Does Economic Freedom Improve Environmental Outcomes?

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0.1 Introduction

When we scrutinize the relationship between capitalism and environmental impacts, we're engaging in a complex dialogue about efficiency, freedom, and sustainability. Markets act as a powerful mechanism for efficient resource allocation. Yet market-based economies, with the intrinsic drive for growth, often neglect the environmental dimension and impact. This oversight manifests in a key shortcoming: the failure to incorporate environmental costs into the pricing of goods and services.

The role of freedom in global economies brings about a dualistic impact on the environment. The positive aspects are rooted in the innovative potential and efficiency that economic freedom encourages. In a capitalist system, the competitive market can be a catalyst for discovering sustainable and economical production methods. Furthermore, the wealth generated in such systems can boost both private and public investments in environmental initiatives. Regulatory efficiency also stands out as an advantage, offering the ability to quickly adapt and respond to emerging environmental challenges. Unfortunately, there are many reasons why this idealized version falls short. At the end of the day, addressing the climate crisis is a collective action dilemma, since the actions of one person are negligible in the grand scheme of things. This makes it difficult for consumers to support climate-focused goods and services in exchange for relatively cheaper alternatives.

Now, the ugly. Capitalism often leads to aggressive resource use, resulting in issues like deforestation, loss of biodiversity, and water pollution. The tendency of capitalism to prioritize short-term profit over long-term sustainability creates a blind spot for environmental considerations. This short-sighted focus on immediate financial returns often overshadows the broader, more enduring impacts on the environment. Additionally, the burden of environmental degradation in capitalist systems is not evenly distributed. Often, it's the less affluent communities that bear the worst of this degradation, leading to a disparity in environmental impact and quality of life. In fact, the wealthiest 10 percent of the global population are responsible for half of global emissions. (Reid 2023)

While capitalism has the potential to foster innovation and generate funds that could benefit environmental conservation, resource exploitation and prioritization of short-term profits present substantial challenges to achieving true environmental sustainability.

0.1.1 What is *Economic Freedom*?

There is certainly a level of subjectivity, or at least a certain amount of uncertainty, when scoring the freedom of an economy. As a result, it seems impossible to create a perfect score for economic freedom. However, this doesn't mean people haven't tried to create a spectrum to measure how free and open different economies are.

The *Economic Freedom of the World: 2022 Annual Report* serves as the backbone of the analysis in this exploration. The dataset has a multitude of columns, the most important of which is gives each country an economic freedom index score on a scale from 1 to 10. According to the Fraser Institute, the pillars of their scoring of economic freedom depend on "personal choice, voluntary exchange, freedom to enter markets and compete, and security of the person and privately owned property." (Gwartney 2022) This economic freedom score is measured in five areas: size of government, legal system and property rights, sound money, freedom to trade internationally, and regulation.

In addition to the economic freedom index column, there are a plethora of interesting variables that can be analyzed in this dataset.

The report discusses how countries that are have higher levels of economic freedom outperform less free countries in indicators of well being. Countries in the top quartile of economic freedom saw an average per-caputa GDP of $48,251 in 2020, while countries in the bottom quartile for economic freedom had an average of $6,542. Furthermore, life expecancy in the top quartile was 80.4 years and 66 years in the bottom quartile in 2020 (Gwartney 2022) However, do these positive impacts of higher economic freedom also lead to better environmental outcomes? This analysis will put this question to the test.

0.1.2 Environmental Outcomes Analyzed

This analysis will consider several environmental outcomes pulled from the World Bank website. These data include freshwater withdrawal as a proportion of available freshwater resources (water stress), net forest depletion as a percentage of GNI, renewable energy output as a percentage of total energy consumption, renewable energy consumption as a percentage of total energy consumption, and methane emissions in metric tons of CO2 per capita (WorldBank 2023) Combined with the economic freedom data, this will allow for the analysis to look at the relationship between economic freedom scores and related variables to environmental outcomes over time in different countries.

0.1.3

0.2 Data Wrangling

First, let's import the libraries we will need to conduct this analysis.

```r
# import libraries
library(here)
library(dplyr)
library(tidyverse)
library(ggplot2)
library(janitor)
library(tidyr)
library(forecast)
library(randomForest)
library(tidyverse)

# clear environment for sanity
rm(list = ls())
```

0.2.1 Data Cleaning

Now, let's import and clean the data containing the freedom index and other scores by country.

```
# read in freedom data
freedom_raw <- read.csv('data/efw_ratings.csv', header = FALSE)
```

This data needs a good bit of clean up. This next code chunk adjusts the column headers and converts column types appropriately.

```
# set the 5th row as the column names
colnames(freedom_raw) <- freedom_raw[5,]

# remove the first 4 rows since they are now empty and clean names, remove columns
freedom <- freedom_raw[-c(1:5), ] %>%
  clean_names() %>%
  subset(select = -na) %>%
  subset(select = c(-na_2, -na_3, -na_4, -na_5)) %>%
  subset(select = -world_bank_region) %>%
  subset(select = -world_bank_current_income_classification_1990_present)

# convert year columns from char to num
freedom <- freedom %>%
  mutate(across(6:ncol(freedom), as.numeric)) %>%
  mutate(economic_freedom_summary_index = as.numeric(as.character(economic_freedom_summary
```

Now, lets move on to reading in the next dataset. The *freedom* data serves as the policy side of the data – now we want to append and compare environmental outcomes based on different political and economic factors.

```
# read in esg data
esg_wb <- read.csv('data/esg_wb.csv') %>%
  clean_names()
```

This data also needs to be cleaned up a bit. Let's get to work.

```
column_names <- c("x1998_yr1998", "x1999_yr1999", "x2000_yr2000",
                  "x2001_yr2001", "x2002_yr2002", "x2003_yr2003",
                  "x2004_yr2004", "x2005_yr2005", "x2006_yr2006",
                  "x2007_yr2007", "x2008_yr2008", "x2009_yr2009",
                  "x2010_yr2010", "x2011_yr2011", "x2012_yr2012",
```

```
                    "x2013_yr2013", "x2014_yr2014", "x2015_yr2015",
                    "x2016_yr2016", "x2017_yr2017", "x2018_yr2018",
                    "x2019_yr2019", "x2020_yr2020", "x2021_yr2021",
                    "x2022_yr2022")

# Function to extract and convert the year part of a column name to numeric
extract_year <- function(column_name) {
  year_str <- substr(column_name, 2, 5)
  as.numeric(year_str)
}

first <- names(esg_wb)[1:4]

# Apply the function to each column name
numeric_years <- sapply(column_names, extract_year)

new_cols <- c(first, numeric_years)

names(esg_wb) <- new_cols

esg_wb <- esg_wb %>%
  mutate(across(5:ncol(.), ~ as.numeric(as.character(.))))
```

```
# make longer so it is compatible to join with freedom data
esg_wb_long <- esg_wb %>%
  pivot_longer(
    cols = '1998':'2022', # Specify the range of columns to pivot
    names_to = "Year", # Name of the new column that will store the years
    values_to = "Value" # Name of the new column that will store the corresponding values
  )
```

Finally, let's merge the datasets together by year and country name.

```
# rename the country column in freedom dataset to match esg_wb_long
names(freedom)[names(freedom) == "countries"] <- "country_name"

# rename the year column in freedom dataset to match esg_wb_long
names(freedom)[names(freedom) == "year"] <- "Year"

# perform the join
freedom_esg <- merge(freedom, esg_wb_long, by = c("Year", "country_name"))
```

```r
freedom_esg <- freedom_esg %>%
  mutate(Year = as.numeric(as.character(Year)),
         Value = as.numeric(as.character(Value)))

# save dataset as a csv
write.csv(freedom_esg, "freedom_esg.csv", row.names = FALSE)
```

Sweet! Now we have the dataset we will be working with in the analysis.

0.2.2 Data Filtering

For convenience, I have created a dataframe for each of the environmental indicators to make the analysis smoother.

```r
water_stress <- freedom_esg %>%
  filter(series_name == "Level of water stress: freshwater withdrawal as a proportion of a

ag_area <- freedom_esg %>%
  filter(series_name == "Agricultural land (% of land area)")

forest_depletion <- freedom_esg %>%
  filter(series_name == "Adjusted savings: net forest depletion (% of GNI)")

renewable_output <- freedom_esg %>%
  filter(series_name == "Renewable electricity output (% of total electricity output)")

renewable_consumption <- freedom_esg %>%
  filter(series_name == "Renewable energy consumption (% of total final energy consumption

methane_emissions <- freedom_esg %>%
  filter(series_name == "Methane emissions (metric tons of CO2 equivalent per capita)")
```

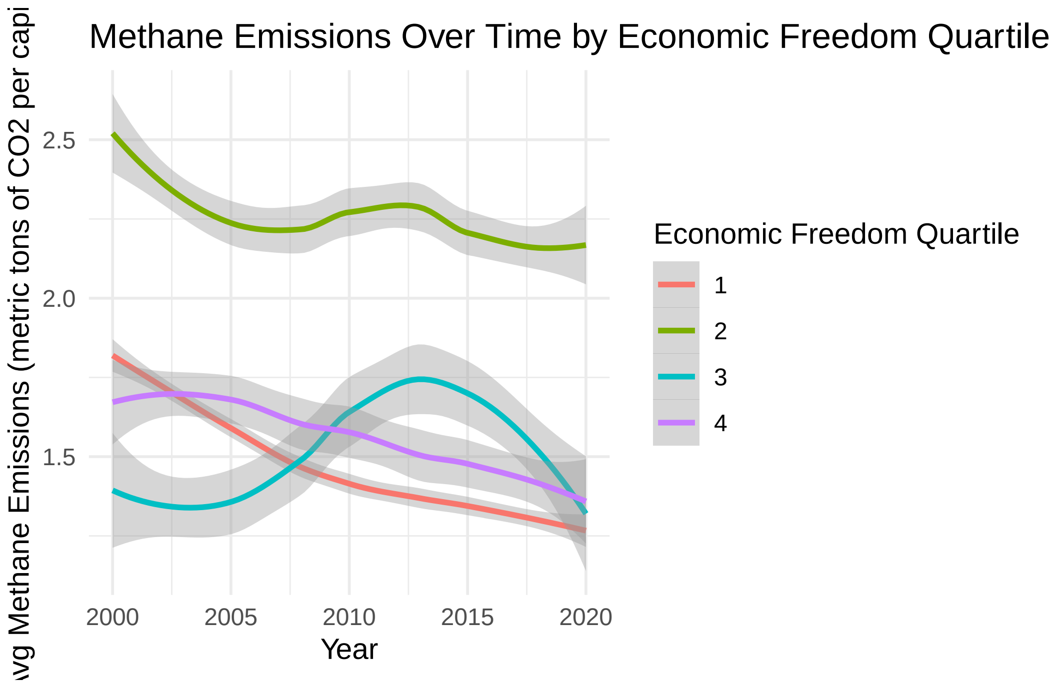
0.3 Analysis

0.3.1 Emissions

In the first piece of analysis, let's look at the methane emissions data. The units for which the emissions are recorded in the dataset are metric tons of CO2 equivalent per capita.

First, let's compare the average emission by economic freedom quartile from 2000 to 2020.

```
# create summary table for mean and stdev of methane emissions for each economic freedom q
methane_emissions_quartile <- methane_emissions %>%
  group_by(Year, quartile) %>%
  summarize(avg_methane = mean(Value, na.rm = TRUE),
            std_methane = sd(Value, na.rm = TRUE)) %>%
  na.omit()

# create bar chart of the above summary table
methane_emissions_plot_with_error <- ggplot(methane_emissions_quartile, aes(x = Year, y =
  geom_smooth(se = TRUE) +
  labs(title = "Methane Emissions Over Time by Economic Freedom Quartile",
       x = "Year",
       y = "Avg Methane Emissions (metric tons of CO2 per capita)",
       color = "Economic Freedom Quartile") +
  theme_minimal()

# display the plot
methane_emissions_plot_with_error
```



Interesting, so the second quartile of economically free countries has the highest methane emissions by a significant amount across the entire time period. Overall, the emissions levels of all quartiles decreased from 2000 to 2020, a positive sign in the hopes of becoming a carbonneutral planet.

Next, let's perform a linear regression on the economic freedom index and methane emissions.

```
# run linear regression
methane_lm <- lm(Value ~ economic_freedom_summary_index, data = methane_emissions)

summary(methane_lm)
```

```
Call:
lm(formula = Value ~ economic_freedom_summary_index, data = methane_emissions)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.6361 -1.0029 -0.7013 -0.0672 14.2312 

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)    
(Intercept)                     1.725557   0.233174   7.400 1.75e-13 ***
economic_freedom_summary_index -0.004037   0.034373  -0.117    0.907    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.028 on 3029 degrees of freedom
  (511 observations deleted due to missingness)
Multiple R-squared:  4.554e-06, Adjusted R-squared:  -0.0003256 
F-statistic: 0.01379 on 1 and 3029 DF,  p-value: 0.9065
```

This regression reveals that there is essentially no relationship between methane emissions and economic freedom, as shown by the exceptionally high p-value. When the freedom score is increased by 1, the economic freedom decreases by a measely .004037. Let's consider the analysis on a single year to see if this is any more significant (which shouldn't be that hard to achieve!).

```
# filter methane data for 2019
methane_emissions_2019 <- methane_emissions %>%
  filter(Year == 2019) %>%
  na.omit()

# run linear regression on 2019 data
methane_lm_2019 <- lm(Value ~ economic_freedom_summary_index, data = methane_emissions_201
```

```r
summary(methane_lm_2019)
```

```

Call:
lm(formula = Value ~ economic_freedom_summary_index, data = methane_emissions_2019)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.3527 -0.7840 -0.6130 -0.1845 10.2183 

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                      0.6073     1.3714   0.443    0.659
economic_freedom_summary_index   0.1196     0.1932   0.619    0.537

Residual standard error: 1.736 on 94 degrees of freedom
Multiple R-squared:  0.004061,  Adjusted R-squared:  -0.006534 
F-statistic: 0.3833 on 1 and 94 DF,  p-value: 0.5373
```

Yikes! A negative adjusted r-squared value. This is a sign that the model is a poor fit for the data and is less informative than the mean of the dependent variable. It can also be due to overfitting, but this is not the case since we are only using one predictor variable. Maybe there is a combination of factors from the multitude of columns coming from the *freedom* dataset that could be useful and informative. Let's take a look.

The code below finds the 10 variables that have the strongest correlation to methane emissions.

```r
# Ensure 'Value' is numeric
methane_emissions$Value <- as.numeric(methane_emissions$Value)

# Select only numeric columns (excluding 'Value' for now)
methane_numeric <- methane_emissions %>%
  select_if(is.numeric) %>%
  dplyr::select(-Value)

# Calculate correlation of each numeric column with the 'Value' column
methane_correlations <- sapply(methane_numeric, function(x) {
  if(is.numeric(x)) {
    return(cor(x, methane_emissions$Value, use = "complete.obs"))
  } else {
    return(NA)
  }
```

```r
})

# Convert to a dataframe for easier viewing
methane_corr_results <- as.data.frame(methane_correlations)

# Sort by the absolute value of correlation to find the strongest correlations
methane_sorted_correlations <- methane_corr_results %>%
  rownames_to_column("series") %>%
  arrange(desc(abs(methane_corr_results)))

# View the results
head(methane_sorted_correlations, 10)
```

```
                                     series methane_correlations
1                        ie_state_ownership           -0.3134906
2                                      data            0.3073977
3                                    data_4           -0.3000107
4          x3b_standard_deviation_of_inflation        -0.2831654
5                x1a_government_consumption           -0.2736432
6                                    data_5           -0.2680756
7                     gender_disparity_index          -0.2157412
8  x1dii_top_marginal_income_and_payroll_tax_rate      0.2132415
9                      x1_size_of_government          -0.2067589
10                  x1d_top_marginal_tax_rate           0.2024452
```

Let's consider the hypothesis that a strong government with stable currency and lower regulatory influence will have higher methane emissions due to the amount of profitability that can be gained through traditional methane production of goods.

```r
methane_emission_2020_selected <- methane_emissions %>%
  filter(Year == 2020) %>%
  dplyr::select(country_name, x1_size_of_government, x3_sound_money, x5_regulation, Value,
  na.omit()

emissions_lm_govt <- lm(Value ~ x1_size_of_government + x3_sound_money + x5_regulation, da

summary(emissions_lm_govt)
```

```
Call:
lm(formula = Value ~ x1_size_of_government + x3_sound_money +
```

```
    x5_regulation, data = methane_emission_2020_selected)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.7025 -0.9243 -0.5214  0.1214 10.3849 

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)  
(Intercept)            2.00245    1.22304   1.637   0.1036  
x1_size_of_government -0.20041    0.11974  -1.674   0.0962 .
x3_sound_money         0.04109    0.11744   0.350   0.7269  
x5_regulation          0.07798    0.16736   0.466   0.6419  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.772 on 157 degrees of freedom
Multiple R-squared:  0.02424,   Adjusted R-squared:  0.005599 
F-statistic:   1.3 on 3 and 157 DF,  p-value: 0.2764
```

INTERPRET HERE

What about sound money? Does having more sound money bode well for carbon emissions?

```r
methane_sm_lm <- lm(formula = Value ~ x3_sound_money + x5_regulation + data, data = renewa

summary(methane_sm_lm)
```

```
Call:
lm(formula = Value ~ x3_sound_money + x5_regulation + data, data = renewable_consumption)

Residuals:
    Min      1Q  Median      3Q     Max 
-77.363 -17.510  -3.389  17.890  72.113 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    115.07453    2.83708  40.561  < 2e-16 ***
x3_sound_money  -3.19271    0.40412  -7.900 3.85e-15 ***
x5_regulation   -5.23430    0.52510  -9.968  < 2e-16 ***
data            -1.02363    0.05894 -17.368  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 25.71 on 3037 degrees of freedom
  (501 observations deleted due to missingness)
Multiple R-squared:   0.26, Adjusted R-squared:  0.2593
F-statistic: 355.7 on 3 and 3037 DF,  p-value: < 2.2e-16
```

0.3.2 Renewable Energy Consumption

Increasing the rate of renewable energy consumption is imperative in the fight against climate change. While it would be logical to assume that private and public ensurers alike would react to the impending climate crisis by increasing demand in renewable energy, this is not really the case. First, let's look at renewable energy consumption rates across each quartile from 2000 to 2020.

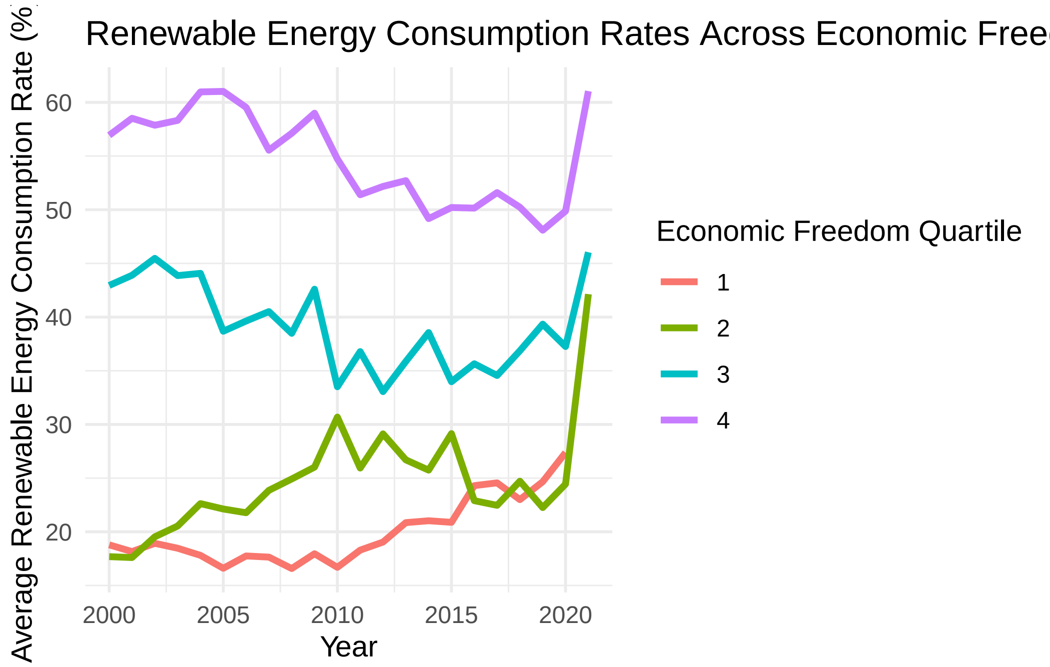
```
# group renewable consumption data by year and quartile
renewable_consumption_summary <- renewable_consumption %>%
  group_by(Year, quartile) %>%
  summarize(avg_consumption = mean(Value, na.rm = TRUE)) %>%
  na.omit()
```

```
`summarise()` has grouped output by 'Year'. You can override using the
`.groups` argument.
```

```
# plot average renewable consumption rate by quartile
renewable_consumption_quartile_plot <- ggplot(renewable_consumption_summary, aes(x = Year,
  geom_line(size = 1.2) +
  labs(title = "Renewable Energy Consumption Rates Across Economic Freedom Quartiles",
       x = "Year",
       y = "Average Renewable Energy Consumption Rate (%)",
       color = "Economic Freedom Quartile") +
  theme_minimal()
```

```
Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
i Please use `linewidth` instead.
```

```
# display plot
renewable_consumption_quartile_plot
```



The graph shows that the 4th quartile renewable energy consumption rate average is the highest among all quartiles, with the 3rd quartile being the second highest by a significant margin from 2000 all the way up until 2020. This is interesting as it reveals that countries with less economic freedom tend to have higher renewable energy consumption rates, possibly because of government regulation that mandates a certain level of consumption be renewable. However, there are alternative hypotheses as well. For instance, it could be that since we know countries that have less freedom tend to have lower GDP and overall economic output, that they simply need less energy overall and can therefore rely more on renewable energy consumption, which might be cheaper and more accessible in many of the poorer regions of the globe. Additionally, fostering a preference for renewable energy in poorer, less free countries can decrease the reliance on oil and natural gas, leading to energy portfolios that are more resilient to fluctuations and spikes in prices.

```r
renewable_pct <- renewable_consumption$Value / 100

rc_glm <- glm(renewable_pct ~ economic_freedom_summary_index, family = binomial, data = re
```

```
Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```r
rc_glm
```

```
Call:  glm(formula = renewable_pct ~ economic_freedom_summary_index,
    family = binomial, data = renewable_consumption)

Coefficients:
                   (Intercept)  economic_freedom_summary_index
                        2.9097                         -0.5383

Degrees of Freedom: 3061 Total (i.e. Null);  3060 Residual
  (480 observations deleted due to missingness)
Null Deviance:      1361
Residual Deviance: 1146     AIC: 3245
```

Next, let's conduct a linear regression to examine the dynamic between economic freedom and renewable consumption for all quartiles.

```
# conduct linear regression for renewable consumption
renewable_consumption_lm <- lm(Value ~ economic_freedom_summary_index, data = renewable_co

# display regression results
summary(renewable_consumption_lm)
```

```
Call:
lm(formula = Value ~ economic_freedom_summary_index, data = renewable_consumption)

Residuals:
    Min      1Q  Median      3Q     Max
-74.323 -19.456  -4.206  19.595  63.122

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                    112.5536     3.1058   36.24   <2e-16 ***
economic_freedom_summary_index -11.6901     0.4583  -25.51   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 27.13 on 3060 degrees of freedom
  (480 observations deleted due to missingness)
Multiple R-squared:  0.1753,    Adjusted R-squared:  0.1751
F-statistic: 650.6 on 1 and 3060 DF,  p-value: < 2.2e-16
```

DISCUSS RESULTS

0.3.3 Renewable Energy Output

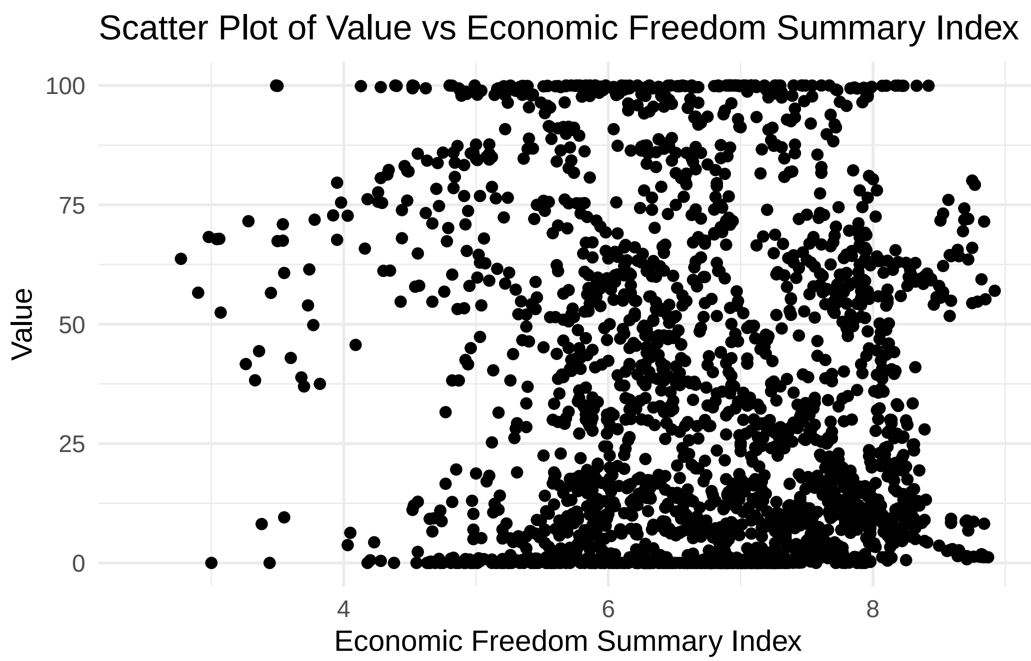
Renewable energy output is valuable in determining a country's economic impact since energy that is consumed can be exported to other countries for consumption. Furthermore, certain countries are better set up to capitalize on the economic gains of producing renewable energy due to regional climate conditions. For example, Costa Rica can produced so much renewable energy that it has enough to export it to countries in the Central American Regional Electricity Market. (Council 2022) Having renewable output rates closer to 100 bodes well for a countries long-term resilience and preparedness for increases in oil prices and the impending need for a total shift to renewable energy. These countries with higher rates are "ahead of the curve" but there are lots of variables that may still make energy demands difficult to meet due to variables outside of that country's control. Let's investigate how economic freedom and renewable energy output are related. Are countries with less economic freedom more likely to have higher renewable energy outputs since the government has more control over the market and regional demand for energy? Or are more free economies more likely to report higher renewable energy outputs due to ________________.

```r
# run linear regression of economic freedon on renewable energy output
renewable_output_lm <- lm(Value ~ economic_freedom_summary_index, data = renewable_output)

summary(renewable_output_lm)
```

```

Call:
lm(formula = Value ~ economic_freedom_summary_index, data = renewable_output)

Residuals:
    Min      1Q  Median      3Q     Max 
-52.717 -29.203  -8.951  26.743  72.335 

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)    
(Intercept)                     66.6093     4.3933  15.162  < 2e-16 ***
economic_freedom_summary_index  -4.6307     0.6492  -7.133 1.32e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 33.3 on 2237 degrees of freedom
  (1303 observations deleted due to missingness)
Multiple R-squared:  0.02224,	Adjusted R-squared:  0.0218 
F-statistic: 50.88 on 1 and 2237 DF,  p-value: 1.321e-12
```

```r
ggplot(renewable_output, aes(x = economic_freedom_summary_index, y = Value)) +
  geom_point() +  # add points
  labs(title = "Scatter Plot of Value vs Economic Freedom Summary Index",
       x = "Economic Freedom Summary Index",
       y = "Value") +
  theme_minimal()  # using a minimal theme for a clean look
```

```
Warning: Removed 1303 rows containing missing values (`geom_point()`).
```

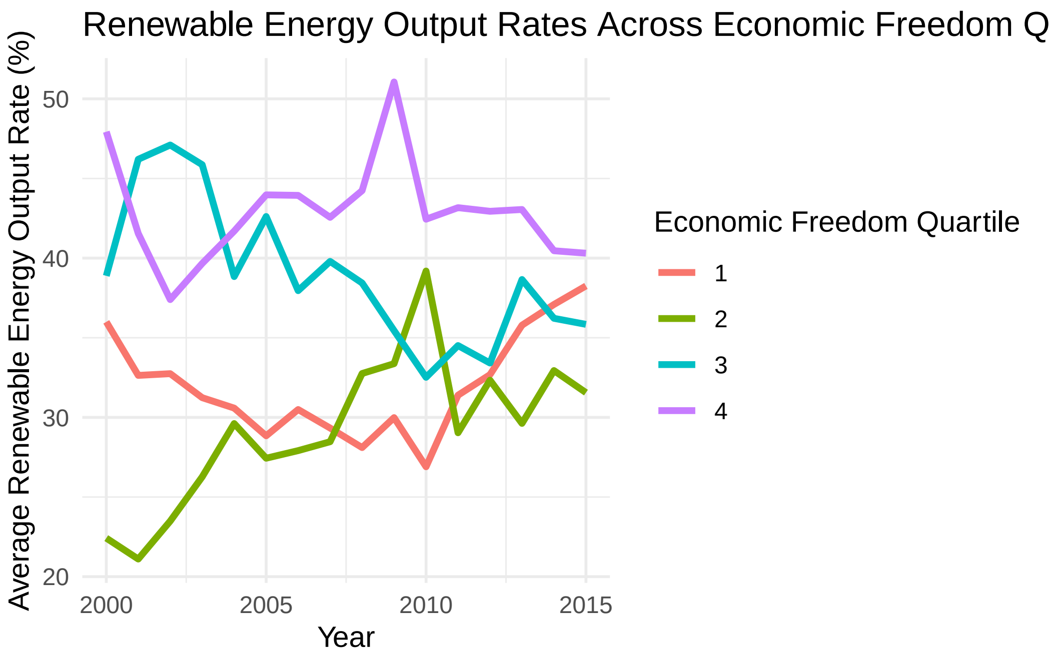


DISCUSS

```r
# group renewable consumption data by year and quartile
renewable_output_summary <- renewable_output %>%
  filter(Year <= 2015) %>%
  group_by(Year, quartile) %>%
  summarize(avg_output = mean(Value, na.rm = TRUE)) %>%
  na.omit()
```

```
`summarise()` has grouped output by 'Year'. You can override using the
`.groups` argument.
```

```r
# plot average renewable consumption rate by quartile
renewable_output_quartile_plot <- ggplot(renewable_output_summary, aes(x = Year, y = avg_o
  geom_line(size = 1.2) +
  labs(title = "Renewable Energy Output Rates Across Economic Freedom Quartiles",
       x = "Year",
       y = "Average Renewable Energy Output Rate (%)",
       color = "Economic Freedom Quartile") +
  theme_minimal()

# display plot
renewable_output_quartile_plot
```



Next, let's investigate if there is a significant difference in renewable energy output across each quartile of economic freedom.

```r
renewable_output$quartile <- factor(renewable_output$quartile)

anova_ro <- aov(Value ~ quartile, data = renewable_output)

summary(anova_ro)
```

```
               Df  Sum Sq Mean Sq F value   Pr(>F)    
quartile        3   62414   20805   18.79 4.93e-12 ***
Residuals    2235 2475053    1107                     
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
1303 observations deleted due to missingness
```

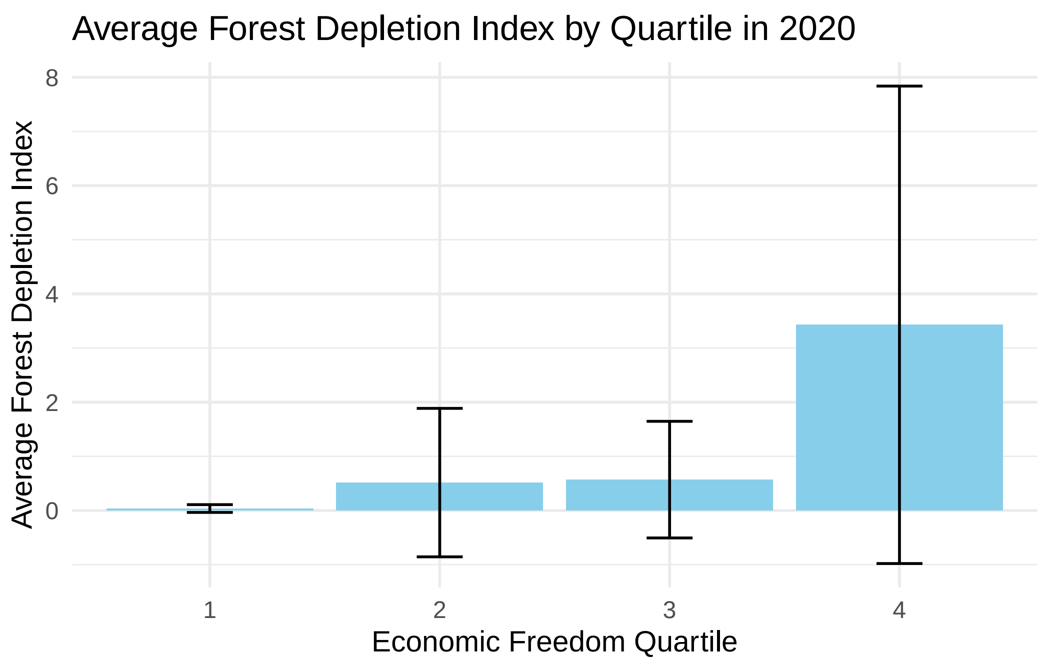
DISCUSS RESULTS.

0.3.4 Forest Depletion

Deforestation is a massive issue that exacerbates the climate crisis. Countries that are cutting down trees at higher rates for timber and clearing land for agriculture come at the expense of the health of ecosystems around the world. Are countries with more freedom cutting down more forests to exploit the profit it has to offer? Or are less free countries that are economically limited on the private side more likely to

```r
forest_depletion_2020_quartile_summary <- forest_depletion %>%
  group_by(quartile) %>%
  filter(Year == 2020) %>%
  summarize(avg_depletion = mean(Value, na.rm = TRUE),
            std_depletion = sd(Value, na.rm = TRUE))
```

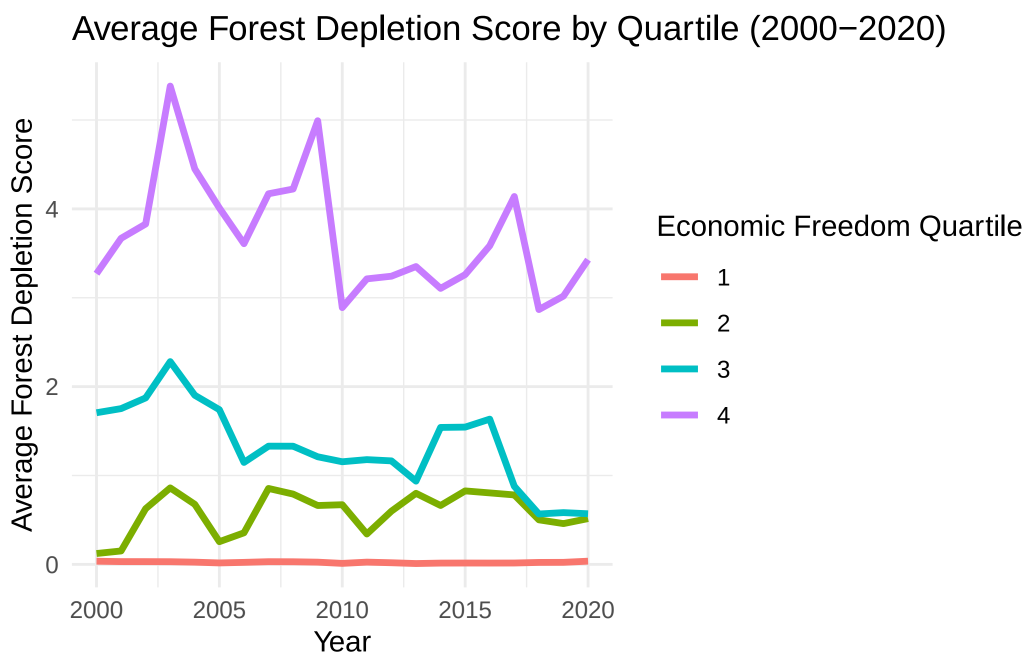
```r
# Plotting
ggplot(forest_depletion_2020_quartile_summary, aes(x = factor(quartile), y = avg_depletion
  geom_bar(stat = "identity", position = position_dodge(), fill = "skyblue") +
  geom_errorbar(aes(ymin = avg_depletion - std_depletion, ymax = avg_depletion + std_deple
               width = 0.2, position = position_dodge(0.9)) +
  labs(title = "Average Forest Depletion Index by Quartile in 2020",
       x = "Economic Freedom Quartile",
       y = "Average Forest Depletion Index") +
  theme_minimal()
```



This visualization provides some strong takeaways.

Now let's look at this over time

```
# Aggregating the forest depletion data by year and quartile
forest_depletion_time_series <- forest_depletion %>%
  group_by(Year, quartile) %>%
  summarize(avg_depletion = mean(Value, na.rm = TRUE),
            std_depletion = sd(Value, na.rm = TRUE)) %>%
  na.omit()

# Plotting a line graph with thicker lines
ggplot(forest_depletion_time_series, aes(x = Year, y = avg_depletion, color = as.factor(qu
  geom_line(size = 1.2) +  # Increase line thickness
  labs(title = "Average Forest Depletion Score by Quartile (2000-2020)",
       x = "Year",
       y = "Average Forest Depletion Score",
       color = "Economic Freedom Quartile") +
  theme_minimal()
```



Let's run an ANOVA test to determine the significance here.

```
forest_depletion_2020 <- forest_depletion %>%
  filter(Year == 2020) %>%
  na.omit()

anova_fd <- aov(Value ~ quartile, data = forest_depletion_2020)

summary(anova_fd)
```

```
            Df Sum Sq Mean Sq F value   Pr(>F)    
quartile     1  34.33   34.33   14.73 0.000228 ***
Residuals   91 211.99    2.33                     
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

DISCUSS RESULTS HERE

0.3.5 Water Stress

```r
# Ensure 'Value' is numeric
water_stress$Value <- as.numeric(water_stress$Value)

# Select only numeric columns (excluding 'Value' for now)
water_stress_numeric <- water_stress %>%
  select_if(is.numeric) %>%
  dplyr::select(-Value)

# Calculate correlation of each numeric column with the 'Value' column
water_stress_correlations <- sapply(water_stress_numeric, function(x) {
  if(is.numeric(x)) {
    return(cor(x, water_stress$Value, use = "complete.obs"))
  } else {
    return(NA)
  }
})

# Convert to a dataframe for easier viewing
water_stress_correlation_results <- as.data.frame(water_stress_correlations)

# Sort by the absolute value of correlation to find the strongest correlations
water_stress_sorted_correlations <- water_stress_correlation_results %>%
  rownames_to_column("series") %>%
  arrange(desc(abs(water_stress_correlation_results)))

# View the results
head(water_stress_sorted_correlations, 10)
```

```
                                          series water_stress_correlations
1                                         data_4                -0.3370701
2                                         data_5                -0.3331397
3                          gender_disparity_index                -0.3300405
4  x1dii_top_marginal_income_and_payroll_tax_rate                 0.2724939
5                              ie_state_ownership                -0.2573339
6                         x1d_top_marginal_tax_rate                0.2517648
7              x3b_standard_deviation_of_inflation               -0.2345262
8                                            data                 0.2053606
9                       x1a_government_consumption               -0.2029093
10                          x2h_police_and_crime                 0.1872722
```

INTERPRET RESULTS

```r
water_stress_lm <- lm(Value ~ data + data_4 + data_5 + ie_state_ownership, data = water_st

summary(water_stress_lm)
```

```
Call:
lm(formula = Value ~ data + data_4 + data_5 + ie_state_ownership,
    data = water_stress)

Residuals:
   Min     1Q Median     3Q    Max
-632.0  -90.4  -18.1   47.9 3381.3

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        361.5887    35.2179  10.267  < 2e-16 ***
data                 8.8282     0.7399  11.931  < 2e-16 ***
data_4              -4.1868     0.6793  -6.163 8.37e-10 ***
data_5              -4.8683     0.7448  -6.537 7.69e-11 ***
ie_state_ownership -22.0182     4.2722  -5.154 2.77e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 289.9 on 2339 degrees of freedom
  (1198 observations deleted due to missingness)
Multiple R-squared:  0.1961,    Adjusted R-squared:  0.1947
F-statistic: 142.6 on 4 and 2339 DF,  p-value: < 2.2e-16
```

DISCUSS RESULTS HERE.

```r
# Assuming 'data' is your dataset and it includes country, year, and various metrics
# Filter the dataset for the year 2020
data_2020 <- filter(freedom, Year == 2020)

# Select relevant columns (metrics) for comparison
relevant_data <- data_2020 %>%
  dplyr::select(country_name, economic_freedom_summary_index, data, data_3, x1_size_of_gov
  na.omit()  # Remove rows with NA values

# Normalize the data
```

```r
normalized_data <- as.data.frame(scale(relevant_data[,-1]))  # Exclude country_name for sc
normalized_data$country_name <- relevant_data$country_name

# Calculate Euclidean distances
switzerland_data <- normalized_data %>% filter(country_name == "Switzerland")
distances <- apply(normalized_data[,-ncol(normalized_data)], 1, function(x) {
  sqrt(sum((x - unlist(switzerland_data[,-ncol(switzerland_data)]))^2))
})

# Combine distances with country names
distance_data <- data.frame(country_name = normalized_data$country_name, distance = distan

# Rank countries by distance
similar_countries <- distance_data %>%
  arrange(distance) %>%
  filter(country_name != "Switzerland")

# View the top similar countries
head(similar_countries, 25)
```

```
    country_name distance
146       Taiwan 1.554085
82   Korea, Rep. 2.121651
79        Jordan 2.458543
78         Japan 2.511936
118       Panama 2.685598
42       Czechia 2.732854
49       Estonia 2.746570
26    Cabo Verde 2.781533
29        Canada 2.815082
74       Ireland 2.826248
32         Chile 2.845195
91     Lithuania 2.864692
38    Costa Rica 2.898260
124     Portugal 2.989666
160      Uruguay 2.997393
23      Bulgaria 3.003527
86        Latvia 3.005952
5        Armenia 3.019764
77       Jamaica 3.021642
126      Romania 3.051458
6      Australia 3.067597
```

```
97         Malta 3.084109
110  New Zealand 3.126053
58       Germany 3.126077
69       Iceland 3.158637
```

0.3.6

0.3.7 Similarity Function

So what we just made can be turned into a function to compare lots of countries. Here is the function:

```r
find_similar_countries_w_methane <- function(data, target_country, top_n = 25) {
  # Filter the dataset for the year 2020
  data_2020 <- filter(data, Year == 2020)

  # Select relevant columns
  relevant_data <- data_2020 %>%
    dplyr::select(country_name, economic_freedom_summary_index, x1_size_of_government, x2_
    na.omit()

  # Normalize the data
  normalized_data <- as.data.frame(scale(relevant_data[,-1]))
  normalized_data$country_name <- relevant_data$country_name

  # Calculate Euclidean distances
  target_country_data <- normalized_data %>% filter(country_name == target_country)
  distances <- apply(normalized_data[,-ncol(normalized_data)], 1, function(x) {
    sqrt(sum((x - unlist(target_country_data[,-ncol(target_country_data)]))^2))
  })

  # Combine distances with country names
  distance_data <- data.frame(country_name = normalized_data$country_name,
                              eucl_distance = distances)

  # Rank countries by distance
  similar_countries <- distance_data %>%
    arrange(eucl_distance) %>%
    filter(country_name != target_country)

    # Filter methane emissions data for 2020
```

```r
  emissions_2020 <- filter(methane_emissions, Year == 2020)

  # Join the methane emissions data
  similar_countries_with_emissions <- merge(similar_countries, emissions_2020, by = "count
    dplyr::select(country_name, eucl_distance, Value) %>%
    arrange(eucl_distance)

  # Return the top similar countries
  head(similar_countries_with_emissions, top_n)
}
```

Now, let's test the function.

```r
find_similar_countries_w_methane(freedom, "Denmark", 25)
```

```
           country_name eucl_distance     Value
1            Luxembourg     0.7318000 0.8815772
2               Finland     0.7342867 0.8149538
3             Australia     0.9688008 5.1250548
4           Netherlands     0.9691750 0.8715177
5                 Japan     1.0558955 0.2042065
6                Sweden     1.0800896 0.4628503
7                Norway     1.0815548 0.8072835
8                Canada     1.0925807 2.6348554
9           New Zealand     1.1156783 6.3341199
10              Germany     1.1405345 0.5641788
11              Ireland     1.1964686 3.0595097
12              Iceland     1.2500208 1.4057751
13       United Kingdom     1.2613322 0.7515615
14              Estonia     1.3180414 0.8251958
15              Austria     1.3206713 0.7696740
16              Belgium     1.4859101 0.6910790
17               Latvia     1.5998452 1.0275522
18        United States     1.6395011 2.2570601
19               France     1.7097647 0.8650367
20              Czechia     1.7209772 1.1573900
21 United Arab Emirates     1.7323338 6.1314669
22                Spain     1.7583522 0.8382282
23            Singapore     1.7786043 0.7646497
24            Lithuania     1.8256855 1.0728030
25                Malta     1.8824874 0.4429875
```

```
function_regression <- lm
```

Omitted Variable Bias

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