Environmental Research Report

Analysis of Worldwide Carbon Emission Contributions

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To Michael S. Regan and global environmental agency administrators/directors,

Abstract:

During the duration of our study, our group focused on better understanding and modeling economic factors into a nation's carbon emissions. Our analysis below highlights this objective in a two-folded manner, centered on understanding how different economic status groups affect a nation's carbon footprint as well as using key economic and demographic characteristics to categorize nations into high, medium, or low carbon emitters. This categorization would enable countries to understand how they compare to other countries around the globe.

To conduct this study, we used the World Inequality Database as our primary source of data to obtain the income bracket distribution, the national wealth, the national income, population, and the nation's carbon footprint from ten countries geographically spread around the world. As a result, we were able to conclude the following:

1. The amount of carbon emissions was not the same across all defined income brackets as the bottom 50% accounted for the most carbon emission within a country
2. By analyzing the logarithmic value of a nation's income, wealth, and population, we have derived a model that predicts and categorizes a country as a high, medium, or low emitter with 95% accuracy.

Introduction

When one turns on the news and sees natural disasters caused by weather, the next topic most meteorologists will expose viewers to is climate change. This global phenomenon is defined as the shifts within temperatures and weather patterns caused by human activities, which lead to significant climatic events. With more and more significant climatic events on the rise, more and more businesses and countries have changed their perspective and level of effort to combat this in the near future (outlining the year 2030 as the target for ensuring and implementing climate initiatives). Companies, such as Apple, have developed more sustainable and climate-conscious global supply chains and operations that aim to be carbon neutral. Similarly, many global countries and leaders have stepped forth to show the importance of this matter through initiatives/agreements such as the Paris Agreement/Paris Accords and establishing other global and national environmental targets.

In conjunction with this shift in climate, there is also a pronounced change within the distribution of wealth within countries across the globe. As the world has adopted technological advancements, the number of billionaires within the world have also increased dramatically. In 2021 alone, the world saw 153 new billionaires – an astounding 3 new billionaires per week (Block, 2022). The creation of this new wealth has only led to an increase in economic disparity within the world. The International Monetary Fund (IMF) discovered that "the current disparities are extreme. The poorest half of the global population owns just €2,900 (in purchasing power parity) per adult, while the top 10 percent owns roughly 190 times as much. Income inequalities are not much better. The richest 10 percent today snap up 52 percent of all income. The poorest half get just 8.5 percent" (Staley, 2022). As seen in the graphic from The IMF in the Appendix (titled A lopsided world), the Fund also concluded from their analysis that 48% of global carbon emissions are caused by the top 10%. Using this as a baseline, we wanted to understand if there was truly a difference on the level of carbon emission between income levels.

To conduct our study, as aforementioned, our dataset was selected from the World Inequality Database (WID), which is one of the most extensive databases on the evolution of world distribution of income and wealth within and between countries. The database is open-access and has compiled valid data from national databases, surveys, fiscal data, and wealth rankings. With its vast array of features, there are many key economic and social inequality questions that could be answered with access to this data. Our group has decided to focus our statistical analysis on the impact of certain economical features on a nation's carbon footprint (Total National CO2 Footprint). For clarification, a nation's total carbon footprint is equal to the combination of CO2 footprint and footprint of other greenhouse gases.

While the dataset/database is vast, we narrowed down our analysis to the following key variables that will help us effectively analyze and assess the impact of economic and demographic statistics on carbon emissions for a subset of ten select countries (The United States, China, India, Germany, the United Kingdom, Canada, Australia, Brazil, Nigeria, and South Africa): national income, GDP, income inequality, population, market-value national wealth, years (from 2000 – 2020). *It is important to note: to help standardize the findings for all countries, the US dollar was the currency selected for the appropriate variables*

This leads to two distinct research questions:

1.How do income brackets (top 10%, middle 40%, bottom 50%) affect a nation's carbon footprint? Based on the research mentioned above as well as additional publications/evidence highlighting that the wealthiest bracket emits notably more tons of carbon compared to the bottom bracket (Ritchie, 2018), we hope to use our data and our model to either validate this evidence or understand the true relationship between the different economic status groups and their respective effects on a nation's carbon footprint. Our assumption refutes the evidence highlighted and is that carbon emissions are comparable amongst the three income brackets.

a. H_0: Carbon emissions are the same across all income brackets.
b. H_A: Carbon emissions vary across income brackets.

If we see a disparity between the three income brackets, we also want to understand the income bracket that emits the most carbon. Is it truly the wealthiest top 10%?

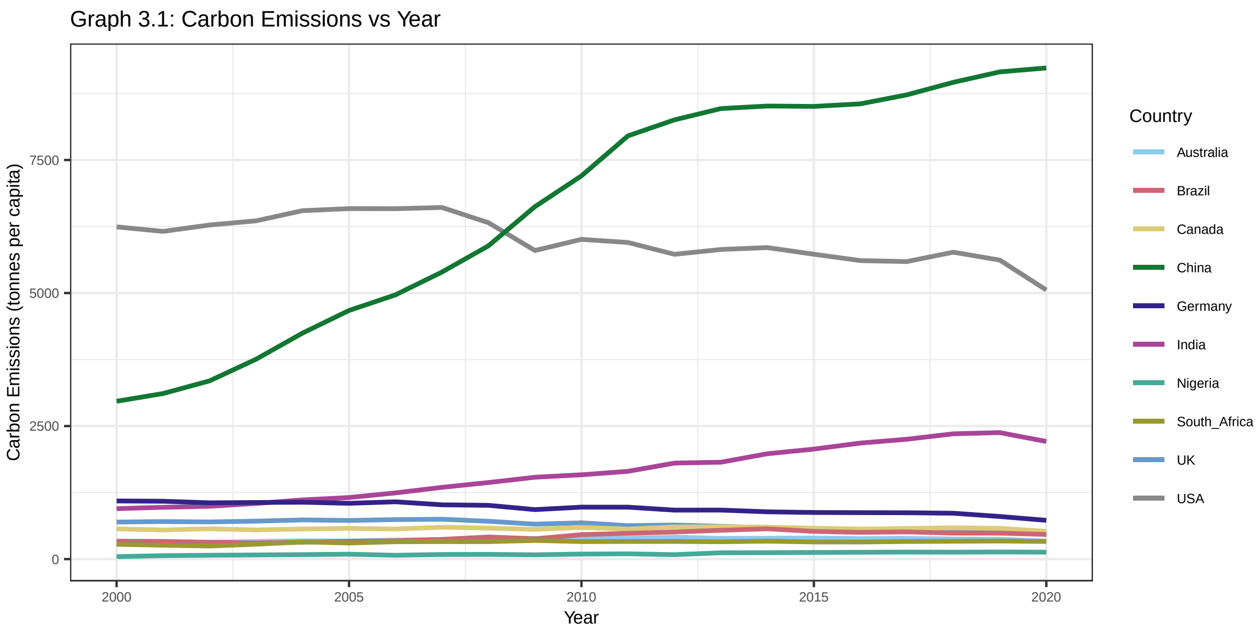
2. Given a nation's economic and demographic statistics, how accurately is an environmentalist able to classify/categorize countries into their appropriate level of carbon emissions? Our hopeful end goal is to create and use a model to predict the appropriate carbon emission category for other countries (unseen data). One of our key assumptions in creating this model is that there are no CO2 changes between any of the income brackets and changes within a country's average wealth over time have not had an impact on the country's respective carbon footprint, and thus, the difference in carbon emission class is proportional.

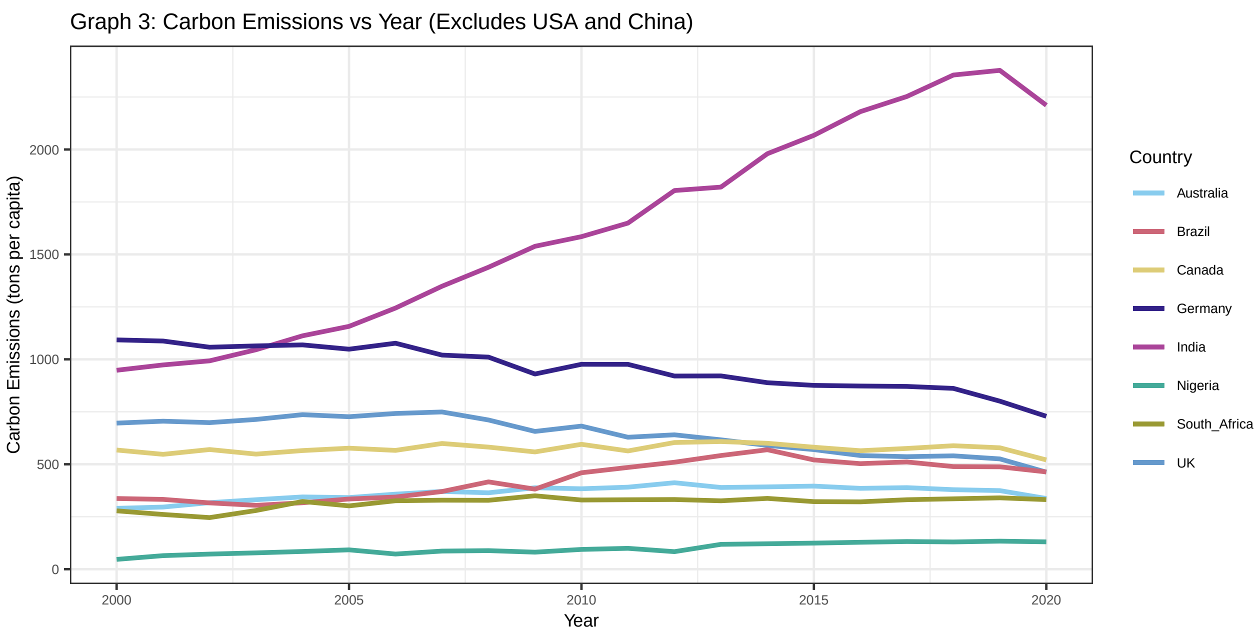
Methods

Data Exploration

To begin our analysis, we explored each country's carbon emission as well as the relationship between that response and the other key economic indicators mentioned above. From the following graphs, we plotted

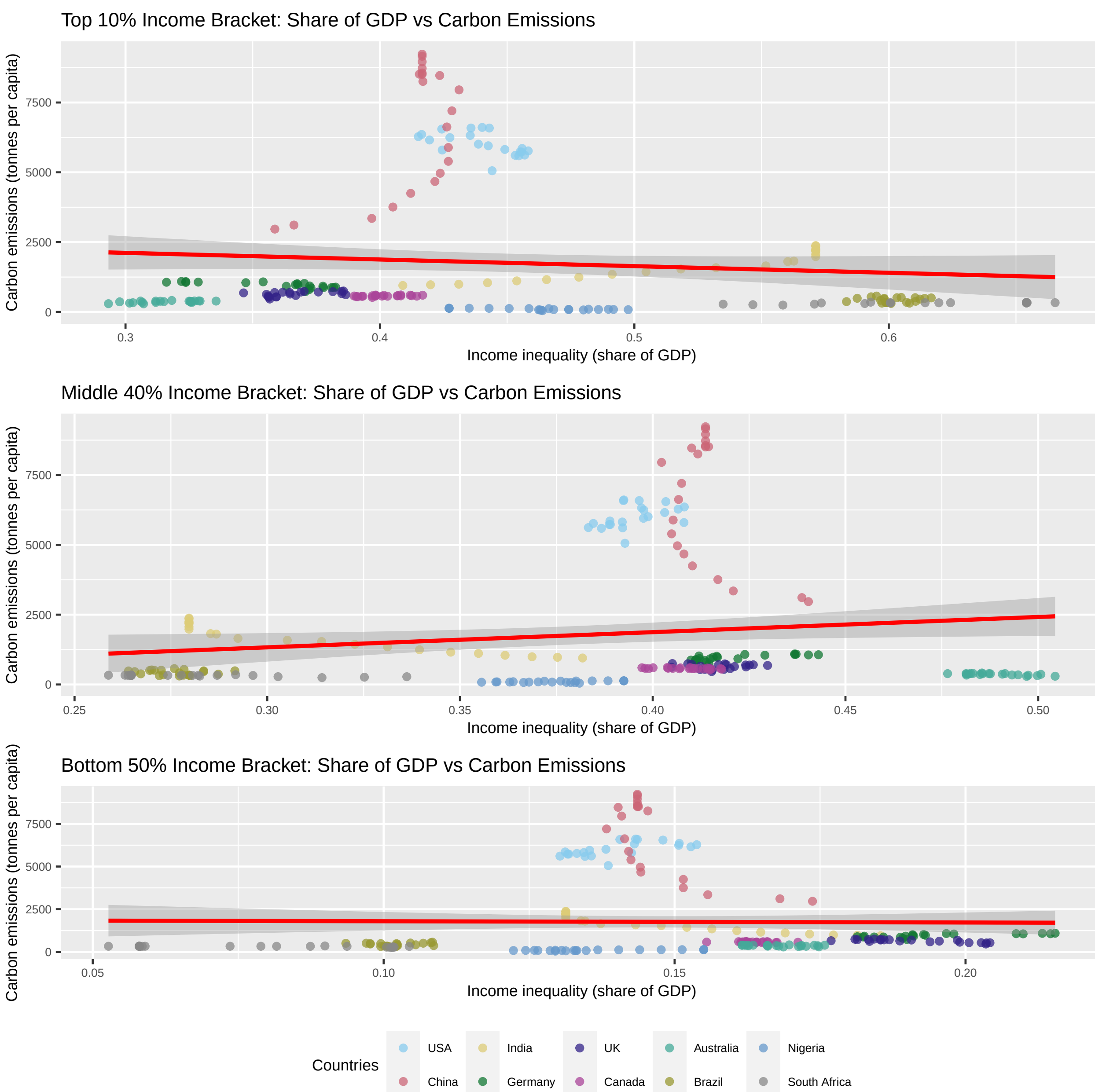
CO2 over time for every country. In the graph on the left, we included all ten countries and realized a disparity in trends between China and USA versus the other eight. Thus, we classify USA and China as high emitters. The graph on the right zooms in on the remaining eight countries, which we classify as medium/low emitters. There is a linear trend for all countries, which allows us to assume linearity for the models we will fit.



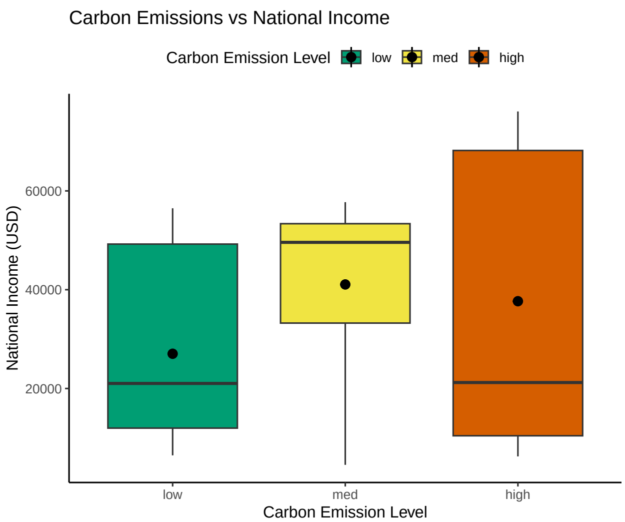


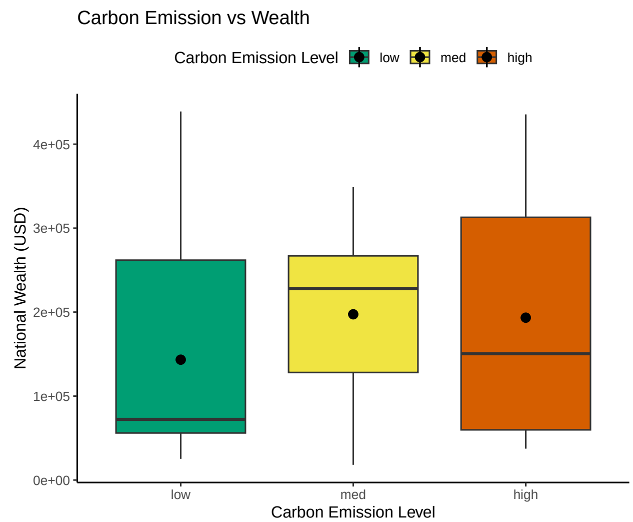
Upon initially recognizing this linear relationship, we took a deeper dive and analyzed each country separately. From the series of graphs found within the Appendix (titled GDP vs CO2) to see if there was a general trend between GDP and CO2 shared between all the countries, we found that there is no common direction. Since the graphs show the differing relationships between GDP and CO2, we would not be able to build a generalizable model that could apply to countries unseen by the model and thus opted not to use GDP as our indicator for national income/wealth. During our initial exploratory analysis, we discovered most countries show positive correlation between wealth and CO2 (except for USA, Germany, and UK). This finding was crucial for model development as the model needs to account for the differences between countries.

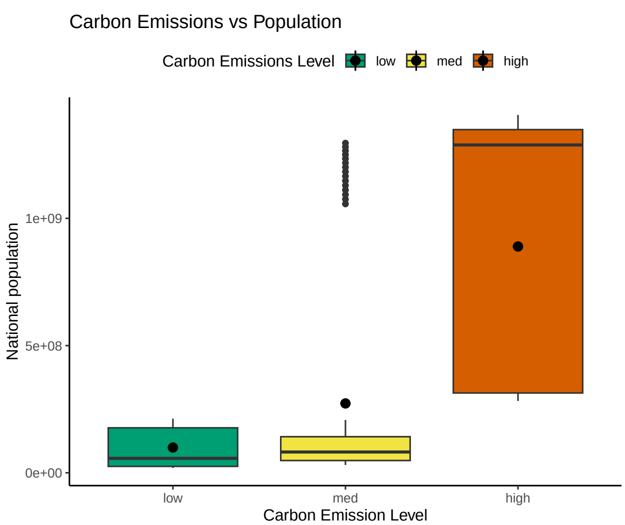
To analyze the distribution and impact of income brackets, we fit a line to each of the above graphs and saw a clear distinction between the high and low emitters. The high emitters, China and USA, rise high above the fit line and the rest either sit on the line or below. This is consistent across the three graphs. To correct for the disparity between the high and low emitters, we need to consider a linear transformation on carbon emissions to create a best fit model.



Citing the IMF, the predictors that are important in properly categorizing the level of carbon emissions for a respective country to include within our best fit model are national income, market-value national wealth, and population size. Per the WID and our trend analysis of GDP, national income is the only income concept that has an internationally agreed definition (established by the United Nations System of National Accounts, see SNA 2008). Similarly, the national economy/wealth - in the national accounts sense – encompasses all domestic sectors, i.e. all entities that are resident of a given country (in the sense of their economic activity), whether they belong to the private sector, the corporate sector, the government sector. Lastly, to account for the disparities between our select countries, it is best to include population. While the WID has additional variables, the variation amongst countries for those respective variables is too country-specific that it would inhibit our ability to create a generalize model. To ensure that our model did not have any missing data, was complete, and representative, we subsetted and selected countries from WID with data available across all aforementioned predictors across all 20 years (2000 – 2020).







Data Modeling and Assessment

To account for the differences between countries, the best fit models for both of our research questions are mixed models. Similar to linear regression models, mixed models will enable us to better analyze the carbon emission while estimating the random effect/impact of each country. In addition to taking the impact of country into account, a mixed model will also take into account any correlation that exists within our data. The generalized linear mixed model can be represented through the following framework/model formula:

$$Y = X_i\beta + Z_j u + \epsilon$$

Question 1: With this initial exploratory data analysis serving as a backdrop, we decided to log transform our outcome variable, carbon emissions, to account for the high variance between high and low emitters (which can be seen through the graph below). We opted to use a linear mixed model as compared to a linear model and included country as a random effect to make our model more generalizable since we found each country followed slightly different trends. After including it, the model no longer violates the linearity assumption (see appendix for previous versions of model 1).

The i and j within the above generalized linear mixed model equal 3 (for the number of income brackets) and 10 (for the number of countries) respectively to represent this research question. This equates to the following model:

$$Log(CO_2) = \beta_1 Top10 + \beta_2 Middle40 + \beta_3 Bottom50 + (1|Country)$$

For this generalized model, we quickly assumed that the similarity amongst the predictors (all three income brackets) would lead to multicollinearity. We were able to confirm this through two distinct measures: 1) all income brackets are related as the shares between the three incomes total 1 and 2) the VIF is greater than 10. However, because the predictors are interdependent but independent from the response variable (carbon emissions), we can continue with our analysis under this assumption.

Table 1: VIF Multicollinearity Check for Q1: CO2 and Income Bracket Analysis

top10	middle40	bottom50
1.68	3.76	4.88

Question 2: In the CO2 vs Income and CO2 vs Wealth graph, we do not see major differences in range and mean among the three carbon emitter levels. However, in the CO2 vs population graph there is a major difference between low/medium emitters compared to high emitters. Logically, this makes sense, since with more people a country requires more resources and energy to accommodate them. Based on this finding, we applied log transformation to all predictor variables (population, national income, and wealth) to normalize the differences amongst the countries.

Our goal is to predict each country's level of carbon emissions for each year. Since the outcome is ranked low, medium, and high, an ordinal model would be the best fit. An ordinal model operates on the proportional odds assumption which we checked with the Brant test and found that the model does not violate this assumption. We also checked for multicollinearity and found that all VIF values fell under the threshold.

Table 2: VIF Multicollinearity Check for Q2: Carbon Emissions and Economic/Demographic Indicators Analysis

income_log	wealth_log	pop_log
1.00	1.34	1.40

Test for X2 df probability
Omnibus 0 3 1 income_log 0 1 0.99 wealth_log 0 1 0.99 pop_log 0 1 0.99

H0: Parallel Regression Assumption holds

Since all assumptions have been held, we fit a cumulative link mixed model to predict the ordinal outcome variable. Similar to the generalized linear mixed model used to represent Question 1, a cumulative link mixed model enables on to analyze ordinal response variables while still maintaining random effects. As we aim to categorize and rank countries based on their respective carbon emission levels, it is more powerful to

Table 4: Proportional Odds Assumption Check for Question 2: Carbon Emissions and Economic/Demographic Indicators Analysis

	X2	df	probability
Omnibus	0.0002	3	1.00
income_log	0.0001	1	0.99
wealth_log	0.0001	1	0.99
pop_log	0.0002	1	0.99

maintain order as compared to a multinomial model. To maintain and account for this order, the generalized linear mixed model is tweaked to the following model:

$$Y = \alpha_j - X_i\beta + Z_{t\,[\,i\,]}u_t + \epsilon$$

where α is the intercept/threshold coefficient between the different level comparison combination (i.e. Low | Medium and Medium | High), the i, j and t within the above cumulative link mixed model equal 3 (for the number of predictors (income, wealth, population)), 3 (for the number of emission levels (low, medium, high), and 10 (for the number of countries) respectively to represent this research question. This equates to the following model:

$$P(Y \leq j) = \alpha_j + \beta_1(Income) + \beta_2(Wealth) + \beta_3(Population) + (1|Country)$$

Results

Model 1: Linear Mixed Model Our resulting model to test the equivalence amongst the income bracket is the following:

$$Log(CO_2) = 126.37Top10 + 127.33Middle40 + 127.12Bottom50 - 117.10$$

With country as our random effect, we need to test the fixed effects with a Wald test. The Wald test compares the coefficient's estimated value with the estimated standard error for the coefficient. Our null hypothesis states that the variance between coefficients for the random effect is zero. With a 5% significance level, we found all three predictors to be statistically significant. The calculated chi-squared values are greater than the chi-square critical value for the degrees of freedom specified (3.84), which reaffirms that we fail to reject the null hypothesis. Therefore, we can confirm there is no variance between the coefficients of the three income brackets when inferring their relationship with carbon emissions.

Table 5: Model 1: Marginal and Conditional R-squared

R2m	R2c
0.06	0.98

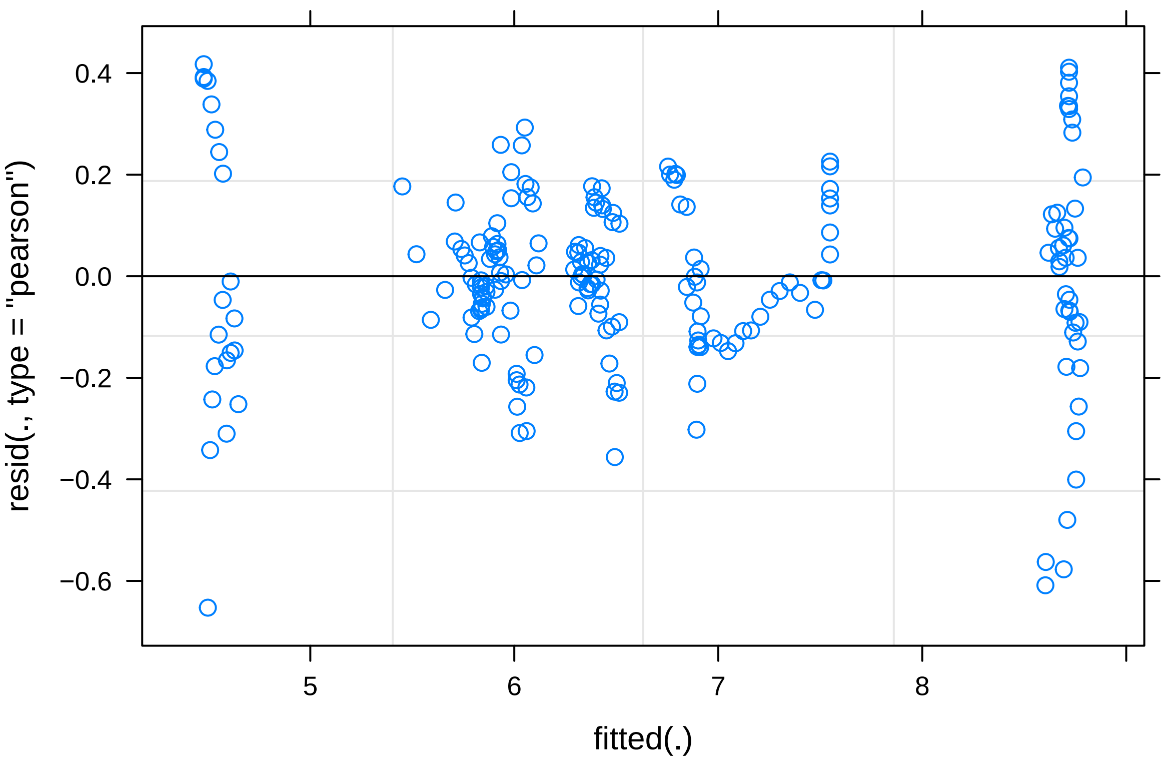
Marginal R-squared is concerned with the variance explained by fixed effects. Our model returned low marginal R-squared (3.4%) which indicates the fixed effects do not explain the variance in the outcome.

Conditional R-squared is concerned with the variance explained by both fixed and random factors of the entire model. We have a very high conditional r-squared that accounts for 98% of the variance in the outcome variable. Which indicates country determines a lot of the outcome variance. Random effects explain additional variance compared to the fixed effects. With just a linear regression model, we still see a very large R-squared (0.97)

Model 2: Cumulative Link Mixed Model Our resulting model to classify a country's carbon emission is the following:

$$Low = 297.41 + 1.16Log(Income) + 12.40Log(Wealth) + 7.60Log(Population) + 186.20$$

With our specified standards for high ($>$ 2000 tons), medium (500 $-$ 2000 tons), and low ($<$ 500 tons) emitters, there are only two countries in the world that fit the definition of a high emitter: USA and China. Since we trained our model with both countries, we do not have other countries to test our model's ability to predict high emitters. However, the disparity between high and low/medium emitters is so large we are more concerned about the precision of our model distinguishing between low and medium emitters. Our test set contains five countries (Argentina, Ghana, Mexico, Norway, and Qatar) that are similar to our training set in that they are geographically spread out and that fall between these two categories and our model predicted their emission levels with 95% accuracy which is greater than the no information rate. As seen through our confusion matrix, there is high sensitivity with the low class and high specificity meaning our model correctly classified most low emitters (approximately 96%).



Cumulative Link Mixed Model fitted with the Laplace approximation

formula: CO2_C ~ income_log + wealth_log + pop_log + (1 | Country) data: m2_data1

link threshold nobs logLik AIC niter max.grad cond.H logit flexible 210 -25.21 62.41 589(5148) 2.68e+01 5.6e+00

Random effects: Groups Name Variance Std.Dev. Country (Intercept) 138.8 11.78
Number of groups: Country 10

Coefficients: Estimate Std. Error z value Pr(>|z|)
income_log 6.816633 0.002120 3216 <2e-16 ***wealth_log 12.149477 0.002279 5331 <2e-16*** pop_log 21.251618 0.002590 8206 <2e-16 *** — Signif. codes: 0 ‘’ ***0.001*** ’’ *0.01* ” 0.05 ‘.’ 0.1 ’ ’ 1

Threshold coefficients: Estimate Std. Error z value low|med 6.014e+02 1.405e-03 428010 med|high 6.274e+02 1.368e-03 458720

Running predictions on a smaller test set:

Table 6: Confusion Matrix - Predicting CO2 Level Classification

	Reference low	Reference med	Reference high
Pred low	94	6	0
Pred med	3	0	0
Pred high	2	0	94

Conclusion:

Through this limited study, we were able to ultimately refute the conclusion presented by the IMF as we did not find an income bracket contributing more to the level of carbon emissions within a country than the other income brackets. While concluding this, we do note that our select and subsetted data analysis may lead to differing results and should be expanded to include more countries, more factors, and more models to see if our conclusion stands or gets closer to the one presented by IMF. As we assessed our prediction results, we were able to conclude that the high accuracy provides evidence that national income, national wealth, and population are good economic and demographic indicators for determining a nation's carbon emissions.

While our personal ambitions were to compose a comprehensive study, we know that limitations within our dataset, our model, and current available R packages lend to us falling short on our thoroughness. As detailed within the Methods section, we found that the income brackets within Question 1 were multicollinear, which in turn impacts the precision of our assessment/understanding of the coefficients for each income bracket. Additionally, it would be ideal to incorporate more descriptive country feature/statistics/information. These additional variables would provide more context to our model and allow for a better comparison to the work studied by IMF. In regard to Question 2, the variation amongst the low, medium, and high levels is not apparent. It would be best to understand if there is a better measure to define these levels to create distinct class, and thus variation amongst the levels. We also found that by testing our model on more countries by the number of countries within our training data (i.e. our initially selected 10 countries). As seen from the results titled within the Appendix, we tried to test on the same number but due to our sample size being small, the accuracy results were poor.

To address these limitation, our future work would consist of the following: 1. Adding supplementary descriptive statistics/feature on a country. We would like to incorporate data on the government sector vs private sector as well as more information on personal wealth to better define the characteristics of each income bracket 2. Adding more countries with carbon emissions that were not represented within our model (i.e. extremely low carbon emission rates). These additional training countries would enable us to test our model on a larger test size. 3. Rather than just using mean, we would want to define variance based on a weighted average and use this information to define unique levels of carbon emissions. Currently, we have the 3 levels of carbon emissions, but this measure would possibly create more levels (i.e. extremely, low, medium, high, extremely high).

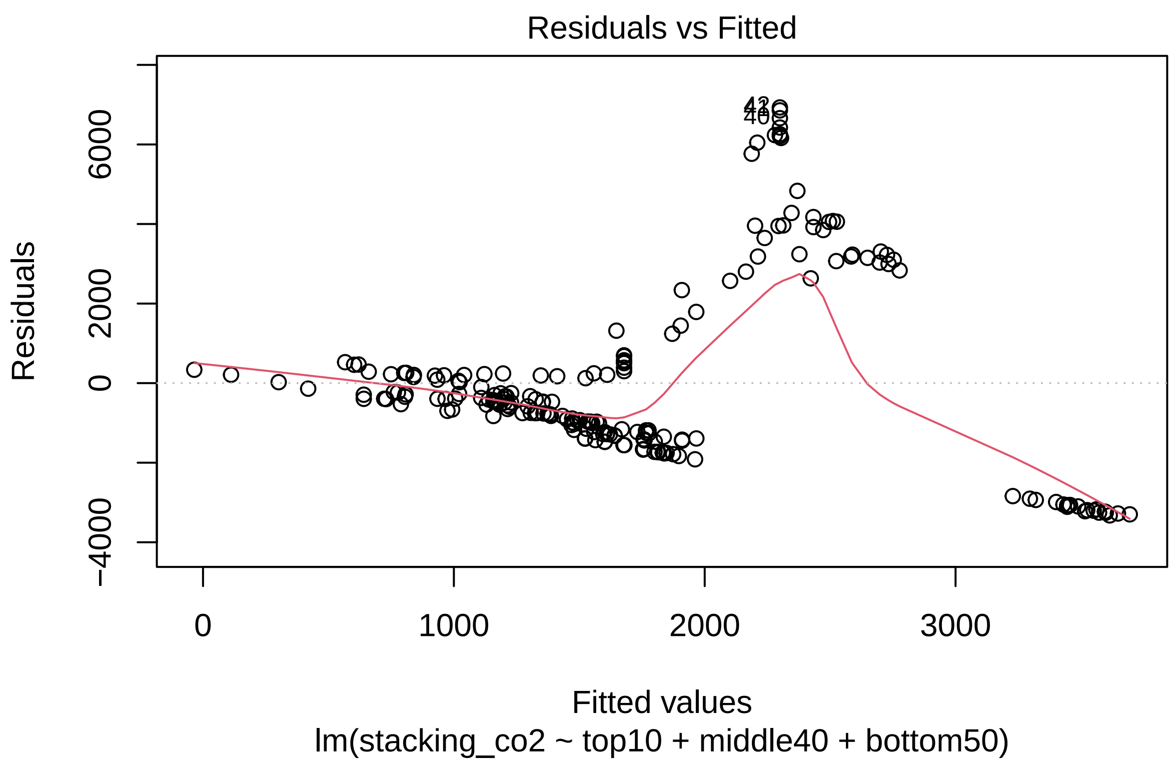
Appendix

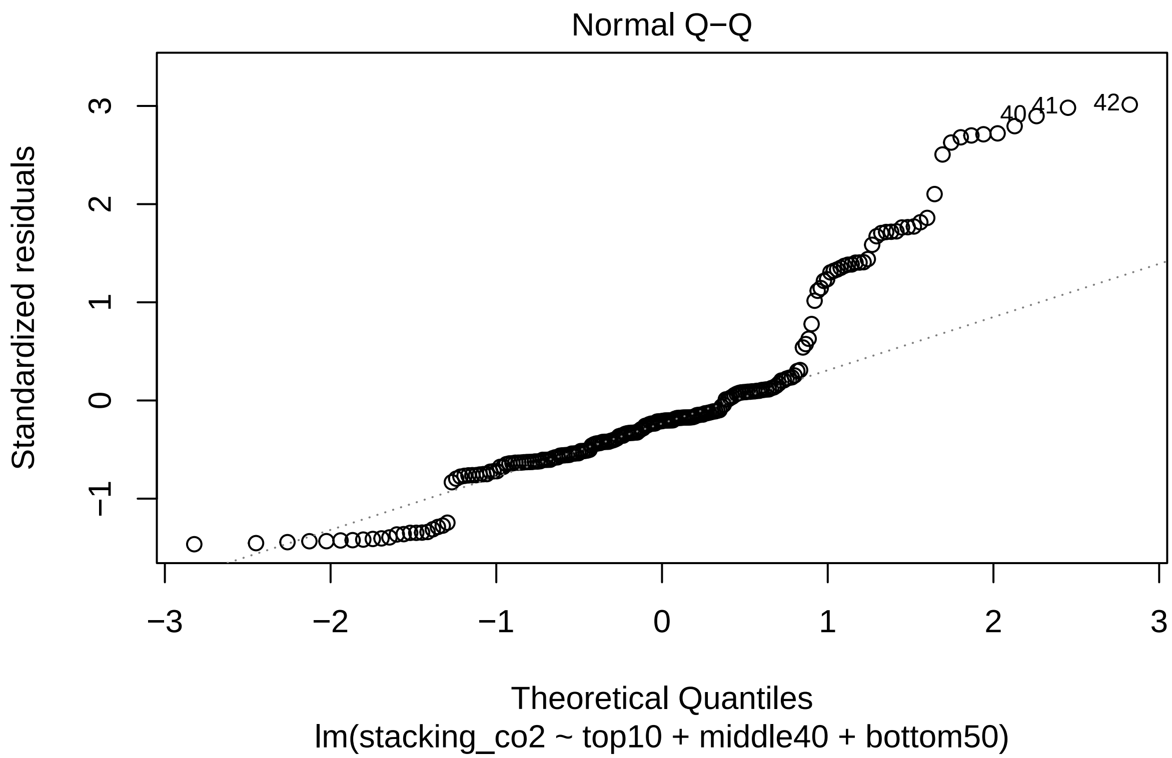
MODEL 1 IMPROVEMENTS

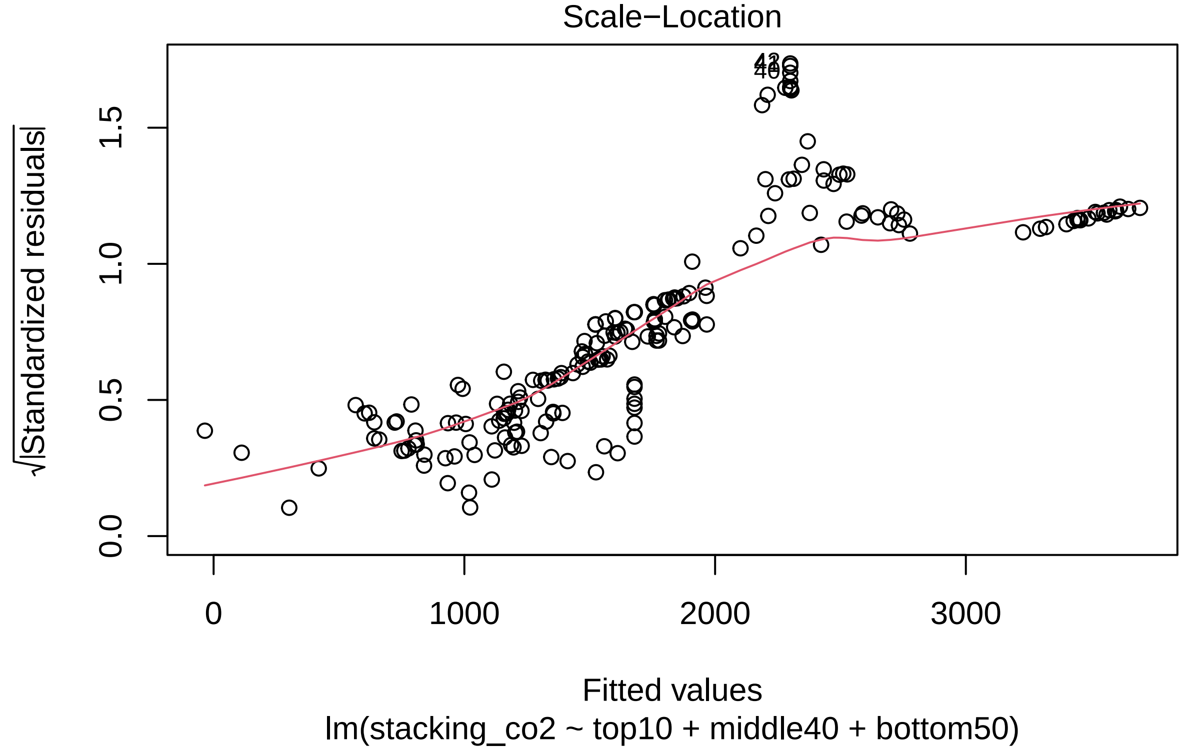
Trial 1:Linear: CO2 = top 10 + middle 40 + bottom 50

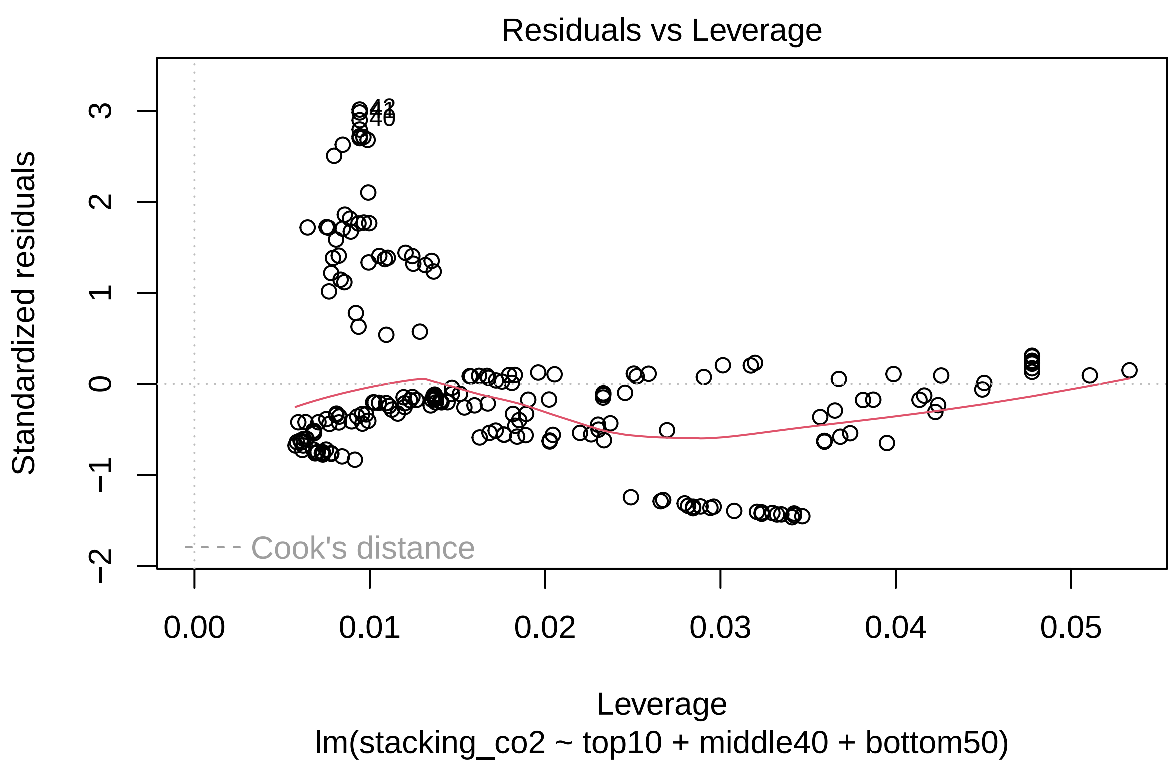
```
##
## Call:
## lm(formula = stacking_co2 ~ top10 + middle40 + bottom50, data = dataset_for_model1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -3324.6 -1379.1  -481.9   297.7  6929.9
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -373043     124532  -2.996  0.00308 **
## top10         377277     126177   2.990  0.00313 **
## middle40      408854     131627   3.106  0.00216 **
## bottom50      341405     122138   2.795  0.00568 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2310 on 206 degrees of freedom
## Multiple R-squared:  0.1058, Adjusted R-squared:  0.09283
## F-statistic: 8.129 on 3 and 206 DF,  p-value: 3.844e-05
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(stacking_co2 ~ top10 + middle40 + bottom50)
40
41
42
−3
−2
−1
0
1
2
3

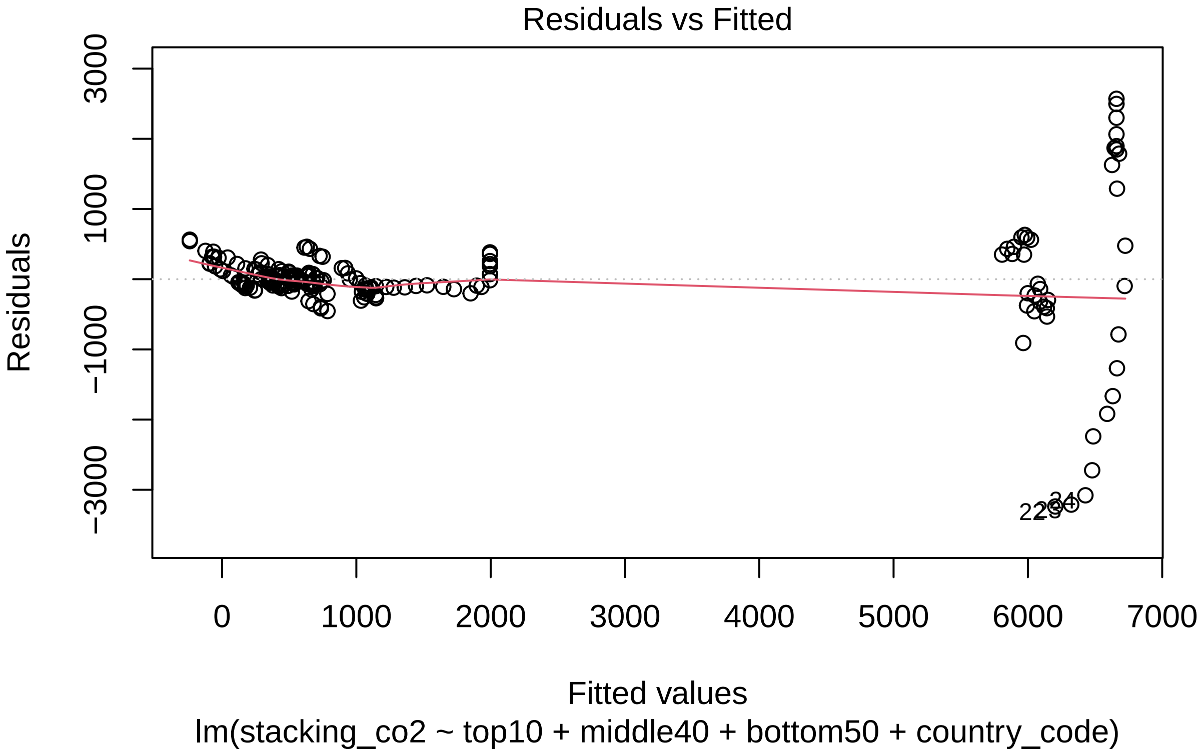

Scale−Location
√|Standardized residuals|
Fitted values
lm(stacking_co2 ~ top10 + middle40 + bottom50)
0.0
0.5
1.0
1.5
0
1000
2000
3000

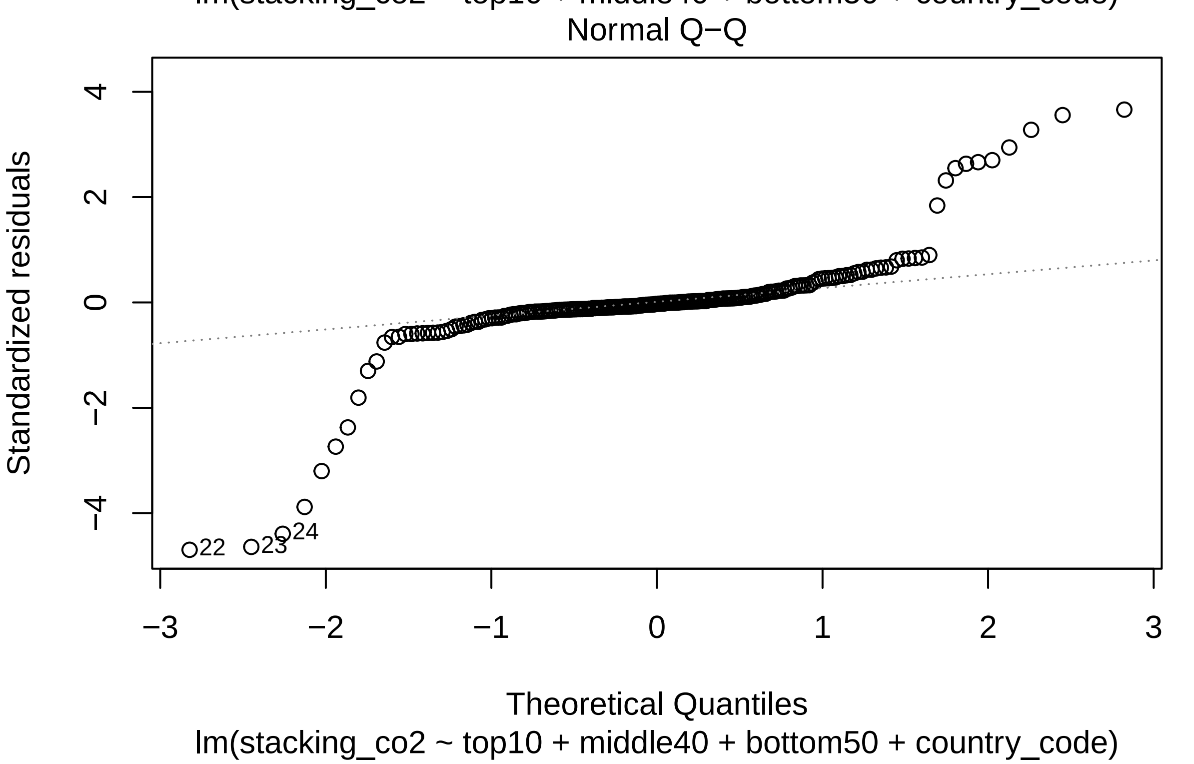


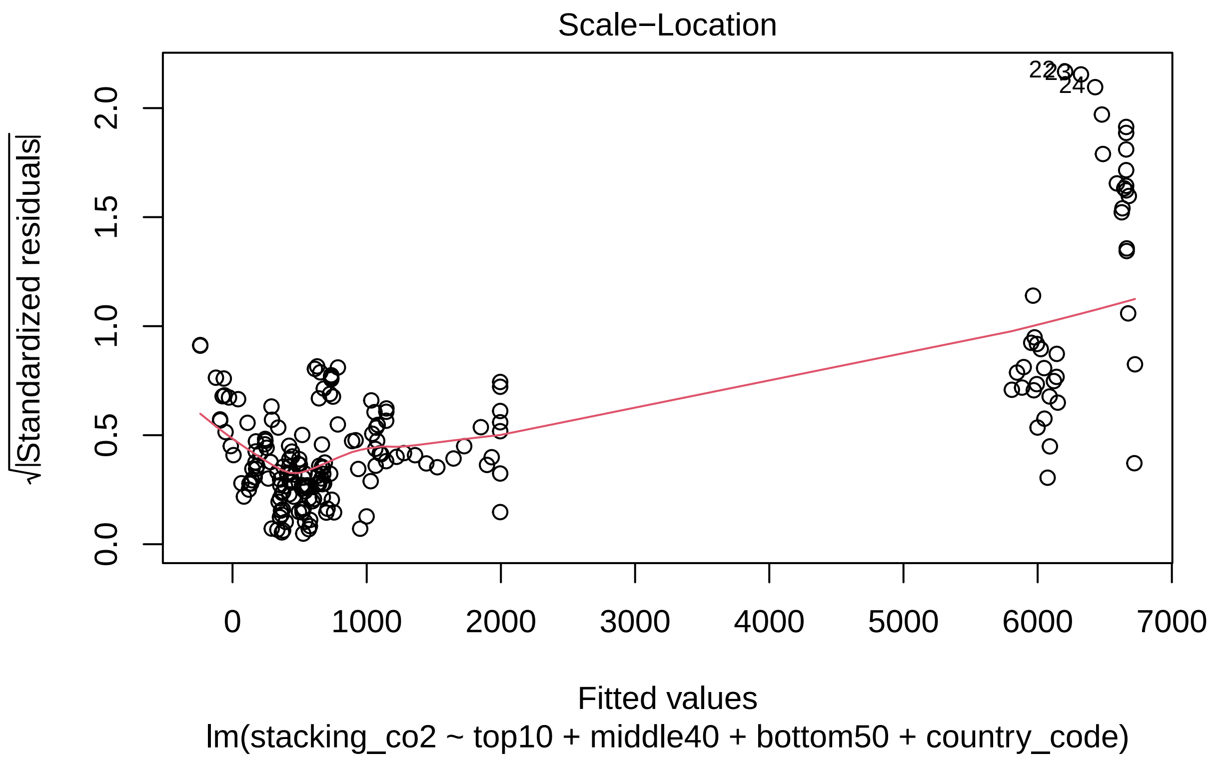
Trial 2: Linear: $CO2 = top\ 10 + middle\ 40 + bottom\ 50 + country$

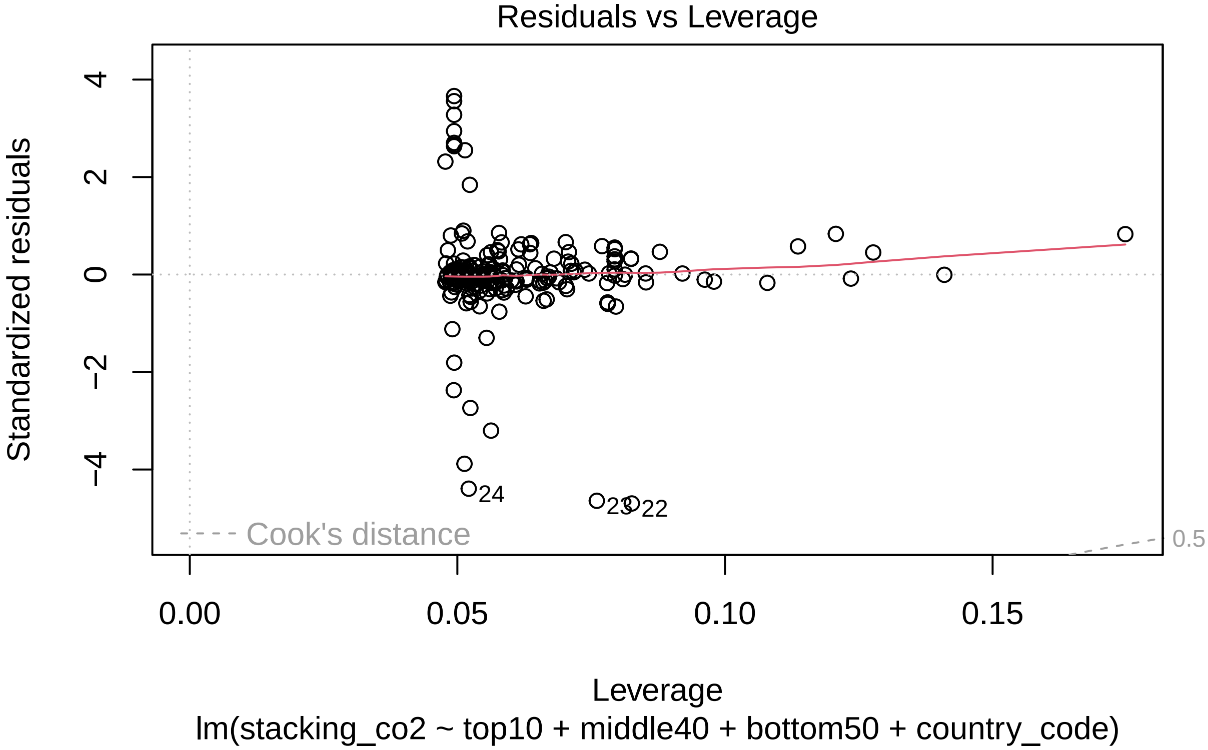
```
##
## Call:
## lm(formula = stacking_co2 ~ top10 + middle40 + bottom50 + country_code,
##     data = dataset_for_model1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3238.2  -114.6   -18.3   132.0  2569.9
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -183712.2   168306.9  -1.092  0.27637
## top10           192681.2   168623.1   1.143  0.25456
## middle40        203193.3   178794.3   1.136  0.25714
## bottom50        175280.3   167319.2   1.048  0.29612
## country_code2      869.6      272.3   3.193  0.00164 **
## country_code3    -4219.2      598.1  -7.054 2.87e-11 ***
## country_code4    -4210.3      408.2 -10.314  < 2e-16 ***
## country_code5    -4546.0      396.8 -11.456  < 2e-16 ***
## country_code6    -4863.0      310.5 -15.662  < 2e-16 ***
## country_code7    -5638.4      639.0  -8.824 5.97e-16 ***
## country_code8    -5742.8      718.2  -7.996 1.07e-13 ***
## country_code9    -5615.3      407.6 -13.778  < 2e-16 ***
## country_code10   -5536.3     1173.0  -4.720 4.47e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 719.7 on 197 degrees of freedom
```

```
## Multiple R-squared:  0.917,  Adjusted R-squared:  0.912
## F-statistic: 181.4 on 12 and 197 DF,  p-value: < 2.2e-16
```





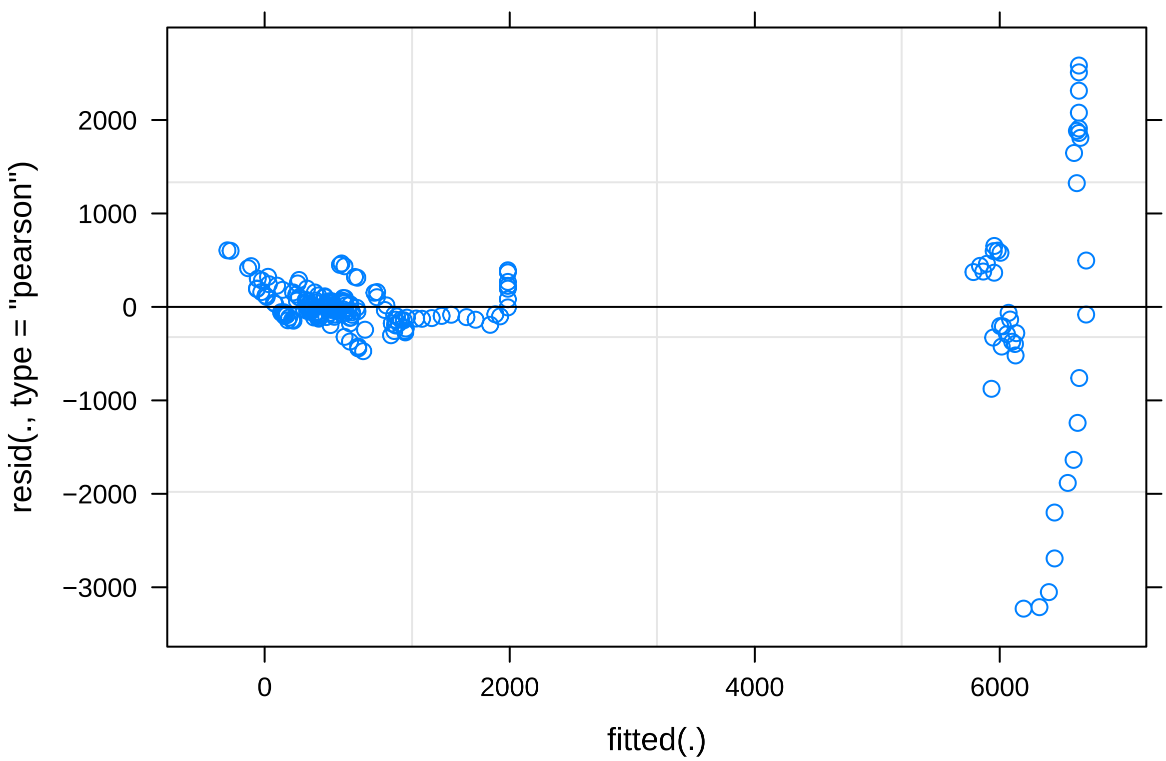




Trial 3: Linear Mixed Model: CO2 = top 10 + middle 40 + bottom 40 + (1 | country)

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: stacking_co2 ~ top10 + middle40 + bottom50 + (1 | country_code)
##    Data: dataset_for_model1
##
```

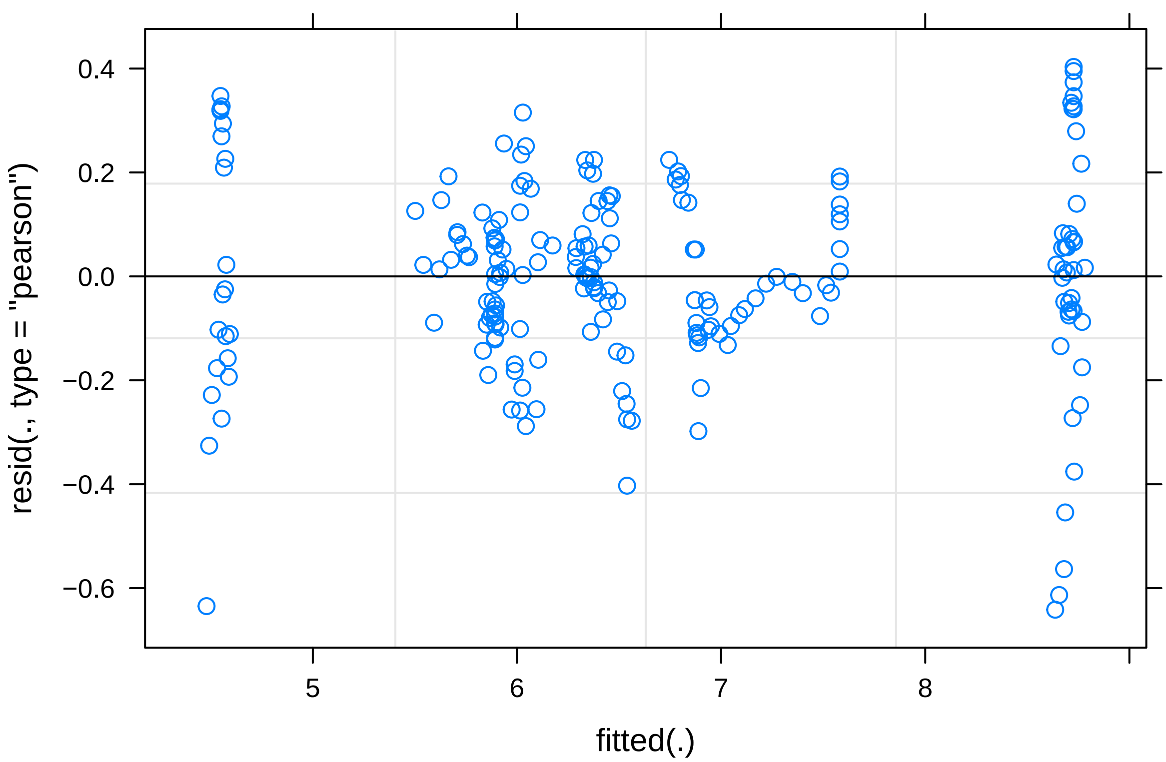
```
## REML criterion at convergence: 3330.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4884 -0.1662 -0.0451  0.1697  3.5910
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  country_code (Intercept) 5752981  2398.5
##  Residual                  517463   719.3
## Number of obs: 210, groups:  country_code, 10
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)  -228460     150644  -1.517
## top10         233313     151216   1.543
## middle40      247508     159968   1.547
## bottom50      214260     150198   1.427
##
## Correlation of Fixed Effects:
##          (Intr) top10  mddl40
## top10    -1.000
## middle40 -1.000  0.999
## bottom50 -0.998  0.999  0.996
```



Try 4 - Linear Mixed Model: log(CO2) = top 10 + middle 40 + bottom 40 + (1 | country)

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: log(stacking_co2) ~ top10 + middle40 + bottom50 + (1 | country_code)
##    Data: dataset_for_model1
```

```
##
## REML criterion at convergence: -56.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.4242 -0.4943  0.0134  0.5760  2.1520
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  country_code (Intercept) 1.70520  1.3058
##  Residual                 0.03509  0.1873
## Number of obs: 210, groups:  country_code, 10
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  -117.10      42.54  -2.753
## top10         126.37      42.67   2.961
## middle40      127.33      45.22   2.816
## bottom50      127.12      42.36   3.001
##
## Correlation of Fixed Effects:
##          (Intr) top10  mddl40
## top10    -1.000
## middle40 -1.000  0.999
## bottom50 -0.998  0.999  0.997
```



MODEL 2 TESTING

Testing Model with 10 countries:

```
##     Year    Country National_Wealth National_Population
```

```
## 1   2000 ARGENTINA       25009.165            36870788
## 2   2001 ARGENTINA       23304.697            37275652
## 3   2002 ARGENTINA       16395.632            37681748
## 4   2003 ARGENTINA       17363.950            38087868
## 5   2004 ARGENTINA       24640.685            38491972
## 6   2005 ARGENTINA       32433.125            38892932
## 7   2006 ARGENTINA       39118.996            39289880
## 8   2007 ARGENTINA       43846.601            39684296
## 9   2008 ARGENTINA       48385.877            40080160
## 10  2009 ARGENTINA       45665.647            40482788
## 11  2010 ARGENTINA       52695.690            40895752
## 12  2011 ARGENTINA       58475.425            41320500
## 13  2012 ARGENTINA       58685.830            41755196
## 14  2013 ARGENTINA       61785.169            42196032
## 15  2014 ARGENTINA       59993.582            42637512
## 16  2015 ARGENTINA       61287.905            43075416
## 17  2016 ARGENTINA       59659.328            43508460
## 18  2017 ARGENTINA       61072.895            43937140
## 19  2018 ARGENTINA       58539.699            44361152
## 20  2019 ARGENTINA       58328.982            44780676
## 21  2020 ARGENTINA       53818.917            45195776
## 22  2000   BELGIUM      348676.942            10282033
## 23  2001   BELGIUM      349500.627            10319019
## 24  2002   BELGIUM      347994.831            10364885
## 25  2003   BELGIUM      349393.957            10419032
## 26  2004   BELGIUM      365854.442            10480117
## 27  2005   BELGIUM      384200.211            10546886
## 28  2006   BELGIUM      402188.977            10619475
## 29  2007   BELGIUM      420299.314            10697572
## 30  2008   BELGIUM      420636.187            10778758
## 31  2009   BELGIUM      415278.644            10859940
## 32  2010   BELGIUM      426197.266            10938739
## 33  2011   BELGIUM      429333.960            11013853
## 34  2012   BELGIUM      431363.824            11085358
## 35  2013   BELGIUM      434698.170            11154009
## 36  2014   BELGIUM      440812.991            11221231
## 37  2015   BELGIUM      447912.939            11287940
## 38  2016   BELGIUM      451728.868            11354420
## 39  2017   BELGIUM      455264.659            11419748
## 40  2018   BELGIUM      456020.498            11482178
## 41  2019   BELGIUM      459613.937            11539328
## 42  2020   BELGIUM      456954.512            11589623
## 43  2000    FRANCE      205839.114            60545335
## 44  2001    FRANCE      210050.944            60970281
## 45  2002    FRANCE      213531.833            61406145
## 46  2003    FRANCE      226966.402            61838483
## 47  2004    FRANCE      250801.819            62257573
## 48  2005    FRANCE      279618.619            62634127
## 49  2006    FRANCE      308625.937            62995134
## 50  2007    FRANCE      327047.766            63387496
## 51  2008    FRANCE      313887.351            63723197
## 52  2009    FRANCE      298441.658            64048540
## 53  2010    FRANCE      307222.438            64325269
## 54  2011    FRANCE      313479.728            64679700
```

```
## 55  2012    FRANCE      308975.575            65031692
## 56  2013    FRANCE      305549.597            65370448
## 57  2014    FRANCE      300443.697            65680936
## 58  2015    FRANCE      295308.003            65953204
## 59  2016    FRANCE      300668.016            66182816
## 60  2017    FRANCE      311648.434            66375188
## 61  2018    FRANCE      319282.635            66542168
## 62  2019    FRANCE      327651.117            66700848
## 63  2020    FRANCE      336602.775            66863724
## 64  2000     GHANA        4396.827            19278856
## 65  2001     GHANA        4733.218            19756928
## 66  2002     GHANA        5679.922            20246380
## 67  2003     GHANA        6478.586            20750300
## 68  2004     GHANA        7732.468            21272324
## 69  2005     GHANA        9284.538            21814642
## 70  2006     GHANA       11770.964            22379056
## 71  2007     GHANA       12311.710            22963946
## 72  2008     GHANA       13002.561            23563824
## 73  2009     GHANA       12664.019            24170940
## 74  2010     GHANA       13125.776            24779620
## 75  2011     GHANA       14555.620            25387712
## 76  2012     GHANA       15226.895            25996450
## 77  2013     GHANA       16847.886            26607644
## 78  2014     GHANA       16404.284            27224472
## 79  2015     GHANA       16013.642            27849204
## 80  2016     GHANA       16153.895            28481944
## 81  2017     GHANA       16893.446            29121464
## 82  2018     GHANA       17463.018            29767102
## 83  2019     GHANA       18503.166            30417856
## 84  2020     GHANA       18511.254            31072940
## 85  2000 INDONESIA        7957.750           211513824
## 86  2001 INDONESIA        9121.683           214427424
## 87  2002 INDONESIA        9937.867           217357792
## 88  2003 INDONESIA       11007.984           220309472
## 89  2004 INDONESIA       11596.653           223285680
## 90  2005 INDONESIA       12714.883           226289472
## 91  2006 INDONESIA       13864.961           229318256
## 92  2007 INDONESIA       15541.166           232374240
## 93  2008 INDONESIA       18038.049           235469760
## 94  2009 INDONESIA       19170.090           238620560
## 95  2010 INDONESIA       21529.578           241834208
## 96  2011 INDONESIA       23125.350           245115984
## 97  2012 INDONESIA       24168.500           248451728
## 98  2013 INDONESIA       24250.555           251805312
## 99  2014 INDONESIA       24331.361           255128080
## 100 2015 INDONESIA       24397.594           258383264
## 101 2016 INDONESIA       26295.220           261556384
## 102 2017 INDONESIA       27884.089           264650960
## 103 2018 INDONESIA       29232.109           267670544
## 104 2019 INDONESIA       32428.721           270625568
## 105 2020 INDONESIA       31943.674           273523616
## 106 2000     JAPAN      269523.469           126926000
## 107 2001     JAPAN      262961.047           127316000
## 108 2002     JAPAN      256474.411           127486000
```

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## 109 2003     JAPAN     254593.729           127694000
## 110 2004     JAPAN     253441.830           127787000
## 111 2005     JAPAN     256339.288           127768000
## 112 2006     JAPAN     265714.568           127901000
## 113 2007     JAPAN     269676.461           128033000
## 114 2008     JAPAN     263732.479           128084000
## 115 2009     JAPAN     253269.946           128032000
## 116 2010     JAPAN     251341.486           128057000
## 117 2011     JAPAN     250497.214           127799000
## 118 2012     JAPAN     250937.460           127515000
## 119 2013     JAPAN     259253.994           127298000
## 120 2014     JAPAN     263550.760           126949000
## 121 2015     JAPAN     261109.013           126767240
## 122 2016     JAPAN     260009.340           126547480
## 123 2017     JAPAN     264992.657           126289432
## 124 2018     JAPAN     267300.283           125991752
## 125 2019     JAPAN     267055.539           125653120
## 126 2020     JAPAN     256606.068           125272928
## 127 2000    MEXICO      77013.688           100895800
## 128 2001    MEXICO      77995.966           102122300
## 129 2002    MEXICO      76352.867           103417900
## 130 2003    MEXICO      75646.204           104719900
## 131 2004    MEXICO      76302.698           105951600
## 132 2005    MEXICO      81719.522           107151000
## 133 2006    MEXICO      84058.881           108408800
## 134 2007    MEXICO      88508.555           109787400
## 135 2008    MEXICO      97624.710           111299000
## 136 2009    MEXICO      99658.047           112852600
## 137 2010    MEXICO      97340.664           114255600
## 138 2011    MEXICO     109807.651           115682900
## 139 2012    MEXICO     120673.878           117053800
## 140 2013    MEXICO     121180.500           118395100
## 141 2014    MEXICO     115706.155           119917504
## 142 2015    MEXICO     108330.408           121415168
## 143 2016    MEXICO     102018.487           122884936
## 144 2017    MEXICO     105416.723           124323632
## 145 2018    MEXICO     111157.673           125731944
## 146 2019    MEXICO     113561.255           127111648
## 147 2020    MEXICO     102268.717           128463944
## 148 2000    NORWAY     182384.809             4499367
## 149 2001    NORWAY     196650.317             4523145
## 150 2002    NORWAY     203547.836             4546019
## 151 2003    NORWAY     208252.180             4570106
## 152 2004    NORWAY     229433.725             4598214
## 153 2005    NORWAY     257655.792             4632364
## 154 2006    NORWAY     287866.703             4672994
## 155 2007    NORWAY     316999.721             4719402
## 156 2008    NORWAY     320204.465             4771019
## 157 2009    NORWAY     328195.063             4826848
## 158 2010    NORWAY     345050.728             4885878
## 159 2011    NORWAY     359589.452             4948330
## 160 2012    NORWAY     370209.320             5013709
## 161 2013    NORWAY     398582.383             5079455
## 162 2014    NORWAY     444855.940             5142265
```

```
## 163 2015    NORWAY      505209.971            5199836
## 164 2016    NORWAY      544478.591            5250949
## 165 2017    NORWAY      556381.560            5296326
## 166 2018    NORWAY      542335.460            5337962
## 167 2019    NORWAY      563551.644            5378857
## 168 2020    NORWAY      617716.147            5421241
## 169 2000     QATAR      958946.648             592468
## 170 2001     QATAR      876650.798             615012
## 171 2002     QATAR      815822.413             640868
## 172 2003     QATAR      739841.944             681788
## 173 2004     QATAR      677994.377             753334
## 174 2005     QATAR      573871.556             865416
## 175 2006     QATAR      512493.379            1022711
## 176 2007     QATAR      447076.455            1218434
## 177 2008     QATAR      375453.357            1436665
## 178 2009     QATAR      320089.121            1654950
## 179 2010     QATAR      304633.695            1856327
## 180 2011     QATAR      306658.405            2035871
## 181 2012     QATAR      293557.619            2196073
## 182 2013     QATAR      294902.572            2336574
## 183 2014     QATAR      298029.626            2459198
## 184 2015     QATAR      321888.360            2565710
## 185 2016     QATAR      315785.200            2654374
## 186 2017     QATAR      298505.799            2724728
## 187 2018     QATAR      289765.551            2781682
## 188 2019     QATAR      282507.048            2832067
## 189 2020     QATAR      270749.044            2881053
## 190 2000    RUSSIA       55810.556          146890100
## 191 2001    RUSSIA       63485.117          146303600
## 192 2002    RUSSIA       73378.970          145167000
## 193 2003    RUSSIA       79037.818          144963600
## 194 2004    RUSSIA       82665.029          144134000
## 195 2005    RUSSIA       86280.828          143801000
## 196 2006    RUSSIA      107673.020          143236000
## 197 2007    RUSSIA      133463.314          142863000
## 198 2008    RUSSIA      137154.216          142748000
## 199 2009    RUSSIA      137264.844          142737000
## 200 2010    RUSSIA      128026.038          142857000
## 201 2011    RUSSIA      112405.087          142865000
## 202 2012    RUSSIA      114242.098          143056000
## 203 2013    RUSSIA      119188.046          143347000
## 204 2014    RUSSIA      121296.178          143667000
## 205 2015    RUSSIA      115470.004          146267000
## 206 2016    RUSSIA      108119.432          146545000
## 207 2017    RUSSIA      104981.669          146800000
## 208 2018    RUSSIA      102877.641          147005728
## 209 2019    RUSSIA      106082.324          147145168
## 210 2020    RUSSIA      105826.542          147207920
##     National_Carbon_Emissions National_Income  pop_log income_log wealth_log
## 1                  139.890359       20415.292 17.42293   9.924039  10.126998
## 2                  128.937970       19127.621 17.43385   9.858889  10.056410
## 3                   82.197850       16057.990 17.44469   9.683962   9.704770
## 4                  107.752136       17460.984 17.45541   9.767724   9.762151
## 5                  126.295772       20604.722 17.46596   9.933276  10.112154
```

```
## 6                     134.255969        22537.768 17.47632  10.022948  10.386936
## 7                     149.306864        23703.238 17.48648  10.073367  10.574363
## 8                     155.085326        25058.123 17.49647  10.128953  10.688452
## 9                     170.176539        26373.236 17.50639  10.180105  10.786963
## 10                    160.036500        24196.463 17.51639  10.093962  10.729102
## 11                    174.548450        27119.370 17.52654  10.208004  10.872289
## 12                    182.576754        29484.515 17.53687  10.291620  10.976362
## 13                    188.108012        29195.382 17.54733  10.281766  10.979954
## 14                    193.475344        30372.487 17.55784  10.321292  11.031419
## 15                    192.412685        29102.452 17.56824  10.278578  11.001993
## 16                    201.589825        29564.202 17.57846  10.294320  11.023338
## 17                    194.803188        28390.326 17.58847  10.253804  10.996406
## 18                    194.792852        28855.749 17.59827  10.270065  11.019823
## 19                    187.564297        27410.801 17.60787  10.218692  10.977460
## 20                    181.390524        26315.633 17.61729  10.177918  10.973854
## 21                    172.320997        23137.458 17.62651  10.049208  10.893380
## 22                    188.903939        52881.689 16.14591  10.875812  12.761901
## 23                    186.908027        52660.768 16.14950  10.871626  12.764261
## 24                    198.238969        53058.557 16.15393  10.879151  12.759943
## 25                    196.263648        52969.143 16.15914  10.877465  12.763955
## 26                    218.050224        54231.141 16.16499  10.901011  12.809991
## 27                    214.082046        55025.282 16.17134  10.915548  12.858919
## 28                    223.480386        55934.459 16.17820  10.931936  12.904677
## 29                    226.243705        57419.731 16.18553  10.958143  12.948722
## 30                    209.302508        57155.802 16.19309  10.953536  12.949524
## 31                    177.647417        54572.589 16.20059  10.907287  12.936705
## 32                    192.356369        55665.301 16.20782  10.927112  12.962658
## 33                    204.479438        55136.135 16.21466  10.917561  12.969990
## 34                    184.267543        56399.963 16.22114  10.940224  12.974707
## 35                    181.976818        56477.220 16.22731  10.941593  12.982407
## 36                    177.203054        56933.704 16.23332  10.949643  12.996376
## 37                    175.978626        57380.253 16.23925  10.957456  13.012354
## 38                    170.474338        57326.657 16.24512  10.956521  13.020837
## 39                    172.083761        58006.808 16.25085  10.968316  13.028634
## 40                    177.236884        58620.028 16.25631  10.978832  13.030293
## 41                    176.354384        58932.717 16.26127  10.984152  13.038142
## 42                    158.718945        54963.188 16.26562  10.914419  13.032339
## 43                    528.065247        50870.223 17.91890  10.837033  12.234850
## 44                    524.591888        51211.444 17.92590  10.843718  12.255105
## 45                    524.888240        50714.575 17.93302  10.833969  12.271541
## 46                    526.957975        50807.830 17.94004  10.835806  12.332557
## 47                    552.701059        51827.086 17.94679  10.855668  12.432418
## 48                    549.584062        52460.364 17.95282  10.867813  12.541182
## 49                    538.174941        53463.721 17.95857  10.886759  12.639885
## 50                    555.743795        54142.691 17.96478  10.899378  12.697862
## 51                    544.976398        53253.430 17.97006  10.882817  12.656789
## 52                    511.905365        51080.914 17.97515  10.841166  12.606330
## 53                    515.695715        51901.369 17.97946  10.857100  12.635327
## 54                    535.055063        52061.960 17.98496  10.860190  12.655490
## 55                    480.180724        51269.428 17.99039  10.844850  12.641018
## 56                    472.519637        51357.472 17.99558  10.846566  12.629867
## 57                    446.188407        51495.083 18.00032  10.849242  12.613016
## 58                    439.970489        51836.572 18.00446  10.855851  12.595774
## 59                    435.907952        52022.681 18.00793  10.859435  12.613762
```

```
## 60                     447.214609       53014.281 18.01083  10.878317  12.649631
## 61                     441.891026       53542.547 18.01335  10.888232  12.673832
## 62                     431.257270       53416.025 18.01573  10.885866  12.699705
## 63                     383.818970       48540.189 18.01817  10.790147  12.726659
## 64                       8.925980        5942.443 16.77452   8.689876   8.388638
## 65                       9.537462        6017.560 16.79901   8.702437   8.462361
## 66                       9.747900        6068.455 16.82349   8.710859   8.644693
## 67                      10.822221        6191.413 16.84807   8.730919   8.776258
## 68                      11.899650        6388.498 16.87292   8.762254   8.953183
## 69                      12.273784        6574.698 16.89809   8.790984   9.136106
## 70                      13.913890        6783.269 16.92364   8.822214   9.373391
## 71                      15.045304        6798.542 16.94944   8.824464   9.418306
## 72                      14.971844        7259.095 16.97522   8.890010   9.472902
## 73                      12.847915        7207.899 17.00066   8.882933   9.446520
## 74                      14.706538        7551.044 17.02553   8.929441   9.482333
## 75                      18.268825        8298.727 17.04978   9.023857   9.585732
## 76                      22.338492        8675.645 17.07347   9.068275   9.630819
## 77                      21.006665        9226.243 17.09671   9.129807   9.731980
## 78                      20.970054        9116.880 17.11963   9.117883   9.705298
## 79                      20.552461        9129.529 17.14231   9.119269   9.681196
## 80                      20.330997        9175.132 17.16478   9.124252   9.689916
## 81                      18.392335        9410.808 17.18699   9.149614   9.734681
## 82                      19.045270        9581.391 17.20891   9.167578   9.767841
## 83                      19.676498        9936.583 17.23054   9.203978   9.825697
## 84                      19.184585        9691.915 17.25185   9.179047   9.826134
## 85                     231.195025        7170.043 19.16980   8.877667   8.981902
## 86                     254.472348        7528.771 19.18348   8.926487   9.118410
## 87                     281.194523        7360.887 19.19706   8.903936   9.204108
## 88                     293.908592        7544.075 19.21054   8.928518   9.306376
## 89                     310.578509        7805.087 19.22396   8.962531   9.358472
## 90                     316.239470        8382.103 19.23733   9.033854   9.450529
## 91                     328.555024        8761.343 19.25062   9.078104   9.537120
## 92                     360.888472        9545.019 19.26386   9.163775   9.651248
## 93                     408.995748       10723.828 19.27709   9.280223   9.800239
## 94                     441.034595       11249.537 19.29039   9.328082   9.861107
## 95                     433.388373       12809.326 19.30376   9.457929   9.977183
## 96                     507.169927       13662.975 19.31724   9.522445  10.048685
## 97                     543.263544       14119.184 19.33076   9.555290  10.092805
## 98                     447.862350       14435.559 19.34417   9.577450  10.096195
## 99                     453.930600       14615.945 19.35728   9.589868  10.099521
## 100                    531.731438       14785.057 19.36995   9.601372  10.102240
## 101                    585.067593       15691.733 19.38216   9.660889  10.177142
## 102                    551.742890       16032.283 19.39392   9.682360  10.235812
## 103                    591.461559       16507.336 19.40527   9.711560  10.283023
## 104                    633.445858       16906.821 19.41625   9.735472  10.386800
## 105                    589.104648       16213.480 19.42690   9.693598  10.371729
## 106                   1529.806012       36871.327 18.65911  10.515189  12.504411
## 107                   1484.293167       36821.194 18.66218  10.513829  12.479761
## 108                   1495.682983       36678.859 18.66352  10.509956  12.454784
## 109                   1507.926953       37168.537 18.66515  10.523218  12.447424
## 110                   1505.798829       37944.344 18.66588  10.543876  12.442890
## 111                   1520.271200       38367.649 18.66573  10.554970  12.454257
## 112                   1495.705011       39120.836 18.66677  10.574410  12.490178
## 113                   1512.410000       39785.161 18.66780  10.591249  12.504978
```

```
## 114                 1485.190093       39108.584 18.66820  10.574097  12.482691
## 115                 1360.532155       36270.689 18.66779  10.498765  12.442211
## 116                 1426.152185       37844.765 18.66799  10.541248  12.434568
## 117                 1516.649743       38862.705 18.66597  10.567790  12.431203
## 118                 1554.314450       39641.384 18.66374  10.587629  12.432959
## 119                 1509.481753       40748.107 18.66204  10.615165  12.465564
## 120                 1447.227147       41107.312 18.65930  10.623941  12.482001
## 121                 1382.743286       41966.577 18.65786  10.644629  12.472693
## 122                 1361.230165       42167.961 18.65613  10.649416  12.468473
## 123                 1344.520181       43022.535 18.65409  10.669479  12.487457
## 124                 1312.425311       43353.801 18.65173  10.677150  12.496128
## 125                 1278.885050       43361.819 18.64904  10.677335  12.495212
## 126                 1214.940797       41567.215 18.64601  10.635067  12.455297
## 127                  435.460043       28703.972 18.42960  10.264791  11.251738
## 128                  446.110349       28166.552 18.44168  10.245890  11.264412
## 129                  449.358874       26651.908 18.45429  10.190616  11.243121
## 130                  471.388135       25510.715 18.46680  10.146854  11.233823
## 131                  464.595391       25862.664 18.47849  10.160556  11.242464
## 132                  505.614600       26004.391 18.48975  10.166021  11.311048
## 133                  520.198822       26781.734 18.50142  10.195475  11.339273
## 134                  501.991241       27011.622 18.51406  10.204023  11.390854
## 135                  518.394251       26742.675 18.52773  10.194016  11.488886
## 136                  494.360844       24849.250 18.54159  10.120583  11.509500
## 137                  498.759307       25849.951 18.55395  10.160064  11.485972
## 138                  513.814262       26295.822 18.56636  10.177165  11.606485
## 139                  542.712226       26696.864 18.57814  10.192301  11.700847
## 140                  542.454042       26349.631 18.58954  10.179210  11.705036
## 141                  532.830634       26776.806 18.60231  10.195291  11.658809
## 142                  512.753358       26829.993 18.61473  10.197276  11.592941
## 143                  498.047264       26781.765 18.62676  10.195477  11.532909
## 144                  480.764663       26725.129 18.63840  10.193360  11.565677
## 145                  473.373928       26560.222 18.64966  10.187170  11.618705
## 146                  460.168841       25909.878 18.66058  10.162380  11.640098
## 147                  437.160399       23306.488 18.67116  10.056487  11.535359
## 148                   38.134063       53794.956 15.31945  10.892935  12.113874
## 149                   38.370006       54580.663 15.32472  10.907435  12.189182
## 150                   39.822721       53813.878 15.32976  10.893287  12.223656
## 151                   45.041955       54600.146 15.33505  10.907792  12.246505
## 152                   44.044175       59542.347 15.34118  10.994443  12.343369
## 153                   45.372235       66243.587 15.34858  11.101094  12.459380
## 154                   48.366768       70234.412 15.35731  11.159594  12.570253
## 155                   53.199529       72623.136 15.36719  11.193039  12.666656
## 156                   50.694074       77272.993 15.37807  11.255100  12.676715
## 157                   48.895794       69454.096 15.38970  11.148421  12.701363
## 158                   51.096242       72505.262 15.40186  11.191414  12.751447
## 159                   51.263500       75948.700 15.41456  11.237813  12.792718
## 160                   50.079263       76750.795 15.42769  11.248319  12.821824
## 161                   48.545604       76237.289 15.44071  11.241606  12.895669
## 162                   48.263366       78102.820 15.45300  11.265781  13.005506
## 163                   48.824628       78669.936 15.46414  11.273016  13.132729
## 164                   49.158957       78225.168 15.47392  11.267347  13.207584
## 165                   48.807778       79514.023 15.48252  11.283689  13.229210
## 166                   48.353885       79792.343 15.49035  11.287183  13.203640
## 167                   46.834488       75563.603 15.49799  11.232730  13.242014
```

```
## 168                 42.151039       74578.996 15.50584  11.219614  13.333784
## 169                 16.342799      121208.722 13.29205  11.705269  13.773591
## 170                 20.056483      116504.915 13.32940  11.665689  13.683864
## 171                 23.789883      118937.605 13.37058  11.686354  13.611952
## 172                 23.013705      118799.908 13.43247  11.685196  13.514192
## 173                 22.461357      118366.649 13.53226  11.681542  13.426894
## 174                 28.482738      112736.858 13.67097  11.632812  13.260161
## 175                 30.906118      109535.417 13.83797  11.604003  13.147043
## 176                 34.476060      104722.899 14.01308  11.559073  13.010485
## 177                 39.698722      100301.314 14.17784  11.515934  12.835890
## 178                 45.482174       90873.757 14.31928  11.417227  12.676355
## 179                 42.188322       93746.625 14.43411  11.448351  12.626865
## 180                 36.116814      101581.375 14.52643  11.528615  12.633490
## 181                 45.537716      100815.699 14.60218  11.521049  12.589829
## 182                 42.083997      101775.236 14.66420  11.530522  12.594400
## 183                 54.223115      102319.195 14.71535  11.535853  12.604948
## 184                 65.638710      105736.610 14.75775  11.568706  12.681960
## 185                 73.067576      107142.928 14.79172  11.581919  12.662818
## 186                 71.190937      103232.110 14.81788  11.544735  12.606545
## 187                 70.508521      100486.899 14.83857  11.517783  12.576827
## 188                 70.573080       98654.106 14.85652  11.499375  12.551459
## 189                 68.808753       93773.983 14.87367  11.448643  12.508948
## 190               1000.184170       18181.608 18.80520   9.808166  10.929718
## 191               1121.805041       19295.552 18.80119   9.867630  11.058561
## 192               1127.911822       20142.392 18.79340   9.910582  11.203393
## 193               1198.609087       21159.458 18.79199   9.959842  11.277682
## 194               1211.773428       23162.866 18.78625  10.050306  11.322552
## 195               1234.833216       24564.092 18.78394  10.109041  11.365363
## 196               1252.908006       26482.671 18.78000  10.184246  11.586854
## 197               1326.405593       28797.440 18.77740  10.268042  11.801582
## 198               1343.326611       30199.191 18.77659  10.315570  11.828861
## 199               1277.715774       27244.480 18.77651  10.212606  11.829668
## 200               1347.782241       28274.816 18.77735  10.249727  11.759989
## 201               1419.294705       30453.418 18.77741  10.323954  11.629864
## 202               1472.754938       31419.532 18.77875  10.355185  11.646075
## 203               1435.072354       31362.965 18.78078  10.353383  11.688458
## 204               1418.432841       31626.459 18.78301  10.361749  11.705991
## 205               1387.906357       30629.599 18.80094  10.329722  11.656766
## 206               1419.957728       29309.228 18.80284  10.285658  11.590992
## 207               1444.064869       29813.418 18.80458  10.302714  11.561541
## 208               1414.577294       31148.307 18.80598  10.346515  11.541296
## 209               1403.710005       31738.982 18.80693  10.365301  11.571971
## 210               1305.450305       30902.737 18.80736  10.338600  11.569557
##     CO2_C        probs predicted_class
## 1     low 1.000000e+00             low
## 2     low 1.000000e+00             low
## 3     low 1.000000e+00             low
## 4     low 1.000000e+00             low
## 5     low 1.000000e+00             low
## 6     low 1.000000e+00             low
## 7     low 1.000000e+00             low
## 8     low 1.000000e+00             low
## 9     low 1.000000e+00             low
## 10    low 1.000000e+00             low
```

```
## 11    low 1.000000e+00            low
## 12    low 9.999999e-01            low
## 13    low 9.999999e-01            low
## 14    low 9.999997e-01            low
## 15    low 9.999998e-01            low
## 16    low 9.999997e-01            low
## 17    low 9.999998e-01            low
## 18    low 9.999997e-01            low
## 19    low 9.999998e-01            low
## 20    low 9.999998e-01            low
## 21    low 9.999999e-01            low
## 22    low 9.775967e-01            low
## 23    low 9.764357e-01            low
## 24    low 9.766901e-01            low
## 25    low 9.746147e-01            low
## 26    low 9.528062e-01            low
## 27    low 9.115855e-01            low
## 28    low 8.448099e-01            low
## 29    low 7.430875e-01            low
## 30    low 7.310599e-01            low
## 31    low 7.605271e-01            low
## 32    low 6.804267e-01            low
## 33    low 6.510899e-01            low
## 34    low 6.200740e-01            low
## 35    low 5.856076e-01            low
## 36    low 5.293584e-01            low
## 37    low 4.663689e-01            med
## 38    low 4.295948e-01            med
## 39    low 3.923379e-01            med
## 40    low 3.747934e-01            med
## 41    low 3.423201e-01            med
## 42    low 3.697663e-01            med
## 43    med 9.577240e-01            low
## 44    med 9.687046e-01            low
## 45    med 9.753782e-01            low
## 46    med 9.889196e-01            low
## 47    med 9.969939e-01            low
## 48    med 9.992600e-01            low
## 49    med 9.997832e-01            low
## 50    med 9.998764e-01            low
## 51    med 9.998298e-01            low
## 52    med 9.997043e-01            low
## 53    med 9.997955e-01            low
## 54    med 9.998388e-01            low
## 55    low 1.648035e-04            med
## 56    low 1.815532e-04            med
## 57    low 2.151654e-04            med
## 58    low 2.562378e-04            med
## 59    low 1.988363e-04            med
## 60    low 1.219626e-04            med
## 61    low 8.761783e-05            med
## 62    low 6.259851e-05            med
## 63    low 4.914912e-05            med
## 64    low 1.000000e+00            low
```

```
## 65    low 1.000000e+00             low
## 66    low 1.000000e+00             low
## 67    low 1.000000e+00             low
## 68    low 1.000000e+00             low
## 69    low 1.000000e+00             low
## 70    low 1.000000e+00             low
## 71    low 1.000000e+00             low
## 72    low 1.000000e+00             low
## 73    low 1.000000e+00             low
## 74    low 1.000000e+00             low
## 75    low 1.000000e+00             low
## 76    low 1.000000e+00             low
## 77    low 1.000000e+00             low
## 78    low 1.000000e+00             low
## 79    low 1.000000e+00             low
## 80    low 1.000000e+00             low
## 81    low 1.000000e+00             low
## 82    low 1.000000e+00             low
## 83    low 1.000000e+00             low
## 84    low 1.000000e+00             low
## 85    low 1.000000e+00             low
## 86    low 1.000000e+00             low
## 87    low 1.000000e+00             low
## 88    low 1.000000e+00             low
## 89    low 1.000000e+00             low
## 90    low 1.000000e+00             low
## 91    low 1.000000e+00             low
## 92    low 1.000000e+00             low
## 93    low 1.000000e+00             low
## 94    low 1.000000e+00             low
## 95    low 9.999999e-01             low
## 96    med 3.418488e-07             med
## 97    med 6.802354e-07             med
## 98    low 9.999992e-01             low
## 99    low 9.999991e-01             low
## 100   med 1.086635e-06             med
## 101   med 3.234587e-06             med
## 102   med 7.507376e-06             med
## 103   med 1.520385e-05             med
## 104   med 6.155015e-05             med
## 105   med 5.273991e-05             med
## 106   med 9.996420e-01             low
## 107   med 9.997258e-01             low
## 108   med 9.997910e-01             low
## 109   med 9.998020e-01             low
## 110   med 9.998064e-01             low
## 111   med 9.997794e-01             low
## 112   med 9.996585e-01             low
## 113   med 9.995820e-01             low
## 114   med 9.996841e-01             low
## 115   med 9.998136e-01             low
## 116   med 9.998202e-01             low
## 117   med 9.998239e-01             low
## 118   med 9.998200e-01             low
```

```
## 119   med 9.997404e-01             low
## 120   med 9.996895e-01             low
## 121   med 9.997178e-01             low
## 122   med 9.997330e-01             low
## 123   med 9.996649e-01             low
## 124   med 9.996320e-01             low
## 125   med 9.996429e-01             low
## 126   med 9.997877e-01             low
## 127   low 9.971411e-01             low
## 128   low 9.964147e-01             low
## 129   low 9.971559e-01             low
## 130   low 9.973501e-01             low
## 131   low 9.967266e-01             low
## 132   med 8.358635e-03             med
## 133   med 1.334566e-02             med
## 134   med 2.772300e-02             med
## 135   med 9.542534e-02             med
## 136   low 8.779529e-01             low
## 137   low 8.933392e-01             low
## 138   med 3.737043e-01             med
## 139   med 6.815994e-01             low
## 140   med 7.077607e-01             low
## 141   med 6.051420e-01             low
## 142   med 4.271760e-01             med
## 143   low 7.208302e-01             low
## 144   low 6.120966e-01             low
## 145   low 4.304433e-01             med
## 146   low 3.544334e-01             med
## 147   low 6.773883e-01             low
## 148   low 1.000000e+00             low
## 149   low 1.000000e+00             low
## 150   low 9.999999e-01             low
## 151   low 9.999999e-01             low
## 152   low 9.999997e-01             low
## 153   low 9.999984e-01             low
## 154   low 9.999926e-01             low
## 155   low 9.999727e-01             low
## 156   low 9.999639e-01             low
## 157   low 9.999527e-01             low
## 158   low 9.998986e-01             low
## 159   low 9.998033e-01             low
## 160   low 9.996844e-01             low
## 161   low 9.991364e-01             low
## 162   low 9.962032e-01             low
## 163   low 9.801361e-01             low
## 164   low 9.479730e-01             low
## 165   low 9.275721e-01             low
## 166   low 9.428671e-01             low
## 167   low 9.115484e-01             low
## 168   low 7.595078e-01             low
## 169   low 9.999936e-01             low
## 170   low 9.999973e-01             low
## 171   low 9.999985e-01             low
## 172   low 9.999993e-01             low
```

```
## 173   low 9.999995e-01            low
## 174   low 9.999998e-01            low
## 175   low 9.999998e-01            low
## 176   low 9.999999e-01            low
## 177   low 1.000000e+00            low
## 178   low 1.000000e+00            low
## 179   low 1.000000e+00            low
## 180   low 1.000000e+00            low
## 181   low 1.000000e+00            low
## 182   low 9.999999e-01            low
## 183   low 9.999999e-01            low
## 184   low 9.999995e-01            low
## 185   low 9.999995e-01            low
## 186   low 9.999997e-01            low
## 187   low 9.999998e-01            low
## 188   low 9.999998e-01            low
## 189   low 9.999999e-01            low
## 190   med 5.404280e-04            med
## 191   med 2.770293e-03            med
## 192   med 1.631623e-02            med
## 193   med 4.183548e-02            med
## 194   med 7.491720e-02            med
## 195   med 1.265291e-01            med
## 196   med 7.052570e-01            low
## 197   med 9.737397e-01            low
## 198   med 9.820210e-01            low
## 199   med 9.799734e-01            low
## 200   med 9.558771e-01            low
## 201   med 8.246484e-01            low
## 202   med 8.576113e-01            low
## 203   med 9.117047e-01            low
## 204   med 9.294809e-01            low
## 205   med 8.876960e-01            low
## 206   med 7.711754e-01            low
## 207   med 7.073743e-01            low
## 208   med 6.666297e-01            low
## 209   med 7.507161e-01            low
## 210   med 7.397715e-01            low
```

```
## Confusion Matrix and Statistics
##
##
##        low med high
##   low  122  17    0
##   med   51  20    0
##   high   0   0    0
##
## Overall Statistics
##
##                Accuracy : 0.6762
##                  95% CI : (0.6084, 0.739)
##     No Information Rate : 0.8238
##     P-Value [Acc > NIR] : 1
##
```

```
##                  Kappa : 0.1805
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: low Class: med Class: high
## Sensitivity              0.7052    0.54054          NA
## Specificity              0.5405    0.70520           1
## Pos Pred Value           0.8777    0.28169          NA
## Neg Pred Value           0.2817    0.87770          NA
## Prevalence               0.8238    0.17619           0
## Detection Rate           0.5810    0.09524           0
## Detection Prevalence     0.6619    0.33810           0
## Balanced Accuracy        0.6229    0.62287          NA
```

$$Log(CO_2) = \beta_1 Top10 + \beta_2 Middle40 + \beta_3 Bottom50 + (1|Country)$$

$$Y = X_i\beta + Z_j u + \epsilon$$

$$CO_2 = \beta_1 Top10 + \beta_2 Middle40 + \beta_3 Bottom50 + (1|Country)$$

```
##    top10 middle40 bottom50
## 1.684168 3.757159 4.882596
```

Table 7: VIF Multi-Collinearity Check for Research Question 1: CO2 and Income Bracket Analysis

top10	middle40	bottom50
1.68	3.76	4.88

Call: polr(formula = CO2_C ~ income_log + wealth_log + pop_log, data = m2_data1, Hess = TRUE)

Coefficients: Value Std. Error t value income_log 3.601 1.1547 3.119 wealth_log 3.354 0.9327 3.596 pop_log 5.329 0.6779 7.860

Intercepts: Value Std. Error t value low|med 173.6421 22.7853 7.6208 med|high 180.1029 23.4115 7.6929

Residual Deviance: 142.6022 AIC: 152.6022 ——————————————— Test for X2 df probability —————————————————— Omnibus 0 3 1 income_log 0 1 0.99 wealth_log 0 1 0.99 pop_log 0 1 0.99 ———————————————

H0: Parallel Regression Assumption holds

Test for X2 df probability

Omnibus 0 3 1 income_log 0 1 0.99 wealth_log 0 1 0.99 pop_log 0 1 0.99 ———————————————

H0: Parallel Regression Assumption holds

Table 8: Proportional Odds Assumption Check for Research Question 2: CO2 and Economic/Demographic Indicators Analysis

	X2	df	probability
Omnibus	0.0002	3	1.00
income_log	0.0001	1	0.99
wealth_log	0.0001	1	0.99
pop_log	0.0002	1	0.99

Table 9: VIF Multi-Collinearity Check for Research Question 2: CO2 and Economic/Demographic Indicators Analysis

income_log	wealth_log	pop_log
1.00	1.34	1.40

$$P(Y \leq j) = \alpha_j + \beta_1 Log(Income) + \beta_2 Log(Wealth) + \beta_3 Log(Population) + (1|Country)$$

$$P(Y \leq j) = \alpha_j + \beta_1 (Income) + \beta_2 (Wealth) + \beta_3 (Population) + (1|Country)$$

$$Y = \alpha_j - X_i \beta + Z_{t\ [\ i\ ]} u_t + \epsilon$$

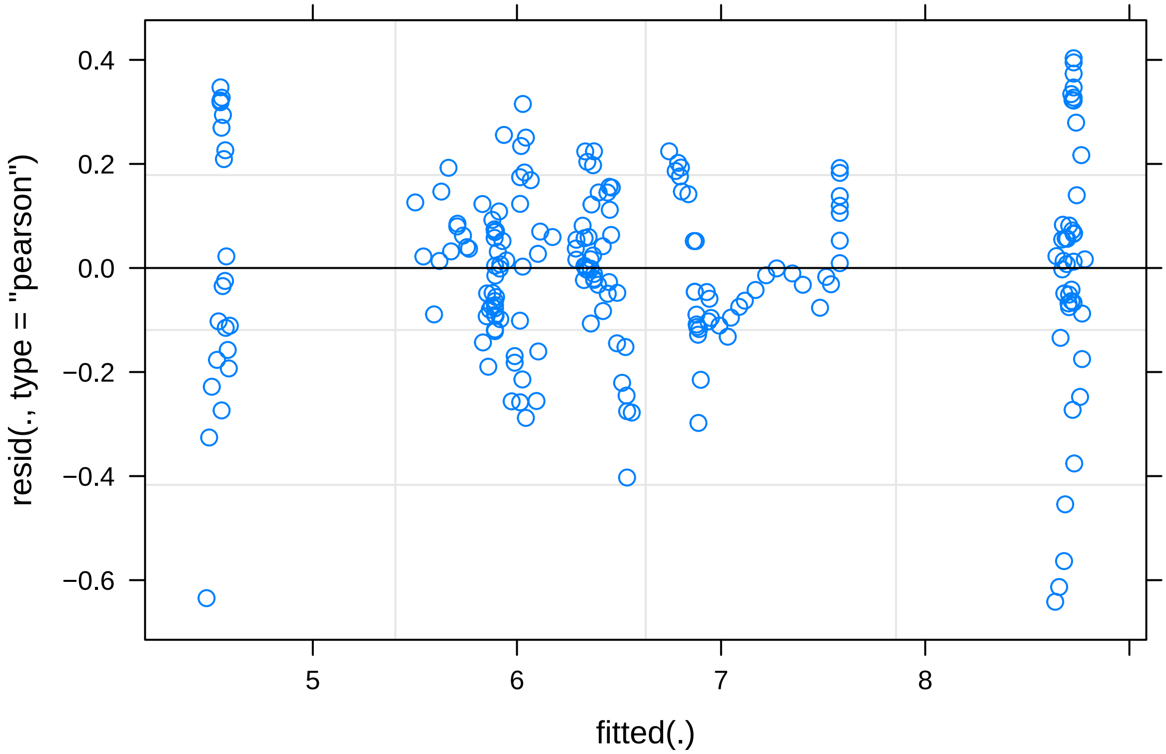
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: log(stacking_co2) ~ top10 + middle40 + bottom50 + (1 | country_code)
##    Data: dataset_for_model1
##
## REML criterion at convergence: -56.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.4242 -0.4943  0.0134  0.5760  2.1520
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  country_code (Intercept) 1.70520  1.3058
##  Residual                 0.03509  0.1873
## Number of obs: 210, groups:  country_code, 10
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  -117.10      42.54  -2.753
## top10         126.37      42.67   2.961
## middle40      127.33      45.22   2.816
## bottom50      127.12      42.36   3.001
##
## Correlation of Fixed Effects:
##          (Intr) top10  mddl40
## top10    -1.000
```

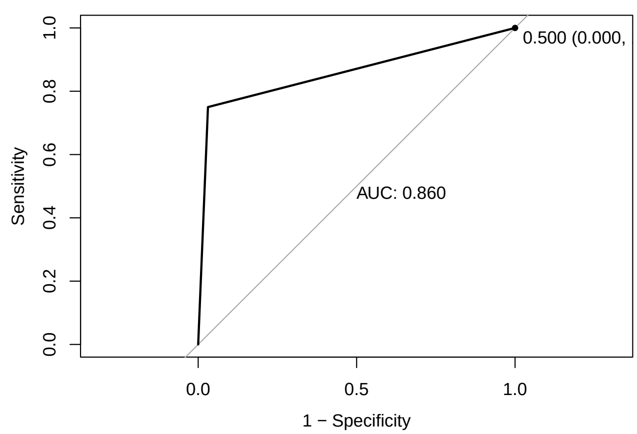
```
## middle40 -1.000  0.999
## bottom50 -0.998  0.999  0.997
```

$$Log(CO_2) = 126.37Top10 + 127.33Middle40 + 127.12Bottom50 - 117.10$$

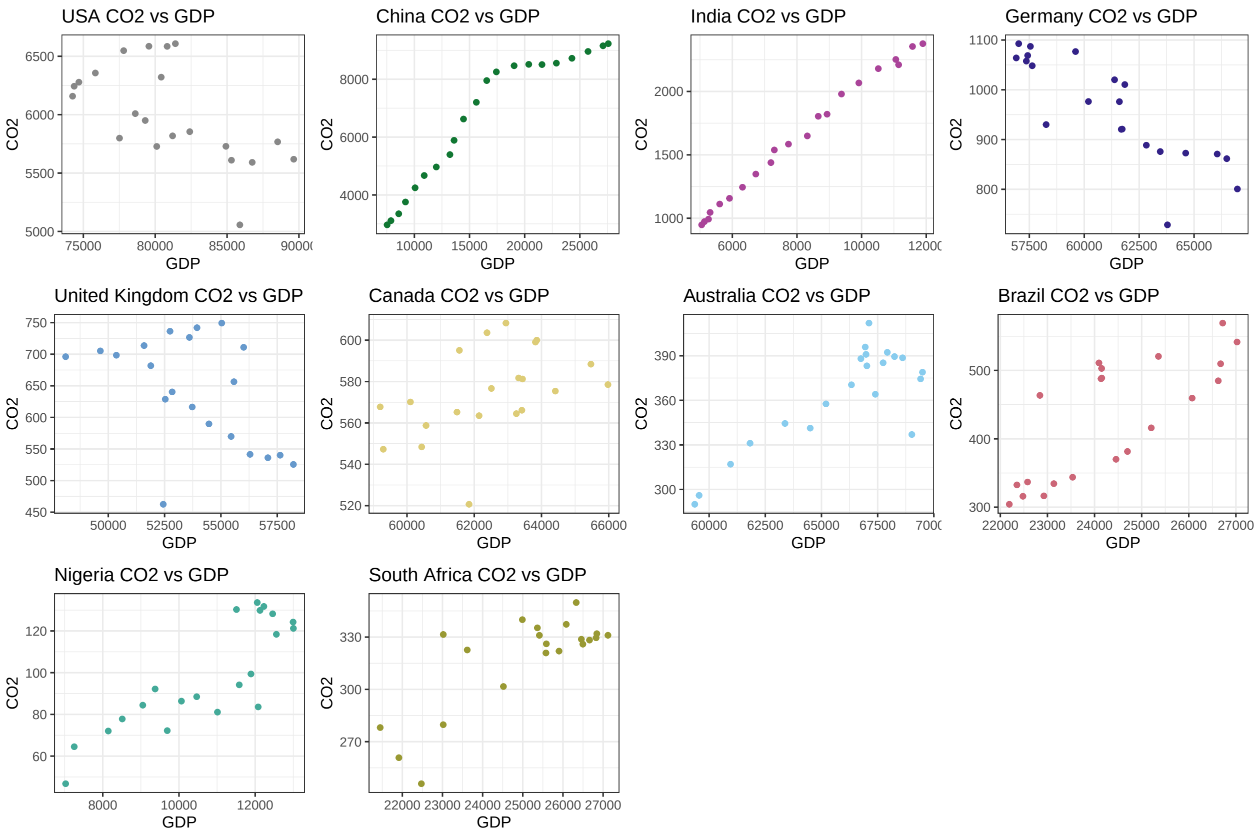
```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## Call:
## clmm2(location = CO2_C ~ income_log + wealth_log + pop_log, random = Country,
##     data = m2_data1, Hess = TRUE)
##
## Random effects:
##              Var  Std.Dev
## Country 186.2037 13.64565
##
## Location coefficients:
##            Estimate   Std. Error z value    Pr(>|z|)
## income_log     1.1593        NaN        NaN NA
## wealth_log    12.4032     0.0003 46835.2735 < 2.22e-16
## pop_log        7.6020        NaN        NaN NA
##
## No scale coefficients
##
## Threshold coefficients:
##          Estimate   Std. Error z value
## low|med    297.4135     0.0143 20813.6807
## med|high   317.0889     3.6050    87.9577
##
## log-likelihood: -29.39725
## AIC: 70.7945
## Condition number of Hessian: 0.004892671
```

$$Low = 297.41 + 1.16Log(Income) + 12.40Log(Wealth) + 7.60Log(Population) + 186.20$$


resid(., type = "pearson")
fitted(.)
0.4
0.2
0.0
−0.2
−0.4
−0.6
5
6
7
8


0.500 (0.000,
AUC: 0.860
Sensitivity
1 − Specificity
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.5
1.0

Appendix



	co2_usa	co2_china	co2_india	co2_germany	co2_uk	co2_canada	co2_australia	co2_brazil	co2_nigira	co2 _south africa
wealth_usa	-0.31									
wealth_china		0.94								
wealth_india			0.99							
wealth_germany				-0.91						
wealth_uk					-0.19					
wealth_canada						0.06				
wealth_australia							0.68			
wealth_brazil								0.95		
wealth_nigira									0.89	
wealth_south africa										0.87

Figure 1: Correlation Matrix

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: log(stacking_co2)
##           Chisq Df Pr(>Chisq)
## top10     8.7687  1   0.003064 **
## middle40 7.9285  1   0.004866 **
```

```
## bottom50 9.0077  1   0.002688 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```