COVID-19 Case Study

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Due before midnight, Feb 26

Contents

1 Background

The outbreak of the novel Corona virus disease 2019 (COVID-19) was declared a public health emergency of international concern by the World Health Organization (WHO) on January 30, 2020. Upwards of 755 million cases have been confirmed worldwide, with nearly 6.8 million associated deaths by Feb of 2023. Within the US alone, there have been over 1.1 million deaths and upwards of 102 million cases reported by Feb of 2023. Governments around the world have implemented and suggested a number of policies to lessen the spread of the pandemic, including mask-wearing requirements, travel restrictions, business and school closures, and even stay-at-home orders. The global pandemic has impacted the lives of individuals in countless ways, and though many countries have begun vaccinating individuals, the long-term impact of the virus remains unclear.

The impact of COVID-19 on a given segment of the population appears to vary drastically based on the socioeconomic characteristics of the segment. In particular, differing rates of infection and fatalities have been reported among different racial groups, age groups, and socioeconomic groups. One of the most important metrics for determining the impact of the pandemic is the death rate, which is the proportion of people within the total population that die due to the the disease.

We assemble this dataset for our research with the goal to investigate the effectiveness of lockdown on flattening the COVID curve. We provide a portion of the cleaned dataset for this case study.

There are two main goals for this case study.

1. We show the dynamic evolvement of COVID cases and COVID-related death at state level.
2. We try to figure out what county-level demographic and policy interventions are associated with mortality rate in the US. We try to construct models to find possible factors related to county-level COVID-19 mortality rates.
3. This is a rather complex project. With our team's help we have made your job easier.
4. Hide all unnecessary lengthy R-output. Keep your write up neat, readable.

Remark1: The data and the statistics reported here were collected before February of 2021.

Remark 2: A group of RAs spent tremendous amount of time working together to assemble the data. It requires data wrangling skills.

Remark 3: Please keep track with the most updated version of this write-up.

2 Data Summary

The data comes from several different sources:

1. County-level infection and fatality data - This dataset gives daily cumulative numbers on infection and fatality for each county.
    - NYC data
2. County-level socioeconomic data - The following are the four relevant datasets from this site.
    i. Income - Poverty level and household income.
    ii. Jobs - Employment type, rate, and change.
    iii. People - Population size, density, education level, race, age, household size, and migration rates.
    iv. County Classifications - Type of county (rural or urban on a rural-urban continuum scale).
3. Intervention Policy Data - This dataset is a manually compiled list of the dates that interventions/lockdown policies were implemented and lifted at the county level.

3 EDA

In this case study, we use the following three nearly cleaned data:

- **covid_county.csv**: County-level socialeconomic information that combines the above-mentioned 4 datasets: Income (Poverty level and household income), Jobs (Employment type, rate, and change), People (Population size, density, education level, race, age, household size, and migration rates), County Classifications
- **covid_rates.csv**: Daily cumulative numbers on infection and fatality for each county
- **covid_intervention.csv**: County-level lockdown intervention.

Among all data, the unique identifier of county is `FIPS`.

The cleaning procedure is attached in `Appendix 2: Data cleaning` You may go through it if you are interested or would like to make any changes.

It may need more data wrangling.

First read in the data.

3.1 Understand the data

The detailed description of variables is in `Appendix 1: Data description`. Please get familiar with the variables. Summarize the two data briefly.

The dataframe "county_data" contains socioeconomic demographic information, in different years, of each of the 3278 counties in the United States, which includes the counties among the 50 states and those in Puerto Rico. The dataframe "covid_rate" contains cumulative statistics for COVID cases and deaths across 397 days (start date: 2020-01-21, end date: 2021-02-20) among the counties.

3.2 COVID case trend

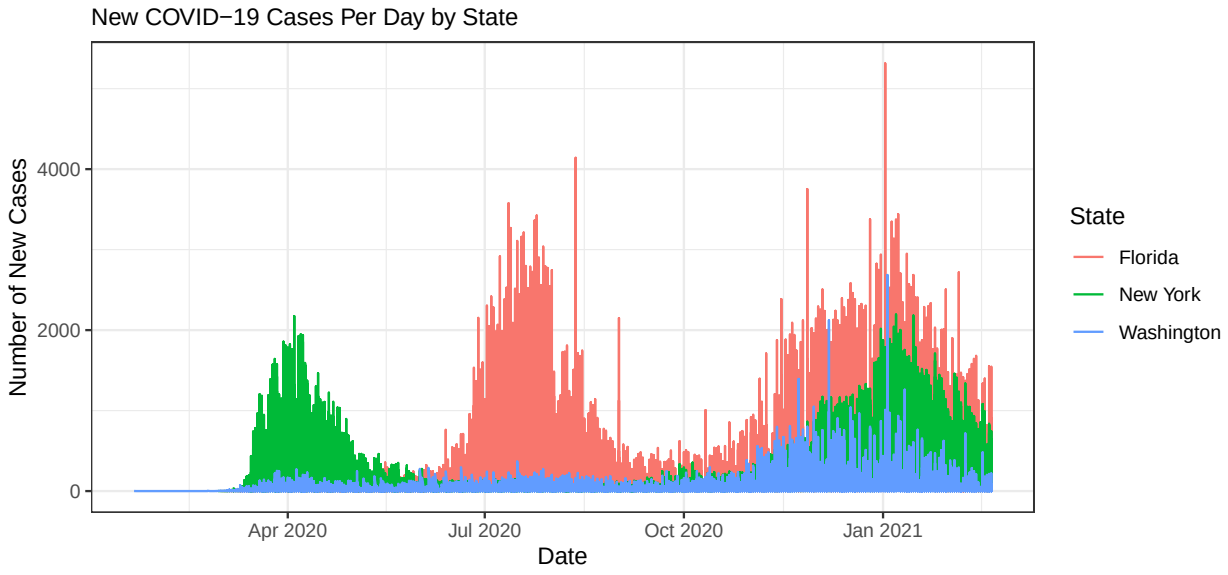
It is crucial to decide the right granularity for visualization and analysis. We will compare daily vs weekly total new cases by state and we will see it is hard to interpret daily report.

i) Plot **new** COVID cases in NY, WA and FL by state and by day. Any irregular pattern? What is the biggest problem of using single day data? **As we can see in Figure 1, it is nearly impossible to interpret more than a year's worth of data using daily values because there are too many data points. Although we can see slight variations in "clumps" of higher daily rates versus lower daily rates, overall it is not feasible to interpret data at this granularity. We can also see a few apparent outliers, but it is challenging to draw any meaningful conclusions. Additionally, without controlling for the population size of the state, we can't be sure whether the number of new cases is large or small relative to the population.**

On a more practical note, COVID testing result release practices varied by county which could bias any daily-level results. For example, while most counties collected and processed COVID tests 7 days a week, aggregated results were often only released on business days. This resulted in apparent population-level spikes in new cases on Mondays, when in reality this was due to the fact that test results from Saturday, Sunday, and Monday were all released on Monday.

```r
#Subset full COVID data to NY, WA, and FL only
covid_subset <- covid_rate %>% filter(State == "New York" | State == "Washington" | State == "Florida")

#Create new variable so that cumulative cases never decreases
#Create new variable to indicate new cases by day
covid_subset <- covid_subset %>%
  arrange(State, County, date) %>%
  group_by(State, County) %>%
  mutate(cum_interim = ifelse(row_number() == 1, cum_cases, ifelse(cum_cases < lag(cum_cases), lag(cum_
  mutate(cum_no_dec = ifelse(row_number() == 1, cum_interim, ifelse(cum_cases < lag(cum_interim), lag(cu

covid_subset <- covid_subset %>%
  arrange(State, County, date) %>%
  group_by(State, County) %>%
  mutate(new_cases = ifelse(row_number() == 1, cum_no_dec, cum_no_dec-lag(cum_no_dec))) %>%
  mutate(new_cases = ifelse(new_cases < 0, 0, new_cases))

#Creating plot by state
incidence_daily <- ggplot(covid_subset, aes(x=date, y=new_cases, color=State)) +
  geom_line() +
  labs(title = "Figure 1: ", subtitle = "New COVID-19 Cases Per Day by State", x = "Date", y = "Number
  theme_bw()
incidence_daily
```

Figure 1:



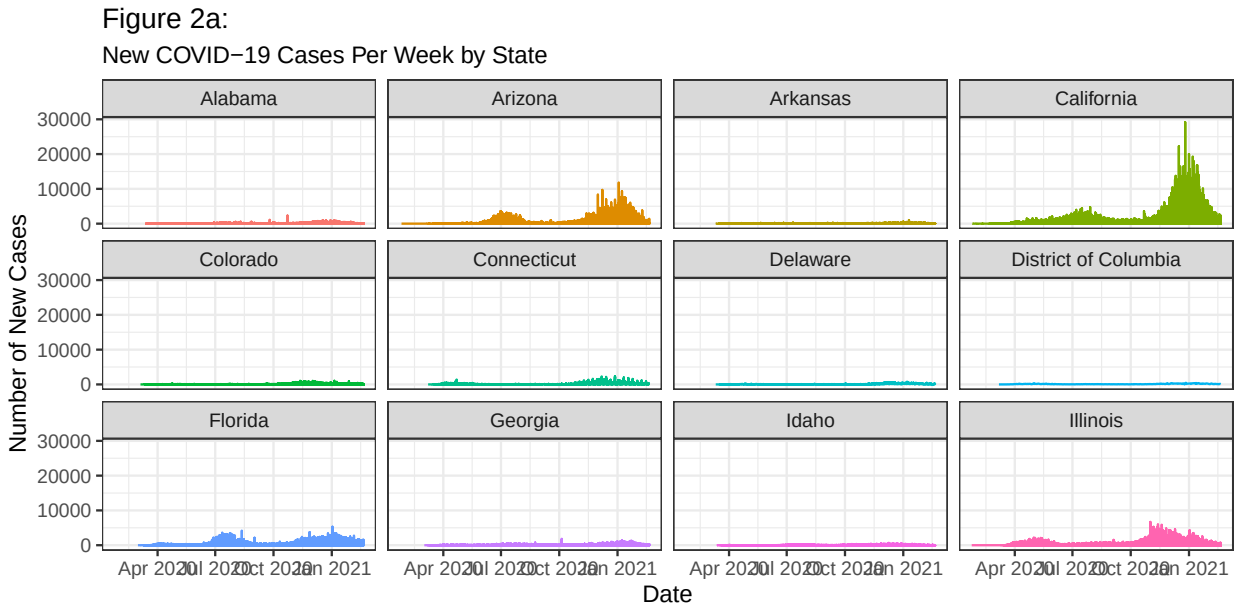
ii) Create **weekly new** cases per 100k `weekly_case_per100k`. Plot the spaghetti plots of `weekly_case_per100k` by state. Use `TotalPopEst2019` as population.

```r
#Repeating above using full COVID dataset
covid_rate <- covid_rate %>%
  arrange(State, County, date) %>%
  group_by(State, County) %>%
  mutate(cum_interim = ifelse(row_number() == 1, cum_cases, ifelse(cum_cases < lag(cum_cases), lag(cum_
```

```
  mutate(cum_no_dec = ifelse(row_number() == 1, cum_interim, ifelse(cum_cases < lag(cum_interim), lag(cu

covid_rate <- covid_rate %>%
  arrange(State, County, date) %>%
  group_by(State, County) %>%
  mutate(new_cases = ifelse(row_number() == 1, cum_no_dec, cum_no_dec-lag(cum_no_dec))) %>%
  mutate(new_cases = ifelse(new_cases < 0, 0, new_cases))

#Creating new variable for weekly cases/100k population
covid_rate <- covid_rate %>%
  arrange(State, County, date) %>%
  group_by(State, County, week) %>%
  mutate(weekly_case = sum(new_cases), pop_100k = TotalPopEst2019/100000, weekly_case_per100k = weekly_

table(covid_rate$State)
```

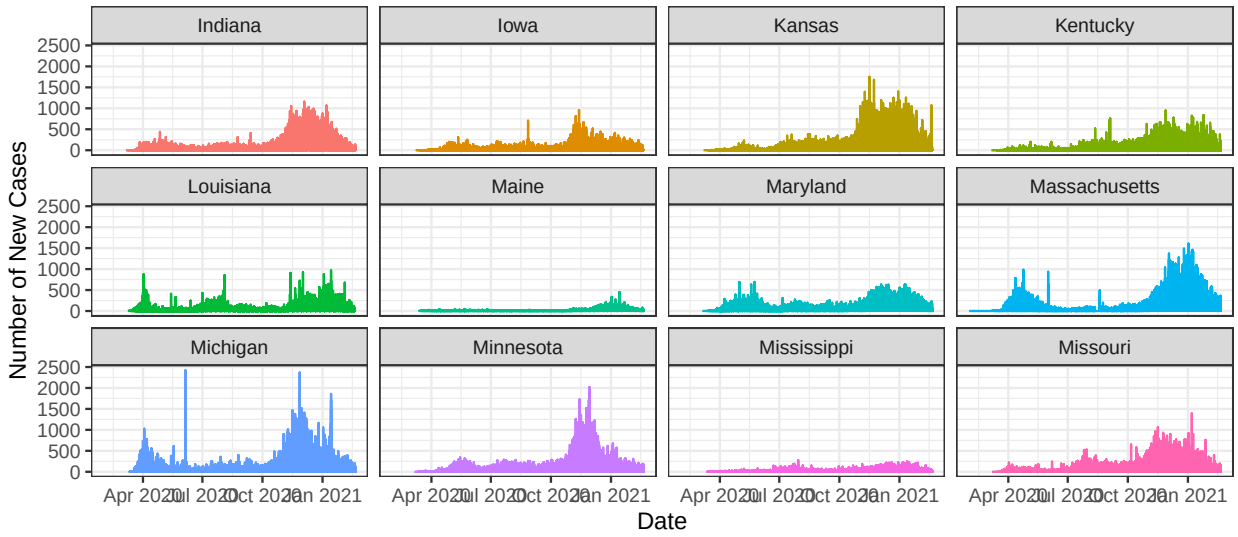
```
##
##              Alabama              Arizona             Arkansas
##                22363                 5130                24722
##           California             Colorado          Connecticut
##                19750                20855                 2740
##             Delaware District of Columbia              Florida
##                 1028                  351                22641
##              Georgia                Idaho             Illinois
##                53032                13504                33241
##              Indiana                 Iowa               Kansas
##                30757                32074                32113
##             Kentucky            Louisiana                Maine
##                38890                21508                 5346
##             Maryland        Massachusetts             Michigan
##                 8156                 4867                27323
##            Minnesota          Mississippi             Missouri
##                28215                27425                36684
##              Montana             Nebraska               Nevada
##                15622                27165                 5151
##        New Hampshire           New Jersey           New Mexico
##                 3407                 7237                10530
##             New York       North Carolina         North Dakota
##                21189                33108                16091
##                 Ohio             Oklahoma               Oregon
##                29326                24864                11685
##         Pennsylvania         Rhode Island       South Carolina
##                22490                 1665                15526
##         South Dakota            Tennessee                Texas
##                20045                31543                79955
##                 Utah              Vermont             Virginia
##                 9181                 4718                43638
##           Washington        West Virginia            Wisconsin
##                13280                17649                23674
##              Wyoming
##                 7530
```

```
incidence_weekly_1 <- ggplot(subset(covid_rate, State %in% c("Alabama", "Arizona", "Arkansas", "Californ
  geom_line() +
  labs(title = "Figure 2a: ", subtitle = "New COVID-19 Cases Per Week by State", x = "Date", y = "Numbe
  facet_wrap(~State) +
  theme_bw() +
  theme(legend.position = "none")

incidence_weekly_2 <- ggplot(subset(covid_rate, State %in% c("Indiana", "Iowa", "Kansas", "Kentucky", "
  geom_line() +
  labs(title = "Figure 2b: ", subtitle = "New COVID-19 Cases Per Week by State", x = "Date", y = "Numbe
  facet_wrap(~State) +
  theme_bw() +
  theme(legend.position = "none")

incidence_weekly_3 <- ggplot(subset(covid_rate, State %in% c("Montana", "Nebraska", "Nevada", "New Hamps
  geom_line() +
  labs(title = "Figure 2c: ", subtitle = "New COVID-19 Cases Per Week by State", x = "Date", y = "Numbe
  facet_wrap(~State) +
  theme_bw() +
  theme(legend.position = "none")

incidence_weekly_4 <- ggplot(subset(covid_rate, State %in% c("Pennsylvania", "Rhode Island", "South Car
  geom_line() +
  labs(title = "Figure 2d: ", subtitle = "New COVID-19 Cases Per Week by State", x = "Date", y = "Numbe
  facet_wrap(~State) +
  theme_bw() +
  theme(legend.position = "none")

incidence_weekly_1
```



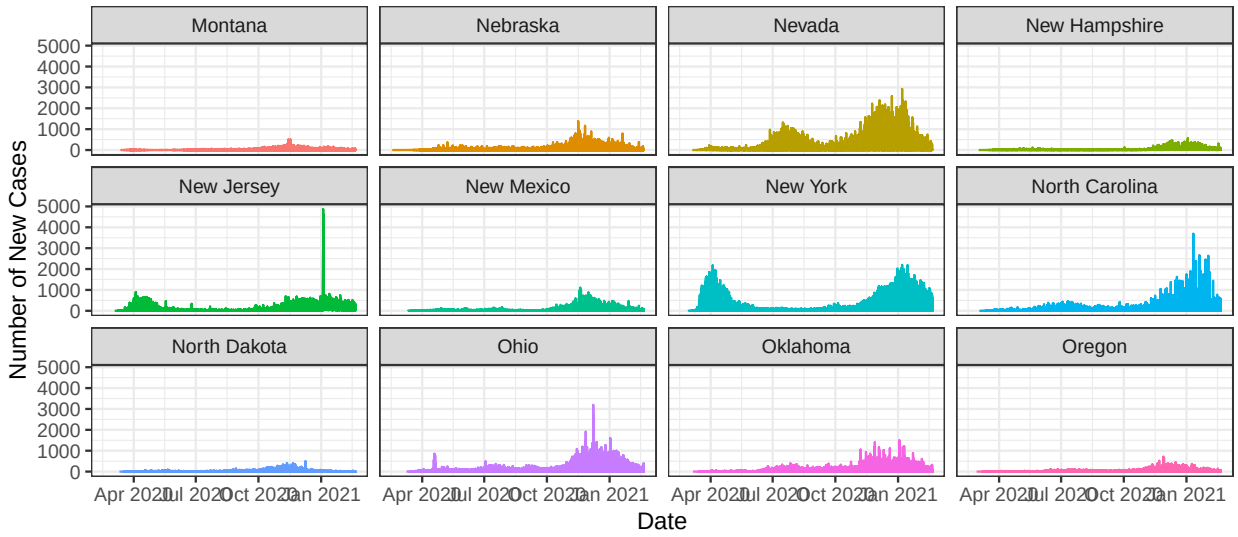

```
incidence_weekly_2
```

Figure 2b:



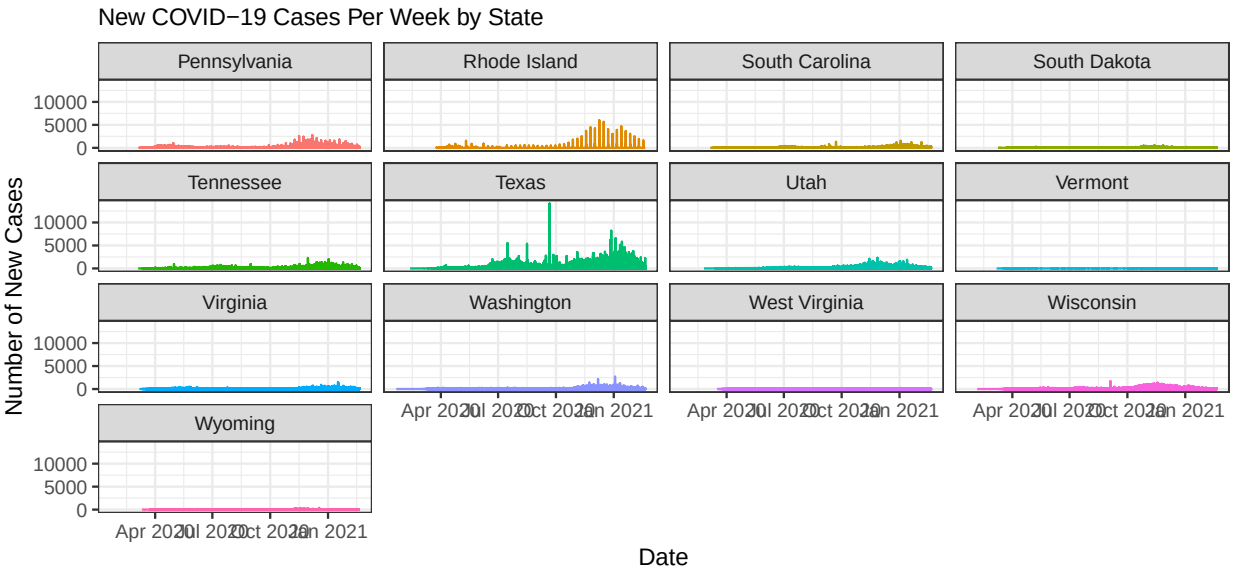

```
incidence_weekly_3
```

Figure 2c:




```
incidence_weekly_4
```

Figure 2d:



iii) Summarize the COVID case trend among states based on the plot in ii). What could be the possible reasons to explain the variabilities? **We can see in Figures 2a-2d that each state in the US experienced slightly different patterns regarding COVID-19 cases. One of the more noticeable differences is in the timing of case peaks. For example, New York appears to have one of the earliest peaks, perhaps driven by the high population density in New York City (NYC) and presence of three major international airports within NYC limits. In contrast, Pennsylvania's largest peak was not until closer to 2021. It is also evident that despite normalizing COVID-19 cases per 100k population, there are drastic differences in cases by state. It is likely that population density is a major driver of this difference; for example, California has a high number of weekly cases whereas Wyoming has a very low number of cases. Population density cannot explain all of the variation, however, as some states with relatively high density, such as Connecticut and Pennsylvania, have low numbers overall. It is possible that some differences are also driven by state- and county-level policies which restricted the flow of people and therefore the spread of COVID-19.**

iv) (Optional) Use `covid_intervention` to see whether the effectiveness of lockdown in flattening the curve.

3.3 COVID death trend

i) For each month in 2020, plot the monthly deaths per 100k heatmap by state on US map. Use the same color range across months. (Hints: Set `limits` argument in `scale_fill_gradient()` or use `facet_wrap()`; use `lubridate::month()` and `lubridate::year()` to extract month and year from date; use `tidyr::complete(state, month, fill = list(new_case_per100k = NA))` to complete the missing months with no cases.)

ii) (Optional) Use `plotly` to animate the monthly maps in i). Does it reveal any systematic way to capture the dynamic changes among states? (Hints: Follow *Appendix 3: Plotly heatmap::* in Module 6 regularization lecture to plot the heatmap using `plotly`. Use `frame` argument in `add_trace()` for animation. `plotly` only recognizes abbreviation of state names. Use `unique(us_map(regions = "states") %>% select(abbr, full))` to get the abbreviation and merge with the data to get state abbreviation.)

4 COVID factor

We now try to build a good parsimonious model to find possible factors related to death rate on county level. Let us not take time series into account for the moment and use the total number as of *Feb 1, 2021*.

i) Create the response variable `total_death_per100k` as the total of number of COVID deaths per 100k by *Feb 1, 2021*. We suggest to take log transformation as `log_total_death_per100k = log(total_death_per100k + 1)`. Merge `total_death_per100k` to `county_data` for the following analysis.

ii) Select possible variables in `county_data` as covariates. We provide `county_data_sub`, a subset variables from `county_data`, for you to get started. Please add any potential variables as you wish.

   a) Report missing values in your final subset of variables.

   b) In the following anaylsis, you may ignore the missing values.

```
#Merge sociodemographic data with COVID data
covid_rate <- covid_rate %>% rename(state_full = State)
names(covid_rate)
```

```
##  [1] "FIPS"                "date"                "County"
##  [4] "state_full"          "cum_cases"           "cum_deaths"
##  [7] "week"                "TotalPopEst2019"     "cum_interim"
## [10] "cum_no_dec"          "new_cases"           "weekly_case"
## [13] "pop_100k"            "weekly_case_per100k"
```

```
covid_county <- full_join(covid_rate, county_data, by = c("FIPS", "County"))


county_data_sub <- county_data %>%
  select(County, State, FIPS, Deep_Pov_All, PovertyAllAgesPct, PerCapitaInc, UnempRate2019, PctEmpFIRE,
```

iii) Use LASSO to choose a parsimonious model with all available sensible county-level information. **Force in State** in the process. Why we need to force in State? You may use `lambda.1se` to choose a smaller model.

iv) Use `Cp` or BIC to fine tune the LASSO model from iii). Again **force in State** in the process. (You could do backward elimination to avoid using `Cp` or BIC)

v) If necessary, reduce the model from iv) to a final model with all variables being significant at 0.05 level. Are the linear model assumptions all reasonably met?

vi) It has been shown that COVID affects elderly the most. It is also claimed that the COVID death rate among African Americans and Latinos is higher. Does your analysis support these arguments?

vii) Based on your final model, summarize your findings. In particular, summarize the state effect controlling for others. Provide intervention recommendations to policy makers to reduce COVID death rate.

viii) What else can we do to improve our model? What other important information we may have missed?

ix) (Optional) Would your findings be very different if you had refined the data in some way or imputed the missing values in part ii). Check PCA lecture, section 10 for imputations via `softImpute`.

5 Executive summary

Please summarize this project as follows (no more than one page):

- Goal of the study
- Data
  - Source and a brief description of the data
  - How do you assemble them together (mostly done by our team but you may present them as if you have done so)
- Analyses
- Methods used
- Findings
- Limitations

6 Appendix 1: Data description

A detailed summary of the variables in each data set follows:

6.1 Infection and fatality data

- date: Date
- county: County name
- state: State name
- fips: County code that uniquely identifies a county
- cases: Number of cumulative COVID-19 infections
- deaths: Number of cumulative COVID-19 deaths

6.2 Socioeconomic demographics

Income: Poverty level and household income

- PovertyUnder18Pct: Poverty rate for children age 0-17, 2018
- Deep_Pov_All: Deep poverty, 2014-18
- Deep_Pov_Children: Deep poverty for children, 2014-18
- PovertyAllAgesPct: Poverty rate, 2018
- MedHHInc: Median household income, 2018 (In 2018 dollars)
- PerCapitaInc: Per capita income in the past 12 months (In 2018 inflation adjusted dollars), 2014-18
- PovertyAllAgesNum: Number of people of all ages in poverty, 2018
- PovertyUnder18Num: Number of people age 0-17 in poverty, 2018

Jobs: Employment type, rate, and change

- UnempRate2007-2019: Unemployment rate, 2007-2019
- NumEmployed2007-2019: Employed, 2007-2019
- NumUnemployed2007-2019: Unemployed, 2007-2019
- PctEmpChange1019: Percent employment change, 2010-19
- PctEmpChange1819: Percent employment change, 2018-19
- PctEmpChange0719: Percent employment change, 2007-19
- PctEmpChange0710: Percent employment change, 2007-10
- NumCivEmployed: Civilian employed population 16 years and over, 2014-18
- NumCivLaborforce2007-2019: Civilian labor force, 2007-2019
- PctEmpFIRE: Percent of the civilian labor force 16 and over employed in finance and insurance, and real estate and rental and leasing, 2014-18
- PctEmpConstruction: Percent of the civilian labor force 16 and over employed in construction, 2014-18
- PctEmpTrans: Percent of the civilian labor force 16 and over employed in transportation, warehousing and utilities, 2014-18
- PctEmpMining: Percent of the civilian labor force 16 and over employed in mining, quarrying, oil and gas extraction, 2014-18
- PctEmpTrade: Percent of the civilian labor force 16 and over employed in wholesale and retail trade, 2014-18
- PctEmpInformation: Percent of the civilian labor force 16 and over employed in information services, 2014-18
- PctEmpAgriculture: Percent of the civilian labor force 16 and over employed in agriculture, forestry, fishing, and hunting, 2014-18
- PctEmpManufacturing: Percent of the civilian labor force 16 and over employed in manufacturing, 2014-18
- PctEmpServices: Percent of the civilian labor force 16 and over employed in services, 2014-18
- PctEmpGovt: Percent of the civilian labor force 16 and over employed in public administration, 2014-18

People: Population size, density, education level, race, age, household size, and migration rates

- PopDensity2010: Population density, 2010
- LandAreaSQMiles2010: Land area in square miles, 2010
- TotalHH: Total number of households, 2014-18
- TotalOccHU: Total number of occupied housing units, 2014-18
- AvgHHSize: Average household size, 2014-18
- OwnHomeNum: Number of owner occupied housing units, 2014-18
- OwnHomePct: Percent of owner occupied housing units, 2014-18
- NonEnglishHHPct: Percent of non-English speaking households of total households, 2014-18
- HH65PlusAlonePct: Percent of persons 65 or older living alone, 2014-18
- FemaleHHPct: Percent of female headed family households of total households, 2014-18
- FemaleHHNum: Number of female headed family households, 2014-18
- NonEnglishHHNum: Number of non-English speaking households, 2014-18
- HH65PlusAloneNum: Number of persons 65 years or older living alone, 2014-18
- Age65AndOlderPct2010: Percent of population 65 or older, 2010
- Age65AndOlderNum2010: Population 65 years or older, 2010
- TotalPop25Plus: Total population 25 and older, 2014-18 - 5-year average
- Under18Pct2010: Percent of population under age 18, 2010
- Under18Num2010: Population under age 18, 2010
- Ed1LessThanHSPct: Percent of persons with no high school diploma or GED, adults 25 and over, 2014-18
- Ed2HSDiplomaOnlyPct: Percent of persons with a high school diploma or GED only, adults 25 and over, 2014-18
- Ed3SomeCollegePct: Percent of persons with some college experience, adults 25 and over, 2014-18
- Ed4AssocDegreePct: Percent of persons with an associate's degree, adults 25 and over, 2014-18

- Ed5CollegePlusPct: Percent of persons with a 4-year college degree or more, adults 25 and over, 2014-18
- Ed1LessThanHSNum: No high school, adults 25 and over, 2014-18
- Ed2HSDiplomaOnlyNum: High school only, adults 25 and over, 2014-18
- Ed3SomeCollegeNum: Some college experience, adults 25 and over, 2014-18
- Ed4AssocDegreeNum: Number of persons with an associate's degree, adults 25 and over, 2014-18
- Ed5CollegePlusNum: College degree 4-years or more, adults 25 and over, 2014-18
- ForeignBornPct: Percent of total population foreign born, 2014-18
- ForeignBornEuropePct: Percent of persons born in Europe, 2014-18
- ForeignBornMexPct: Percent of persons born in Mexico, 2014-18
- ForeignBornCentralSouthAmPct: Percent of persons born in Central or South America, 2014-18
- ForeignBornAsiaPct: Percent of persons born in Asia, 2014-18
- ForeignBornCaribPct: Percent of persons born in the Caribbean, 2014-18
- ForeignBornAfricaPct: Percent of persons born in Africa, 2014-18
- ForeignBornNum: Number of people foreign born, 2014-18
- ForeignBornCentralSouthAmNum: Number of persons born in Central or South America, 2014-18
- ForeignBornEuropeNum: Number of persons born in Europe, 2014-18
- ForeignBornMexNum: Number of persons born in Mexico, 2014-18
- ForeignBornAfricaNum: Number of persons born in Africa, 2014-18
- ForeignBornAsiaNum: Number of persons born in Asia, 2014-18
- ForeignBornCaribNum: Number of persons born in the Caribbean, 2014-18
- Net_International_Migration_Rate_2010_2019: Net international migration rate, 2010-19
- Net_International_Migration_2010_2019: Net international migration, 2010-19
- Net_International_Migration_2000_2010: Net international migration, 2000-10

- Immigration_Rate_2000_2010: Net international migration rate, 2000-10
- NetMigrationRate0010: Net migration rate, 2000-10
- NetMigrationRate1019: Net migration rate, 2010-19
- NetMigrationNum0010: Net migration, 2000-10
- NetMigration1019: Net Migration, 2010-19
- NaturalChangeRate1019: Natural population change rate, 2010-19
- NaturalChangeRate0010: Natural population change rate, 2000-10
- NaturalChangeNum0010: Natural change, 2000-10
- NaturalChange1019: Natural population change, 2010-19
- TotalPop2010: Population size 4/1/2010 Census
- TotalPopEst2010: Population size 7/1/2010
- TotalPopEst2011: Population size 7/1/2011
- TotalPopEst2012: Population size 7/1/2012
- TotalPopEst2013: Population size 7/1/2013
- TotalPopEst2014: Population size 7/1/2014
- TotalPopEst2015: Population size 7/1/2015
- TotalPopEst2016: Population size 7/1/2016
- TotalPopEst2017: Population size 7/1/2017
- TotalPopEst2018: Population size 7/1/2018
- TotalPopEst2019: Population size 7/1/2019
- TotalPopACS: Total population, 2014-18 - 5-year average
- TotalPopEstBase2010: County Population estimate base 4/1/2010
- NonHispanicAsianPopChangeRate0010: Population change rate Non-Hispanic Asian, 2000-10
- PopChangeRate1819: Population change rate, 2018-19
- PopChangeRate1019: Population change rate, 2010-19
- PopChangeRate0010: Population change rate, 2000-10

- NonHispanicNativeAmericanPopChangeRate0010: Population change rate Non-Hispanic Native American, 2000-10
- HispanicPopChangeRate0010: Population change rate Hispanic, 2000-10
- MultipleRacePopChangeRate0010: Population change rate multiple race, 2000-10
- NonHispanicWhitePopChangeRate0010: Population change rate Non-Hispanic White, 2000-10
- NonHispanicBlackPopChangeRate0010: Population change rate Non-Hispanic African American, 2000-10
- MultipleRacePct2010: Percent multiple race, 2010
- WhiteNonHispanicPct2010: Percent Non-Hispanic White, 2010
- NativeAmericanNonHispanicPct2010: Percent Non-Hispanic Native American, 2010
- BlackNonHispanicPct2010: Percent Non-Hispanic African American, 2010
- AsianNonHispanicPct2010: Percent Non-Hispanic Asian, 2010
- HispanicPct2010: Percent Hispanic, 2010
- MultipleRaceNum2010: Population size multiple race, 2010
- WhiteNonHispanicNum2010: Population size Non-Hispanic White, 2010
- BlackNonHispanicNum2010: Population size Non-Hispanic African American, 2010
- NativeAmericanNonHispanicNum2010: Population size Non-Hispanic Native American, 2010
- AsianNonHispanicNum2010: Population size Non-Hispanic Asian, 2010
- HispanicNum2010: Population size Hispanic, 2010

##County classifications

Type of county (rural or urban on a rural-urban continuum scale)

- Type_2015_Recreation_NO: Recreation counties, 2015 edition
- Type_2015_Farming_NO: Farming-dependent counties, 2015 edition

- Type_2015_Mining_NO: Mining-dependent counties, 2015 edition
- Type_2015_Government_NO: Federal/State government-dependent counties, 2015 edition
- Type_2015_Update: County typology economic types, 2015 edition
- Type_2015_Manufacturing_NO: Manufacturing-dependent counties, 2015 edition
- Type_2015_Nonspecialized_NO: Nonspecialized counties, 2015 edition
- RecreationDependent2000: Nonmetro recreation-dependent, 1997-00
- ManufacturingDependent2000: Manufacturing-dependent, 1998-00
- FarmDependent2003: Farm-dependent, 1998-00
- EconomicDependence2000: Economic dependence, 1998-00
- RuralUrbanContinuumCode2003: Rural-urban continuum code, 2003
- UrbanInfluenceCode2003: Urban influence code, 2003
- RuralUrbanContinuumCode2013: Rural-urban continuum code, 2013
- UrbanInfluenceCode2013: Urban influence code, 2013
- Noncore2013: Nonmetro noncore, outside Micropolitan and Metropolitan, 2013
- Micropolitan2013: Micropolitan, 2013
- Nonmetro2013: Nonmetro, 2013
- Metro2013: Metro, 2013
- Metro_Adjacent2013: Nonmetro, adjacent to metro area, 2013
- Noncore2003: Nonmetro noncore, outside Micropolitan and Metropolitan, 2003
- Micropolitan2003: Micropolitan, 2003
- Metro2003: Metro, 2003
- Nonmetro2003: Nonmetro, 2003
- NonmetroNotAdj2003: Nonmetro, nonadjacent to metro area, 2003
- NonmetroAdj2003: Nonmetro, adjacent to metro area, 2003

- Oil_Gas_Change: Change in the value of onshore oil and natural gas production, 2000-11
- Gas_Change: Change in the value of onshore natural gas production, 2000-11
- Oil_Change: Change in the value of onshore oil production, 2000-11
- Hipov: High poverty counties, 2014-18
- Perpov_1980_0711: Persistent poverty counties, 2015 edition
- PersistentChildPoverty_1980_2011: Persistent child poverty counties, 2015 edition
- PersistentChildPoverty2004: Persistent child poverty counties, 2004
- PersistentPoverty2000: Persistent poverty counties, 2004
- Low_Education_2015_update: Low education counties, 2015 edition
- LowEducation2000: Low education, 2000
- HiCreativeClass2000: Creative class, 2000
- HiAmenity: High natural amenities
- RetirementDestination2000: Retirement destination, 1990-00
- Low_Employment_2015_update: Low employment counties, 2015 edition
- Population_loss_2015_update: Population loss counties, 2015 edition
- Retirement_Destination_2015_Update: Retirement destination counties, 2015 edition

7 Appendix 2: Data cleaning

The raw data sets are dirty and need transforming before we can do our EDA. It takes time and efforts to clean and merge different data sources so we provide the final output of the cleaned and merged data. The cleaning procedure is as follows. Please read through to understand what is in the cleaned data. We set `eval = data_cleaned` in the following cleaning chunks so that these cleaning chunks will only run if any of `data/covid_county.csv`, `data/covid_rates.csv` or `data/covid_intervention.csv` does not exist.

```
# Indicator to check whether the data files exist
data_cleaned <- !(file.exists("data/covid_county.csv") &
                    file.exists("data/covid_rates.csv") &
                    file.exists("data/covid_intervention.csv"))
```

We first read in the table using `data.table::fread()`, as we did last time.

```r
# COVID case/mortality rate data
covid_rates <- fread("data/us_counties.csv", na.strings = c("NA", "", "."))
nyc <- fread("data/nycdata.csv", na.strings = c("NA", "", "."))

# Socioeconomic data
income <- fread("data/income.csv", na.strings = c("NA", "", "."))
jobs <- fread("data/jobs.csv", na.strings = c("NA", "", "."))
people <- fread("data/people.csv", na.strings = c("NA", "", "."))
county_class <- fread("data/county_classifications.csv", na.strings = c("NA", "", "."))

# Internvention policy data
int_dates <- fread("data/intervention_dates.csv", na.strings = c("NA", "", "."))
```

7.1 Clean NYC data

The original NYC data contains more information than we need. We extract only the number of cases and deaths and format it the same as the `covid_rates` data.

```r
# NYC county fips matching table
nyc_fips <- data.table(FIPS = c('36005', '36047', '36061', '36081', '36085'),
                       County = c("BX", "BK", "MN", "QN", "SI"))

# nyc case
nyc_case <- nyc[,.(date = as.Date(date_of_interest, "%m/%d/%Y"),
                   BX = BX_CASE_COUNT,
                   BK = BK_CASE_COUNT,
                   MN = MN_CASE_COUNT,
                   QN = QN_CASE_COUNT,
                   SI = SI_CASE_COUNT)]

nyc_case %<>%
  pivot_longer(cols = BX:SI,
               names_to = "County",
               values_to = "cases") %>%
  arrange(date) %>%
  group_by(County) %>%
  mutate(cum_cases = cumsum(cases))

# nyc death
nyc_death <- nyc[,.(date = as.Date(date_of_interest, "%m/%d/%Y"),
                   BX = BX_DEATH_COUNT,
                   BK = BK_DEATH_COUNT,
                   MN = MN_DEATH_COUNT,
                   QN = QN_DEATH_COUNT,
                   SI = SI_DEATH_COUNT)]

nyc_death %<>%
  pivot_longer(cols = BX:SI,
               names_to = "County",
               values_to = "deaths") %>%
  arrange(date) %>%
  group_by(County) %>%
```

```
  mutate(cum_deaths = cumsum(deaths))

nyc_rates <- merge(nyc_case,
                   nyc_death,
                   by = c("date", "County"),
                   all.x= T)

nyc_rates <- merge(nyc_rates,
                   nyc_fips,
                   by = "County")

nyc_rates$State <- "New York"
nyc_rates %<>%
  select(date, FIPS, County, State, cum_cases, cum_deaths) %>%
  arrange(FIPS, date)
```

7.2 Continental US cases

We only consider cases and death in continental US. Alaska, Hawaii, and Puerto Rico have 02, 15, and 72 as their respective first 2 digits of their FIPS. We use the `%/%` operator for integer division to get the first 2 digits of FIPS. We also remove Virgin Islands and Northern Mariana Islands. All data of counties in NYC are aggregated as `County == "New York City"` in `covid_rates` with no FIPS, so we combine the NYC data into `covid_rate`.

```
covid_rates <- covid_rates %>%
  arrange(fips, date) %>%
  filter(!(fips %/% 1000 %in% c(2, 15, 72))) %>%
  filter(county != "New York City") %>%
  filter(!(state %in% c("Virgin Islands", "Northern Mariana Islands"))) %>%
  rename(FIPS = "fips",
         County = "county",
         State = "state",
         cum_cases = "cases",
         cum_deaths = "deaths")


covid_rates$date <- as.Date(covid_rates$date)

covid_rates <- rbind(covid_rates,
                     nyc_rates)
```

7.3 COVID date to week

We set the week of Jan 21, 2020 (the first case of COVID case in US) as the first week (2020-01-19 to 2020-01-25).

```
covid_rates[, week := (interval("2020-01-19", date) %/% weeks(1)) + 1]
```

7.4 COVID infection/mortality rates

Merge the `TotalPopEst2019` variable from the demographic data with `covid_rates` by FIPS.

```
covid_rates <- merge(covid_rates[!is.na(FIPS)],
                     people[,.(FIPS = as.character(FIPS),
                               TotalPopEst2019)],
                     by = "FIPS",
                     all.x = TRUE)
```

7.5 NA in COVID data

NA values in the `covid_rates` data set correspond to a county not having confirmed cases/deaths. We replace the NA values in these columns with zeros. FIPS for Kansas city, Missouri, Rhode Island and some others are missing. We drop them for the moment and output the data up to week 57 as `covid_rates.csv`.

```
covid_rates$cum_cases[is.na(covid_rates$cum_cases)] <- 0
covid_rates$cum_deaths[is.na(covid_rates$cum_deaths)] <- 0
```

```
fwrite(covid_rates %>%
         filter(week < 58) %>%
         arrange(FIPS, date),
       "data/covid_rates.csv")
```

7.6 Formatting date in `int_dates`

We convert the columns representing dates in `int_dates` to R Date types using `as.Date()`. We will need to specify that the `origin` parameter is `"0001-01-01"`. We output the data as `covid_intervention.csv`.

```
int_dates <- int_dates[-1,]
date_cols <- names(int_dates)[-(1:3)]
int_dates[, (date_cols) := lapply(.SD, as.Date, origin = "0001-01-01"),
          .SDcols = date_cols]

fwrite(int_dates, "data/covid_intervention.csv")
```

7.7 Merge demographic data

Merge the demographic data sets by FIPS and output as `covid_county.csv`.

```
countydata <-
  merge(x = income,
        y = merge(
          x = people,
          y = jobs,
          by = c("FIPS", "State", "County")),
        by = c("FIPS", "State", "County"),
        all = TRUE)


countydata <-
  merge(
    x = countydata,
    y = county_class %>% rename(FIPS = FIPStxt),
```

```
    by = c("FIPS", "State", "County"),
    all = TRUE
  )

# Check dimensions
# They are now 3279 x 208
dim(countydata)
fwrite(countydata, "data/covid_county.csv")
```