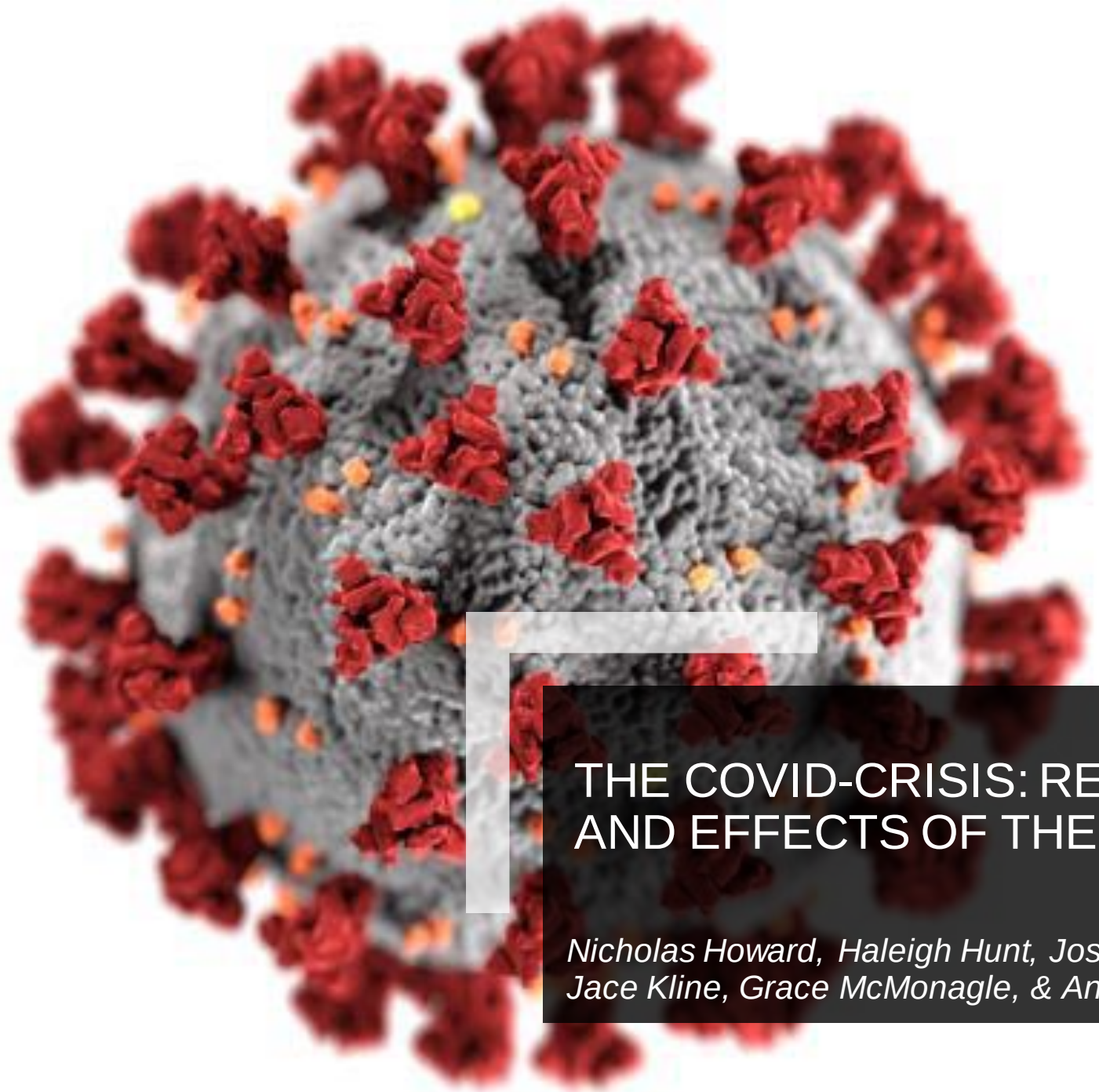
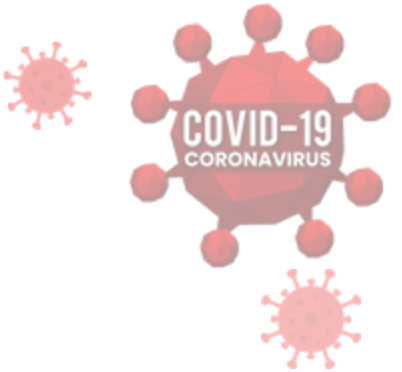


THE COVID-CRISIS: RESPONSE AND EFFECTS OF THE PANDEMIC

Nicholas Howard, Haleigh Hunt, Joseph Karnes, Jace Kline, Grace McMonagle, & Anoop Uchagawkar

BACKGROUND AND MOTIVATION OF OUR STUDIES

Why study COVID-19 statistics?

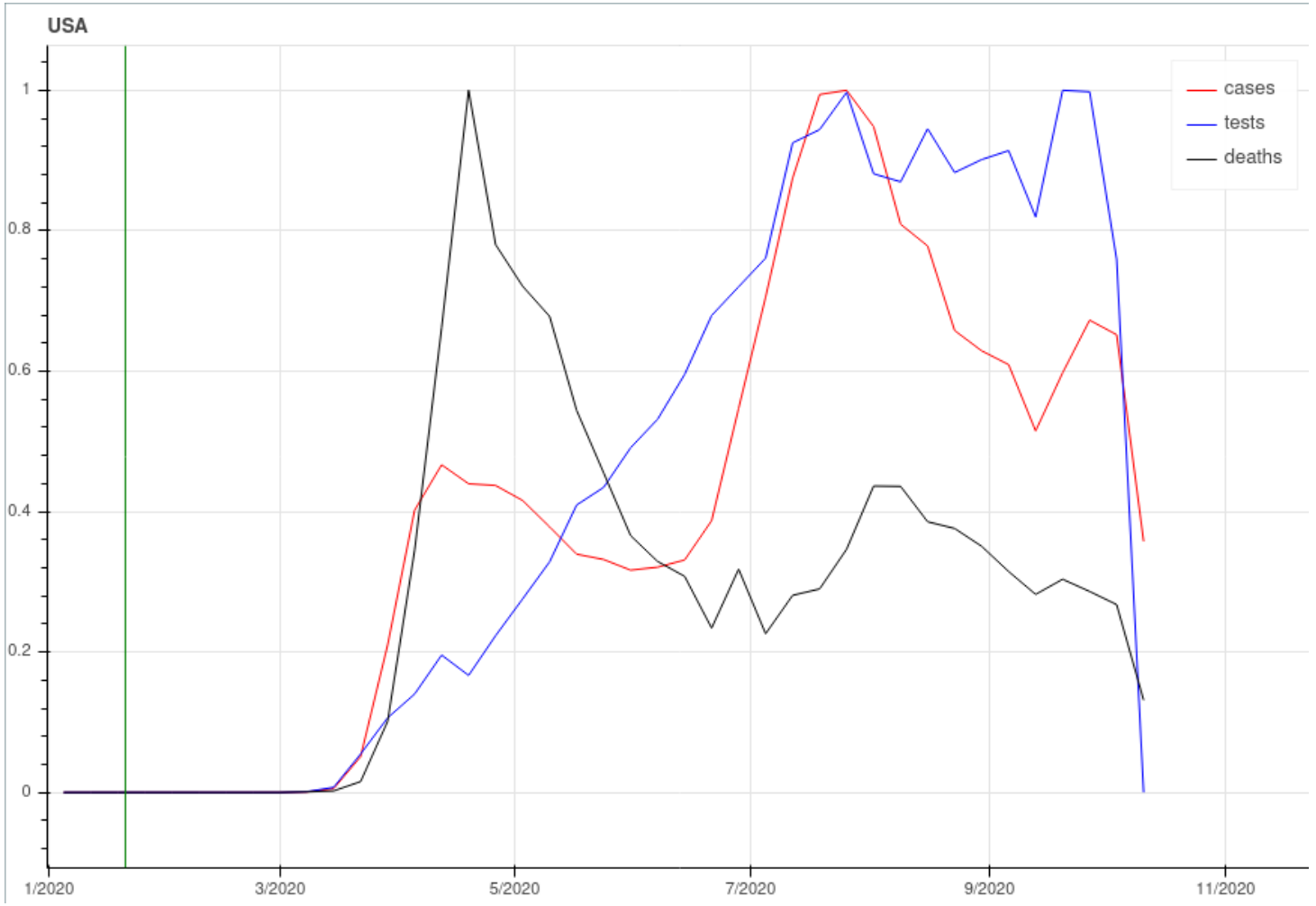


- Has had a profound effect on the world
  - Several major countries enforced lockdowns and the global economy has taken a hit
- Wanted to see effects of response
  - How effective was policy implementation?
  - Were stricter rules responsible for a downturn in COVID-19 cases?
- Wanted to analyze effects of the pandemic
  - How did this pandemic effect people economically/mentally?
  - How did our lowered activity affect the world around us?

- Main data sets
  - Our world in data (OWID) COVID-19 dataset
    - Contains several COVID-19 statistics like deaths, new cases, total cases and many more
    - https://github.com/owid/covid-19-data/tree/master/public/data
  - Government Response Tracker dataset
    - Provides information regarding the "strictness" of a government's response to the pandemic
    - https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker#data
  - Coronanet Policy dataset
    - Provides information on major policies enacted by different governments during the pandemic
    - https://www.coronanet-project.org/index.html

COMPARING COVID IMPACT AND POLICIES ACROSS COUNTRIES

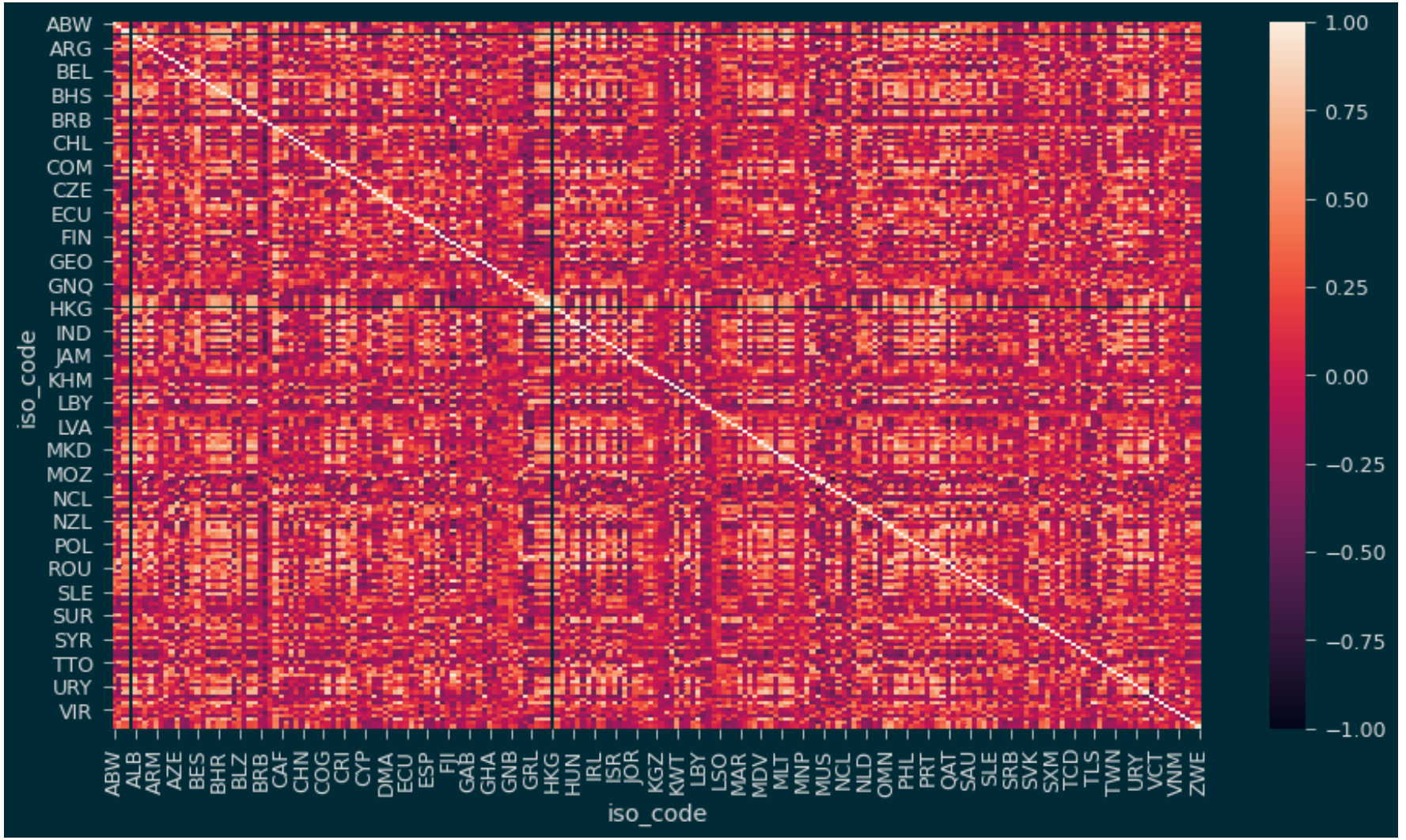
case data & policy data



Covid Data

- Cases
- Tests
- Deaths
- Correlation

Case Load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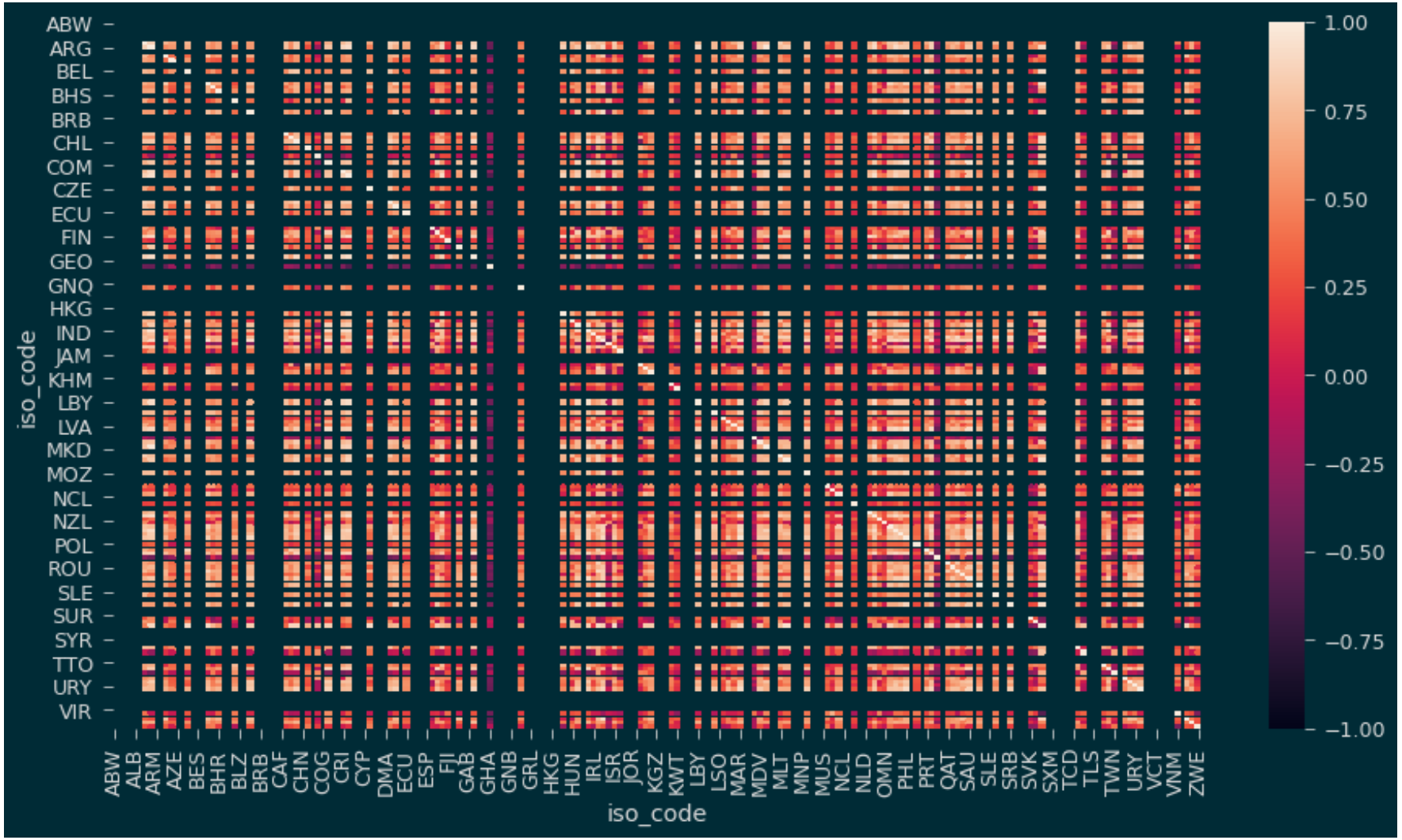
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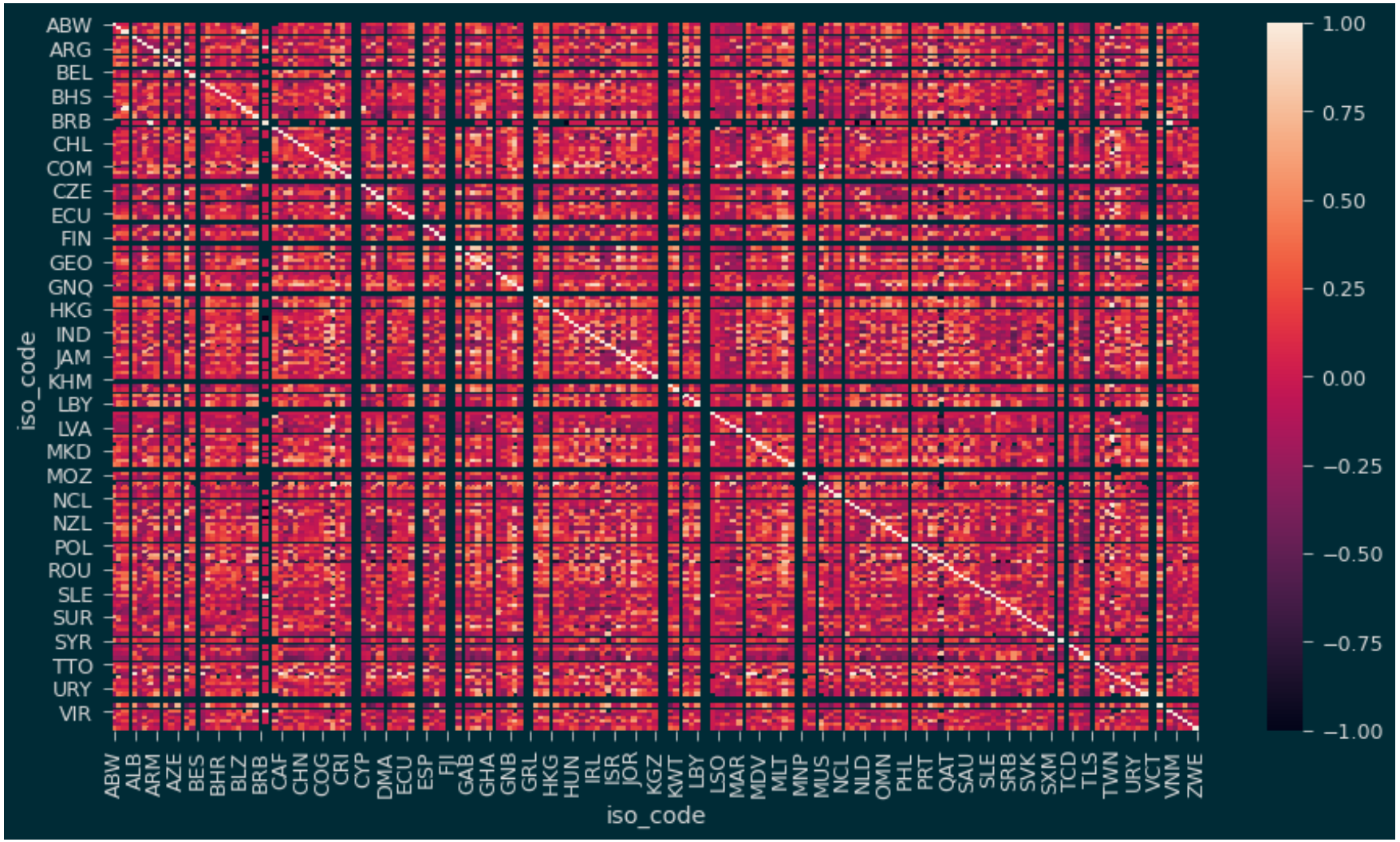
Death Count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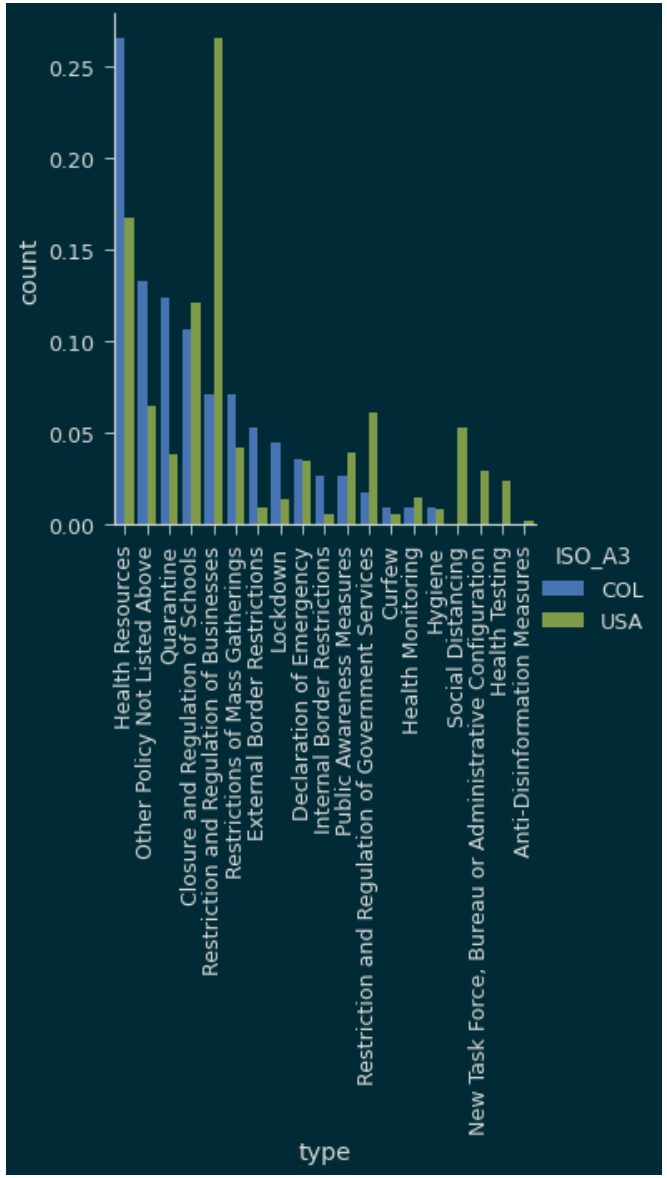
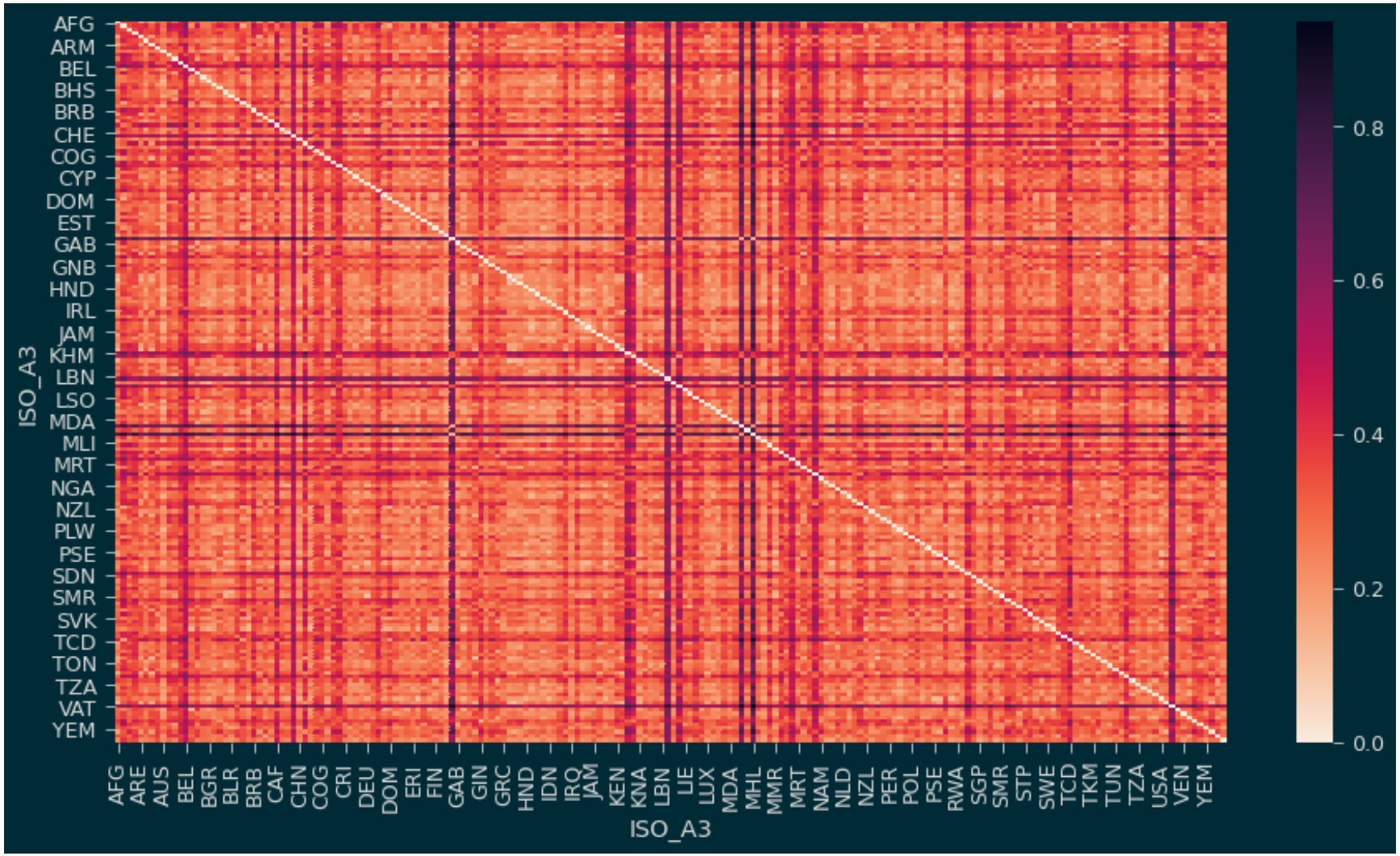


Policy

- Features
- Types
- Distance

Policy Distance



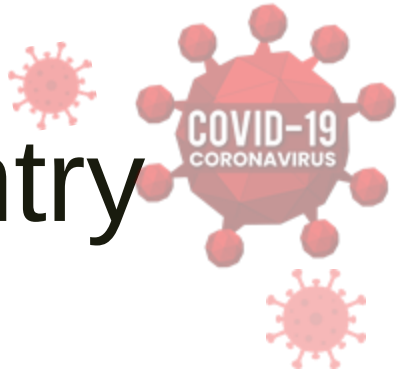
Bringing it together

	distance	cases	deaths
distance	1.000000	-0.138304	-0.094349
cases	-0.138304	1.000000	0.302036
deaths	-0.094349	0.302036	1.000000

EFFECTS OF POLICY TYPE AND NUMBER ON NEW CASES COVID-19

case data & policy data

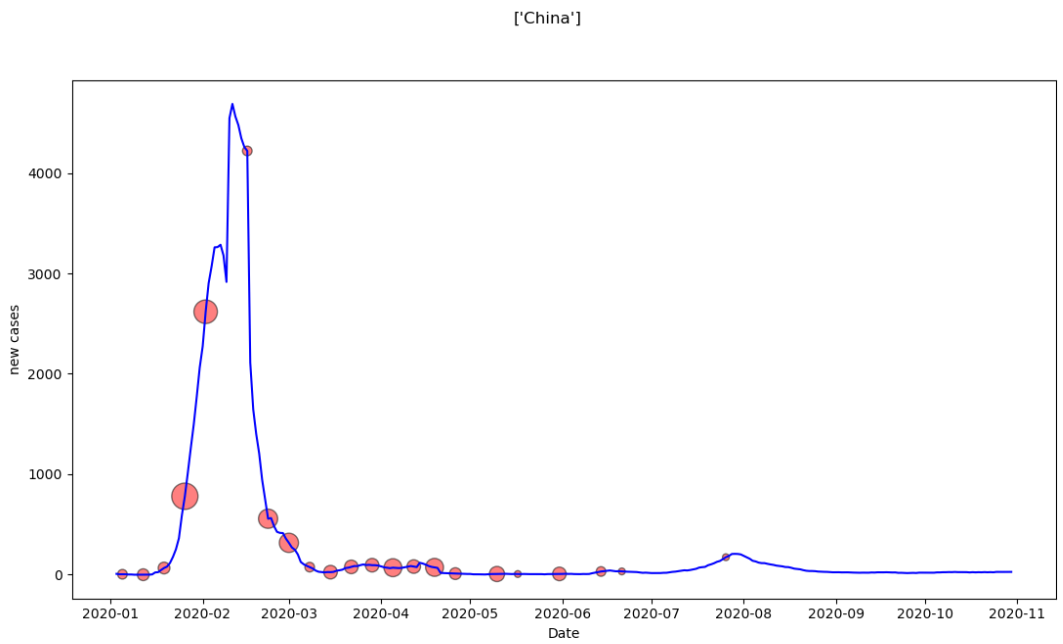
COVID-19 Policy Number by Country

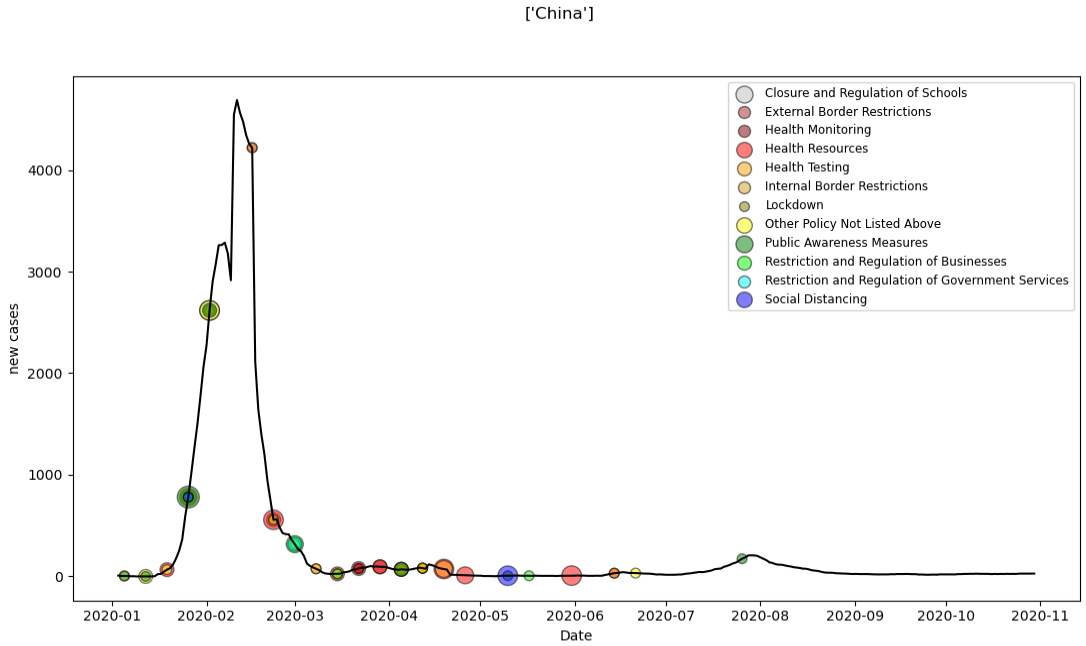


- Data used in analysis:
  - Case data from the top 3 populated countries
  - Trend of daily new cases obtained from decomposition
  - Count of national policies enacted per week
  - 7 and 28-day average of the change in new cases as a metric
- Can also be done with differing types of policies

China

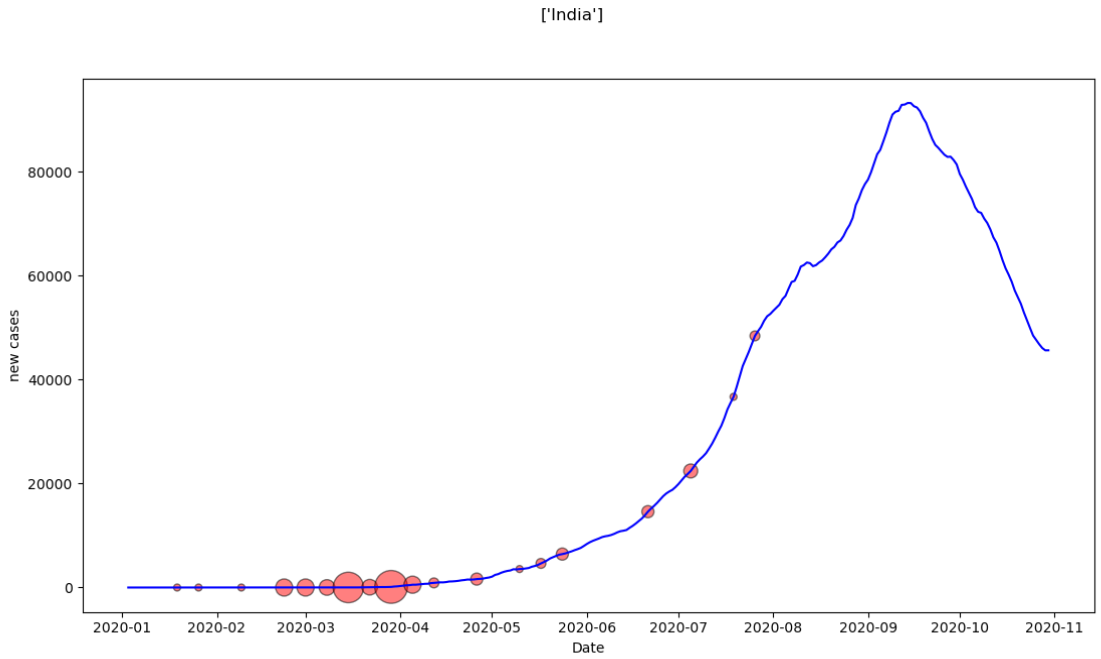
date_start	count	7-day case change	28-day change	trend
1/5/2020	2	-2.4	22.61428571	4.571429
1/12/2020	3	-2.142857143	91.96428571	0
1/19/2020	3	19.42857143	93.10714286	66.71429
1/26/2020	15	75.57142857	66.82142857	781.1429
2/2/2020	12	275	-0.642857143	2618
2/9/2020	0	2.428571429	-72	2914.857
2/16/2020	2	-85.71428571	-91.46428571	4219.143
2/23/2020	8	-194.2857143	-70.89285714	557.2857
3/1/2020	8	-10.42857143	-20.78571429	317.2857
3/8/2020	2	-75.42857143	-16.46428571	75.42857
3/15/2020	4	-3.428571429	0.071428571	25.42857
3/22/2020	4	6.142857143	2.535714286	77.85714
3/29/2020	4	6.857142857	-1.678571429	94.85714
4/5/2020	7	-9.285714286	-3.678571429	69.85714
4/12/2020	4	6.428571429	-1.642857143	81.14286
4/19/2020	7	-10.71428571	-2.785714286	73.14286
4/26/2020	3	-1.142857143	-0.428571429	10.85714
5/3/2020	0	-1.142857143	-0.25	4
5/10/2020	5	1.857142857	0.107142857	7.142857
5/17/2020	1	-1.285714286	-0.214285714	6.714286
5/24/2020	0	-0.428571429	1.928571429	5.428571
5/31/2020	4	0.285714286	0.928571429	8
6/7/2020	0	0.571428571	0.464285714	5.571429
6/14/2020	2	7.285714286	0.321428571	32
6/21/2020	1	-4.428571429	-0.892857143	33
6/28/2020	0	-1.571428571	1.821428571	18.85714
7/5/2020	0	0	5.75	18.85714
7/12/2020	0	2.428571429	5.5	44.14286
7/19/2020	0	6.428571429	2.035714286	77.85714
7/26/2020	1	14.14285714	-0.535714286	174.1429

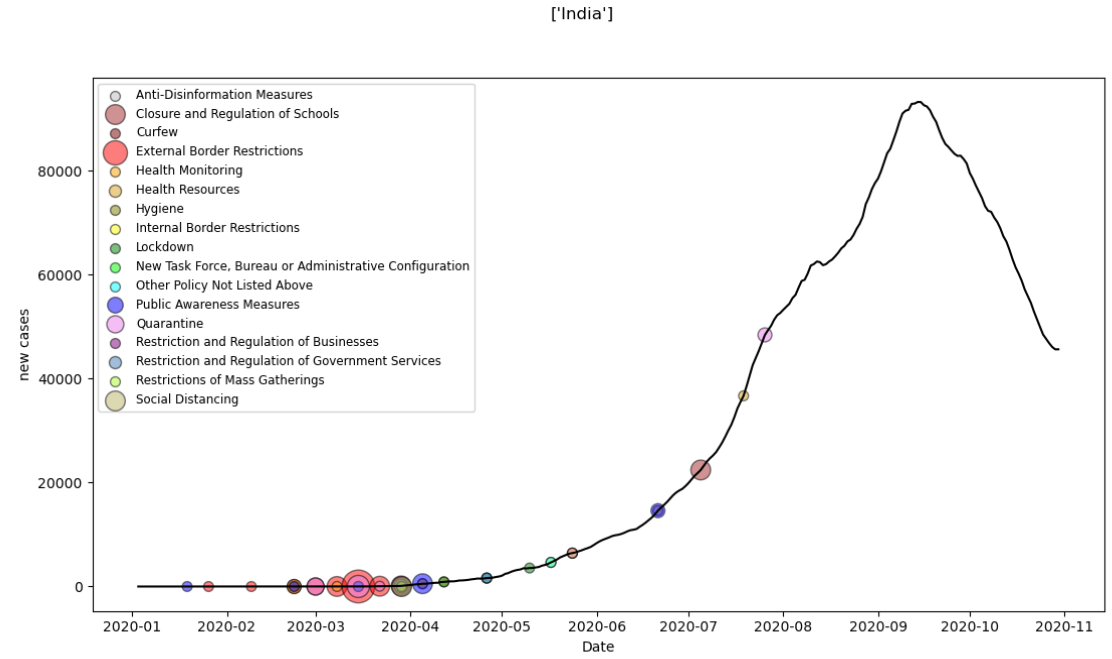




India

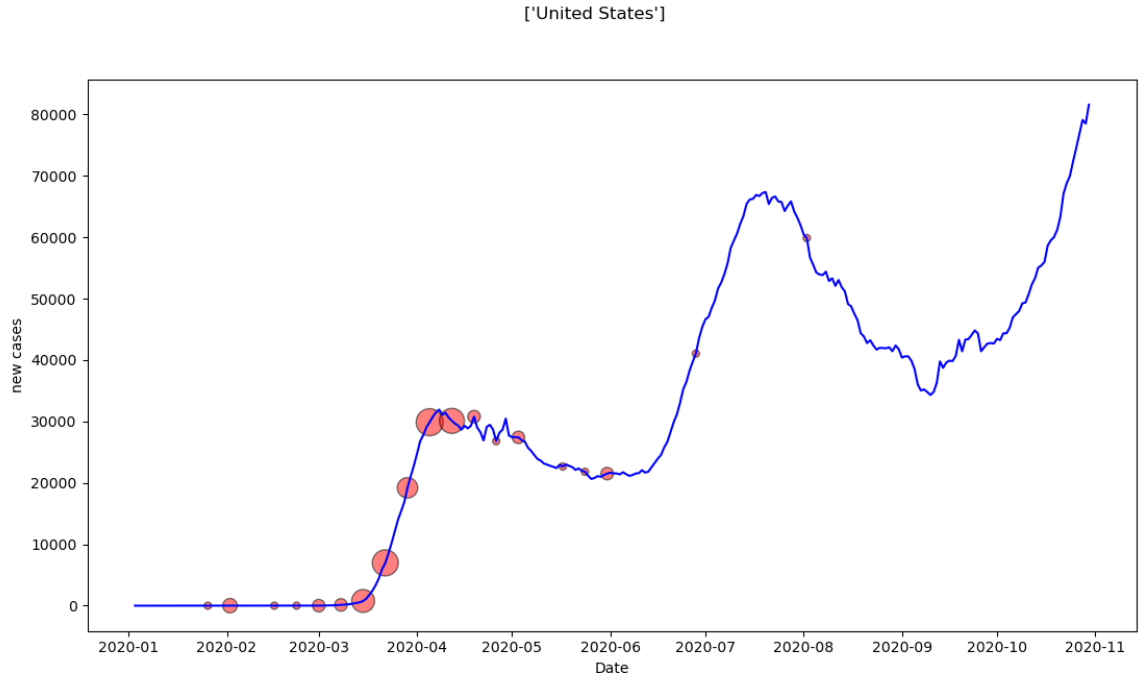
date_start	count	7-day case change	28-day change	trend
2/2/2020	1	0	7.11E-15	0
2/9/2020	2	0	7.11E-15	0
2/16/2020	1	0	0.25	0
2/23/2020	2	0	1.5	0
3/1/2020	1	0	5.571428571	0.857
3/8/2020	7	1	4.428571429	
3/15/2020	14	5	4.071428571	23.71
3/22/2020	22	16.28571429	10.82142857	73.43
3/29/2020	5	-4.571428571	6.571428571	120.3
4/5/2020	40	-0.428571429	10.25	172.9
4/12/2020	26	32	6.642857143	300.1
4/19/2020	8	-0.714285714	7.25	328
4/26/2020	10	10.14285714	7.285714286	339.4
5/3/2020	6	-14.85714286	19.75	365.7
5/10/2020	2	34.42857143	9.464285714	382.6
5/17/2020	3	-0.571428571	16.42857143	535.3
5/24/2020	0	60	17.32142857	667
5/31/2020	0	-56	9.892857143	626.3
6/7/2020	1	62.28571429	29.57142857	789.6
6/14/2020	0	3	16.21428571	1046
6/21/2020	10	30.28571429	23.46428571	1071
6/28/2020	1	22.71428571	18.78571429	1213
7/5/2020	0	8.857142857	17.25	1406
7/12/2020	0	32	4.035714286	1764
7/19/2020	0	11.57142857	21.64285714	1614
7/26/2020	2	16.57142857	21.17857143	1740
8/2/2020	1	-44	7.928571429	1858
8/9/2020	1	102.4285714	62.42857143	1960

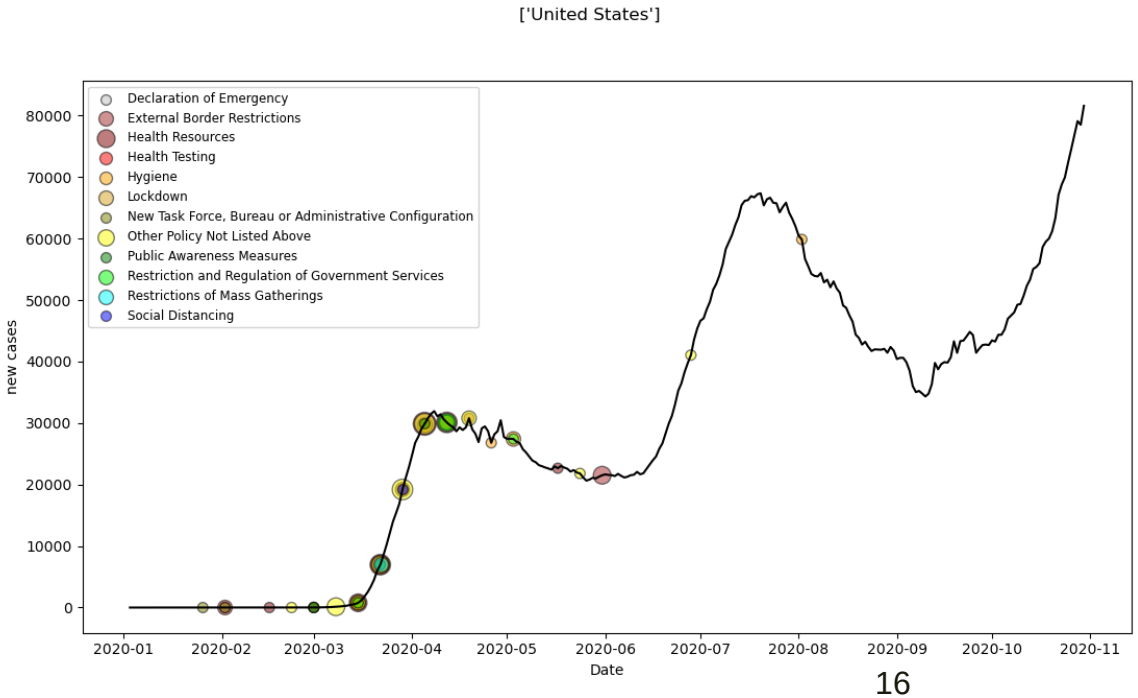




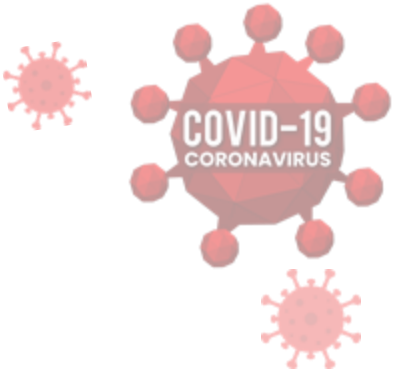
USA

date_start	count	7-day case change	28-day change	trend
1/26/2020	1	0	2.27E-13	0.5714
2/2/2020	4	0.142857143	2.27E-13	0.8571
2/9/2020	0	-0.142857143	0.071428571	0.2857
2/16/2020	1	0	3.392857143	0.2857
2/23/2020	1	0	27.75	5.4286
3/1/2020	3	0.428571429	254.3928571	10.286
3/8/2020	3	13.14285714	713.4285714	128.57
3/15/2020	10	97.42857143	1220.607143	771.71
3/22/2020	13	906.5714286	986.2142857	6972
3/29/2020	8	1836.571429	921.3928571	19198
4/5/2020	14	2041.857143	1019.642857	29884
4/12/2020	12	-840.1428571	-178	30101
4/19/2020	3	647.2857143	-99.25	30789
4/26/2020	1	2229.571429	-301.25	26792
5/3/2020	3	-2748.714286	-974.75	27413
5/10/2020	0	-525.1428571	-213.9642857	23641
5/17/2020	1	-160.7142857	-121.0357143	22658
5/24/2020	1	-464.4285714	37.60714286	21806
5/31/2020	3	294.4285714	461.5	21516
6/7/2020	0	-153.4285714	685.3214286	21147
6/14/2020	0	473.8571429	821.3571429	22554
6/21/2020	0	1231.142857	1339.678571	29899
6/28/2020	1	1189.714286	1056.821429	41059
7/5/2020	0	390.7142857	821.8571429	51667
7/12/2020	0	2547.142857	470.9285714	62211
7/19/2020	0	99.71428571	-243.9285714	67212
7/26/2020	0	249.8571429	-559.4285714	64277
8/2/2020	1	-1013	-754.2857143	59870





Overall Conclusions

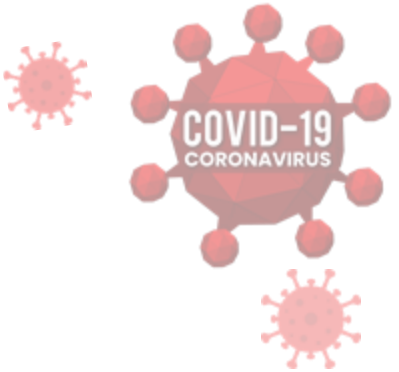


- Policy types did not seem to have a profound impact, as they were scattered throughout the pandemic
- Bulk policies seemed to have a better overall effect on the climb in new cases, but it depends on other factors
- Deeper analysis can be done by extending the investigation to when the policies ended/how long they lasted

QUALITY OF COUNTRY'S RESPONSES TO THE COVID-19 PANDEMIC

case data & policy data

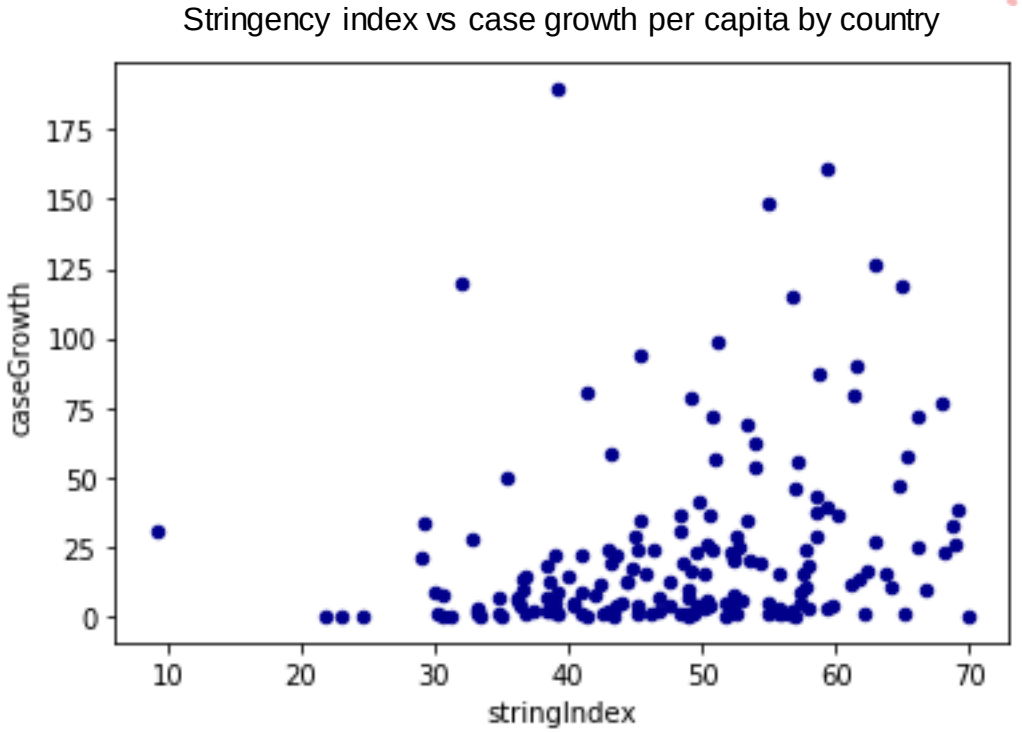
Quality metrics



- Stringency index
  - *Value between 0-100 measuring how strict of a response a country had based on closures, mandates, and other policies*
  - *Averaged throughout the time of the pandemic (January 1, 2020 – current)*
- Case growth
  - *Average value of new cases per day per capita for each country*
- Time until closure
  - *Number of days since January 1, 2020 that country-imposed school closures and workplace closures*

Independence of Variables

- Surprisingly, the stringency index and case growth had little meaningful relation.
- We see a slight positive correlation; however we assume the variables are independent for our analysis

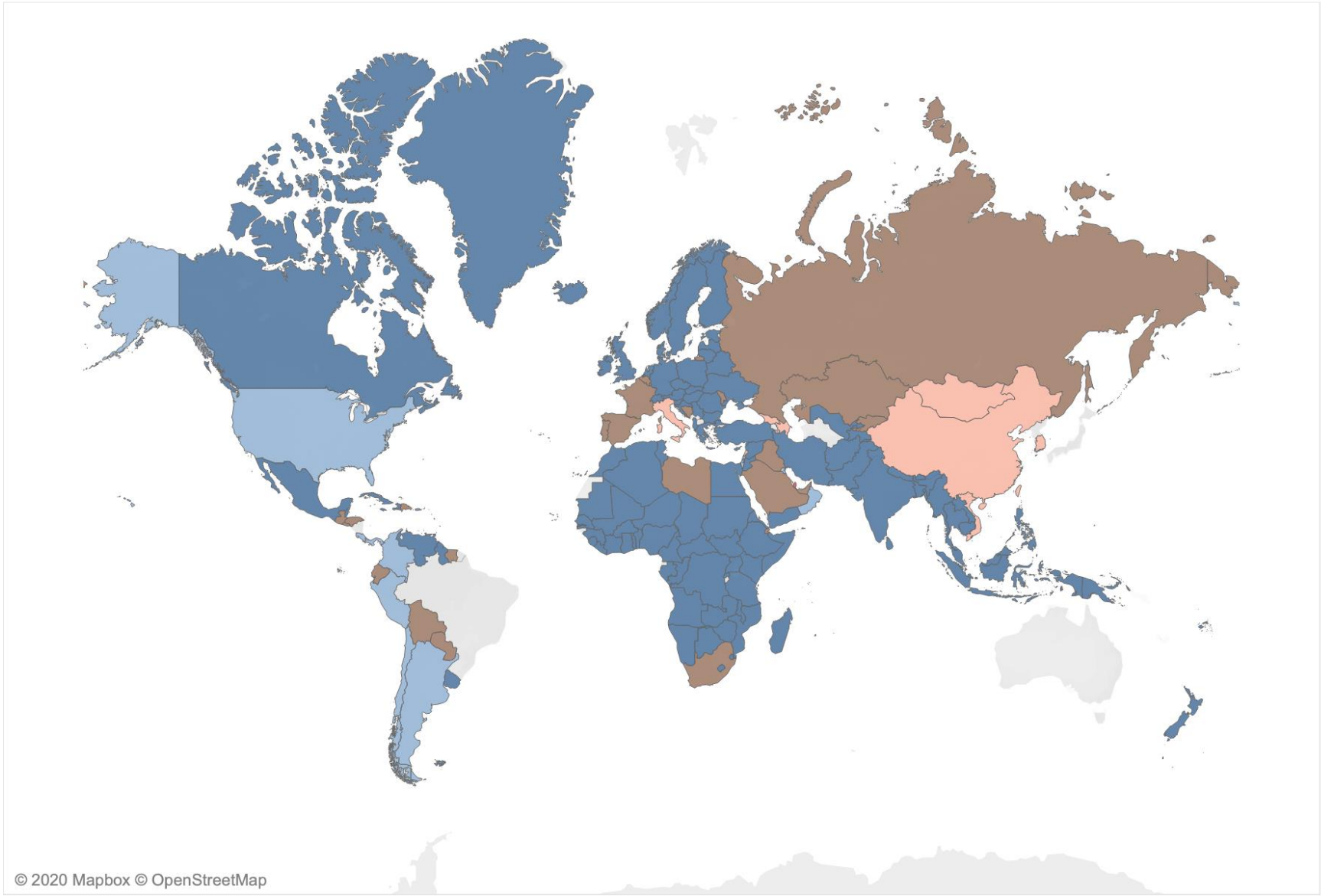


Clustering Models

- Each model has 5 clusters
  - *Very Poor Response*
  - *Poor Response*
  - *Neutral Response*
  - *Good Response*
  - *Excellent Response*

- Agglomerative Clustering
- K-Means Clustering

Agglomerative Clustering



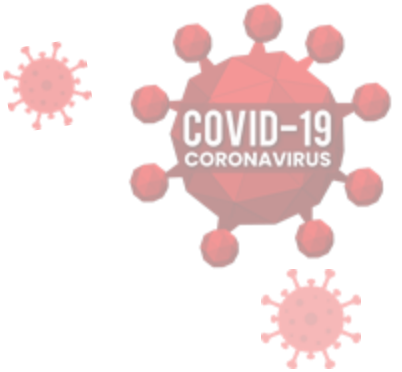
Response Category:

0 – Good
1 – Poor
2 – Very Poor
3 – Excellent
4 - Neutral

EXPLORING THE EFFECTS OF MASK USE IN US COUNTIES

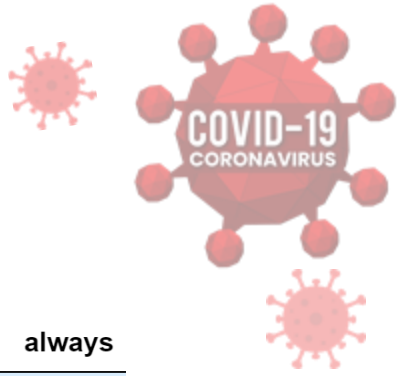
case data & mask use data

Mask Use - Overview



- Data contains self-reported mask use by US county
- Explore mask use correlation with cases and deaths by county
- Incorporate population and land area data to account for county differences
- Build clustering model to cluster similar counties based on mask use and population density

The Data



1. Mask use by US county

	county_fips_code	never	rarely	sometimes	frequently	always
0	1001	0.053	0.074	0.134	0.295	0.444
1	1003	0.083	0.059	0.098	0.323	0.436

2. Cases/Deaths by US county over time

	date	county	state_name	county_fips_code	confirmed_cases	deaths
0	2020-03-24	Autauga	Alabama	1001	1	0
1	2020-03-25	Autauga	Alabama	1001	4	0

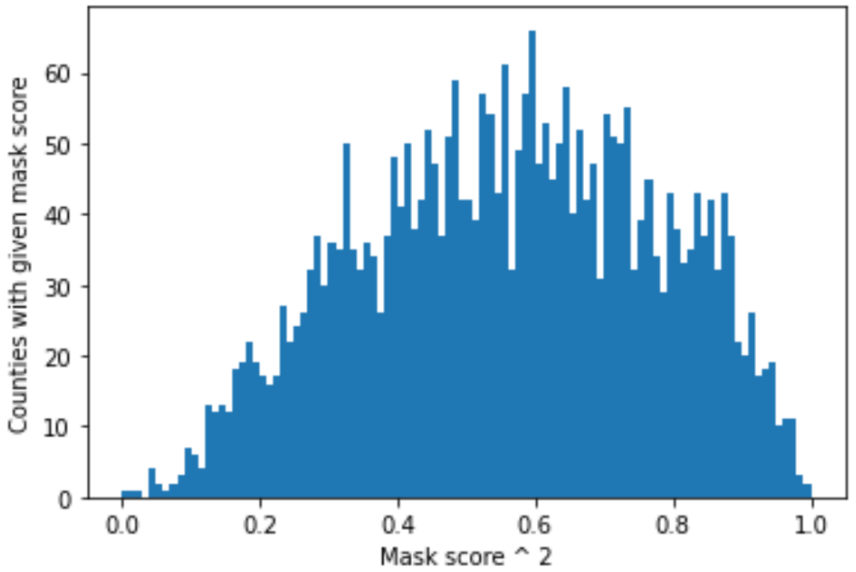
3. US County Population and Land Area Data

	population	landarea
county_fips_code		
1001	55514	594.44
1003	190790	1589.78

Mask Score

- Create a *Mask Score* for each county
  - *Mask score = (-1 * never) + (-0.5 * rarely) + (0.5 * frequently) + (1 * always)*
  - *Make it standardized and normalized*
  - *This resulted in a skewed distribution*
  - *Remedy: mask score = mask score ^ 2*

- Mask score values range from 0 to 1



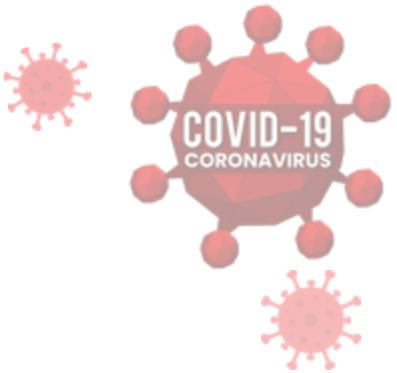
Summarizing Cases/Deaths data

- For each county...
  - *Daily change in cases/deaths (avg, max)*
  - *Weekly change in cases/deaths (avg, max)*
  - *Monthly change in cases/deaths (avg, max)*
  - *Total change in cases/deaths*

county_fips_code	daily_change_cases_max	daily_change_deaths_max	daily_change_cases_mean	daily_change_deaths_mean	weekly_change_cases_max	weekly
1001	83.0	2.0	9.573460	0.142180	168.0	
1003	357.0	8.0	29.149321	0.312217	862.0	

- Problem
  - *These measures do not factor in population or population density*

Scaling Cases/Deaths data

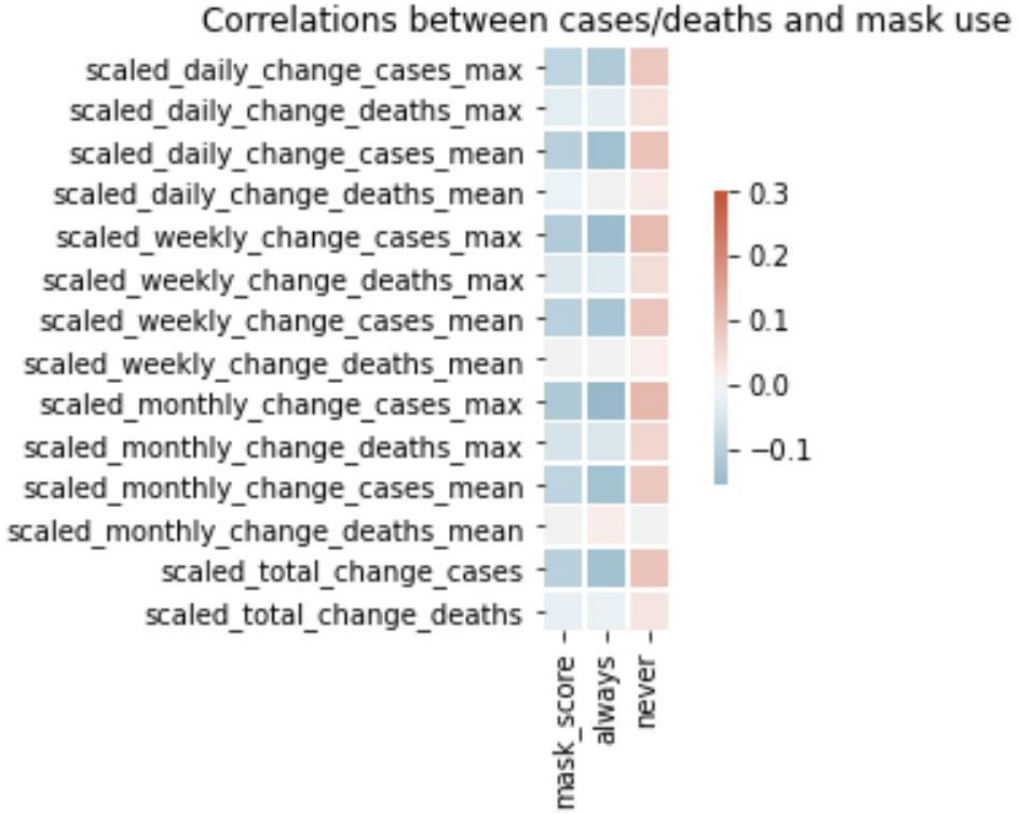


- Problem
  - *Raw cases/deaths measures do not account for population or population density of a particular county in relation to others*
- Solution
  - *Divide by raw population*
  - *Divide by population density*
  - *Scaled measure = (measure * county area) / (population ^ 2)*
  - *Creates a relative measure that we can use to compare county cases/deaths growth measures*

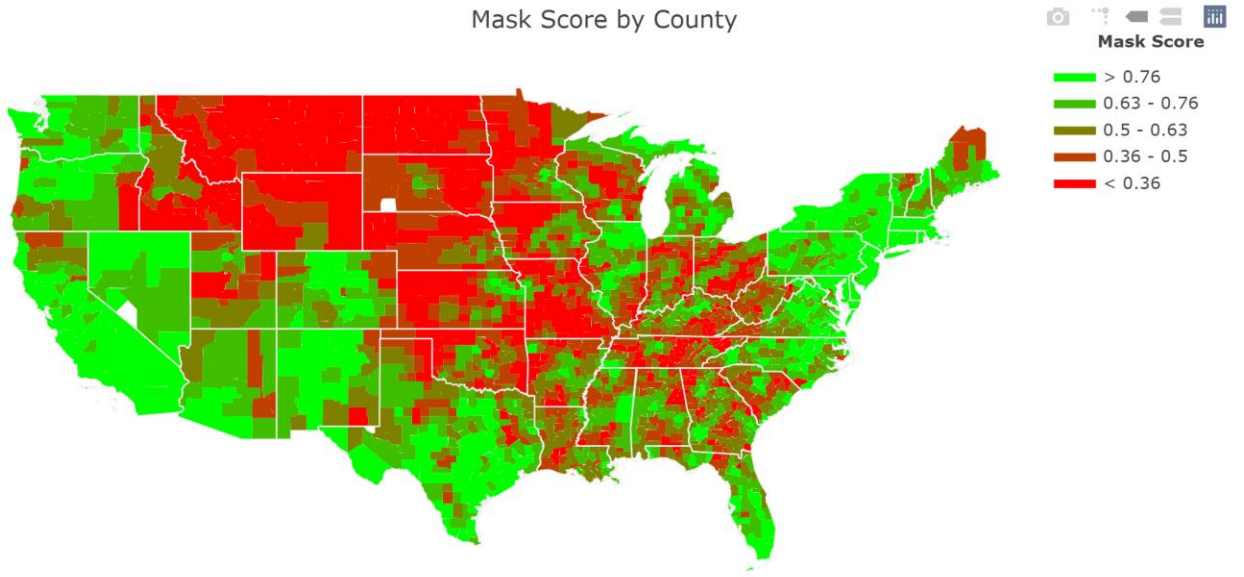
county_fips_code	scaled_daily_change_cases_max	scaled_daily_change_deaths_max	scaled_daily_change_cases_mean	scaled_daily_change_deaths_mean
1001	0.160096	0.003858	0.018466	0.000274
1003	0.155917	0.003494	0.012731	0.000136

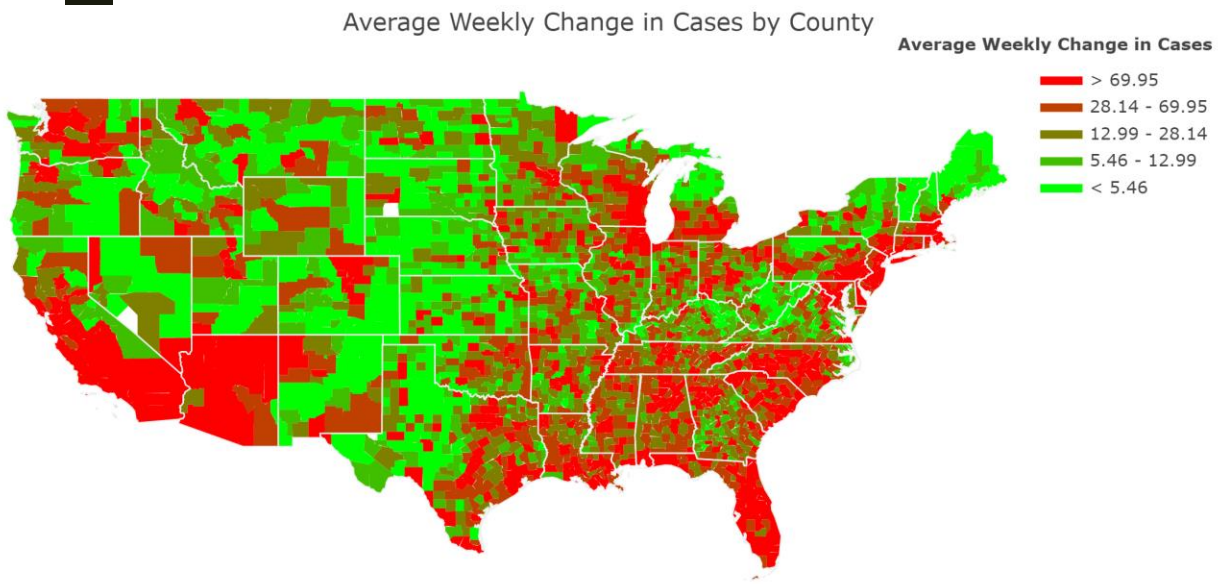
Finding Correlations

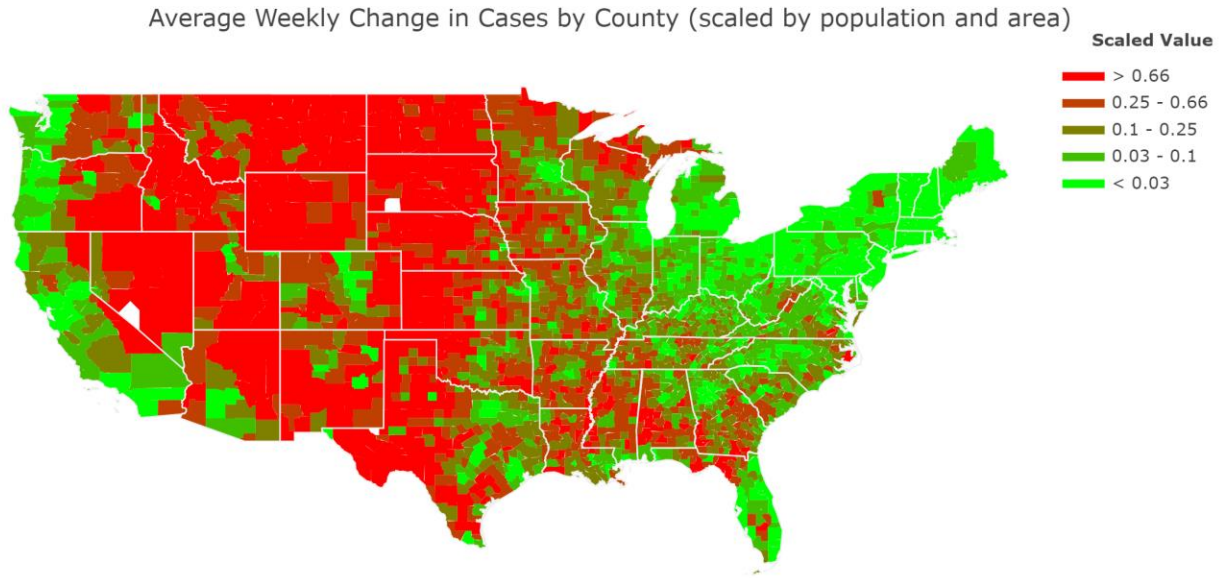
- We now have relative measures for cases/deaths growth for each county at different time scales (daily, weekly, monthly, total)
- We correlate these measures with mask-wearing tendencies for each county



Geographical Plots

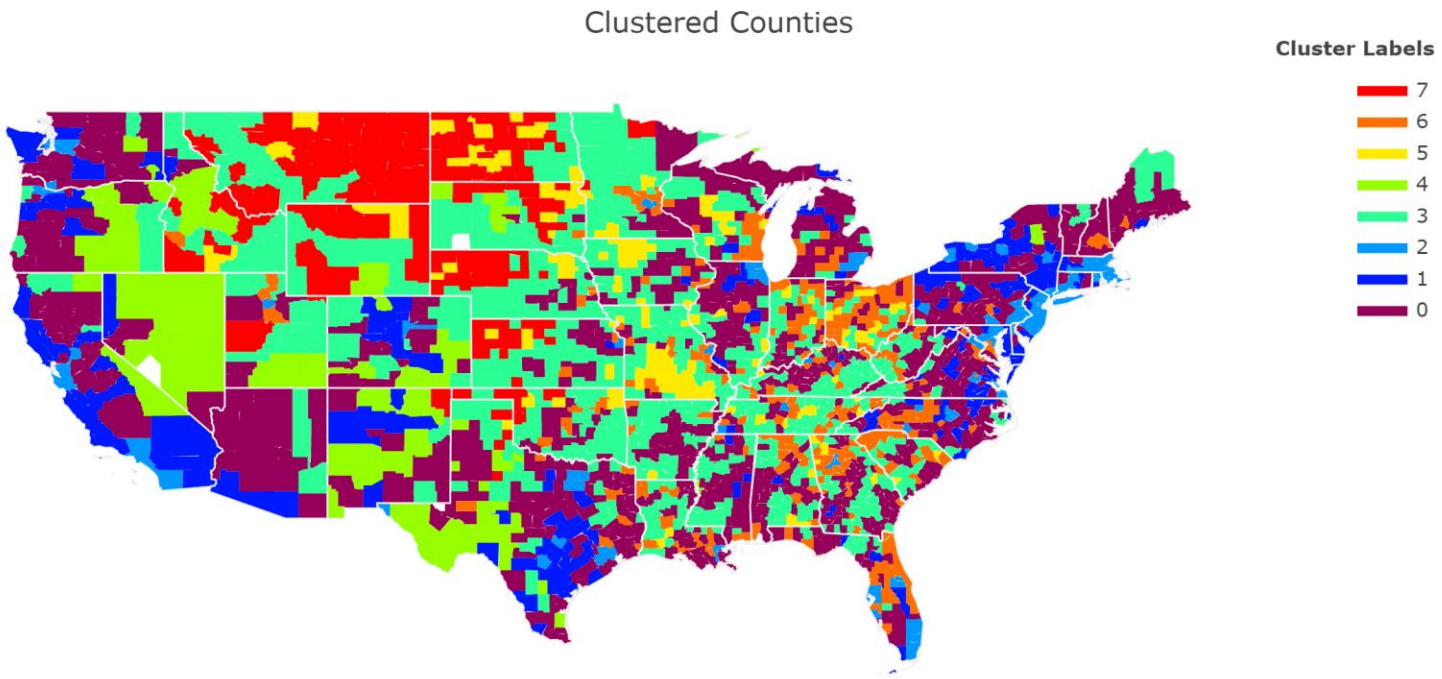


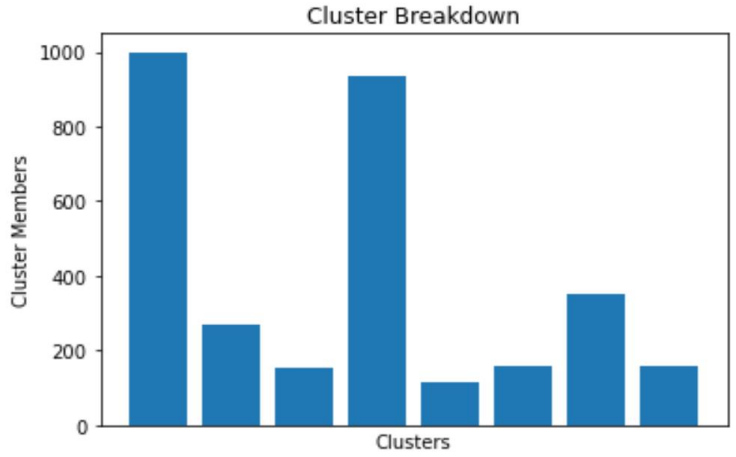


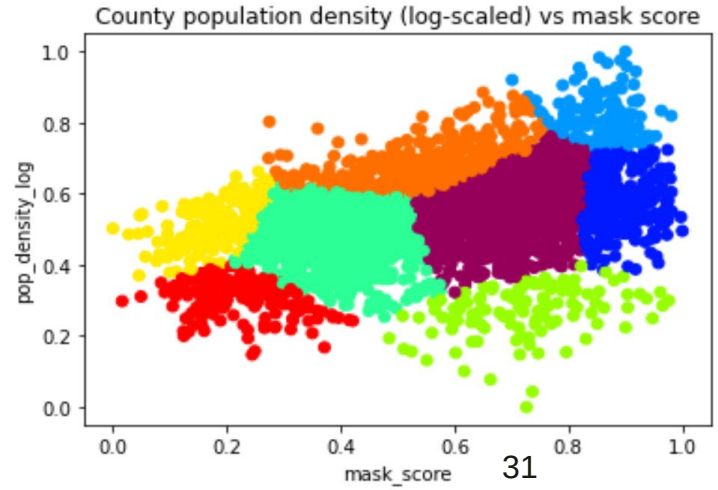


Clustering Counties

- Build a clustering model based on mask score and population density
  - *Use normalized, log-scaled population density*
- Algorithm: Spectral clustering



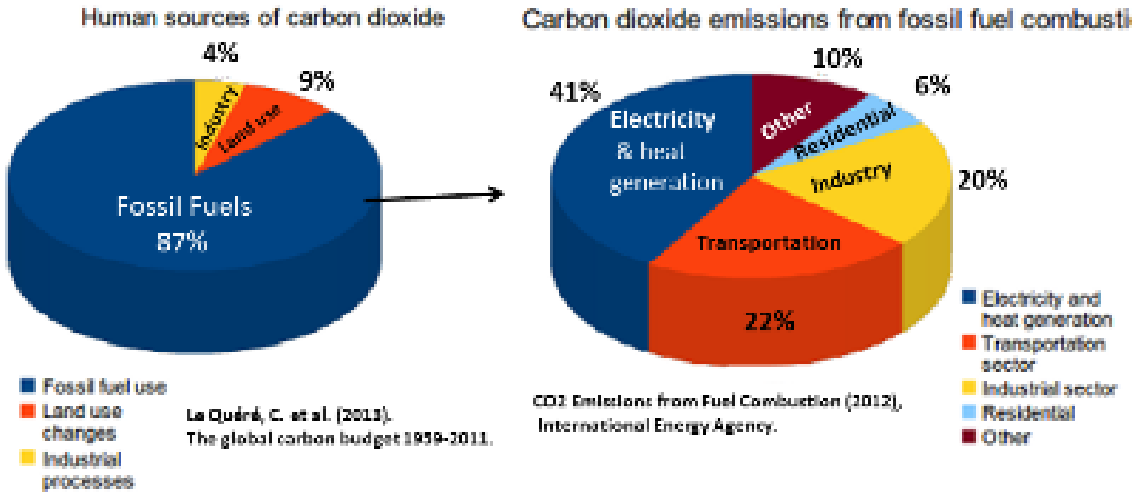




CO_2 EMISSION TRENDS– COMPARISON STUDY

CO_2 emission data

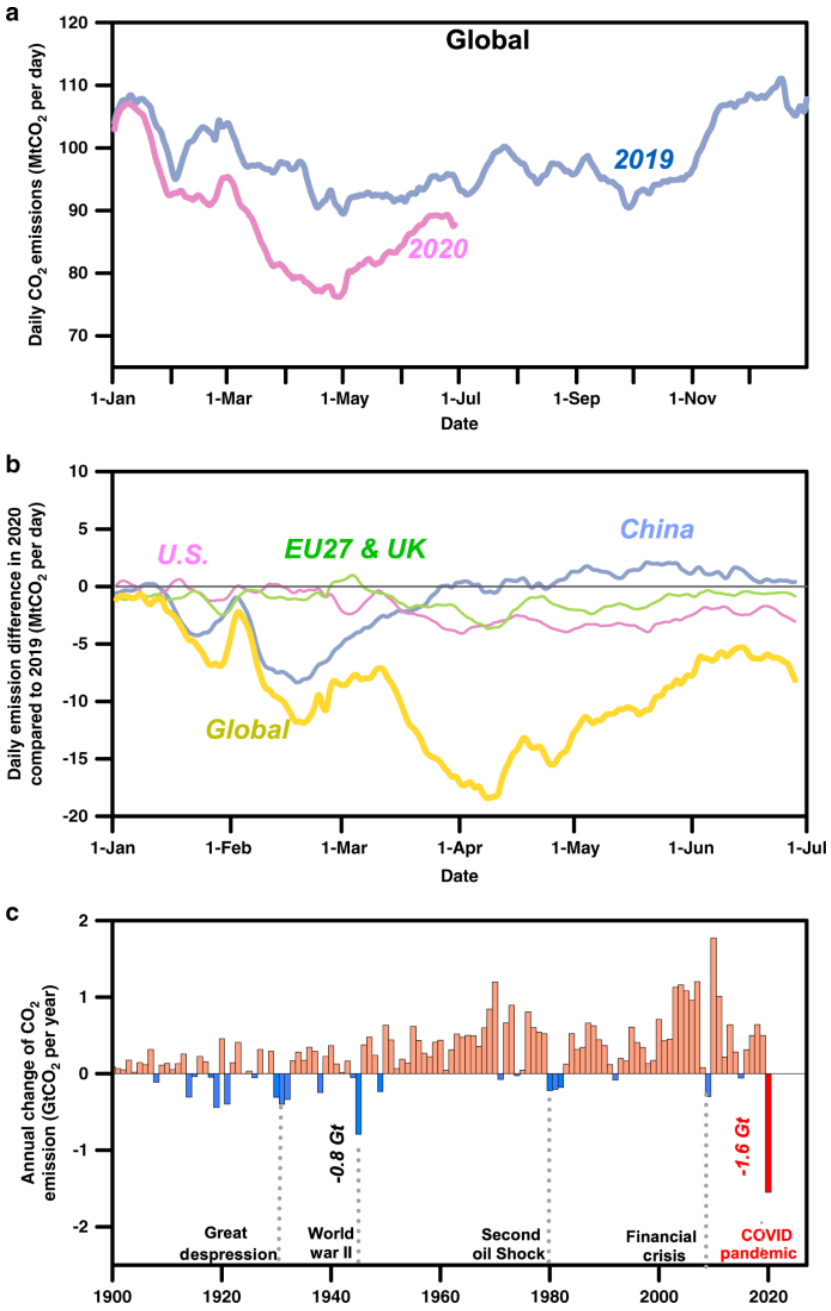
Sources of our CO2 emissions by sectors



1) The International Energy Agency (IEA) - 5% decline

2) Le Quer et al. Used confinement index – 17 % less than 2019

3) Overall 8.8% CO2 decline was estimated in the first quarter 2020

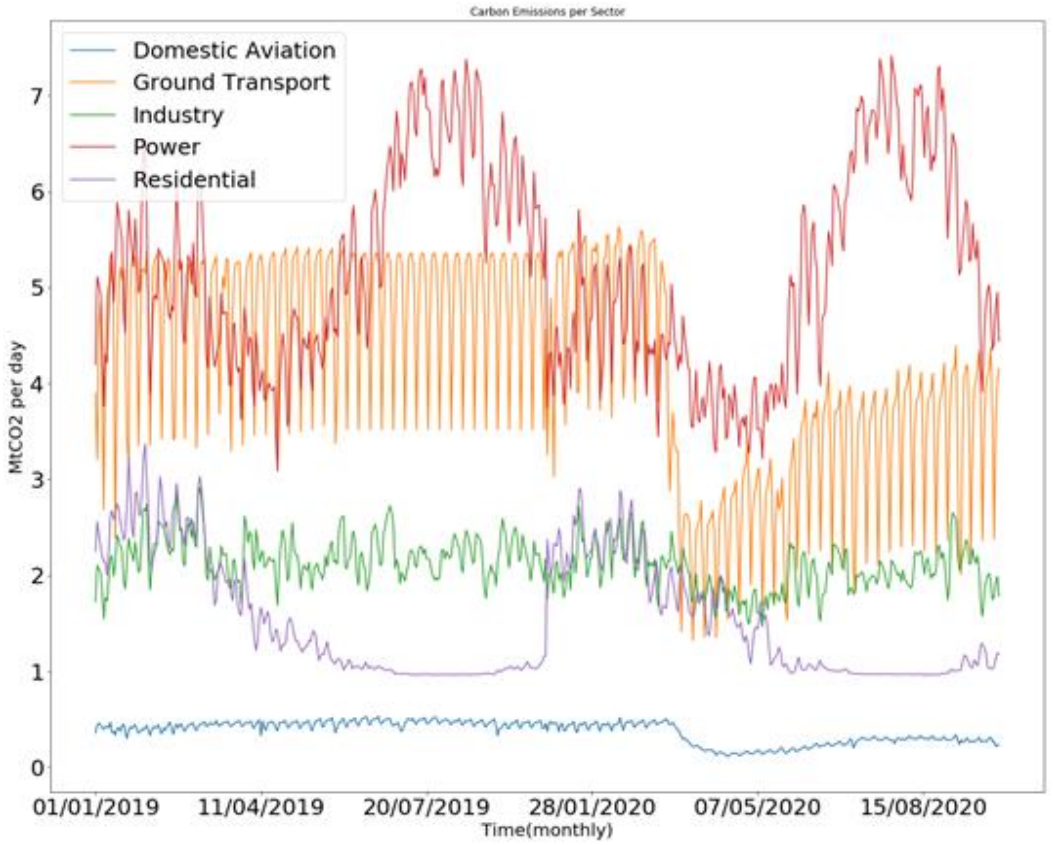


http://www.onlyzerocarbon.org/sources_co2.html

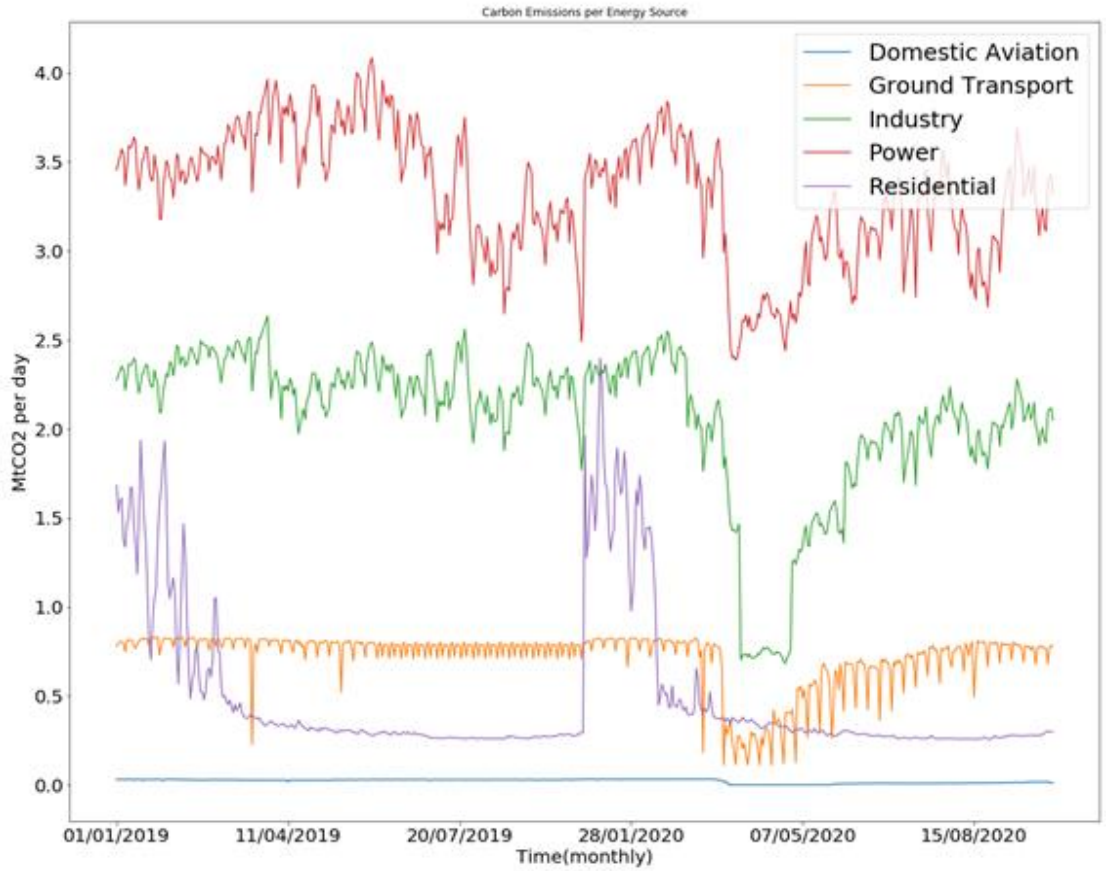
Le Quere et al. DOI: 10.1038/s41467-020-18922-7

Sector-wise emission trends with different countries

US



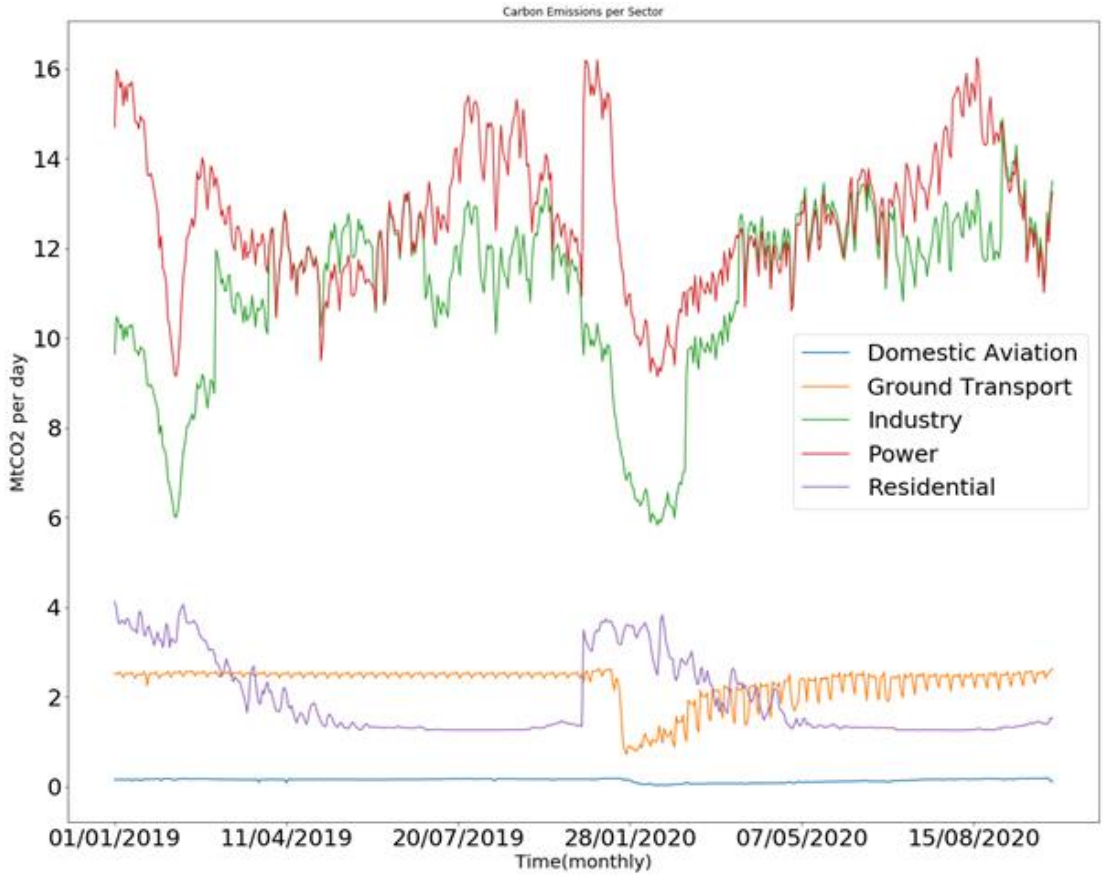
India



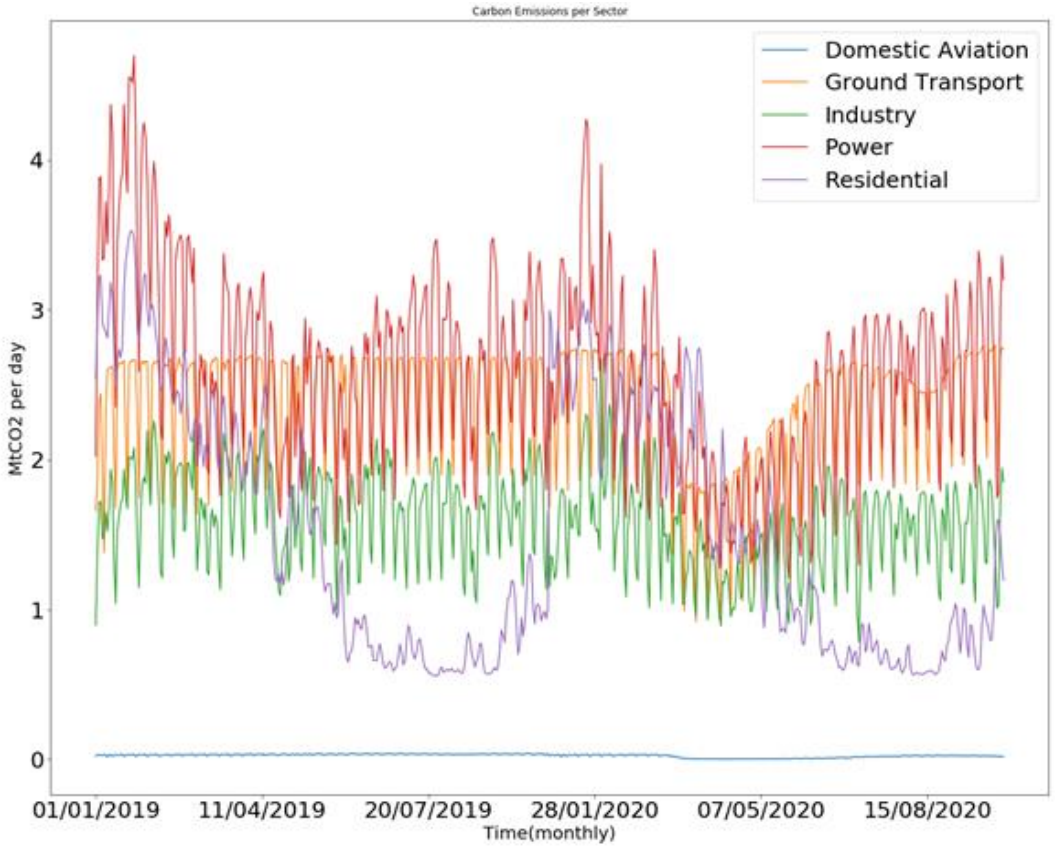
The highest contribution comes from the ground transportation, but it varies with countries and the policies that affected both COVID spread and the lockdown

Sector-wise emission trends with different countries

China

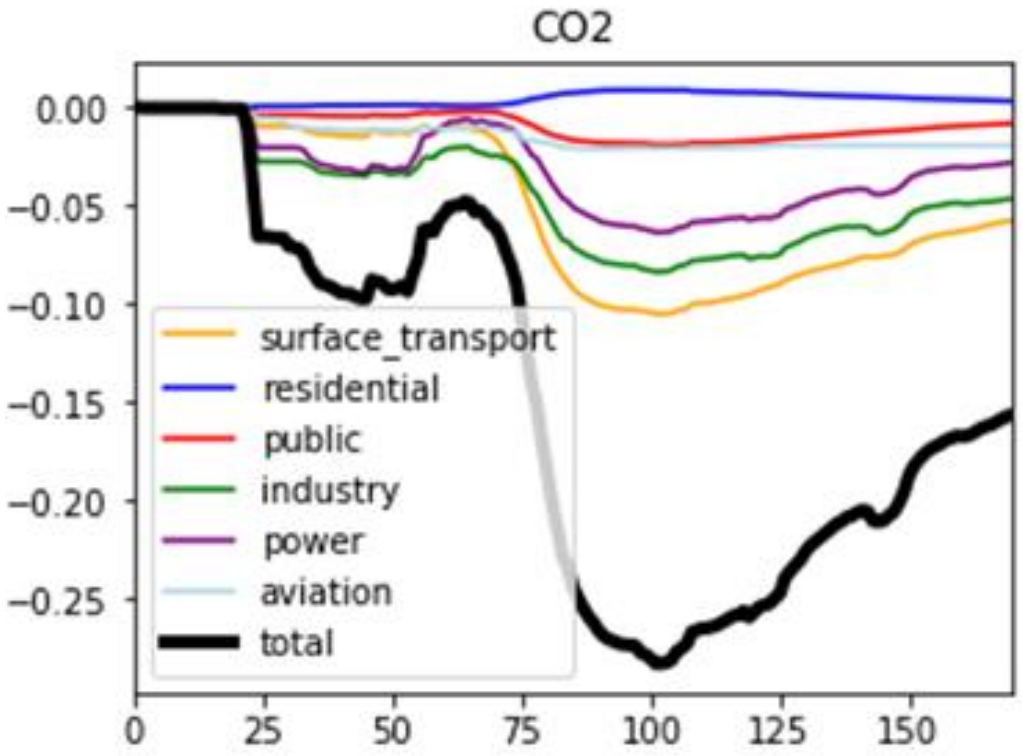


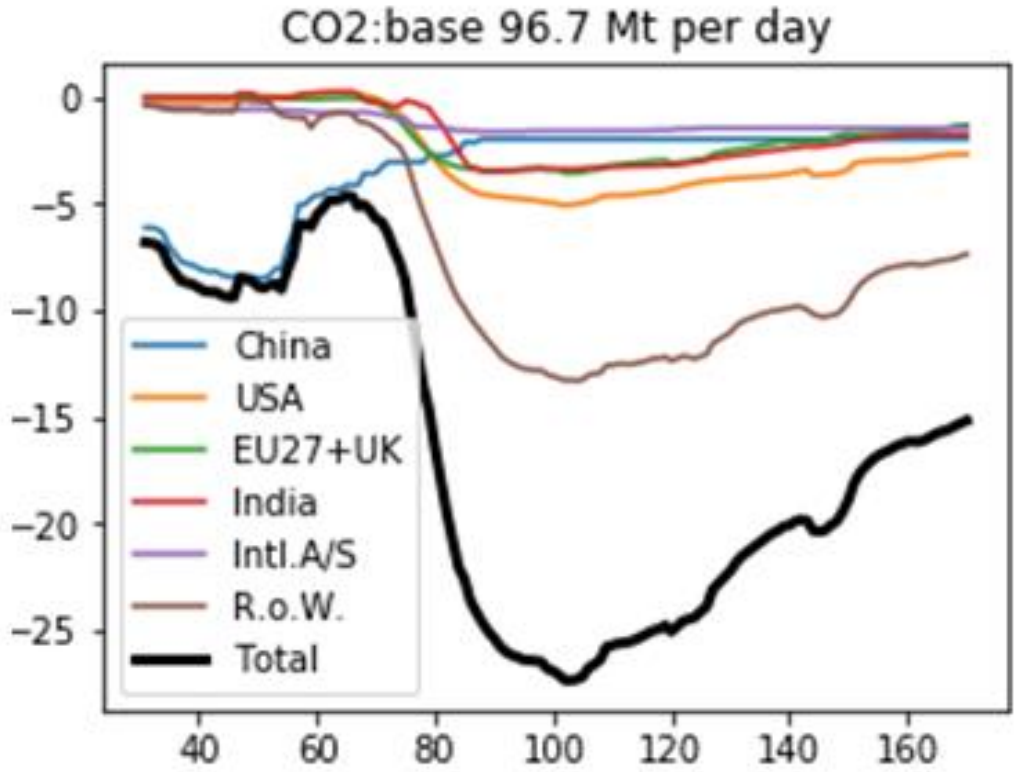
UK and Europe



Global averaged absolute emission change – by sector

Google mobility trends

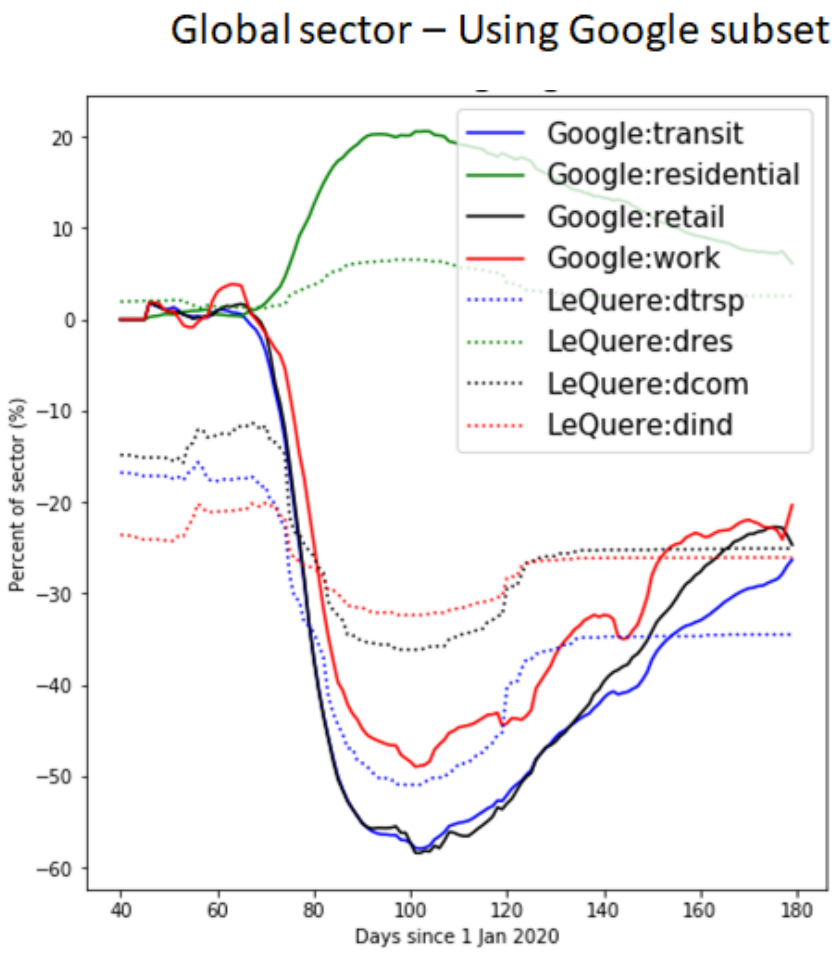


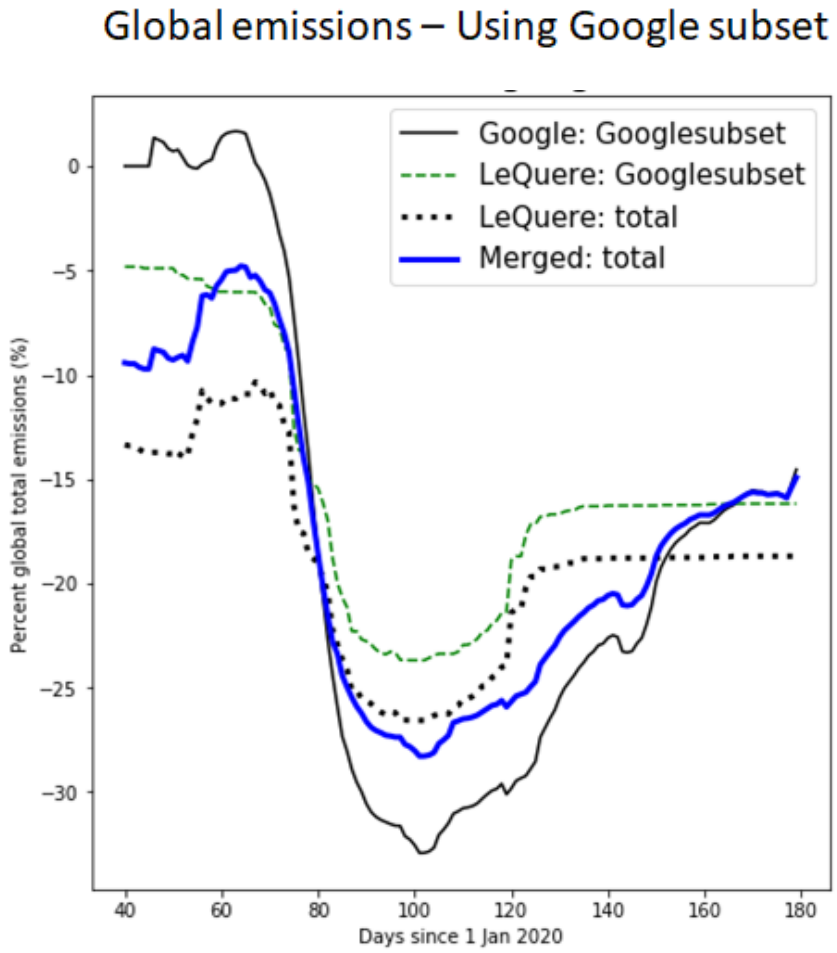


https://www.google.com/covid19/mobility/
https://www.apple.com/covid19/mobility

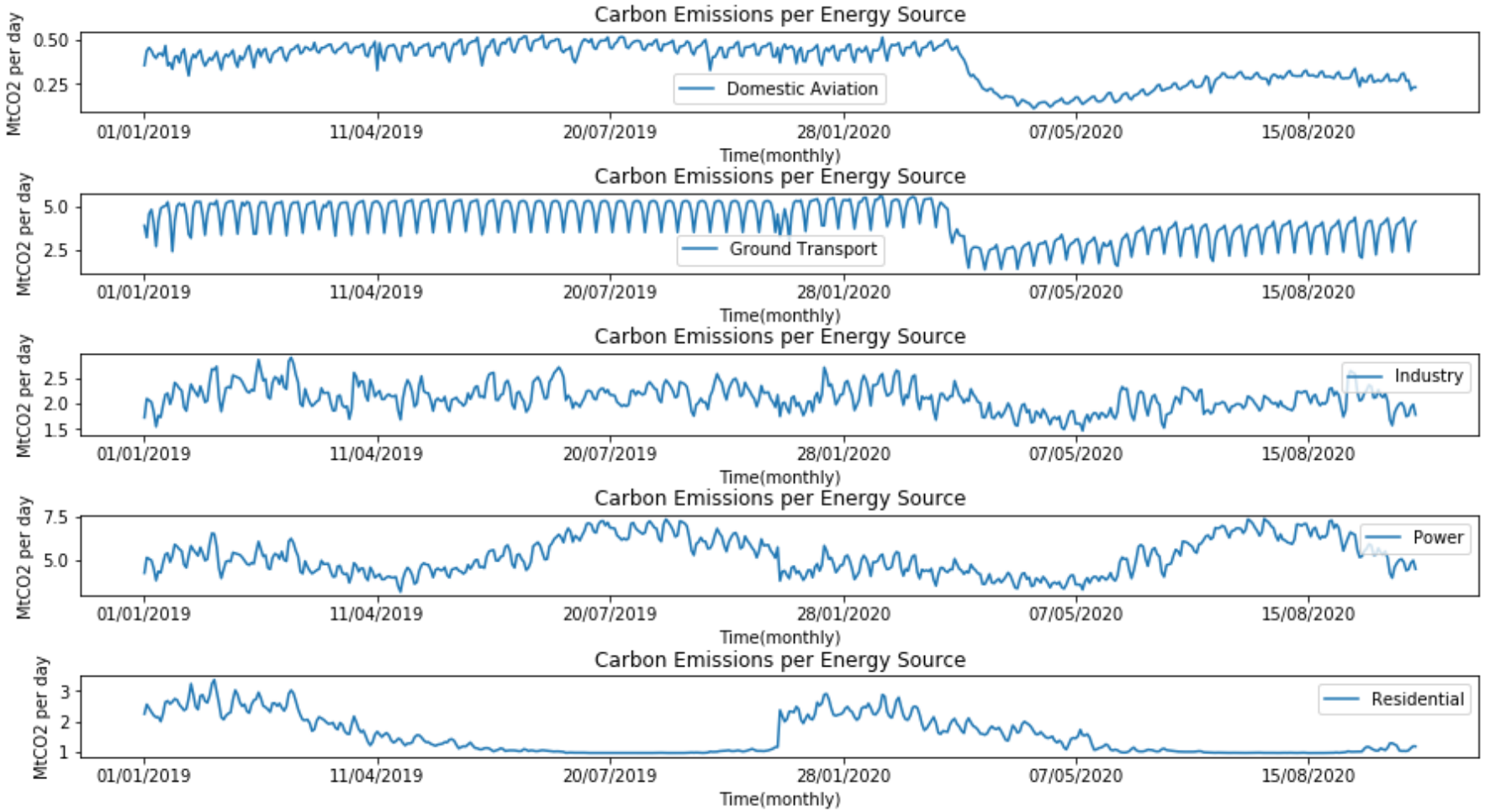
https://data.europa.eu/doi/10.2904/JRC_DATASET_EDGAR

Global averaged absolute emission change – CO2 emission

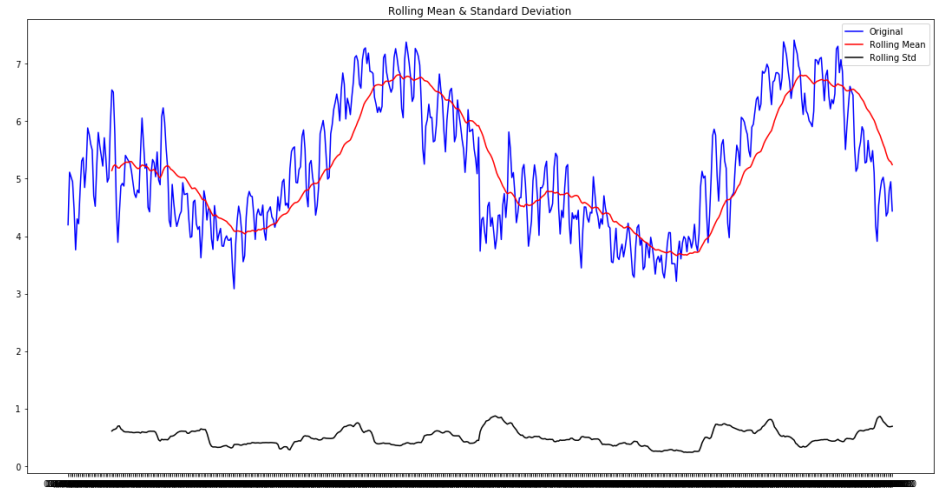


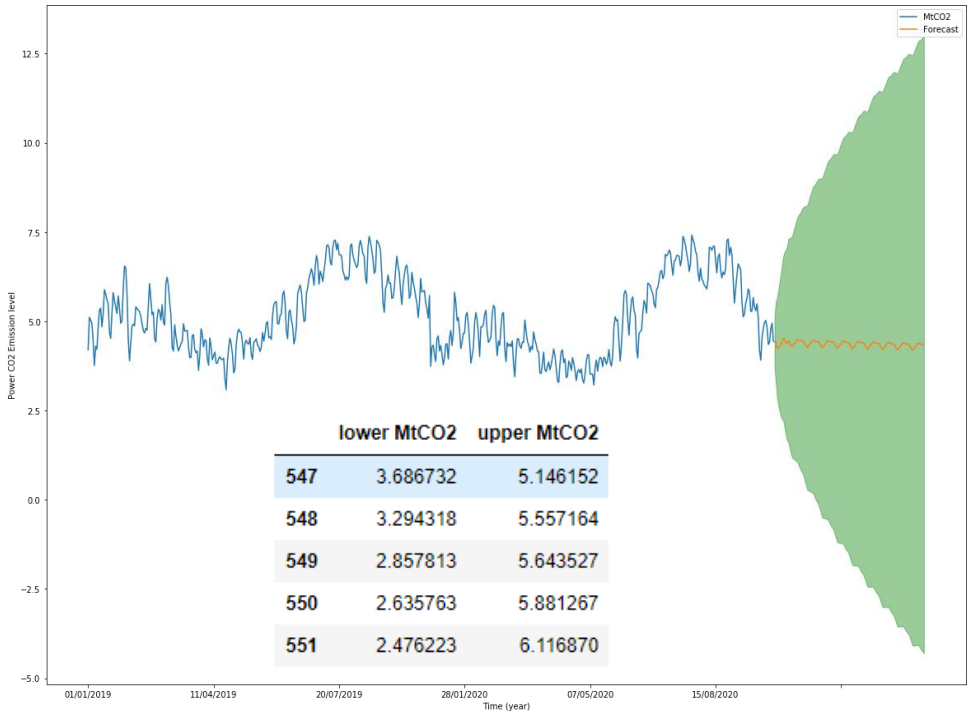


Time series – Case study

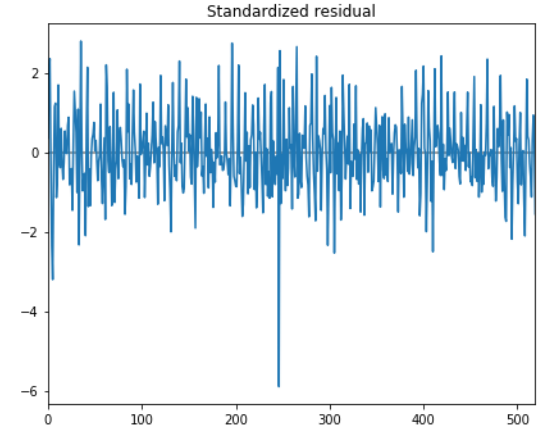


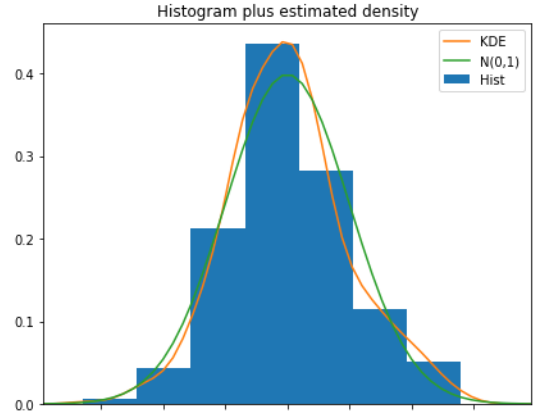
Transform the dataset to stationary

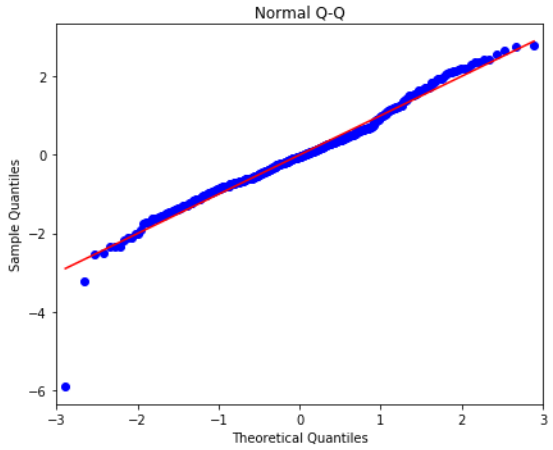


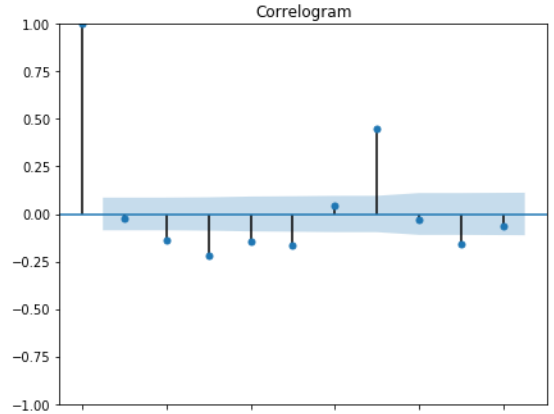


	lower MtCO2	upper MtCO2
547	3.686732	5.146152
548	3.294318	5.557164
549	2.857813	5.643527
550	2.635763	5.881267
551	2.476223	6.116870







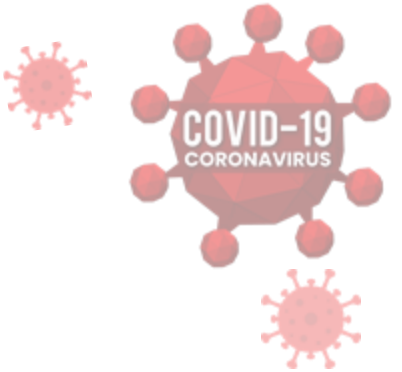


date	lower MtCO2	upper MtCO2
26/07/2020	5.671551	7.133506
27/07/2020	5.972886	7.434401
28/07/2020	6.793070	8.254573
29/07/2020	6.427583	7.889082
30/07/2020	6.504173	7.965671

SECOND-ORDER PSYCHOLOGICAL IMPACTS OF COVID-19

anxiety/depression rate data

Psychological Impacts - Overview



- Data contains anxiety/depression incidence amongst US citizens over the year 2020
- Psychological effects, unemployment, bankruptcy, etc. are examples of second-order implications of the COVID-19 pandemic
- Observe anxiety/depression trends over time among different subgroups of the US population
- Compare the trends of unemployment to the trends of anxiety/depression in the US

The Data

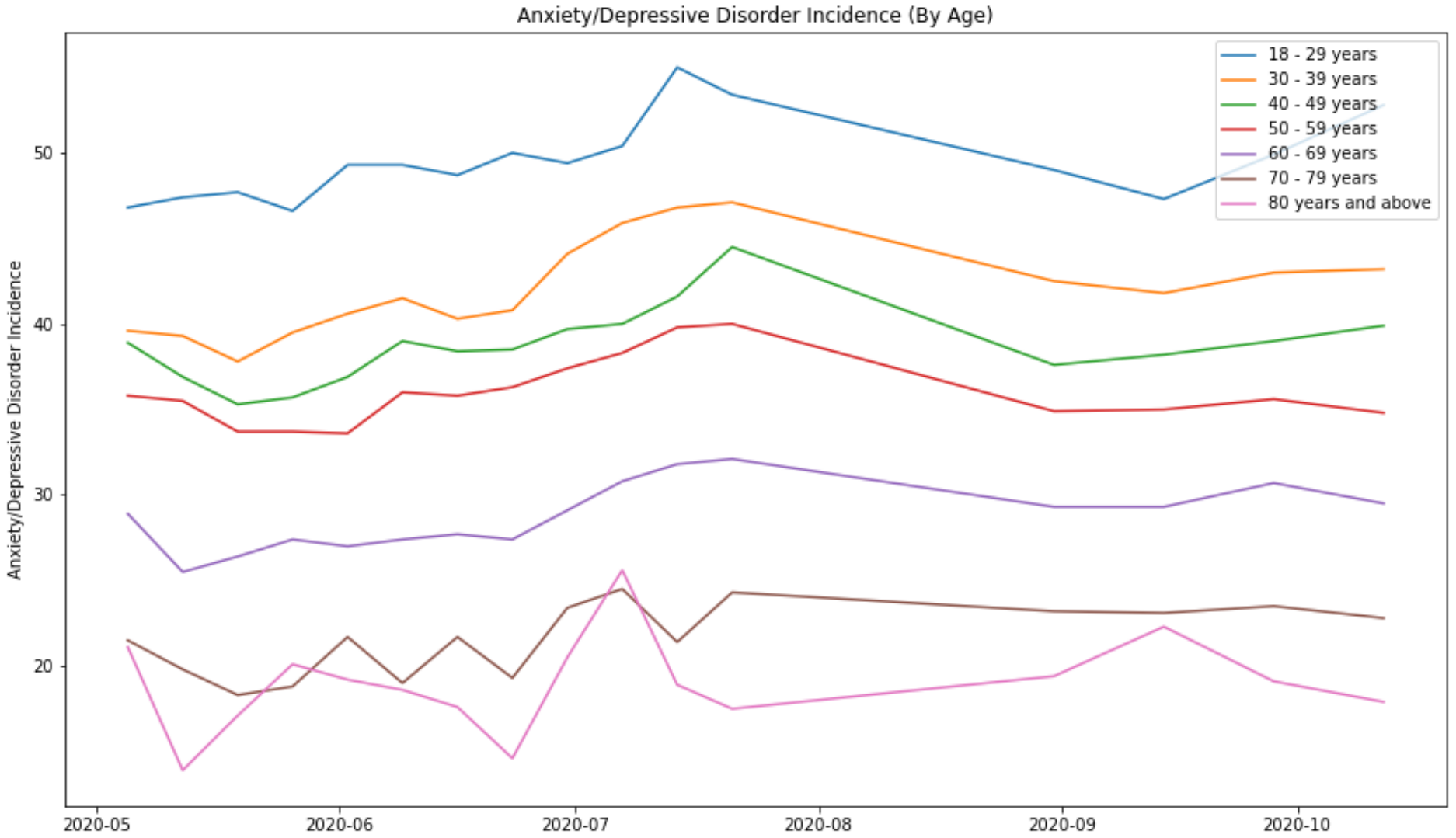
- CDC dataset outlining the indicators of an and depression amongst different subgrou of the US population
  - *Age*
  - *Education*
  - *Gender*
  - *Ethnicity*
  - *State*

	Phase	Indicator	Group	State	Subgroup	Time Period	Time Period Label	Value
0	1	Symptoms of Depressive Disorder	By State	United States	United States	1	Apr 23 - May 5	23.5
1	1	Symptoms of Depressive Disorder	By Age	United States	18 - 29 years	1	Apr 23 - May 5	32.7

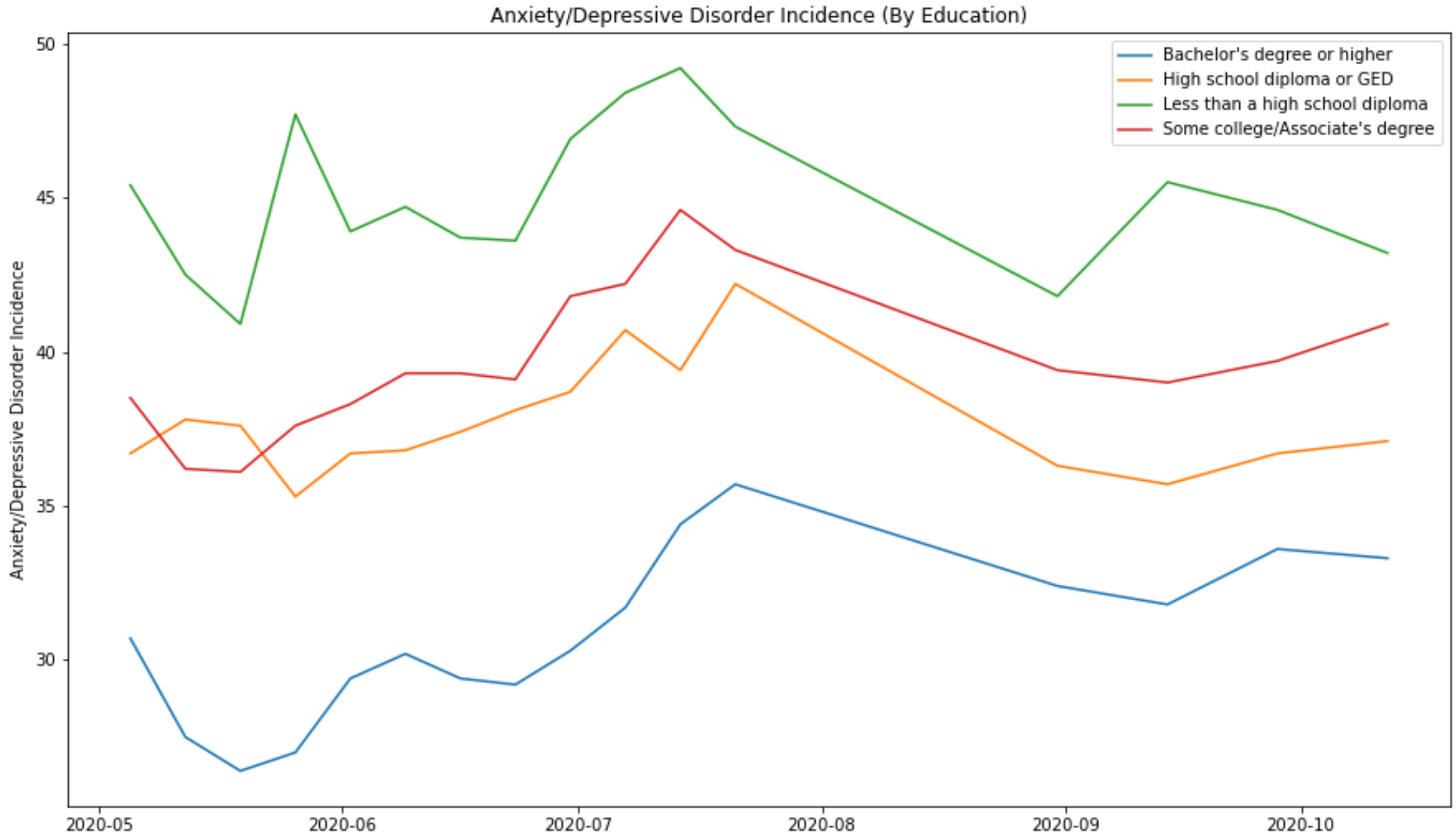
- Federal Monthly Unemployment Rate dataset from 1948 to October 2020

	DATE	UNRATE
0	1948-01-01	3.4
1	1948-02-01	3.8

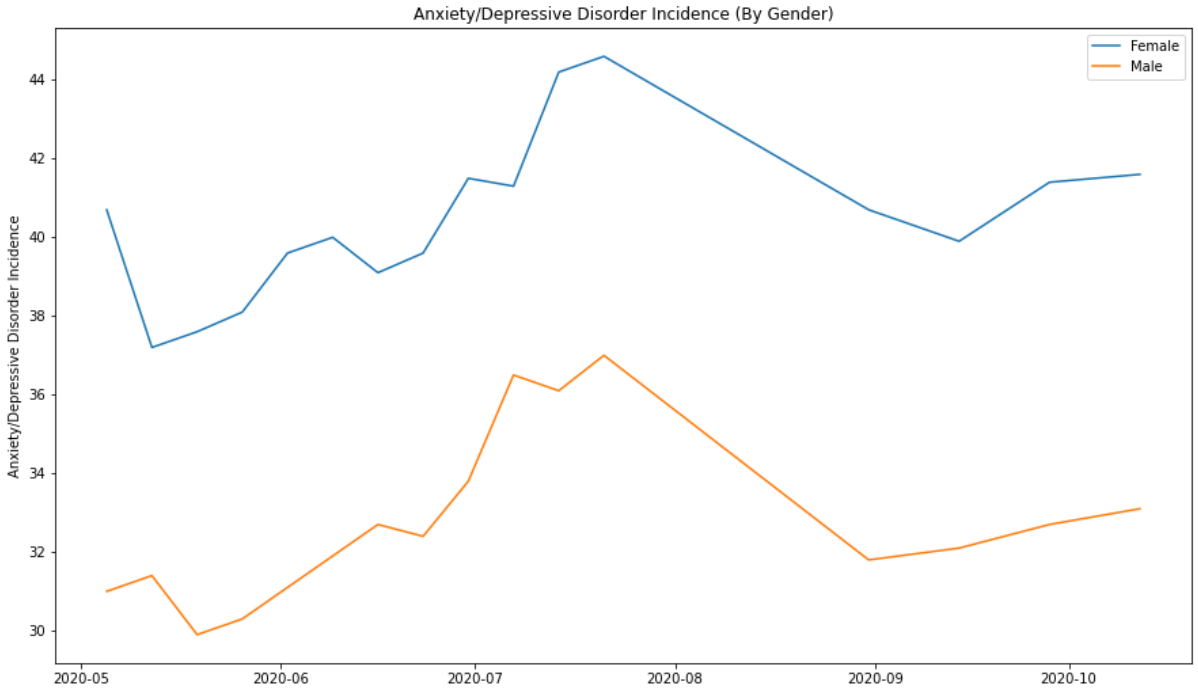
Depression/Anxiety by Age



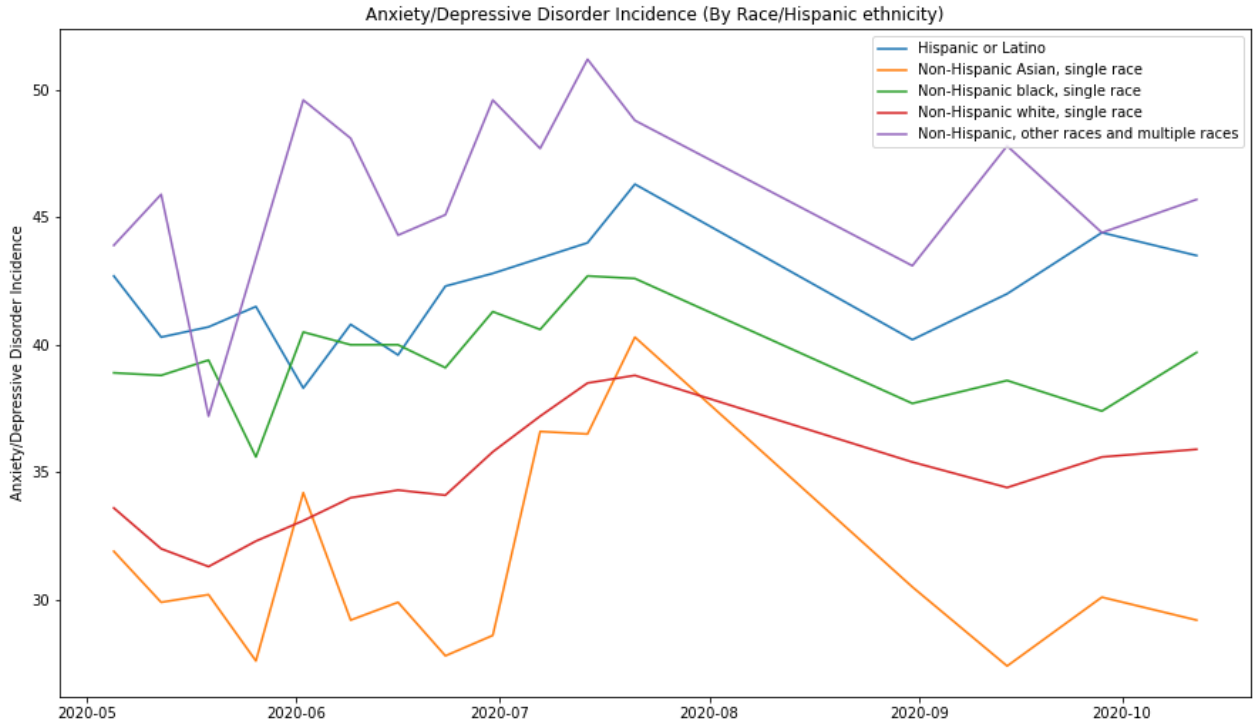
Depression/Anxiety by Education



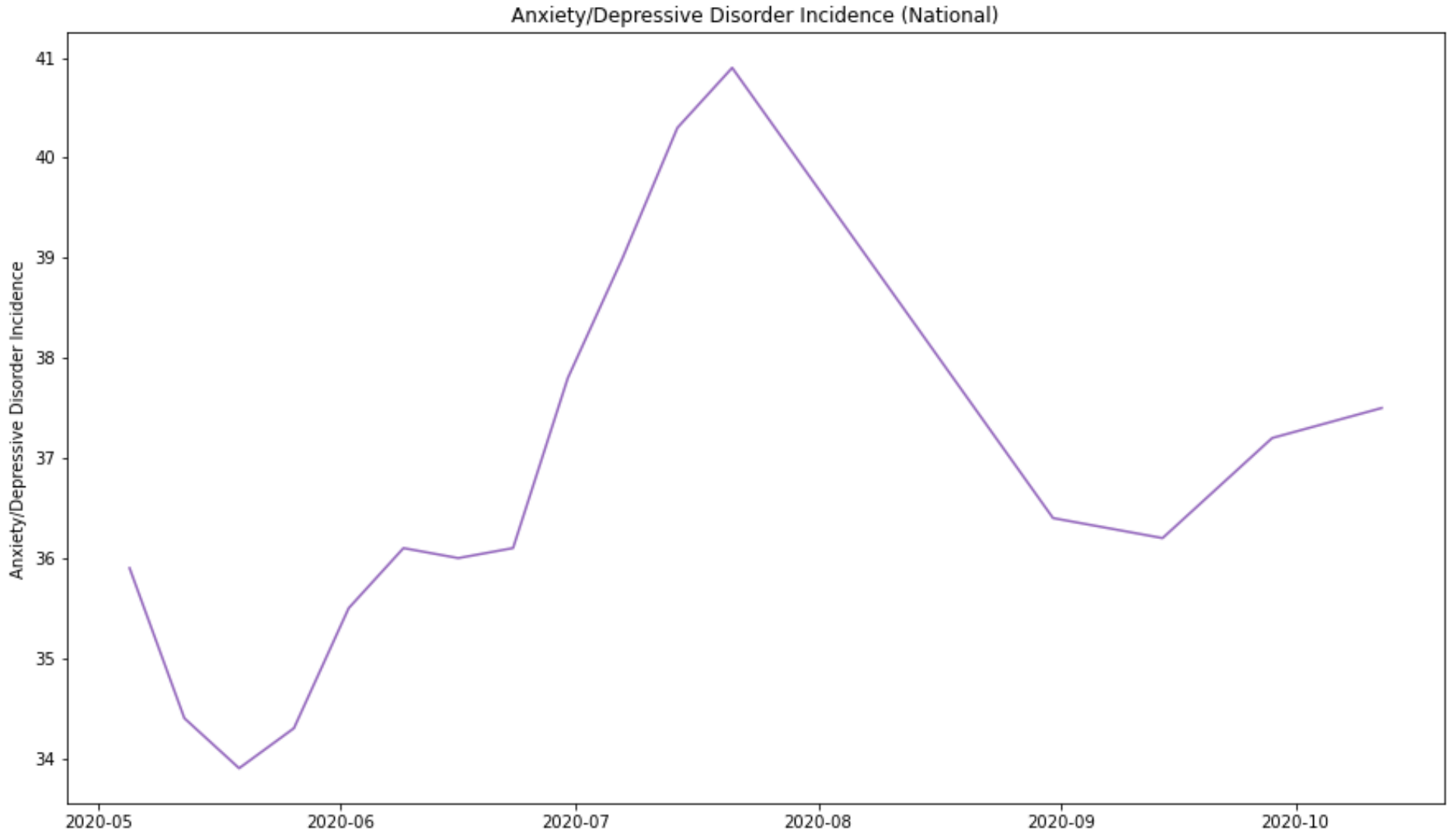
Depression/Anxiety by Gender



Depression/Anxiety by Race/Ethnicity

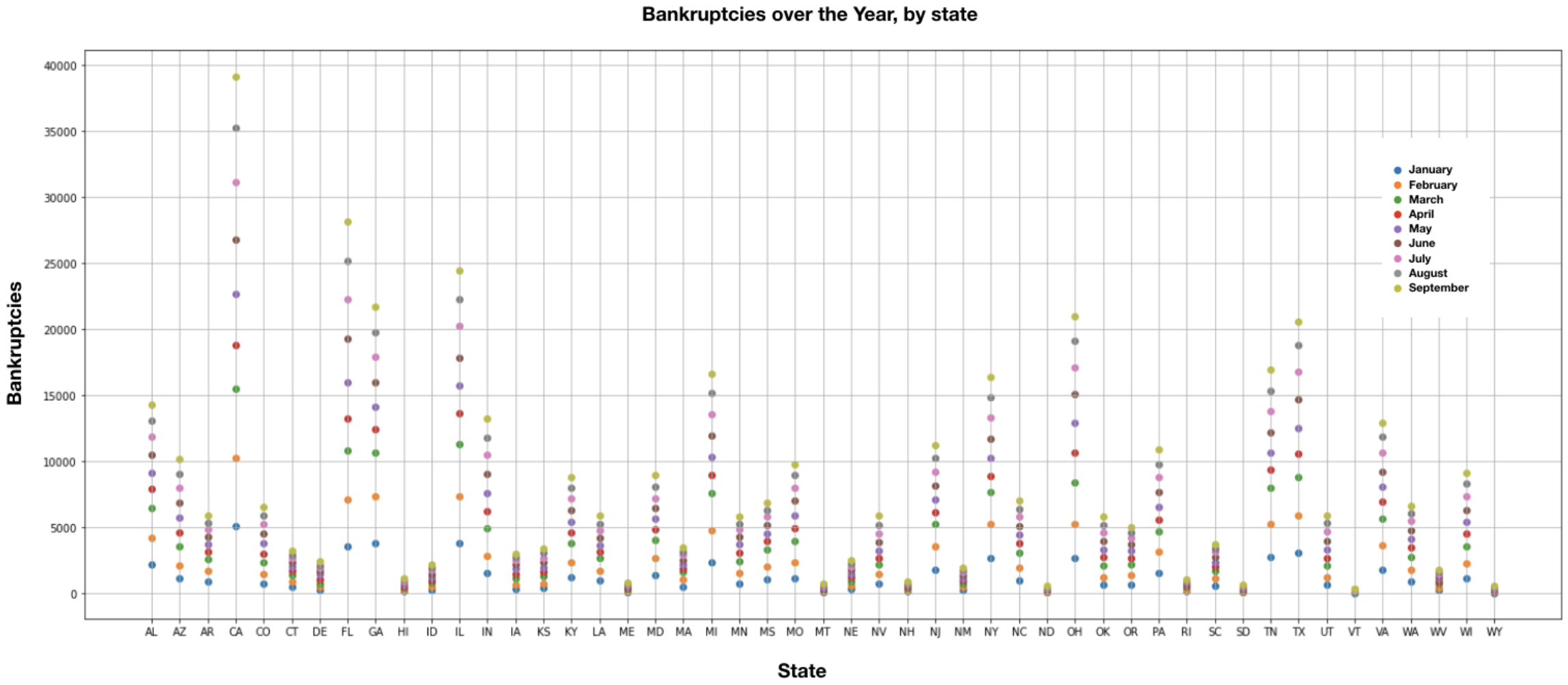


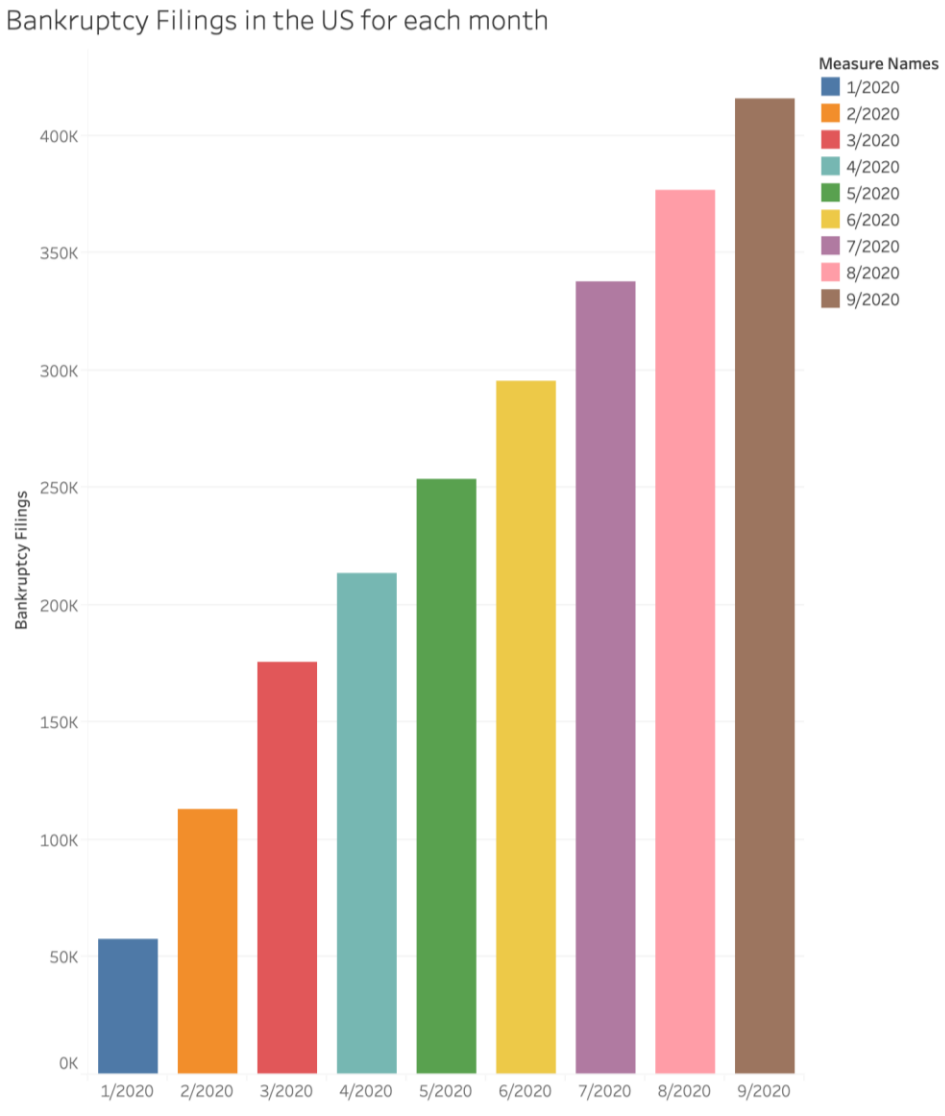
Depression/Anxiety - National

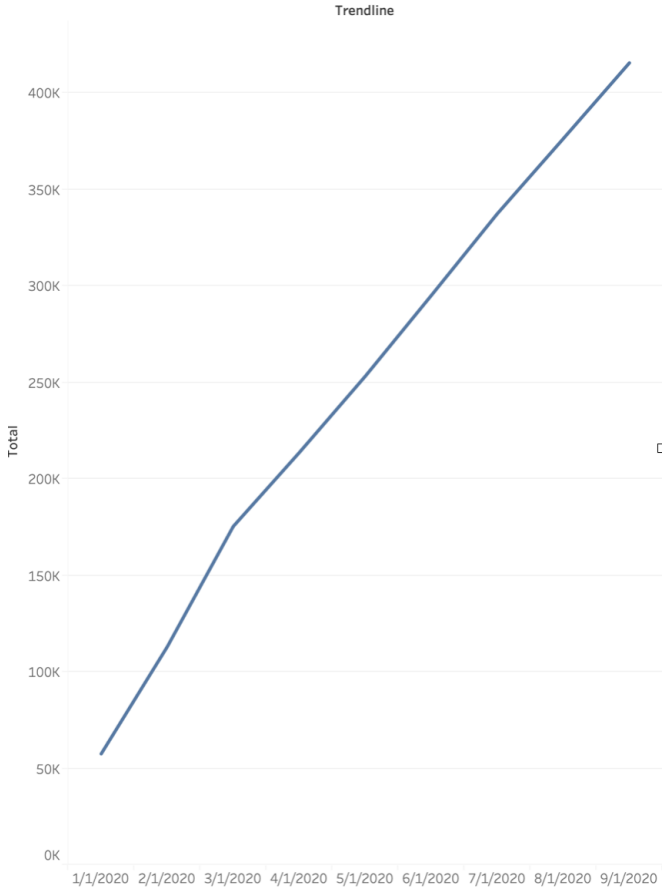


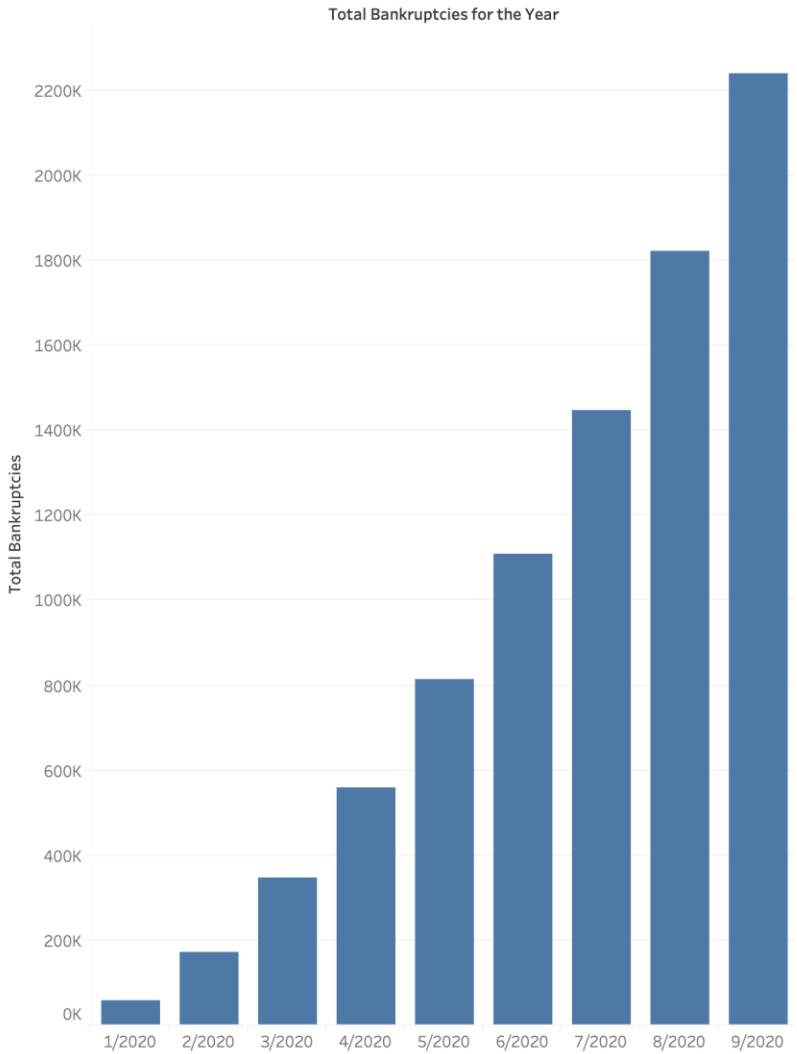
Comparing Unemployment Trends

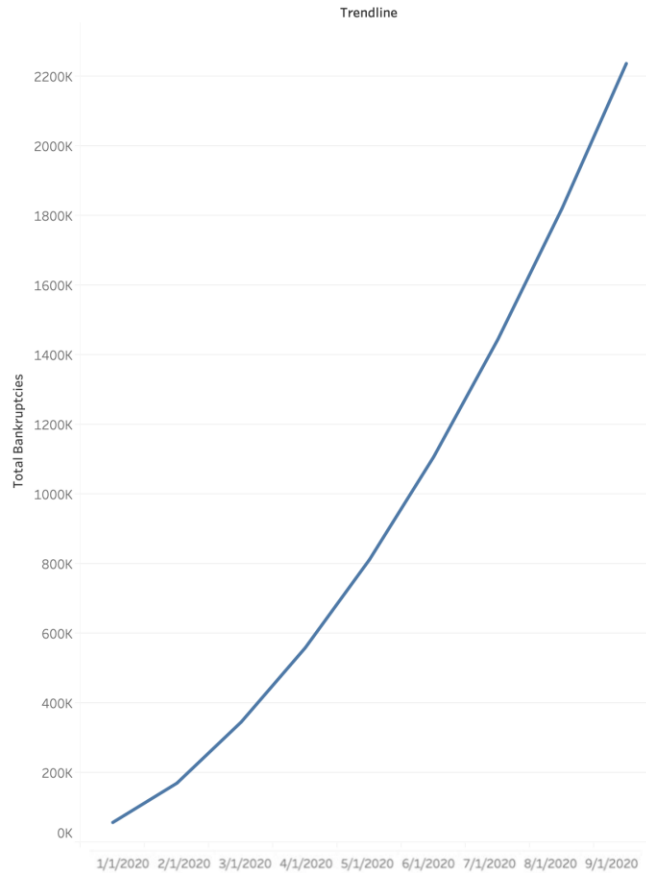
CORRELATION BETWEEN COVID AND BANKRUPTCIES


Bankruptcies over the Year, by state
Bankruptcies
State
40000
35000
30000
25000
20000
15000
10000
5000
0
AL AZ AR CA CO CT DE FL GA HI ID IL IN IA KS KY LA ME MD MA MI MN MS MO MT NE NV NH NJ NM NY NC ND OH OK OR PA RI SC SD TN TX UT VT VA WA WV WI WY
January
February
March
April
May
June
July
August
September

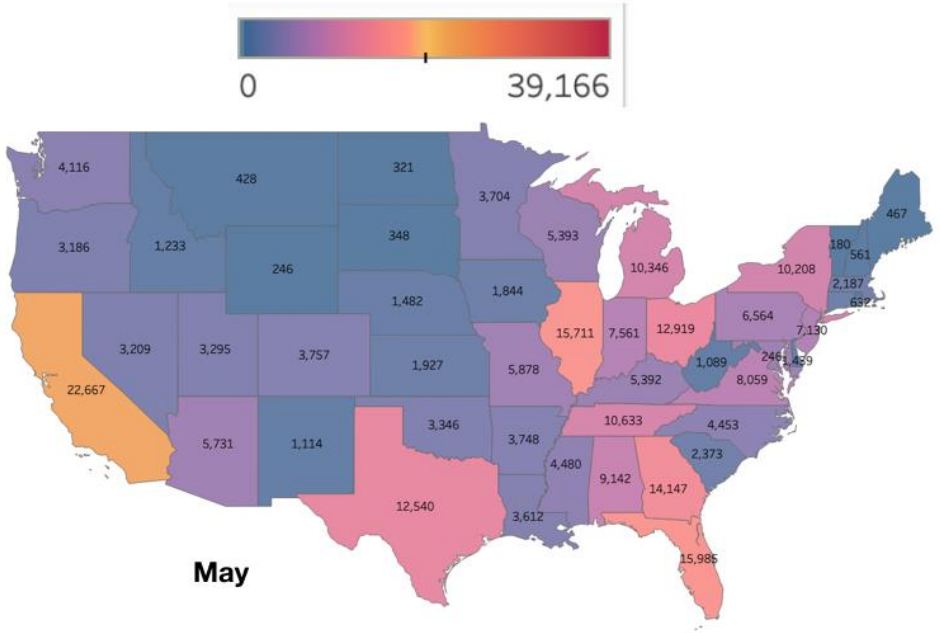

Bankruptcy Filings in the US for each month
Measure Names
1/2020
2/2020
3/2020
4/2020
5/2020
6/2020
7/2020
8/2020
9/2020
Bankruptcy Filings
400K
350K
300K
250K
200K
150K
100K
50K
0K
1/2020
2/2020
3/2020
4/2020
5/2020
6/2020
7/2020
8/2020
9/2020

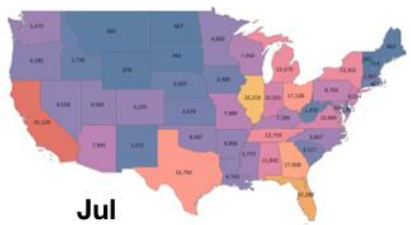

Trendline
Total
400K
350K
300K
250K
200K
150K
100K
50K
0K
1/1/2020
2/1/2020
3/1/2020
4/1/2020
5/1/2020
6/1/2020
7/1/2020
8/1/2020
9/1/2020


Total Bankruptcies for the Year
Total Bankruptcies
2200K
2000K
1800K
1600K
1400K
1200K
1000K
800K
600K
400K
200K
0K
1/2020
2/2020
3/2020
4/2020
5/2020
6/2020
7/2020
8/2020
9/2020

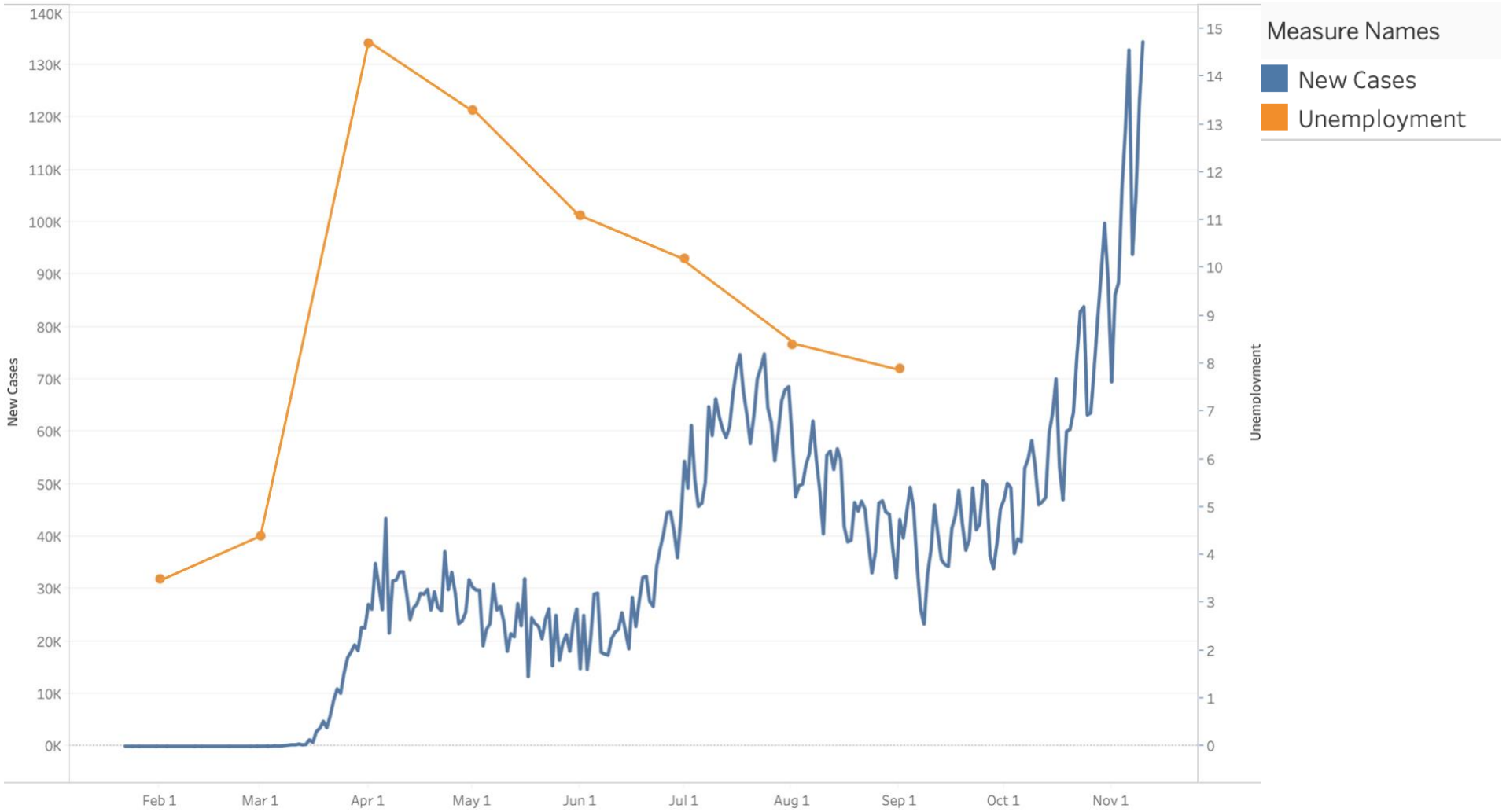

Trendline
Total Bankruptcies
2200K
2000K
1800K
1600K
1400K
1200K
1000K
800K
600K
400K
200K
0K
1/1/2020
2/1/2020
3/1/2020
4/1/2020
5/1/2020
6/1/2020
7/1/2020
8/1/2020
9/1/2020

US Heat Map for Bankruptcy

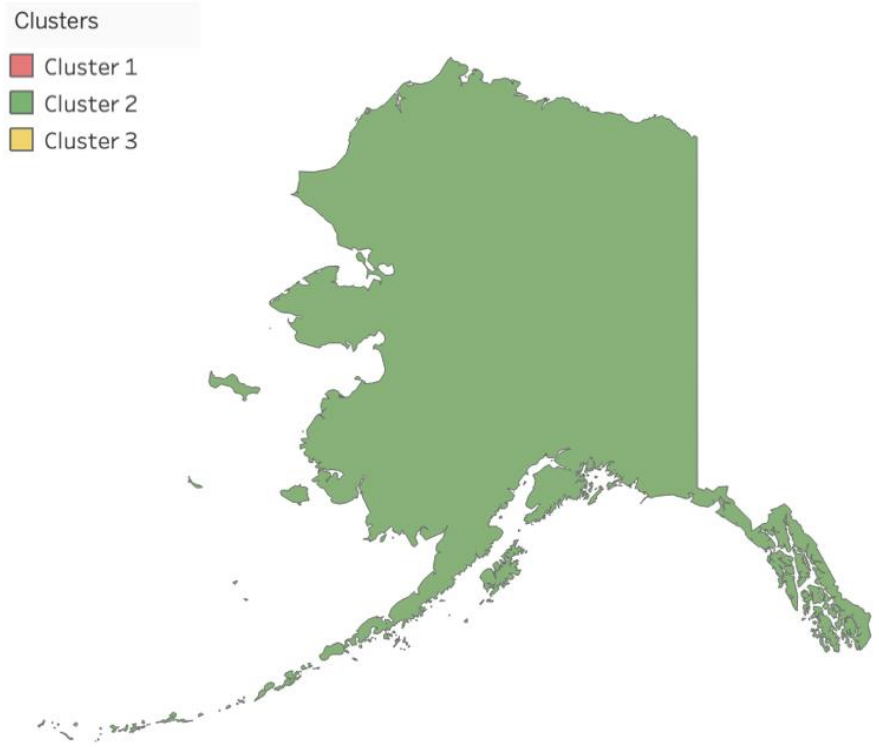




Unemployment VS. COVID Cases

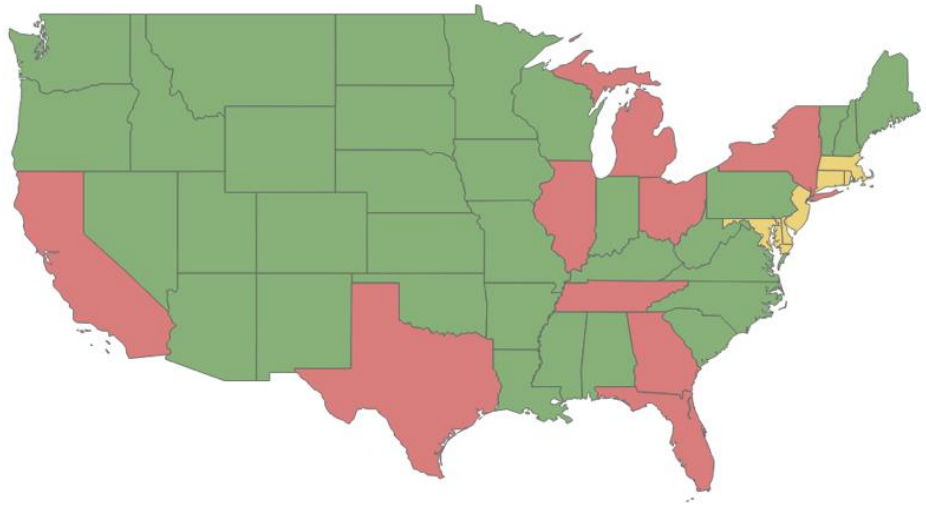


Analysis of Bankruptcy in Respect to Population, Density and Cost of Living

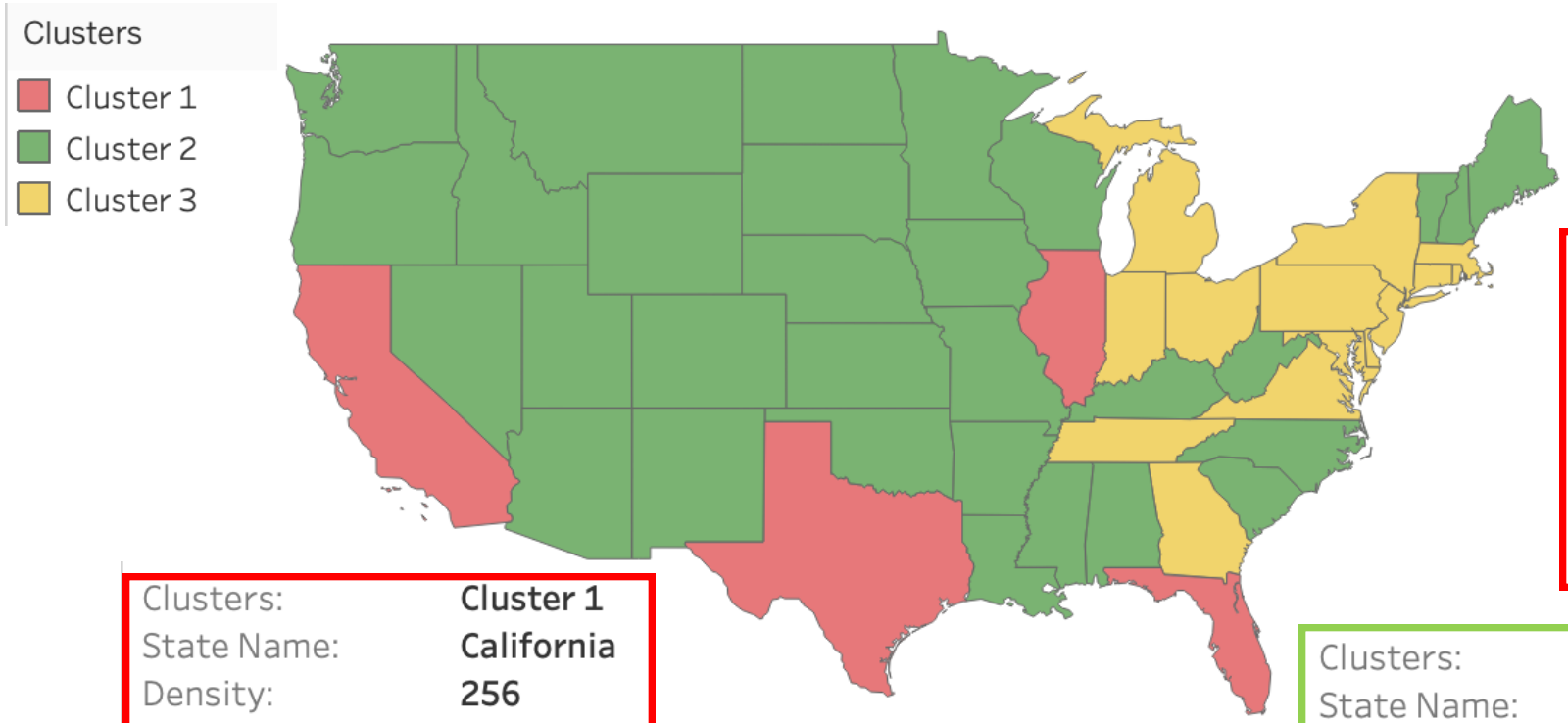


Analysis of Variance:

Variable	F-statistic	p-value	Model: Sum of Squares	Model: DF	Error: Sum of Squares	Error: DF
Sum of Density	17.36	2.265E-06	1.756	2	2.378	47
Sum of Total Bankruptcies	16.43	3.878E-06	1.644	2	2.351	47
Sum of Index	8.074	0.0009676	0.523	2	1.522	47



Clustering with COVID Cases



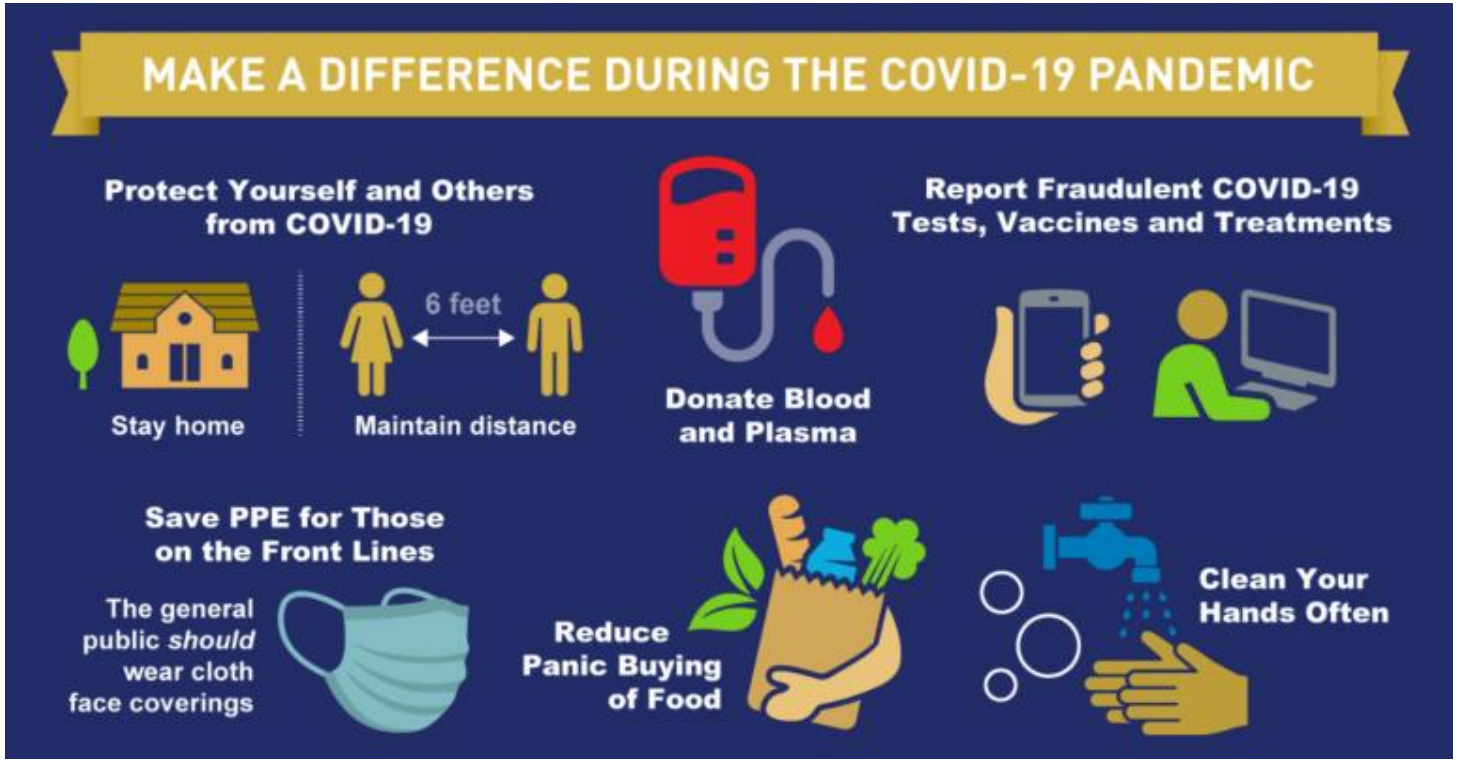
Clusters:	Cluster 3
State Name:	New York
Density:	413
Index:	133.7
Population:	19,440,500
Total Cases:	275,952
Total Bankruptcies:	90,892

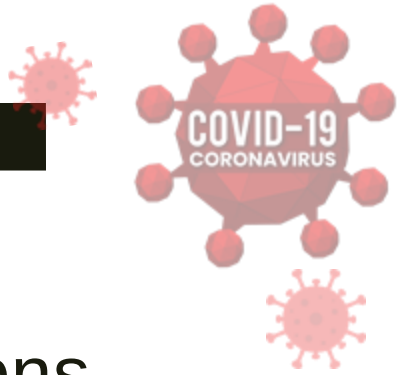
Clusters:	Cluster 1
State Name:	Illinois
Density:	228
Index:	95.8
Population:	12,659,700
Total Cases:	562,985
Total Bankruptcies:	136,586

Clusters:	Cluster 1
State Name:	California
Density:	256
Index:	138.5
Population:	39,937,500
Total Cases:	1,008,377
Total Bankruptcies:	204,541

Clusters:	Cluster 1
State Name:	Texas
Density:	113
Index:	92.3
Population:	29,472,300
Total Cases:	1,014,160
Total Bankruptcies:	111,675

Clusters:	Cluster 2
State Name:	Kansas
Density:	36
Index:	87.9
Population:	2,910,360
Total Cases:	115,507
Total Bankruptcies:	17,367





Conclusions

- There is not just one cause for the growth of the pandemic
- The pandemic has had lasting effects on everyone

THANK YOU!

QUESTIONS?