Empirical study: Causal effect and causal inference

Topic: COVID-19 mortality rate

In [2]:
```
# Libraries
import numpy as np
from numpy.linalg import inv
import statsmodels.formula.api as smf

# Make print quality look significantly better.
%config InlineBackend.figure_format = 'svg'

import seaborn as sns
import matplotlib.pyplot as plt

sns.set_style("darkgrid")

import pandas as pd
from linearmodels import IV2SLS, IVLIML, IVGMM, IVGMMCUE
import linearmodels.iv as iv
import scipy.stats as stats
```

Research question and motivation

The purpose of this project is to identify the factors correlated with the COVID-19 mortality rate. We hope to increase the level of understanding concerning factors that render some states more vulnerable to the virus than others. As coronavirus continues its spread across the globe, even modest, but early advances in such knowledge could lead to a significant reduction in loss of life.[1]

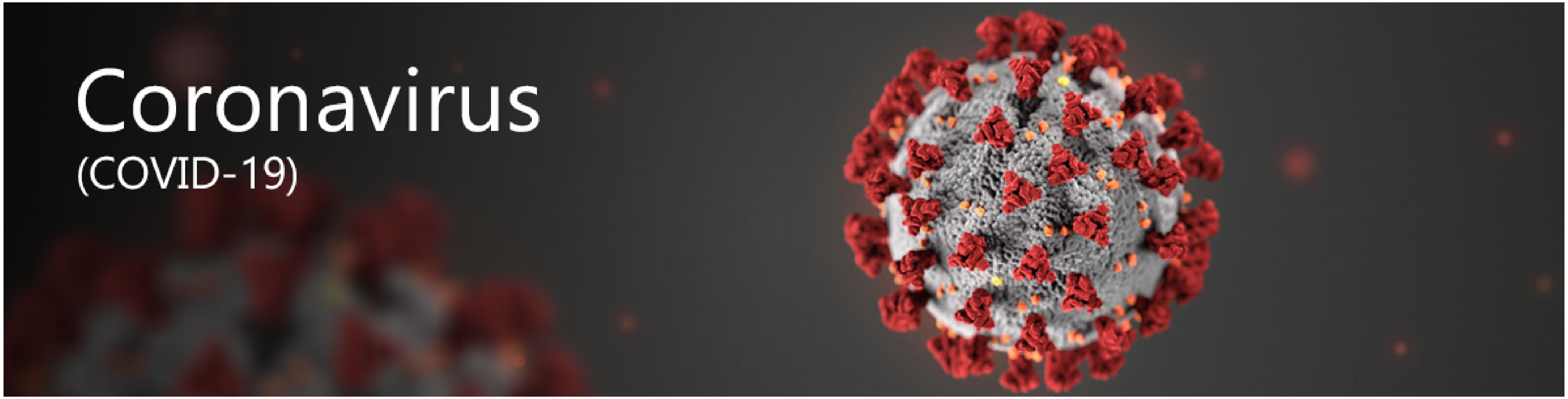
The infection fatality rate, the probability of dying for a person who is infected, is one of the most important features of the coronavirus disease 2019 (COVID-19) pandemic. The expected total mortality burden of COVID-19 is directly related to the infection fatality rate. Moreover, justification for various non-pharmacological public health interventions depends on the infection fatality rate. Some stringent interventions that potentially also result in more noticeable collateral harms may be considered appropriate, if the infection fatality rate is high. Conversely, the same measures may fall short of acceptable risk–benefit thresholds, if the infection fatality rate is low.[2]

We will examine Population Density and its effect on target variable - Fatality Rate.

Population density has a marked impact on spread of the pandemic. Population density can be defined as a measurement of the average number of individuals per unit of geographic area (Liu et al. 2020).[3] The higher the population density, the faster diseases can spread. Population density is likely just one of many key factors that determine the vulnerability of a specific location to the virus. In smaller communities, the virus has targeted nursing homes, community houses, funeral parlors, and of course cruise ships, which are like dense small cities at sea.[4]

We chose mortality rate as our target variable as it is less likely than case rates (e.g. infection rate) to be distorted by local variations in testing policy.

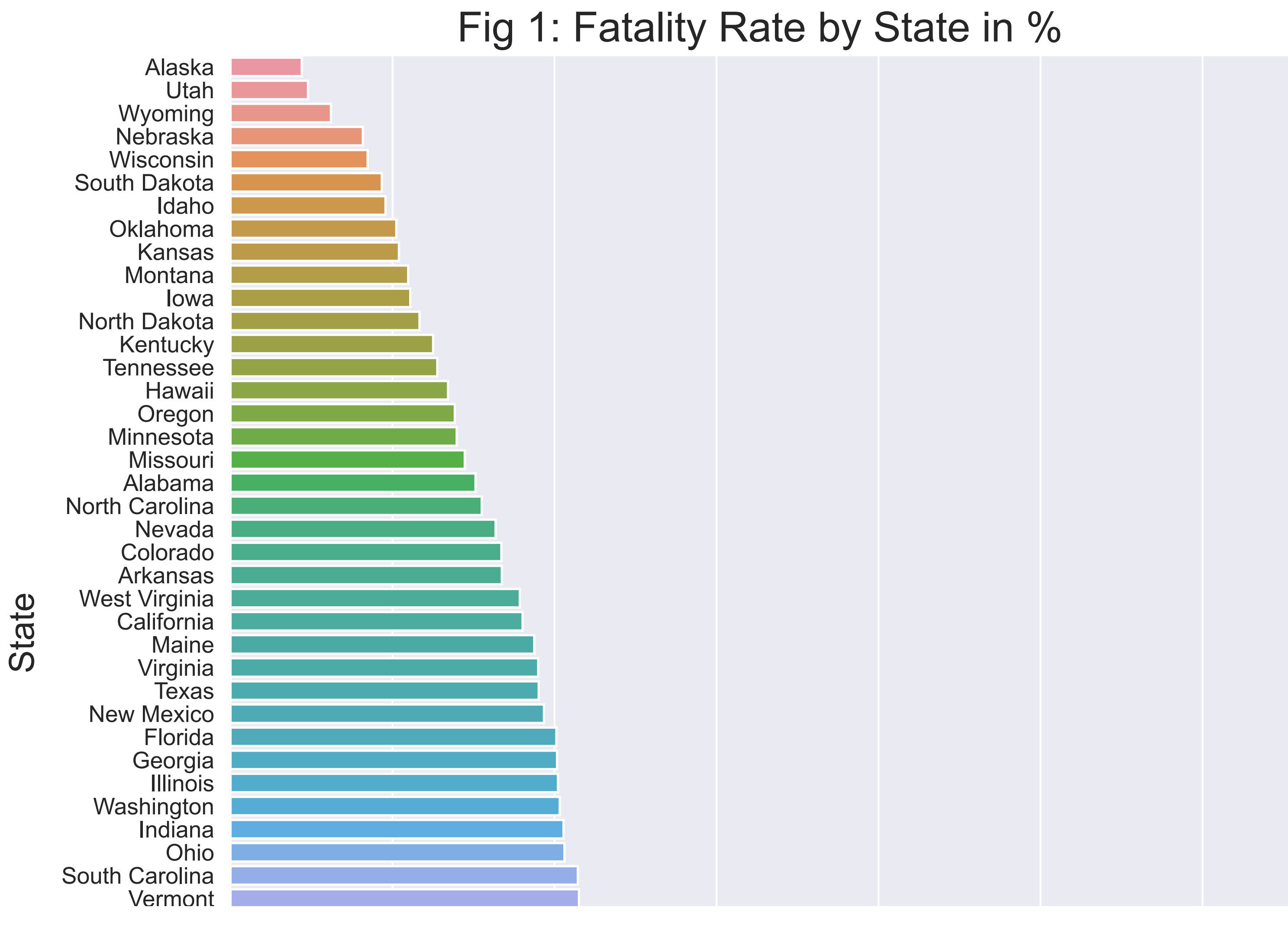
Motivation for research

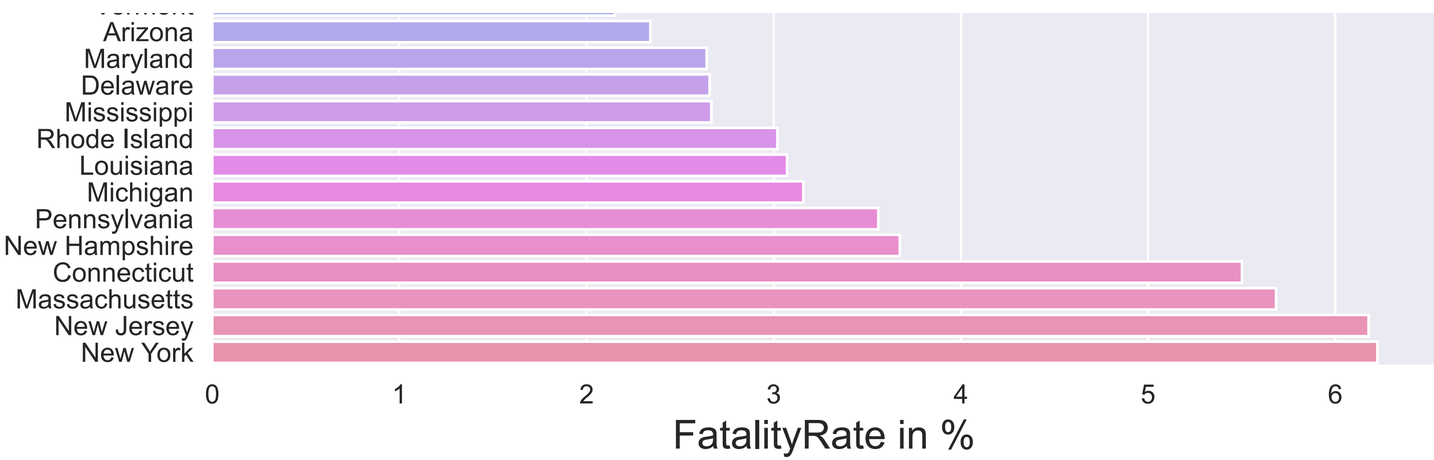


Based on Figure 1, the top 3 states with the highest mortality rate are New York, New Jersey, Massachusetts and bottom 3 states are Alaska, Utah, Wyoming. We would like to have a better understanding 'Why Fatality Rate varies across states?'.

In [57]:

```
#Fatality Rate by State
plt.figure(figsize=(8,8))
# make barplot and sort bars
sns.barplot(x='FatalityRate',
            y="State",
            data=main_df1,
            order=main_df1.sort_values('FatalityRate').State)
# set labels
plt.xlabel("FatalityRate in %", size=15)
plt.ylabel("State", size=15)
plt.title("Fig 1: Fatality Rate by State in %", size=18)
plt.tight_layout()
```



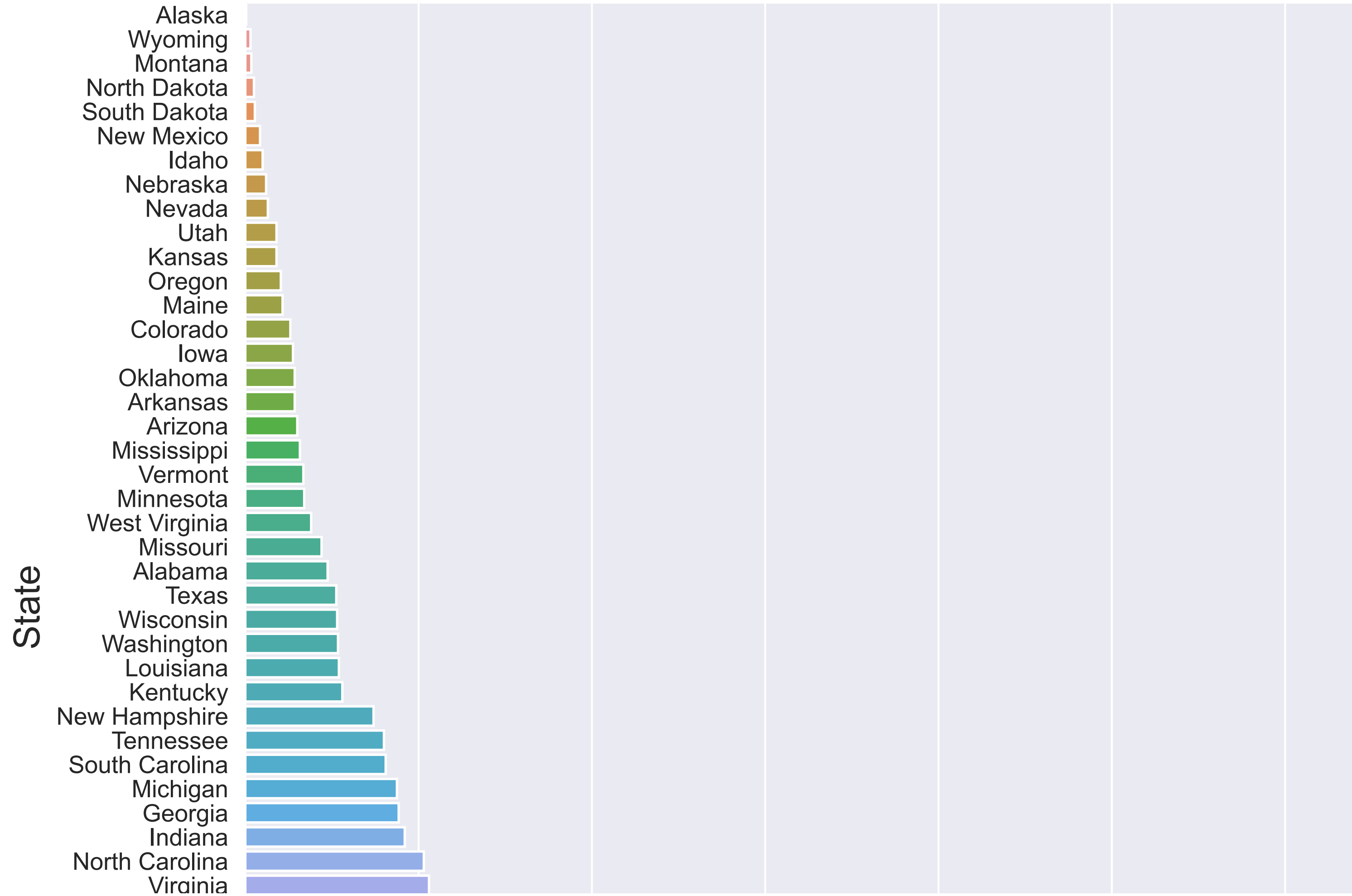


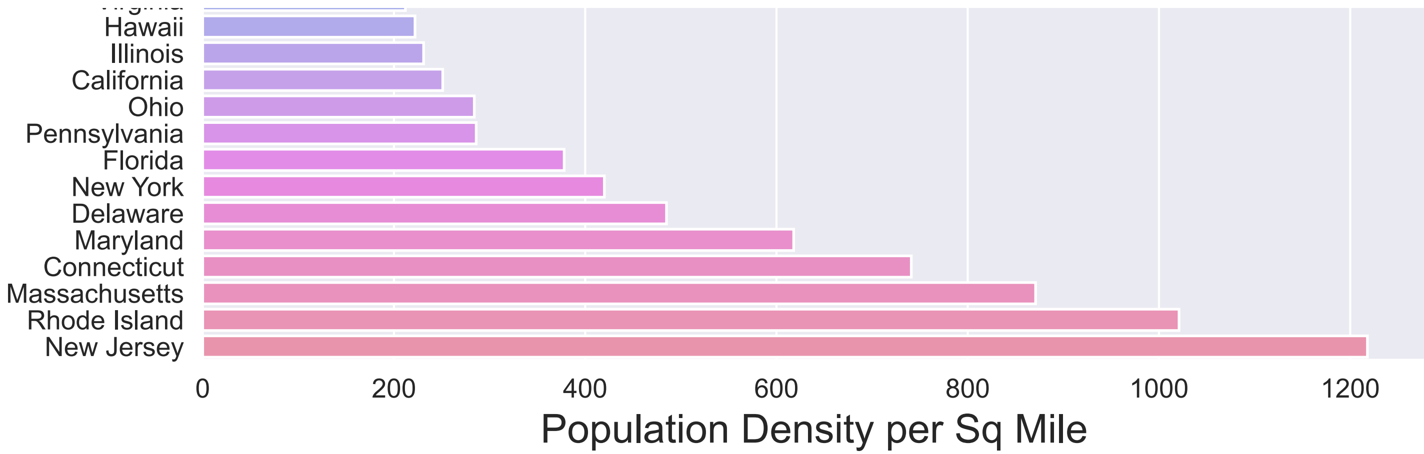
Based on Figure 2, the top 3 states with highest population density are New Jersey, Rhode Island, Massachusetts and bottom 3 states are Alaska, Wyoming, Montana.

In [55]:

```python
#Population Density by State
plt.figure(figsize=(8,8))
# make barplot and sort bars
sns.barplot(x='DEN',
            y="State",
            data=main_df1,
            order=main_df1.sort_values('DEN').State)
# set labels
plt.xlabel("Population Density per Sq Mile", size=15)
plt.ylabel("State", size=15)
plt.title("Fig 2: Population Density by State (per square mile)", size=18)
plt.tight_layout()
```

Fig 2: Population Density by State (per square mile)





As per results from charts above (Fig 1 and Fig 2), we will examine the effect of Population Density on Fatality Rate.

In [59]:
```
main_df1['logDen'] = np.log(main_df1['DEN'])
g = sns.lmplot(x='logDen', y='FatalityRate', data=main_df1)
g.fig.suptitle('Fig 3: Relationship between Density and Fatality Rate')
```

Out[59]: `Text(0.5, 0.98, 'Fig 3: Relationship between Density and Fatality Rate')`

Target and Focal Variables

Fatality Rate- Dependent Variable

Population Density (Social Variable) - the increased population density increases exposure to all communicable pathogens as it is getting more difficult for people to keep social distance. On the other side, people living in rural areas are more likely to maintain some sort of social distance. Therefore, people living in areas with high population density are more likely to be infected with a heavy viral load which could increase the severity of COVID-19 and lead to death. We expect the coefficient of this variable to be positive.[1]

Uploading Datasets and cleaning up the data

In [54]:
```
xls = pd.ExcelFile(Revised_dataset_V2.xlsx')
df1 = pd.read_excel(xls, 'DataSet V5')
df2 = pd.read_excel(xls, 'List of data variables')
df3 = pd.read_csv(OxCGRT_US_latest.csv',encoding='unicode_escape')
```

In [5]:
```python
#Checking the columns in df1
list(df1)
```

Out[5]:
```
['No.',
 'State',
 'HCExpenditures',
 'HCExpenditures_Level',
 'HI_Coverage_Total_Pop%',
 'HI_Coverage_Total_Pop_Level',
 'Uninsured_Coverage_Total_Pop%',
 'Highschool_GraduateRate%',
 'Highschool_GraduateRate_Level',
 'Bachelors_degree_GraduateRate%',
 'Bachelors_degree_GraduateRate_Level',
 'PopulationDensity_mi2',
 'Total_Number_Residents',
 'Total_Number_Residents_Level',
 'Total_Hospital_Admissions',
 'Number_of_COVID_Cases',
 'Number_of_COVID_Cases_Level',
 'Infection_Rate_Total_Test_as_denominator%',
 'Infection_Rate_Total_Residents_as_denominator%',
 'Number_of_Deaths_from_COVID',
 'COVID_Fatality_Rate%',
 'Total_COVID_Tests_with_Results',
 'Total_COVID_Tests_with_Results_Level',
 'Daily_Covid_Tests_per_mil',
 'MedianIncome_Annual',
 'MedianIncome_Annual_Level',
 'NoDoctor_12Months%',
 'SeverelyObese%',
 'Share_of_adults_under_age_65_at_risk%',
 'Share_of_adults_under_age_65_at_risk_Level',
 'Share_of_adults_over_age_65_at_risk%',
 'Share_of_adults_over_age_65_at_risk_Level',
 'Diabetes_death_rate%',
 'Health_Care_Expenditures_per_Capita',
 'Health_Care_Expenditures_per_Capita_Level',
 'Total_Hospital_Beds',
 'Mortality_rate',
 'Average_Family_Deductible',
 'Average_Single_Deductible',
 'Unemployment_Claims',
```

```
'Unemployment_Claims_Level',
'Unemployment_Rate%',
'Total_People_Experiencing_Homelessness',
'Total_People_Experiencing_Homelessness_Level',
'Total_Gross_State_Product ',
'Total_Gross_State_Product_Level',
'Health_Professional_Shortage_Area',
'Adults_with_no_Personal_Doctor%',
'Hospital_Admissions',
'ICU_Beds',
'Employee_Premium_Contribution',
'Population_Ages_65+%',
'Population_Ages_65+_Level',
'Smoker_rate_adults%',
'Adults_with_Asthma%',
'Avg_Heathcare_cost_growth_rate%',
'Primary_Care_Physicians',
' Total_Number_of_Certified_Nursing_Facilities',
'Face_Mask_Adoption%',
'Effective Reproduction Number',
'LifeExpectancyatBirth',
'UrbanizationRate',
'Gini',
'Votes ',
'Votes_Level',
'VotePercentage_Trump%',
'VotePercentage_Trump_Level',
'COVID_Fatality_Rate2%',
'2020_trump_campaign_rallies_frequency']
```

In [61]:
```
df3['Date'].head()
```

Out[61]:
```
0    20200101
1    20200102
2    20200103
3    20200104
4    20200105
Name: Date, dtype: int64
```

In [7]:
```
df3['Date'] = pd.to_datetime(df3['Date'], format='%Y%m%d')
```

In [62]:
```python
df3['State'] = df3['RegionName']
df3['State'].unique()
```

Out[62]:
```
array([nan, 'Alaska', 'Alabama', 'Arkansas', 'Arizona', 'California',
       'Colorado', 'Connecticut', 'Washington DC', 'Delaware', 'Florida',
       'Georgia', 'Hawaii', 'Iowa', 'Idaho', 'Illinois', 'Indiana',
       'Kansas', 'Kentucky', 'Louisiana', 'Massachusetts', 'Maryland',
       'Maine', 'Michigan', 'Minnesota', 'Missouri', 'Mississippi',
       'Montana', 'North Carolina', 'North Dakota', 'Nebraska',
       'New Hampshire', 'New Jersey', 'New Mexico', 'Nevada', 'New York',
       'Ohio', 'Oklahoma', 'Oregon', 'Pennsylvania', 'Rhode Island',
       'South Carolina', 'South Dakota', 'Tennessee', 'Texas', 'Utah',
       'Virginia', 'Vermont', 'Washington', 'Wisconsin', 'West Virginia',
       'Wyoming'], dtype=object)
```

In [9]:
```python
main = pd.merge(df1, df3, how='inner', on="State")
```

In [66]:
```python
main.head()
```

Out[66]:

	No.	State	HCExpenditures	HCExpenditures_Level	HI_Coverage_Total_Pop%	HI_Coverage_Total_Pop_Level	Uninsured_Coverage_Total_Pop%	Highscho
0	1	Alabama	35263	1	90.3	0	9.7	
1	1	Alabama	35263	1	90.3	0	9.7	
2	1	Alabama	35263	1	90.3	0	9.7	
3	1	Alabama	35263	1	90.3	0	9.7	
4	1	Alabama	35263	1	90.3	0	9.7	

5 rows × 141 columns

In [64]:
```python
len(main.columns)
```

Out[64]: 141

In [12]:
```python
# Subsetting by Date to be '11-13-2020' as this is when most of the data was collected
main_df = main[(main['Date']== "2020-11-13")]
```

In [13]:

```
# Selecting only columns of our interest into one dataframe
main_df1 = main_df.filter([
    "State", 'HCExpenditures', 'Health_Care_Expenditures_per_Capita',
    'MedianIncome_Annual', 'Uninsured_Coverage_Total_Pop%',
    'Population_Ages_65+%', 'PopulationDensity_mi2', 'Total_Hospital_Beds',
    'Face_Mask_Adoption%', 'Total_Gross_State_Product',
    'GovernmentResponseIndexForDisplay', 'StringencyIndexForDisplay',
    'EconomicSupportIndexForDisplay', 'ContainmentHealthIndexForDisplay',
    'Bachelors_degree_GraduateRate%',
    'Infection_Rate_Total_Test_as_denominator%',
    'Infection_Rate_Total_Residents_as_denominator%', 'COVID_Fatality_Rate%',
    'Daily_Covid_Tests_per_mil', 'NoDoctor_12Months%',
    'Share_of_adults_over_age_65_at_risk%', 'Unemployment_Claims',
    'Adults_with_no_Personal_Doctor%',
    'Health_Professional_Shortage_Area', 'Primary_Care_Physicians',
    'VotePercentage_Trump%', 'Total_Number_Residents', 'Number_of_COVID_Cases',
    'Number_of_Deaths_from_COVID', 'Total_COVID_Tests_with_Results',
    'ICU_Beds', 'Effective Reproduction Number', 'LifeExpectancyatBirth',
    'UrbanizationRate', 'SeverelyObese%', 'Gini','Population_Ages_65+_Level','Share_of_adults_over_age_65_at_risk_Level','Unem
```

In [68]:

```python
# Checking all the columns in DataFrame and choose columns of interest only
for col in main_df.columns:
    print(col)
```

```
No.
State
HCExpenditures
HCExpenditures_Level
HI_Coverage_Total_Pop%
HI_Coverage_Total_Pop_Level
Uninsured_Coverage_Total_Pop%
Highschool_GraduateRate%
Highschool_GraduateRate_Level
Bachelors_degree_GraduateRate%
Bachelors_degree_GraduateRate_Level
PopulationDensity_mi2
Total_Number_Residents
Total_Number_Residents_Level
Total_Hospital_Admissions
Number_of_COVID_Cases
Number_of_COVID_Cases_Level
Infection_Rate_Total_Test_as_denominator%
Infection_Rate_Total_Residents_as_denominator%
```

In [15]:

```python
# Selecting only columns of our interest into one dataframe
main_df1 = main_df.filter([
    "State", 'HCExpenditures', 'Health_Care_Expenditures_per_Capita',
    'MedianIncome_Annual', 'Uninsured_Coverage_Total_Pop%',
    'Population_Ages_65+%', 'PopulationDensity_mi2', 'Total_Hospital_Beds',
    'Face_Mask_Adoption%', 'Total_Gross_State_Product',
    'GovernmentResponseIndexForDisplay', 'StringencyIndexForDisplay',
    'EconomicSupportIndexForDisplay', 'ContainmentHealthIndexForDisplay',
    'Bachelors_degree_GraduateRate%',
    'Infection_Rate_Total_Test_as_denominator%',
    'Infection_Rate_Total_Residents_as_denominator%', 'COVID_Fatality_Rate%',
    'Daily_Covid_Tests_per_mil', 'NoDoctor_12Months%',
    'Share_of_adults_over_age_65_at_risk%', 'Unemployment_Claims',
    'Adults_with_no_Personal_Doctor%',
    'Health_Professional_Shortage_Area', 'Primary_Care_Physicians',
    'VotePercentage_Trump%', 'Total_Number_Residents', 'Number_of_COVID_Cases',
    'Number_of_Deaths_from_COVID', 'Total_COVID_Tests_with_Results',
    'ICU_Beds', 'Effective Reproduction Number', 'LifeExpectancyatBirth',
    'UrbanizationRate', 'SeverelyObese%', 'Gini','Population_Ages_65+_Level','Share_of_adults_over_age_65_at_risk_Level','Unem
```

In [16]:

```python
# Raname Some of the Variables
main_df1.rename(columns={'HCExpenditures': 'HC_Exp'}, inplace=True)
main_df1.rename(
    columns={'Uninsured_Coverage_Total_Pop%': 'Uninsured_TotalPop_rate'},
    inplace=True)
main_df1.rename(columns={'Population_Ages_65+%': 'Pop_above_65_rate'},
                inplace=True)
main_df1.rename(columns={'Face_Mask_Adoption%': 'Face_Mask_Adoption_rate'},
                inplace=True)
main_df1.rename(
    columns={'Bachelors_degree_GraduateRate%': 'Bachelors_Graduate_Rate'},
    inplace=True)
main_df1.rename(columns={'Infection_Rate_Total_Test_as_denominator%': 'IR'},
                inplace=True)
main_df1.rename(
    columns={'Infection_Rate_Total_Residents_as_denominator%': 'IR_pop'},
    inplace=True)
main_df1.rename(columns={'COVID_Fatality_Rate%': 'FatalityRate'}, inplace=True)
```

In [17]:

```python
main_df1.to_csv("finaldataset.csv", index = False)
```

Description of Datasets

COVID 19 Dataset

We collected 47 variables covering two data types: medical and demographic.

The COVID 19 dataset was collected from different sources:

- Government organizations(CDC, Agency for Healthcare, Bureau of Health, Labor Statistics, Department of Labour, US Census Bureau, etc.)
- Non-profit foundations (Kaiser Family Foundation, Johns Hopkins University, Wikipedia)
- For profit organizations (YouGov, NBC News)

The data for collected on a state level (51 states)

Note: please see **Appendix 1** for full list of data sources.

Policy Dataset

Dataset was collected from The Oxford COVID-19 Government Response Tracker (OxCGRT) website.

OxCGRT provides information on 20 indicators of government responses.

Eight of the policy indicators (C1-C8) record information on containment and closure policies, such as school closures and restrictions in movement.

Four of the indicators (E1-E4) record economic policies, such as income support to citizens or provision of foreign aid. Eight of the indicators (H1-H8) record health system policies such as the COVID-19 testing regime, emergency investments into healthcare and most recently, vaccination policies.

The data from the 20 indicators is aggregated into a set of four common indices, reporting a number between 1 and 100 to reflect the level of government action on the topics in question:

- Overall Government Response Index(all indicators). It records how the response of governments has varied over all indicators in the database, becoming stronger or weaker over the course of the outbreak.
- Containment and Health index (all C and H indicators). It combines ‘lockdown’ restrictions and closures with measures such as testing policy and contact tracing, short term investment in healthcare, as well investments in vaccine.
- Economic Support Index (all E indicators). It records measures such as income support and debt relief
- Original Stringency Index (all indicators). It records the strictness of ‘lockdown style’ policies that primarily restrict people’s behaviour).

Note: please see **Appendix 1** for full list of data sources.

Visualization of Combined Datasets

The combined dataset has no missing values or duplicates. Please refer to the graphs below for details.

In [18]:
```
print(main_df1.shape)
```

```
(50, 38)
```

In [19]:

```python
# Info on Combined Dataset
main_df1.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 38 columns):
 #   Column                                 Non-Null Count  Dtype  
---  ------                                 --------------  -----  
 0   State                                  50 non-null     object 
 1   HC_Exp                                 50 non-null     int64  
 2   Health_Care_Expenditures_per_Capita    50 non-null     int64  
 3   MedianIncome_Annual                    50 non-null     int64  
 4   Uninsured_TotalPop_rate                50 non-null     float64
 5   Pop_above_65_rate                      50 non-null     float64
 6   PopulationDensity_mi2                  50 non-null     int64  
 7   Total_Hospital_Beds                    50 non-null     float64
 8   Face_Mask_Adoption_rate                50 non-null     float64
 9   GovernmentResponseIndexForDisplay      50 non-null     float64
 10  StringencyIndexForDisplay              50 non-null     float64
 11  EconomicSupportIndexForDisplay         50 non-null     float64
 12  ContainmentHealthIndexForDisplay       50 non-null     float64
 13  Bachelors_Graduate_Rate                50 non-null     float64
 14  IR                                     50 non-null     float64
 15  IR_pop                                 50 non-null     float64
 16  FatalityRate                           50 non-null     float64
 17  Daily_Covid_Tests_per_mil              50 non-null     int64  
 18  NoDoctor_12Months%                     50 non-null     float64
 19  Share_of_adults_over_age_65_at_risk%   50 non-null     float64
 20  Unemployment_Claims                    50 non-null     int64  
 21  Adults_with_no_Personal_Doctor%        50 non-null     float64
 22  Health_Professional_Shortage_Area      50 non-null     int64  
 23  Primary_Care_Physicians                50 non-null     int64  
 24  VotePercentage_Trump%                  50 non-null     float64
 25  Total_Number_Residents                 50 non-null     int64  
 26  Number_of_COVID_Cases                  50 non-null     int64  
 27  Number_of_Deaths_from_COVID            50 non-null     int64  
 28  Total_COVID_Tests_with_Results         50 non-null     int64  
 29  ICU_Beds                               50 non-null     float64
 30  Effective Reproduction Number          50 non-null     float64
 31  LifeExpectancyatBirth                  50 non-null     float64
 32  UrbanizationRate                       50 non-null     float64
 33  SeverelyObese%                         50 non-null     float64
 34  Gini                                   50 non-null     float64
```

```
 35  Population_Ages_65+_Level                   50 non-null     int64
 36  Share_of_adults_over_age_65_at_risk_Level  50 non-null     int64
 37  Unemployment_Rate%                          50 non-null     float64
dtypes: float64(23), int64(14), object(1)
memory usage: 15.0+ KB
```

In [20]:
```
# Basic Statistical Summary of the data
main_df1.describe().T
```

Out[20]:

	count	mean	std	min	25%	50%	75%	max
HC_Exp	50.0	5.109908e+04	5.614452e+04	4856.000000	1.522600e+04	3.531100e+04	6.109000e+04	2.919890e+05
Health_Care_Expenditures_per_Capita	50.0	8.259920e+03	1.157627e+03	5982.000000	7.381000e+03	8.091500e+03	8.917500e+03	1.106400e+04
MedianIncome_Annual	50.0	5.979260e+04	9.854763e+03	43469.000000	5.291050e+04	5.828650e+04	6.749200e+04	8.077600e+04
Uninsured_TotalPop_rate	50.0	8.468000e+00	3.065505e+00	3.000000	6.400000e+00	7.950000e+00	1.017500e+01	1.840000e+01
Pop_above_65_rate	50.0	1.649000e+01	1.882817e+00	11.100000	1.570000e+01	1.645000e+01	1.742500e+01	2.060000e+01
PopulationDensity_mi2	50.0	2.000800e+02	2.661631e+02	1.000000	4.525000e+01	1.055000e+02	2.195000e+02	1.218000e+03
Total_Hospital_Beds	50.0	2.600000e+00	7.145714e-01	1.600000	2.100000e+00	2.450000e+00	3.075000e+00	4.800000e+00
Face_Mask_Adoption_rate	50.0	4.036000e+01	7.241490e+00	23.000000	3.600000e+01	3.900000e+01	4.500000e+01	5.800000e+01
GovernmentResponseIndexForDisplay	50.0	4.867660e+01	1.142430e+01	21.090000	3.971250e+01	4.857000e+01	5.540500e+01	7.500000e+01
StringencyIndexForDisplay	50.0	4.474100e+01	1.294311e+01	7.410000	3.657000e+01	4.352000e+01	5.254750e+01	7.593000e+01
EconomicSupportIndexForDisplay	50.0	3.975000e+01	2.727996e+01	0.000000	2.500000e+01	3.750000e+01	6.250000e+01	1.000000e+02
ContainmentHealthIndexForDisplay	50.0	4.995220e+01	1.061519e+01	20.540000	4.114500e+01	4.985000e+01	5.580250e+01	7.321000e+01
Bachelors_Graduate_Rate	50.0	3.011400e+01	5.056498e+00	19.900000	2.692500e+01	2.945000e+01	3.290000e+01	4.210000e+01
IR	50.0	7.148810e-02	3.897341e-02	0.006015	4.617526e-02	6.491048e-02	8.544299e-02	1.815320e-01
IR_pop	50.0	3.465358e-02	1.477074e-02	0.004586	2.636126e-02	3.642514e-02	4.290106e-02	8.290287e-02
FatalityRate	50.0	2.094866e+00	1.356549e+00	0.440125	1.257229e+00	1.839039e+00	2.293422e+00	6.225241e+00
Daily_Covid_Tests_per_mil	50.0	5.240020e+03	3.032497e+03	1258.000000	3.092500e+03	4.576000e+03	6.860000e+03	1.497200e+04
NoDoctor_12Months%	50.0	1.275815e+01	2.634249e+00	8.200000	1.067500e+01	1.260000e+01	1.445000e+01	1.880000e+01
Share_of_adults_over_age_65_at_risk%	50.0	5.585600e+01	4.077222e+00	48.400000	5.245000e+01	5.615000e+01	5.937500e+01	6.250000e+01
Unemployment_Claims	50.0	1.471818e+04	2.404637e+04	482.000000	3.342000e+03	6.442000e+03	1.536400e+04	1.521760e+05
Adults_with_no_Personal_Doctor%	50.0	2.252253e+01	5.623222e+00	11.600000	1.785000e+01	2.266321e+01	2.637500e+01	3.370000e+01
Health_Professional_Shortage_Area	50.0	1.425200e+02	1.102610e+02	13.000000	7.300000e+01	1.180000e+02	1.745000e+02	6.260000e+02
Primary_Care_Physicians	50.0	9.664020e+03	1.080828e+04	650.000000	2.937250e+03	6.222500e+03	1.157175e+04	5.458000e+04
VotePercentage_Trump%	50.0	5.044200e+01	1.020922e+01	31.700000	4.267500e+01	4.960000e+01	5.845000e+01	7.000000e+01
Total_Number_Residents	50.0	6.371556e+06	7.215709e+06	562700.000000	1.781575e+06	4.408950e+06	7.342425e+06	3.864270e+07

	count	mean	std	min	25%	50%	75%	max
Number_of_COVID_Cases	50.0	2.105521e+05	2.300851e+05	2743.000000	6.073100e+04	1.461450e+05	2.590448e+05	1.031205e+06
Number_of_Deaths_from_COVID	50.0	4.822400e+03	6.470427e+03	59.000000	7.467500e+02	2.564000e+03	5.459250e+03	3.397500e+04
Total_COVID_Tests_with_Results	50.0	3.272968e+06	3.913977e+06	317236.000000	9.315292e+05	1.966896e+06	3.795938e+06	2.034207e+07
ICU_Beds	50.0	2.658000e+00	6.308692e-01	1.600000	2.125000e+00	2.650000e+00	3.175000e+00	3.900000e+00
Effective Reproduction Number	50.0	1.143704e+00	9.485104e-02	0.896545	1.093635e+00	1.127306e+00	1.200835e+00	1.428242e+00
LifeExpectancyatBirth	50.0	7.875400e+01	1.797301e+00	74.800000	7.792500e+01	7.910000e+01	7.987500e+01	8.230000e+01
UrbanizationRate	50.0	7.358800e-01	1.456857e-01	0.387000	6.510000e-01	7.375000e-01	8.695000e-01	9.500000e-01
SeverelyObese%	50.0	5.400604e+00	1.132641e+00	2.900000	4.550000e+00	5.315094e+00	6.175000e+00	7.600000e+00
Gini	50.0	4.646480e-01	2.101533e-02	0.406300	4.519750e-01	4.673500e-01	4.789000e-01	5.229000e-01
Population_Ages_65+_Level	50.0	1.020000e+00	8.204031e-01	0.000000	0.000000e+00	1.000000e+00	2.000000e+00	2.000000e+00
Share_of_adults_over_age_6								

limit_output extension: Maximum message size of 10000 exceeded with 10832 characters

Missing Values

In [21]:
```python
# No missing values
main_df1.isna().sum()
```

Out[21]:
```
State                                      0
HC_Exp                                     0
Health_Care_Expenditures_per_Capita        0
MedianIncome_Annual                        0
Uninsured_TotalPop_rate                    0
Pop_above_65_rate                          0
PopulationDensity_mi2                      0
Total_Hospital_Beds                        0
Face_Mask_Adoption_rate                    0
GovernmentResponseIndexForDisplay          0
StringencyIndexForDisplay                  0
EconomicSupportIndexForDisplay             0
ContainmentHealthIndexForDisplay           0
Bachelors_Graduate_Rate                    0
IR                                         0
IR_pop                                     0
FatalityRate                               0
Daily_Covid_Tests_per_mil                  0
NoDoctor_12Months%                         0
Share_of_adults_over_age_65_at_risk%       0
Unemployment_Claims                        0
Adults_with_no_Personal_Doctor%            0
Health_Professional_Shortage_Area          0
Primary_Care_Physicians                    0
VotePercentage_Trump%                      0
Total_Number_Residents                     0
Number_of_COVID_Cases                      0
Number_of_Deaths_from_COVID                0
Total_COVID_Tests_with_Results             0
ICU_Beds                                   0
Effective Reproduction Number              0
LifeExpectancyatBirth                      0
UrbanizationRate                           0
SeverelyObese%                             0
Gini                                       0
Population_Ages_65+_Level                  0
Share_of_adults_over_age_65_at_risk_Level  0
Unemployment_Rate%                         0
dtype: int64
```

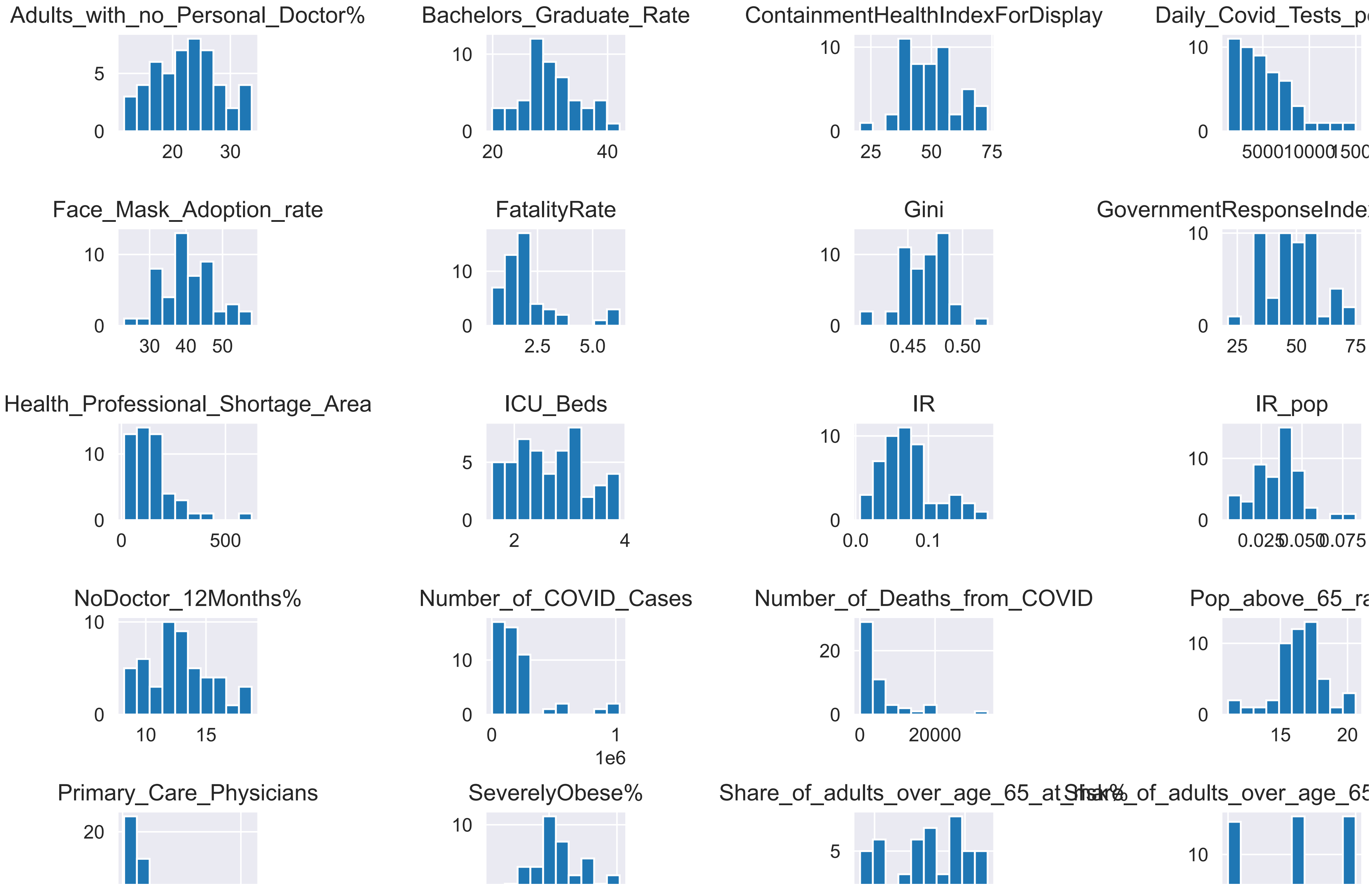
In [22]:
```
# No duplicates
duplicate_entries = main_df1[main_df1.duplicated()]
duplicate_entries.shape
```
Out[22]:
```
(0, 38)
```

Histoplots

We want to find more insights about distribution and relationship between variables.

In [23]:

```
# Histoplots
# Checking data skewness
main_df1.hist(bins=10, figsize=(16,10))
plt.tight_layout()
plt.subplots_adjust(hspace=1)
plt.show()
```



Correlation Matrix Heatmap

Samples of **Positive Correlation** are:

- 'No Doctor for the last 12 months' and 'Uninsured Population'
- 'Median Income' and 'Life Expectancy at birth'
- 'Unemployment Claim' and 'Health Care Expenditure'

Samples of **Negative Correlation** are:

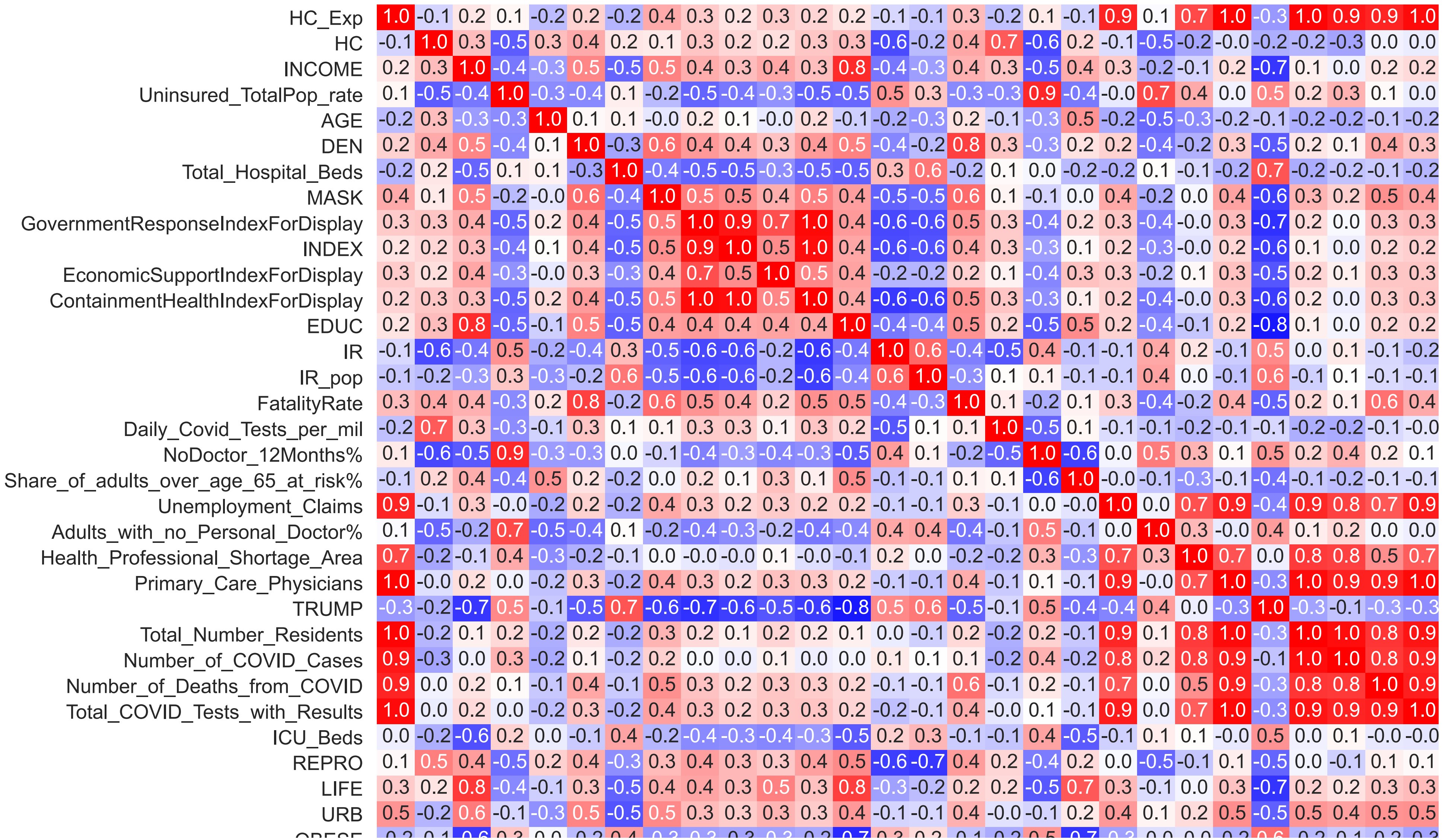
- 'Infection Rate' and 'Stringency Index'
- 'Severe Obesity' and 'Life Expectancy at Birth'
- 'Health Care Expenditure per capita' and 'Uninsured total population rate'

Note: Correlation does not imply causation

In [69]:

```python
# Correlation Matrix
plt.figure(figsize=(18, 10))
sns.heatmap(main_df1.corr(),
            cmap='bwr',
            annot=True,
           fmt=".1f",
            annot_kws={'size':10})
```

Out[69]: <matplotlib.axes._subplots.AxesSubplot at 0x12cefebe0>



	HC_Exp	HC	INCOME	Uninsured_TotalPop_rate	AGE	DEN	Total_Hospital_Beds	MASK	GovernmentResponseIndexForDisplay	INDEX	EconomicSupportIndexForDisplay	ContainmentHealthIndexForDisplay	EDUC	IR	IR_pop	FatalityRate	Daily_Covid_Tests_per_mil	NoDoctor_12Months%	Share_of_adults_over_age_65_at_risk%	Unemployment_Claims	Adults_with_no_Personal_Doctor%	Health_Professional_Shortage_Area	Primary_Care_Physicians	TRUMP	Total_Number_Residents	Number_of_COVID_Cases	Number_of_Deaths_from_COVID	Total_COVID_Tests_with_Results
OBESE	-0.2	-0.1	-0.6	0.3	0.0	-0.2	0.4	-0.3	-0.3	-0.3	-0.3	-0.2	-0.7	0.3	0.2	-0.1	-0.2	0.5	-0.7	-0.3	-0.0	-0.0	-0.2	0.6	-0.2	-0.1	-0.2	-0.3
Gini	0.5	-0.1	-0.3	0.0	0.2	0.4	0.1	0.3	0.3	0.3	0.2	0.3	-0.1	0.0	-0.0	0.6	-0.2	0.2	-0.2	0.4	-0.1	0.3	0.5	-0.1	0.5	0.5	0.6	0.6
AGELevel	-0.2	0.3	-0.2	-0.3	0.8	0.2	-0.1	0.0	0.3	0.2	0.0	0.3	-0.0	-0.2	-0.4	0.2	0.0	-0.3	0.4	-0.3	-0.4	-0.3	-0.1	-0.2	-0.2	-0.3	-0.1	-0.2
AGELevelShare	-0.1	0.2	0.3	-0.3	0.4	0.2	-0.2	-0.0	0.2	0.1	0.3	0.1	0.4	-0.1	-0.1	0.1	0.1	-0.5	0.9	-0.0	-0.0	-0.3	-0.1	-0.4	-0.1	-0.1	-0.0	-0.0
UNEMP	0.3	-0.0	0.2	-0.2	0.1	0.3	-0.4	0.7	0.5	0.5	0.2	0.5	0.1	-0.4	-0.4	0.3	0.0	-0.1	0.0	0.4	-0.1	0.1	0.4	-0.5	0.3	0.2	0.3	0.4
DEN_fitted	0.5	0.1	0.4	-0.2	-0.0	0.7	-0.3	0.6	0.6	0.5	0.4	0.6	0.5	-0.3	-0.3	0.8	-0.0	-0.1	-0.1	0.4	-0.4	0.1	0.5	-0.5	0.4	0.3	0.6	0.5
resid_iv	-0.2	-0.0	0.0	0.2	-0.3	-0.2	0.1	0.0	-0.0	0.0	-0.0	0.0	0.0	-0.0	-0.0	0.2	0.1	0.2	-0.1	-0.1	0.4	-0.1	-0.1	0.2	-0.2	-0.2	0.1	-0.1
DEN_resid	0.1	0.0	0.0	-0.3	0.4	0.4	-0.2	0.2	-0.0	-0.1	-0.1	-0.0	0.0	-0.0	-0.1	0.1	-0.2	-0.2	0.1	0.0	-0.5	-0.2	0.1	-0.2	0.1	0.1	0.0	0.1
DEN_resid1	0.4	-0.0	-0.1	-0.2	0.4	0.3	0.0	0.2	0.0	-0.0	0.0	0.1	0.0	0.0	-0.0	0.3	-0.2	-0.1	0.1	0.2	-0.4	0.1	0.4	-0.2	0.4	0.4	0.4	0.4
logDen	0.4	0.1	0.3	-0.3	0.2	0.8	-0.3	0.6	0.4	0.4	0.2	0.4	0.4	-0.3	-0.3	0.7	-0.1	-0.1	0.0	0.3	-0.6	-0.0	0.5	-0.6	0.4	0.4	0.5	0.5

Renaming of Variables

In [24]:
```
main_df1.rename(columns={'PopulationDensity_mi2': 'DEN'}, inplace=True)
main_df1.rename(columns={'Pop_above_65_rate': 'AGE'}, inplace=True)
main_df1.rename(columns={'Face_Mask_Adoption_rate': 'MASK'}, inplace=True)
main_df1.rename(columns={'Bachelors_Graduate_Rate': 'EDUC'},inplace=True)  ## How much % of population is graduated
main_df1.rename(columns={'Health_Care_Expenditures_per_Capita': 'HC'}, inplace=True)
main_df1.rename(columns={'MedianIncome_Annual': 'INCOME'}, inplace=True)
main_df1.rename(columns={'StringencyIndexForDisplay': 'INDEX'}, inplace=True)
main_df1.rename(columns={'LifeExpectancyatBirth': 'LIFE'}, inplace=True)
main_df1.rename(columns={'UrbanizationRate': 'URB'}, inplace=True)
main_df1.rename(columns={'SeverelyObese%': 'OBESE'}, inplace=True)
main_df1.rename(columns={'Effective Reproduction Number': 'REPRO'},inplace=True)
main_df1.rename(columns={'VotePercentage_Trump%': 'TRUMP'}, inplace=True)
main_df1.rename(columns={'Population_Ages_65+_Level': 'AGELevel'}, inplace=True)
main_df1.rename(columns={'Share_of_adults_over_age_65_at_risk_Level': 'AGELevelShare'}, inplace=True)
main_df1.rename(columns={'Unemployment_Rate%': 'UNEMP'}, inplace=True)
```

In [25]:
```
main_df1.head()
```

Out[25]:

	State	HC_Exp	HC	INCOME	Uninsured_TotalPop_rate	AGE	DEN	Total_Hospital_Beds	MASK	GovernmentResponseIndexForDisplay	...	Total_CC
0	Alabama	35263	7281	48123	9.7	16.9	95	3.1	38.0	36.46	...	
1	Alaska	8151	11064	73181	11.5	11.8	1	2.2	42.0	52.08	...	
2	Arizona	43356	6452	56581	11.1	17.5	60	1.9	36.0	48.70	...	
3	Arkansas	21980	7408	45869	9.1	17.0	57	3.2	39.0	51.04	...	
4	California	291989	7549	71805	7.8	14.3	251	1.8	52.0	65.89	...	

5 rows × 38 columns

Models and Results

Simple Linear Regression:

$$\text{Fatality Rate} = \beta_0 + \beta_1 * PopulationDensity + e$$

with β the **average causal effect** of Population Density on Fatality Rate

The **null hypothesis** is

$$\mathbb{H}_0 : \beta = \beta_0$$

The **alternative hypothesis** is

$$\mathbb{H}_1 : \beta \neq \beta_0$$

Null hypothesis states that the true value of β equals the hypothesized value β_0. Alternative hypothesis states that the true value of β does not equal the hypothesized value.

Our main goal is to assess whether or not a coefficient β equals a specific value β0.

Simple Regression & Forward Selection

In order to alleviate omitted variables bias, we need to think about finding control variables, which may directly correlated to focal x (Population Density) and directly influence y(Fatality Rate from COVID-19). We will discuss each of the variables separately. Here you can see a list of confounding variables:

- Population Density - DEN
- Population Ages 65+% - AGELevelShare
- Health Care Expenditures per Capita - HC
- Bachelors Degree Graduate Rate - EDUC
- SeverelyObese% - OBESE
- Life Expectancy at Birth - LIFE
- Infection Rate -IR

Population Density

REG1: Population Density is the Focal 'X' and Fatality Rate is dependent variable 'Y'

Population Density (Social Variable) - the increased population density increases exposure to all communicable pathogens as it is getting more difficult for people to keep social distance.[1]

While people living in areas which are not so populated are more likely to maintain some sort of social distance. Therefore, people living in areas with high population density are more likely to be infected with a heavy viral load which could increase the severity of COVID-19 and lead to death. We expect the coefficient of this variable to be positive.

In [26]:

```python
# Step 1: Simple Linear Regression
reg1 = smf.ols(formula='FatalityRate ~ np.log(DEN)', data=main_df1)
results_1 = reg1.fit()
print('results_1.summary(): \n{}\n'.format(results_1.summary()))
```

```
results_1.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.466
Model:                            OLS   Adj. R-squared:                  0.455
Method:                 Least Squares   F-statistic:                     41.87
Date:                Tue, 11 May 2021   Prob (F-statistic):           4.76e-08
Time:                        10:53:14   Log-Likelihood:                -70.009
No. Observations:                  50   AIC:                             144.0
Df Residuals:                      48   BIC:                             147.8
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept      -0.8548      0.477     -1.791      0.080      -1.814       0.105
np.log(DEN)     0.6529      0.101      6.471      0.000       0.450       0.856
==============================================================================
Omnibus:                       13.248   Durbin-Watson:                   1.836
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               13.866
Skew:                           1.162   Prob(JB):                     0.000975
Kurtosis:                       4.118   Cond. No.                         16.6
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Note: The coefficient for population density is significant as p-value is 0.000.

Share of adults over age 65 at risk Level

Population Age 65+% - the coefficient is expected to be positive as an increase in population over 65 years of age are more prone to die from pneumonia and respiratory failure caused by COVID-19.

Definition of variable 'Share of adults over age 65 at risk Level': Older adults (ages 65 or older, rather than 60 and older) with heart disease, chronic obstructive pulmonary disease (COPD), uncontrolled asthma, diabetes, or a BMI greater than 40.[1]

In [27]:
```
reg_2 = smf.ols(
    formula=
    'FatalityRate ~  np.log(DEN) + AGELevelShare',
    data=main_df1)
results_2 = reg_2.fit()
print('results_2.summary(): \n{}\n'.format(results_2.summary()))
```

```
results_2.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.490
Model:                            OLS   Adj. R-squared:                  0.469
Method:                 Least Squares   F-statistic:                     22.62
Date:                Tue, 11 May 2021   Prob (F-statistic):           1.31e-07
Time:                        10:55:30   Log-Likelihood:                -68.832
No. Observations:                  50   AIC:                             143.7
Df Residuals:                      47   BIC:                             149.4
Df Model:                           2
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -1.1445      0.509     -2.249      0.029      -2.168      -0.121
np.log(DEN)       0.6585      0.100      6.607      0.000       0.458       0.859
AGELevelShare     0.2593      0.172      1.505      0.139      -0.087       0.606
==============================================================================
Omnibus:                       11.517   Durbin-Watson:                   1.906
Prob(Omnibus):                  0.003   Jarque-Bera (JB):               11.456
Skew:                           1.036   Prob(JB):                      0.00325
Kurtosis:                       4.097   Cond. No.                         18.4
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Note: The coefficient for population density slightly increased but it is still significant as p-value is 0.000.

Health Care Expenditures per Capita

Health Care Expenditures per Capita - better Health Care system means that patients who get infected with COVID-19 are able to get treatment on time and less prone to die. It is expected to have a negative effect on the death rate as an increase in Health Care Expenditure implied better healthcare for the patients infected and prone to COVID-19 infection and death.[1]

In [28]:

```python
reg_3 = smf.ols(
    formula=
    'FatalityRate ~  np.log(DEN)+ AGELevelShare+ HC',
    data=main_df1)
results_3 = reg_3.fit()
print('results_3.summary(): \n{}\n'.format(results_3.summary()))
```

```
results_3.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.588
Model:                            OLS   Adj. R-squared:                  0.561
Method:                 Least Squares   F-statistic:                     21.90
Date:                Tue, 11 May 2021   Prob (F-statistic):           5.89e-09
Time:                        10:55:37   Log-Likelihood:                -63.510
No. Observations:                  50   AIC:                             135.0
Df Residuals:                      46   BIC:                             142.7
Df Model:                           3
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -4.0018      0.981     -4.080      0.000      -5.976      -2.027
np.log(DEN)       0.6288      0.091      6.908      0.000       0.446       0.812
AGELevelShare     0.1616      0.159      1.014      0.316      -0.159       0.482
HC                0.0004      0.000      3.303      0.002       0.000       0.001
==============================================================================
Omnibus:                        6.210   Durbin-Watson:                   1.833
Prob(Omnibus):                  0.045   Jarque-Bera (JB):                5.203
Skew:                           0.753   Prob(JB):                       0.0742
Kurtosis:                       3.477   Cond. No.                     6.44e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.44e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Note: The coefficient for population density slightly dropped but it is still significant as p-value is 0.000.

Bachelors Degree Graduation Rate

Bachelors Degree Graduate Rate (Social Variable) - lack of education was also expected to harm the COVID-19 mortality rates, as a better-educated population are more informed about the prevention and treatment of COVID-19.

In [29]:
```python
reg_4 = smf.ols(
    formula=
    'FatalityRate ~  np.log(DEN) + AGELevelShare + HC+ EDUC',
    data=main_df1)
results_4 = reg_4.fit()
print('results_4.summary(): \n{}\n'.format(results_4.summary()))
```

```
results_4.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.597
Model:                            OLS   Adj. R-squared:                  0.561
Method:                 Least Squares   F-statistic:                     16.63
Date:                Tue, 11 May 2021   Prob (F-statistic):           1.95e-08
Time:                        10:55:40   Log-Likelihood:                -62.999
No. Observations:                  50   AIC:                             136.0
Df Residuals:                      45   BIC:                             145.6
Df Model:                           4
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -4.4401      1.082     -4.105      0.000      -6.619      -2.261
np.log(DEN)       0.5863      0.101      5.795      0.000       0.383       0.790
AGELevelShare     0.0820      0.180      0.457      0.650      -0.280       0.444
HC                0.0003      0.000      2.955      0.005       0.000       0.001
EDUC              0.0314      0.033      0.965      0.340      -0.034       0.097
==============================================================================
Omnibus:                        6.750   Durbin-Watson:                   1.910
Prob(Omnibus):                  0.034   Jarque-Bera (JB):                5.929
Skew:                           0.823   Prob(JB):                       0.0516
Kurtosis:                       3.368   Cond. No.                     7.10e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.1e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Note: The coefficient for population density keeps dropping slightly but it is still significant as p-value is 0.000.

Obesity

Obesity increases risk for hospitalization, ICU admission, IMV requirement and death among patients with COVID-19. Patients who are older and have pre-existing chronic medical conditions, including obesity, cardiovascular diseases, diabetes, cancers and chronic respiratory diseases and kidney diseases were found to be vulnerable to severe COVID-19.[1]

In [30]:

```python
reg_5 = smf.ols(
    formula=
    'FatalityRate ~  np.log(DEN) + AGELevelShare+ HC+ EDUC + OBESE',
    data=main_df1)
results_5 = reg_5.fit()
print('results_5.summary(): \n{}\n'.format(results_5.summary()))
```

```
results_5.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.597
Model:                            OLS   Adj. R-squared:                  0.551
Method:                 Least Squares   F-statistic:                     13.02
Date:                Tue, 11 May 2021   Prob (F-statistic):           8.59e-08
Time:                        10:56:26   Log-Likelihood:                -62.992
No. Observations:                  50   AIC:                             138.0
Df Residuals:                      44   BIC:                             149.5
Df Model:                           5
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -4.6231      2.009     -2.301      0.026      -8.672      -0.574
np.log(DEN)       0.5825      0.108      5.384      0.000       0.364       0.800
AGELevelShare     0.0920      0.203      0.452      0.653      -0.318       0.502
HC                0.0003      0.000      2.797      0.008    9.57e-05       0.001
EDUC              0.0347      0.045      0.769      0.446      -0.056       0.126
OBESE             0.0217      0.200      0.109      0.914      -0.380       0.424
==============================================================================
Omnibus:                        6.790   Durbin-Watson:                   1.903
Prob(Omnibus):                  0.034   Jarque-Bera (JB):                5.964
Skew:                           0.825   Prob(JB):                       0.0507
Kurtosis:                       3.377   Cond. No.                     1.31e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.31e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Note: The coefficient for population density is getting more stable and continues to hold significant p-value of 0.000.

Life expectancy at birth

The coefficient of 'Life Expectancy at Birth' could be positive or negative, depending on how you look at it. Greater life expectancy at birth is an indication of good health of the population with a good immune system, which can fight the disease; therefore, 'Life Expectancy at birth' should have a positive coefficient.

At the same time a greater life expectancy at birth implies people live longer with aging, and thus more prone to die of COVID-19 if infected. In this case, it can have a negative coefficient.[1]

In [31]:

```
reg_6 = smf.ols(
    formula=
    'FatalityRate ~  np.log(DEN) + AGELevelShare + HC+ EDUC + OBESE + LIFE',
    data=main_df1)
results_6 = reg_6.fit()
print('results_6.summary(): \n{}\n'.format(results_6.summary()))
```

```
results_6.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.598
Model:                            OLS   Adj. R-squared:                  0.541
Method:                 Least Squares   F-statistic:                     10.64
Date:                Tue, 11 May 2021   Prob (F-statistic):           3.17e-07
Time:                        10:56:28   Log-Likelihood:                -62.933
No. Observations:                  50   AIC:                             139.9
Df Residuals:                      43   BIC:                             153.2
Df Model:                           6
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -0.4342     13.280     -0.033      0.974     -27.215      26.347
np.log(DEN)       0.5826      0.109      5.331      0.000       0.362       0.803
AGELevelShare     0.1131      0.216      0.524      0.603      -0.322       0.548
HC                0.0003      0.000      2.755      0.009    9.14e-05       0.001
EDUC              0.0411      0.050      0.825      0.414      -0.059       0.142
OBESE            -0.0207      0.241     -0.086      0.932      -0.507       0.466
LIFE             -0.0529      0.166     -0.319      0.751      -0.387       0.281
==============================================================================
Omnibus:                        7.886   Durbin-Watson:                   1.919
Prob(Omnibus):                  0.019   Jarque-Bera (JB):                7.060
Skew:                           0.881   Prob(JB):                       0.0293
Kurtosis:                       3.535   Cond. No.                     8.53e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.53e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Note: The coefficient for population density is getting more stable (slightly increased) and continues to hold significant p-value of 0.000.

Infection Rate

If you have more people with COVID-19, chances of its transmission to vulnerable group of people increases.

In [32]:

```python
reg_7 = smf.ols(
    formula=
    'FatalityRate ~  np.log(DEN) + AGELevelShare + HC+ EDUC + OBESE + LIFE + IR',
    data=main_df1)
results_7 = reg_7.fit()
print('results_7.summary(): \n{}\n'.format(results_7.summary()))
```

```
results_7.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.598
Model:                            OLS   Adj. R-squared:                  0.531
Method:                 Least Squares   F-statistic:                     8.911
Date:                Tue, 11 May 2021   Prob (F-statistic):           1.10e-06
Time:                        10:56:33   Log-Likelihood:                -62.931
No. Observations:                  50   AIC:                             141.9
Df Residuals:                      42   BIC:                             157.2
Df Model:                           7
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -0.4874     13.475     -0.036      0.971     -27.681      26.706
np.log(DEN)       0.5812      0.114      5.089      0.000       0.351       0.812
AGELevelShare     0.1160      0.225      0.515      0.610      -0.339       0.571
HC                0.0003      0.000      2.130      0.039    1.77e-05       0.001
EDUC              0.0411      0.050      0.816      0.419      -0.061       0.143
OBESE            -0.0154      0.264     -0.058      0.954      -0.548       0.517
LIFE             -0.0517      0.169     -0.306      0.761      -0.393       0.289
IR               -0.2542      4.866     -0.052      0.959     -10.074       9.565
==============================================================================
Omnibus:                        7.884   Durbin-Watson:                   1.926
Prob(Omnibus):                  0.019   Jarque-Bera (JB):                7.055
Skew:                           0.880   Prob(JB):                       0.0294
Kurtosis:                       3.538   Cond. No.                     8.55e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.55e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Note: The magnitude for population density keeps getting more stable and continues to hold significant p-value of 0.000. We stop adding confounding factors at this point.

Multiple Regression

$$\text{FatalityRate} = \beta_0 + \beta_1 * DEN + \beta_2 * AGELevelShare + \beta_3 * HC + \beta_4 * EDUC + \beta_5 * OBESE + \beta_6 * LIFE + \beta_7 * IR + e$$

In [33]:

```python
# Consider multiple regression
reg_mul = smf.ols(
    formula=
    'FatalityRate ~  np.log(DEN) + AGELevelShare + HC+ EDUC + OBESE + LIFE + IR',
    data=main_df1)
results_mul = reg_mul.fit()
print('results_mul.summary(): \n{}\n'.format(results_mul.summary()))
```

```
results_mul.summary():
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.598
Model:                            OLS   Adj. R-squared:                  0.531
Method:                 Least Squares   F-statistic:                     8.911
Date:                Tue, 11 May 2021   Prob (F-statistic):           1.10e-06
Time:                        10:56:36   Log-Likelihood:                -62.931
No. Observations:                  50   AIC:                             141.9
Df Residuals:                      42   BIC:                             157.2
Df Model:                           7
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -0.4874     13.475     -0.036      0.971     -27.681      26.706
np.log(DEN)       0.5812      0.114      5.089      0.000       0.351       0.812
AGELevelShare     0.1160      0.225      0.515      0.610      -0.339       0.571
HC                0.0003      0.000      2.130      0.039    1.77e-05       0.001
EDUC              0.0411      0.050      0.816      0.419      -0.061       0.143
OBESE            -0.0154      0.264     -0.058      0.954      -0.548       0.517
LIFE             -0.0517      0.169     -0.306      0.761      -0.393       0.289
IR               -0.2542      4.866     -0.052      0.959     -10.074       9.565
==============================================================================
Omnibus:                        7.884   Durbin-Watson:                   1.926
Prob(Omnibus):                  0.019   Jarque-Bera (JB):                7.055
Skew:                           0.880   Prob(JB):                       0.0294
Kurtosis:                       3.538   Cond. No.                     8.55e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.55e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Conditional Variance Matrix

Covariance measures the directional relationship between the returns on two variables. A positive covariance means that variables move together while a negative covariance means they move inversely.

In [33]:

```
# We can call the conditional variance matrix from results object
results_mul.cov_params()
```

Out[33]:

	Intercept	np.log(DEN)	AGELevelShare	HC	EDUC	OBESE	LIFE	IR
Intercept	181.576247	0.088223	0.708482	1.923086e-06	0.198039	-2.236193	-2.246712	4.959904
np.log(DEN)	0.088223	0.013039	-0.000199	4.163843e-06	-0.002669	-0.010265	-0.000703	0.138351
AGELevelShare	0.708482	-0.000199	0.050838	-9.730771e-06	0.001474	0.015735	-0.010016	-0.274747
HC	0.000002	0.000004	-0.000010	2.490510e-08	-0.000002	-0.000016	-0.000001	0.000467
EDUC	0.198039	-0.002669	0.001474	-2.167276e-06	0.002542	0.003785	-0.003383	-0.002142
OBESE	-2.236193	-0.010265	0.015735	-1.554670e-05	0.003785	0.069676	0.024627	-0.487527
LIFE	-2.246712	-0.000703	-0.010016	-1.278145e-06	-0.003383	0.024627	0.028531	-0.103547
IR	4.959904	0.138351	-0.274747	4.667036e-04	-0.002142	-0.487527	-0.103547	23.676045

Confidence Interval for all betas

In [34]:
```
# Check Confidence Interval for all betas
results_mul.conf_int()
```

Out[34]:

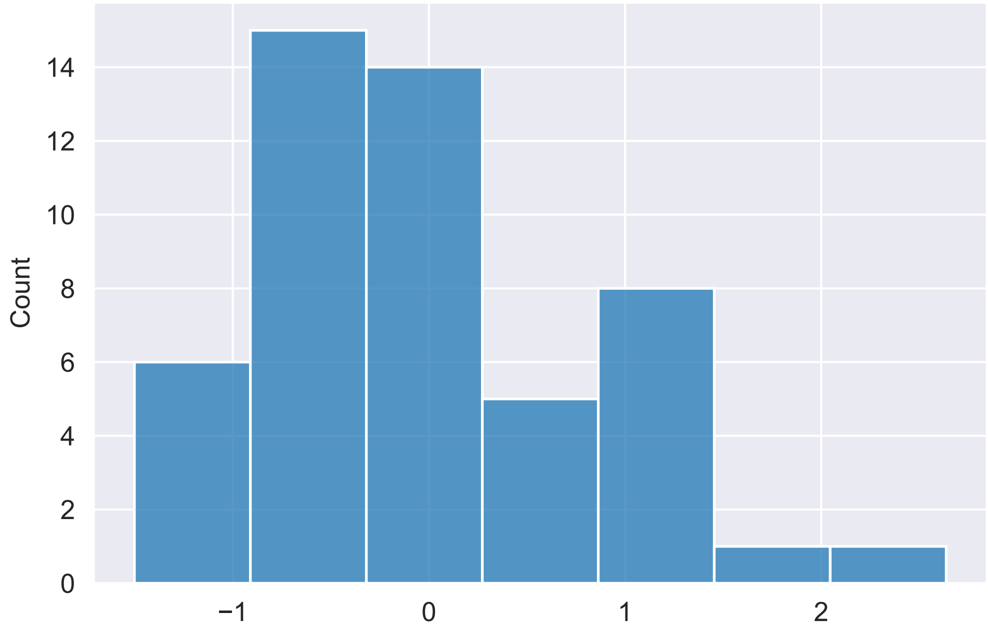
	0	1
Intercept	-27.681147	26.706248
np.log(DEN)	0.350720	0.811602
AGELevelShare	-0.339000	0.571046
HC	0.000018	0.000655
EDUC	-0.060608	0.142879
OBESE	-0.548138	0.517259
LIFE	-0.392627	0.289127
IR	-10.073805	9.565374

Residuals Histoplot

In [35]:

```
# Extract the residuals and plot
sns.histplot(results_mul.resid)
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1269b4c10>



Hypothesis Testing

Null hypothesis

H0: beta_j = 0

t statistic

The t-test assesses whether the beta coefficient is significantly different from zero.

In [36]:
```
# two-sided hypothesis testing
# Null hypothesis: beta_j = 0
stats.t.ppf(1 - 0.05 / 2, df=results_mul.df_resid)
```

Out[36]:
```
2.018081697095881
```

In [37]:
```
# reproduce t statistic:
tstat = results_mul.params / results_mul.bse
print(f'tstat: \n{tstat}\n')
```

```
tstat:
Intercept        -0.036174
np.log(DEN)       5.089495
AGELevelShare     0.514577
HC                2.130258
EDUC              0.815920
OBESE            -0.058492
LIFE             -0.306371
IR               -0.052245
dtype: float64
```

In [38]:
```
np.abs(tstat) > stats.t.ppf(1 - 0.05 / 2, df=results_mul.df_resid)
```

Out[38]:
```
Intercept        False
np.log(DEN)       True
AGELevelShare    False
HC                True
EDUC             False
OBESE            False
LIFE             False
IR               False
dtype: bool
```

Result: We can see that in hypothesis testing for Population Density we will reject H0 in favor of H1 and conclude that beta j is significantly different from zero.

In [39]:
```
# We can easily compute the p values for equivalent test
# reproduce p value:
pval = 2 * stats.t.cdf(-abs(tstat), df=results_mul.df_resid)
print(f'pval: \n{pval}\n')
pval < 0.05
```

```
pval:
[9.71314753e-01 7.95749740e-06 6.09545996e-01 3.90514073e-02
 4.19149424e-01 9.53634134e-01 7.60835719e-01 9.58580924e-01]
```

Out[39]:
```
array([False,  True, False,  True, False, False, False, False])
```

In [40]:
```
# Automated T-test:
hypotheses = ['np.log(DEN) = 0']
ttest = results_mul.t_test(hypotheses)
tstat = ttest.statistic[0][0]
tpval = ttest.pvalue
print(f'tstat: {tstat}\n')
print(f'tpval: {tpval}\n')
```

```
tstat: 5.0894952733745535

tpval: 7.957497399142922e-06
```

P-value is below 0.05 so we reject Null Hypothesis and conclude that beta is significantly different from zero.

Endogeneity Handling

We need to consider if both the dependent variable and a regressor are simultaneously determined or they can theoretically affect each other in different scenarios. If this is the case, then the variables should be treated as endogenous.

$$\text{Fatality Rate} = \beta_0 + \beta_1 * PopulationDensity + e$$

If COVID-19 Fatality Rate is affected by **unobserved** 'Wealth of the population' in a particular state, and individuals with higher wealth choose to live in bigger cities with higher Population Density, then e contains unobserved Wealth, so Popultion Density and e will be *positively correlated*.

Hence Population Density is **endogenous**.

In order to **identify** the *unknown* $\boldsymbol{\beta}$ in **structual model**, we need the help of **IVs** to converse the **structual model** into two **linear projection models**.

In order to handle **endogeneity**, we need to find **instruments**, which are determined outside the system for $(y_i, \boldsymbol{x}_{2i})$, causally determine $\boldsymbol{x}_{2i}$, but do not causally determine y_i except through $\boldsymbol{x}_{2i}$.

Presents of IV can be used to estimate consistently the parameters in equation.

The reason for choosing 2SLS over OLS is that we think OLS estimators beta0 and beta1 are inconsistent due to correlation between x and u.

IV must be: \

1) Uncorrelated with other unobserved factors affecting FatalityRate
2) It should not have direct affect on FatalityRate
3) It must be correlated with Population Density

Null Hypothesis: $\mathbf{H}_0 : \delta_1 = 0$

Failing to reject $\mathbf{H}_0 : \delta_1 = 0$ indicates that no obvious evidence for **endogeneity** of y_2

We reject the null hypothesis that DEN is exogenous and conclude that DEN is indeed an endogenous variable.

IV Selection

An ideal instrumental variable affects the regressor (Population Density) but does not directly influence the dependent variable (Covid-19 Fatality Rate) except through the indirect effect on the regressor.

Median Income Annual and **Gini Index** are potential IV choices:

- If a state has High Annual Median Income, it indicates that Population Density will be higher in that state as more people will migrate to the state trying to find a job.
- However, **Median Income Annual** does not directly affect if a person gets infected by Covid-19 and dies from it, so should not have a direct effect on Covid-19 Fatality Rate
- Gini Index - is a measure of statistical dispersion intended to represent the income inequality or wealth inequality within a nation or any other group of people.

To get the **consistent estimator** for $\boldsymbol{\beta}$, we introduce **Two-Stage Least Squares**

2SLS

In [41]:

```python
# 1st stage (reduced form):
reg_redf = smf.ols(formula='np.log(DEN) ~ AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR + Gini + INCOME', #GINI AND INCOME ARE
                   data=main_df1)
results_redf = reg_redf.fit()
main_df1['DEN_fitted'] = results_redf.fittedvalues

# print regression table:
table_redf = pd.DataFrame({'b': round(results_redf.params, 4),
                           'se': round(results_redf.bse, 4),
                           't': round(results_redf.tvalues, 4),
                           'pval': round(results_redf.pvalues, 4)})
print(f'table_redf: \n{table_redf}\n')
```

```
table_redf:
                     b       se       t    pval
Intercept     -22.4724  16.6658 -1.3484  0.1849
AGELevelShare   0.0885   0.2617  0.3382  0.7370
HC             -0.0002   0.0002 -1.3948  0.1706
EDUC            0.1080   0.0606  1.7804  0.0824
OBESE           0.6464   0.2625  2.4623  0.0181
LIFE            0.0034   0.2157  0.0158  0.9875
IR             -7.1001   4.9768 -1.4266  0.1613
Gini           40.3526   7.4471  5.4186  0.0000
INCOME          0.0001   0.0000  1.5961  0.1181
```

In [42]:

```python
# 2nd stage:
reg_secstg = smf.ols(formula='FatalityRate ~ DEN_fitted + AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR',
                     data=main_df1)
results_secstg = reg_secstg.fit()

# print regression table:
table_secstg = pd.DataFrame({'b': round(results_secstg.params, 4),
                             'se': round(results_secstg.bse, 4),
                             't': round(results_secstg.tvalues, 4),
                             'pval': round(results_secstg.pvalues, 4)})
print(f'table_secstg: \n{table_secstg}\n')
```

table_secstg:

	b	se	t	pval
Intercept	2.8813	11.4743	0.2511	0.8030
DEN_fitted	1.0791	0.1495	7.2160	0.0000
AGELevelShare	0.1084	0.1916	0.5659	0.5745
HC	0.0005	0.0001	3.5646	0.0009
EDUC	-0.0608	0.0488	-1.2465	0.2195
OBESE	-0.4074	0.2415	-1.6871	0.0990
LIFE	-0.0786	0.1436	-0.5473	0.5871
IR	5.0287	4.3067	1.1676	0.2495

In [43]:
```
# IV automatically:
reg_iv = iv.IV2SLS.from_formula(
    formula='FatalityRate ~ 1 + AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR+ [np.log(DEN) ~ Gini+INCOME]',
    data=main_df1)
results_iv = reg_iv.fit(cov_type='unadjusted', debiased=True)   #GET APPROPRIATE STANDART ERROR

# print regression table:
table_iv = pd.DataFrame({'b': round(results_iv.params, 4),
                         'se': round(results_iv.std_errors, 4),
                         't': round(results_iv.tstats, 4),
                         'pval': round(results_iv.pvalues, 4)})
print(f'table_iv: \n{table_iv}\n')
```

```
table_iv:
                    b       se       t    pval
Intercept      2.8813  16.2777  0.1770  0.8604
AGELevelShare  0.1084   0.2718  0.3989  0.6920
HC             0.0005   0.0002  2.5127  0.0159
EDUC          -0.0608   0.0692 -0.8786  0.3846
OBESE         -0.4074   0.3426 -1.1892  0.2410
LIFE          -0.0786   0.2038 -0.3858  0.7016
IR             5.0287   6.1096  0.8231  0.4151
np.log(DEN)    1.0791   0.2121  5.0866  0.0000
```

We completed 2SLS using two different OLSs as well as utilizing a package -IV2SLS. Both of the approaches provided us with similar results for beta for `log Density` , beta=1.0791. However, there is a difference in Standard Error. Standard Error of automatic 2SLS is 0.2121 and Standard Error using two separate OLS is 0.1495. Standard Error using two OLS is misleading as the computer treats each of the OLSs, 1st and 2nd OLS, separately. Therefore, we choose to use automatic 2SLS approach using the package IV2SLS.

Solution for beta using OLS is smaller than it is in 2SLS. It appears that OLS underestimates true effect of beta.

Sargant Test

We need to test the assumption that **IVs are not correlated with the error term** in the equation of interest. If IVs are endogenous than we need to find different IVs. Since we have overidentifying restrictions, we are going to perform the Sargan–Hansen test.

The test of overidentifying restrictions regresses the residuals from an 2SLS regression on all instruments and exogenous variables. It is based on the observation that the residuals should be uncorrelated with the set of exogenous variables if the instruments are truly exogenous.

- **Null Hypothesis: All IVs are exogenous (IVs are uncorrelated to Error Term)**
- **Alternative Hypothesis: IVs are correlated to Error Term.**

In [44]:

```
# We got residualts from 2SLS and regress it on all exogenous variables and IVs

# IV automatically:
reg_iv = iv.IV2SLS.from_formula(
    formula='FatalityRate ~ 1 + AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR+ [np.log(DEN) ~ Gini+INCOME]',
    data=main_df1)
results_iv = reg_iv.fit(cov_type='unadjusted', debiased=True)   #GET APPROPRIATE STANDART ERROR


# auxiliary regression:
main_df1['resid_iv'] = results_iv.resids

reg_aux = smf.ols(formula='resid_iv ~ AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR+ Gini+INCOME',
                  data=main_df1)
results_aux = reg_aux.fit()
```

In [45]:

```
# calculations for test:
r2 = results_aux.rsquared
n = results_aux.nobs
teststat = n * r2
pval = 1 - stats.chi2.cdf(teststat, 1)

print(f'r2: {r2}\n')
print(f'n: {n}\n')
print(f'teststat: {teststat}\n')
print(f'pval: {pval}\n')
```

```
r2: 0.0004487911181826343

n: 50.0

teststat: 0.022439555909131714

pval: 0.8809236841949758
```

P-Value is above 0.05, therefore, we cannot reject Null Hypothesis and may conclude that IVs are not correlated to Error. It supports the validity of IVs we found.

Testing for Endogeneity

- Next, we can use *Hausman-Wu test* to test for Endogeneity.
- The **2SLS estimator** is *less efficient* than **OLS estimator** when the explanatory variables are **exogenous**
- Therefore, if **no endogeneity** problem occurs, then we prefer **OLS estimator**.

Suppose the **structural model**:

$$y_1 = \beta_0 + \beta_1 y_2 + \beta_2 z_1 + \beta_3 z_2 + u_1$$

where y_2 (Population Density) is suspected **endogenous**

- We also have available **IVs** z_3 (Gini Index) and z_4 (Income) excluded from the above model. In terms of the first stage **linear prediction model** of
$$y_2 = \pi_0 + \pi_1 z_1 + \pi_2 z_2 + \pi_3 z_3 + \pi_4 z_4 + v_2$$
we know that y_2 (Population Density) is **not endogenous** if and only if v_2 is *uncorrelated* to u_1 in the **structural model**. Idealy speaking, we can just test the statistical significance of δ_1 in the **simple projection model**:
$$u_1 = \delta_1 v_2 + e_1$$
- In practice, we will collect the first stage **linear prediction model** *residuals* and conduct the following auxiliary regression:
$$y_1 = \beta_0 + \beta_1 y_2 + \beta_2 z_1 + \beta_3 z_2 + \delta_1 \hat{v}_2 + \text{ error}$$

- **$\mathbf{H0}$:δ1=0**
- *Failing to reject $\mathbf{H0}$:δ1=0 indicates that no obvious evidence for endogeneity of Population Density (y2)**

In [46]:

```
# 1st stage (reduced form):
reg_redf = smf.ols(formula='np.log(DEN) ~ AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR + Gini+INCOME', #GINI and income are I\
                   data=main_df1)
results_redf = reg_redf.fit()
main_df1['DEN_resid'] = results_redf.resid
```

In [47]:

```
# 2nd stage:
reg_secstg = smf.ols(formula='FatalityRate ~ DEN_resid +np.log(DEN) + AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR',
                     data=main_df1)
results_secstg = reg_secstg.fit()
```

In [48]:
```python
# print regression table:
table_secstg = pd.DataFrame({'b': round(results_secstg.params, 4),
                             'se': round(results_secstg.bse, 4),
                             't': round(results_secstg.tvalues, 4),
                             'pval': round(results_secstg.pvalues, 4)})
print(f'table_secstg: \n{table_secstg}\n')
```

```
table_secstg:
                     b       se       t    pval
Intercept       2.8813  11.1969  0.2573  0.7982
DEN_resid      -0.8598   0.1918 -4.4838  0.0001
np.log(DEN)     1.0791   0.1459  7.3948  0.0000
AGELevelShare   0.1084   0.1869  0.5799  0.5652
HC              0.0005   0.0001  3.6529  0.0007
EDUC           -0.0608   0.0476 -1.2773  0.2087
OBESE          -0.4074   0.2357 -1.7288  0.0914
LIFE           -0.0786   0.1402 -0.5608  0.5780
IR              5.0287   4.2026  1.1966  0.2384
```

We can reject Null Hypothesis and conclude that we have evidence for endogeneity of **Population Density**, therefore, we need to continue our research to find more IVs.

Because of this result, we will explore other variables as IVs for 2SLS. We add **Unemployment** and **Urbanization** as IVs. Both of those variables affects the regressor (Population Density) but do not directly influence the dependent variable (Covid-19 Fatality Rate) except through the indirect effect on the regressor.

Reason for choosing **Unemployment**:[5]

- Highly dense areas tend to have lower unemployment rate.
- However, **Unemployment** does not directly affect if a person gets infected by Covid-19 and dies from it, so should not have a direct effect on Covid-19 Fatality Rate.

Reason for choosing **Urbanization**:[6]

- **Urbanization** - the urban population as a percentage of the total population by U.S. region and state. States with high urbanization rate have higher density. Some of the states might have high population over larger geographical area but they are not densely populated.

To get the **consistent estimator** for β, we introduce **Two-Stage Least Squares**

Additional IVs

In [49]:

```
#ADD ON ANOTHER 2SLS
# IV automatically:
reg_iv1 = iv.IV2SLS.from_formula(
    formula='FatalityRate ~ 1 + AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR+ [np.log(DEN)~ UNEMP+URB]',
    data=main_df1)
results_iv1 = reg_iv1.fit(cov_type='unadjusted', debiased=True)   #GET APPROPRIATE STANDART ERROR

# print regression table:
table_iv1 = pd.DataFrame({'b': round(results_iv1.params, 4),
                         'se': round(results_iv1.std_errors, 4),
                         't': round(results_iv1.tstats, 4),
                         'pval': round(results_iv1.pvalues, 4)})
print(f'table_iv1 \n{table_iv1}\n')
```

```
table_iv1
                    b       se       t    pval
Intercept      1.3137  14.3638  0.0915  0.9276
AGELevelShare  0.1120   0.2396  0.4672  0.6428
HC             0.0004   0.0002  2.3959  0.0211
EDUC          -0.0134   0.0633 -0.2108  0.8340
OBESE         -0.2250   0.3091 -0.7279  0.4707
LIFE          -0.0661   0.1797 -0.3678  0.7148
IR             2.5704   5.4594  0.4708  0.6402
np.log(DEN)    0.8474   0.2048  4.1370  0.0002
```

In [51]:

```
# 1st stage (reduced form):

reg_redf1 = smf.ols(formula='np.log(DEN) ~ AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR + UNEMP +URB', #GINI and income are I\
                   data=main_df1)
results_redf1 = reg_redf1.fit()
main_df1['DEN_resid1'] = results_redf1.resid

# 2nd stage:
reg_secstg1 = smf.ols(formula='FatalityRate ~ DEN_resid1 +np.log(DEN) + AGELevelShare + HC+ EDUC + OBESE +  LIFE + IR',
                     data=main_df1)
results_secstg1 = reg_secstg1.fit()
```

In [52]:

```
# print regression table:
table_secstg1 = pd.DataFrame({'b': round(results_secstg1.params, 4),
                              'se': round(results_secstg1.bse, 4),
                              't': round(results_secstg1.tvalues, 4),
                              'pval': round(results_secstg1.pvalues, 4)})
print(f'table_secstg1: \n{table_secstg1}\n')
```

```
table_secstg1:
                    b       se       t    pval
Intercept      1.3137  13.1923  0.0996  0.9212
DEN_resid1    -0.4102   0.2335 -1.7566  0.0865
np.log(DEN)    0.8474   0.1881  4.5044  0.0001
AGELevelShare  0.1120   0.2201  0.5087  0.6137
HC             0.0004   0.0002  2.6087  0.0126
EDUC          -0.0134   0.0582 -0.2295  0.8196
OBESE         -0.2250   0.2839 -0.7925  0.4326
LIFE          -0.0661   0.1651 -0.4005  0.6909
IR             2.5704   5.0142  0.5126  0.6110
```

We fail to reject Null Hypothesis at 1% and 5% when we change the IVs. We conclude that there are no evidence for endogeneity of **Population Density** when we use IVs such as **Unemployment** and **Urbanization**.

We conclude that the population density has a significant effect on **Fatality Rate** and by using the following variables such as AGELevelShare, HC , EDUC, OBESE, LIFE, IR and IVs being Urban and Unemployment rates, the focal X remains stable.

One of the limitations is that our dataset has a lot of variables but limited rows due to number of US States.

Conclusion and Limitations

This project estimates and analyzes the causal effect of Population Density on the COVID-19 mortality rate. COVID-19 has been more fatal than many recent epidemics, which makes its death toll relevant to understanding the pandemic more broadly and help to better prepare for future pandemics.

Understanding the reasons behind Fatality Rate being high in some of the areas and not others will help Government to come up with measurements to mitigate the pressure on the Health Care system during pandemic outbreak and potentially save lives of millions.

The estimated results suggest that the population density has a statistically significant positive effect on the COVID-19 mortality rate.

IV Limitations: In a small sample, the IV estimator can have a substantial bias. According to the law of large numbers, IV estimator is consistent for b1:plim(b1^)=b1, provided assumptions are satisfied. If either assumptions fails, the IV estimators are not consistent. One feature of the IV estimator is that, when x and u in fact correlated so that IV Estimation is actually needed - it is essentially never unbiased. IV estimator has an approximate normal distribution in large sample size.

There are considerable limitations to any study employing data aggregated to the state level. Ours is no exception. Such data will likely not capture factors relevant to our research question that more refined data would reveal. Despite these limitations, we hope that this study will serve as the basis for future research in this area.[1]

Appendix

Reference Articles and Research Papers

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Appendix 1: Data Sources

COVID 19 Dataset

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https://www.nbcnews.com/politics/2020-elections/president-results (https://www.nbcnews.com/politics/2020-elections/president-results) https://www.prb.org/which-us-states-are-the-oldest/ (https://www.prb.org/which-us-states-are-the-oldest/) Johns Hopkins University, COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) (https://coronavirus.jhu.edu/map.html).

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Effective Reproduction Number https://rt.live/ (https://rt.live/)

Policy Dataset

Dataset can be downloaded from https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker (https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker)