PS4_AndrewYu

August 11, 2023

To get started, make a copy of this file and save to your "My Drive" in Google.

1 How much does the U.S. owe India for climate related damages?

First, you will consider policies around "loss and damage", or what (if any) payments are owed by countries that have been responsible for most of the historical carbon emissions to countries that have suffered most of the damage from those emissions. How big should these payments be? In particular, how much damage have historical emissions from the U.S. caused in India, the world's most populous country with the largest number of people living below the poverty line? Answering this question will involve combining multiple data streams, utilizing output from a climate model, and computing counterfactual scenerios.

[2]:
```
import numpy as np
import sys
import pandas as pd
import matplotlib.pyplot as mplt
import seaborn as sb

from google.colab import drive
drive.mount('/content/drive')
FOLDERNAME = "Stanford Summer Session/DATASCI 154/PS4"
```

```
Mounted at /content/drive
```

1.1 Step 1: How much carbon has the U.S. emitted?

In this part, you will visualize historical emissions from the U.S. and the world from 1750-2020, consider how the U.S. has contributed to overall emissions, and decide from which year the U.S. should be held responsible for its emissions.

1. Load in the U.S. historical emissions file `us_emissions_1750_2020.csv` and the world historical emissions file `wrld_emissions_1750_2020.csv` using `read_csv` from the `pandas` package. Merge the two datasets together by `year`, keeping only the rows corresponding to years with data from the world and the U.S. (hint: this is an inner join in `merge`).

[2]:
```
#NOTE: In these files, unit of emissions is GtC, gigatonnes of carbon
#Both datasets have a variable called 'year' that stores the year. You will␣
↪want to merge on this variable.
```

```python
#We only want to keep rows that coorespond to year that are present in both the␣
↪U.S. AND the world data.

us_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/
↪us_emissions_1750_2020.csv")
wrld_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/
↪wrld_emissions_1750_2020.csv")
merged_df = pd.merge(us_df, wrld_df, left_on="year", right_on="year",␣
↪how="inner")
merged_df
```

[2]:

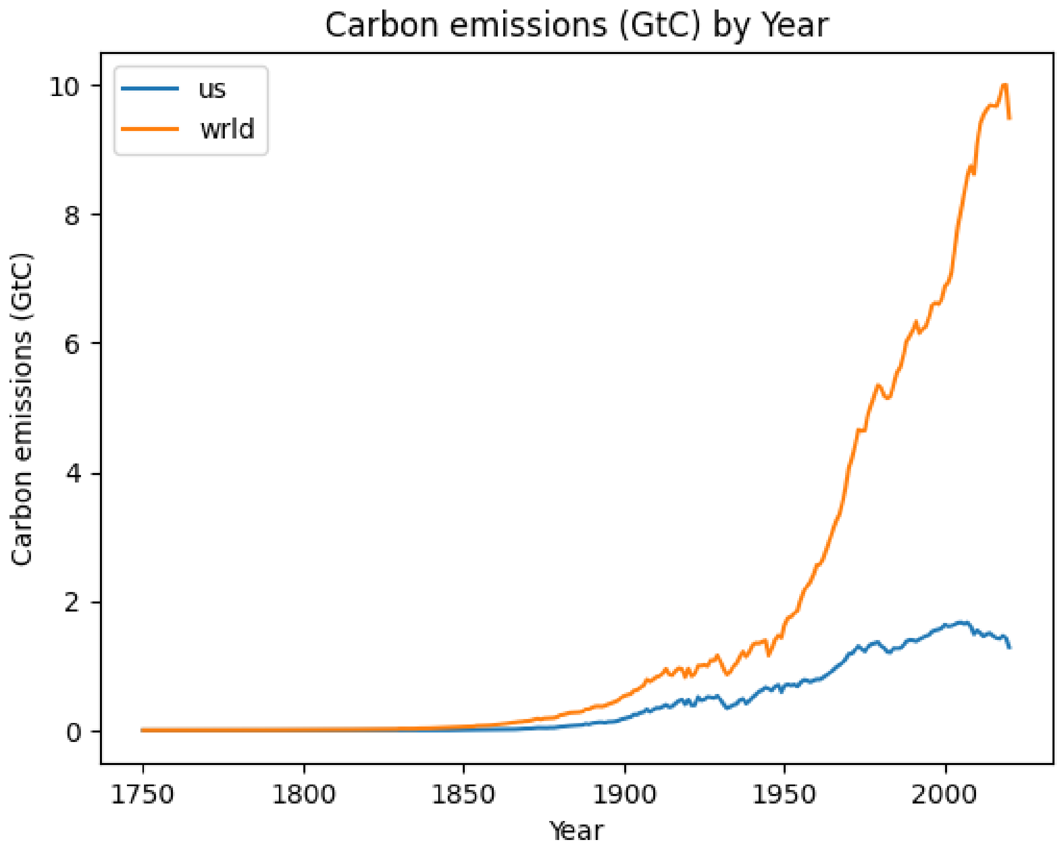
```
    emitter_country  year  emissions_gtc  emissions_gtc_wrld
0               USA  1750       0.000000            0.002548
1               USA  1751       0.000000            0.002548
2               USA  1752       0.000000            0.002549
3               USA  1753       0.000000            0.002549
4               USA  1754       0.000000            0.002550
..              …   …             …                 …
266             USA  2016       1.429979            9.660071
267             USA  2017       1.419006            9.789029
268             USA  2018       1.464711            9.985324
269             USA  2019       1.432103           10.000682
270             USA  2020       1.284134            9.484267

[271 rows x 4 columns]
```

2. Create a graph with year on the x-axis, carbon emissions on the y-axis, and two lines, one for the World and one for the U.S.

[3]:

```python
mplt.plot(us_df["year"], us_df["emissions_gtc"], label="us")
mplt.plot(wrld_df["year"], wrld_df["emissions_gtc_wrld"], label="wrld")
mplt.legend()
mplt.title("Carbon emissions (GtC) by Year")
mplt.xlabel("Year")
mplt.ylabel("Carbon emissions (GtC)")
mplt.show()
```



3. The first key question you have to take a stand on is, “since when”? Are we going to hold the U.S. accountable for all of its historical emissions since the 1700s? Or just since industrial times? Or maybe just since we first knew that carbon emissions might be harmful, somewhere around 1980? Or the first UN climate change conference in 1992? Or in 2006, the year Al Gore released “Inconvenient Truth”? Please decide when the US started to be responsible for the impacts of these emissions, and briefly justify your decision.

I would take since industrial times (~1850s), since this period was when processes utilizing carbon-fuels really started to take off and carbon emissions consequently ramped up. Since U.S. had the first if not one of the first mover’s advantage, they would have started off contributing to a large majority of the emissions and for a long time to come.

1.2 Step 2: How much global warming did these emissions cause?

Now, we’re going to use the output of an open source “reduced complexity” climate model called FaIR. FaIR is a way to estimate how a given pulse of carbon emissions (e.g. what I emitted when I drove to work today), or how different histories of carbon emissions (e.g. US carbon emissions since 1950), have warmed the global average temperature. We used FaIR to estimate the change in “global mean surface temperature” (GMST) due to global historical emissions. We also used FaIR to estimate what the change in GMST would have been had U.S. emissions dropped to zero the year the U.S. began being responsible for its emissions. We will use the estimate of counterfactual emissions in our calculation of climate related damages.

4. Read in the results from the FaIR model stored in the file `temperature_response_emissions_history.csv` and display the first five rows of data. The columns should be: `temp_response` (the estimated effect of emissions, including U.S. emissions, on global temperature in `year`),`temp_response_nousa` (the estimated effect of emissions, excluding U.S. emissions, on global temperature in `year`), `year` (the year the estimated effects were experienced), `damange_start_year` (the year the U.S. began being responsible for its emissions).

[4]:
```
#Load in the file `temperature_response_to_emissions_history.csv`

temp_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/
 ↪temperature_response_to_emissions_history.csv")
temp_df.head(5)
```

[4]:
```
   temp_response  temp_response_nousa  year  damage_start_year
0       0.000001             0.000001  1770               1770
1       0.000004             0.000004  1771               1770
2       0.000010             0.000010  1772               1770
3       0.000016             0.000016  1773               1770
4       0.000023             0.000023  1774               1770
```

5. Create a new variable in your dataframe to store the difference in the temperature response when U.S. emissions are included versus when they are excluded. Note that this difference reflects the global temperature response attributable to U.S. emissions, and should be positive. After you have created new variable, display the first five rows of your dataframe to check your work.

[5]:
```
temp_df["temp_response_usa"] = temp_df["temp_response"] -␣
 ↪temp_df["temp_response_nousa"]
temp_df.head(5)
```

[5]:
```
   temp_response  temp_response_nousa  year  damage_start_year  \
0       0.000001             0.000001  1770               1770
1       0.000004             0.000004  1771               1770
2       0.000010             0.000010  1772               1770
3       0.000016             0.000016  1773               1770
4       0.000023             0.000023  1774               1770

   temp_response_usa
0                0.0
1                0.0
2                0.0
3                0.0
4                0.0
```

6. FaIR is a non-linear model, so the temperature change attributed to U.S. emissions in a given year will depend on when you started "counting" U.S. emissions. For example, the

temperature change in 1980 that is attributable to U.S. emissions will be larger if you started counting the impact of U.S. emissions in 1850 vs. if you started counting in 1975. This dataset contains the results of running FaIR with different start years. Find the different start years represented in the data, identify the start year closest to the year you chose in Part 1, and only keep rows cooresponding to this start year.

[6]:
```
#Use df['column name'].unique() to find the unique start years

temp_df["damage_start_year"].unique()
```

[6]:
```
array([1770, 1780, 1790, 1800, 1810, 1820, 1830, 1840, 1850, 1860, 1870,
       1880, 1890, 1900, 1910, 1920, 1930, 1940, 1950, 1960, 1970, 1980,
       1990, 2000, 2010])
```

[7]:
```
#In a new dataframe, only keep rows that meet the condition describe in␣
 ↪question 6.
#Note 1: The symbol for equals is ==
#Note 2: In this dataframe, the years are stored as ints, so you do not need␣
 ↪quotes around the year in your condition

temp_df = temp_df[temp_df["damage_start_year"] == 1850]
temp_df
```

[7]:
```
      temp_response  temp_response_nousa  year  damage_start_year  \
1728       0.000016             0.000015  1850               1850
1729       0.000070             0.000062  1851               1850
1730       0.000152             0.000135  1852               1850
1731       0.000246             0.000217  1853               1850
1732       0.000350             0.000308  1854               1850
…              …                   …     …                …
1894       0.689001             0.517757  2016               1850
1895       0.704583             0.531356  2017               1850
1896       0.720282             0.545100  2018               1850
1897       0.736140             0.559010  2019               1850
1898       0.751967             0.572933  2020               1850

      temp_response_usa
1728           0.000002
1729           0.000007
1730           0.000017
1731           0.000029
1732           0.000043
…                  …
1894           0.171243
1895           0.173227
1896           0.175183
1897           0.177131
```

```
1898           0.179033

[171 rows x 5 columns]
```

1.3 Step 3: What was the effect of these emissions on temperatures in India?

FaIR gives us the global temperature change. But warming is not uniform across the globe: the higher latitudes warm faster than the tropics, and land warms faster than ocean. So we next need to ask: for a given amount of global warming, how much would we expect India to warm? Here we are going to use an approach called "pattern scaling", which uses information from even fancier climate models (called "general circulation models", or GCMs) to estimate changes in a whole host of climate parameters. We will not run these models ourselves, since they require years on a supercomputer. Instead, we're just going to take an average value for the "warming ratio", i.e. the ratio that tells us how much India warms if the globe warms by 1 degree. To estimate total warming in India due to U.S. emissions, we need to multiply the change in global temperature due to U.S. emissions from FaIR with the average warming ratio in India.

7. First, load the data stored in the `india_data.csv` file. Then, add information from the temperature response dataframe to the India dataframe through a merge, only keeping rows that cooresponds to years that are present in both datasets. Finally, create a new variable that represents the estimated temperature change in India due to U.S. emissions. After you are finished, display the first five rows of your dataset and check your work.

[8]:
```python
india_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/india_data.csv")
merged_india_df = pd.merge(india_df, temp_df, left_on="year", right_on="year",␣
 ↪how="inner")
merged_india_df["est_temp_change"] = merged_india_df["temp_response_usa"] *␣
 ↪merged_india_df["warming_ratio"]
merged_india_df.head(5)
```

[8]:
```
  country_code  year  temperature    gdp_pcap  population  warming_ratio  \
0          IND  1960    25.488705  302.671819   445954579       0.834365
1          IND  1961    24.632089  307.727896   456351876       0.834365
2          IND  1962    24.681752  310.376725   467024193       0.834365
3          IND  1963    25.177380  322.284061   477933619       0.834365
4          IND  1964    25.272684  339.203690   489059309       0.834365

   temp_response  temp_response_nousa  damage_start_year  temp_response_usa  \
0       0.138294             0.083234               1850           0.055060
1       0.142565             0.086199               1850           0.056366
2       0.146976             0.089288               1850           0.057688
3       0.151534             0.092496               1850           0.059038
4       0.156298             0.095864               1850           0.060434

   est_temp_change
0         0.045940
1         0.047030
2         0.048133
```

```
3          0.049259
4          0.050424
```

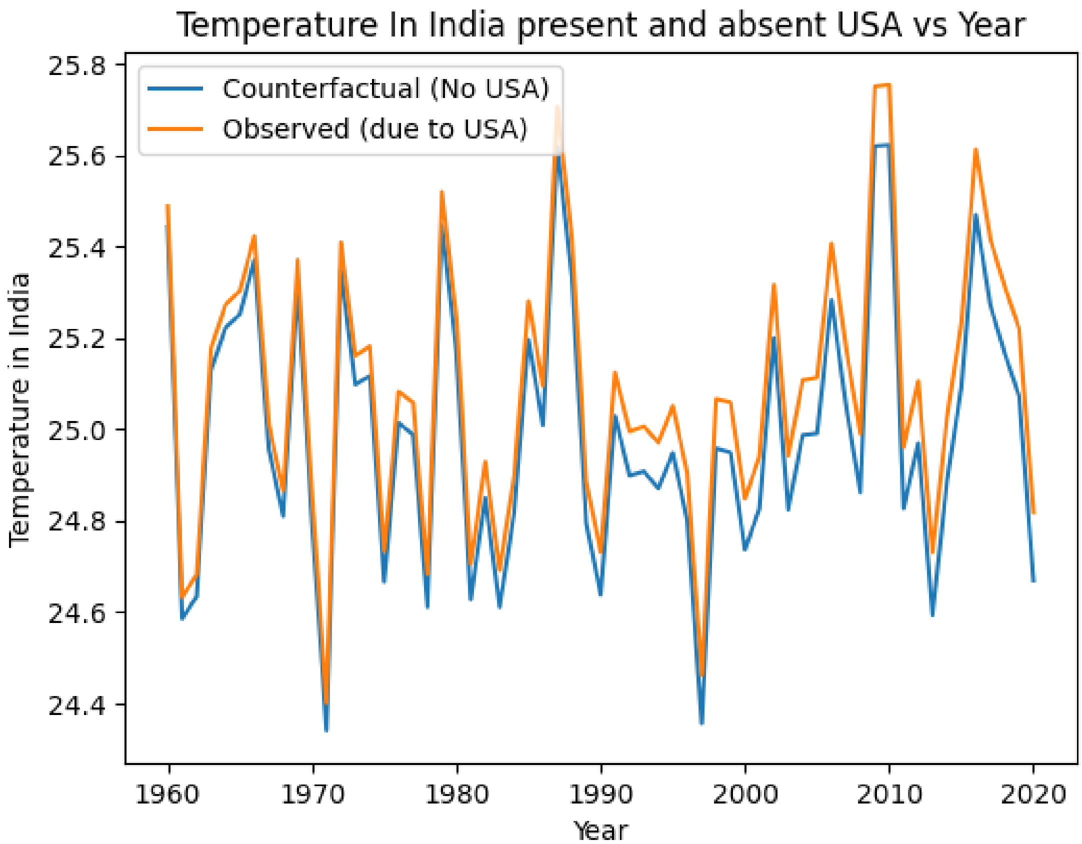
8. Now, we are going to estimate counterfactual temperatures in India, or what temperatures in India would have been had the U.S. had no emissions after the selected start year. For each year, we can estimate this by subtracting the estimated temperature change in India from the actual observed temperature in India.

[9]:
```python
#Create a new variable to store the counterfactual India temperature (what␣
↪temperature would have been in India absent U.S. emissions)
#Reminder 1: The actual observed temperature in India is stored as `temperature`
#Reminder 2: You created a variable of the estimated temperature change in␣
↪India in question 7

merged_india_df["temp_india_nousa"] = merged_india_df["temperature"] -␣
↪merged_india_df["est_temp_change"]
```

9. Plot temperature vs. year for the observed temperature and for the estimated counterfactual temperature with no U.S. emissions. Year should be on the x-axis, temperature should be on the y-axis, and you should have two lines, one for the observed temperature, and one for the estimated counterfactual temperature.

[10]:
```python
mplt.plot(merged_india_df["year"], merged_india_df["temp_india_nousa"],␣
↪label="Counterfactual (No USA)")
mplt.plot(merged_india_df["year"], merged_india_df["temperature"],␣
↪label="Observed (due to USA)")
mplt.title("Temperature In India present and absent USA vs Year")
mplt.xlabel("Year")
mplt.ylabel("Temperature in India")
mplt.legend()
mplt.show()
```



1.4 Step 4: What is the economic impact of an additional degree of warming?

Now we turn to economic data to try to understand the relationship between warming temperatures and economic output. We're going to use data on per capita gross domestic product (GDP) for India for over a half century, and use estimates from the literature on how past temperature changes have affected growth in GDP per capita.

The growth rate in per capita GDP in year i is given by $\frac{per\ capita\ GDP_i - per\ capita\ GDP_{i-1}}{per\ capita\ GDP_{i-1}}$

Burke, Hsiang, and Miguel (2015) estimate than for a country that's as hot as India, a year that is 1 degree C hotter than average has a per-capita growth rate that is 1 percentage point lower. I.e. if the per-capita GDP India is growing at 5% a year, then in a year that is +1C hotter than average, it only grows 4% in that year, and in a year that is +2C hotter than average, it only grows 3% in that year.

We will then combine this temperature/per-capita growth relationship with our estimates of how much cooler India would have been without US emissions to calculate the impact of US emissions on the Indian economy.

10. First, we will compute the observed per-capita GDP growth rate for India.

```
[11]: #Note: Using df['variable_name'].pct_change() will be helpful

merged_india_df["gdp_growth_usa"] = merged_india_df['gdp_pcap'].pct_change()
```

11. Now, we are going to compute counterfactual growth, that is what the per captia GDP would have been in India had there been no U.S. emissions after the selected start year.

```
[12]: #First, we will create a new variable that stores the change in per-capita GDP␣
 ↪due to U.S. emissions.
#In question 7 you estimated the change in temperatures in India due to U.S.␣
 ↪emissions.
#We know that for every 1 degree increase in temperature, per-capita GDP has a␣
 ↪1 percent decrease.

# merged_india_df["gdp_growth_nousa"] = merged_india_df["gdp_growth_usa"] +␣
 ↪merged_india_df["est_temp_change"]
```

```
[13]: #In question 10, you created a variable for the actual observed per-capita GDP␣
 ↪growth.
#You just created a variable that gives the change in per-capita GDP growth due␣
 ↪to U.S. emissions.
#Use these to create a second new variable that gives the counterfactual␣
 ↪per-capita GDP growth if there had been zero U.S. emissions

merged_india_df["gdp_growth_nousa"] = merged_india_df["gdp_growth_usa"] +␣
 ↪(merged_india_df["est_temp_change"] * 0.01)
merged_india_df
```

```
[13]:    country_code  year  temperature     gdp_pcap  population  warming_ratio  \
0           IND  1960    25.488705   302.671819   445954579       0.834365
1           IND  1961    24.632089   307.727896   456351876       0.834365
2           IND  1962    24.681752   310.376725   467024193       0.834365
3           IND  1963    25.177380   322.284061   477933619       0.834365
4           IND  1964    25.272684   339.203690   489059309       0.834365
..          …   …          …          …          …            …
56          IND  2016    25.612235  1719.318076  1338636340       0.834365
57          IND  2017    25.416638  1816.730876  1354195680       0.834365
58          IND  2018    25.312273  1915.435271  1369003306       0.834365
59          IND  2019    25.219532  1972.757821  1383112050       0.834365
60          IND  2020    24.817982  1797.759777  1396387127       0.834365

    temp_response  temp_response_nousa  damage_start_year  temp_response_usa  \
0        0.138294             0.083234               1850           0.055060
1        0.142565             0.086199               1850           0.056366
2        0.146976             0.089288               1850           0.057688
3        0.151534             0.092496               1850           0.059038
4        0.156298             0.095864               1850           0.060434
```

```
..       …          …          …          …
56   0.689001   0.517757      1850   0.171243
57   0.704583   0.531356      1850   0.173227
58   0.720282   0.545100      1850   0.175183
59   0.736140   0.559010      1850   0.177131
60   0.751967   0.572933      1850   0.179033

    est_temp_change  temp_india_nousa  gdp_growth_usa  gdp_growth_nousa
0          0.045940         25.442765             NaN               NaN
1          0.047030         24.585059        0.016705          0.017175
2          0.048133         24.633619        0.008608          0.009089
3          0.049259         25.128120        0.038364          0.038857
4          0.050424         25.222260        0.052499          0.053003
..              …                 …               …               …
56         0.142879         25.469356        0.070822          0.072251
57         0.144535         25.272103        0.056658          0.058103
58         0.146166         25.166106        0.054331          0.055792
59         0.147792         25.071741        0.029927          0.031405
60         0.149379         24.668603       -0.088707         -0.087214

[61 rows x 14 columns]
```

12. Now, let's start to consider the effect of U.S. emissions on per capita GDP over time.

Recall that if per capita GDP growth is 2% in year 1, then per capita GDP in year 2 can be written as $per\ capita\ GDP_{year2} = 1.02 * per\ capita\ GDP_{year1}$.

Also recall that growth compounds, so if the growth in year 2 is 3%, then $per\ capita\ GDP_{year3} = 1.02 * 1.03 * per\ capita\ GDP_{year1}$.

[14]:
```
#First, perform arithmetic to adjust your counterfactual growth variable so␣
 ↪that it can be used in calculations like the ones above.
#i.e. if your growth rate is .02, it should transform to 1.02.

merged_india_df['gdp_growth_nousa_helper'] =␣
 ↪merged_india_df['gdp_growth_nousa'] + 1
```

[15]:
```
#Now, create a new variable to calculate the cumulative counterfactual growth␣
 ↪in each year.
#Note: df['variable name'].cumprod() will be helpful

merged_india_df['gdp_growth_cum'] = merged_india_df['gdp_growth_nousa_helper'].
 ↪cumprod()
```

[16]:
```
#Then, create a variable that stores damages each year.
#Damages are the difference between counterfactual per capita GDP absent US␣
 ↪Emissions & observed per capita GDP.
```

```python
#To find counterfactual per capita GDP, use an equation in the question above,␣
↪per capita GDP data from the first year you consider,
#and the cumulative counterfactual growth variable you just constructed.

# Still CORRECT?

merged_india_df['gdp_pcap_nousa'] = merged_india_df['gdp_growth_cum'] *␣
↪merged_india_df.loc[0, "gdp_pcap"]
merged_india_df['damages_pcap'] = merged_india_df['gdp_pcap_nousa'] -␣
↪merged_india_df['gdp_pcap']

merged_india_df
```

[16]:

```
   country_code  year  temperature     gdp_pcap  population  warming_ratio  \
0           IND  1960    25.488705   302.671819   445954579       0.834365
1           IND  1961    24.632089   307.727896   456351876       0.834365
2           IND  1962    24.681752   310.376725   467024193       0.834365
3           IND  1963    25.177380   322.284061   477933619       0.834365
4           IND  1964    25.272684   339.203690   489059309       0.834365
..          ...   ...          ...          ...         ...            ...
56          IND  2016    25.612235  1719.318076  1338636340       0.834365
57          IND  2017    25.416638  1816.730876  1354195680       0.834365
58          IND  2018    25.312273  1915.435271  1369003306       0.834365
59          IND  2019    25.219532  1972.757821  1383112050       0.834365
60          IND  2020    24.817982  1797.759777  1396387127       0.834365

    temp_response  temp_response_nousa  damage_start_year  temp_response_usa  \
0        0.138294             0.083234               1850           0.055060
1        0.142565             0.086199               1850           0.056366
2        0.146976             0.089288               1850           0.057688
3        0.151534             0.092496               1850           0.059038
4        0.156298             0.095864               1850           0.060434
..            ...                  ...                ...                ...
56       0.689001             0.517757               1850           0.171243
57       0.704583             0.531356               1850           0.173227
58       0.720282             0.545100               1850           0.175183
59       0.736140             0.559010               1850           0.177131
60       0.751967             0.572933               1850           0.179033

    est_temp_change  temp_india_nousa  gdp_growth_usa  gdp_growth_nousa  \
0          0.045940         25.442765             NaN               NaN
1          0.047030         24.585059        0.016705          0.017175
2          0.048133         24.633619        0.008608          0.009089
3          0.049259         25.128120        0.038364          0.038857
4          0.050424         25.222260        0.052499          0.053003
..              ...               ...             ...               ...
56         0.142879         25.469356        0.070822          0.072251
```

```
57         0.144535         25.272103       0.056658         0.058103
58         0.146166         25.166106       0.054331         0.055792
59         0.147792         25.071741       0.029927         0.031405
60         0.149379         24.668603      -0.088707        -0.087214

    gdp_growth_nousa_helper  gdp_growth_cum  gdp_pcap_nousa  damages_pcap
0                       NaN             NaN             NaN           NaN
1                  1.017175        1.017175      307.870244      0.142347
2                  1.009089        1.026420      310.668484      0.291759
3                  1.038857        1.066304      322.740046      0.455985
4                  1.053003        1.122821      339.846353      0.642663
..                      …               …               …            …
56                 1.072251        5.969832     1806.899904     87.581828
57                 1.058103        6.316698     1911.886498     95.155623
58                 1.055792        6.669122     2018.555310    103.120039
59                 1.031405        6.878563     2081.947153    109.189332
60                 0.912786        6.278659     1900.373214    102.613437

[61 rows x 18 columns]
```

1.5 Step 5: What does the US owe India?

Here, you put it all together. Step 2 gave you the total amount of global warming, Step 3 translated this into country specific warming, and Step 4 told you how to translate this country specific warming into impacts on per capita GDP in each year. Now, we want to know the total sum that the US owes India since the start year you selected in step 1.

13. We want to find total GDP losses in each year, which is per capita GDP losses in each year times population in that year, and then we sum across years to get the total impact.Print the total losses. Note that the units for this number are dollars.

[17]:
```
merged_india_df['damages'] = merged_india_df['damages_pcap'] *␣
 ↪merged_india_df['population']
merged_india_df.head(5)
```

[17]:
```
  country_code  year  temperature    gdp_pcap  population  warming_ratio  \
0          IND  1960    25.488705  302.671819   445954579       0.834365
1          IND  1961    24.632089  307.727896   456351876       0.834365
2          IND  1962    24.681752  310.376725   467024193       0.834365
3          IND  1963    25.177380  322.284061   477933619       0.834365
4          IND  1964    25.272684  339.203690   489059309       0.834365

   temp_response  temp_response_nousa  damage_start_year  temp_response_usa  \
0       0.138294             0.083234               1850           0.055060
1       0.142565             0.086199               1850           0.056366
2       0.146976             0.089288               1850           0.057688
3       0.151534             0.092496               1850           0.059038
4       0.156298             0.095864               1850           0.060434
```

```
   est_temp_change  temp_india_nousa  gdp_growth_usa  gdp_growth_nousa  \
0         0.045940         25.442765             NaN               NaN
1         0.047030         24.585059        0.016705          0.017175
2         0.048133         24.633619        0.008608          0.009089
3         0.049259         25.128120        0.038364          0.038857
4         0.050424         25.222260        0.052499          0.053003

   gdp_growth_nousa_helper  gdp_growth_cum  gdp_pcap_nousa  damages_pcap  \
0                      NaN             NaN             NaN           NaN
1                 1.017175        1.017175      307.870244      0.142347
2                 1.009089        1.026420      310.668484      0.291759
3                 1.038857        1.066304      322.740046      0.455985
4                 1.053003        1.122821      339.846353      0.642663

        damages
0           NaN
1  6.496036e+07
2  1.362584e+08
3  2.179307e+08
4  3.143003e+08
```

[18]:
```python
print('Total losses across all years: '"${:.2f}".
 ↪format(merged_india_df["damages"].sum()))
```

```
Total losses across all years: $1803157244654.03
```

14. In question 13, you computed total GDP losses each year. Please discuss whether these values are large or not. Some possible things to compare against: Are they large relative to total Indian GDP? relative to US aid flows to India? Relative to total US commitments to climate finance?

[19]:
```python
merged_india_df["gdp_usa"] = merged_india_df['gdp_pcap'] *␣
 ↪merged_india_df['population']
merged_india_df
```

[19]:
```
   country_code  year  temperature     gdp_pcap  population  warming_ratio  \
0           IND  1960    25.488705   302.671819   445954579       0.834365
1           IND  1961    24.632089   307.727896   456351876       0.834365
2           IND  1962    24.681752   310.376725   467024193       0.834365
3           IND  1963    25.177380   322.284061   477933619       0.834365
4           IND  1964    25.272684   339.203690   489059309       0.834365
..          …     …          …           …          …              …
56          IND  2016    25.612235  1719.318076  1338636340       0.834365
57          IND  2017    25.416638  1816.730876  1354195680       0.834365
58          IND  2018    25.312273  1915.435271  1369003306       0.834365
59          IND  2019    25.219532  1972.757821  1383112050       0.834365
60          IND  2020    24.817982  1797.759777  1396387127       0.834365
```

```
   temp_response  temp_response_nousa  damage_start_year  temp_response_usa  \
0       0.138294             0.083234               1850           0.055060
1       0.142565             0.086199               1850           0.056366
2       0.146976             0.089288               1850           0.057688
3       0.151534             0.092496               1850           0.059038
4       0.156298             0.095864               1850           0.060434
..           …                    …                 …                  …
56      0.689001             0.517757               1850           0.171243
57      0.704583             0.531356               1850           0.173227
58      0.720282             0.545100               1850           0.175183
59      0.736140             0.559010               1850           0.177131
60      0.751967             0.572933               1850           0.179033

   est_temp_change  temp_india_nousa  gdp_growth_usa  gdp_growth_nousa  \
0         0.045940         25.442765             NaN               NaN
1         0.047030         24.585059        0.016705          0.017175
2         0.048133         24.633619        0.008608          0.009089
3         0.049259         25.128120        0.038364          0.038857
4         0.050424         25.222260        0.052499          0.053003
..             …                 …               …                 …
56        0.142879         25.469356        0.070822          0.072251
57        0.144535         25.272103        0.056658          0.058103
58        0.146166         25.166106        0.054331          0.055792
59        0.147792         25.071741        0.029927          0.031405
60        0.149379         24.668603       -0.088707         -0.087214

   gdp_growth_nousa_helper  gdp_growth_cum  gdp_pcap_nousa  damages_pcap  \
0                      NaN             NaN             NaN           NaN
1                 1.017175        1.017175      307.870244      0.142347
2                 1.009089        1.026420      310.668484      0.291759
3                 1.038857        1.066304      322.740046      0.455985
4                 1.053003        1.122821      339.846353      0.642663
..                     …               …               …             …
56                1.072251        5.969832     1806.899904     87.581828
57                1.058103        6.316698     1911.886498     95.155623
58                1.055792        6.669122     2018.555310    103.120039
59                1.031405        6.878563     2081.947153    109.189332
60                0.912786        6.278659     1900.373214    102.613437

         damages       gdp_usa
0            NaN  1.349779e+11
1   6.496036e+07  1.404322e+11
2   1.362584e+08  1.449534e+11
3   2.179307e+08  1.540304e+11
4   3.143003e+08  1.658907e+11
..           …             …
```

```
56  1.172402e+11  2.301542e+12
57  1.288593e+11  2.460209e+12
58  1.411717e+11  2.622237e+12
59  1.510211e+11  2.728545e+12
60  1.432881e+11  2.510369e+12

[61 rows x 20 columns]
```

[20]:
```python
merged_india_df[merged_india_df["year"] >= 1968]
```

[20]:
```
   country_code  year  temperature    gdp_pcap  population  warming_ratio  \
8           IND  1968    24.864921  338.432624   533431909       0.834365
9           IND  1969    25.370798  352.883206   545314670       0.834365
10          IND  1970    24.855112  362.991056   557501301       0.834365
11          IND  1971    24.400626  360.717461   569999178       0.834365
12          IND  1972    25.409436  350.561000   582837973       0.834365
13          IND  1973    25.160753  353.783265   596107483       0.834365
14          IND  1974    25.181807  349.725681   609721951       0.834365
15          IND  1975    24.732879  372.964621   623524219       0.834365
16          IND  1976    25.082480  370.528803   637451448       0.834365
17          IND  1977    25.058150  388.407475   651685628       0.834365
18          IND  1978    24.682738  401.312505   666267760       0.834365
19          IND  1979    25.519935  371.663128   681248383       0.834365
20          IND  1980    25.244368  387.640860   696828385       0.834365
21          IND  1981    24.704863  401.484584   712869298       0.834365
22          IND  1982    24.928712  405.876646   729169466       0.834365
23          IND  1983    24.691563  425.472513   745826546       0.834365
24          IND  1984    24.898426  431.702996   762895156       0.834365
25          IND  1985    25.280229  444.232664   780242084       0.834365
26          IND  1986    25.095257  455.228162   797878993       0.834365
27          IND  1987    25.706438  463.055750   815716125       0.834365
28          IND  1988    25.422756  496.856131   833729681       0.834365
29          IND  1989    24.886397  515.410609   852012673       0.834365
30          IND  1990    24.730676  532.754550   870452165       0.834365
31          IND  1991    25.123832  527.514516   888941756       0.834365
32          IND  1992    24.994918  545.399465   907574049       0.834365
33          IND  1993    25.006085  560.161941   926351297       0.834365
34          IND  1994    24.970018  585.964621   945261958       0.834365
35          IND  1995    25.050528  618.367769   964279129       0.834365
36          IND  1996    24.904581  652.566081   983281218       0.834365
37          IND  1997    24.461394  666.420154  1002335230       0.834365
38          IND  1998    25.066260  694.735303  1021434576       0.834365
39          IND  1999    25.058738  742.658952  1040500054       0.834365
40          IND  2000    24.847981  757.668747  1059633675       0.834365
41          IND  2001    24.939831  780.606234  1078970907       0.834365
42          IND  2002    25.315932  796.724786  1098313039       0.834365
43          IND  2003    24.942000  845.274844  1117415123       0.834365
```

44	IND	2004	25.107121	897.628233	1136264583	0.834365
45	IND	2005	25.112937	953.567973	1154638713	0.834365
46	IND	2006	25.406946	1014.627641	1172373788	0.834365
47	IND	2007	25.178387	1075.994087	1189691809	0.834365
48	IND	2008	24.989473	1093.076551	1206734806	0.834365
49	IND	2009	25.750380	1162.498808	1223640160	0.834365
50	IND	2010	25.754610	1244.366016	1240613620	0.834365
51	IND	2011	24.960799	1292.821206	1257621191	0.834365
52	IND	2012	25.104733	1346.675910	1274487215	0.834365
53	IND	2013	24.730155	1415.828722	1291132063	0.834365
54	IND	2014	25.024655	1503.421507	1307246509	0.834365
55	IND	2015	25.232487	1605.605445	1322866505	0.834365
56	IND	2016	25.612235	1719.318076	1338636340	0.834365
57	IND	2017	25.416638	1816.730876	1354195680	0.834365
58	IND	2018	25.312273	1915.435271	1369003306	0.834365
59	IND	2019	25.219532	1972.757821	1383112050	0.834365
60	IND	2020	24.817982	1797.759777	1396387127	0.834365

	temp_response	temp_response_nousa	damage_start_year	temp_response_usa	\
8	0.177729	0.111127	1850	0.066602	
9	0.183723	0.115418	1850	0.068304	
10	0.190084	0.119996	1850	0.070089	
11	0.196856	0.124895	1850	0.071961	
12	0.204001	0.130099	1850	0.073903	
13	0.211500	0.135584	1850	0.075916	
14	0.219306	0.141317	1850	0.077989	
15	0.227282	0.147220	1850	0.080062	
16	0.235401	0.153278	1850	0.082123	
17	0.243763	0.159541	1850	0.084222	
18	0.252400	0.166026	1850	0.086374	
19	0.261294	0.172731	1850	0.088563	
20	0.270388	0.179629	1850	0.090759	
21	0.279537	0.186615	1850	0.092922	
22	0.288617	0.193593	1850	0.095024	
23	0.297627	0.200568	1850	0.097059	
24	0.306666	0.207601	1850	0.099065	
25	0.315856	0.214772	1850	0.101084	
26	0.325244	0.222131	1850	0.103113	
27	0.334819	0.229671	1850	0.105148	
28	0.344615	0.237399	1850	0.107217	
29	0.354661	0.245324	1850	0.109337	
30	0.364906	0.253412	1850	0.111494	
31	0.375315	0.261659	1850	0.113656	
32	0.385816	0.270002	1850	0.115814	
33	0.396297	0.278305	1850	0.117992	
34	0.406763	0.286560	1850	0.120203	
35	0.417290	0.294844	1850	0.122446	

36	0.427956	0.303233	1850	0.124723
37	0.438795	0.311751	1850	0.127044
38	0.449738	0.320334	1850	0.129404
39	0.460718	0.328925	1850	0.131793
40	0.471787	0.337570	1850	0.134218
41	0.483011	0.346334	1850	0.136676
42	0.494391	0.355248	1850	0.139144
43	0.506002	0.364391	1850	0.141610
44	0.517990	0.373906	1850	0.144084
45	0.530429	0.383860	1850	0.146569
46	0.543298	0.394248	1850	0.149049
47	0.556573	0.405061	1850	0.151512
48	0.570220	0.416271	1850	0.153949
49	0.584105	0.427791	1850	0.156315
50	0.598175	0.439588	1850	0.158587
51	0.612599	0.451798	1850	0.160801
52	0.627451	0.464492	1850	0.162959
53	0.642612	0.477553	1850	0.165059
54	0.657974	0.490835	1850	0.167139
55	0.673460	0.504251	1850	0.169209
56	0.689001	0.517757	1850	0.171243
57	0.704583	0.531356	1850	0.173227
58	0.720282	0.545100	1850	0.175183
59	0.736140	0.559010	1850	0.177131
60	0.751967	0.572933	1850	0.179033

	est_temp_change	temp_india_nousa	gdp_growth_usa	gdp_growth_nousa	\
8	0.055571	24.809350	0.012262	0.012818	
9	0.056991	25.313807	0.042699	0.043268	
10	0.058480	24.796632	0.028644	0.029228	
11	0.060042	24.340585	-0.006264	-0.005663	
12	0.061662	25.347774	-0.028156	-0.027540	
13	0.063342	25.097411	0.009192	0.009825	
14	0.065071	25.116736	-0.011469	-0.010818	
15	0.066801	24.666078	0.066449	0.067117	
16	0.068521	25.013960	-0.006531	-0.005846	
17	0.070272	24.987879	0.048252	0.048954	
18	0.072068	24.610671	0.033225	0.033946	
19	0.073894	25.446041	-0.073881	-0.073142	
20	0.075726	25.168642	0.042990	0.043747	
21	0.077531	24.627333	0.035713	0.036488	
22	0.079285	24.849427	0.010940	0.011732	
23	0.080983	24.610580	0.048280	0.049090	
24	0.082656	24.815770	0.014644	0.015470	
25	0.084341	25.195888	0.029024	0.029867	
26	0.086034	25.009223	0.024752	0.025612	
27	0.087732	25.618706	0.017195	0.018072	

28	0.089458	25.333299	0.072994	0.073889
29	0.091227	24.795170	0.037344	0.038256
30	0.093027	24.637649	0.033651	0.034581
31	0.094830	25.029001	-0.009836	-0.008887
32	0.096631	24.898287	0.033904	0.034870
33	0.098448	24.907636	0.027067	0.028052
34	0.100293	24.869725	0.046063	0.047066
35	0.102165	24.948364	0.055299	0.056320
36	0.104065	24.800516	0.055304	0.056345
37	0.106001	24.355393	0.021230	0.022290
38	0.107970	24.958290	0.042488	0.043568
39	0.109964	24.948774	0.068981	0.070081
40	0.111987	24.735994	0.020211	0.021331
41	0.114038	24.825793	0.030274	0.031414
42	0.116097	25.199835	0.020649	0.021810
43	0.118155	24.823846	0.060937	0.062119
44	0.120219	24.986902	0.061937	0.063139
45	0.122292	24.990645	0.062319	0.063542
46	0.124362	25.282584	0.064033	0.065276
47	0.126417	25.051970	0.060482	0.061746
48	0.128450	24.861023	0.015876	0.017160
49	0.130423	25.619957	0.063511	0.064815
50	0.132320	25.622290	0.070423	0.071747
51	0.134167	24.826632	0.038940	0.040281
52	0.135967	24.968765	0.041657	0.043016
53	0.137720	24.592435	0.051351	0.052728
54	0.139455	24.885200	0.061867	0.063261
55	0.141182	25.091304	0.067968	0.069379
56	0.142879	25.469356	0.070822	0.072251
57	0.144535	25.272103	0.056658	0.058103
58	0.146166	25.166106	0.054331	0.055792
59	0.147792	25.071741	0.029927	0.031405
60	0.149379	24.668603	-0.088707	-0.087214

	gdp_growth_nousa_helper	gdp_growth_cum	gdp_pcap_nousa	damages_pcap \
8	1.012818	1.122673	339.801426	1.368802
9	1.043268	1.171249	354.504109	1.620903
10	1.029228	1.205483	364.865701	1.874644
11	0.994337	1.198656	362.799435	2.081974
12	0.972460	1.165646	352.808061	2.247062
13	1.009825	1.177098	356.274456	2.491191
14	0.989182	1.164364	352.420131	2.694451
15	1.067117	1.242513	376.073534	3.108914
16	0.994154	1.235249	373.875101	3.346298
17	1.048954	1.295720	392.177966	3.770491
18	1.033946	1.339705	405.490906	4.178401
19	0.926858	1.241716	375.832457	4.169329

20	1.043747	1.296038	392.274031	4.633171
21	1.036488	1.343327	406.587352	5.102768
22	1.011732	1.359088	411.357599	5.480953
23	1.049090	1.425806	431.551217	6.078705
24	1.015470	1.447863	438.227419	6.524423
25	1.029867	1.491107	451.316057	7.083393
26	1.025612	1.529297	462.875165	7.647003
27	1.018072	1.556935	471.240331	8.184581
28	1.073889	1.671975	506.059700	9.203569
29	1.038256	1.735938	525.419538	10.008929
30	1.034581	1.795969	543.589069	10.834519
31	0.991113	1.780007	538.757957	11.243441
32	1.034870	1.842077	557.544713	12.145249
33	1.028052	1.893750	573.184821	13.022880
34	1.047066	1.982881	600.162240	14.197618
35	1.056320	2.094558	633.963654	15.595885
36	1.056345	2.212575	669.684216	17.118135
37	1.022290	2.261894	684.611581	18.191427
38	1.043568	2.360441	714.438831	19.703528
39	1.070081	2.525862	764.507277	21.848325
40	1.021331	2.579741	780.814793	23.146046
41	1.031414	2.660781	805.343423	24.737189
42	1.021810	2.718812	822.907745	26.182959
43	1.062119	2.887701	874.025620	28.750776
44	1.063139	3.070026	929.210477	31.582245
45	1.063542	3.265103	988.254758	34.686785
46	1.065276	3.478238	1052.764528	38.136887
47	1.061746	3.693005	1117.768428	41.774341
48	1.017160	3.756378	1136.949871	43.873320
49	1.064815	3.999848	1210.641410	48.142602
50	1.071747	4.286824	1297.500902	53.134886
51	1.040281	4.459503	1349.765963	56.944757
52	1.043016	4.651335	1407.828043	61.152133
53	1.052728	4.896590	1482.059916	66.231194
54	1.063261	5.206355	1575.817021	72.395514
55	1.069379	5.567569	1685.146284	79.540840
56	1.072251	5.969832	1806.899904	87.581828
57	1.058103	6.316698	1911.886498	95.155623
58	1.055792	6.669122	2018.555310	103.120039
59	1.031405	6.878563	2081.947153	109.189332
60	0.912786	6.278659	1900.373214	102.613437

	damages	gdp_usa
8	7.301627e+08	1.805308e+11
9	8.839024e+08	1.924324e+11
10	1.045117e+09	2.023680e+11
11	1.186723e+09	2.056087e+11

12	1.309673e+09	2.043203e+11
13	1.485018e+09	2.108929e+11
14	1.642866e+09	2.132354e+11
15	1.938483e+09	2.325525e+11
16	2.133103e+09	2.361941e+11
17	2.457175e+09	2.531196e+11
18	2.783934e+09	2.673816e+11
19	2.840349e+09	2.531949e+11
20	3.228525e+09	2.701192e+11
21	3.637606e+09	2.862060e+11
22	3.996543e+09	2.959529e+11
23	4.533659e+09	3.173287e+11
24	4.977451e+09	3.293441e+11
25	5.526761e+09	3.466090e+11
26	6.101383e+09	3.632170e+11
27	6.676295e+09	3.777220e+11
28	7.673289e+09	4.142437e+11
29	8.527734e+09	4.391364e+11
30	9.430930e+09	4.637374e+11
31	9.994764e+09	4.689297e+11
32	1.102271e+10	4.949904e+11
33	1.206376e+10	5.189067e+11
34	1.342047e+10	5.538901e+11
35	1.503879e+10	5.962791e+11
36	1.683194e+10	6.416560e+11
37	1.823391e+10	6.679764e+11
38	2.012586e+10	7.096267e+11
39	2.273318e+10	7.727367e+11
40	2.452633e+10	8.028513e+11
41	2.669071e+10	8.422514e+11
42	2.875709e+10	8.750532e+11
43	3.212655e+10	9.445229e+11
44	3.588579e+10	1.019943e+12
45	4.005070e+10	1.101026e+12
46	4.471069e+10	1.189523e+12
47	4.969859e+10	1.280101e+12
48	5.294346e+10	1.319054e+12
49	5.890922e+10	1.422480e+12
50	6.591986e+10	1.543777e+12
51	7.161493e+10	1.625879e+12
52	7.793761e+10	1.716321e+12
53	8.551322e+10	1.828022e+12
54	9.463878e+10	1.965343e+12
55	1.052219e+11	2.124002e+12
56	1.172402e+11	2.301542e+12
57	1.288593e+11	2.460209e+12
58	1.411717e+11	2.622237e+12

```
59  1.510211e+11  2.728545e+12
60  1.432881e+11  2.510369e+12
```

Looking at the "damages" column, which is the total GDP losses per year, these values are indeed very large. Starting off even at 1961, the damage amounts to $65.0 million, which is an immense amount for India especially in the past.

Relative to total Indian GDP: I calculated gdp_usa, which is India's observed GDP in the presence of U.S' effects. From 1961 to 1968, the damages amount is 3 orders of magnitudes lower, and thus is not really that significant. However, this amount starts increasing exponentially and is mostly only 1 order of magnitude lower. This effectively means India's current GDP is only 90% of what the counterfactual could be, due to U.S carbon emissions indirectly.

Relative to US aid flows to India: Taken from Wikipedia, "in the period 1946-2012, India has been the recipient of highest aid from United States. The amount of economic aid, adjusted to inflation then, was reported to be USD 65.1 billion." This amount is definitely insufficient to compensate for the GDP losses for 1 year, much less the entire stated period. In 2010 alone, India had a GDP loss of $65.9 billion.

Relative to total US commitments to climate finance: With reference to this site, in April 2023, "the United States is providing $1 billion to the Green Climate Fund (GCF), bringing total U.S. contributions to the GCF to $2 billion." This is a very insignificant amount comparatively, as most recently in 2020 alone, India's damages has amounted to $143 billion

15. Discuss whether you think this calculation adequately captures what the US owes to India for past climate damages. Do you think the US owes more than this? Less? Why?

I think this is inadequate, as this climate damage only comes from increased temperatures. Climate damage negatively affects working environments as well, as such the air quality, erraticness of weather, and extreme events like natural disasters that altogether impact productivity and overall economic stability much more heavily. In fact, all of these can contribute to increase mortality rates which is further GDP loss.

16. Please read this article about 10 pathways to change. Then, please discuss how your findings could be incorporated into one of these theories of change.

These findings could be incorporated into the Power Politics/Power Elites theory of change, which focuses on influencing policy by working directly with elite decision makers and influencers, with the assumption that some individuals and groups hold more power than others, and influencing one policy area does not necessarily confer influence in other areas.

They can also be used in combination with the Media Influence or Agenda-Setting theory for a more powerful effect. This theory states that political issues emphasized in media coverage strongly influence the public agenda and assumes media shapes reality, has inherent biases, and different outlets have varying influence.

Since the findings indicate that the immense economic losses India has suffered due to US carbon emissions far exceed the aid provided by the US to India over the same time period, advocates could provide these findings to mainstream and social media outlets to create a compelling media narrative. This not only informs the broader public and raises awareness, but also has the ability to attract attention from influential US policymakers or political elites, especially during presidential elections or such. This will help make the case that the US should drastically increase climate financing and aid to impacted countries like India in the future.

Targeting political elites like Congressional committee members overseeing climate and foreign aid policies, White House/administration officials, and leaders from government agencies like USAID and the State Department, or high-profile media like New York Times, NPR, CNN would help push the agenda for palpable change.

17. Please re-run the notebook for the start year of 2000, and comment on how your results change if you pick a different start year.

[3]:
```
us_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/
↪us_emissions_1750_2020.csv")
wrld_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/
↪wrld_emissions_1750_2020.csv")
merged_df = pd.merge(us_df, wrld_df, left_on="year", right_on="year",␣
↪how="inner")
temp_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/
↪temperature_response_to_emissions_history.csv")
temp_df["temp_response_usa"] = temp_df["temp_response"] -␣
↪temp_df["temp_response_nousa"]
temp_df = temp_df[temp_df["damage_start_year"] == 2000]
india_df = pd.read_csv(f"/content/drive/My Drive/{FOLDERNAME}/india_data.csv")
merged_india_df = pd.merge(india_df, temp_df, left_on="year", right_on="year",␣
↪how="inner")
merged_india_df["est_temp_change"] = merged_india_df["temp_response_usa"] *␣
↪merged_india_df["warming_ratio"]
merged_india_df["temp_india_nousa"] = merged_india_df["temperature"] -␣
↪merged_india_df["est_temp_change"]
merged_india_df["gdp_growth_usa"] = merged_india_df['gdp_pcap'].pct_change()
merged_india_df["gdp_growth_nousa"] = merged_india_df["gdp_growth_usa"] +␣
↪(merged_india_df["est_temp_change"] * 0.01)
merged_india_df['gdp_growth_nousa_helper'] =␣
↪merged_india_df['gdp_growth_nousa'] + 1
merged_india_df['gdp_growth_cum'] = merged_india_df['gdp_growth_nousa_helper'].
↪cumprod()
merged_india_df['gdp_pcap_nousa'] = merged_india_df['gdp_growth_cum'] *␣
↪merged_india_df.loc[0, "gdp_pcap"]
merged_india_df['damages_pcap'] = merged_india_df['gdp_pcap_nousa'] -␣
↪merged_india_df['gdp_pcap']
merged_india_df['damages'] = merged_india_df['damages_pcap'] *␣
↪merged_india_df['population']
print('Total losses across all years: '"${:.2f}".
↪format(merged_india_df["damages"].sum()))
merged_india_df["gdp_usa"] = merged_india_df['gdp_pcap'] *␣
↪merged_india_df['population']
merged_india_df
```

```
Total losses across all years: $71309494084.84
```

[3]:

	country_code	year	temperature	gdp_pcap	population	warming_ratio	\
0	IND	2000	24.847981	757.668747	1059633675	0.834365	
1	IND	2001	24.939831	780.606234	1078970907	0.834365	
2	IND	2002	25.315932	796.724786	1098313039	0.834365	
3	IND	2003	24.942000	845.274844	1117415123	0.834365	
4	IND	2004	25.107121	897.628233	1136264583	0.834365	
5	IND	2005	25.112937	953.567973	1154638713	0.834365	
6	IND	2006	25.406946	1014.627641	1172373788	0.834365	
7	IND	2007	25.178387	1075.994087	1189691809	0.834365	
8	IND	2008	24.989473	1093.076551	1206734806	0.834365	
9	IND	2009	25.750380	1162.498808	1223640160	0.834365	
10	IND	2010	25.754610	1244.366016	1240613620	0.834365	
11	IND	2011	24.960799	1292.821206	1257621191	0.834365	
12	IND	2012	25.104733	1346.675910	1274487215	0.834365	
13	IND	2013	24.730155	1415.828722	1291132063	0.834365	
14	IND	2014	25.024655	1503.421507	1307246509	0.834365	
15	IND	2015	25.232487	1605.605445	1322866505	0.834365	
16	IND	2016	25.612235	1719.318076	1338636340	0.834365	
17	IND	2017	25.416638	1816.730876	1354195680	0.834365	
18	IND	2018	25.312273	1915.435271	1369003306	0.834365	
19	IND	2019	25.219532	1972.757821	1383112050	0.834365	
20	IND	2020	24.817982	1797.759777	1396387127	0.834365	

	temp_response	temp_response_nousa	damage_start_year	temp_response_usa	\
0	0.002078	0.001584	2000	0.000494	
1	0.008901	0.006802	2000	0.002099	
2	0.019253	0.014757	2000	0.004496	
3	0.030969	0.023822	2000	0.007147	
4	0.043642	0.033709	2000	0.009932	
5	0.057167	0.044353	2000	0.012814	
6	0.071435	0.055678	2000	0.015757	
7	0.086353	0.067623	2000	0.018730	
8	0.101829	0.080116	2000	0.021713	
9	0.117669	0.093026	2000	0.024643	
10	0.133779	0.106292	2000	0.027488	
11	0.150321	0.120034	2000	0.030287	
12	0.167344	0.134307	2000	0.033037	
13	0.184694	0.148966	2000	0.035728	
14	0.202236	0.163843	2000	0.038394	
15	0.219878	0.178836	2000	0.041041	
16	0.237534	0.193895	2000	0.043638	
17	0.255186	0.209015	2000	0.046171	
18	0.272913	0.224250	2000	0.048663	
19	0.290754	0.239618	2000	0.051137	
20	0.308496	0.254952	2000	0.053544	

	est_temp_change	temp_india_nousa	gdp_growth_usa	gdp_growth_nousa	\
0	0.000412	24.847569	NaN	NaN	
1	0.001751	24.938080	0.030274	0.030291	
2	0.003752	25.312181	0.020649	0.020686	
3	0.005964	24.936037	0.060937	0.060997	
4	0.008287	25.098834	0.061937	0.062019	
5	0.010692	25.102245	0.062319	0.062426	
6	0.013147	25.393799	0.064033	0.064164	
7	0.015628	25.162759	0.060482	0.060638	
8	0.018117	24.971356	0.015876	0.016057	
9	0.020561	25.729820	0.063511	0.063716	
10	0.022935	25.731675	0.070423	0.070653	
11	0.025270	24.935529	0.038940	0.039192	
12	0.027565	25.077168	0.041657	0.041932	
13	0.029810	24.700345	0.051351	0.051649	
14	0.032034	24.992620	0.061867	0.062187	
15	0.034243	25.198244	0.067968	0.068310	
16	0.036410	25.575825	0.070822	0.071186	
17	0.038523	25.378114	0.056658	0.057043	
18	0.040603	25.271670	0.054331	0.054737	
19	0.042667	25.176865	0.029927	0.030353	
20	0.044675	24.773307	-0.088707	-0.088261	

	gdp_growth_nousa_helper	gdp_growth_cum	gdp_pcap_nousa	damages_pcap	\
0	NaN	NaN	NaN	NaN	
1	1.030291	1.030291	780.619504	0.013270	
2	1.020686	1.051604	796.767616	0.042831	
3	1.060997	1.115749	845.367801	0.092956	
4	1.062019	1.184947	897.797004	0.168771	
5	1.062426	1.258919	953.843254	0.275281	
6	1.064164	1.339696	1015.045950	0.418309	
7	1.060638	1.420933	1076.596326	0.602239	
8	1.016057	1.443749	1093.883394	0.806843	
9	1.063716	1.535739	1163.581806	1.082998	
10	1.070653	1.644244	1245.792147	1.426131	
11	1.039192	1.708686	1294.617684	1.796478	
12	1.041932	1.780335	1348.904086	2.228176	
13	1.051649	1.872287	1418.573423	2.744701	
14	1.062187	1.988719	1506.790443	3.368936	
15	1.068310	2.124569	1609.719336	4.113891	
16	1.071186	2.275809	1724.309429	4.991352	
17	1.057043	2.405628	1822.669290	5.938415	
18	1.054737	2.537305	1922.436378	7.001107	
19	1.030353	2.614320	1980.788689	8.030868	
20	0.911739	2.383579	1805.963174	8.203398	

```
         damages       gdp_usa
0            NaN  8.028513e+11
1   1.431827e+07  8.422514e+11
2   4.704155e+07  8.750532e+11
3   1.038707e+08  9.445229e+11
4   1.917685e+08  1.019943e+12
5   3.178499e+08  1.101026e+12
6   4.904144e+08  1.189523e+12
7   7.164787e+08  1.280101e+12
8   9.736451e+08  1.319054e+12
9   1.325200e+09  1.422480e+12
10  1.769278e+09  1.543777e+12
11  2.259289e+09  1.625879e+12
12  2.839782e+09  1.716321e+12
13  3.543772e+09  1.828022e+12
14  4.404029e+09  1.965343e+12
15  5.442129e+09  2.124002e+12
16  6.681606e+09  2.301542e+12
17  8.041775e+09  2.460209e+12
18  9.584538e+09  2.622237e+12
19  1.110759e+10  2.728545e+12
20  1.145512e+10  2.510369e+12
```

I initally chose start year 1850, but the data on India only started from 1960, and the loss was \$1 803 157 244 654.03, compared to this start year of 2000, which amounted to just \$71 309 494 084.84

Therefore, choosing an earlier year causes the damages to differ by 2 orders of magnitude (100x) more. Additionally, starting earlier means the damages would have more time to compound, thus rising exponentially faster, resulting in exponentially higher damages.

[ ]:
```
# If it contains spaces, use '\ ' to represent each space E.g. 'Summer\ PSet\ 1.
 ↪ipynb'
FILENAME = "PS4_AndrewYu.ipynb"

%cd drive/My\ Drive
%cd $FOLDERNAME
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
 ↪texlive-plain-generic
!pip install PyPDF2

!jupyter nbconvert --log-level CRITICAL --to pdf $FILENAME
```

```
/content/drive/My Drive
/content/drive/My Drive/Stanford Summer Session/DATASCI 154/PS4
Reading package lists… Done
Building dependency tree… Done
Reading state information… Done
```