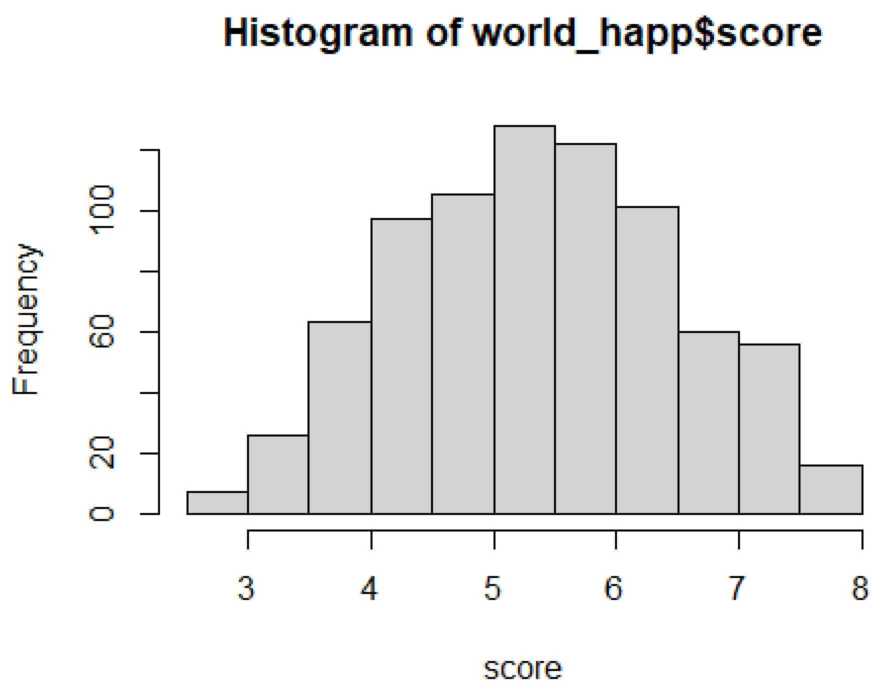

```r
hist(world_happ_subset_balanced$score)
```




```r
boxplot(world_happ$score,xlab = 'score')
```




```
hist(world_happ$score,xlab = 'score')
```



Outcome variable has solid normality and no outliers.

```r
max(world_happ$generosity)

## [1] 0.8380752

max(world_happ$perceptions.corruption)

## [1] 0.55191

max(world_happ$social.support)

## [1] 1.644

# confirm structure of data frame
str(world_happ)

## 'data.frame':    781 obs. of  9 variables:
##  $ country               : chr  "Switzerland" "Denmark" "Norway" "Finland"
...
##  $ year                  : Factor w/ 5 levels "2015","2016",..: 1 2 3 4 5
1 2 3 4 5 ...
##  $ GDP.per.capita        : num  1.4 1.44 1.62 1.3 1.34 ...
##  $ social.support        : num  1.35 1.16 1.53 1.59 1.59 ...
##  $ life.expectancy       : num  0.941 0.795 0.797 0.874 0.986 ...
##  $ freedom.choices       : num  0.666 0.579 0.635 0.681 0.596 ...
##  $ perceptions.corruption: num  0.42 0.445 0.316 0.393 0.393 ...
##  $ generosity            : num  0.297 0.362 0.362 0.202 0.153 ...
##  $ score                 : num  7.59 7.53 7.54 7.63 7.77 ...

(m0 <- lmer(score~year + (1 | country ), world_happ)) # simplest model, full
data set

## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ year + (1 | country)
##    Data: world_happ
## REML criterion at convergence: 755.3864
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 1.0968
##  Residual             0.2362
## Number of obs: 781, groups:  country, 169
## Fixed Effects:
## (Intercept)     year2016     year2017     year2018     year2019
##    5.377710    -0.017508    -0.017466     0.008582     0.046416

(m0.balanced <- lmer(score~year + (1 | country ),
world_happ_subset_balanced)) # simplest model; all five waves

## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ year + (1 | country)
##    Data: world_happ_subset_balanced
## REML criterion at convergence: 638.5185
## Random effects:
```

```
##  Groups   Name        Std.Dev.
##  country  (Intercept) 1.1059
##  Residual             0.2348
## Number of obs: 700, groups:  country, 140
## Fixed Effects:
## (Intercept)     year2016     year2017     year2018     year2019
##    5.396043    -0.006550     0.003393     0.034586     0.079771
```

```
#(m0.1 <- lmer(score~year + (year | country ), world_happ_subset_4ormore)) #
subset data
#commented out because causing error due to non-convergence
```

```
(m1.0 <- lmer(score~year + GDP.per.capita  + (1 | country ), world_happ)) #
random effects on country only
```

```
## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ year + GDP.per.capita + (1 | country)
##    Data: world_happ
## REML criterion at convergence: 589.711
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.6464
##  Residual             0.2376
## Number of obs: 781, groups:  country, 169
## Fixed Effects:
##    (Intercept)        year2016        year2017        year2018
year2019
##        3.70691        -0.21912        -0.29473        -0.07989        -
0.08722
## GDP.per.capita
##        1.97572
```

```
(m1.balanced <- lmer(score~year + GDP.per.capita  + (1 | country ),
world_happ_subset_balanced)) # random effects on country only
```

```
## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ year + GDP.per.capita + (1 | country)
##    Data: world_happ_subset_balanced
## REML criterion at convergence: 497.576
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.6418
##  Residual             0.2362
## Number of obs: 700, groups:  country, 140
## Fixed Effects:
##    (Intercept)        year2016        year2017        year2018
year2019
##        3.63420        -0.21766        -0.28719        -0.05529        -
0.05910
## GDP.per.capita
##        2.05711
```

```
#(m1.1 <- lmer(score~ GDP.per.capita  + (year | country ),
world_happ_subset_balanced)) #random on year & country
#commented out because causing error due to non-convergence

(m2.0 <- lmer(score~year + GDP.per.capita  + life.expectancy + (1 | country
), world_happ))

## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ year + GDP.per.capita + life.expectancy + (1 | country)
##    Data: world_happ
## REML criterion at convergence: 581.3654
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.6222
##  Residual             0.2383
## Number of obs: 781, groups:  country, 169
## Fixed Effects:
##     (Intercept)         year2016         year2017         year2018
##         3.51014         -0.13443         -0.20032         -0.04484
##        year2019   GDP.per.capita  life.expectancy
##        -0.13518          1.69470          0.69095

(m2.balanced <- lmer(score~year + GDP.per.capita  + life.expectancy + (1 |
country ), world_happ_subset_balanced))

## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ year + GDP.per.capita + life.expectancy + (1 | country)
##    Data: world_happ_subset_balanced
## REML criterion at convergence: 491.5063
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.6169
##  Residual             0.2371
## Number of obs: 700, groups:  country, 140
## Fixed Effects:
##     (Intercept)         year2016         year2017         year2018
##         3.41780         -0.13781         -0.19826         -0.02227
##        year2019   GDP.per.capita  life.expectancy
##        -0.10792          1.80564          0.66661

#(m2.1 <- lmer(score~year + GDP.per.capita  + life.expectancy + (year |
country ), world_happ_subset_balanced))
#commented out because causing error due to non-convergence

(m3.0 <- lmer(score~year + GDP.per.capita  + life.expectancy +
perceptions.corruption + (1 | country ), world_happ))

## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula:
## score ~ year + GDP.per.capita + life.expectancy + perceptions.corruption +
##     (1 | country)
```

```
##    Data: world_happ
## REML criterion at convergence: 571.0397
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.6029
##  Residual             0.2383
## Number of obs: 781, groups:  country, 169
## Fixed Effects:
##            (Intercept)                year2016                year2017
##                3.42952                -0.12307                -0.17595
##               year2018                year2019          GDP.per.capita
##               -0.01668                -0.10325                 1.63273
##        life.expectancy  perceptions.corruption
##                0.69656                 0.89947
```

```
(m3.balanced <- lmer(score~year + GDP.per.capita  + life.expectancy +
perceptions.corruption + (1 | country ), world_happ_subset_balanced))
```

```
## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula:
## score ~ year + GDP.per.capita + life.expectancy + perceptions.corruption +
##     (1 | country)
##    Data: world_happ_subset_balanced
## REML criterion at convergence: 481.574
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.5978
##  Residual             0.2369
## Number of obs: 700, groups:  country, 140
## Fixed Effects:
##            (Intercept)                year2016                year2017
##               3.355234               -0.123710               -0.169695
##               year2018                year2019          GDP.per.capita
##               0.007179               -0.075567                1.719894
##        life.expectancy  perceptions.corruption
##               0.677742                0.928588
```

```
#(m3.1 <- lmer(score~year + GDP.per.capita  + life.expectancy +
perceptions.corruption + (year | country), world_happ_subset_balanced))
#commented out because causing error due to non-convergence
```

```
(m4.0 <- lmer(score~year + GDP.per.capita  + life.expectancy +
perceptions.corruption + social.support
              + (1 | country ), world_happ))
```

```
## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula:
## score ~ year + GDP.per.capita + life.expectancy + perceptions.corruption +
##     social.support + (1 | country)
##    Data: world_happ
## REML criterion at convergence: 526.4771
```

```
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.5331
##  Residual             0.2370
## Number of obs: 781, groups:  country, 169
## Fixed Effects:
##            (Intercept)                year2016                year2017
##                 2.8522                  0.0914                 -0.3083
##               year2018                year2019          GDP.per.capita
##                -0.2063                 -0.2749                  1.2832
##        life.expectancy  perceptions.corruption          social.support
##                 0.6640                  0.9524                  0.8968

(m4.balanced <- lmer(score~year + GDP.per.capita  + life.expectancy +
perceptions.corruption + social.support
              + (1 | country ), world_happ_subset_balanced))

## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula:
## score ~ year + GDP.per.capita + life.expectancy + perceptions.corruption +
##     social.support + (1 | country)
##    Data: world_happ_subset_balanced
## REML criterion at convergence: 449.1663
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.5250
##  Residual             0.2371
## Number of obs: 700, groups:  country, 140
## Fixed Effects:
##            (Intercept)                year2016                year2017
##                2.79860                 0.07098                -0.29781
##               year2018                year2019          GDP.per.capita
##               -0.17289                -0.24160                 1.41144
##        life.expectancy  perceptions.corruption          social.support
##                0.65830                 0.95741                 0.82985

#(m4.1 <- lmer(score ~ year + GDP.per.capita + perceptions.corruption +
life.expectancy  + social.support + ( year | country ),
world_happ_subset_balanced))
#commented out because causing error due to non-convergence

(m5.0 <- lmer(score~as.factor(year) + GDP.per.capita  + life.expectancy +
perceptions.corruption + social.support +
              freedom.choices + (1 | country ), world_happ))

## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
##     perceptions.corruption + social.support + freedom.choices +
##     (1 | country)
##    Data: world_happ
## REML criterion at convergence: 506.5476
```

```
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.4971
##  Residual             0.2373
## Number of obs: 781, groups:  country, 169
## Fixed Effects:
##            (Intercept)     as.factor(year)2016     as.factor(year)2017
##                 2.6476                  0.1313                 -0.2749
##    as.factor(year)2018     as.factor(year)2019          GDP.per.capita
##                -0.2208                 -0.2296                  1.2276
##        life.expectancy  perceptions.corruption          social.support
##                 0.6535                  0.6238                  0.8196
##        freedom.choices
##                 0.8867
```

```
(m5.balanced <- lmer(score~as.factor(year) + GDP.per.capita  +
life.expectancy + perceptions.corruption + social.support + freedom.choices +
(1 | country ), world_happ_subset_balanced))
```

```
## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
##     perceptions.corruption + social.support + freedom.choices +
##     (1 | country)
##    Data: world_happ_subset_balanced
## REML criterion at convergence: 437.0482
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.4998
##  Residual             0.2371
## Number of obs: 700, groups:  country, 140
## Fixed Effects:
##            (Intercept)     as.factor(year)2016     as.factor(year)2017
##                 2.6322                  0.1003                 -0.2661
##    as.factor(year)2018     as.factor(year)2019          GDP.per.capita
##                -0.1818                 -0.2012                  1.3748
##        life.expectancy  perceptions.corruption          social.support
##                 0.6589                  0.6818                  0.7428
##        freedom.choices
##                 0.7522
```

```
#(m5.1 <- lmer(score ~ year + GDP.per.capita  + life.expectancy +
perceptions.corruption + social.support + freedom.choices  + ( year | country
), world_happ_subset_balanced))
#commented out because causing error due to non-convergence
```

```
(m6.0 <- lmer(score~as.factor(year) + GDP.per.capita  + life.expectancy +
perceptions.corruption + social.support +
              freedom.choices + generosity + (1 | country ), world_happ))
```

```
## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
```

```
##     perceptions.corruption + social.support + freedom.choices +
##     generosity + (1 | country)
##    Data: world_happ
## REML criterion at convergence: 502.9225
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.4935
##  Residual             0.2370
## Number of obs: 781, groups:  country, 169
## Fixed Effects:
##            (Intercept)     as.factor(year)2016     as.factor(year)2017
##                 2.5470                  0.1176                 -0.2964
##    as.factor(year)2018     as.factor(year)2019          GDP.per.capita
##                -0.2004                 -0.2079                  1.2771
##        life.expectancy  perceptions.corruption          social.support
##                 0.5947                  0.5641                  0.8311
##        freedom.choices              generosity
##                 0.8276                  0.4976
```

```
(m6.balanced <- lmer(score~as.factor(year) + GDP.per.capita  +
life.expectancy + perceptions.corruption + social.support + freedom.choices +
generosity + (1 | country ), world_happ_subset_balanced))
```

```
## Linear mixed model fit by REML ['lmerModLmerTest']
## Formula: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
##     perceptions.corruption + social.support + freedom.choices +
##     generosity + (1 | country)
##    Data: world_happ_subset_balanced
## REML criterion at convergence: 433.7354
## Random effects:
##  Groups   Name        Std.Dev.
##  country  (Intercept) 0.4945
##  Residual             0.2370
## Number of obs: 700, groups:  country, 140
## Fixed Effects:
##            (Intercept)     as.factor(year)2016     as.factor(year)2017
##                2.52972                 0.08684                -0.28625
##    as.factor(year)2018     as.factor(year)2019          GDP.per.capita
##               -0.16062                -0.17948                 1.42364
##        life.expectancy  perceptions.corruption          social.support
##                0.61087                 0.62179                 0.75214
##        freedom.choices              generosity
##                0.68983                 0.49831
```

```
#(m6.1 <- lmer(score~ year + GDP.per.capita  + life.expectancy +
perceptions.corruption + social.support +
#            freedom.choices  + generosity + ( as.factor(year) | country ),
world_happ_subset_balanced))
#commented out because causing error due to non-convergence
```

Now to find which is the best model. All are nested models, so I will start with the most complex and use the ANOVA function to work my way down to the least complex.

All of the models in which both country and year were allowed to have random effects had issues. Either they did not converge, or their boundaries were singular. As a result, I used the less complex models with only the country as a random effect.

```
anova(m6.balanced,m5.balanced)

## refitting model(s) with ML (instead of REML)

## Data: world_happ_subset_balanced
## Models:
## m5.balanced: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
## m5.balanced:     perceptions.corruption + social.support + freedom.choices
+
## m5.balanced:     (1 | country)
## m6.balanced: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
## m6.balanced:     perceptions.corruption + social.support + freedom.choices
+
## m6.balanced:     generosity + (1 | country)
##             npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m5.balanced   12 425.98 480.59 -200.99   401.98
## m6.balanced   13 423.55 482.71 -198.77   397.55 4.4336  1    0.03524 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

With a p value of 0.03524, we reject the null. Therefore we keep the more complex model m6.balanced.

```
anova(m6.balanced,m4.balanced) # m6.balanced is the most significant model
overall

## refitting model(s) with ML (instead of REML)

## Data: world_happ_subset_balanced
## Models:
## m4.balanced: score ~ year + GDP.per.capita + life.expectancy +
perceptions.corruption +
## m4.balanced:     social.support + (1 | country)
## m6.balanced: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
## m6.balanced:     perceptions.corruption + social.support + freedom.choices
+
## m6.balanced:     generosity + (1 | country)
##             npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m4.balanced   11 437.76 487.82 -207.88   415.76
## m6.balanced   13 423.55 482.71 -198.77   397.55 18.213  2   0.000111 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(m6.balanced,m3.balanced)
```

```
## refitting model(s) with ML (instead of REML)

## Data: world_happ_subset_balanced
## Models:
## m3.balanced: score ~ year + GDP.per.capita + life.expectancy +
perceptions.corruption +
## m3.balanced:     (1 | country)
## m6.balanced: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
## m6.balanced:     perceptions.corruption + social.support + freedom.choices
+
## m6.balanced:     generosity + (1 | country)
##              npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m3.balanced   10 471.00 516.51 -225.50   451.00
## m6.balanced   13 423.55 482.71 -198.77   397.55 53.451  3  1.469e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(m6.balanced,m2.balanced)
```

```
## refitting model(s) with ML (instead of REML)

## Data: world_happ_subset_balanced
## Models:
## m2.balanced: score ~ year + GDP.per.capita + life.expectancy + (1 |
country)
## m6.balanced: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
## m6.balanced:     perceptions.corruption + social.support + freedom.choices
+
## m6.balanced:     generosity + (1 | country)
##              npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m2.balanced    9 479.78 520.74 -230.89   461.78
## m6.balanced   13 423.55 482.71 -198.77   397.55 64.234  4   3.73e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(m6.balanced,m1.balanced)
```

```
## refitting model(s) with ML (instead of REML)

## Data: world_happ_subset_balanced
## Models:
## m1.balanced: score ~ year + GDP.per.capita + (1 | country)
## m6.balanced: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
## m6.balanced:     perceptions.corruption + social.support + freedom.choices
+
## m6.balanced:     generosity + (1 | country)
##              npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m1.balanced    8 484.95 521.36 -234.47   468.95
## m6.balanced   13 423.55 482.71 -198.77   397.55 71.403  5  5.229e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(m6.balanced,m0.balanced)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: world_happ_subset_balanced
## Models:
## m0.balanced: score ~ year + (1 | country)
## m6.balanced: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
## m6.balanced:     perceptions.corruption + social.support + freedom.choices
+
## m6.balanced:     generosity + (1 | country)
##             npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m0.balanced    7 627.21 659.07 -306.60   613.21
## m6.balanced   13 423.55 482.71 -198.77   397.55 215.66  6  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

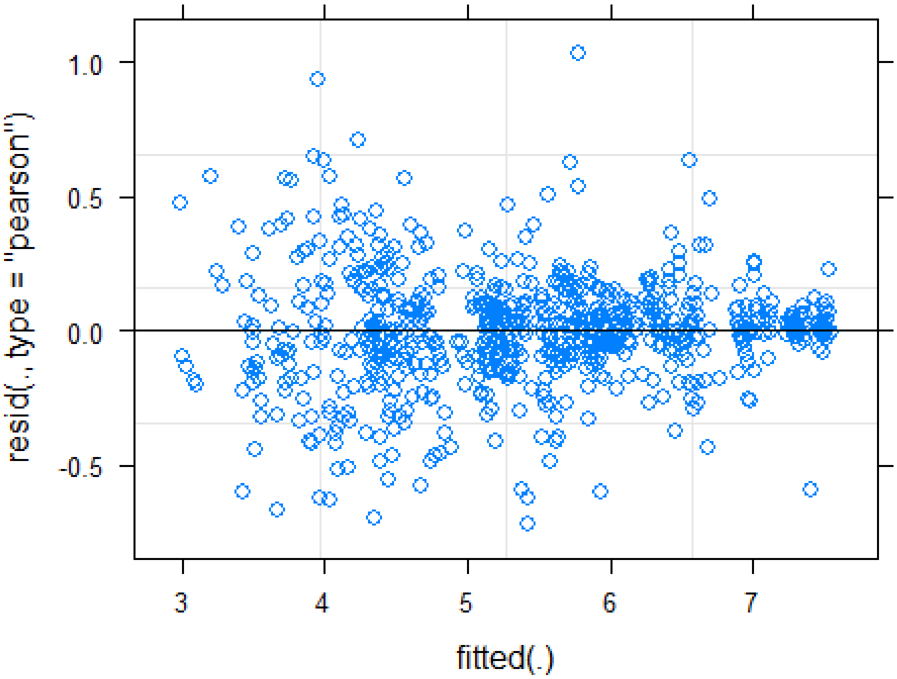
In each model, model 6 is significant.

```r
summary(m6.balanced)
```

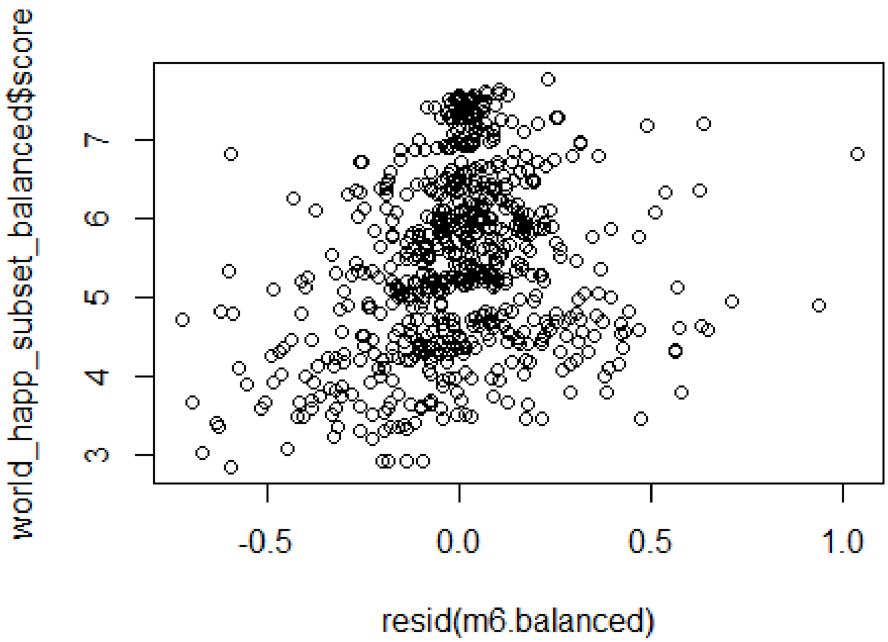
```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
##     perceptions.corruption + social.support + freedom.choices +
##     generosity + (1 | country)
##    Data: world_happ_subset_balanced
##
## REML criterion at convergence: 433.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0428 -0.4110  0.0210  0.4211  4.3707
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  country  (Intercept) 0.24451  0.4945
##  Residual             0.05619  0.2370
## Number of obs: 700, groups:  country, 140
##
## Fixed effects:
##                         Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)              2.52972    0.15287 235.90565  16.549  < 2e-16 ***
## as.factor(year)2016      0.08684    0.05154 672.16348   1.685 0.092511 .
## as.factor(year)2017     -0.28625    0.05217 659.73828  -5.487 5.85e-08 ***
## as.factor(year)2018     -0.16062    0.04459 688.40337  -3.602 0.000339 ***
## as.factor(year)2019     -0.17948    0.04573 669.08985  -3.925 9.59e-05 ***
## GDP.per.capita           1.42364    0.15339 411.82725   9.281  < 2e-16 ***
## life.expectancy          0.61087    0.22814 526.07969   2.678 0.007647 **
## perceptions.corruption   0.62179    0.27991 637.15861   2.221 0.026674 *
## social.support           0.75214    0.13375 608.89320   5.624 2.85e-08 ***
```

```
## freedom.choices          0.68983    0.20260 670.91197   3.405 0.000701 ***
## generosity               0.49831    0.23841 561.59916   2.090 0.037055 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) a.()2016 a.()2017 a.()2018 a.()2019 GDP.p. lf.xpc
prcpt.
## as.fc()2016 -0.431
## as.fc()2017  0.074  0.359
## as.fc()2018  0.141 -0.054    0.611
## as.fc()2019  0.292 -0.286    0.259    0.564
## GDP.per.cpt  0.001 -0.696   -0.504   -0.023    0.279
## lif.xpctncy -0.324  0.508    0.651    0.286   -0.335   -0.616
## prcptns.crr  0.022  0.042    0.123    0.173    0.112   -0.157  0.012
## socil.spprt -0.444  0.525   -0.445   -0.625   -0.587   -0.290 -0.075
0.044
## freedm.chcs -0.184  0.124    0.187   -0.071    0.233   -0.056 -0.016 -
0.267
## generosity  -0.298 -0.144   -0.187    0.235    0.238    0.164 -0.114 -
0.107
##             scl.sp frdm.c
## as.fc()2016
## as.fc()2017
## as.fc()2018
## as.fc()2019
## GDP.per.cpt
## lif.xpctncy
## prcptns.crr
## socil.spprt
## freedm.chcs -0.223
## generosity   0.019 -0.158
```

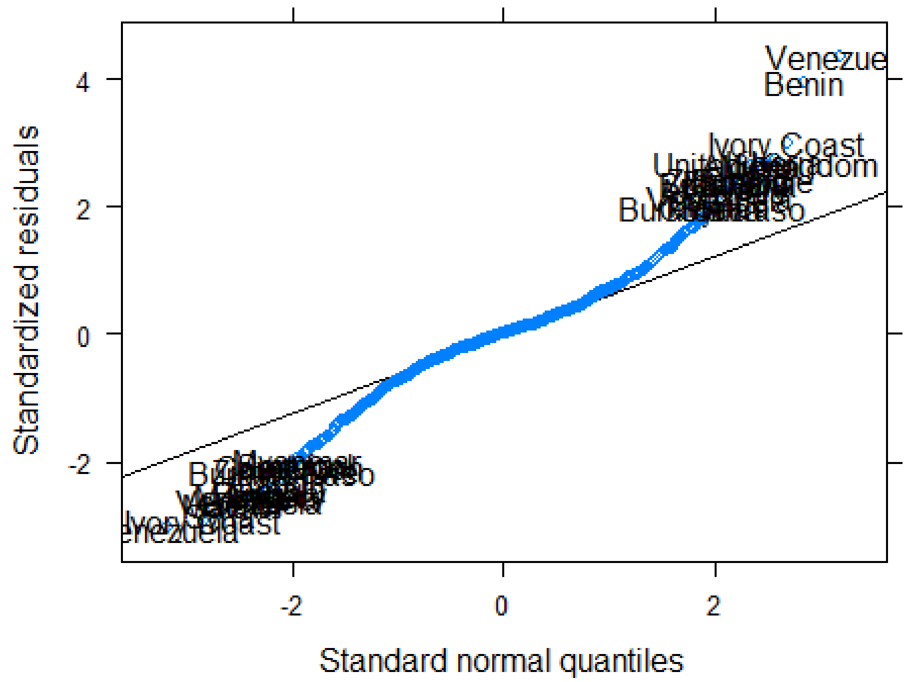
```
plot(m6.balanced)
```




```
# Test Assumptions

#resid() calls for the residuals of the model, Score was our initial outcome variables;Plots the residuals vs observed
Plot.Model.6.Balanced.Linearity<-
plot(resid(m6.balanced),world_happ_subset_balanced$score)
```




```
world_happ_subset_balanced$Model.6Bal.Res<- residuals(m6.balanced) #extracts
the residuals and places them in a new column in our original data table
world_happ_subset_balanced$Abs.Model.6Bal.Res <-
abs(world_happ_subset_balanced$Model.6Bal.Res) #creates a new column with the
absolute value of the residuals
world_happ_subset_balanced$Model.6Bal.Res2 <-
(world_happ_subset_balanced$Abs.Model.6Bal.Res)^2 #squares the absolute
values of the residuals to provide the more robust estimate
Levene.Model.6Bal <- lm(Model.6Bal.Res2 ~ score,
data=world_happ_subset_balanced) #ANOVA of the squared residuals
anova(Levene.Model.6Bal) #displays the results

## Analysis of Variance Table
##
## Response: Model.6Bal.Res2
##            Df Sum Sq Mean Sq F value    Pr(>F)
## score       1 0.3296 0.32964  39.468 5.869e-10 ***
## Residuals 698 5.8298 0.00835
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

qqmath(m6.balanced, id=0.05)
```




```
#(ranef(m6.balanced)[["country"]])
(rownames(ranef(m6.balanced)[["country"]])[which(abs(ranef(m6.balanced)[["cou
ntry"]])>1)])

## [1] "Botswana"   "Costa Rica" "Rwanda"     "Sri Lanka"  "Syria"

# "Botswana"   "Costa Rica" "Rwanda"     "Sri Lanka"  "Syria"
#-1.505080  1.112693 -1.049933 -1.190229 -1.060280

#ranef(m6.balanced)[["country"]][which(abs(ranef(m6.balanced)[["country"]])>1
),]
#which(abs(ranef(m6.balanced)[["country"]])>1)
#ranef(m6.balanced)[["country"]][which(abs(ranef(m6.balanced)[["country"]])>1
)]

summary(m6.balanced)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: score ~ as.factor(year) + GDP.per.capita + life.expectancy +
##     perceptions.corruption + social.support + freedom.choices +
##     generosity + (1 | country)
##    Data: world_happ_subset_balanced
##
## REML criterion at convergence: 433.7
##
## Scaled residuals:
```

```
##      Min      1Q  Median      3Q     Max 
## -3.0428 -0.4110  0.0210  0.4211  4.3707 
## 
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  country  (Intercept) 0.24451  0.4945  
##  Residual             0.05619  0.2370  
## Number of obs: 700, groups:  country, 140
## 
## Fixed effects:
##                          Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)               2.52972    0.15287 235.90565  16.549  < 2e-16 ***
## as.factor(year)2016       0.08684    0.05154 672.16348   1.685 0.092511 .
## as.factor(year)2017      -0.28625    0.05217 659.73828  -5.487 5.85e-08 ***
## as.factor(year)2018      -0.16062    0.04459 688.40337  -3.602 0.000339 ***
## as.factor(year)2019      -0.17948    0.04573 669.08985  -3.925 9.59e-05 ***
## GDP.per.capita            1.42364    0.15339 411.82725   9.281  < 2e-16 ***
## life.expectancy           0.61087    0.22814 526.07969   2.678 0.007647 **
## perceptions.corruption    0.62179    0.27991 637.15861   2.221 0.026674 *
## social.support            0.75214    0.13375 608.89320   5.624 2.85e-08 ***
## freedom.choices           0.68983    0.20260 670.91197   3.405 0.000701 ***
## generosity                0.49831    0.23841 561.59916   2.090 0.037055 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Correlation of Fixed Effects:
##             (Intr) a.()2016 a.()2017 a.()2018 a.()2019 GDP.p. lf.xpc
prcpt.
## as.fc()2016 -0.431                                                    
## as.fc()2017  0.074  0.359                                             
## as.fc()2018  0.141 -0.054    0.611                                    
## as.fc()2019  0.292 -0.286    0.259    0.564                           
## GDP.per.cpt  0.001 -0.696   -0.504   -0.023    0.279                  
## lif.xpctncy -0.324  0.508    0.651    0.286   -0.335   -0.616         
## prcptns.crr  0.022  0.042    0.123    0.173    0.112   -0.157  0.012  
## socil.spprt -0.444  0.525   -0.445   -0.625   -0.587   -0.290 -0.075
0.044
## freedm.chcs -0.184  0.124    0.187   -0.071    0.233   -0.056 -0.016 -
0.267
## generosity  -0.298 -0.144   -0.187    0.235    0.238    0.164 -0.114 -
0.107
##             scl.sp frdm.c
## as.fc()2016              
## as.fc()2017              
## as.fc()2018              
## as.fc()2019              
## GDP.per.cpt              
## lif.xpctncy              
## prcptns.crr              
## socil.spprt              
```

```
## freedm.chcs -0.223
## generosity   0.019 -0.158
```