Various Impacts of the Citizens' Opinions about Government's Roles

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Code for Part 1

Set-Up

In [1]:

```
# Importing packages
import datetime as dt
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import numpy as np
import psycopg2
import pandas as pd
import random
import seaborn as sns
import statsmodels.formula.api as smf
from IPython.display import Image

# Connecting to covid19db.org
conn = psycopg2.connect(
    host='covid19db.org',
    port=5432,
    dbname='covid19',
    user='covid19',
    password='covid19')
cur = conn.cursor()
```

Functions

In [2]:

```
def cases_by_govresp(govresp,data):
    '''The mean total confirmed cases per million at specified government response index'''

    return data[abs(data["gov_resp"]-govresp)<1]["total confirmed/million"].mean()
```

In [3]:

```
def random_low_high_countries(data):
    '''Returns six random countries; three with lower initial responses and three with higher.
       These countries are more than half a standard deviation away from the mean'''

    i_response= data["initial_response"]
    low= i_response.mean()-(i_response.std()/2)
    high= i_response.mean()+(i_response.std()/2)

    low_countries= list(data[data["initial_response"]<low].country.unique())
    high_countries= list(data[data["initial_response"]>high].country.unique())

    random_lowitems = random.sample(low_countries, 3)
    random_highitems = random.sample(high_countries, 3)

    low_high= random_lowitems + random_highitems

    return low_high
```

Data Colletion

Epidemiology Data

In [4]:

```
# Collecting country-level data
sql_command = """SELECT date,country,countrycode,confirmed,dead FROM epidemiology WHERE
               adm_area_1 IS NULL AND
               adm_area_2 IS NULL AND
               adm_area_3 IS NULL AND
               source= 'WRD_WHO'
               ORDER BY
                   date"""

df_epidemiology = pd.read_sql(sql_command, conn)
df_epidemiology["date"]=pd.to_datetime(df_epidemiology['date'], format='%Y-%m-%d')
df_epidemiology["confirmed"]=df_epidemiology["confirmed"].astype(int)
df_epidemiology["dead"]=df_epidemiology["dead"].astype(int)
```

```
# Creating a new column for daily confirmed cases
for country in df_epidemiology.country.unique():
    mask = df_epidemiology["country"]==country
    df_epidemiology.loc[mask,"confirmed/day"] = df_epidemiology[mask]['confirmed'].diff()
    df_epidemiology.loc[mask,"dead/day"] = df_epidemiology[mask]['dead'].diff()
df_epidemiology['confirmed/day'].fillna(0,inplace=True)
df_epidemiology['dead/day'].fillna(0,inplace=True)
```

Population Data

In [5]:

```
sql_command = """SELECT value, country, countrycode FROM world_bank WHERE
                   indicator_name = 'Population, total' AND
                   year=2019"""

df_pop = pd.read_sql(sql_command, conn)
df_pop.rename(columns={"value": "population"},inplace=True)
df_pop["population(m)"]=df_pop["population"]/1000000

# Merging with epidemiology data
df_epi=pd.merge(df_epidemiology,df_pop,on=["country","countrycode"], how='left')

# Exluding countries without population data
df_epi.dropna(inplace=True)

# Creating new columns for epidemiology data normalized by population
df_epi["confirmed/million"]= df_epi["confirmed/day"]/df_epi["population(m)"]
df_epi["dead/million"]= df_epi["dead/day"]/df_epi["population(m)"]
df_epi["total confirmed/million"]= df_epi["confirmed"]/df_epi["population(m)"]
df_epi["total dead/million"]= df_epi["dead"]/df_epi["population(m)"]
```

Government Response Data

In [7]:

```
sql_command ="""SELECT date, country, countrycode, government_response_index_for_display
                FROM government_response
                WHERE adm_area_1 IS NULL
                ORDER BY date """

df_govtrack= pd.read_sql(sql_command, conn)
df_govtrack.rename(columns={"government_response_index_for_display": "gov_resp"},inplace=True)
df_govtrack["date"]=pd.to_datetime(df_govtrack['date'], format='%Y-%m-%d')
df_govtrack.dropna(inplace=True)

#Merge with epidemiology data
gov_epi = pd.merge(df_govtrack, df_epi, on=['country','countrycode','date'])#, right_on = ['country','countrycc
```

Survey Data

In [9]:

```
# E037: The question on Government Responsibility
questions=["E037"]
wave = "2008-2010"

sql_command = """SELECT * FROM surveys WHERE wave=%(wave)s AND adm_area_1 IS NULL AND adm_area_2 IS NULL AND ad
df_surveys = pd.read_sql(sql_command, conn, params={'wave': wave})

# Cleaning Data
survey= pd.DataFrame()
survey["country"]=np.zeros(len(df_surveys))
survey["countrycode"]=np.zeros(len(df_surveys))

for i in range(len(df_surveys)):
    survey["country"].loc[i]=df_surveys["country"].loc[i]
    survey["countrycode"].loc[i]=df_surveys["countrycode"].loc[i]
    for j in questions:
        title= df_surveys.properties[i][j]["Label"]
        liste=[]
        for k,v in df_surveys.properties[i][j]["Frequencies"].items():
            if k[-2]!="-":
                varie= int(k[-2:].replace("_",""))*v
                liste.append(varie)
                survey.loc[i,title]=sum(liste)
```

Data Analysis

In [10]:

```
# Initial responses for the first hundred cases
aggr= {"gov_resp":[np.ptp,min,max], "date":np.ptp, "confirmed":np.ptp}

initial=gov_epi[(gov_epi["confirmed"]>0.1)&(gov_epi["confirmed"]<100)].groupby("country").agg(aggr)
initial.reset_index(inplace=True)
initial["daily case rate"]=initial["confirmed"]["ptp"]/initial["date"]["ptp"].dt.days
initial["initial_response"]=(initial["gov_resp"]["min"]+1)*(initial["gov_resp"]["ptp"]+1)/(initial["daily case
```

In [11]:

```
# Merging the responses with survey data
response_data= initial[["country","initial_response"]].droplevel(1,axis=1)
all_df= pd.merge(survey,response_data,on="country")
all_df.rename(columns={"Government responsibility":"Government_responsibility"},inplace=True)
```

In [12]:

```
# Regression model for initial responses and government responsibility
```

```
form_1 = 'initial_response ~ Government_responsibility'
fit_1 = smf.ols(formula = form_1, data = all_df).fit()
```

Figures

Figure 1

In [84]:
```
# Daily Confirmed Cases per Million
def figure_1():
    subset= ['Luxembourg', 'Estonia', 'Belarus','Italy','Romania','Russia', 'Turkey', 'Portugal']
    color_list = ["r","b","g","c","m","y","tab:orange","tab:purple"]
    epi=df_epi.groupby('country').resample('W-MON', on='date').mean().reset_index().sort_values(by='date')
    i=0
    plt.figure(figsize=(10,10))
    for country in subset:
        mask= epi["country"]==country
        plt.plot(epi[mask]["date"],epi[mask]['confirmed/million'],linestyle='-', color=color_list[i])
        plt.legend(subset)
        i+=1
    plt.ylabel("Daily confirmed cases per million")
    plt.title("Figure 1: Daily Confirmed Cases per Million",fontsize=25)
    plt.savefig("Figure_1.png")
    plt.show()
```

Figure 2

In [88]:
```
# Initial Responses of Several Countries
def figure_2():
    countries= random_low_high_countries(initial)

    fig, axs = plt.subplots(2, 3,figsize=(15,15),sharey=True)
    fig.suptitle('Figure 2: Initial Responses of Several Countries', fontsize=25)
    fig.subplots_adjust(wspace=0.23,hspace=0.3)
    rows = ['Lower initial response score','Higher initial response score']
    for ax, row in zip(axs[:,0], rows):
        ax.set_ylabel(row, rotation=90, fontsize=25,color='xkcd:dark maroon')
    for ax in axs[0,:]:
        ax.set_facecolor('xkcd:ice blue')
    for ax in axs[1,:]:
        ax.set_facecolor('xkcd:pale lilac')

    filtered_data=gov_epi[(gov_epi["confirmed"]<100)].sort_values("date")
    for idx, country in enumerate(countries):
        data = filtered_data[filtered_data['country'] == country]
        date = data['date']
        total_confirmed = data['confirmed']
        gov_response = data['gov_resp']
        argmin = total_confirmed.ne(0).idxmax()
        axs[idx // 3, idx % 3].plot(date, total_confirmed, label="Total Confirmed", color="xkcd:prussian blue")

        first_case = (date[argmin], int(total_confirmed[argmin]))
        axs[idx // 3, idx % 3].plot([first_case[0]], [first_case[1]], marker="*", ls="", c="green", markersize=
        axs[idx // 3, idx % 3].annotate("First case", (first_case[0]-dt.timedelta(days=5), first_case[1]-6),col

        axis = axs[idx // 3, idx % 3].twinx()
        axis.set_ylim([-3,70])
        axis.plot(date, gov_response, label="Gov Resp", color="xkcd:dirty orange")
        axis.tick_params(axis='y', labelcolor="xkcd:dirty orange")

        lines, labels = axs[idx // 3, idx % 3].get_legend_handles_labels()
        lines2, labels2 = axis.get_legend_handles_labels()
        axis.legend(lines + lines2, labels + labels2, loc='upper right')

        axs[idx // 3, idx % 3].set_title(country.upper(),fontsize=15,color="xkcd:dark maroon")
        axs[idx // 3, idx % 3].tick_params(axis='y', labelcolor="xkcd:prussian blue")
        axs[idx // 3, idx % 3].tick_params(labelrotation=35)
        axs[idx // 3, idx % 3].yaxis.set_tick_params(which='both', labelbottom=True)

    plt.savefig("Figure 2.png")
    plt.show()
```

Figure 3

In [91]:
```
# Regression model for initial response and government responsibility
def figure_3():
    g = sns.lmplot(x="Government_responsibility", y="initial_response", data=all_df)
    g.fig.suptitle("Figure 3: Regression Model for Government Responsibility and Initial Responses by Country",
                   fontsize=15, fontdict={"weight": "bold"})

    g.set(xlabel='Government Responsibility', ylabel='Initial Response')
    plt.savefig("Figure 3.png",bbox_inches='tight')
    plt.show()
```

Tables

Table 1

In [16]:
```
# Responses at the date of the first positive cases
non_zero= gov_epi[gov_epi["confirmed"]!= 0]
```

```
i = non_zero.groupby("country")["confirmed"].idxmin()
first_case=non_zero.loc[i]

table_1 = pd.DataFrame([],columns=["Mean","Std Dev.","Min.","Max."],
                           index=["Government Response"])

table_1.loc["Government Response"]= [first_case["gov_resp"].mean(),first_case["gov_resp"].std(),first_case["gov
                      first_case["gov_resp"].max()]
```

Table 2

In [17]:

```
# World Values Survey "Government Responsibility" answers
table_2 = pd.DataFrame([],columns=["Mean","Std Dev.","Min.","Max."],
                           index=["Government Responsibility"])

table_2.loc["Government Responsibility"]= [survey["Government responsibility"].mean(),survey["Government respon
                                           survey["Government responsibility"].min(),survey["Government respons


# Countries with minimum and maximum values
minim = survey["Government responsibility"].idxmin()
maxim = survey["Government responsibility"].idxmax()

min_country=survey.loc[minim,"country"]
max_country=survey.loc[maxim,"country"]
```

Table 3

In [18]:

```
# Important Parameters for the Regression Model for initial response and government responsibility
table_3 = pd.DataFrame([],columns=["R squared","Coefficient for Gov. Resp.","p-value for Gov. Resp."],
                           index=["Regression Model"])

table_3.loc["Regression Model"]= [fit_1.rsquared,fit_1.params[1],fit_1.pvalues[1]]
```

Code for Part 2

Set-Up

In [24]:

```
# Importing packages
import apikeys
import requests
import bs4
import time
from scipy import stats
```

Data Collection and Cleaning

Wikipedia and Information about Presidents

In [25]:

```
# Head of States
DOMAIN = "https://en.wikipedia.org"

s = requests.Session()
s.headers.update({'User-agent': 'Python/Elmira wikicrawl0.2'})

article = "List_of_current_heads_of_state_and_government"
req = s.get(f"{DOMAIN}/wiki/{article}")
soup = bs4.BeautifulSoup(req.content, 'html.parser')
indiatable=soup.find('table',{'wikitable plainrowheaders'})
pre=pd.read_html(str(indiatable))
pre=pd.DataFrame(pre[0])

# Only the countries with World Values Survey data
for i in range(len(pre)):
    if pre.loc[i,"State"] not in survey["country"].unique():
        pre.drop([i],inplace=True)

pre.reset_index(inplace=True,drop=True)
pre.drop(columns="Head of government",inplace=True)

# Drop repetative rows
pre.drop([5,6,8,12,19,43,44,46],inplace=True)
pre.reset_index(inplace=True,drop=True)
```

In [26]:

```
twitter_accounts= np.array(['ilirmetazyrtar','Arm_President','vanderbellen', 0,0,0,'PresidentOfBg',0,
                'AnastasiadesCY',0,0,'AlarKaris','niinisto','EmmanuelMacron',0,
                0,0,0,'PresidentISL','PresidentIRL','Quirinale','valstsgriba','GitanasNauseda',0,'presidentmt',
                'sandumaiamd','predsjednik_cg',0,0,'AndrzejDuda','presidencia','KlausIohannis','KremlinRussia_E
                'avucic','ZuzanaCaputova','BorutPahor',0, 0,'ParmelinG','RTErdogan','ZelenskyyUa',0])
```

In [27]:

```
pre["accounts"]=twitter_accounts
pre.reset_index(inplace=True, drop=True)

# Merging with World Values survey data
```

```
pres=pd.merge(pre,survey,left_on="State",right_on="country")

# Drop monarchs
pres.drop([4,10,23,27,28,36,37,41],inplace=True)
pres.reset_index(inplace=True)

# New Column for categorizing those with active accounts and those without
for i in range(len(pres)):
    if pres.loc[i,"accounts"]=="0":
        pres.loc[i,"Active Twitter Account"]= "No"
    else:
        pres.loc[i,"Active Twitter Account"]="Yes"
```

In [28]:

```
# Selecting those with active Twitter accounts
actives= pre.copy()
for i in range(len(actives)):
    if '0' in actives.loc[i,"accounts"]:
        actives.drop([i],inplace=True)
actives.reset_index(inplace=True,drop=True)
```

Twitter Data

In [29]:

```
# Retrieving id numbers and number of followers with usernames
ids=pd.DataFrame()
headers = {"Authorization": "Bearer {}".format(apikeys.BEARER_TOKEN)}
for account in actives["accounts"].unique():
    url = f"https://api.twitter.com/2/users/by?usernames={account}&tweet.fields=author_id&user.fields=public_me
    response = requests.request("GET", url, headers=headers)
    tweets = response.json()
    tweets=pd.json_normalize(tweets["data"])
    ids=ids.append(tweets)
    ids.reset_index(drop=True, inplace=True)
    time.sleep(2)

ids.rename(columns={"public_metrics.followers_count":"followers"},inplace=True)
ids=ids[["id","username","followers"]]

# Merge for the country names
ids_pre=pd.merge(ids,pre,how="left",left_on="username",right_on="accounts")
```

In [330…

```
# Retrieving last 100 mentions with id numbers
tweets_all=pd.DataFrame()
n = datetime.datetime.now(dt.timezone.utc)
end_time = n.isoformat()

headers = {"Authorization": "Bearer {}".format(apikeys.BEARER_TOKEN)}
for i in ids["id"].unique():
    url=f"https://api.twitter.com/2/users/{i}/mentions"
    params={
        "end_time":end_time,
        "max_results":100,
        "tweet.fields":"created_at,lang,public_metrics,text",
        "expansions":"author_id",
        "user.fields":"created_at,description,entities,id,name,public_metrics,username"}
    response = requests.request("GET", url, headers=headers,params=params)
    tweets = response.json()
    tweet=pd.json_normalize(tweets["data"])
    tweet["users"]=i
    tweets_all=tweets_all.append(tweet)
    tweets_all.reset_index(drop=True, inplace=True)
```

In [37]:

```
# Merging and sorting
tweets_df=pd.merge(tweets_all,ids, right_on=["id","username"],left_on=["users","username"])
tweets_df['created_at']=pd.to_datetime(tweets_df['created_at'])
tweets_df=tweets_df.sort_values(by=['created_at'])
```

In [39]:

```
# Calculating the frequency of mentions
means= tweets_df.groupby('username')['created_at'].apply(lambda x: x.diff().mean())
means=means.to_frame()
means.reset_index(inplace=True)
for i in range(len(means)):
    means.loc[i,"seconds"]= means.loc[i,"created_at"].total_seconds()

# Merge to collect all information together
mean=pd.merge(means,ids_pre[["username","State","followers"]],how="left",left_on="username",right_on="username"
mean.rename(columns={"State":"country"},inplace=True)
```

In [40]:

```
# Merge with population data
mean_pop=pd.merge(mean,df_pop, on="country")
```

Data Analysis

In [41]:

```
# Calculate mention score
mean["mention_score"]=1/(mean["followers"]*mean["seconds"])
```

```python
# Merge with World Values Survey data
mean_survey=pd.merge(mean,survey,on="country")

# Transforming to log-scale
mean_survey["ln_mention"]=np.log(mean_survey["mention_score"])
```

In [42]:

```python
# Regression model for mention score and government responsibility
mean_survey.rename(columns={"Government responsibility":"Government_responsibility"},inplace=True)

form_3 = 'ln_mention ~ Government_responsibility'
fit_3 = smf.ols(formula = form_3, data = mean_survey).fit()
```

Figures

Figure 4

In [93]:

```python
# Regression model with log-log scale
def figure_4():
    mean_pop["ln_pop"]=np.log(mean_pop["population(m)"])
    mean_pop["ln_seconds"]=np.log(mean_pop["seconds"])

    g = sns.lmplot(x="ln_pop", y="ln_seconds", data=mean_pop)
    g.fig.suptitle("Figure 4: Regression Model for Frequency of Mentions and Population in millions",
                   fontsize=15, fontdict={"weight": "bold"})

    g.set(xlabel='Log(Population(m))', ylabel='Log(Average seconds between consecutive mentions)')
    plt.savefig("Figure 4.png",bbox_inches='tight')
    plt.show()
```

Figure 5

In [94]:

```python
# Violin plot for presidents with an active Twitter account and those without one
def figure_5():
    g = sns.violinplot(y=pres["Government responsibility"],x=pres["Active Twitter Account"])
    g.set_title("Figure 5: Differences of Having an Active Twitter Account",
                   fontsize=15, fontdict={"weight": "bold"})

    g.set(xlabel='Active Twitter Account', ylabel='Government responsibility')
    plt.savefig("Figure 5.png",bbox_inches='tight')
    plt.show()
```

Figure 6

In [95]:

```python
# Regression model for mention score and government responsibility
def figure_6():
    g = g = sns.lmplot(x="Government_responsibility",y="ln_mention",data=mean_survey)
    g.fig.suptitle("Figure 6: Regression Model for Government Responsibility and Mention Scores by Country",
                   fontsize=15, fontdict={"weight": "bold"})

    g.set(xlabel='Government Responsibility', ylabel='Log(Mention Score)')
    plt.savefig("Figure 6.png",bbox_inches='tight')
    plt.show()
```

Tables

Table 4

In [46]:

```python
# Summary statistics for frequency and followers
table_4 = pd.DataFrame([],columns=["Mean","Std Dev.","Min.","Max."],index=["Seconds","Followers"])

table_4.loc["Seconds"]= [mean["seconds"].mean(),mean["seconds"].std(),mean["seconds"].min(),mean["seconds"].max

table_4.loc["Followers"]= [mean["followers"].mean(),mean["followers"].std(),mean["followers"].min(),mean["follo

# Countries with minimum and maximum values
min_fo = mean["followers"].idxmin()
min_freq = mean["seconds"].idxmax()

min_followers=mean.loc[min_fo,"country"]
min_freq=mean.loc[min_freq,"country"]
```

Table 5

In [47]:

```python
# Important parameters for the Regression Model of seconds and population
form_2 = 'ln_seconds ~ ln_pop'
fit_2 = smf.ols(formula = form_2, data = mean_pop).fit()

table_5 = pd.DataFrame([],columns=["R squared","Coefficient"],
                           index=["Regression Model"])

table_5.loc["Regression Model"]= [fit_2.rsquared,fit_2.params[1]]
```

Table 6

In [48]:

```python
# T-test for comparing the differences of having an active Twitter account or not
```

```
test=stats.ttest_ind(pres["Government responsibility"][pres["Active Twitter Account"]=="Yes"],
                 pres["Government responsibility"][pres["Active Twitter Account"]=="No"])
p_value=test[1]
```

Table 7

In [49]:
```
# Important Parameters for the Regression Model for mention score and government responsibility
table_7 = pd.DataFrame([],columns=["R squared","Coefficient for Gov. Resp.","p-value for Gov. Resp."],
                              index=["Regression Model"])

table_7.loc["Regression Model"]= [fit_3.rsquared,fit_3.params[1],fit_3.pvalues[1]]
```

Part 1: Introduction

The COVID-19, after its emergence in China in late 2019, spread swiftly and was declared a global pandemic by mid-March the following year by the World Health Organization (WHO). The rapid spread and the gravity of COVID-19 caused governments to start taking precautionary measures to decelerate the transmission. Some measures include wearing compulsory masks, closing schools and workplaces, lockdowns, cancellations of public events and gatherings, and contact tracing. However, the policies implemented, the speed of first responses, and their enforcement standards varied among governments. These variations were moulded by many structural elements of respective societies, including the countries' overall resources and institutional structures. (Egger et al., 2021; Maor & Howlett, 2020) The cultural elements such as institutional trust and individualism further diversified the response to the pandemic. (Chen et al., 2021; Maaravi et al., 2021)

Individualism and collectivism have been seen as key cultural features to explain cross-cultural differences in societies. (Hofstede, 1980; Hui&Triandis,1986; Parsons, 1951) "The relationship between the individual and the collectivity in human society is not only a matter of ways of living together, it is intimately linked with societal norms. It, therefore, affects both people's mental programming and the structure and functioning of many institutions." (Hofstede, 2001) Individualism emphasizes individual autonomy and control, whereas collectivism prioritizes collective action and responsibility. These societal norms directly influence the organization and functioning of governance. The individualistic norms lay the foundations for liberalism as individualism emphasized "the right to individual freedom and self-realization." (Wood, 1972) The limitation of state intervention in liberal theory protects both individual liberty and the rule of law. "Limiting arbitrary power encourages confidence that the law will be fair and thereby increases the state's ability to secure cooperation without the imposition of force." (Starr, 2007) Therefore, one might question whether the individualistic nature of a society affects the government's response to COVID-19 by understating government action and responsibility. Subsequently, the first part of this paper explores the following research question:

> RQ_1: Do the opinions of citizens towards the responsibility of governments affect the initial governmental responses to COVID-19 in different countries?

Methods

The data I use to address my research question is from the OxCOVID19 Database. (Mahdi et al., 2020) To analyze the different courses of the pandemic in several countries, I use both the epidemiology table and the country statistics table. In particular, I calculate the daily cases from the epidemiology table and merge it with population data from the World Bank dataset to be able to evaluate daily confirmed cases per million through time. To analyze different governments' responses to COVID-19, I use data from the government response table, specifically the "government response index." (Hale et al., 2020) The index is calculated by combining 16 policy actions including but not limited to the closure of schools, cancellation of public events and stay at home requirements. To explore the differences in the attribution of responsibility to governments, I use data from World Values Survey (Inglehart et al., 2014); specifically, the question on government responsibility where an answer value of 1 means "People should take more responsibility" and the value 10 means "The government should take more responsibility", and the values in between indicate intermediary answers.

To be able to compare various initial responses to COVID-19, I construct an initial response score.

$ Initial\:Response\:Score= \frac{(GR_{t}+1)(GR_{T}- GR_{t}+1)}{Case\:Rate}$ where; $Case\:Rate=\frac{(Cases_{T}- Cases_{t})}{T-t}$

The small "t" refers to the date first cases are reported in a country and they big "T" refers to the date total cases go over 100. The government response index at the date first case seen in the country is multiplied by the increase in the government response index at the date in which the total cases reach a hundred.It is then divided by the average daily rate of new positive COVID-19 cases during the first hundred cases. The values in the numerator are all increased by 1 to avoid reduction to zero. I take the answers to the government responsibility question and correlate it to the countries' different initial response scores to explore the relationship between these two variables.

Results

After the first cases were confirmed in Wuhan, China, in late 2019, COVID-19 started spreading across the world. By March 11th, there were over 120,000 cases worldwide when WHO declared it a global pandemic. By the time this paper is written, after two years since the first confirmed case, there has been a total of over 260 million positive cases and 5 million deaths across the world. Yet, although some similarities exist, all countries' experiences with the virus were different.

In [86]:
```
figure_1()
```

Figure 1: Daily Confirmed Cases per Million

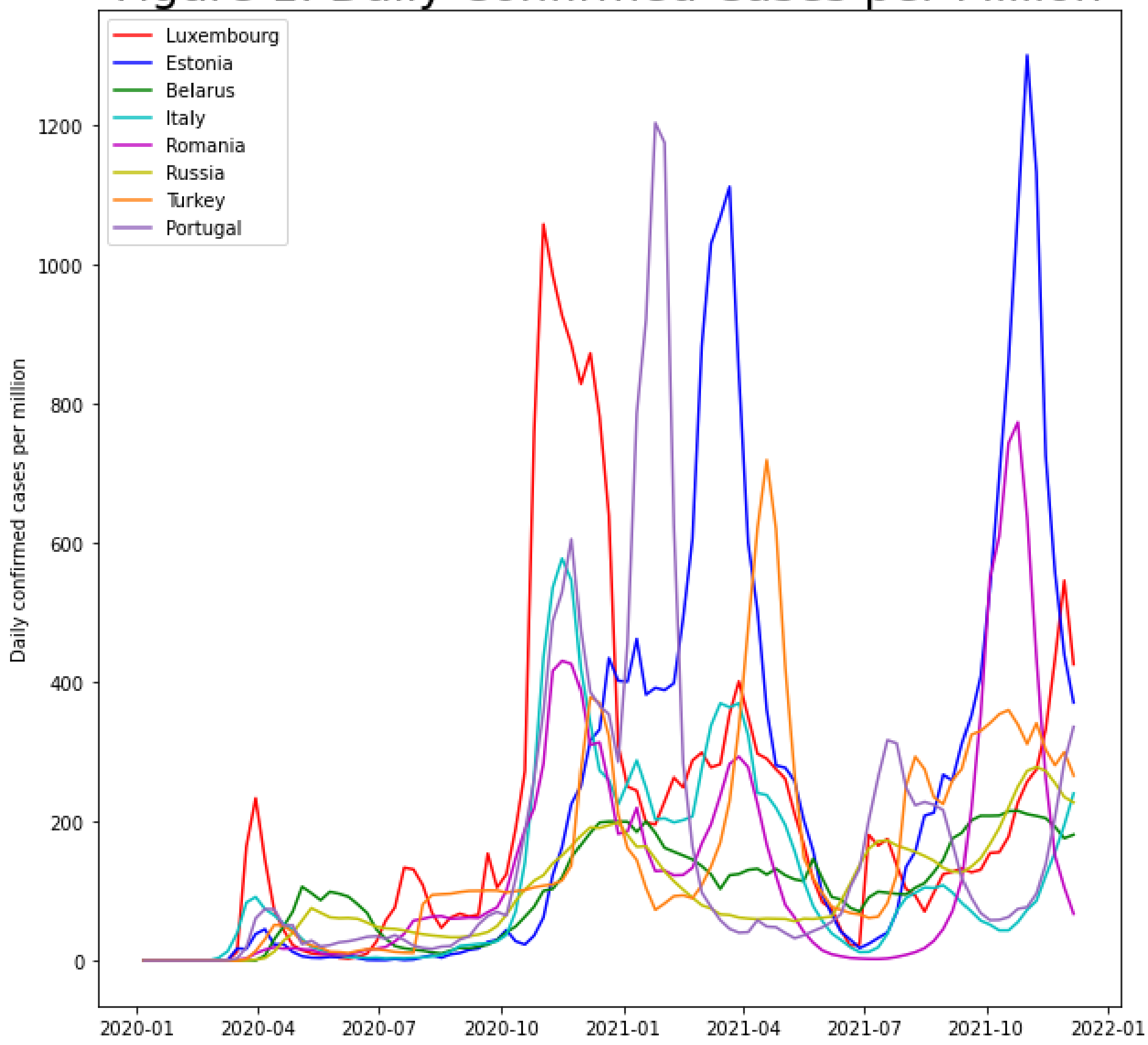


Figure 1 shows daily confirmed cases per million over time for a subset of countries. Although there are differences in the volume of daily new cases per million, most countries have experienced three waves of peaks. The severity of the waves and the overall course vary for many reasons, including healthcare capacities and standards and the demographic distribution in respective countries. Another critical factor affecting the severity of the effects of the disease is the policies governments implement to control and slow down the transmission. However, the speed and the intensity of responses varied amongst countries.

In [20]:

```
display("Table 1")
display(table_1)
value= cases_by_govresp(68.23,gov_epi)
print("The average total confirmed cases per million for a government response index of 68.23 is "+ str("%.1f"
```

'Table 1'

	Mean	Std Dev.	Min.	Max.
Government Response	19.326201	15.446196	0.0	68.23

```
The average total confirmed cases per million for a government response index of 68.23 is 20503.1 cases.
```

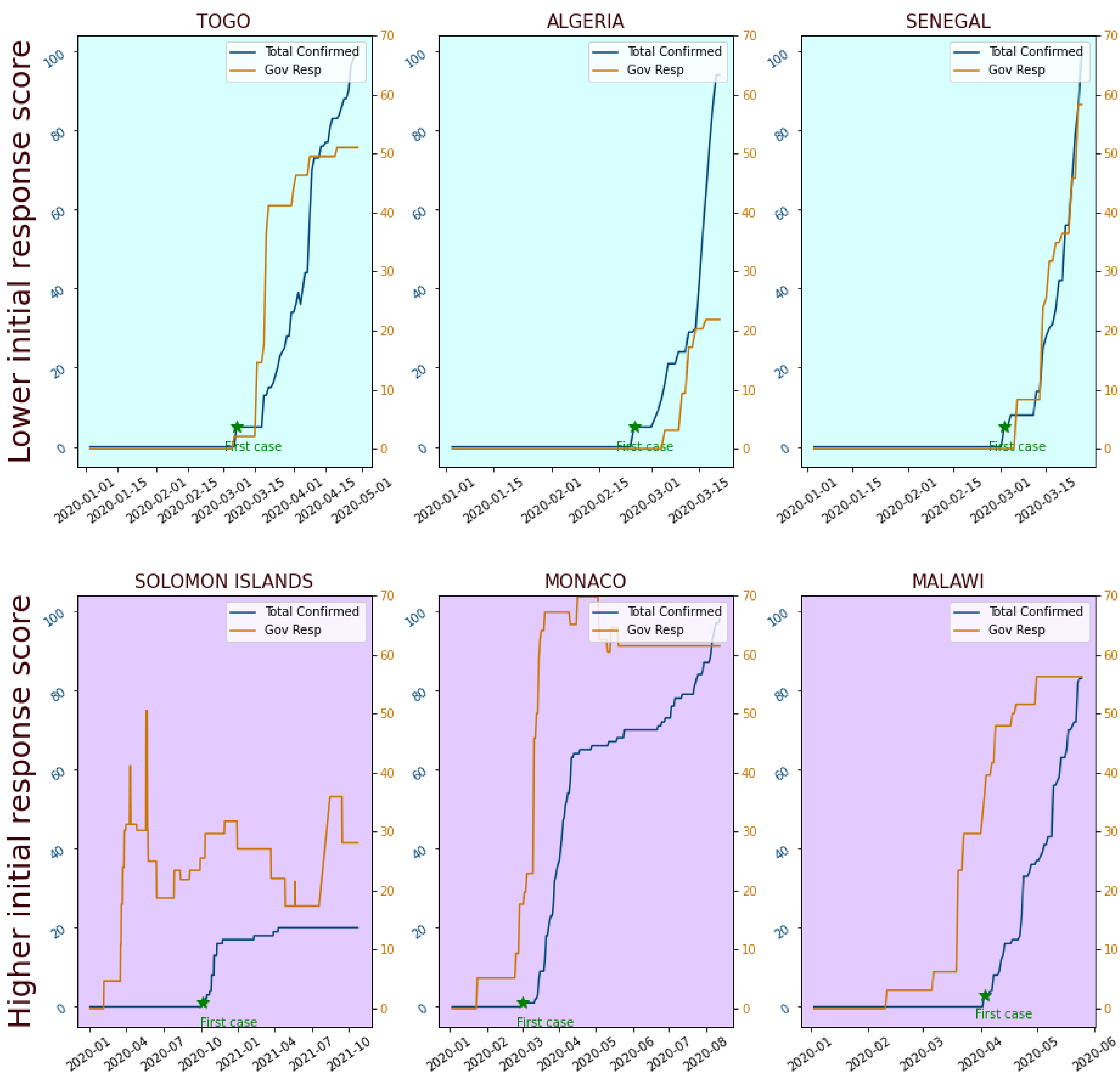
Table 1 illustrates the range of different responses at the date the first positive case was seen. The relatively high standard deviation indicates the high variance in the responses. There were countries where no response policies were implemented, but there were also countries whose response index was 68.23, a response score usually reported at a total of approximately 20,503 confirmed cases per million.

The initial response score was derived to quantify both the speed and the intensity of the initial responses of countries at the very first 100 confirmed cases. It is normalized by the rate of new daily confirmed cases.

In [89]:

```
figure_2()
```

Figure 2: Initial Responses of Several Countries



The first row of plots in Figure 2 shows three random examples of countries with relatively lower initial response scores, their total confirmed cases, and the government response index. The second row of figures plots the same variables for countries with relatively higher initial response scores. These countries were more than half a standard deviation away from the mean of initial response scores. Countries with higher initial response scores either had higher government response values at the date of the first case or increased their responses to higher levels than countries with lower initial response scores or both.

In [22]:

```
display("Table 2")
display(table_2)
print("The country with the minimum value is " + min_country + ".")
print("The country with the maximum value is " + max_country +".")
```

'Table 2'

	Mean	Std Dev.	Min.	Max.
Government Responsibility	4.809436	0.586923	3.742163	6.417677

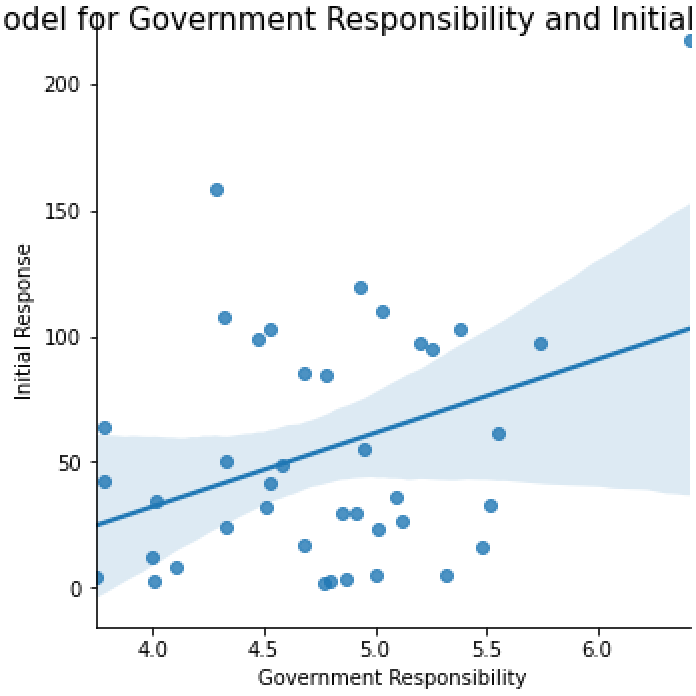
```
The country with the minimum value is United Kingdom.
The country with the maximum value is Georgia.
```

Table 2 describes the government responsibility answers from World Values Survey (Inglehart et al., 2014). The mean and the standard deviation suggests a tendency towards neutral answers, a value of 5 with a slight lean towards the answer "People should take more responsibility." The minimum value where individual responsibility is valued more than governmental responsibility belongs to the United Kingdom, whereas the maximum value belongs to Georgia. These values also map onto the individualism scores of Hofstede (2011), where the United Kingdom with a score of 89 is one of the countries with the highest individualist scores.

In [92]:

```
figure_3()
display("Table 3")
display(table_3)
```

Figure 3: Regression Model for Government Responsibility and Initial Responses by Country



`'Table 3'`

	R squared	Coefficient for Gov. Resp.	p-value for Gov. Resp.
Regression Model	0.123415	29.288303	0.026231

Figure 3 and Table 3 explore the relationship between the amount of responsibility attributed to governments and the initial response scores. The low R^2 indicates a high amount of unexplained variance, which is understandable considering other factors affecting initial response scores, such as the overall resources of the respective countries. The variance in the initial responses cannot only be explained by the opinions on government responsibility. However, the low p-value suggests that the null hypothesis can be rejected and that there is indeed a relationship between these independent and dependent variables. Thus, the opinions on government responsibility did have an impact on the initial responses. By looking at both the regression model and the coefficient, one can conclude that this relationship is positive. Countries whose citizens think governments should take more responsibility than individuals had higher initial responses as the virus started transmitting in their territories.

Part 2: Introduction

Twitter has been a platform for users to share information and interact with each other through likes, retweets, and mentions. However, some accounts and their tweets receive more interaction than others. This popularity is usually referred to as "influence." (Anger & Kittl, 2011; Bakshy et al., 2011; Cha et al., 2010) There are many methods to measure influence on Twitter. The number of followers, likes, retweets and mentions can all be factors in measuring the influence a user has on Twitter. There can be many underlying reasons to account for the level of influence users have, ranging from content to the social status of the person who owns the account.

Some of the most influential figures on Twitter have been politicians and presidents of countries. Presidents have increasingly been using Twitter as a medium of communication. Twitter creates many opportunities for presidents; it provides citizens with political information, allows presidents to communicate directly with citizens, unlike the traditional unidirectional way, and allows them to respond to other politicians and recent events instantaneously. (Fontaine & Gomez, 2020) Citizens similarly benefit from this interactive nature of Twitter. They can start political discussions in a public space and include the politicians in the conversation. Therefore, the mentions of a president's account are a valuable resource of information. Other users mention the presidents' accounts for many reasons, including showing appreciation or critique. Although the content of the mentions is very important, the volume of mentions received can also be an important indicator. It might illustrate the amount of political discussion or perceptions of a president's approachability.

In this part of the paper, I will compare the influence of presidents of several countries on Twitter through the frequency of mentions they receive. However, the number of followers an account has can affect the frequency of mentions received in various ways. The number of followers might simply show that more people are interested in the person's account, and therefore more people might mention the account. The frequency of mentions can also increase with more posts, and accounts with more followers tend to post more. (Huberman et al., 2009) Therefore in this paper, the frequency of mentions received will be normalized by the number of followers. By merging the Twitter data with the answers to the World Values Survey (Inglehart et al., 2014) question asking whether governments or individuals should take more responsibility, I will explore whether these opinions impact the frequency of mentions received by the presidents of the respective countries. Like explained in part one, the answers about government responsibility shed light on opinions on governments' roles. In this part, I will investigate whether these political opinions influence the frequency of mentions received by presidents.

In sum, the second part of this paper investigates the following research question:

> RQ_2: Do citizens' opinions towards the responsibility of governments affect the volume of mentions the countries' presidents receive on Twitter?

Methods

To address the second research question, I use the answers to the World Value Survey (Inglehart et al., 2014) asking about the opinions on government responsibility. For Twitter data, I use Twitter API v2 endpoints through the academic research access. I retrieved the id numbers and number of followers using usernames through the "Users lookup" endpoints. Then, I use the id numbers for the "User mention timeline" endpoint to retrieve the last 100 mentions of presidents with active Twitter accounts. I calculate the frequency of mentions by taking the mean of the differences in times of consecutive mentions.

I, then, construct an equation for a mention score in an attempt to normalize these average frequencies in seconds with the number of followers the account has. The formulation of the score is similar to that of the "interactor ratio" (Anger & Kittl, 2011), which is an indicator of influence that calculates the number of mentions received per follower. Considering the mean of seconds between mentions is inversely proportional with the amount of interaction an account receives, we calculate the mention score as follows:

$ Mention\:Score= \frac{1}{(Seconds)(Followers)}$

Therefore, if both the seconds' value and the number of followers is high, the score takes its minimum value. This refers to the scenario in which the account has a high number of followers, but the frequency of mentions is low. For this scenario, the mention score is at its minimum. The mention score will be used as the response variable for the regression with the government responsibility answers of each country.

Results

The influence that presidents of different countries have on Twitter vary. Although influence can be measured in many different ways with different indicators, in this paper, the focus will be on the number of followers and the frequency of mentions received.

In [51]:
```
display("Table 4")
display(table_4)
print("The country with the least number of followers is " + min_followers + ".")
print("The country whose president is least frequently mentioned is " + min_freq + ".")
```

```
'Table 4'
```

	Mean	Std Dev.	Min.	Max.
Seconds	3423.467818	4550.01908	2.285714	17906.020408
Followers	1183344.692308	3760066.176765	4653	18179525

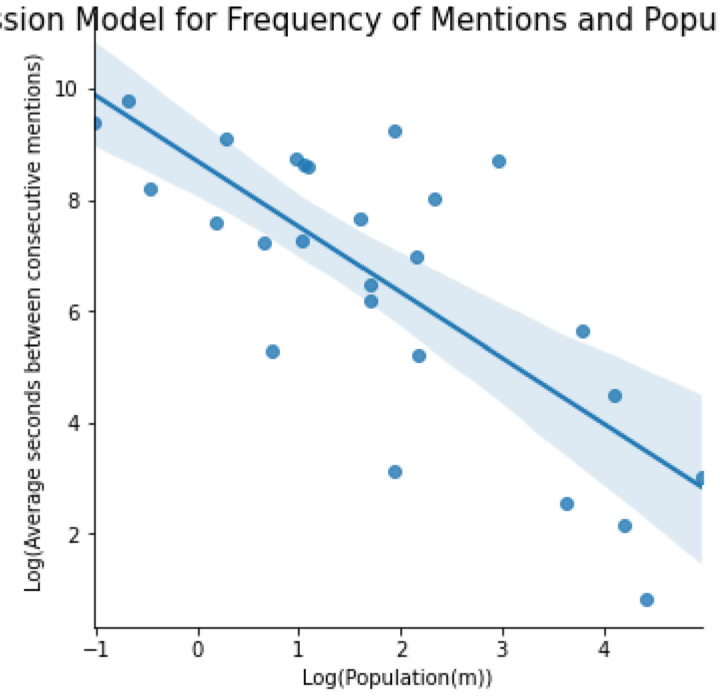
```
The country with the least number of followers is Estonia.
The country whose president is least frequently mentioned is Malta.
```

The 26 presidents have a mean of over a million followers. The standard deviation and the range of the number of followers they have are very high, confirming that presidents have different influence levels on Twitter. The variation is also valid with the range and standard deviation of average seconds between mentions. The most frequently mentioned account receives a mention every 2 seconds, whereas the least frequently mentioned one receives every 5 hours on average. These two variables do not directly map onto each other. Although the president of Estonia is the one with the least followers, the least frequently mentioned president is Malta's.

The levels of influence of presidents' accounts on Twitter vary for many reasons. Some countries have been known to receive more media and social media attention than others. One of the most important but challenging to unpack cause of this would be the social-political-economic status. However, a more direct and straightforward cause of the variety in the influence of presidents on Twitter is the size of that country's population.

In [96]:
```
figure_4()
display("Table 5")
display(table_5)
```

Figure 4: Regression Model for Frequency of Mentions and Population in millions




```
'Table 5'
```

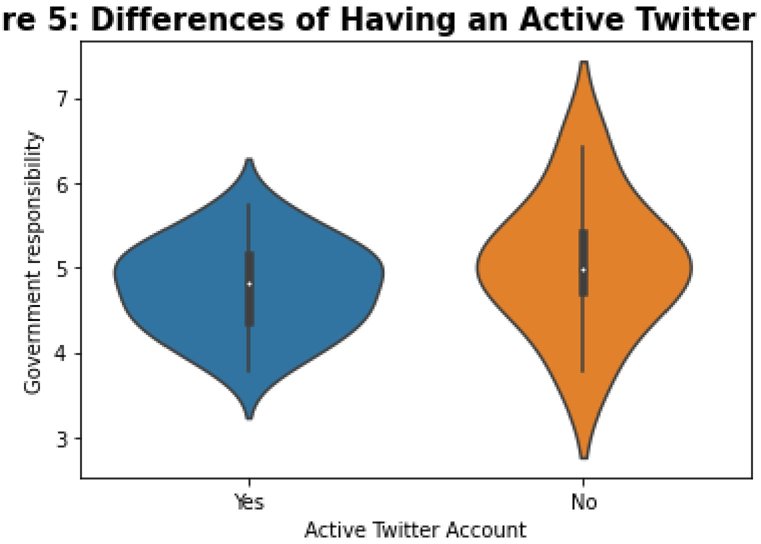
	R squared	Coefficient
Regression Model	0.577477	-1.177215

The size of the country's population directly affects the frequency of mentions received. The relatively high R^2 illustrates the strength of the relationship. The more populated a country is the less seconds between consecutive mentions on average.

Could there be other ideological reasons to account for the variation in influence levels? Do perceptions of governments and the roles attached to them have effects on the Twitter presences of the head of those states? To address the research question, I use the accounts of presidents with active Twitter accounts. Of the 40 countries that responded to World Values Survey (Inglehart et al., 2014), only 26 had presidents with active Twitter accounts. I start the analysis by first investigating whether having an active account on Twitter relates to different opinions on government responsibility?

In [97]:
```
figure_5()
print("The p-value for the t-test is "+ str("%.2f" % p_value) + ".")
```

Figure 5: Differences of Having an Active Twitter Account




```
The p-value for the t-test is 0.26.
```

Of the 14 heads of state with no active Twitter account, the 8 monarchs were excluded since almost all royals choose not to have a personal Twitter account. To visually compare the government responsibility answers of countries with a president with an active Twitter account and those that do not, I choose a violin plot. Then, I conduct a t-test to test if there is a significant difference between the means. The violin plot shows, and the t-test concludes with the high p-value that there is no significant relationship between a country's president having an active Twitter account and the responsibility attributed to that government by its citizens.

By limiting the analysis to the presidents with an active Twitter account, we can test whether the amount of responsibility attributed to governments has a significant relationship with the volume of interactions received by the presidents' accounts, calculated by the mention score.

In [98]:
```
figure_6()
display("Table 7")
display(table_7)
```

Figure 6: Regression Model for Government Responsibility and Mention Scores by Country

'Table 7'

	R squared	Coefficient for Gov. Resp.	p-value for Gov. Resp.
Regression Model	0.231233	0.995061	0.012891

When the mention score is in its linear scale, the residuals are not uniformly scattered. Also, to be able to integrate the very large values to the model, I prefer a log scale. The relatively low R^2 suggests that the survey responses cannot explain much of the variance in the mention scores. Yet, the low p-value concludes that there is indeed a statistically significant effect of the amount of responsibility attributed to the governments on the mention scores of presidents' Twitter accounts. The positive coefficient indicates that the correlation is positive and that the countries in which citizens think governments should take more responsibility than the individuals have their presidents' Twitter accounts mentioned more even though they have fewer followers.

Limitations and Conclusions

The claims made in the first part of this paper are dependent on the validity of the data used. The epistemology data is composed of information collected from different countries, which might have different transparencies about reporting data. The survey data from World Values Survey (Inglehart et al., 2014) might also be biased since a question about the government and politics in general may cause response bias by creating pressure to comply with the social norms, even more so in some countries than others. The claim that the countries where citizens think governments should take more responsibility than the individuals have a higher initial response rate raises questions about directionality. Do governments react to COVID-19 more swiftly and extensively because they are attributed more responsibility by their societies, or do citizens think that governments should take more responsibility because their governments actually have the means, capacity and intentions to act effectively in a time of emergence? To address this problem, future work can focus on the citizens' opinions on government responsibility and how those relate to the politics in a society. Does citizens' attribution of responsibility legitimize more government action, or are those opinions the very building blocks of politics in those societies?

The results of the second part of this paper are limited by the nature of the data collected. Most importantly, the size of the data is limited. The size of the data is especially important for the claims made because this data only captures a limited amount of time. Therefore, the volume of mentions received might easily be affected by recent news or events in the countries. In addition, the time I retrieved these mentions corresponds to different times of the day in different countries, which would affect the frequency of mentions. These would complicate generalizations about the accounts' influence and interaction levels. Future work should integrate more data to comment on the bigger picture and spot patterns in a wider time range. The results from the second part suggest that there is indeed a significant relationship between the citizens' opinions on governments' responsibilities and the volume of mentions their presidents receive. This suggests that people's perception of governments' roles affects how much their politicians receive interaction on Twitter. But how can this result be interpreted? Are citizens who think governments should take more responsibility more actively participating in political debate? Or perhaps in countries where people think governments should take more responsibility, governments actually do take more responsibility, and therefore there are more political actions to debate on. A broader study addressing these questions can explore the social and political implications of the citizens' opinions on government roles. Methods like sentiment analysis can further effectively detect whether the mentions are predominantly approvals or critiques. Revealing the attitudes in the mentions would clarify what kind of political discussions the different perceptions of governments initiate.

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In [56]:

```
# Word Count
from notebook import notebookapp
from ipykernel import get_connection_file
from pathlib import Path
import requests
```

```python
def notebook_path():

    connection_file = Path(get_connection_file())
    kernel_id = connection_file.stem.split('-',1)[1]

    for srv in notebookapp.list_running_servers():
        if srv['token']=='' and not srv['password']:
            req = requests.get(srv['url']+'api/sessions')
        else:
            req = requests.get(srv['url']+
                'api/sessions?token='+srv['token'])

        sessions = req.json()

        for sess in sessions:
            if sess['kernel']['id'] == kernel_id:
                return Path(srv['notebook_dir']) / sess['notebook']['path']

    return None
```

In [57]:

```python
import nbformat

with open("Sum.ipynb", encoding='utf-8') as f:
    nb = nbformat.read(f,4)

word_count = 0
for cell in nb.cells:
    if cell.cell_type == "markdown" and cell['source'][:12] != "# References":
        word_count += len(cell['source'].replace('#','').lstrip().split(' '))

print(f"The word count, excluding references, is {word_count}")
```

```
The word count, excluding references, is 3250
```