Do ESG Scores Reflect Real Environmental Impact?

Nelly Nie

Contents

0.1 2. Data Cleaning & Preparation 2
0.2 3. Exploratory Visualization 4
0.3 4. Correlation and Linear Regression 5
0.4 5. LOESS Smoother 7
0.5 7. Summary of Results 9
0.6 8. Conclusion 9
0.7 9. Appendix 10

##Introduction This analysis investigates whether ESG environmental scores correlate with actual CO emissions. Using company-level ESG ratings and historical emissions data, we assess the strength and significance of this relationship, focusing especially on firms with high emissions exposure.

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.2     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(readr)
library(fuzzyjoin)
library(dplyr)
library(ggplot2)
library(stringdist)
```

```
##
## Attaching package: 'stringdist'
##
## The following object is masked from 'package:tidyr':
##
##     extract
```

##1.Load Data

```
esg_data <- read_csv("data/data.csv")
```

```
## Rows: 722 Columns: 21
## -- Column specification --------------------------------------------------------
## Delimiter: ","
```

```
## chr (16): ticker, name, currency, exchange, industry, logo, weburl, environm...
## dbl  (5): environment_score, social_score, governance_score, total_score, cik
##
## 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.
```

```r
emissions <- read_csv("data/emissions_medium_granularity.csv")
```

```
## Rows: 12551 Columns: 7
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (4): parent_entity, parent_type, commodity, production_unit
## dbl (3): year, production_value, total_emissions_MtCO2e
##
## 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.
```

0.1 2. Data Cleaning & Preparation

```r
# Step 1: Filter irrelevant data
esg_clean <- esg_data %>%
  select(name, ticker, industry, environment_score, social_score, governance_score, total_score, total_g
  filter(!is.na(environment_score))

emissions_latest <- emissions %>%
  group_by(parent_entity) %>%
  filter(year == max(year)) %>%
  summarise(total_emissions = sum(total_emissions_MtCO2e, na.rm = TRUE)) %>%
  ungroup()
```

```r
# Step 2: Remove duplicates by choosing closest match
fuzzy_merged <- stringdist_left_join(
  esg_clean,
  emissions_latest,
  by = c("name" = "parent_entity"),
  method = "jw",
  max_dist = 0.25
)

fuzzy_merged_clean <- fuzzy_merged %>%
  mutate(dist = stringdist(name, parent_entity, method = "jw")) %>%
  group_by(name) %>%
  slice_min(order_by = dist, n = 1) %>%
  ungroup() %>%
  select(-dist)  # optional cleanup
```

```r
# Step 3: Check for successful matches
summary(fuzzy_merged_clean$total_emissions)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.     NA's
##    11.34    51.41    98.81   634.84   172.56 12290.38      697
```

```r
glimpse(fuzzy_merged_clean)
```

```
## Rows: 722
## Columns: 10
```

```
## $ name               <chr> "3M Co", "A O Smith Corp", "ABIOMED Inc", "ABVC Biop~
## $ ticker             <chr> "mmm", "aos", "abmd", "abvc", "aciu", "acad", "acev"~
## $ industry           <chr> "Industrial Conglomerates", "Building", "Health Care~
## $ environment_score <dbl> 526, 510, 500, 220, 250, 230, 225, 500, 410, 220, 23~
## $ social_score       <dbl> 310, 315, 324, 212, 296, 230, 211, 327, 232, 219, 26~
## $ governance_score  <dbl> 305, 310, 305, 205, 305, 305, 215, 300, 325, 215, 31~
## $ total_score        <dbl> 1141, 1135, 1129, 637, 851, 765, 651, 1127, 967, 654~
## $ total_grade        <chr> "BBB", "BBB", "BBB", "B", "BB", "BB", "B", "BBB", "B~
## $ parent_entity      <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
## $ total_emissions    <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
```

```r
# Check if any company name still has >1 match
fuzzy_merged_clean %>%
  count(name) %>%
  filter(n > 1)
```

```
## # A tibble: 0 x 2
## # i 2 variables: name <chr>, n <int>
```

```r
fuzzy_merged_clean %>%
  filter(!is.na(total_emissions)) %>%
  select(name, parent_entity, total_emissions)
```

```
## # A tibble: 25 x 3
##    name                  parent_entity  total_emissions
##    <chr>                 <chr>                    <dbl>
##  1 CME Group Inc         OMV Group                 58.8
##  2 CMS Energy Corp       SM Energy                 21.9
##  3 Chevron Corp          Chevron                  454.
##  4 Cigna Corp            China (Coal)           12290.
##  5 Conocophillips        ConocoPhillips           260.
##  6 Coterra Energy Inc    Coterra Energy            98.8
##  7 Devon Energy Corp     Devon Energy              91.2
##  8 Diamondback Energy Inc Devon Energy             91.2
##  9 EOG Resources Inc     EOG Resources            136.
## 10 Entergy Corp          Antero                    82.9
## # i 15 more rows
```

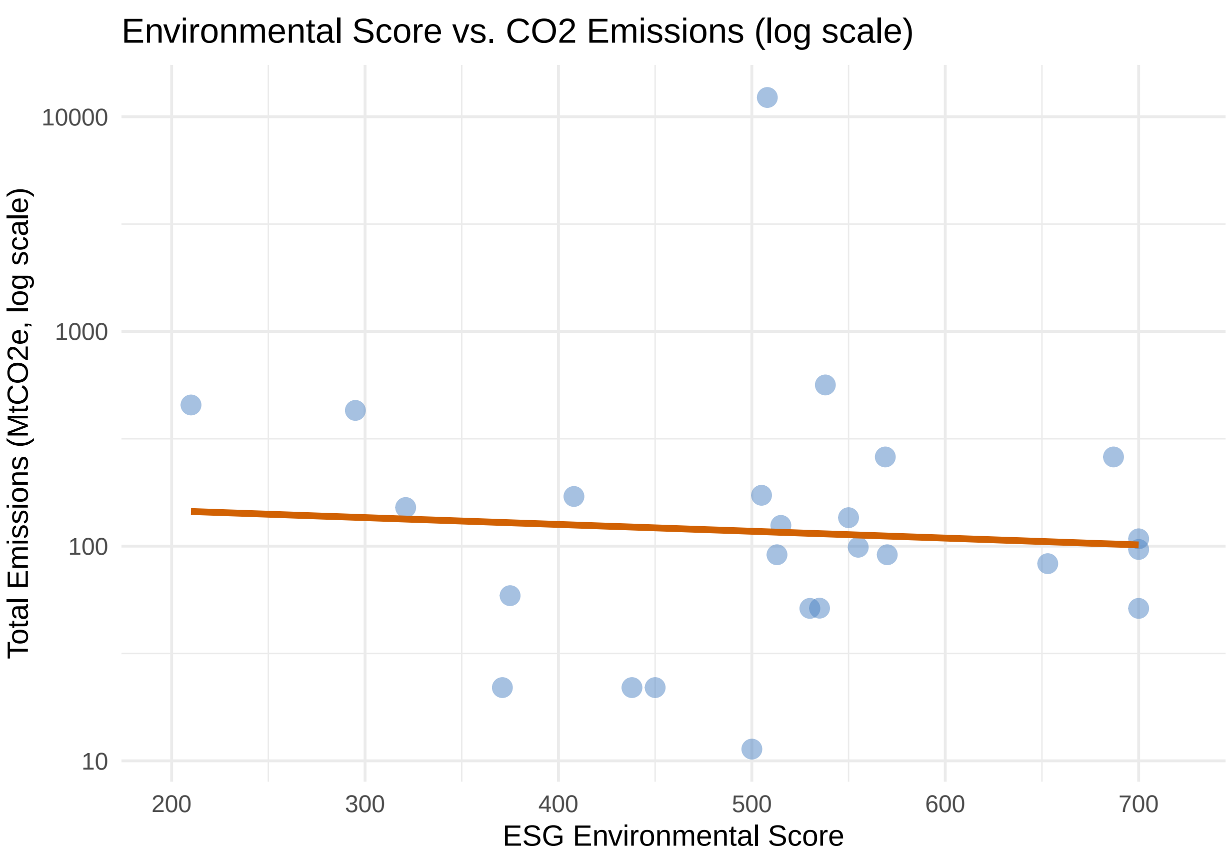
```r
fuzzy_merged <- stringdist_left_join(
  esg_clean,
  emissions_latest,
  by = c("name" = "parent_entity"),
  method = "jw",
  max_dist = 0.25  # bump this up from 0.15
)

fuzzy_merged_clean <- fuzzy_merged %>%
  mutate(dist = stringdist(name, parent_entity, method = "jw")) %>%
  group_by(name) %>%
  slice_min(order_by = dist, n = 1) %>%
  ungroup() %>%
  select(-dist)

fuzzy_merged_clean %>%
  summarise(
    total_rows = n(),
```

```
    matched = sum(!is.na(total_emissions)),
    unmatched = sum(is.na(total_emissions))
  )
```

```
## # A tibble: 1 x 3
##   total_rows matched unmatched
##        <int>   <int>     <int>
## 1        722      25       697
```

0.2 3. Exploratory Visualization

```
ggplot(fuzzy_merged_clean, aes(x = environment_score, y = total_emissions)) +
  geom_point(alpha = 0.5, size = 3, color = "#4E84C4") +
  scale_y_log10() +
  geom_smooth(method = "lm", se = FALSE, color = "#D16103", size = 1.2) +
  labs(
    title = "Environmental Score vs. CO2 Emissions (log scale)",
    x = "ESG Environmental Score",
    y = "Total Emissions (MtCO2e, log scale)"
  ) +
  theme_minimal()
```




```
matched_count <- sum(!is.na(fuzzy_merged_clean$total_emissions))
unmatched_count <- sum(is.na(fuzzy_merged_clean$total_emissions))
zero_count <- sum(fuzzy_merged_clean$total_emissions == 0, na.rm = TRUE)

cat("Matched records:", matched_count, "\n")
```

```
## Matched records: 25
```

```r
cat("Unmatched (NA) records:", unmatched_count, "\n")
```

```
## Unmatched (NA) records: 697
```

```r
cat("Zero emission records:", zero_count, "\n")
```

```
## Zero emission records: 0
```

Only 25 firms successfully matched. Most others had unmatched or missing emissions data. Skewness in CO emissions due to one or two large emitters (max > 12,000 MtCO e).

0.3 4. Correlation and Linear Regression

```r
cor.test(fuzzy_merged_clean$environment_score, log10(fuzzy_merged_clean$total_emissions))
```

```
##
##  Pearson's product-moment correlation
##
## data:  fuzzy_merged_clean$environment_score and log10(fuzzy_merged_clean$total_emissions)
## t = -0.3285, df = 23, p-value = 0.7455
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.4512816  0.3358637
## sample estimates:
##         cor
## -0.06833607
```

```r
model <- lm(log10(total_emissions) ~ environment_score, data = fuzzy_merged_clean)
summary(model)
```

```
##
## Call:
## lm(formula = log10(total_emissions) ~ environment_score, data = fuzzy_merged_clean)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.0146 -0.3397 -0.0211  0.1693  2.0229
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.2281071  0.5062726   4.401 0.000207 ***
## environment_score -0.0003177  0.0009673  -0.328 0.745509
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6128 on 23 degrees of freedom
##   (697 observations deleted due to missingness)
## Multiple R-squared:  0.00467,    Adjusted R-squared:  -0.03861
## F-statistic: 0.1079 on 1 and 23 DF,  p-value: 0.7455
```

Environmental Score vs. CO Emissions (log) Pearson correlation: r = -0.068, p = 0.75 Regression coefficient: -0.00032 (not significant, p = 0.75) $R^2 = 0.005$ → No significant relationship between environmental score and emissions.

```r
model_ln <- lm(log(total_emissions) ~ environment_score, data = fuzzy_merged_clean)
summary(model_ln)
```

```
##
## Call:
## lm(formula = log(total_emissions) ~ environment_score, data = fuzzy_merged_clean)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.3361 -0.7821 -0.0486  0.3898  4.6578
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        5.1304061  1.1657357   4.401 0.000207 ***
## environment_score -0.0007316  0.0022272  -0.328 0.745509
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.411 on 23 degrees of freedom
##   (697 observations deleted due to missingness)
## Multiple R-squared:  0.00467,    Adjusted R-squared:  -0.03861
## F-statistic: 0.1079 on 1 and 23 DF,  p-value: 0.7455
```

Coefficient (slope): -0.00073 p-value: 0.75 $R^2 = 0.005$ Conclusion: ESG scores in this dataset appear poorly aligned with actual emissions. This raises concerns about greenwashing and highlights the need for better ESG data transparency.

```r
model_log2 <- lm(log2(total_emissions) ~ environment_score, data = fuzzy_merged_clean)
summary(model_log2)
```

```
##
## Call:
## lm(formula = log2(total_emissions) ~ environment_score, data = fuzzy_merged_clean)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.3703 -1.1283 -0.0701  0.5624  6.7198
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        7.401611   1.681801   4.401 0.000207 ***
## environment_score -0.001056   0.003213  -0.328 0.745509
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.036 on 23 degrees of freedom
##   (697 observations deleted due to missingness)
## Multiple R-squared:  0.00467,    Adjusted R-squared:  -0.03861
## F-statistic: 0.1079 on 1 and 23 DF,  p-value: 0.7455
```

Coefficient (slope): −0.00106 p-value: 0.75 $R^2 = 0.005$ Conclusion: The regression shows no statistically significant relationship between a company's environmental score and its log emissions. The near-zero R^2 indicates that ESG scores explain virtually none of the variation in actual emissions. This further supports the concern that current ESG ratings may not reflect real environmental performance.

```r
summary(lm(log10(total_emissions) ~ social_score, data = fuzzy_merged_clean))
```

```
##
```

```
## Call:
## lm(formula = log10(total_emissions) ~ social_score, data = fuzzy_merged_clean)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.03935 -0.37290 -0.01435  0.14462  2.01932
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.3486829  0.4346626   5.403 1.72e-05 ***
## social_score -0.0008489  0.0012565  -0.676    0.506
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6082 on 23 degrees of freedom
##   (697 observations deleted due to missingness)
## Multiple R-squared:  0.01946,    Adjusted R-squared:  -0.02317
## F-statistic: 0.4565 on 1 and 23 DF,  p-value: 0.506
```

Coefficient: –0.00085 p-value: 0.51 $R^2 = 0.019$ Conclusion: There is no statistically significant relationship between social scores and CO emissions. The extremely low R^2 indicates that social scores explain less than 2% of emission variation. This suggests social scores may capture other aspects of ESG performance but not climate impact.

```r
summary(lm(log10(total_emissions) ~ governance_score, data = fuzzy_merged_clean))
```

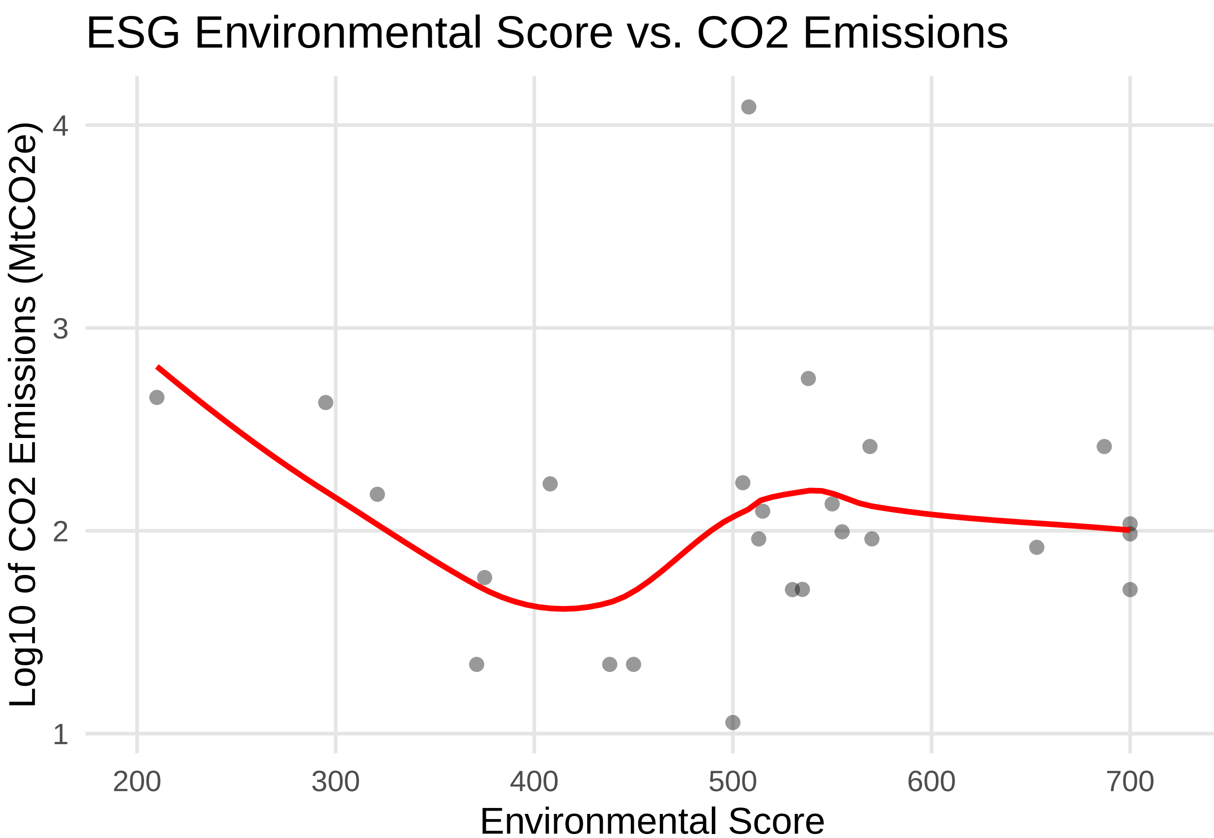
```
##
## Call:
## lm(formula = log10(total_emissions) ~ governance_score, data = fuzzy_merged_clean)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.8477 -0.2547 -0.1389  0.1813  1.9165
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.190878   0.569581   2.091   0.0478 *
## governance_score 0.003168   0.002017   1.571   0.1298
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5837 on 23 degrees of freedom
##   (697 observations deleted due to missingness)
## Multiple R-squared:  0.09692,    Adjusted R-squared:  0.05765
## F-statistic: 2.468 on 1 and 23 DF,  p-value: 0.1298
```

Coefficient: +0.00317 p-value: 0.13 $R^2 = 0.097$ Conclusion: Although not statistically significant at the 5% level, the governance score shows a slight positive correlation with emissions. This could reflect the fact that larger, more bureaucratic firms may have better governance ratings but also produce more emissions. However, the low R^2 still indicates that governance scores explain little of the emissions variance.

0.4 5. LOESS Smoother

```r
library(ggplot2)
ggplot(fuzzy_merged_clean, aes(x = environment_score, y = log10(total_emissions))) +
```

```r
  geom_point(alpha = 0.4, size = 2) +
  geom_smooth(method = "loess", color = "red", se = FALSE, span = 0.75) +
  labs(
    title = "ESG Environmental Score vs. CO2 Emissions",
    x = "Environmental Score",
    y = "Log10 of CO2 Emissions (MtCO2e)"
  ) +
  theme_minimal(base_size = 14)+
  theme(
    panel.grid.major = element_line(color = "gray90"),
    panel.grid.minor = element_blank()
  )
```



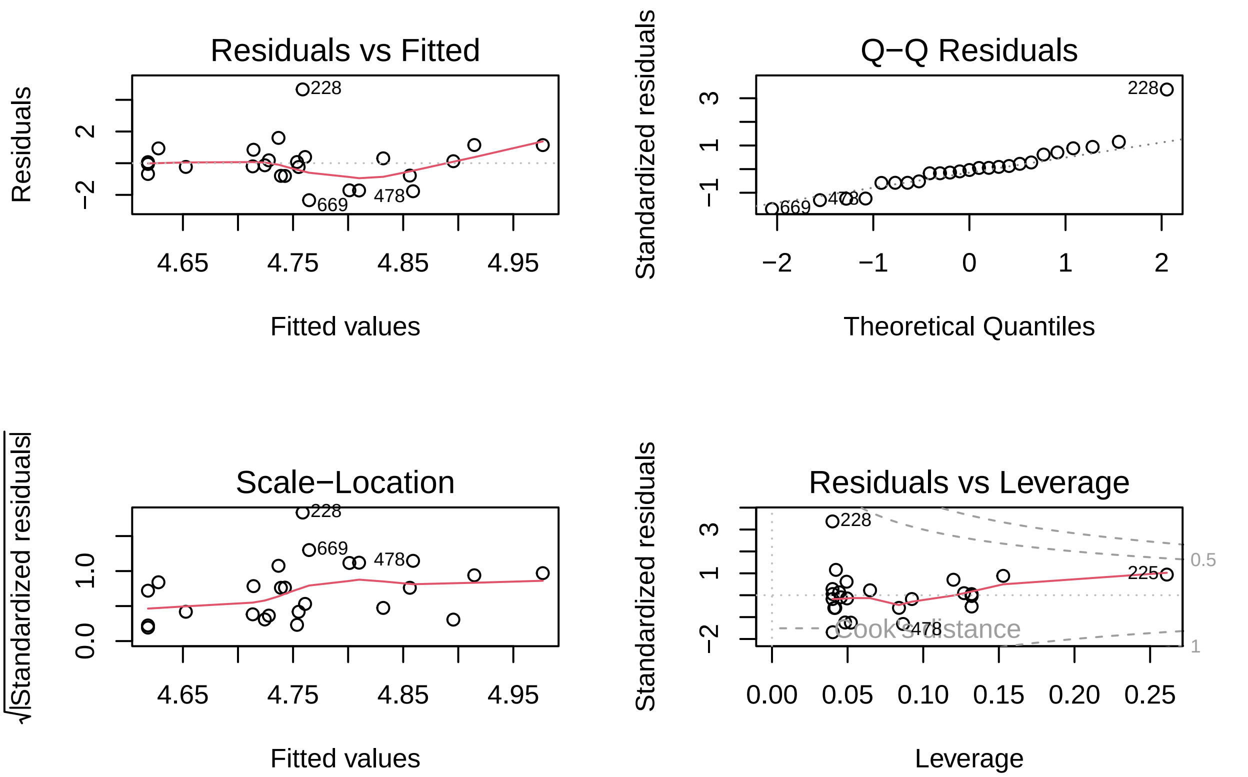
While the correlation is weak and statistically insignificant, the nonlinear pattern suggests an interesting shape: Firms with lower environmental scores tend to have higher emissions, aligning with expectations. However, for firms with moderate to high scores (400–600), emissions do not consistently decline — in fact, emissions slightly increase and then flatten out. ## 6. Diagnostics

```r
cor.test(fuzzy_merged_clean$environment_score,
         log(fuzzy_merged_clean$total_emissions),
         method = "pearson")
```

```
##
##  Pearson's product-moment correlation
##
## data:  fuzzy_merged_clean$environment_score and log(fuzzy_merged_clean$total_emissions)
## t = -0.3285, df = 23, p-value = 0.7455
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
```

```
##  -0.4512816  0.3358637
## sample estimates:
##         cor
## -0.06833607
```

```
par(mfrow = c(2, 2))
plot(model_ln)
```



Regression Diagnostics: The residual plots suggest that while most assumptions are reasonably met, there are a few mild deviations from normality (Q-Q plot) and potential mild heteroskedasticity (Scale-Location). A few influential observations (e.g., point 228) have moderate leverage but do not exceed Cook's threshold. Overall, the linear model remains interpretable, though results should be interpreted with caution given the weak R^2 and small sample size.

0.5 7. Summary of Results

• Slope: -0.0003 → A 1-point increase in environmental score correlates with a ~0.03% decrease in CO emissions — though the effect is statistically insignificant. • p-value: 0.7455 → No evidence of a meaningful relationship between environmental score and emissions. • R^2: ~0.005 → ESG score explains less than 1% of the variance in carbon emissions.

Despite ESG scores being widely used to evaluate corporate responsibility, these results suggest that high scores do not reliably correspond to low carbon output — at least not in this subset of companies with emissions data. The LOESS and residual plots further support this conclusion, showing high variance and weak fit.

0.6 8. Conclusion

This analysis finds **no statistically significant relationship** between ESG environmental scores and actual carbon emissions among companies in this matched sample. While ESG ratings may capture qualitative policies, intentions, or disclosures, they do not appear to reflect real environmental performance — especially in high-emitting sectors.

For investors, regulators, and ESG-focused institutions, this calls for greater scrutiny into how ESG metrics are constructed, and whether they can be relied upon as indicators of measurable impact. This case study highlights the need for stronger alignment between ESG scoring frameworks and independently verified environmental outcomes.

0.7 9. Appendix

```r
summary(emissions)
```

```
##       year      parent_entity      parent_type         commodity
##  Min.   :1854   Length:12551       Length:12551       Length:12551
##  1st Qu.:1973   Class :character   Class :character   Class :character
##  Median :1994   Mode  :character   Mode  :character   Mode  :character
##  Mean   :1987
##  3rd Qu.:2009
##  Max.   :2022
##  production_value    production_unit    total_emissions_MtCO2e
##  Min.   :    0.004   Length:12551       Min.   :   0.000
##  1st Qu.:   10.601   Class :character   1st Qu.:   8.785
##  Median :   63.204   Mode  :character   Median :  33.059
##  Mean   :  412.677                      Mean   : 113.206
##  3rd Qu.:  320.665                      3rd Qu.: 102.155
##  Max.   :27192.000                      Max.   :8646.906
```

```r
glimpse(emissions)
```

```
## Rows: 12,551
## Columns: 7
## $ year                   <dbl> 1962, 1962, 1963, 1963, 1964, 1964, 1965, 1965,~
## $ parent_entity          <chr> "Abu Dhabi National Oil Company", "Abu Dhabi Na~
## $ parent_type            <chr> "State-owned Entity", "State-owned Entity", "St~
## $ commodity              <chr> "Oil & NGL", "Natural Gas", "Oil & NGL", "Natur~
## $ production_value       <dbl> 0.91250, 1.84325, 1.82500, 4.42380, 7.30000, 17~
## $ production_unit        <chr> "Million bbl/yr", "Bcf/yr", "Million bbl/yr", "~
## $ total_emissions_MtCO2e <dbl> 0.3638848, 0.1343552, 0.7277697, 0.3224525, 2.9~
```

```r
glimpse(esg_data)
```

```
## Rows: 722
## Columns: 21
## $ ticker               <chr> "dis", "gm", "gww", "mhk", "lyv", "lvs", "clx", "~
## $ name                 <chr> "Walt Disney Co", "General Motors Co", "WW Graing~
## $ currency             <chr> "USD", "USD", "USD", "USD", "USD", "USD", "USD", ~
## $ exchange             <chr> "NEW YORK STOCK EXCHANGE, INC.", "NEW YORK STOCK ~
## $ industry             <chr> "Media", "Automobiles", "Trading Companies and Di~
## $ logo                 <chr> "https://static.finnhub.io/logo/ef50b4a2b263c8472~
## $ weburl               <chr> "https://thewaltdisneycompany.com/", "https://www~
## $ environment_grade    <chr> "A", "A", "B", "A", "BBB", "A", "A", "B", "B", "B~
## $ environment_level    <chr> "High", "High", "Medium", "High", "High", "High",~
## $ social_grade         <chr> "BB", "BB", "BB", "B", "BB", "BB", "BB", "B", "B"~
## $ social_level         <chr> "Medium", "Medium", "Medium", "Medium", "Medium",~
## $ governance_grade     <chr> "BB", "B", "B", "BB", "B", "BB", "BB", "B", "B", ~
## $ governance_level     <chr> "Medium", "Medium", "Medium", "Medium", "Medium",~
## $ environment_score    <dbl> 510, 510, 255, 570, 492, 547, 560, 203, 270, 220,~
```

```
## $ social_score        <dbl> 316, 303, 385, 298, 310, 318, 350, 200, 211, 221,~
## $ governance_score    <dbl> 321, 255, 240, 303, 250, 313, 345, 205, 265, 300,~
## $ total_score         <dbl> 1147, 1068, 880, 1171, 1052, 1178, 1255, 608, 746~
## $ last_processing_date <chr> "19-04-2022", "17-04-2022", "19-04-2022", "18-04-~
## $ total_grade         <chr> "BBB", "BBB", "BB", "BBB", "BBB", "BBB", "A", "B"~
## $ total_level         <chr> "High", "High", "Medium", "High", "High", "High",~
## $ cik                 <dbl> 1744489, 1467858, 277135, 851968, 1335258, 130051~
```

```r
summary(esg_data)
```

```
##     ticker              name             currency           exchange
##  Length:722         Length:722         Length:722         Length:722
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##    industry             logo              weburl          environment_grade
##  Length:722         Length:722         Length:722         Length:722
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##  environment_level  social_grade       social_level       governance_grade
##  Length:722         Length:722         Length:722         Length:722
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##  governance_level   environment_score  social_score   governance_score
##  Length:722         Min.   :200.0     Min.   :160.0   Min.   : 75.0
##  Class :character   1st Qu.:240.0     1st Qu.:243.0   1st Qu.:235.0
##  Mode  :character   Median :483.0     Median :302.0   Median :300.0
##                     Mean   :404.8     Mean   :292.2   Mean   :278.8
##                     3rd Qu.:518.8     3rd Qu.:322.8   3rd Qu.:310.0
##                     Max.   :719.0     Max.   :667.0   Max.   :475.0
##   total_score     last_processing_date total_grade        total_level
##  Min.   : 600.0   Length:722           Length:722         Length:722
##  1st Qu.: 763.0   Class :character     Class :character   Class :character
##  Median :1046.0   Mode  :character     Mode  :character   Mode  :character
##  Mean   : 975.8
##  3rd Qu.:1144.0
##  Max.   :1536.0
##       cik
##  Min.   :   1800
##  1st Qu.: 723157
##  Median :1046189
##  Mean   : 989792
##  3rd Qu.:1470094
##  Max.   :1914023
```