Relationship between Spread of COVID-19 and Race and Ethnicity Demographics

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1 Introduction

The rapid global spread of Coronavirus-19(SARS-Cov-2) caught households and governments by surprise. Yet, based on history, pandemic researchers have been warning about the likelihood of such an event. So far this century, the world has already confronted an array of viral scares, Severe Acute Respiratory Syndrome (SARS), H1N1(Swine flu), Middle East respiratory syndrome (MERS), Ebola, Zika and Dengue. This increase has been attributed to urbanization, globalization and increased human consumption of animal proteins as society becomes more prosperous[1]

Touted as the "great equalizer" that transcends wealth, fame, prestige and age[2], in reality, Coronavirus-19 has had a varied impact on different social, economic, racial and ethinic demographics[3]. In this research, we focus on race and ethnicity demographics. A report from the Center for Disease Control and Prevention (hereafter referred to as the CDC) observed[3] that People of Color (POC) are much more likely to get infected, hospitalized and die from Coronavirus-19 and hence in this research question we analyze the relationship of Coronavirus-19 cases between people of different ethnicities. Specifically, our research question is:

Is a higher percentage of People of Color, or Hispanic or Latino population associated with an increased incidence of Coronavirus-19 cases per hundred thousand residents, in the conterminous United States?

People of Color in the scope of this research are defined as people who do not identify as belonging to a white race only. Hispanic or Latino as a demographic is an ethnicity and not a race, i.e. a person of Latin origin could identify as white or any other race. Hence we include both as separate variables.

The primary COVID data source provided as part of this study are state level statistics of Coronavirus-19 cases and Coronavirus-19 death rates. We consider two states to be equally affected by Coronavirus-19 only if they have the same rate of occurrence of Coronavirus-19, i.e the number of Coronavirus-19 cases as a fraction of the total populations is the same. We chose the primary response variable as 'cases per one hundred thousand residents' for this reason. We consider two states to have equal representation of people of color only if the rate of occurrence of people of color is the same in the two states. Specifically, the number of people of color as a fraction of the total population of the state is the same between the two states. Hence we chose the *percentage of people of color in state population* as one of our primary response variable. Similarly, we consider two states to have equal representation of people who identify as Hispanic or Latino if the rate of occurrence of people who identify as Hispanic or Latino is the same in the two states. Specifically, the number of people who identify as Hispanic or Latino as a fraction of the total population of the state is the same between the two states.Hence we chose the *percentage of people who identify as Hispanic or Latino in state population* as one of our primary response variable.

2 Model Building Process

2.1 Objective and definitions

The overarching objective of our study is to answer the research question in the context of covariate categories such as each state's COVID policies(example: Stay at home mandates), each state's socio-economic conditions(such as people below poverty line) and as COVID spreads through physical proximity, each state's measured mobility of people during the COVID time period of study.

Definitions and terminology

1. Conterminous United States (hereafter referred to as CONUS) refers to the contiguous 48 states and includes Washington D.C. In the rest of this document we will use the short form CONUS instead.
2. In this document we will use the terms COVID-19 or COVID interchangeably with Coronavirus-19.
3. In the description of the datasets we will use **record** to describe the row of the table. Each record may contain values for several fields, these fields are the columns of the table. The term columns and fields will be used interchangeably in this document. The data engineering and the subsequent modeling of this data has been in the 'R' programming language.
4. To reduce the confounding effects of the distribution of vaccines to the number of COVID cases, we have restricted the analysis to before the availability of vaccines in the United States. The first vaccine, outside the vaccine study, was administered on Dec 14th 2020. There are references to this date in the following sections we refer to it as the *vaccine availability date*.
5. Mobility in the context of this study is the duration of time people spend at a given category of locations, such as parks or at their workplace, as compared to a baseline. These categories of parameters and their operationalizaiton will be discussed in detail in the following sections.
6. We also use the phrase *time period of interest*. This denotes the time between 02/15/20 and the *vaccine availability date*. 02/15/20 is the date for the first record of the Google community mobility dataset described in detail in section 2.3.3

2.2 Data loading and cleaning

We now provide the data sources we used for the analysis and a description of their usage. We follow a consistent methodology in this section:

1. We provide a brief description of the raw data to provide the user context of its usage
2. We point to the section in the appendix which describes the process of obtaining this raw data
3. Also in the appendix is a description of converting the raw data into a processed table that is used for this analysis. Of the four datasets that were used for this analysis only one required this intermediate step
4. A description of the processed CSV
5. Steps of processing the CSV into operationalized variables for model generation. This section also contains the handling of missing data

As we describe the above process, we also makes notes of any limitations in the data which we later discuss in the 'limitations of the model' section(section 4)

2.3 Data description and processing individual datasets

2.3.1 New York Times COVID dataset

"Data from The New York Times, based on reports from state and local health agencies."
Hyperlink: Github
Data downloaded on: 03/25/2021

2.3.1.1 Summary of raw data

New York Times has compiled an easily accessible dataset tracking daily COVID cases and COVID related deaths for each state. The dataset is in the format of a table where each row has five fields, namely, name of the state, code for the state, date, number of COVID cases, number of COVID deaths. The COVID cases on a given record (row) is the **cumulative count** of all cases till that date. The COVID deaths are also cumulative, similar to COVID cases. States have records for each date starting with the first reported case or death. The state of Washington has the first recorded case, recorded on January 21st 2020. The dataset is updated continuously on a 3 day lag. In the rest of this document, we will refer to this dataset as the *NYT COVID Dataset*

COVID cases are the primary response variable in our analysis. The dataset consists of the cases reported by each state's government. As stated in the NYT dataset "Some governments continue to report only confirmed cases, while others are reporting both confirmed and probable cases. Other governments are reporting the two types of numbers combined without providing a way to separate the confirmed from the probable." [6]. We recognize this as a limitation of the provided dataset and discuss this in section 4(limitations of the model)

- Confirmed cases are counts of individuals whose Coronavirus infections were confirmed by a laboratory test and reported by a federal, state, territorial or local government agency. Only tests that detect viral RNA in a sample are considered confirmatory. These are often called molecular or RT-PCR tests.
- Probable cases count individuals who did not have a confirmed test but were evaluated by public health officials using criteria developed by states and the federal government and reported by a health department.

2.3.1.2 Data engineering

Appendix section 6.2 describes the step-by-step process of downloading and saving the raw data file as a CSV. There was no processing of the CSV other than the steps described below in **Data processing in steps** section 2.2.1.4.

2.3.1.3 Description of CSV

There are five fields in the data: date, state, fips, cases and deaths. On the day we downloaded the dataset (03/25/21) there were 21,354 records and the last record was for 03/25/2021. The description of the fields are in Table 1.

2.3.1.4 Data processing in steps

1. We load the CSV as an 'R' data frame
2. We then extract one record per state for the vaccine availability date of Dec 14th 2020. As described earlier, this is the cumulative count of all cases and deaths for that state as of Dec 14th 2020.
3. As our research question is restricted to the number of COVID cases in a state, we remove the column associated with deaths
4. We remove the columns 'date' as the data frame now only contains cases from one date (Dec 14th 2020)

Table 1: Description of fields for the raw New York Times COVID dataset

Raw Field Name	Description
date	Date for the record
state	Name of US state or territories
fips	A code used by the census bureau to uniquely identify regions and sub regions
cases	Total number of COVID cases for the state(given in state field) as of the date(given in the date field)
deaths	Total number of COVID deaths for the state(given in state field) as of the date(given in the date field)

5. The column fips is a code used by the census bureau to uniquely identify regions and sub regions. fips would have been the preferred method to merge different dataset but not all datasets had the fips field hence we removed column 'fips' as it is redundant with 'state'.
6. The variables in the processed dataframe are shown below
7. Note that there were no missing values in the dataset.
8. Henceforth in this document we will call this data frame the *NYT COVID data frame*. The complete list of variables after the cleaning and processing are listed in Table 2.

Table 2: Variables of the NYT COVID data frame

Variable name	Description
state	Name of US state or territories
cases	Total number of COVID cases as of 12/14/2020 for the state

2.3.2 US Census Bureau 2019 American Community Survey dataset

"U.S. Census Bureau, 2019 American Community Survey 1-Year Estimates"
Hyperlink: US Census
Data downloaded on: 03/26/2021

2.3.2.1 Summary of raw data

The US Census Bureau's 2019 American Community Survey data provides estimates on demographics for each US state. The American Community Survey is an ongoing survey conducted by the Census Bureau throughout the year to track demographic trends. There is literature on the ACS survey and sampling methodology included in our git repository. We utilized the ACS Demographic and Housing Estimates section which includes population and percent of total population figures by sex and age, race, and ethnicity by state and territory. Below is a description of the data in the report.

ACS Demographic and Housing Estimates Report Sections

1. Sex and Age - Male/Female and various age categorizations
2. One Race - Total Population identifying as one race * White, Black or African American, American Indian and Alaska Native, Asian, Native Hawaiian, or Other * Some categories have further categorizations within race

3. Two or more Races - Total population identifying as two or more races
4. Combined - Race alone or in combined with one or more races * White, Black or African American, American Indian and Alaska Native, Asian, Native Hawaiian, or Other
5. Hispanic or Latino and Race - Separate categorization from race * Hispanic or Latino (of any race) * Not Hispanic or Latino

For our analysis, we utilized population by one race(bullet 2 in list) and Hispanic or Latino and Race categorization(bullet 5 in list) sections.

Limitations: The American Community Survey is an **estimation** of the population demographics that is compiled on an ongoing basis.

2.3.2.2 Data Engineering

Here we describe the processing of the data after it has been loaded into the 'R' environment as a dataframe. There was no processing of the CSV other than the steps described in **Data processing in steps** section 2.2.2.4. Appendix section 6.3 describes the step-by-step process of downloading and saving the raw data file as a CSV.

2.3.2.3 Description of the CSV file

1. There are 54 rows in the CSV file. The first two rows are the header
    1. The first header has the following information:
        1. GEO_ID - unique id for each geographic location in the US
        2. NAME - Name for the geographic region, example Alabama, Alaska
        3. 356 coded fields with demographic information, the codes are of the form DP05_XXXXX. Where XXXXX represents a code corresponding to a categor, for example DP05_0001E
    2. The second header contains the descriptive names for the columns. An example mapping of the first header row with the second header row is shown below, they are of the format 'first row header' -> 'second row header':
        4. GEO_ID -> id
        5. NAME -> Geographic Area Name
        6. DP05_0001E -> Estimate!!SEX AND AGE!!Total population

2.3.2.4 Data processing in steps

1. When we load the CSV to 'R' as a dataframe
    a. We use the first header row(coded) as the column names
    b. We eliminate the row with the second header
2. We now filter the data frame to **keep three columns** and rename them with more descriptive names. The descriptive names will be used in this analysis. See Table 3 for more details.
3. Note that there were no missing values in the dataset.
4. Henceforth in this document we will call this data frame the **US census data frame**. The complete list of variables after the cleaning and processing are listed in Table 3.

2.3.3 Google's Community Mobility Report dataset

Google's Community Mobility Report
Google LLC "Google COVID-19 Community Mobility Reports"
Hyperlink: Google mobility
Data downloaded on: 03/25/2021

Table 3: Raw fields and variables(after processing) of the US Census Bureau data set

Raw Field Name	Variable name	Description
NAME	state	Name of the geographic region. Includes CONUS, Alaska, Hawaii, Puerto Rico
DP05_001E	Total.Population	Estimated, based on a 2019 survey, total population of the state
DP05_0037PE	Percent.White	Estimated, based on the 2019 survey, the percent of the population of the state who identify as white race only
DP05_0071PE	Percent.Hispanic.Or.Latino	Estimated, based on the 2019 survey, the percent of the population of the state who identify as hispanic or latino

2.3.3.1 Summary of raw data

Google has aggregated data to provide insights into how communities have responded to COVID 19 and policies. As described in the Google documentation "These datasets show how visits and length of stay at different places change compared to a baseline. We calculate these changes using the same kind of aggregated and anonymized data used to show popular times for places in Google Maps." The baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The data is at the national, state, and county level for the US and internationally. For the purpose of this report, we are focusing on the US at the state level. We will refer to this dataset as the *Google community mobility report*.

The reported data consists of six metrics comparing the baseline of people's mobility patterns from location and duration prior to and during COVID. The mobility location categories include recreation and retail, grocery and pharmacy, transit stations, parks, workplaces, and residential. Note that an increase from baseline in the category 'residential' indicates an increase in time people stay at home. As one would expect, transit stations, workplaces, parks, retail, grocery typically have been below baseline during COVID while residential is above baseline.**Note:** In this document we use the word *mobility* in this context.

Limitations: Data is limited to individuals who voluntarily participated in the study data and are Android users. Location accuracy and the labeling of places varies across regions. Google advises that this has implications for comparing regions. Refer to Google documentation for more information.

2.3.3.2 Data enginering

Here we describe the processing of the data after it has been loaded into the 'R' environment as a dataframe. There was no processing of the CSV other than the steps described in **Data processing in steps** section 2.2.3.4. Appendix section 6.4 describes the step-by-step process of downloading and saving the raw data file as a CSV.

2.3.3.3 Description of CSV

There are 15 columns(fields) in the dataset and they are shown in Table 4. There are 812,066 rows in the raw file with one header row and the remaining are records

2.3.3.4 Data processing in steps

1. We load the 'CSV' into an 'R' dataframe
2. We filter the dataframe to keep records that are the average for the entire state. This is done by removing all records that are empty for the iso_3166_2_code field. This removed 64894 records from the data leaving 16371 records
3. We now filter the data frame to **keep nine columns** listed in Table 6 column name "Raw field name"

Table 4: Description of fields for the raw Google's Community Mobility dataset

Raw Field Name	Description
country_region_code	Country code. Example: US - United States
country_region	Name of the country. Example: United States
sub_region_1	Name of the subregion. The sub region in the US would correspond to a state, or a union territory.
sub_region_2	Name of the subregion of sub_region_1. In the US this would correspond to a county with the state.
metro_area	A metropolitan area or metro is a region consisting of a densely populated urban core and its less-populated surrounding territories under the same administrative division, sharing industry, infrastructure and housing.[8]
iso_3166_2_code	The purpose of ISO 3166-2 is to establish an international standard of short and unique alphanumeric codes to represent the relevant administrative divisions and dependent territories of all countries. In the US this corresponds to states and District of Columbia
census_fips	A code used by the census bureau to uniquely identify regions and sub regions
place_id	Unique ID for each geographical location
date	Date for which the mobility data is reported
retail_and_recreation_percent_change_from_baseline	Percentage change from baseline of visits and length of stay at retail and recreational locations
grocery_and_pharmacy_percent_change_from_baseline	Percentage change from baseline of visits and length of stay at a grocery or pharmacy
parks_percent_change_from_baseline	Percentage change from baseline of visits and length of stay at a grocery or pharmacy
transit_stations_percent_change_from_baseline	Percentage change from baseline of visits and length in public transit stations
workplaces_percent_change_from_baseline	Percentage change from baseline of visits and length of stay at the workplace
residential_percent_change_from_baseline	Percentage change from baseline of visits and length of stay at home.

4. We remove records that have dates greater than the vaccine availability date of Dec 14th 2020. This removed 867 records and 15504 records remained. Including the start and end dates, there are 304 days in the dataset. As there are 50 States and District of Columbia. This translates to 304 X 51 = 15,504 records, consistent with the number of records remaining.
5. Missing data points were found for two fields, parks_percent_change_from_baseline and transit_stations_percent_change_from_baseline The count of missing values for each of these per state are shown in the table below. Google's documentation simply states that "When the data doesn't meet quality and privacy thresholds, you might see empty fields for certain places and dates." As this information is insufficient to make qualitative judgments about the missing data, we proceed with the aggregation ignoring these missing values.

Table 5: Count of missing records from Google's Community Mobility dataset

state	parks_percent_change_from_baseline	transit_stations_percent_change_from_baseline
Alaska	26	25
Arkansas	7	0
Delaware	66	6
Idaho	44	0
Iowa	22	0
Kansas	16	0
Kentucky	1	0
Maine	25	25
Montana	25	3
Nebraska	25	0
New Hampshire	26	22
North Dakota	35	0
Rhode Island	27	0
South Dakota	27	25
Vermont	26	25
West Virginia	17	3
Wyoming	33	1

6. To operationalize the mobility variables from 304 days to a state level summary, for each state, we take the average of each mobility field, for example transit_stations_percent_change_from_baseline, for the 304 days. For the field parks_percent_change_from_baseline, the number of days varies per state due to the elimination of records with missing values For the field transit_stations_percent_change_from_baseline, the number of days varies per state due to the elimination of records with missing values. The averaged variables are given new names as shown in Table 6.
7. In the final step we filter the data frame to keep only the variables described in the Table 6 and remove all other fields
8. Henceforth in this document we will call this data frame the **Google community mobility estimates**. The complete list of variables after the cleaning and processing are listed in Table 6.

Table 6: Raw fields and variables(after processing) of the Google's Community Mobility dataset

Raw Field Name	Variable name	Description
sub_region_1	state	Name of the geographic region. Includes CONUS, Alaska and Hawaii
date	date	Date for the record
retail_and_recreation_percent_change_from_baseline	Recreation	Average over the 304 days, percentage change from baseline of visits and length of stay at retail and recreational locations
grocery_and_pharmacy_percent_change_from_baseline	Grocery	Average over the 304 days, percentage change from baseline of visits and length of stay at a grocery or pharmacy
parks_percent_change_from_baseline	Parks	Average over the 304 days, percentage change from baseline of visits and length of stay at parks
transit_stations_percent_change_from_baseline	Transit	Average over the 304 days, percentage change from baseline of visits and length in public transit stations
workplaces_percent_change_from_baseline	Workplace	Average over the 304 days, percentage change from baseline of visits and length of stay at the workplace
residential_percent_change_from_baseline	Residential	Average over the 304 days, percentage change from baseline of visits and length of stay at home

2.3.4 Covid 19 US State Policy Database

"Raifman J, Nocka K, Jones D, Bor J, Lipson S, Jay J, and Chan P. (2020)."COVID-19 US state policy database."
Review Policy Details Google Sheets: http://www.tinyurl.com/statepolicies
Github: Github Data download date: 03/25/2021

2.3.4.1 Summary of raw data

The state policy dataset contains a compilation of policies at the state level, that have been enacted as a result of COVID 19. It also contains state level economic indicators, population details, health care metrics, and other information pertinent to COVID research. In the rest of this document, we will refer to this dataset as the **State Policy Dataset**. The dataset contains start and end dates for a wide range of policies including stay at home orders, masks mandates, restaurant and bar closures, gym closures, essential business closures, and others. State policies affecting public exposure to COVID are critical to our analysis as they impact our response metrics of COVID cases. We discuss the policies used in our analysis in the data exploration section. The dataset has been compiled and maintained by researchers and students at the Boston University School of Public Health. Per the documentation, the dates are as of policy implementation and consists of orders or directives and not guidance or recommendations.

Limitations: This dataset only describes the policies enacted by the state but does not present the adherence of these policies by the residents. This dataset also had missing data points that we substituted using publicly available information. This is discussed in **Data processing in steps** section 2.2.4.4

2.3.4.2 Data engineering

Here we describe the processing of the data after it has been loaded into the 'R' environment as a dataframe. Appendix section 6.5 describes the step-by-step process of downloading and saving the raw data file as a CSV.

2.3.4.3 Description of CSV

1. State Policy data has 56 rows. The first 5 rows are the header and field metadata followed by 51 records for each state and Washington DC
    1. 5 records contain column descriptions (records have been compiled into metadata file, refer to Appendix 6.5 for location)
        a. Attribute Code (header)
        b. Attribute Description
        c. Attribute Category
        d. Attribute Type (start, end, attribute)
        e. Attribute Unit (ex: date, text, flag,)
    2. 51 records - 50 states and Washington DC
    3. 219 fields (fill in), 3 state identifiers and 216 state policy and characteristic related fields
        a. State, Postcode, Fips
        b. 216 fields with corresponding Attribute Code
2. For our research, we utilize state characteristics data and policy data. The policy data is primarily in the form of start and end dates

2.3.4.4 Data processing in steps

1. We first load the 'CSV' into a 'R' dataframe
2. We filtered to keep the state data and the columns for the policies we want to incorporate in our analysis

    a. 32 Columns include state, characteristics, and corresponding start and end dates
    b. Primary cleaning was converting date fields to date format and number to numeric
    c. Primary validation was ensuring start and end dates were populated where expected (see next step for missing values)

3. Not all states had a policy in place which showed 0 in the dataset; we replaced it with NA; we identified missing start dates in 6 cases and used the NBC News resource shown below to fill in those dates.**Source:** https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736

- Montana and Wyoming - FM_ALL - Face Mask Mandate Start Date
- Connecticut, Kentucky, Texas - STAYHOME - Stay at Home start date
- New Mexico - Stay at Home end date
- Oklahoma - missing start date but left as 0 because no statewide stay at home

4. To operationalize these start and end dates for each category we calculate the number of days the policy was in effect for the *time period of interest*. We restrict the analysis to the vaccine availability date and hence do not count days for dates higher than Dec 14th 2020 . The following steps were performed for extracting this information

5. Specific policy implementation, i.e. when a policy started and when a policy ended varied by state.
6. We calculated the number of days the policy was in effect as the time between the start date and the minimum of the end date or Dec 14th 2020.
7. If a policy was implemented in a state as two phases then we added the number of days the policy was implemented in the first and the second phases.
8. Henceforth in this document we will call this data frame the **US State policy data frame**. The complete list of variables after the cleaning and processing are listed in Table 7.

Table 7: Variables after data processing ofUS State Policy dataset

Variable name	Description
state	STATE
state.code	STATE CODE
Says.Stay.At.Home	min(STAYHOME, 2020-12-14) minus STHM_END
Days.With.Mask	min(FM_END, 2020-12-14) minus FM_ALL
Days.Restaurant.Closed	min(ENDREST, 2020-12-14) minus CLREST + min(ENDREST2, 2020-12-14) minus CLRST2
Days.Bar.Closed	min(END_BRS, 2020-12-14) minus CLOSEBAR + min(END_BRS2, 2020-12-14) minus CLBAR2
Days.Gym.Closed	min(END_GYM, 2020-12-14) minus CLGYM + min(END_CLGYM2, 2020-12-14) minus CLGYM2
Days.Nonesst.bussi.Closed	min(END_BSNS, 2020-12-14) minus CLBSNS
Religious.Event.Exempt	as.numeric(RELIGX)
state.land.sq.mile	as.numeric(SQML)
Percent.Poverty	as.numeric(POV18)

2.4 Merging of all datasets

In the data loading and cleaning section we had described how individual datasets were handled. In this section we describe how the datasets are combined into one dataframe for exploratory data analysis and model generation

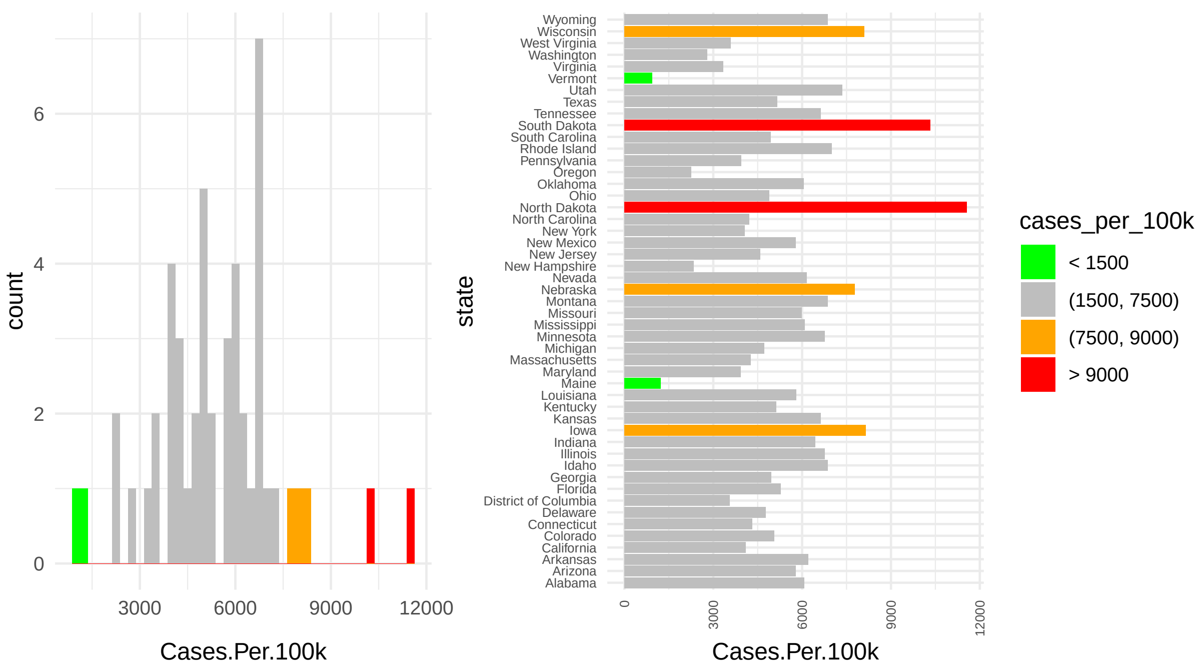
1. As the research question is focussed on the conterminous United States(CONUS); we remove all geographic regions other than the CONUS from the *US Census data frame*
2. With the *US census data frame* next we merge the *NYT COVID data frame*, the *Google community mobility estimates* data frame and the *US State Policy data frame.* We perform this operation as a **left join** on the 'state' field. In this operation the census data frame is the left data frame, i.e. only the states that exist in the census data frame are now a part of this new data frame.
3. The left join operations ends with a data frame that has all the variables from the individual datasets for the CONUS regions. Henceforth we will call this dataframe as the *Main data frame*

3 Exploratory data analysis(EDA)

3.1 Modeling objectives and variables

1. Our model 1 objective is to observe the association between our primary response variable, namely, *COVID cases per hundred thousand residents* and the primary explanatory variables, namely, *percentage of people of color in state population* and *percentage of Hispanics or Latino in state population.*
2. Our objective for model 2 is to create a parsimonious model that describes the association between *COVID cases per hundred thousand residents* and *percentage of people of color in state population* and *percentage of Hispanics or Latino in state population* considering the context of other covariates such as the US State COVID Policies and Socioeconomic Conditions and community *mobility* estimates.
3. Our objective for model 3 is to create a model with the best predictive power for our primary response variable of *COVID cases per hundered thousand residents*

Fig 1: Histogram(left) and Bar graph(right) of Cases.Per.100K for each state
Highest Cases.Per.100k are in North and South Dakota and the lowest are in Maine and Vermont



3.1.1 Primary Response Variable

As we had described in the introduction section, we considered '***Coronavirus-19 cases per hundred thousand residents***' as our primary response variables. We consider two states to be equally affected by COVID, only if they have the same rate of occurrence of COVID, i.e the number of COVID cases as a fraction of the total populations is the same. We standardized the total cases per state into total cases per 100,000 residents of state using the following formula:

$$\text{Cases.Per.100K} = \frac{\text{cases}}{\text{Total.Population}} \times 100,000$$

The total number of cases per state is available as the variable 'cases' from the *NYT COVID dataframe.* Each states population is available as the variable 'Total.Population' from the *US Census dataframe.* Both of these variables are described in detail in the data engineering section. As the ratio $cases/Total.Population$ represents the fraction of population of COVID-19 cases, we multiply it by 100,000 to scale the fraction to one hundred thousand residents. With this transformation *Cases.Per.100K* now represents the operationalized variable for the primary response variables 'Covid cases per one hundred thousand residents'

A discussion on the primary response variable
Fig 1(left) shows the histogram of *Cases.Per.100k*. We do not observe heavy tails in the histogram of *Cases.Per.100k*. We identify two data points that are higher than the bulk of the distribution and highlight them in red. Using the bar graph on **Fig 1(right)** we identify those two points as the states, North Dakota and South Dakota. Similarly, we identify two data points that are lower than the bulk of the distribution and identify it as the state of Maine and Vermont. We also take note of the states marked in orange that are on the high of the bulk of the distribution of *Cases.Per.100k*. These states are Nebraska, Iowa and Wisconsin. As these seven states are likely to have high leverage in the regression models, we pay special attention to these while deciding on the covariates.

3.1.2 Primary Explanatory Variables:

People of color: As we had described in the introduction section, we considered 'percentage of People of color in the state population' as one of our primary explanatory variables. We consider two states to have equal representation of people of color only if the rate of occurrence of people of color is the same, i.e. the number of people of color as a fraction of the total state population is the same. The total population of a state, in percentages, can be summed as two components, namely, percentage of people who identify as white only and percentage of people who do not identify as white only . As we have defined, in the introduction, that "People of Color in the scope of this research are defined as people who do not identify as belonging to a white race only"; we calculate the percentage of the population of people of color in the state population by subtracting the percentage of the population who identify as white from one hundred percent. Specifically,

$$\text{Percent.People.Of.Color} = 100 - \text{Percent.White}$$

With this transformation *Percent.People.Of.Color* now represents the operationalized variable for 'percentage of the population of people of color in the state population'

Hispanic or latino: As we had described in the introduction section, we considered 'percentage of Hispanic or Latino people in the state population' as one of our primary explanatory variables. We consider two states to have equal representation of Hispanic or Latino people if the rate of occurrence of Hispanic or Latino people is the same, i.e. the number of Hispanic or Latino people as a fraction of the total state population is the same. Hispanic or Latino as a demographic is an ethnicity and not a race, i.e. a person of Latin origin could identify as white or any other race. Hence we included it as a separate explanatory variable from persons of color. We used the variable *Percent.Hispanic.Or.Latino* from the *US Census data frame* without transformations for the operationalization of 'percentage of Hispanic or Latino people in the state population'.

3.1.3 Covariate explanatory variables

As stated in the objective, the covariate variables are included to provide context to the analysis. The key categories we had identified and the corresponding variables are listed below. Note that the detailed extraction of these from their corresponding datasets is in the data engineering section.

3.1.3.1 State COVID Policies and Socioeconomic Conditions:
The following variables were extracted from the State Policy dataframe without any transformation:

1. *Days.Stay.At.Home*: Number of days stay at home order was issued in the time period of interest.

2. *Days.With.Mask*: Number of days the mandate to wear a mask was on in the time period of interest.

3. *Days.Restaurant.Closed*: Number of days restaurants were mandated to close in the time period of interest.
4. *Days.Bar.Closed*: Number of days bars were mandated to close in the time period of interest.
5. *Days.Gym.Closed*: Number of days Gyms were mandated to close in the time period of interest.
6. *Days.Nonesst.bussi.Closed*: Number of days non-essential businesses were mandated to close in the time period of interest.
7. *Percent.Poverty*: Percentage of population of the state below the poverty line.

Fig 2: State COVID policy mandates for the time period of interest(02/15/20 to 12/14/20)
The presence of a line is an indicator that the mandate is in effect

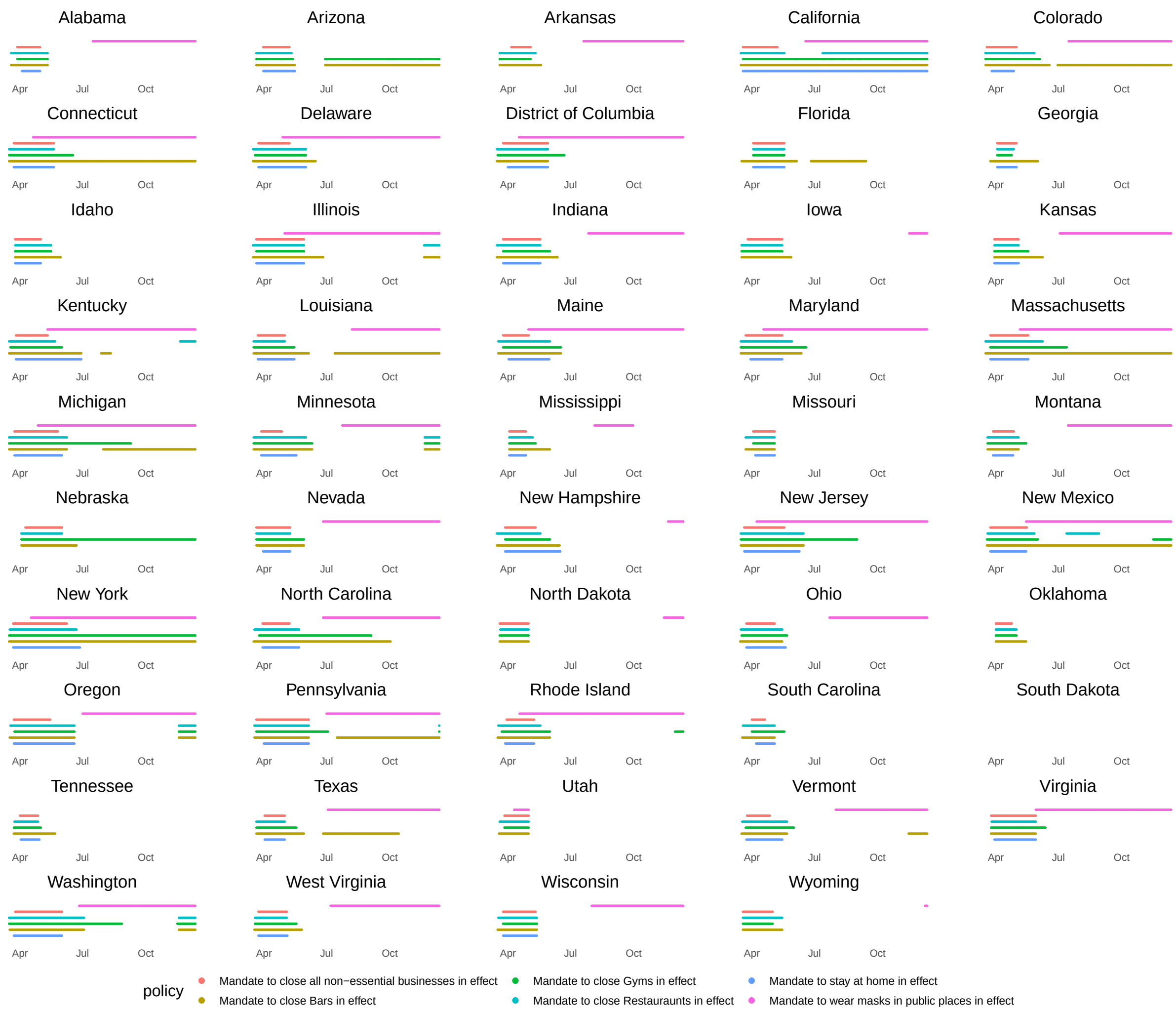


Fig 2 shows the timeline of when each State executed the different mandates such as ‘stay at home’ or ‘wearing masks in public places’. In the discussion of the primary response variable (**Fig 1**) we had observed that North and South Dakota had high *Cases.Per.100k*. In **Fig 2** we observe that South Dakota had not implemented any COVID related state mandates during the time period of interest. North Dakota although did implement state mandates, it was only for a short period of time relative to other states. Take note that North Dakota did not implement Stay at Home order at any time and the Mandate to wear masks was for a short time in the period of interest. We had also noted in **Fig 1** states that were high in *Cases.Per.100k* but not as high as North and South Dakota. We had marked them in orange and the states are Nebraska, Iowa and Wisconsin. We note that neither Nebraska or Iowa implement a stay at home mandate. The mask

mandate was initiated for Iowa but only for a short time in the period of interest. Wisconsin, on other hand, implemented a stay at home mandate for a short period.We also observes that states such as Washington and New Mexico had multiple phases of mandate implementation. With these observations we make a qualitative assessment that the sum of days a mandate was in effect in a state would provide useful information for the model. We then expect that the operationalized variables for stay at home order, i.e. *Days.Stay.At.Home* and for mask mandates, i.e. *Days.With.Mask* would have an impact on *Covid.Cases.Per.100k*.

3.1.3.2 Google Community Mobility: The following variables were extracted from the Google Community Mobility Estimates data frame without any transformation:

1. *Residential*: Average relative change in the length of stay at home during the time period of interest.
2. *Workplace*: Average relative change in the length of stay at the workplace during the time period of interest.
3. *Grocery*: Average relative change in the length of stay at the grocery or pharmacy during the time period of interest.
4. *Parks*: Average relative change in the length of stay at the Park or areas of recreation during the time period of interest.
5. *Transit*: Average relative change in the length of stay in transit stations, such as bus and train stops, during the time period of interest.

3.1.4 Summary table of all variables

Table 8: Response, explanatory and covariate variables summary statistics and categories

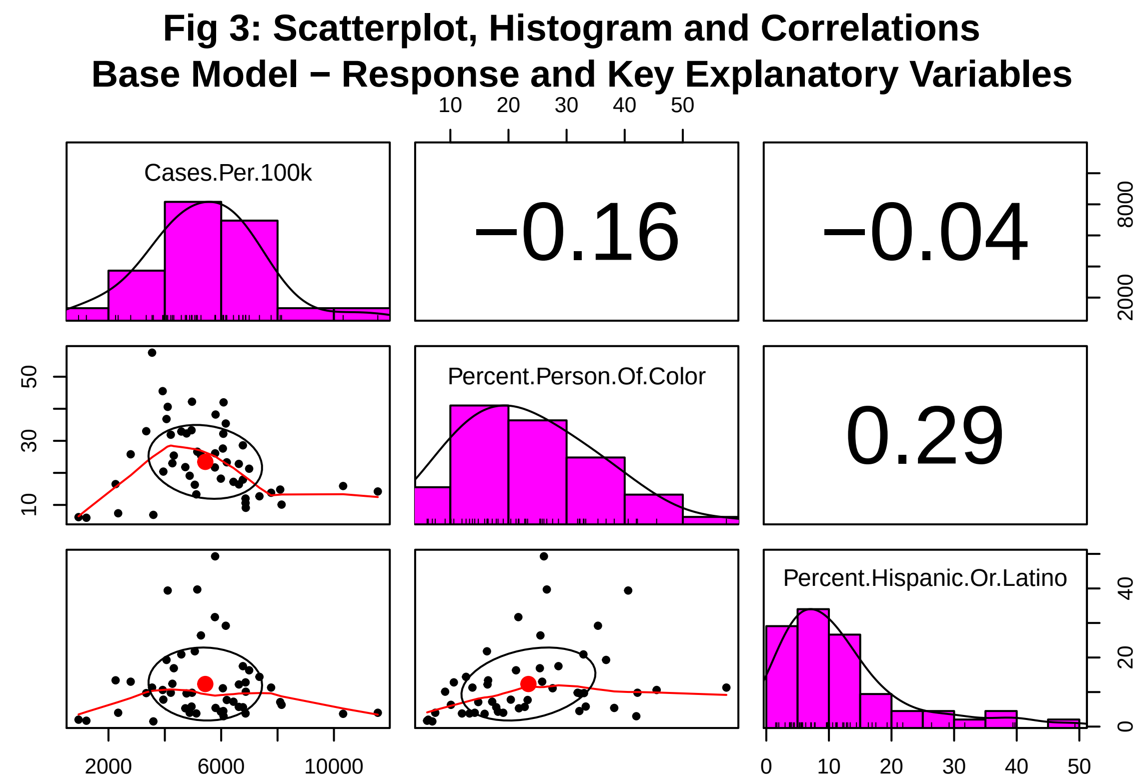
variable	source	category	min	mean	max
Percent.Hispanic.Or.Latino	US Census Bureau	Socioeconomic (Primary explanatory)	2	49	49
Recreation	Google communit mobility	Community mobility	-47	-3	-3
Grocery	Google communit mobility	Community mobility	-20	16	16
Parks	Google communit mobility	Community mobility	-34	153	153
Transit	Google communit mobility	Community mobility	-61	16	16
Workplace	Google communit mobility	Community mobility	-47	-19	-19
Residential	Google communit mobility	Community mobility	5	16	16
Days.Stay.At.Home	US State Policy	State Policy	0	270	270
Days.Restaurant.Closed	US State Policy	State Policy	0	217	217
Days.Bar.Closed	US State Policy	State Policy	0	273	273
Days.Gym.Closed	US State Policy	State Policy	0	273	273
Days.Nonessential.Closed	US State Policy	State Policy	0	78	78
Percent.Poverty	US State Policy	Socioeconomic	8	20	20
Religious.Event.Exempt	US State Policy	State Policy	0	1	1
Cases.Per.100k	NYT COVID/US Census	Primary response	939	11557	11557
Percent.Person.Of.Color	US Census Bureau(transformed)	Socioeconomic (Primary explanatory)	6	58	58

3.2 Variable selection for model development

Note on terminology: We use the category column in Table 8 to describes variables in this section of the document

3.2.1 Variables for model 1

As our objective for model 1 was to only includes our primary explanatory variables *Percent.People.Of.Color* and *Percent.Hispanic.Or.Latino*. We generated a scatter plot matrices using the 'psych' package in 'R' to visualize the relationship between *Cases.Per.100k, Percent.People.Of.Color and Percent.Hispanic.Or.Latino*.

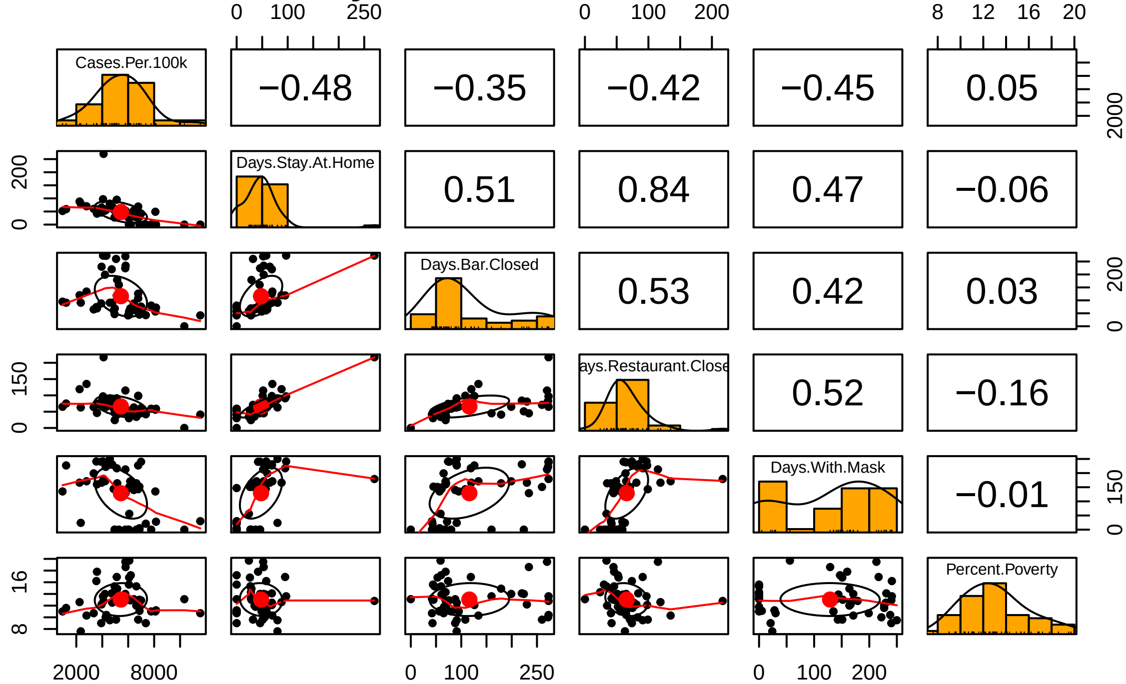


As both of the explanatory variables did not demonstrate a nonlinear relationship with *Cases.Per.100k* in the scatterplot as seen in **Fig 3**, and were well distributed without heavy tails in the histogram in **Fig 3**, no transformations was required. The Pearson's correlations coefficient between *Percent.Hispanic.Or.Latino* and *Cases.Per.100K* and between *Percent.People.Of.Color* and *Cases.Per.100K* were low on their own.

3.2.2 Selection of Covariates for Model 2

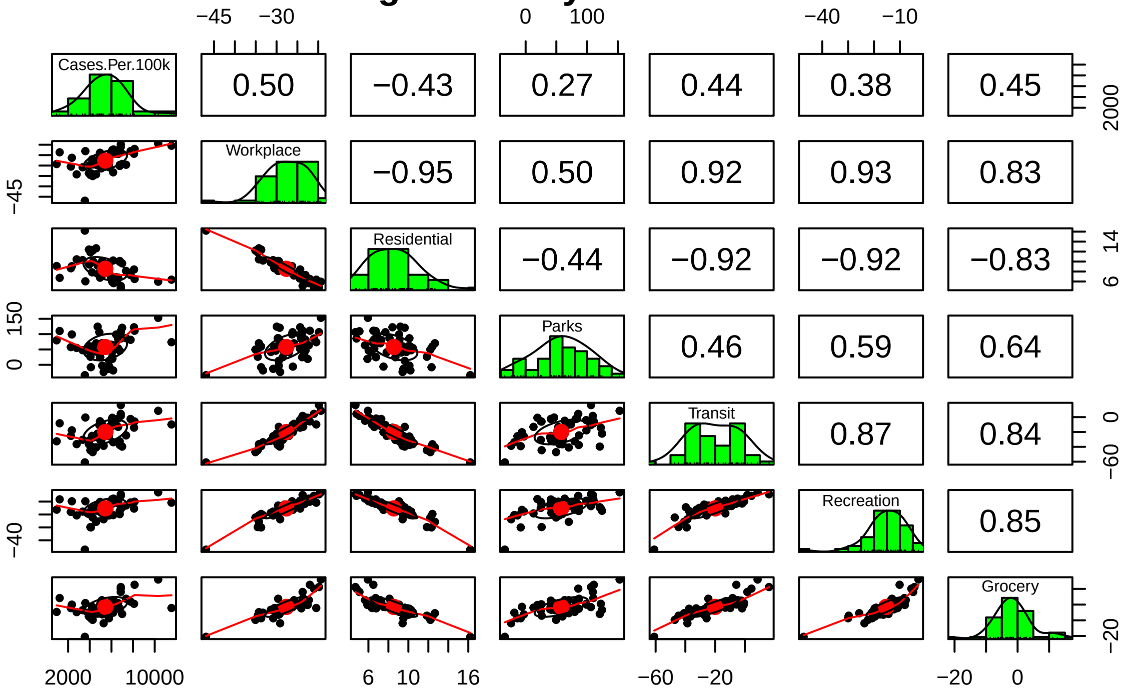
We first combined the variable categories of State Policy and Socioeconomic Conditions and analyzed them together. We treated the community mobility variables on their own. We now generated two additional scatter plot matrices using the 'psych' package in 'R', to visualize the relationship between *Cases.Per.100k* and the covariate variables. We then used these scatter plots to identify variables that have the strongest explanatory benefit to *Cases.Per.100k*. We also used the scatter plots to identify transformations that may be required to address any non-linearities in the relationships to *Cases.Per.100k*. The two scatter plots are **Fig 4** and **Fig 5**.

Fig 4: Scatterplot, Histogram and Correlations
State Policy and Socioeconomic Observations



As discussed in **section 3.13.1** we had hypothesized that among the variables, we expected *Days.Stay.At.Home* and *Days.With.Mask* to be the strongest predictors for *Cases.Per.100k*. Intuition tells us that when people were isolating by staying at home there was reduced opportunity for virus transmission and this variable hence encompasses all other restrictions. Matching our expectation, upon viewing the scatterplot of correlations in **Fig 4**, we found the highest correlation between *Cases.Per.100k* and the closure variables in this dataset was for *Days.Stay.At.Home* vs *Cases.Per.100k*, hence we selected this variable as a parameter for our main model. While the absolute correlation factor of 0.46 was strongest, we noticed that there was clustering in the data points. Since there were clustered values between 0 and 270 as seen in the histograms in **Fig 4**, we proceeded with a square root transformation as a logarithmic transformation would not be feasible. As checked whether the transformations improved the linear relationship between *Days.Stay.At.Home* and *Cases.Per.100k* by comparing the the Pearson correlation coefficient before and after the transformation. We noted that the transformation increased the correlation from 0.46 to 0.63. We also observed that although we expected a relationship between poverty rate and infection rate, there was no correlation found for this variable and the response variable therefore, we did not include it in our models. Finally, for the parsimony and explain-ability of the model we consider only the *Days.Stay.At.Home* covariate for model 2 and included the remaining variables for model 3.

Fig 5: Scatterplot, Histogram and Correlations
Google Mobility Observations



Next we considered the Community Mobility category of variables from the *Google community mobility data frame*. When considering the potential variables in the dataset, we expected *Residential* and *Workplace* to be the two strongest indicators. The intuition we followed was that most adults spend most time either at home or at work. A greater than zero value for *Residential* represents an increase in time people spent at home. We expect an increase in *Residential* to be associated with a decrease in *Cases.Per.100k.* We also expect a correlation that an increase in residential is inversely correlated with all other mobility parameters such as workplace, parks etc.As more time spent at home is less time spent in other locations.

Due to the physical interactions that are difficult to avoid in a workplace environment, we expect an increase in *Cases.Per.100k* where *Workplace* mobility was higher. While comparing these explanatory variables with *Cases.Per.100k*, we noticed that many were moderately correlated with a Pearson's correlation coefficient between 0.4 and 0.59 as seen in the correlation table **Fig 5**, and consistent with our expectation that a reduction in overall mobility would also correlate to a reduction in infection rate. The most strongly correlated variable we found in this dataset was *Workplace.* As this feature was strongly correlated, 0.80-0.95 with most other variables in the dataset and highest correlated *Cases.Per.100k* as seen in figure 5, we selected this to be our next key variable from this dataset. We did not choose *Residential* for two reasons; first, we had already included the *Days.Stay.At.Home* from the State Policy Dataset which is a similar indicator to residential mobility. As stay-at-home mandate is asking people to stay more at home and *Residential* is the measured estimate of the same parameter.Second, our objective was to create a parsimonious model with good explainability and the high *Residential* to *Workplace* correlation would not have allowed for that. As *Workplace* variable was evenly distributed and did not show a non-linearity with *Cases.Per.100k*, no transformation was performed on this variable.

3.2.3 Selection of Covariates for Model 3

As previously stated, the objective for model 3 is to produce the best fit without the limitation of explainability. To produce an improved model we will add all of the community mobility variables and state policy variables to the model. We validate the additions of these variables in the model evaluation section.

3.3 Model development

For all of our model hypothesis testing we followed standard practice by utilizing a maximum acceptance level with p-value of 0.05. A regression table with all discussed results is provided following the model section.

3.3.1 Model 1

Primary Response Variable:
* Cases per 100K Residents, ($Cases.Per.100k$)
Primary Explanatory Variables:
* Percentage Person of Color Residents, ($Percent.Person.Of.Color$)
* Percentage Hispanic or Latino Residents, ($Percent.Hispanic.Or.Latino$)

Base model

$$\text{Cases per 100,000 Residents} = \beta_0 + \beta_1 \times \text{Percent Person of Color} + \beta_2 \times \text{Percent Hispanic or Latino} + \epsilon$$

Following the standard practice of using a p-value of 0.05 we observe the following hypotheses for our base model, as seen in the subsequent regression table. Null Hypotheses:

$$H_0 : \beta_i = 0 \text{ Where i is the index for each coefficient of the regression equation}$$

Alternative Hypotheses:

$$H_A : \beta_i \neq 0, \text{ Where i is the index for each coefficient of the regression equation}$$

As required for model 1 of this study, our base model only includes our primary explanatory variables, but does not show any statistical significance based on our standard practice of an acceptance criteria p-value of 0.05 and has an adjusted R-squared value of -0.17 as seen in Regression Table as **Fig 6**. As none of our covariate's coefficients showed a p-value ≤ 0.05, we fail to reject the null hypothesis that the coefficients are not 0. Although not statistically significant, this model was a crucial starting point for bringing in the key variables that are needed to reject or fail to reject the null hypothesis that a State's increased percentage of People of Color and Hispanic or Latino residents has no difference in the rate of coronavirus spread.

3.3.2 Model 2

Primary Response Variables:
* Cases per 100K Residents ($Cases.Per.100k$)
Primary Explanatory Variables:
* Percentage Person of Color Residents ($Percent.People.Of.Color$)
* Percentage Hispanic or Latino Residents ($Percent.Hispanic.Or.Latino$)
Additional Covariates:
* Workplace Mobility change from Baseline ($Workplace$)
* Square Root of Days with Stay at Home Order in effect $\sqrt{Days.Stay.At.Home}$

Improved model

$$\text{Cases per 100,000 Residents} = \beta_0 + \beta_1 \times \text{Percent Person of Color}+$$

$$\beta_2 \times \text{Percent Hispanic or Latino} + \beta_3 \times \text{Workplace Mobility} + \beta_4 \times \sqrt{\text{Days Stay at Home}} + \epsilon$$

```
## Model 2 VIF Test Maximum:

## [1] 2.192514
```

First we conducted a Value Inflation Factor (VIF) test, which measures how much the variance of a regression coefficient is inflated due to multicollinearity in the model, using the guideline threshold value of 4 indicating strong collinearity between our covariates. The resulting maximum value found was 2.193 which does not indicate perfect or nearly perfect collinearity and allows us to continue the evaluation.

Following the standard practice of using a p-value of 0.05 we observe the following hypotheses for our second model, as seen in the following regression table. Null Hypotheses:

$$H_0 : \beta_i = 0 \text{ Where i is the index for each coefficient of the regression equation}$$

Alternative Hypotheses:

$$H_A : \beta_i \neq 0, \text{ Where i is the index for each coefficient of the regression equation}$$

This model brought considerable improvement in our covariate's significance. Using our previously stated acceptance criteria of a p-value ≤ 0.05, we detected statistical significance on $\beta_2 = 46.069$, $\beta_3 = 164.157$ and $\beta_4 = -315.922$, giving a final model of:

$$\text{Cases per 100,000 Residents} = 10,656.500 + 29.121 \times \text{Percent.Person.Of.Color}+$$

$$46.069 \times \text{Percent Hispanic or Latino} + 164.157 \times \text{Workplace Mobility} - 315.922 \times \sqrt{\text{Days Stay at Home}} + \epsilon$$

Model 2 was a much better fit for the population as our adjusted R-squared value increased from -0.17 to 0.451 as seen in the Regression Table in **Fig 6**. Although we did not see significance in the features representing the percentage of persons of color (*Percent.Person.Of.Color*) variable, the standard errors on all variables were greatly reduced.

Finally, we conducted an Analysis of Variance between Model 1 and Model 2 with our standard p-value criteria of 0.05. For the ANOVA test, we use a null hypothesis that there is no improvement in performance from the inclusion of the added variables in Model 2 vs Model 1 alternative hypothesis that there is an improvement between iterations.

```
## Analysis of Variance Table
##
## Model 1: Cases.Per.100k ~ 1 + Percent.Person.Of.Color + Percent.Hispanic.Or.Latino
## Model 2: Cases.Per.100k ~ 1 + Percent.Person.Of.Color + Percent.Hispanic.Or.Latino +
##     Workplace + sqrt(Days.Stay.At.Home)
##   Res.Df       RSS Df Sum of Sq      F    Pr(>F)
## 1     46 190081681
## 2     44  98229931  2  91851750 20.572 4.928e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Conducting this test(test results above), we observed an F score of 20.572 that corresponds to a p-value of 4.928e-07 which rejects the null hypothesis that there is no improvement between Model 1 and Model 2.

With the confirmation that there is an improvement between the models' performance we can now address what this model conveys. To interpret the meaning of this model, each variable must be looked at independently. As the minimum value of the percent Hispanic or Latino variable is 1.5% and this includes the entire population in question, the intercept term may never be met on its own with all explanatory variables at 0 and therefore does not have a valid independent interpretation within the bounds of this model. It can only be used to explain the overall model relationships. When reviewing the remaining explanatory variables, all covariate impact to the *Cases.Per.100k* may be reviewed independently under the guideline that all other variables are to remain unchanged(*Ceteris Paribus*).

1. The coefficient $\beta_1 = 29.121$ represents an increased infection rate of 29.121 *Cases.Per.100k* residents if *Percent.People.Of.Color* in a state is increased by 1 unit while all other variables are unchanged. As the unit of *Percent.People.Of.Color* is percentage, a 1 unit increase represents a 1% increase in people of color as a fraction of the state population.
2. Coefficient $\beta_2 = 46.069$ represents an increased infection rate of 46.069 *Cases.Per.100k* residents if *Percent.Hispanic.Or.Latino* is increased in a state by 1 keeping all else equal. As the unit of *Percent.Hispanic.Or.Latino* is percentage, a 1 unit increase represents a 1% increase in Hispanic or Latino as a fraction of the state population.
3. Coefficient $\beta_3 = 164.157$ represents an increase of 164.157 *Cases.Per.100k* residents if the residents spend an extra 1 percent of their time at work relative to the baseline, keeping all other variables unchanged. This aligns with our expectation that more people physically attending workplaces is associated with an increase in Covid cases.
4. Finally, $\beta_4 = -315.922$. This represents a decrease in *Cases.Per.100k* with increase in *Days.Stay.At.Home* which is the total days that a stay at home order was in place for each state. As the covariate has a square root relationship with the response, we make the following numeric approximation to describe the relationship; a 10% increase in *Days.Stay.At.Home* is associated with a $0.7 \times 315.922 \times 0.1 = 22.1$ decrease in *Cases.Per.100k* residents.This aligns closely with the intuition that isolation would reduce the spread of COVID-19.

3.3.3 Model 3

Although model 2 provided a good fit and described the relationship between the variables belonging to the overall population, we then search for an improved model that provided an even better fit without the need for explain-ability. In addition to the parameters of model 2 we included:

1. Square root of days that a mask mandate: *Days.With.Mask* was in place
2. All of the remaining closure parameters that were not included in model 2 as a single term that is the summation of the square roots of each closure term: *Days.Bar.Closed*, *Days.Restaurant.Closed*, *Days.Gym.Closed*, and *Days.Nonessential*
3. A square root transformation was used for all variables within the State Policy dataset as we saw strong clustering and wide distributions between states.
4. By performing this transformation and including the total of all mandate durations, we were able to create a random variable which was heavily weighted to states with a more aggressive response to COVID, i.e. more total closure days for every category of closure. that proved effective in isolating state behaviors.
5. Finally, we included the remaining mobility terms. As the remaining mobility values: *Parks*, *Recreation*, *Residential*, *Transit* and *Grocery*, were a combination of negative and positive values, we took the square of each and summed them together into a single mobility term.

These additional variables gave us a final model of:

$$\text{Cases.Per.100k} = 9,545.145 + 63.112 \times \text{Percent.People.Of.Color} + \ 63.342 \times \text{Percent.Hispanic.Or.Latino} +$$

$$206.339 \times \text{Workplace} - 292.031 \times \sqrt{\text{Days.Stay.At.Home}} - 7.933 \times \sqrt{\text{Days.With.Mask}} +$$

$$0.150 \times \left(\text{Residential}^2 + \text{Grocery}^2 + \text{Recreation}^2 + \text{Parks}^2 + \text{Transit}^2 \right) +$$

$$7.469 \times \left(\sqrt{\text{Days.Gym.Closed}} + \sqrt{\text{Days.Bar.Closed}} + \sqrt{\text{Days.Restaurant.Closed}} + \sqrt{\text{Days.Nonessential.Closed}} \right) + \epsilon$$

After incorporating these remaining features we verified that there was no strong collinearity by conducting a value inflation factor test with the guideline that a VIF of 4 or larger represents strong collinearity. The test provided a resulting maximum value of 2.848 validating the assumption that the variables were neither perfectly nor nearly collinear.

```
## Model 3 VIF Test Maximum:

## [1] 2.84885
```

To build confidence in our model, we validated if the added variables impacted our model by once again conducting an ANOVA F-test between Model 2 and Model 3. We followed standard practice and set a threshold p-value of 0.05, with a null hypothesis that there was no improvement with the addition of more variables from model 2 and model 3 and an alternative hypothesis that there was an improvement found with the inclusion of the added variables between Models 2 and 3.

```
## Analysis of Variance Table
##
## Model 1: Cases.Per.100k ~ 1 + Percent.Person.Of.Color + Percent.Hispanic.Or.Latino +
##     Workplace + sqrt(Days.Stay.At.Home)
## Model 2: Cases.Per.100k ~ 1 + Percent.Person.Of.Color + Percent.Hispanic.Or.Latino +
##     Workplace + sqrt(Days.Stay.At.Home) + sqrt(Days.With.Mask) +
##     I(Residential^2 + Grocery^2 + Recreation^2 + Parks^2 + Transit^2) +
##     I(sqrt(Days.Gym.Closed) + sqrt(Days.Bar.Closed) + sqrt(Days.Restaurant.Closed) +
##         sqrt(Days.Nonessential.Closed))
##   Res.Df      RSS Df Sum of Sq     F Pr(>F)
## 1     44 98229931
## 2     41 80154370  3  18075561 3.082 0.0378 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The F-test generated(test results above) an F-statistic of 3.092 and a p-value of 0.0378, again rejecting the null hypothesis that there was no improvement in our model 3 iteration. As seen in the **Fig 6** generated using the Stargazer package, the adjusted R-Squared value was increased from 0.451 in model 2 to 0.519 for model 3 confirming that the model prediction was improved with these additional parameters.

To evaluate the coefficients we again follow the standard practice of using a p-value of 0.05 we observe the following hypotheses for our third model: Null Hypotheses:

$$H_0 : \beta_i = 0 \text{ Where i is the index for each coefficient of the regression equation}$$

Alternative Hypotheses:

$$H_A : \beta_i \neq 0, \text{ Where i is the index for each coefficient of the regression equation}$$

In our hypothesis testing, as seen in the following regression table**(Fig 6)**, we found statistical significance to reject the null hypothesis for β_0, β_1, β_2, β_3, β_4, and β_5. Therefore, we conclude that $\beta_0 = 9,545.145$,

$\beta_1 = 63.112$, $\beta_2 = 63.342$, $\beta_3 = 206.339$, $\beta_4 = -292.031$, $\beta_6 = 0.150$ which can all be found in our regression table in **Fig 6** below. This left us with a final model of:

$$\text{Cases.Per.100k} = 9,545.145 + 63.112 \times \text{Percent.People.Of.Color} + 63.342 \times \text{Percent.Hispanic.Or.Latino}+$$

$$206.339 \times \text{Workplace} - 292.031 \times \sqrt{\text{Days.Stay.At.Home}} - 7.933 \times \sqrt{Days.With.Mask}+$$

$$0.150 \times \sum \left(Residential^2, Grocery^2, Recreation^2, Parks^2, Transit^2 \right) +$$

$$7.469 \times \sum \left(\sqrt{Days.Gym.Closed}, \sqrt{Days.Bar.Closed}, \sqrt{Days.Restaurant.Closed}, \sqrt{Days.Nonessential.Closed} \right) + \epsilon$$

3.3.4 Model Regression Table

Fig 6: SARS Coronavirus-19 Cases per 100,000 Residents Covariate Regression Table using Classic Standard Errors

	Dependent variable:		
	Reported Coronavirus-19 Cases per 100,000 Residents		
	Base Model	Efficient Model	Best Fit Model
	(1)	(2)	(3)
Intercept	6,075.423	10,656.500	9,545.145
	(686.648)***	(1,286.931)***	(1,358.792)***
	p = 0.000	p = 0.000	p = 0.00000
State - Percentage of Residents People of Color	−28.295	29.121	63.112
	(26.580)	(22.991)	(25.760)**
	p = 0.293	p = 0.212	p = 0.019
State - Percentage of Residents Hispanic or Latino	1.904	46.069	64.342
	(28.985)	(22.787)**	(23.305)***
	p = 0.948	p = 0.050	p = 0.009
Workplace Mobility Impact		164.157	206.339
		(62.347)**	(66.493)***
		p = 0.012	p = 0.004
Square Root of Days State was Under Stay at Home Order		−315.922	−292.031
		(79.847)***	(89.657)***
		p = 0.0003	p = 0.003
Square Root of Days with Mask Mandate			−7.933
			(45.154)
			p = 0.862
Sum of Squares, All Other Mobility Scores			0.150
			(0.051)***
			p = 0.006
Sum of Square Roots, All Other Closures			7.469
			(37.760)
			p = 0.845
Observations	49	49	49
R^2	0.025	0.496	0.589
Adjusted R^2	−0.017	0.451	0.519
Residual Std. Error	2,032.784 (df = 46)	1,494.155 (df = 44)	1,398.208 (df = 41)
Note:			*p<0.1; **p<0.05; ***p<0.01

3.3.4.1 Discussion on causality The reader would note that the authors did not make causal claims in the discussion of the models.

1. Elaborating on the observation that "an increase in the hispanic population is associated with an increase in cases per 100k"; there could be several underlying reasons for this association. One relating to the Socioeconomic status is the jobs held by people who identify as hispanic or Latino could also

play a role in this association. Specifically, occupying jobs that require physical presence could increase the chances of the spread of COVID among this demographic. We have discussed this variable in the omitted variable section.

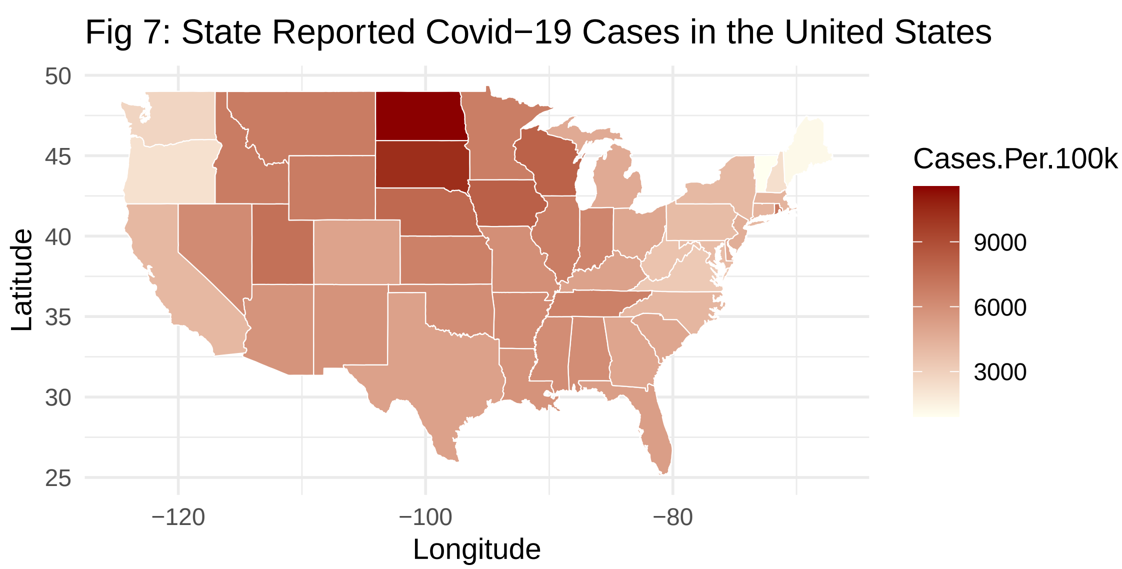
2. As physical isolation reduces the spread of COVID[12], we would then expect that the claim that the "increase in *Days.Stay.At.Home* is associated with a decrease in *Cases.Per.100k*" could be considered a causal relationship.
3. As physical proximity increases the spread of COVID[12], we would then expect that the claim that the "increase in *Workplace* is associated with an increase in *Cases.Per.100k*" could also be considered a causal relationship.

3.4 Dicussion on the assumption for the Classical Linear Model

In this section we only discuss model 2 assumptions

3.4.1 IID

3.4.1.1 Independence With respect to independence, let's recall that independence relates to how we define our population and the process by which the samples are obtained. In this case we are not using random selection since we are using the entire population (all contiguous U.S. states and Washington DC). As such, there might be clustering between states due to their geographical location. In all cases, states are connected to at least one other, and the virus can be spread across open borders, especially to neighbors. States with more lenient restrictions such, as South Dakota where no mask mandates were ever set in place, can spread the virus to other states even if the other states enacted a statewide order such as North Dakota[7] From the map **Fig 7** we can see how both states have cases in the same range. Similarly, Oregon and Washington state also have cases in the same range.



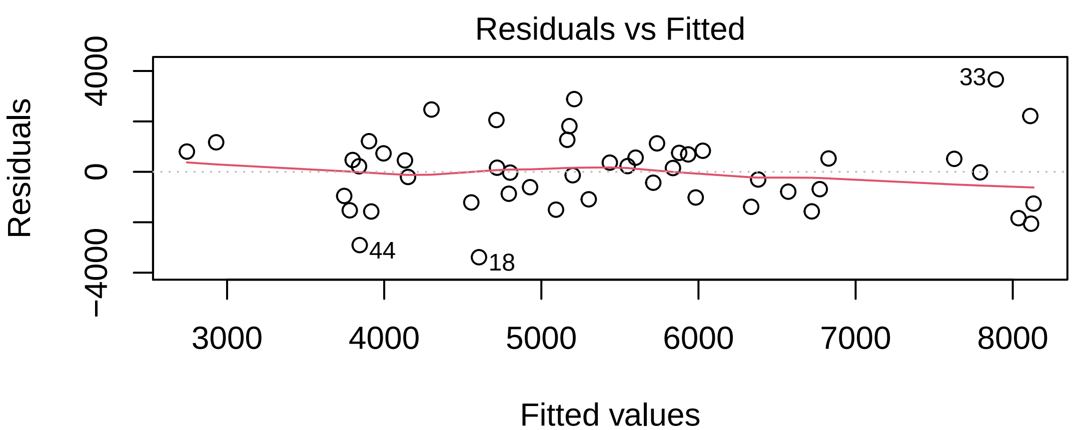
Dr. Ashish Jha, dean of the Brown University School of Public Health said: "In some ways, the whole country is essentially living with the strategy of the least effective states because states interconnect and one state not doing a good job will continue to spread the virus to other states,"[8]. Despite the CDC recommendations, people are still travelling from low COVID-19 positivity rates states to states with high positivity rates either for leisure or work related which can expose them to COVID-19, and therefore spread the virus to loved ones when they return back home.

3.4.1.2 Identically Distributed With respect to the Identically distributed assumption, it refers to all observations coming from the same distribution, however each state is responsible to collect their own data, but some are reporting inaccurate results[9]. In addition, not all states have the same testing levels, which can cause sick people not getting tested and consequently they might have a lower number of cases than states with higher testing rates. Thus, the identical distribution assumption might not hold either. Therefore, our observations fail to meet the IID assumption. Because our observations didn't meet the IID assumption, our OLS regression model might produce estimates that are biased.

3.4.2 Linear conditional mean

In order to test this assumption, we plot model the model prediction for the fitted values and the corresponding residuals as a sctter plot **Fig 8**

Fig 8: Fitted values Vs Residuals



As we can see from the plot above, the residuals bounce randomly around the y=0 line. Since we don't see evidence of non-linearity, the assumption that the relationship is linear is reasonable.

3.4.3 No perfect collinearity

In the presence of multicollinearity, the solution of the regression model becomes unstable. Since our regression model didn't drop a coefficient, we don't have perfect collinearity.

```
##                (Intercept)    Percent.Person.Of.Color
##                10656.49932                   29.12132
## Percent.Hispanic.Or.Latino                  Workplace
##                   46.06886                  164.15653
##    sqrt(Days.Stay.At.Home)
##                 -315.92175
```

We are also going to compute the variance inflation factor (VIF) which measures how much the variance of a regression coefficient is inflated due to multicollinearity in the model. We are using the guideline that a VIF of 4 or larger represents strong collinearity.

```
##    Percent.Person.Of.Color Percent.Hispanic.Or.Latino
##                   1.510818                   1.247972
##                  Workplace    sqrt(Days.Stay.At.Home)
##                   2.192514                   1.464738
```

For *Percent.People.Of.Color* we got a value of 1.51 which means that the standard error for its respective coefficient is $\sqrt{1.51} \approx 1.22$ times larger than if *Percent.People.Of.Color* had 0 correlation with the other predictor variables.

For *Percent.Hispanic.Or.Latino* we got a value of 1.29 which means that the standard error for its respective coefficient is $\sqrt{1.25} \approx 1.11$ times larger than if *Percent.Hispanic.Or.Latino* had 0 correlation with the other predictor variables.

For *Workplace* we got a value of 1.93 which means that the standard error for its respective coefficient is $\sqrt{2.19} \approx 1.48$ times larger than if Workplace had 0 correlation with the other predictor variables.

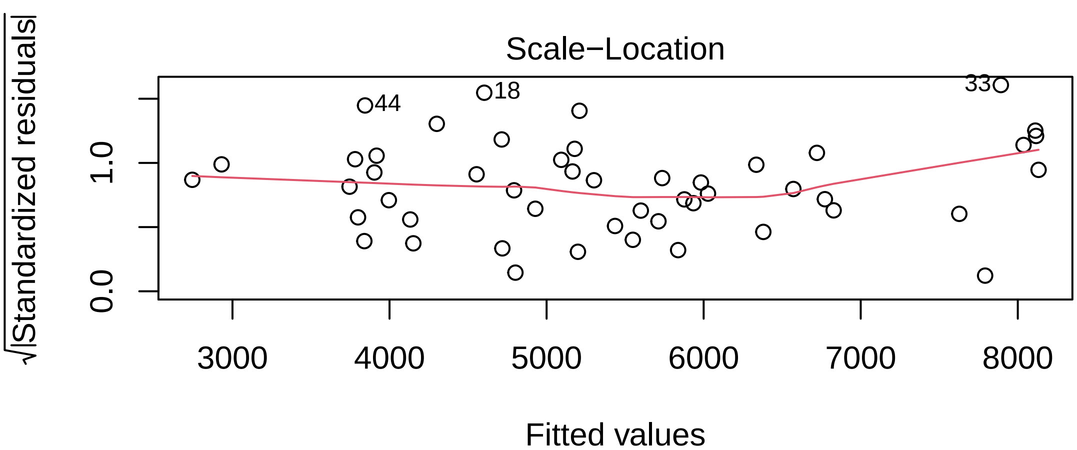
For $\sqrt{\text{Days.Stay.At.Home}}$ we got a value of 1.36 which means that the standard error for its respective coefficient is $\sqrt{1.46} \approx 1.21$ times larger than if $\sqrt{Days.Stay.At.Home}$ had 0 correlation with the other predictor variables.

Because all of these VIF scores are smaller than 4, they indicate absence of multicollinearity. Thus, our model meets the "No perfect collinearity" assumption.

3.4.4 Homoskedasticity

This assumption help us to determine the validity of our standard errors. One way to test homeskedasticity is to examine the scale-location plot **Fig 9**. Homoskedasticity would show up on this plot as a flat smoothing curve.

Fig 9: Scale location plot



There seems to be a deep increase for fitted values greater than 6000, suggesting a problem with heteroskedasticity. In order to confirm this, we are running a Breusch-Pagan test from the `lmtest` package the `bptest` function. We follow standard practice and use a significance level of 0.05.

$$H_o : \text{There is no evidence for heteroskedastic error variance (homoskedasticity)}$$
$$H_a : \text{There is heteroskedasticity}$$

```
##
##  studentized Breusch-Pagan test
##
## data:  model_2
## BP = 8.0811, df = 4, p-value = 0.08865
```

Because our p-value = 0.09 > 0.05, we fail to reject our null hypothesis that there is no evidence for heteroskedastic error variance, so we conclude that we don't have evidence of heteroskedastic error variance.

3.4.5 Normally distributed error

We follow standard practice and use a significance level of 0.05. We are also performing a Shapiro-Wilk's test, which is based on the correlation between the data and the corresponding normal scores with

$$H_o : \text{residual errors are normally distributed}$$

$$H_a : \text{residual errors are not normally distributed}$$

```
##
##  Shapiro-Wilk normality test
##
## data:  model_2$residuals
## W = 0.98968, p-value = 0.9422
```

Because our p-value = 0.94 > 0.05, we fail to reject our null hypothesis which implies that there is no evidence that shows that residual errors are not different from a normal distribution. Therefore, the "Normally Distributed Errors" assumption holds, and we can trust the t-value and p-value for every coefficient.

3.5 Discussion on confidence intervals

95% Confidence Intervals:

```
##                                   2.5 %      97.5 %
## (Intercept)                 8062.859929 13250.13871
## Percent.Person.Of.Color      -17.214401    75.45704
## Percent.Hispanic.Or.Latino     0.145103    91.99262
## Workplace                     38.503960   289.80910
## sqrt(Days.Stay.At.Home)     -476.842784  -155.00072
```

$\beta_{\text{Percent.People.Of.Color}}$: We are 95% confident that the coefficient of Percent of People of Color is between -17.21 and 75.46. Since the confidence interval contains 0, we can conclude there is no significant evidence of a linear relationship between Percent.People.Of.Color and Cases.Per.100k, just like we found in the model results.

$\beta_{\text{Percent.Hispanic.Or.Latino}}$: We are 95% confident that the coefficient of State-Percentage of Residents Hispanic or Latino is between 0.15 and 91.99.

$\beta_{\text{Workplace}}$: We are 95% confident that the coefficient of Workplace Mobility is between 38.51 and 289.81.

$\beta_{\sqrt{Days.Stay.At.Home}}$: We are 95% confident that the coefficient of Square Root of Days is between -476.84 and -155.00.

4 Limitations of the model

4.1 Limitations in data

We called out specific limitations that existed for the individual data sets used to build the model in section 2.2. We will discuss these limitations with respect to the primary response variables and the primary explanatory variables selected to build the model.

The primary explanatory variable Cases.Per.100k as defined in section 3.1.1 is sourced from 'cases' in the NY Times Covid Dataset and 'Total Population' in the US Census data frame.

1.For the NYT Times Dataset, we called out that certain states reported confirmed cases while other states reported confirmed and probable cases. This is a limitation of the data that adds to the error term to the model. 2. The number of reported cases were also affected by the testing rate and testing availability in each state.This is a limitation of the data that adds to the error term to the model. 3. The rate of spread of COVID within a state changed dramatically during a given period, with spikes during periods associated with spring break or US holidays. This could introduce variability to the analysis that could not be explained with the analyzed variables. We mitigated this risk by using a long time period for the analysis of 304 days.

We had noted that the US Census dataset was an estimate based on survey and hence had limitations. The ACS document shows the standard error for the parameters is 0.1% and the the ACS provides documentation on the sampling methodology and accuracy of the estimates that have been added as a reference[10]. A 0.1% error is unlikely to impact these results and hence we do not sonsider this a limitation.

For the US State policy dataset we do not know the adherence of these policies by the residents of the state. Mandates for restaurant, bar, and gym closures are more likely to be adhered to as these policies affected businesses and had stricter government enforcement. Bussinesses also received incentives such as CARES Act and other federal assistance programs to support compliance. Furthermore, we get also get a measure of the compliance from the Google community mobility dataset. What we do not have information on is the compliance to mask mandates. We have discusses its implications in the Omitted Variable Bias section.

Google Community mobility dataset provides specific details that location data and accuracy of landmarks may vary across regions. Furthermore, the data is collected only on Android users who have agreed to a part of this study. This potentially introduces bias in the sample. This is a limitation of the data that adds to the error term to the model.

4.2 Discussion of Omitted Variables

4.2.1 Mask compliance rate

We are going to focus on the relationship between Mask.Compliance.Rate and $\sqrt{\text{Days.Stay.At.Home}}$. An increase in the mask compliance rate might reduce Cases.Per.100k. Many states do have mask mandates in place, but not everyone complies with the mandate since some states do not enforce this order. For instance, in Michigan, several law enforcement agencies are not enforcing the mandate due to lack of staffing or because they feel they don't have the authority to enforce it. [1] However, if more people started wearing the mask the number of cases would drop since the virus spreads through airborne transmission. According to the CDC, more people wearing masks would reduce "[. . .] the spread of respiratory droplets into the air when a person coughs, sneezes, or talks and by reducing the inhalation of these droplets by the wearer." [2], so Mask.Compliance.Rate and Cases.Per.100k has a positive relationship. With respect to Mask.Compliance.Rate and $\sqrt{\text{Days.Stay.At.Home}}$ has a negative relationship since expanding the stay at home order longer, less people are expected be on the streets, so they won't need to wear masks, since they are not allowed to leave their home unless they are essential workers or need to shop for essential needs. Therefore, Mask.Compliance.Rate is biased in the negative direction. Since the coefficient that is associated with $\sqrt{\text{Days.Stay.At.Home}}$ is equal to -310.47, which is negative, we will say that it is biased away from zero.

4.2.2 Trust for governmental policy responses

We are going to focus now on the relationship between Trust.Governmental.Policy.Responses and $\sqrt{\text{Days.Stay.At.Home}}$. An increase in *trust in goernmental policy responses* might reduce Cases.Per.100k. Marien and Hooghe (2011) argue that trust increases law compliance. Then, people would likely comply with mandates and follow the CDC guidelines such as masking up, staying at home, avoiding large gatherings, among others, which might reduce the spread of the virus, and consequently the number of COVID cases. Thus, `people trust on state government percentage` and Cases.Per.100k has a negative relationship. With respect to `people trust for governmental policy responses` and $\sqrt{\text{Days.Stay.At.Home}}$ there is a positive relationship because expanding the stay at home order might increase the trust for the government. Most people would understand that stricter confinement is necessary in order to stop the spread of the virus. Therefore, *trust in goernmental policy responses* is biased in the negative direction. Since the coefficient that is associated with $\sqrt{\text{Days.Stay.At.Home}}$ is equal to -310.47, which is negative, we will say that it is biased away from zero.

4.2.3 Socio-economic status relating to essential worker

Here we describe the relationship between '*Percent.Hispanic.Or.Latino*' and confounding variable Socio-Economic status, namely 'essential workers'. A study by the economic policy institute observes that people who identify as Hispanic or Latino hold a disproportionate[3], with respect to their population fraction, number of jobs in the 'essential workers' category. This would indicate a positive coefficient in the relationship between model variable *Percent.Hispanic.Or.Latino* and the socio-economic variable essential workers, let's call this the first coefficient. As the model has suggested that the increase in workplace mobility is associated with an increase in the primary response variable *Covid.Cases.Per.100K*, we expect a positive coefficient between essential workers and *Covid.Cases.Per.100K*, let's call this our second coefficient. As both the first and second coefficients are positive then the sign of our omitted variable bias is positive. As the coefficient of the association between *Percent.Hispanic.Or.Latino* is positive and the primary response variable is positive this suggests an away from zero bias. This in turn suggest that the coefficient of association between *Percent.Hispanic.Or.Latino* and *Covid.Cases.Per.100K* will move towards zero in the presence of the confounding variable 'essential workers' making the claim that "an increase in *Percent.Hispanic.Or.Latino* is associated with an increase in *Covid.Cases.Per.100K*", weaker.

5 Conclusion

During its initial spread Coronavirus was described as the great equalizer that transcended socioeconomic and demographic differences[1]. In hindsight it is clear that COVID has had a varied impact depending on an individuals demographic[3]. For example, jobs in the technology industry have moved to off-site locations, such as work from home, whereas jobs in the travel and leisure industry have been eliminated due to the lack of demand. In some states every non-essential business was mandated to temporarily close down, which has had a severe economic impact to some businesses and their employees. In this research topic we focus on understanding the relationship of the race and ethnicity demographic to the spread of COVID. Hence our research question was "Is a higher percentage of people of color, or Hispanic or Latino population associated with an increased incidence of COVID-19 cases per hundred thousand residents, in the conterminous United States?".

Taking the other factors such as State mandated shutdowns and people's change in mobility into consideration, we observed that an increase in percent of people who identify as Hispanic or Latino in the state is indeed associated with an increase in COVID case rate. Specifically, we noted that a 1% increase in population of people of Hispanic or Latino origin in a state is associated with 46 more cases per 100,000 residents in that state. As a guide for managing future pandemics, this significant increase from baseline would suggest that the policies and practices implemented by the state and the residents must differ based on the ethnicity of the population. Further research is required to determine the causal factors and hence the necessary policies for management.

As coefficient for the association between COVID case rate and percent of people who we defined as People of Color was not statistically significant, we were unable to answer the research question for this demographic. Through this modeling effort we also observed that the stay at home mandate had an impact on the COVID case rate. Specifically, an increase in the number of days a state mandated a stay at home order, during the time of the study, was associated with a decrease in the COVID case rate for that state. Finally, we also observed that a relative increase in the number of people going to work was associated with an increase in the number of COVID cases.

6 References

[1] https://www.gavi.org/vaccineswork/5-reasons-why-pandemics-like-covid-19-are-becoming-more-likely
[2] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7224347/
[3] https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-race-ethnicity.html
[4] U.S. Census Bureau, Overview of Race and Hispanic Origin: 2010 https://www.census.gov/prod/cen2010/briefs/c2010br-02.pdf
[5] US Geological Survey "What constitutes the United States, what are the official definitions?". https://www.usgs.gov/faqs/what-constitutes-united-states-what-are-official-definitions?qt-news_science_products=0#qt-news_science_products accessed Mar. 30 2021.
[6] https://github.com/nytimes/covid-19-data - Readme.MD
[7] https://www.aarp.org/health/healthy-living/info-2020/states-mask-mandates-coronavirus.html
[8] https://www.propublica.org/article/states-with-few-coronavirus-restrictions-are-spreading-the-virus-beyond-their-borders
[9] https://khn.org/news/some-states-are-reporting-incomplete-covid-19-results-blurring-the-full-picture/
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7 Appendix

7.1 Code folder structure

We follow the data science cookie cutter code structure. All the raw downloaded data from the different sources is stored in the 'data/external' folder. The code for crunching the data is in the 'src' folder. The following scripts are used for each of the datasets: * source_census.R for US census dataset * source_nyt.R for NYT covid dataset * source_mobility.R for Google mobility dataset * source_state_policy.R for State policy dataset. This uses a processed file that is stored in 'data/processed'. The processing of the RAW dataset into the 'processed' dataset is done using the script below * Converts dates and numerics into correct data type * Calculates difftime between policy start date and the minimum of policy end date and '2020-12-14' * Renames variables **The entry point for the entire analysis is covid_cases.RMD in the results folder**

7.2 New York Times COVID Dataset

Source: "Data from The New York Times, based on reports from state and local health agencies." Hyperlink: Github SHA for commit: f15e12d42cf4be38173387ab1cfc9e823671efc5

7.2.1 Steps for downloading the data

These instructions are for a Unix based system.

1. In the code 'data–external' folder run the following command: git clone https://github.com/nytimes/covid-19-data.git

2. At this point there will be a folder created called 'covid-19-data' that contains the required dataset. The file that is used for this analysis is us-states.csv

3. First change working into the folder where the data was cloned. As this dataset is updated daily, next step is to checkout the specific dataset used for this analysis.

- cd covid-19-data
- git checkout f15e12d42cf4be38173387ab1cfc9e823671efc5

4. The main entry point notebook(covid_cases.Rmd) automatically sources the script 'source_nyt.R' for converting this file to required dataframe for analysis. The data engineering steps and handling of missing data is described in the Data engineering section on the New York Times COVID Dataset.

7.3 US Census Bureau 2019 American Community Survey

Source: "U.S. Census Bureau, 2019 American Community Survey 1-Year Estimates accessed Mar. 26 2021" Hyperlink:Census

7.3.1 Steps for downloading the data

1. Go to American Community Survey link (above)
2. Use the Download button to download ACSDP1Y2019.DP05_YYYY-MM-DDTSSSSSS.zip folder including 3 files

```
* File 1: ACSDP1Y2019.DP05_data_witH_0verlays_2021-04-01T121500.csv
* File 2: ACSDP1Y2019.DP05_metadata_2021-04-01T121500.csv
* File 3: ACSDP1Y2019.DP05_table_title_2021-04-01T121500.txt
```

3. Unzip to ‘data/external’ folder

7.4 Google’s Community Mobility Report

Google LLC “Google COVID-19 Community Mobility Reports”. Hyperlink: Google community mobility

7.4.1 Steps for downloading the data

1. Go to COVID-19 Community Mobility Reports. Click the Regions CSVs and download files which will be a zipped folder of csv files (Region_Mobility_Report_CSVs.zip) with 1 for each country (region) for 2020 and 2021 (2 files per region).
2. Unzip to ‘data/external’
3. The US files are directly converted to data frame in the analysis US 2020: 2020_US_Region_Mobility_Report.csv US 2021: 2021_US_Region_Mobility_Report.csv

7.5 Covid 19 US State Policy Database

Source: “Raifman J, Nocka K, Jones D, Bor J, Lipson S, Jay J, and Chan P. (2020).”COVID-19 US state policy database." Review Policy Details Google Sheets: url Github:State policy

7.5.1 Steps for downloading the data

1. Go to COVID-19-US-State-Policy-Database Github
2. Download the xlsx file COVID-19 US state policy database M_DD_YYYY.xlsx to ‘data/raw/covid_policy_data’
3. Manually convert the first tab ‘State policy changes’, which contains the compiled data, into a csv in ‘data/raw/covid_policy_data’
4. Convert the file into a dataframe and follow the data covid_state_policy_data_cleaning.Rmd
5. Metadata - data/raw/covid_policy_data/Covid19_USState_PolicyDB_032621_attrlist.csv

Researchers at the Boston University School of Public Health have put in a considerable amount of time building and maintaining this dataset. Refer to the github and google site for more details.