

CAN NATURAL FACTORS EXPLAIN ANY CROSS-COUNTRY DIFFERENCES IN CARBON DIOXIDE EMISSIONS?

12/8/2020

Anson Ma (#20916612)
Tahmid Bari (#20864394)

Group 9



FACULTY OF
ENGINEERING

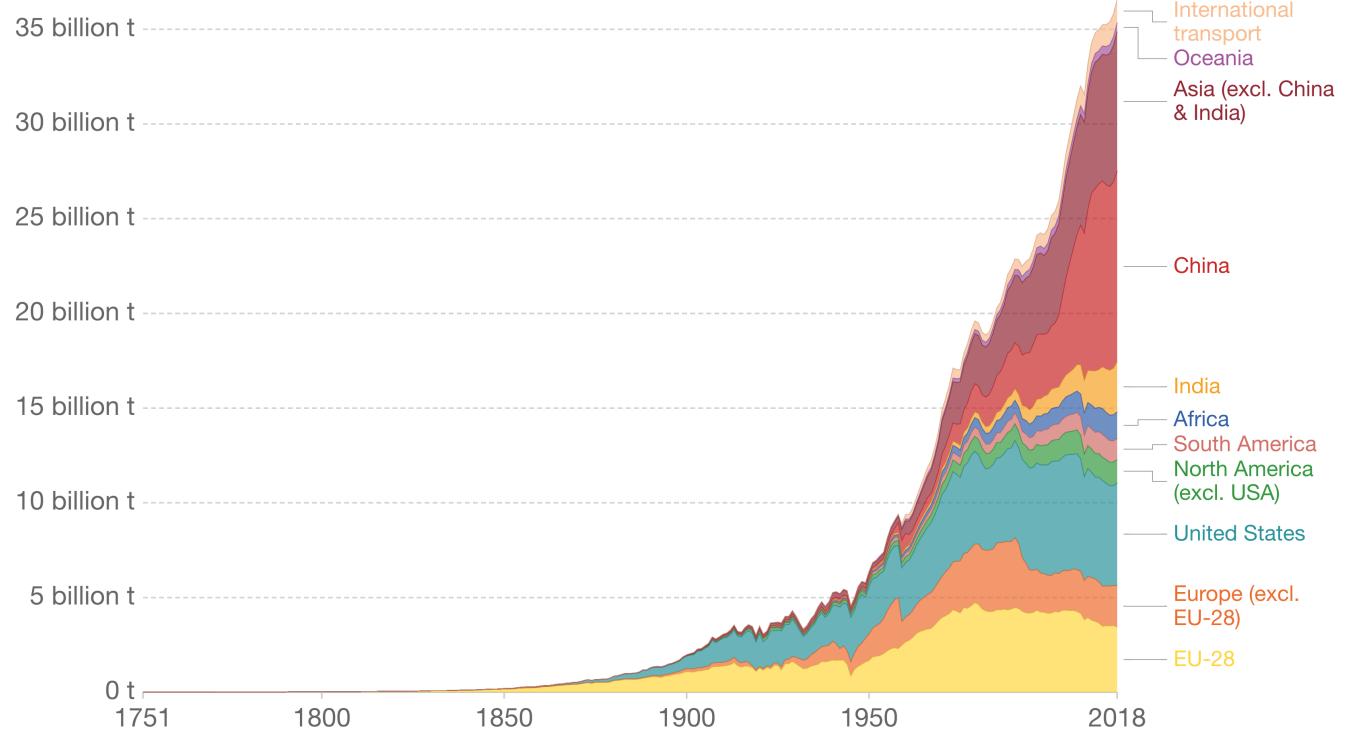


OVERVIEW

- Carbon dioxide (CO₂) is an important heat-trapping gas, which is released through human activities such as deforestation and burning fossil fuels, as well as natural processes such as respiration and volcanic eruptions.
- Over the past decade, human activities have raised atmospheric concentrations of CO₂ by 47% above pre-industrial levels and presented one of the world's most pressing challenges to combat climate change.
- However, far from stabilizing concentrations, the global CO₂ emissions are in fact still rising and accumulating. The world has not yet peaked.

Annual total CO₂ emissions, by world region

This measures CO₂ emissions from fossil fuels and cement production only – land use change is not included.



Source: Carbon Dioxide Information Analysis Center (CDIAC); Global Carbon Project (GCP)

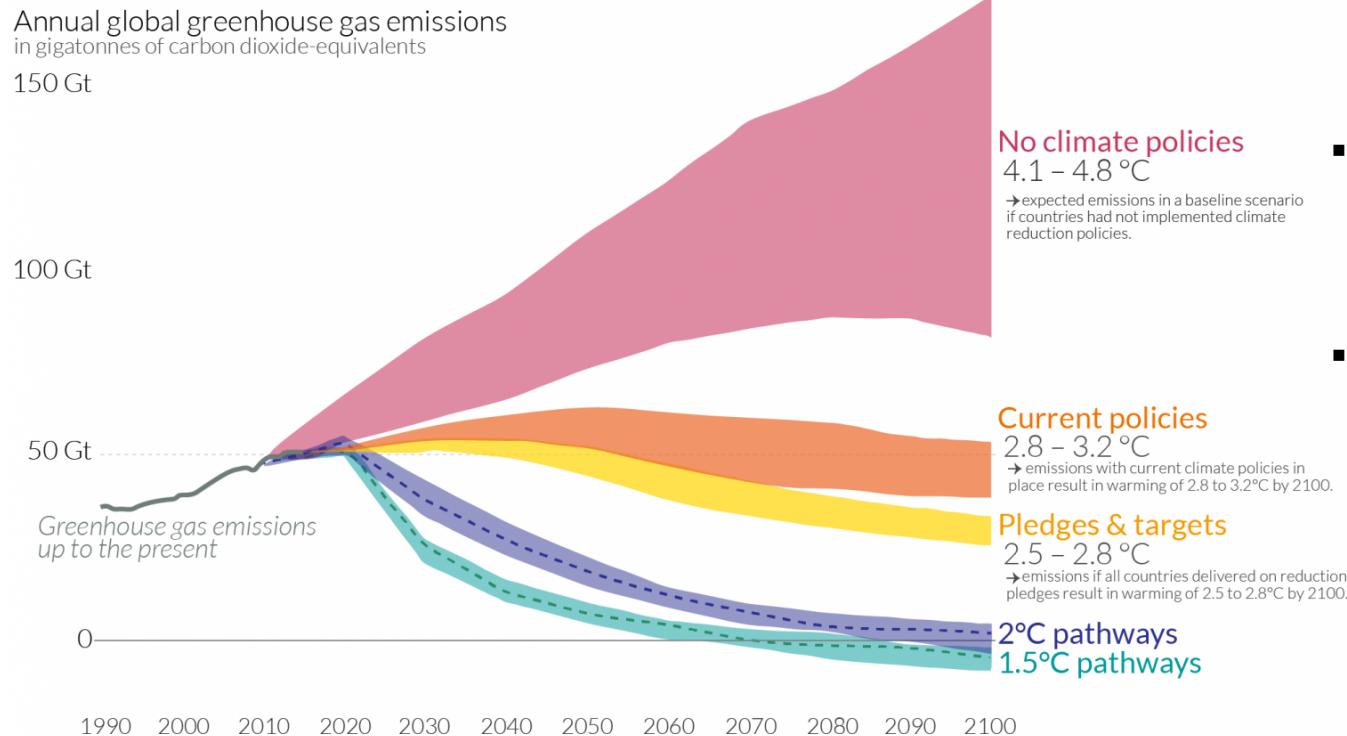
Note: 'Statistical differences' included in the GCP dataset is not included here.

OurWorldInData.org/co2-and-other-greenhouse-gas-emissions • CC BY

OVERVIEW

Global greenhouse gas emissions and warming scenarios

- Each pathway comes with uncertainty, marked by the shading from low to high emissions under each scenario.
- Warming refers to the expected global temperature rise by 2100, relative to pre-industrial temperatures.



Data source: Climate Action Tracker (based on national policies and pledges as of December 2019).
[OurWorldInData.org](#) – Research and data to make progress against the world's largest problems.

Licensed under CC-BY by the authors Hannah Ritchie & Max Roser.

- A changing climate has a range of potential ecological, physical, and health impacts, including extreme weathers, sea-level rise; altered crop growth; disrupted water systems.
- If countries achieved their current pledges and targets, there would be an in the coming years. In this regard, the world is making some progress.
- But if our aim is to limit global warming to “well below 2°C” as laid out in the Paris Agreement, we are clearly still far from the rates of progress we would need to achieve international targets.

LITERATURE REVIEW

- The question of responsibility for climate change is central to public and policy discourse over actions to cut greenhouse gas emissions and limit adverse impacts.
- The United Nations Framework Convention on Climate Change (UNFCCC) has established the principle of “common but differentiated responsibilities” among nations, signaling the recognition that nations that had produced the larger share of historical emissions will bear greater responsibilities. (UNFCCC, 1998)
- Reflecting this principle, the Paris Agreement establishes common commitments, for example to global net-zero greenhouse gas emissions in the second half of this century, while allowing flexibility in mitigation efforts to accommodate different national capacities and circumstances (United Nations, 2015)



LITERATURE REVIEW



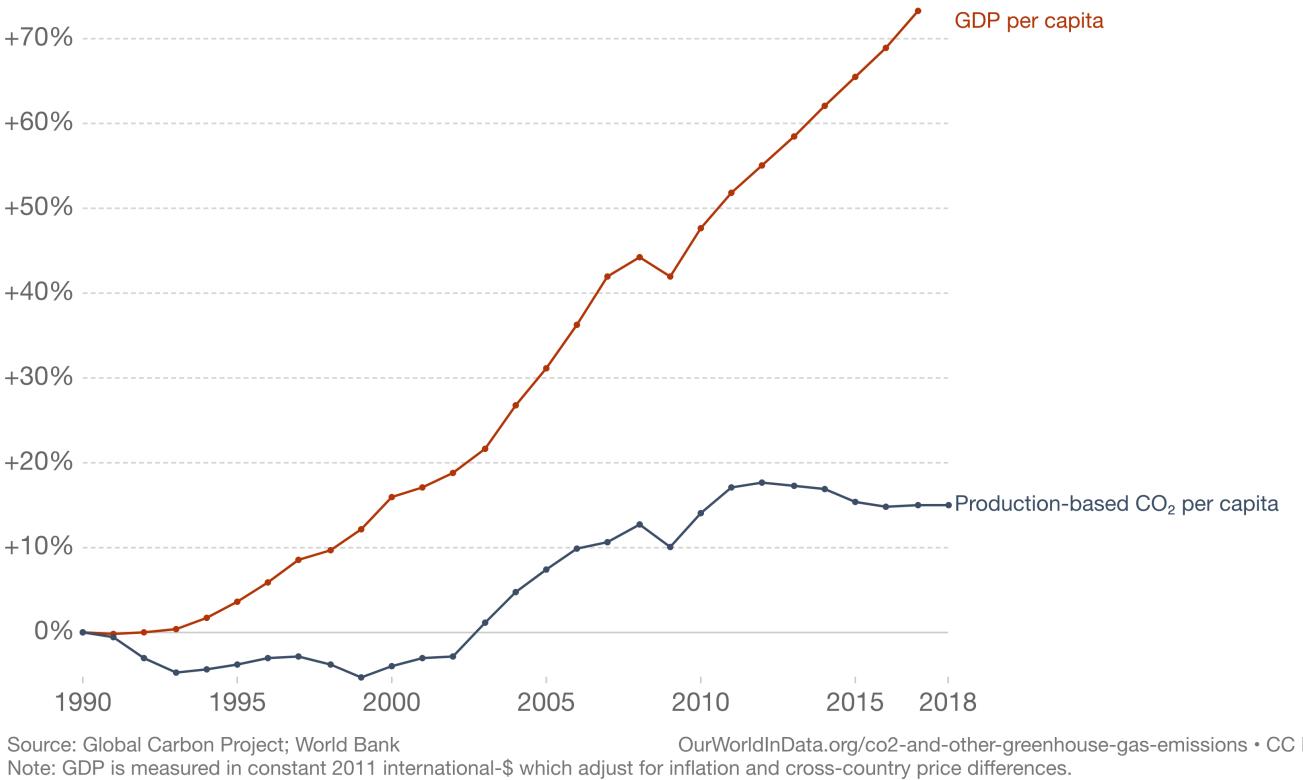
- The relationship between economic growth and environmental quality does exist. This relationship could be positive before economies cross a certain level of income. Reaching a ‘sustainable development’ is possible, thus turning economic growth compatible with environmental quality, after that certain level of income. (Hu et al., 2011)
- The share of renewables and non-renewable energy sources are important to explain differences in emissions. They suggest a significant change in the trend of economic and environmental efficiency in European countries and put forward the high disparities existing among them. (Moutinho et al., 2017)
- The growth of renewable energy consumption has a significant positive and negative impact on economic output and CO₂ emissions respectively. Institutions have a positive influence on economic growth and a reducing effect on CO₂ emissions. (Bhattacharya et al., 2017)
- A comparison of the national results at the product level points out that country characteristics, like energy supply, population density and the availability of district heating, influence variation in household CO₂ emissions between and within countries. (Kerkhof et al., 2009)

OBJECTIVE

- A number of countries, have managed to reduce CO₂ emissions whilst increasing gross domestic product (GDP).
- The objective of this project is to examine the relationship between CO₂ emissions, GDP and natural factors through statistical methods.
- Natural factors include the differences in average climate temperatures, the proportion of urban land areas, and the availability of renewable and fossil fuel resources.
- While many studies have shown the empirical relationship between CO₂ emissions and income, the question to what extent natural factor determines cross-country differences in CO₂ emissions has been somehow neglected.

Change in per capita CO₂ emissions and GDP, World

Annual consumption-based emissions are domestic emissions adjusted for trade. If a country imports goods the CO₂ emissions needed to produce such goods are added to its domestic emissions; if it exports goods then this is subtracted.



OBJECTIVE



Lower-income: Ethiopia



Lower-middle-income: Vietnam



Middle-income: Thailand



High-income: Japan

Categorization: World Bank

METHODOLOGY

- DEPENDENT VARIABLE TEST OF NORMALITY
 - Apply the Kolmogorov–Smirnov test (K–S test) and Shapiro–Wilk (S–W test) to check the normality of the Dependent Variable (DV)
- UNIVARIATE ANALYSIS: SAMPLE t-TEST
 - Apply Sample t-test to compare the mean of DV on 4 countries
 - Construct 95% confidence intervals around the largest and the smallest mean
- MULTIVARIATE ANALYSIS: OLS REGRESSION MODEL
 - Apply Ordinary least squares (OLS) regression model
 - Residual analysis to check for normality
 - Breusch–Pagan test to check for heteroskedasticity



PROPOSED MODEL

$$Y_i = a_i + b_{i1}x_{i1} + b_{i2}x_{i1}^2 + b_{i3}x_{i3} + b_{i4}x_{i4} + b_{i5}x_{i5} + b_{i6}x_{i6} + b_{i7}x_{i7} + e_i$$

Where (Neumayer E, 2002)

Y = CO_2 emission per capita

x_1 = GDP per capita

x_1^2 = squared GDP per capita

x_3 = lowest monthly average temperature

x_4 = highest monthly average temperature

x_5 = percentage of urban land in total land area

x_6 = percentage of renewable energy use in total energy use

x_7 = percentage of fossil fuel consumption in total energy use

ε = error term

DATA

- The raw data is consisted of a panel covering 25 years from 1991-2015 on 4 countries collected form the World Bank to maintain consistency, expecting a better significant model

Variable	Variable Name	Description	Type	Mean	SD	Minimum	Maximum
Y	co2_emission	carbon dioxide emission per capita	continuous	3.440	3.740	0.041	9.881
x1	gdp_capita	US\$ gross domestic product per capita	continuous	10,764	12,139	347	40,396
x2	gdp_capita2	squared US\$ gross domestic product per capita	continuous	261,744,033	430,488,940	120,120	1,631,856,465
x3	lowest_temp	lowest monthly average temperature	continuous	15.754	9.755	-1.908	24..544
x4	highest_temp	highest monthly average temperature	continuous	25.807	2.497	20.688	30.336
x5	urban_area	percentage of urban land in total land area	continuous	10.247	11.907	0.517	29.816
x6	renewable_energy	percentage of renewable energy use in total energy use	continuous	43.679	35.481	3.568	97.740
x7	fossil_fuel	percentage of fossil fuel consumption in total energy use	continuous	54.392	32.842	2.245	94.633

Table.: Descriptive Statistics

DEPENDENT VARIABLE TEST OF NORMALITY

- The Kolmogorov-Smirnov test (K-S test) compares the data with a known distribution and tells us if they have the same distribution. It is commonly used as a test for normality to see if our data is normally distributed. The hypotheses:

H_0 : The data is normally distributed

H_1 : The data is not normally distributed

- The K-S test p-value is less than $\alpha = 0.05$, therefore did not fail to reject H_0 concluding the data are not normally distributed. Again, this is expected given the dv_normality object was created via the rnorm() and co2 emission as runif() function.

```
Two-sample Kolmogorov-Smirnov test  
data: dv_normality and co2_emission  
D = 0.48, p-value = 0.0002033  
alternative hypothesis: two-sided
```

- The shapiro.test() function in R (program) employs the Shapiro-Wilk test (S-W test) on data to test whether the data are normally distributed. Use of the Shapiro-Wilk test is (less-sensitive) and contingent on univariate and continuous data. The hypotheses:

H_0 : The data is normally distributed

H_1 : The data is not normally distributed

- The S-W test p-value is greater than $\alpha = 0.05$, therefore failing to reject H_0 concluding the data are normally distributed. Again, this is expected given the dv_normality object was created via the rnorm() function.

```
Shapiro-Wilk normality test  
data: dv_normality  
W = 0.99876, p-value = 0.7254
```

DEPENDENT VARIABLE TEST OF NORMALITY

- The S-W test is also performed on the DV = CO2_emission, followed by another S-W test on the squared values to check the normality of the DV.

Using the CO2_emission (dependent variable), we have performed the S-W Test using R					
Country	W	p-value	alpha	Results	Comments
Japan	0.9359	0.1072	0.05	p-value > alpha	Normally Distributed
Thailand	0.95715	0.3386	0.05	p-value > alpha	Normally Distributed
Vietnam	0.92054	0.04629	0.05	p-value < alpha	Not Normally Distributed
Ethiopia	0.86383	0.002671	0.05	p-value < alpha	Normally Distributed

By squaring the CO2_emission (dependent variable), we have performed the S-W Test using R					
Country	W	p-value	alpha	Results	Comments
Japan	0.94169	0.1474	0.05	p-value > alpha	Normally Distributed
Thailand	0.96402	0.4768	0.05	p-value > alpha	Normally Distributed
Vietnam	0.87207	0.003933	0.05	p-value < alpha	Not Normally Distributed
Ethiopia	0.74232	2.13E-05	0.05	p-value > alpha	Normally Distributed

UNIVARIATE ANALYSIS: SAMPLE t-TEST

	Japan	Thailand		Japan	Vietnam
Mean	9.391375457	3.103616614	Mean	9.39138	0.979067422
Variance	0.108738244	0.568406843	Variance	0.108738	0.299928883
Observations	26	26	Observations	26	26
Pearson Correlation	0.447874747		Pearson Correlation	0.216848	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	25		df	25	
t Stat	47.55965533		t Stat	74.6308	
P(T<=t) one-tail	2.41779E-26		P(T<=t) one-tail	3.35E-31	
t Critical one-tail	1.708140761		t Critical one-tail	1.708141	
P(T<=t) two-tail	4.83558E-26		P(T<=t) two-tail	6.71E-31	
t Critical two-tail	2.059538553		t Critical two-tail	2.059539	

Japan: mean ($H_0 = 9.391375457$) >
Thailand: mean ($H_a = 3.103617$)

Japan: mean (9.391375457) >
Vietnam: mean (0.979067422)

	Japan	Ethiopia		Thailand	Vietnam
Mean	9.391375457	0.070484373	Mean	3.103616614	0.979067422
Variance	0.108738244	0.000552898	Variance	0.568406843	0.299928883
Observations	26	26	Observations	26	26
Pearson Correlation	0.06671267		Pearson Correlation	0.937013138	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	25		df	25	
t Stat	144.4497966		t Stat	35.22874312	
P(T<=t) one-tail	2.35866E-38		P(T<=t) one-tail	3.93694E-23	
t Critical one-tail	1.708140761		t Critical one-tail	1.708140761	
P(T<=t) two-tail	4.71732E-38		P(T<=t) two-tail	7.87387E-23	
t Critical two-tail	2.059538553		t Critical two-tail	2.059538553	

Japan: mean ($H_0 = 9.391375457$) >
Ethiopia: mean ($H_a = 0.070484$)

Thailand: mean ($H_0 = 3.103616614$) >
Vietnam: mean ($H_a = 0.979067422$)

UNIVARIATE ANALYSIS: CONFIDENCE INTERVAL

Construct 95% confidence intervals around the largest mean and the smallest mean.

(Largest) Mean - Japan	(Smallest) Mean - Ethiopia						
9.391375457	3.103616614	6.287759	(Largest) Mean	9.320891	Sample SD	4.206154	
9.391375457	0.979067422	8.412308	(Smallest) Min	0.908583	Margin of Error	5.829324914	
9.391375457	0.070484373	9.320891	(Largest) Mean LB (Mean - E)	3.491566	confidence coefficient	0.95	
3.103616614	0.979067422	2.124549	(Largest) Mean UB (Mean + E)	15.15022	alpha	0.05	
3.103616614	0.070484373	3.033132	(Smallest) Min LB (Mean - E)	-4.92074			
0.979067422	0.070484373	0.908583	(Smallest) Min UB (Mean + E)	6.737908			
(Largest) Mean - Japan		9.32089	(Smallest) Mean - Ethiopia		0.90858		
Sample SD		3.48848	Sample SD		3.48848		
Margin of Error		3.660936	Margin of Error		3.660936		

MULTIVARIATE ANALYSIS: OLS REGRESSION

Model:	Regression							
Dependent Variable:	co2_emission							
	R-Squared	Adj.R-Sqr.	Std.Err.Reg.	Std.Dep.Var.	# Fitted	# Missing	Critical t	Confidence
	0.998	0.998	0.181	3.740	100	4	1.986	95.0%
Variable	Coefficient	Std.Err.	t-Statistic	P-value	Lower95%	Upper95%	VIF	Std. Coeff.
Constant	0.009380	1.095	0.009	0.993	-2.166	2.184	0.000	0.000
fossil_fuel	0.015	0.009280	1.660	0.100	-0.003029	0.034	280.701	0.135
gdp_capita	0.000295	0.000015	19.538	0.000	0.000265	0.000325	101.212	0.956
gdp_capita2	-4.766E-09	2.981E-10	-15.986	0.000	-5.358E-09	-4.174E-09	49.776	-0.549
highest_temp	-0.034	0.026	-1.337	0.185	-0.085	0.017	12.302	-0.023
lowest_temp	-0.035	0.011	-3.037	0.003	-0.057	-0.012	37.162	-0.090
renewable_energy	0.013	0.010	1.289	0.201	-0.007050	0.033	389.579	0.124
urban_area	0.149	0.016	9.195	0.000	0.117	0.181	112.320	0.474
	Mean Error	RMSE	MAE	Minimum	Maximum	MAPE	A-D* stat	
Fitted (n=100)	0.000	0.174	0.130	-0.919	0.366	32.1%	1.00 (P=0.012)	

Using RegressIt to generate the Model_1 based on the DV = CO₂_emission

RESIDUAL ANALYSIS

Residual -vs- Predicted
Model 1 for co2_emission (7 variables, n=100)

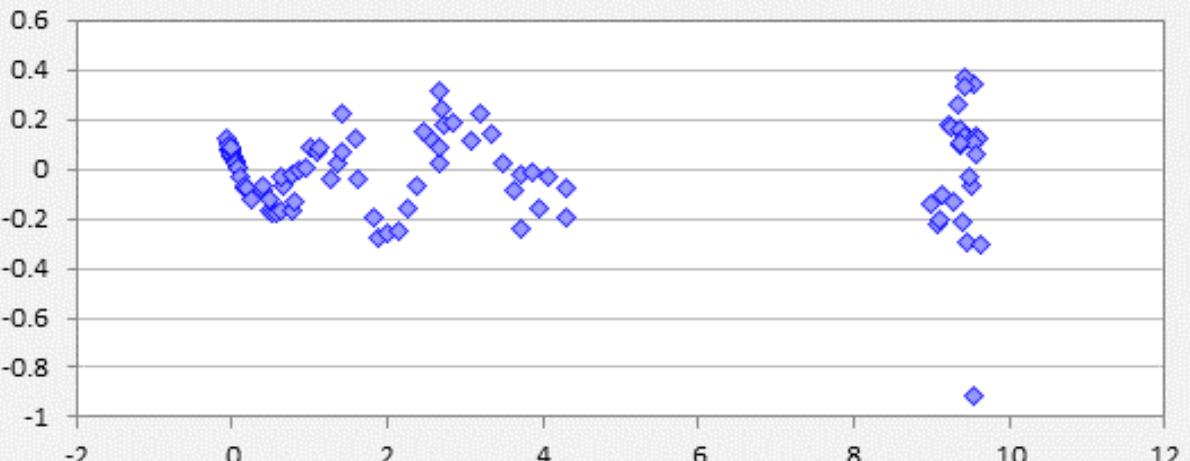


Figure.: Plot of the Residual -vs- Predicted

Histogram of Residuals
Model 1 for co2_emission (7 variables, n=100)

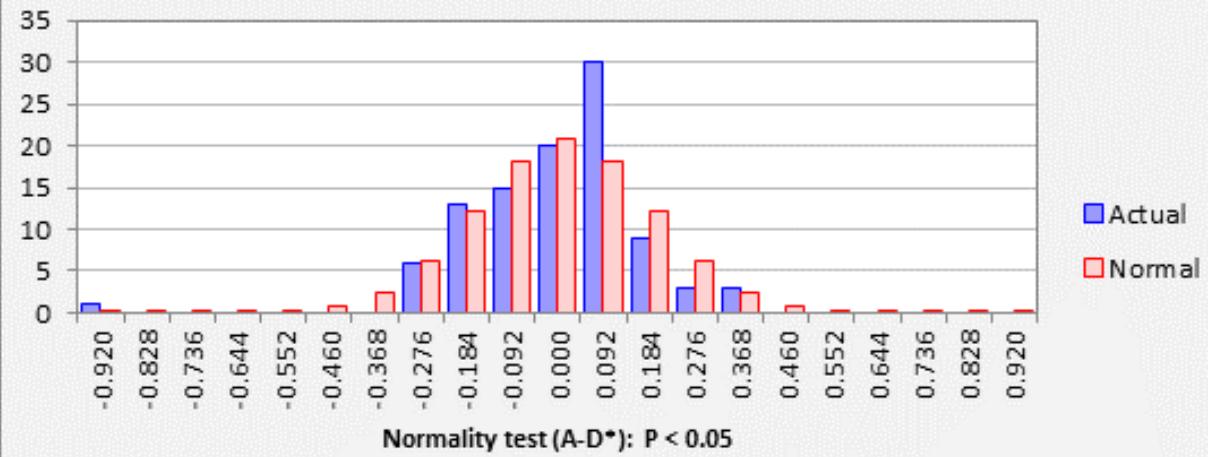


Figure.: Histogram of Residuals

RESIDUAL ANALYSIS

- The density plot provides a visual judgment about whether the distribution is bell shaped. The black line represents the residual data, and the blue line represents the normal distribution given the μ and σ values of residual. Note: The residual data appears as bell shaped and does fit the normal distribution model given the parameters calculated via the residual data.

```
Shapiro-wilk normality test
data: d3_residual$residual
W = 0.91241, p-value = 5.696e-06

describe(d3_residual$residual)
   vars   n  mean    sd median trimmed  mad   min   max range skew kurtosis    se
X1     1 100  0.17 0.02    0.01  0.14 -0.92 0.37  1.29 -1.35  6.04  0.02
```

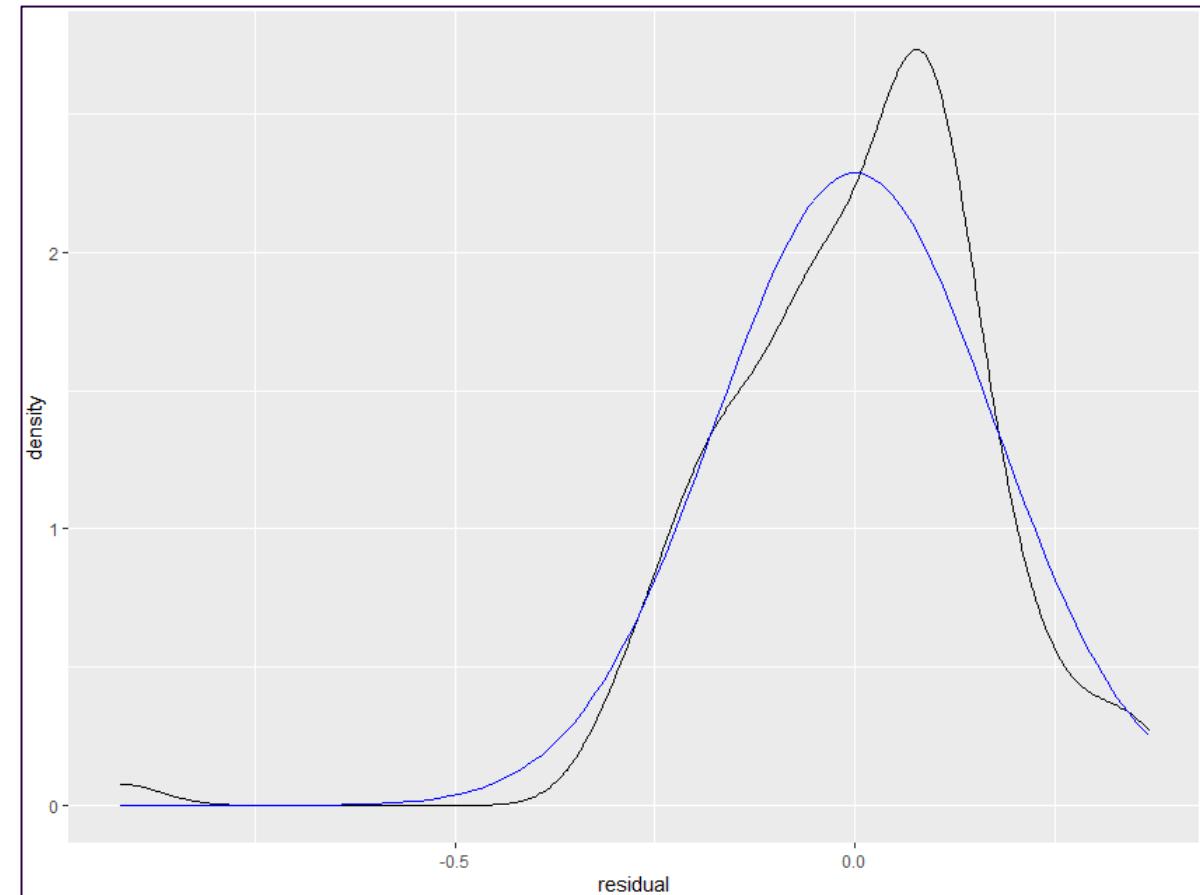


Figure.: Density plot of the residuals

RESIDUAL ANALYSIS: HETROSKEDECITY

- The Breusch-Pagan test is a test for heteroscedasticity of errors in regression. Heteroscedasticity means “differently scattered”; this is opposite to homoscedastic, which means “same scatter.” Homoscedasticity in regression is an important assumption; if the assumption is violated, you won’t be able to use regression analysis.

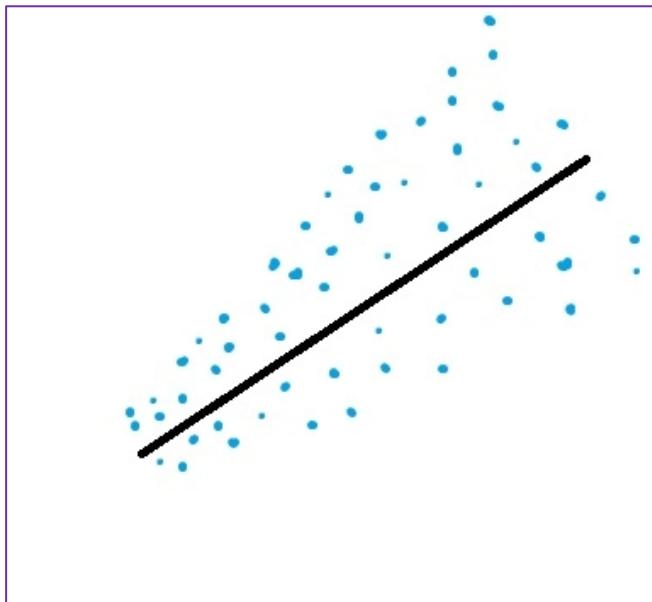


Figure.: Sample of heteroskedastic data

- Check for heteroskedasticity: There seems to be no evident pattern. However, it does seem to look as if there's more variation in residuals in this sample data from the linear regression.

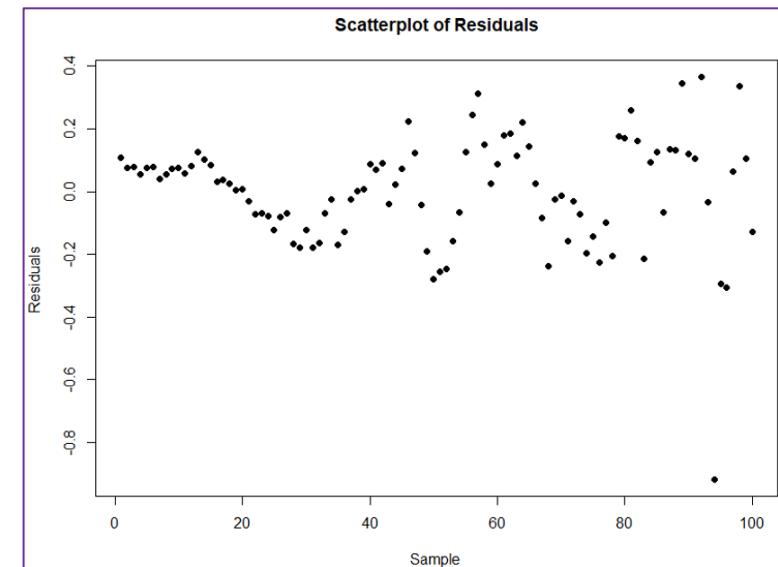


Figure.: Scatter plot of the residuals

IMPLICATIONS AND CONCLUSION

- Natural factors can explain cross-country differences in CO₂ emissions only to some limited extent only.
- Countries having colder climate, or a lower availability of renewable resources have higher fossil fuel consumption than countries with warmer climates or a higher availability of renewable resources.
- There is a relationship between CO₂ emissions with GDP growth and fossil fuels. As the value of GDP, urban area, renewable energy increases; CO₂ emissions decreases.
- Countries with having low natural conditions (temperature) demanded higher carbon emissions than countries at roughly the same income levels



LIMITATIONS OF THE MODEL



- There was a huge data gap in between the high-income and low-income country in terms of dependent and all independent variables.
- Used the square of GDP per-capita
- Taken the percentage of urban land in total land area, renewable energy use in total energy use, fossil fuel consumption in total energy use.

FUTURE WORK

- During a pandemic situation, we would want to extend out the model.
 - Further reading:

Impact of COVID-19 outbreak measures of lockdown on the Italian Carbon Footprint
(Rugani, et al. 2020)
- To study government initiatives that impact on the carbon-footprint.
 - The dynamic impact of renewable energy and institutions on economic output and CO₂ emissions across regions
(Bhattacharya, et al., 2017)
- To include the usage of plastic and bio-degradable items.



APPENDIX

Variable Name	Description	Type	Source	Website
country	countries under analysis	categorical	–	–
country_code	country code	categorical	–	–
year	calendar year	integer	–	–
co2_emission	carbon dioxide emission per capita	continuous	The World Bank	https://data.worldbank.org/indicator/EN.ATM.CO2E.PC
gdp_capita	US\$ gross domestic product per capita	continuous	The World Bank	https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
gdp_capita2	squared US\$ gross domestic product per capita	continuous	The World Bank	https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
lowest_temp	lowest monthly average temperature	continuous	The World Bank	https://climateknowledgeportal.worldbank.org/download-data
highest_temp	highest monthly average temperature	continuous	The World Bank	https://climateknowledgeportal.worldbank.org/download-data
urban_area	percentage of urban land in total land area	continuous	The World Bank	https://data.worldbank.org/indicator/AG.LND.TOTL.UR.K2
renewable_energy	percentage of renewable energy use in total energy use	continuous	The World Bank	https://data.worldbank.org/indicator/EG.FEC.RNEW.ZS
fossil_fuel	percentage of fossil fuel consumption in total energy use	continuous	The World Bank	https://data.worldbank.org/indicator/EG.USE.COMM.FO.ZS

Table.: Description of the Variables

REFERENCES

- Bhattacharya M, Churchill S A, Paramati S R (2017). ‘The dynamic impact of renewable energy and institutions on economic output and CO₂ emissions across regions’. Renewable Energy 111, Pp 157-167
- Hu Z G, Yuan J H, Hu Z (2011). ‘Study on China’s low carbon development in an Economy-Energy-Electricity-Environment framework.’ Energy Policy 39 (5), Pp 2596–2605.
- Kerkhof C A, Benders M J R, Moll C H (2009), ‘Determinants of variation in household CO₂ emissions between and within countries’. Energy Policy 37 (4), Pp 1509-1517
- Moutinho V, Madaleno M, Margarita R (2017), ‘The economic and environmental efficiency assessment in EU cross-country: Evidence from DEA and quantile regression approach’ Ecological Indicators 78, Pp 85-97

REFERENCES

- Neumayer, E (2002). ‘Can Natural Factors Explain Any Cross-Country Differences in Carbon Dioxide Emissions?’ Energy Policy 30 (1), Pp 7-12.
- Ritchie, H and Roser, M (2017). ‘CO₂ and Greenhouse Gas Emissions’ [Online Resource]. <https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions>
- UNFCCC (1998). ‘Kyoto Protocol to the United Nations Framework Convention on Climate Change’ [Online Resource]. <http://unfccc.int/resource/docs/convkp/kpeng.pdf>
- United Nations (2015). ‘Paris Agreement’. [Online Resource]. <https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement>
- World Bank, World Development Indicators. (2016). ‘CO₂ emissions (metric tons per capita)’ [Data file]. <https://data.worldbank.org/indicator/EN.ATM.CO2E.PC>

REFERENCES

- World Bank, World Development Indicators. (2019). ‘GDP per capita (current US\$)’ [Data file]. <https://data.worldbank.org/indicator/NY.GDP.PCAP.CD>
- World Bank, World Development Indicators. (2016). ‘Climate Change Knowledge Portal’ [Data file]. <https://climateknowledgeportal.worldbank.org/download-data>
- World Bank, World Development Indicators. (2013). ‘Urban land area (sq.km)’ [Data file]. <https://data.worldbank.org/indicator/AG.LND.TOTL.UR.K2>
- World Bank, World Development Indicators. (2018). ‘Land area (sq.km)’ [Data file]. <https://data.worldbank.org/indicator/AG.LND.TOTL.K2>

REFERENCES

- World Bank, World Development Indicators. (2015). ‘Renewable energy consumption (% of total final energy consumption)’ [Data file].

<https://data.worldbank.org/indicator/EG.FEC.RNEW.ZS>

- World Bank, World Development Indicators. (2015). ‘Fossil fuel energy consumption (% of total final consumption)’ [Data file].

<https://data.worldbank.org/indicator/EG.USE.COMM.FO.ZS>

THANK YOU.



UNIVERSITY OF
WATERLOO

| FACULTY OF
ENGINEERING

UNIVERSITY OF
WATERLOO



FACULTY OF ENGINEERING