research_question_1

```r
library(tidyverse)
library(readxl)
library(dplyr)
library(ggplot2)
```

```r
#Read the dataset, select the columns to be used and drop the missing data
energy_rq1 <- read_excel("owid-energy-data.xlsx") %>%
  select(country, year, gdp, population, carbon_intensity_elec,fossil_share_elec,electricity_
  mutate(gdp_per_capita = gdp / population) %>%
  filter(!is.na(carbon_intensity_elec),
         !is.na(gdp_per_capita))

glimpse(energy_rq1)
```

```
Rows: 3,800
Columns: 8
$ country                <chr> "Afghanistan", "Afghanistan", "Afghanistan", "A~
$ year                   <dbl> 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007,~
$ gdp                    <dbl> 11283793920, 11021273088, 18804871168, 21074343~
$ population             <dbl> 20130279, 20284252, 21378081, 22733007, 2356059~
$ carbon_intensity_elec  <dbl> 250.000, 217.391, 169.014, 241.758, 227.848, 21~
$ fossil_share_elec      <dbl> 35.417, 27.536, 21.127, 30.769, 29.114, 28.049,~
$ electricity_generation <dbl> 0.48, 0.69, 0.71, 0.91, 0.79, 0.82, 0.90, 1.01,~
$ gdp_per_capita         <dbl> 560.5384, 543.3414, 879.6333, 927.0372, 947.877~
```

Research question 1:

Does a country's GDP per capita significantly affect the carbon intensity of its electricity generation, and does this relationship differ between high-income and low-income countries?

- Outcome variable (include the name/description and type of variable):

- carbon_intensity_elec **(continuous)** measures the amount of carbon dioxide emitted per unit of electricity generated (grams of CO per kilowatt-hour). It captures how carbon-efficient a country's electricity production is — lower values indicate cleaner, more renewable-based power systems.

```r
head(energy_rq1, 5)
```

```
# A tibble: 5 x 8
  country      year       gdp population carbon_intensity_elec fossil_share_elec
  <chr>       <dbl>     <dbl>      <dbl>                 <dbl>             <dbl>
1 Afghanistan  2000   1.13e10   20130279                  250               35.4
2 Afghanistan  2001   1.10e10   20284252                  217.              27.5
3 Afghanistan  2002   1.88e10   21378081                  169.              21.1
4 Afghanistan  2003   2.11e10   22733007                  242.              30.8
5 Afghanistan  2004   2.23e10   23560598                  228.              29.1
# i 2 more variables: electricity_generation <dbl>, gdp_per_capita <dbl>
```

Because the OWID Energy dataset does not include income classifications, we merged it with a separate World Bank income-group dataset (from same source) that provides each country's income level by year. This merge, done using country name and year, allows us to include income group as a key predictor and test whether the GDP–carbon-intensity relationship differs across income categories.

```r
income <- read.csv(
  "https://raw.githubusercontent.com/owid/owid-datasets/master/datasets/Country%20Income%20C
)
head(income, 5)
```

```
       Entity Year Income.classification..World.Bank.2017.
1 Afghanistan 1987                                       1
2 Afghanistan 1988                                       1
3 Afghanistan 1989                                       1
4 Afghanistan 1990                                       1
5 Afghanistan 1991                                       1
```

```
income <- income %>%
  rename(
    country = Entity,
    income_code = Income.classification..World.Bank.2017.,
    year = Year
  )

income <- income %>%
  mutate(income_group = case_when(
    income_code == 4 ~ "High income",
    income_code == 3 ~ "Upper middle income",
    income_code == 2 ~ "Lower middle income",
    income_code == 1 ~ "Low income"
  ))
```

```
energy_income <- energy_rq1 %>%
  left_join(income, by = c("country", "year"))

head(energy_income)
```

```
# A tibble: 6 x 10
  country      year       gdp population carbon_intensity_elec fossil_share_elec
  <chr>       <dbl>     <dbl>      <dbl>                 <dbl>             <dbl>
1 Afghanistan  2000   1.13e10   20130279                  250               35.4
2 Afghanistan  2001   1.10e10   20284252                  217.              27.5
3 Afghanistan  2002   1.88e10   21378081                  169.              21.1
4 Afghanistan  2003   2.11e10   22733007                  242.              30.8
5 Afghanistan  2004   2.23e10   23560598                  228.              29.1
6 Afghanistan  2005   2.54e10   24404520                  220.              28.0
# i 4 more variables: electricity_generation <dbl>, gdp_per_capita <dbl>,
#   income_code <int>, income_group <chr>
```

Clean Data

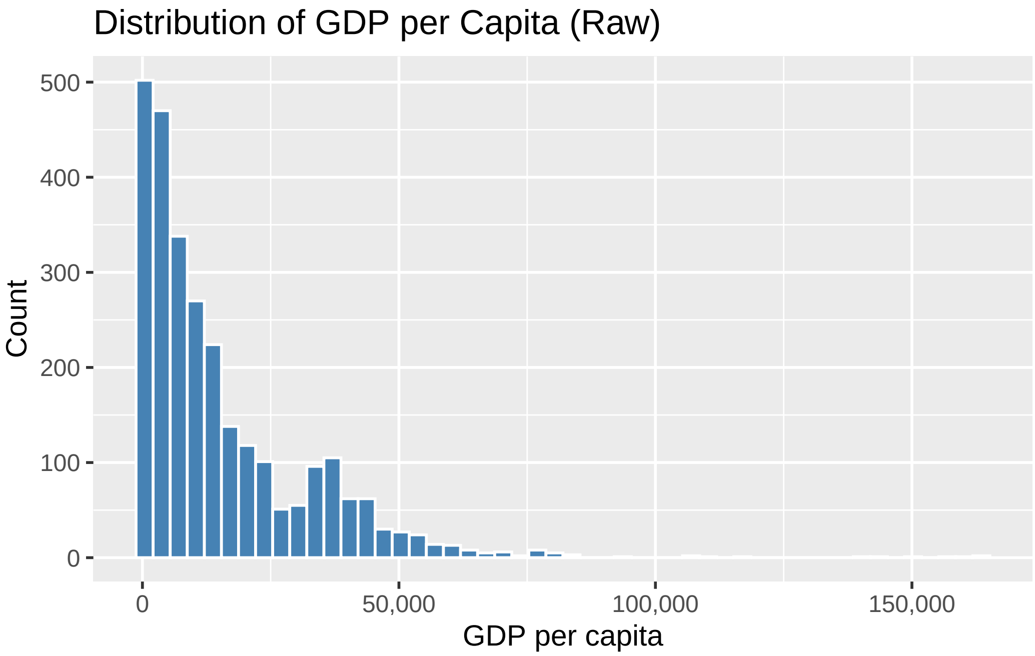
```
library(dplyr)

cleaned <- energy_income %>%
  filter(
    !is.na(carbon_intensity_elec),
```

```r
    !is.na(gdp_per_capita),
    !is.na(income_group)
  ) %>%
  mutate(
    log_gdp = log(gdp_per_capita),
    income_group = factor(income_group)   # ensure categorical
  )

cleaned$income_group <- factor(cleaned$income_group,
                               levels = c("Low income",
                                          "Lower middle income",
                                          "Upper middle income",
                                          "High income"))


head(cleaned)
```

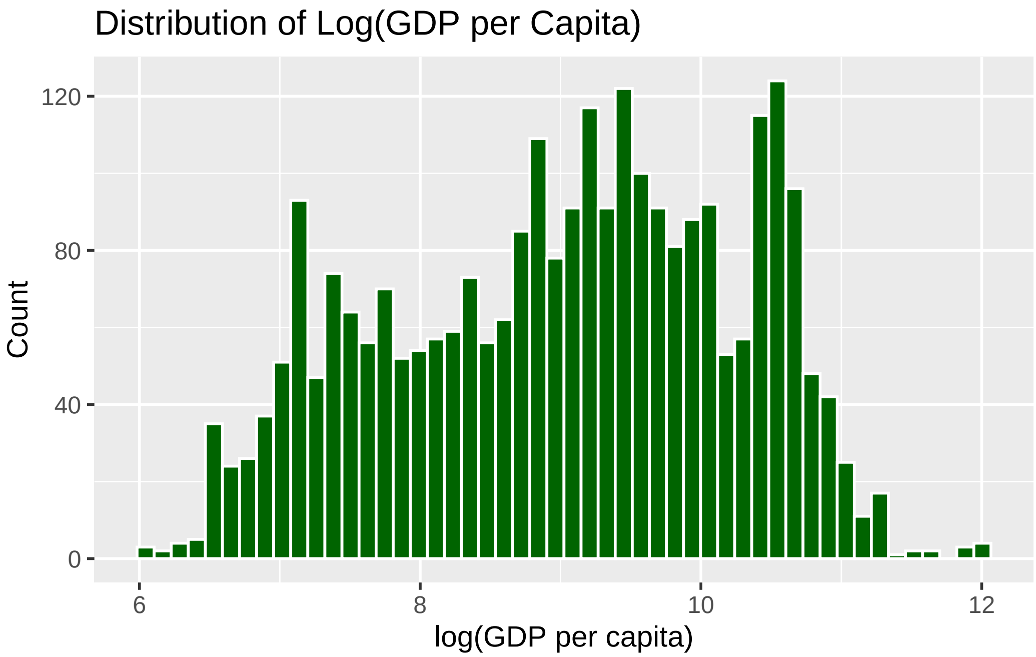
```
# A tibble: 6 x 11
  country      year       gdp population carbon_intensity_elec fossil_share_elec
  <chr>       <dbl>     <dbl>      <dbl>                 <dbl>             <dbl>
1 Afghanistan  2000   1.13e10   20130279                  250               35.4
2 Afghanistan  2001   1.10e10   20284252                  217.              27.5
3 Afghanistan  2002   1.88e10   21378081                  169.              21.1
4 Afghanistan  2003   2.11e10   22733007                  242.              30.8
5 Afghanistan  2004   2.23e10   23560598                  228.              29.1
6 Afghanistan  2005   2.54e10   24404520                  220.              28.0
# i 5 more variables: electricity_generation <dbl>, gdp_per_capita <dbl>,
#   income_code <int>, income_group <fct>, log_gdp <dbl>
```

EDA

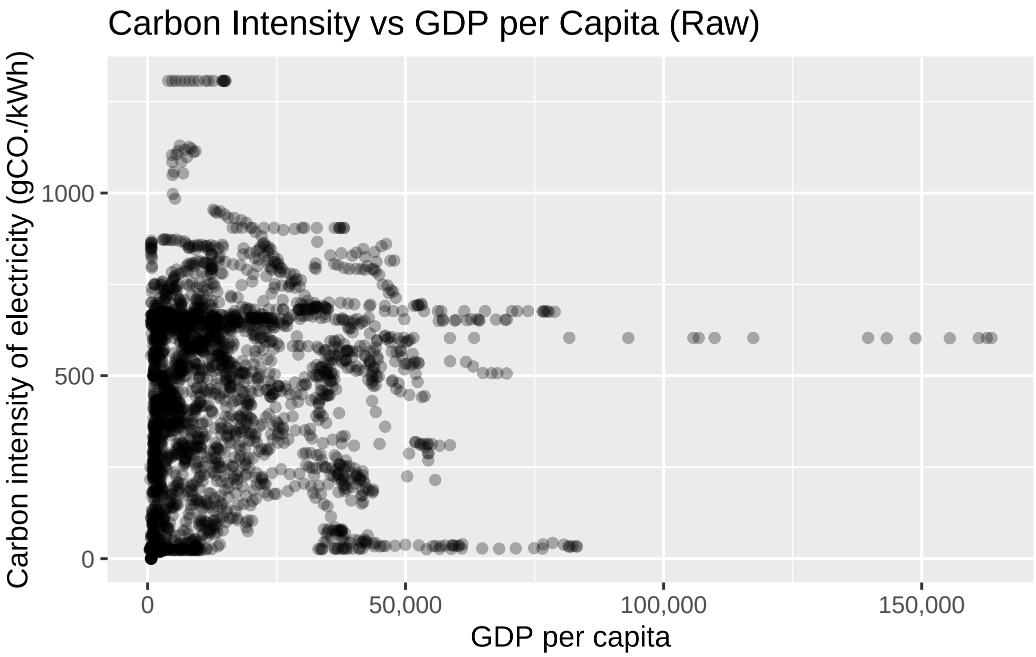
```r
library(ggplot2)

ggplot(cleaned, aes(x = gdp_per_capita)) +
  geom_histogram(bins = 50, fill = "steelblue", color = "white") +
  scale_x_continuous(labels = scales::comma) +
  labs(
    title = "Distribution of GDP per Capita (Raw)",
    x = "GDP per capita",
    y = "Count"
  )
```



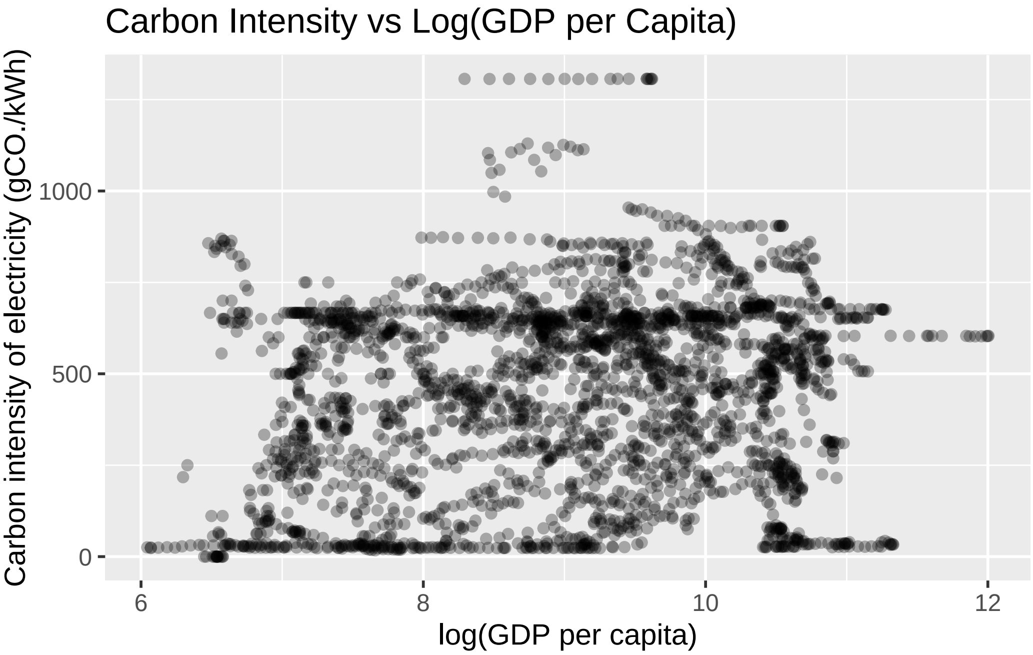
```
ggplot(cleaned, aes(x = log_gdp)) +
  geom_histogram(bins = 50, fill = "darkgreen", color = "white") +
  labs(
    title = "Distribution of Log(GDP per Capita)",
    x = "log(GDP per capita)",
    y = "Count"
  )
```



```
ggplot(cleaned, aes(x = gdp_per_capita, y = carbon_intensity_elec)) +
  geom_point(alpha = 0.3) +
  scale_x_continuous(labels = scales::comma) +
  labs(
    title = "Carbon Intensity vs GDP per Capita (Raw)",
    x = "GDP per capita",
    y = "Carbon intensity of electricity (gCO /kWh)"
  )
```



```
ggplot(cleaned, aes(x = log_gdp, y = carbon_intensity_elec)) +
  geom_point(alpha = 0.3) +
  labs(
    title = "Carbon Intensity vs Log(GDP per Capita)",
    x = "log(GDP per capita)",
    y = "Carbon intensity of electricity (gCO /kWh)"
  )
```



In the histogram, GDP per capita is extremely right-skewed, with most countries clustered at low values and a long tail of very high-income countries. Log-transforming GDP produces a more symmetric distribution appropriate for linear modeling. In the scatter plot, the relationship between GDP and carbon intensity is curved and compresses most observations into a narrow region at low GDP levels. Using log(GDP) spreads the data more evenly and produces a clearer, more linear relationship suitable for regression.

Does GDP per capita affect carbon intensity, and does this relationship differ by income group?

This model requires an interaction term.

```r
model <- lm(
  carbon_intensity_elec ~ log_gdp * income_group,
  data = cleaned
)

summary(model)
```

```
Call:
lm(formula = carbon_intensity_elec ~ log_gdp * income_group,
    data = cleaned)
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-484.22 -203.46   28.01  181.72  853.69 

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                              -404.65     126.40  -3.201  0.00138
log_gdp                                   104.75      17.02   6.156 8.55e-10
income_groupLower middle income           262.54     217.00   1.210  0.22644
income_groupUpper middle income           178.96     310.01   0.577  0.56381
income_groupHigh income                  1722.88     273.46   6.300 3.45e-10
log_gdp:income_groupLower middle income   -33.00      26.49  -1.245  0.21307
log_gdp:income_groupUpper middle income   -27.91      34.29  -0.814  0.41571
log_gdp:income_groupHigh income          -185.81      28.72  -6.471 1.15e-10
                                           
(Intercept)                             ** 
log_gdp                                 ***
income_groupLower middle income            
income_groupUpper middle income            
income_groupHigh income                 ***
log_gdp:income_groupLower middle income    
log_gdp:income_groupUpper middle income    
log_gdp:income_groupHigh income         ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 247.2 on 2741 degrees of freedom
Multiple R-squared:  0.06329,   Adjusted R-squared:  0.06089 
F-statistic: 26.46 on 7 and 2741 DF,  p-value: < 2.2e-16
```

```
confint(model)
```

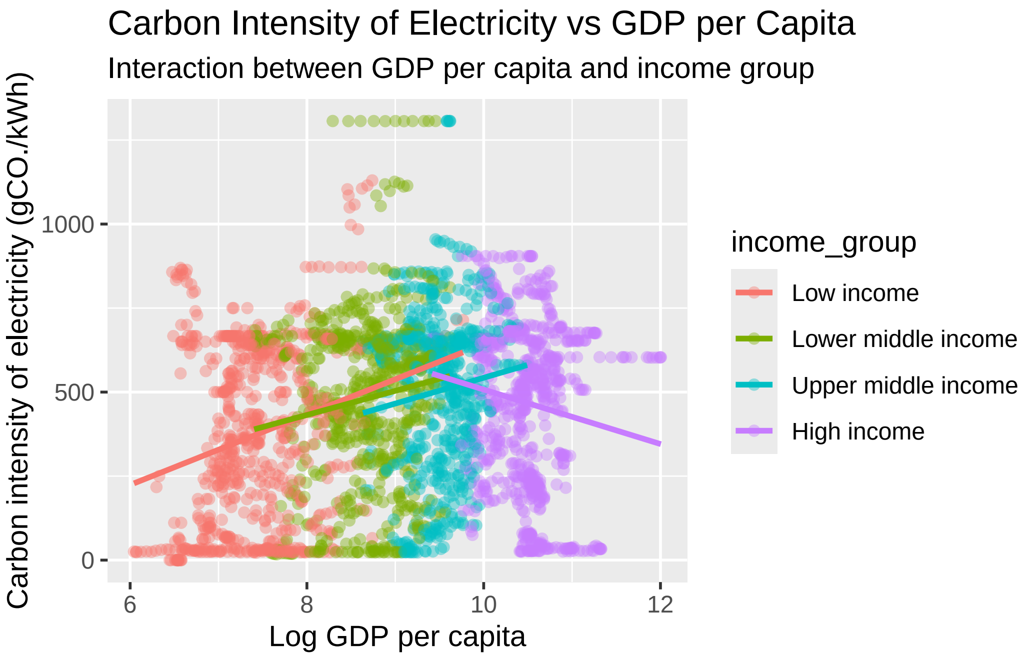
```
                                             2.5 %     97.5 %
(Intercept)                             -652.49450 -156.80330
log_gdp                                   71.38483  138.11560
income_groupLower middle income         -162.96320  688.03799
income_groupUpper middle income         -428.92212  786.83574
income_groupHigh income                 1186.65892 2259.09261
log_gdp:income_groupLower middle income  -84.94172   18.95155
log_gdp:income_groupUpper middle income  -95.14456   39.32257
log_gdp:income_groupHigh income         -242.12178 -129.50780
```

```r
coefs <- coef(model)

#  Low income  (reference)
slope_low <- coefs["log_gdp"]

# Lower middle income
slope_lower_middle <- coefs["log_gdp"] +
  coefs["log_gdp:income_groupLower middle income"]

# Upper middle income
slope_upper_middle <- coefs["log_gdp"] +
  coefs["log_gdp:income_groupUpper middle income"]

# High income
slope_high <- coefs["log_gdp"] +
  coefs["log_gdp:income_groupHigh income"]

c(slope_low, slope_lower_middle, slope_upper_middle, slope_high)
```

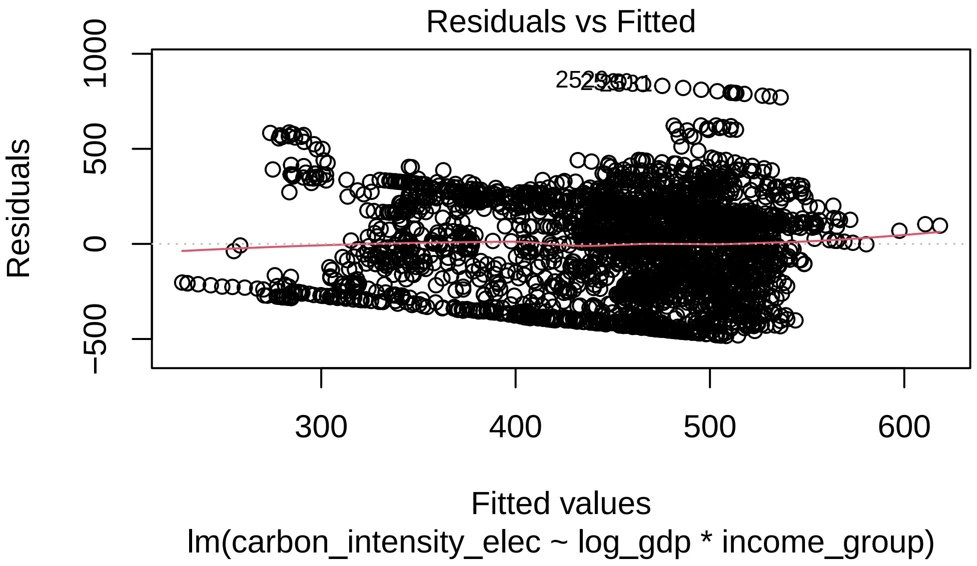
```
  log_gdp   log_gdp   log_gdp   log_gdp 
104.75022  71.75513  76.83922 -81.06457 
```

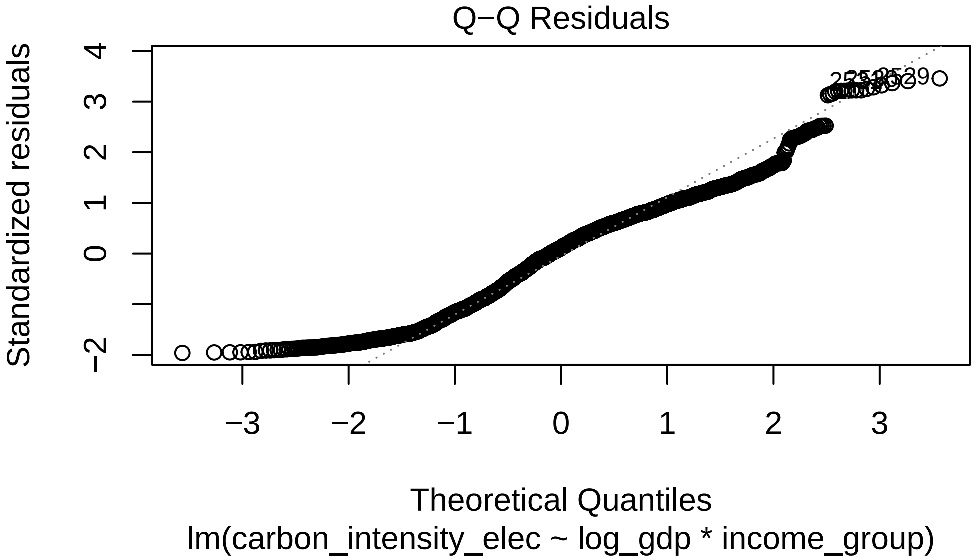
```r
library(ggplot2)

ggplot(cleaned, aes(x = log_gdp, y = carbon_intensity_elec, color = income_group)) +
  geom_point(alpha = 0.4) +
  geom_smooth(method = "lm", se = FALSE) +
  labs(
    title = "Carbon Intensity of Electricity vs GDP per Capita",
    subtitle = "Interaction between GDP per capita and income group",
    x = "Log GDP per capita",
    y = "Carbon intensity of electricity (gCO /kWh)"
  )
```

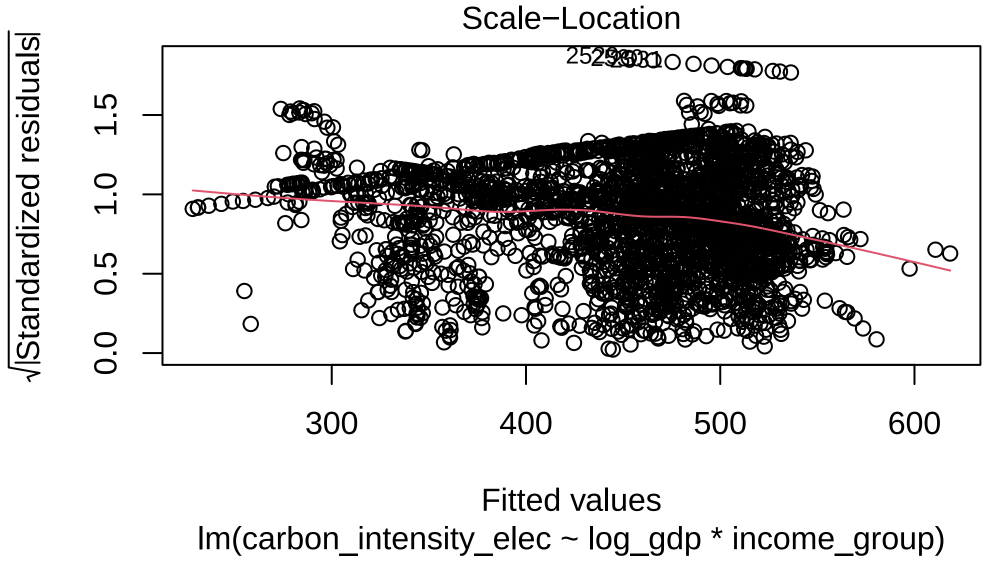
```
`geom_smooth()` using formula = 'y ~ x'
```

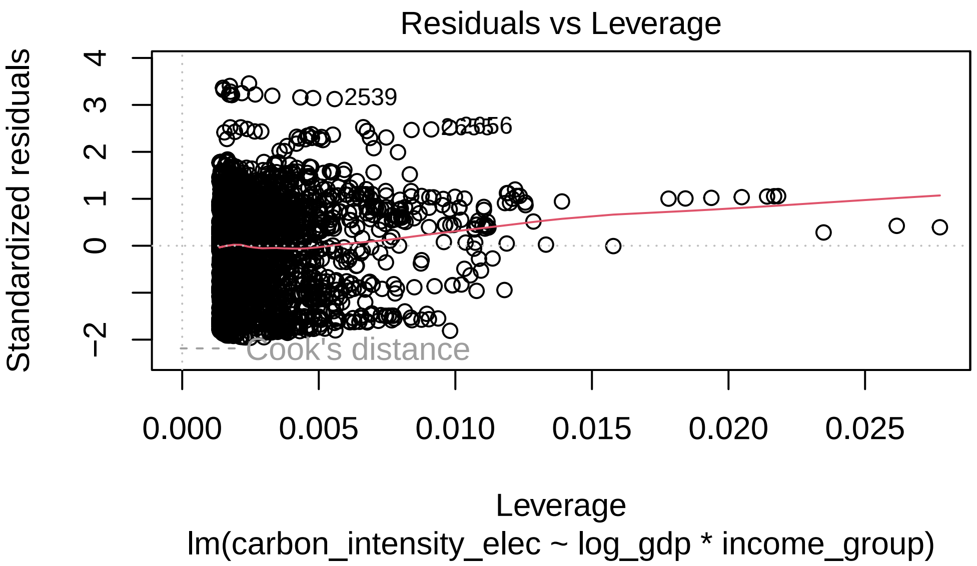

Carbon Intensity of Electricity vs GDP per Capita
Interaction between GDP per capita and income group
Carbon intensity of electricity (gCO./kWh)
1000
500
0
6
8
10
12
Log GDP per capita
income_group
Low income
Lower middle income
Upper middle income
High income

```
plot(model)
```


Residuals vs Fitted
Residuals
1000
500
0
−500
2529
300
400
500
600
Fitted values
lm(carbon_intensity_elec ~ log_gdp * income_group)


Q−Q Residuals
Standardized residuals
4
3
2
1
0
−2
−3
−2
−1
0
1
2
3
2529
Theoretical Quantiles
lm(carbon_intensity_elec ~ log_gdp * income_group)


Scale−Location
√|Standardized residuals|
1.5
1.0
0.5
0.0
300
400
500
600
Fitted values
lm(carbon_intensity_elec ~ log_gdp * income_group)



```r
confint(model)
```

```
                                              2.5 %      97.5 %
(Intercept)                              -652.49450 -156.80330
log_gdp                                    71.38483  138.11560
income_groupLower middle income          -162.96320  688.03799
income_groupUpper middle income          -428.92212  786.83574
income_groupHigh income                  1186.65892 2259.09261
log_gdp:income_groupLower middle income   -84.94172   18.95155
log_gdp:income_groupUpper middle income   -95.14456   39.32257
log_gdp:income_groupHigh income          -242.12178 -129.50780
```