Climate Change is not a joke | CAPP 122 Course Project | Winter 2023

Statistical Model and Comparative Data Analysis

Regression Discontinuity Design

We have used Regression Discontinuity Design (RDD) to capture the differences in the Climate funding by MDBs before and after the Paris Climate Agreement on our dataset. Regression Discontinuity Analysis (RDA) is a statistical method used to estimate the causal effect of a treatment or intervention by exploiting a naturally occurring discontinuity in a continuous variable, such as time. RDA is used when random assignment to a treatment and control group is not possible or ethical, and when the treatment variable is not continuous. The RDA model estimates the treatment effect by comparing the outcomes just above and just below the discontinuity threshold. The idea is that groups on either side of the threshold are similar in all other respects except for their treatment status.

Key Assumptions of RDD

- Discontinuity in the treatment variable is not affected by other observable or unobservable factors that could also affect the outcome variable
- Most appropriate when the discontinuity in the treatment variable is expected to be large and sharp
- The sample size is sufficiently large to estimate the treatment effect with precision

Model Estimation for the Project

$$\bar{Y}_a = \alpha + \rho T_r + \gamma R + e_a$$

where Treatment variable:

$T_r = 1$ if: $a \varepsilon 2017$

$T_r = 0$ if: $a < 2017$

The variable that determines treatment (R) is called the running variable.

The treatment T is a discontinuous function of an observed running variable.

In this model: R = ‘Year’ variable, T = ‘cutoff Year’ variable (2017), Y = Commitment Amount (either in millions of $ or log10 of commitment amount.

RDA method involves estimating two separate linear regression models, one for pre-treatment data (years before 2017) and another for post-treatment data (years from 2017 onwards), and comparing the estimated coefficients to measure the treatment effect of the Paris Agreement.

Why RDD is suitable for our model?

- Treatment depends on the running variable
- Outcome has a discontinuity (The effect of Paris Climate Agreement) at the expected value of the running variable

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- Variation in treatment near cutoff is random (cannot precisely control the running variable near the cutoff)
- Sample size of above 800 observations or more would be considered relatively large
- RD design identifies causal treatment effects if:
  except for T (treatment), all factors determining Y evolve smoothly around the cutoff (c)

Assumptions/Things to Note:

- Since we're running the analysis on same countries pre and post the Paris agreement, we expect the only difference between pre and post to be the treatment effect (The Paris Agreement)
- We are taking 2017 as the cutoff year, although the Paris agreement was ratified in November 2016. This is because we expect the changes in funding, if any, to start taking place with a lag effect. (The Paris Agreement itself was adopted in December 2015, but it was ratified (made effective) by the most of countries by November 2016
- There were some missing values for Commitment Amount for some projects in datasets. Our hypothesis is that this represents anomalies in data handling and representation by MDBs. We have dropped some observations for missing values in the Commitment Amount instead of assuming those to be zero
- We are only looking at Year as our explanatory/running variable in this model, however, we realize that there could be other factors that explain the differences in Commitment Amount (pre and post the agreement). One such variable could be the demand for climate projects by individual countries that can impact the level of funding provided by MDBs in different years. However, since our analysis is cumulative (for total climate projects for all countries), we assume that the variation is smooth both pre and post the Paris agreement
- Size of countries, especially in terms of population, can determine the amount of funding received by an individual country from an MDB. However, since our countries are the same for both datasets and for both periods (pre and post the Paris agreement) we expect that its effect on the total Commitment amount evolves smoothly around the cutoff
- The overall economic conditions of the recipient countries could play a role in the amount of climate-related financing they receive. For instance, countries with weaker economies may receive less funding compared to those with stronger economies. However, since our dataset remains the same for pre and post periods, we expect the model to account for these differences
- Political considerations: The political environment of the recipient countries, including their stance on climate change, may affect the amount of funding they receive. Countries that are more supportive of climate change initiatives may receive more funding compared to those that are not
- Finally, the priorities of the donors, including the World Bank, could also influence the amount of funding provided for climate change initiatives. Donors may have different priorities for funding different regions or types of projects, which could affect the amount of funding provided to different countries or regions.

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Findings from Statistical Analysis

Source of Data: World Bank

Importing Packages and Running Regressions

Code Snippet:

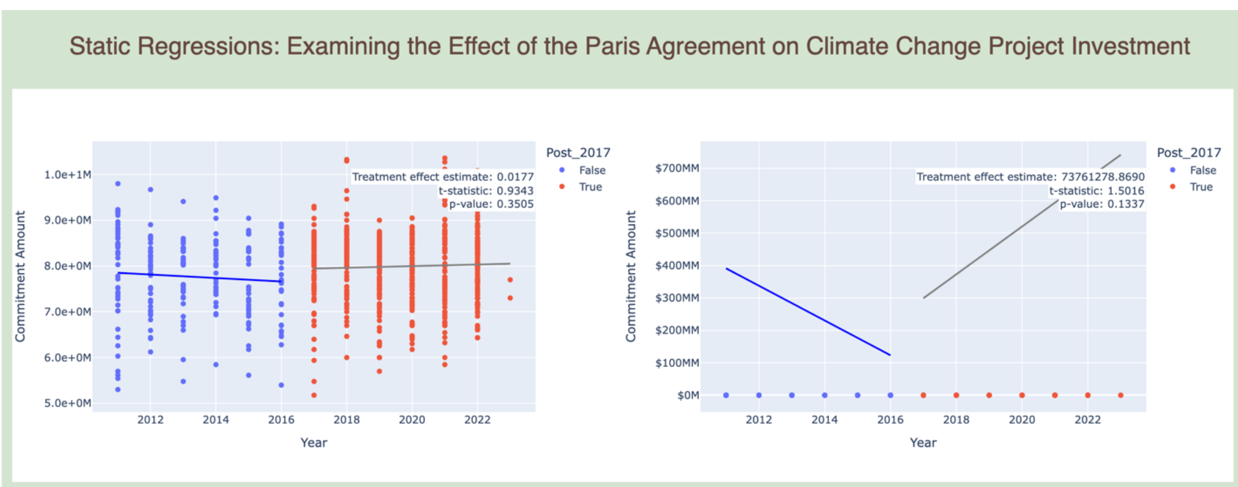
```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
import plotly.express as px
import statsmodels.api as sm
from scipy import stats

# Convert Commitment_Amount to log10
df['Commitment_Amount'] = np.log10(df['Commitment_Amount'])
treatment_model = LinearRegression().fit(treatment[['Year']], treatment['Commitment_Amount'])
control_model = LinearRegression().fit(control[['Year']], control['Commitment_Amount'])

treatment_effect = treatment_model.coef_[0]

# Calculate the treatment effect and its standard error using statsmodels
treatment_model = sm.OLS(treatment['Commitment_Amount'], sm.add_constant(treatment['Year'])).fit()
treatment_effect = treatment_model.params['Year']
treatment_effect_se = treatment_model.bse['Year']

# Calculate the t-statistic and p-value for the treatment effect using statsmodels
t_stat = treatment_effect / treatment_effect_se
p_value = 2 * (1 - stats.t.cdf(abs(t_stat), df=treatment_model.df_resid))
```



Hypotheses for the Model:

H0: No treatment effect i.e. Paris Agreement had no significant impact on climate-related funding provided by the World Bank to countries in the Asia Pacific region

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HA: Treatment had a significant impact on climate-related funding provided by the World Bank to countries in the Asia Pacific region

The results of the RDA are presented in the output we provided, here is a summary interpretation of **log model** for each of these results:

- Treatment effect estimate: This value of 0.0177 is the estimated treatment effect of the Paris Agreement on climate-related funding. Specifically, this represents the average difference in the log10 commitment amount between the post-treatment (i.e., after 2017) and pre-treatment (i.e., before 2017) periods, holding all other variables constant. In other words, this is the estimated change in funding due to the Paris Agreement
- Treatment R-squared and Control R-squared: These values of 0.0014 and 0.0056 respectively, represent the proportion of variance in the dependent variable (log10 commitment amount) that is explained by the independent variable (Year) for the treatment and control groups separately
- t-statistic: This value of 0.93 represents the calculated t-statistic for the treatment effect estimate. The t-statistic measures the difference between the estimated treatment effect and zero, in units of standard error. In this case, the t-statistic is less than 2, which suggests that the estimated treatment effect is not statistically significant at conventional levels (i.e., alpha=0.05)
- p-value: This value of 0.35 is the calculated two-tailed p-value associated with the t-statistic. The p-value represents the probability of observing a t-statistic as extreme or more extreme than the observed value, assuming the null hypothesis of no treatment effect is true. In this case, the p-value is greater than 0.05, which indicates that we fail to reject the null hypothesis of no treatment effect. Therefore, we cannot conclude that the Paris Agreement had a significant impact on climate-related funding provided by the World Bank to countries in the Asia Pacific region

The results of the RDA are presented in the output we provided, here is a summary interpretation of **linear model** for each of these results:

- The treatment effect estimate by the model is 73761278. This means that there is a positive effect of being in the post-treatment period (i.e., after 2017) on the amount of climate-related financing provided by the World Bank to countries in the Asia Pacific. Specifically, the estimate suggests that the post-treatment period is associated with an increase in climate-related financing of approximately 73.76 million dollars on average as compared to the pre-treatment period (i.e., before 2017)
- The t-statistic of 1.5016 suggests that the treatment effect estimate is statistically significant at the 10% level (assuming a two-tailed test), but not significant at the 5% level. The p-value of 0.1337 indicates that there is a 13.37% probability of observing a treatment effect estimate as large or larger than 73761278, assuming that there is actually no treatment effect (i.e., the null hypothesis is true)
- Overall, these results suggest that there may be a positive effect of the Paris Agreement on climate-related financing provided by the World Bank to countries in the Asia Pacific, but further analysis would be needed to determine the significance of this effect and to control for other potential factors that may influence climate-related financing

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Conclusion

Overall, based on these results, we can conclude that there is no statistically significant evidence at 5% significance level to suggest that the Paris Agreement had a significant impact on climate-related funding provided by the World Bank to countries in the Asia Pacific region. If we interpret the results at 10% significance level, then we can state there is a positive impact on climate related financing after the Paris Agreement. However, considering the convention of using 5% significance level, we fail to reject the null hypothesis of no effect.

However, it is important to note that these findings are based on the assumptions and limitations of the RDA method and the specific data and model used in this analysis. Therefore, caution should be exercised in interpreting these results and drawing broad conclusions about the impact of the Paris Agreement on climate finance

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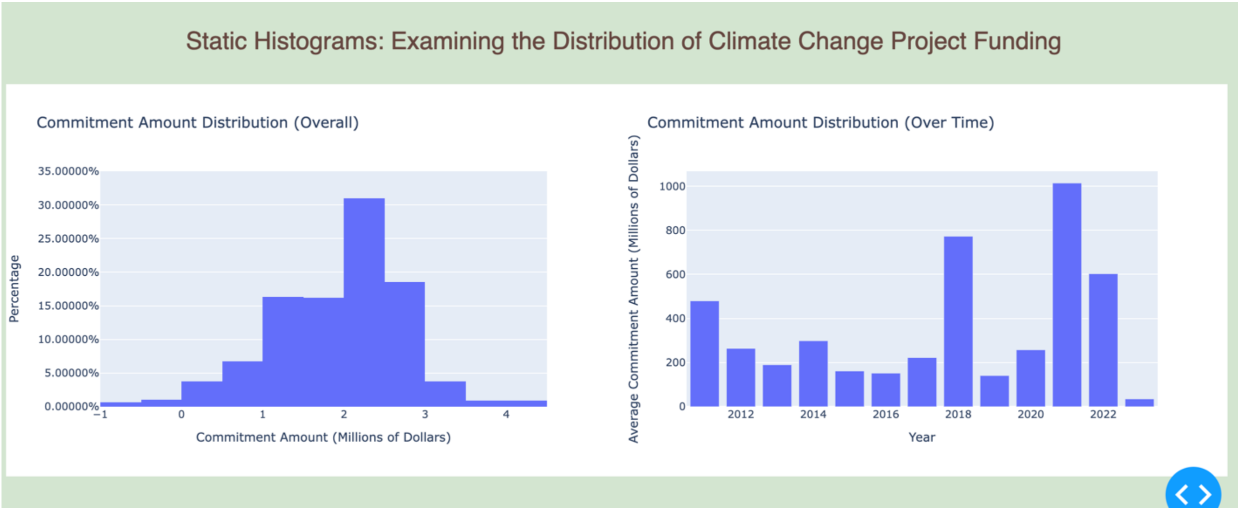
Exploratory Data Analysis



We show how the Climate financing (in terms of Commitment Amount) varies on average year on year from 2011 till date. We expect the climate financing to increase after the Paris Agreement. We can see from the Bar Plot on the right hand side that on average the climate financing by the World Bank after the Paris Agreement is higher than before the agreement, although there are some significant variations year on year.

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ND-Gain Index

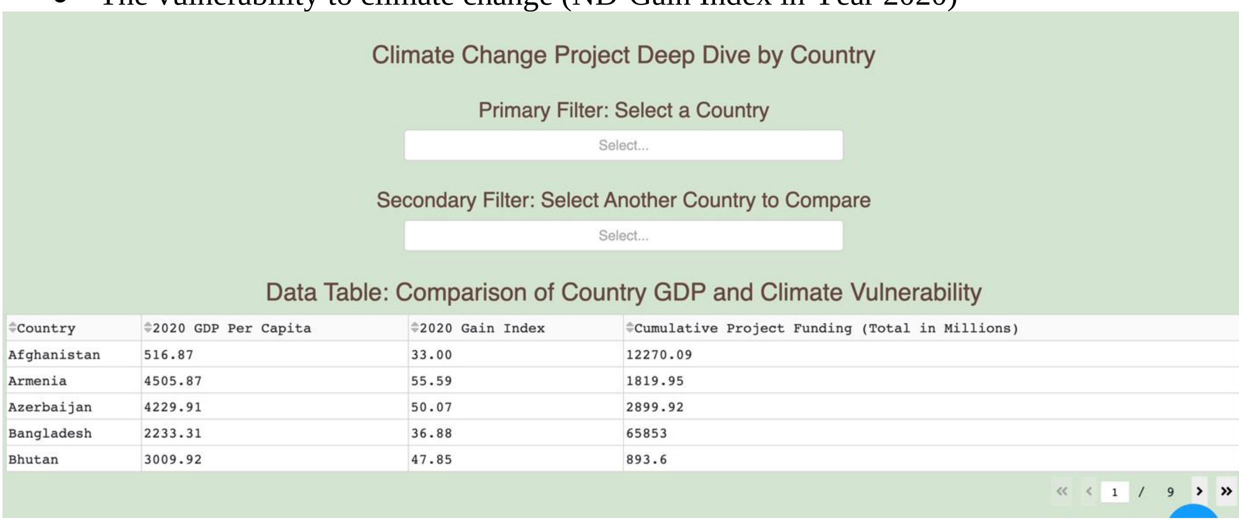
The most commonly used climate vulnerability index for countries is the ND-GAIN (Notre Dame Global Adaptation Initiative) Index. This index measures a country's vulnerability to climate change and readiness to adapt based on a range of indicators, including exposure, sensitivity, adaptive capacity, and readiness. Higher value for ND-Gain Index is better. Read more here: https://gain.nd.edu/our-work/country-index/

GDP Per Capita

GDP per capita is a measure of the economic output of a country, divided by the number of people living in that country. It is often used as an indicator of the standard of living in a country and its economic well-being.
Read more here: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

We have used these two indicators to account for differences between individual countries in terms of the size of relative economies and their vulnerability index. We have provided a dashboard for users to compare countries based on three indicators:

- According to the funding they received from two MDBs (Total Commitment Amount)
- The size of countries' economies (GDP Per Capita in Year 2020)
- The vulnerability to climate change (ND-Gain Index in Year 2020)



Country	2020 GDP Per Capita	2020 Gain Index	Cumulative Project Funding (Total in Millions)
Afghanistan	516.87	33.00	12270.09
Armenia	4505.87	55.59	1819.95
Azerbaijan	4229.91	50.07	2899.92
Bangladesh	2233.31	36.88	65853
Bhutan	3009.92	47.85	893.6

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