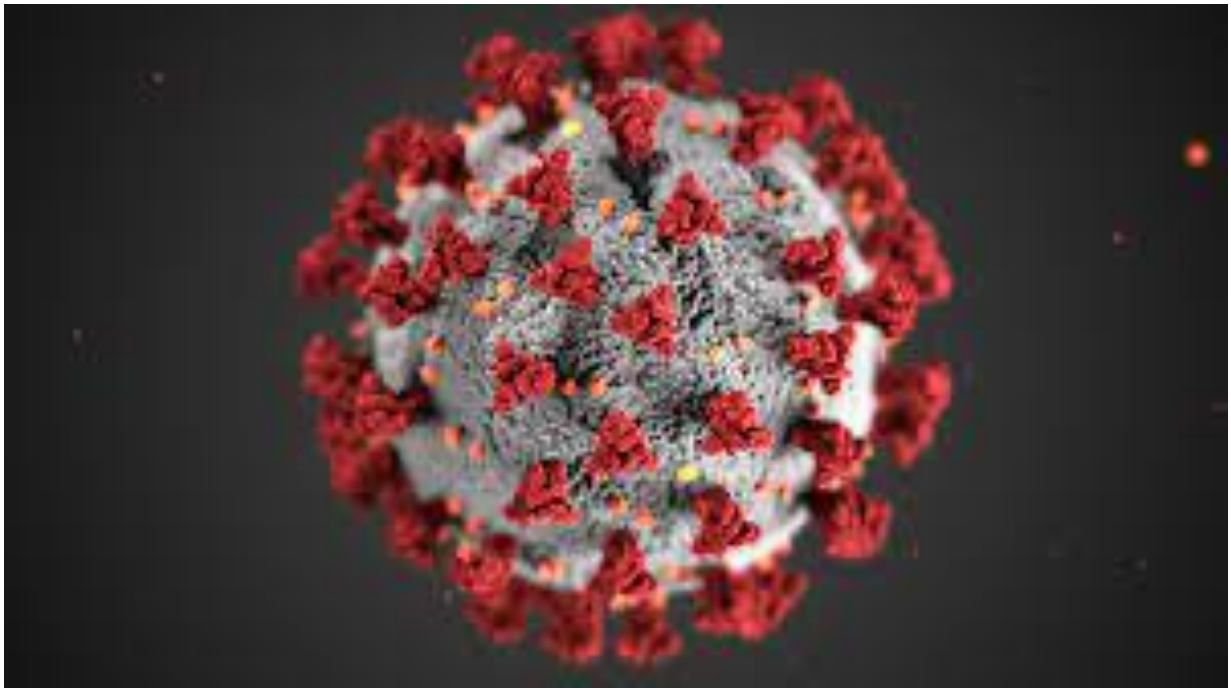
COVID-19 Data & Visualization



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15 March 2021

CSE 5331

EXECUTIVE OUTLINE

This study was conducted to explore the data surrounding the COVID-19 virus. After sifting through data and generating visualizations as well as comparing the different government orders set to control the virus, we saw numerous relationship between different variables that allow us to make predictions of how the virus might spread throughout a county based on the median age, population density, wealth levels, and education levels of that county.

The study concluded that the wealthier the population and the higher education of the population, the less likely it was to have high case numbers and deaths, but the lower the wealth and education levels, the more likely it was to have higher cases and deaths. It also concluded that because of the response to limit the elderly's contact with the virus, the older the population's median age means the lower the chances of high COVID case numbers and deaths.

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BUSINESS UNDERSTANDING

COVID-19 is a respiratory disease that was discovered in 2019. It is caused by a new coronavirus called SARS-CoV-2. Scientists believe the virus mainly spreads from person to person when an infected person coughs, sneezes, or talks [1]. However, not every person that becomes infected through respiratory droplets develops symptoms. On the other hand, those that have symptoms can range from mild to severe. There are high risk and low risk categories for the population. An example of the high risk category is people with underlying medical conditions or adults 65 years and older [1].

Social distancing is one of the key components of slowing the spread of the virus. It means you keep at least six feet away from people that are not from your household. This holds true for indoor and outdoor spaces [2]. The virus spreads via respiratory droplets, so it is important to practice social distancing to prevent the spread. Another reason that social distancing is important is because it assists in flattening the curve. Figure 1 explains the "curve" scientists refer to. The dark purple curve represents the projected amount of people who will contract the disease over a certain amount of time without safety precautions implemented. The lined purple graph represents social dinstancing's effect on the curve — hence, "flattening the curve" [3].

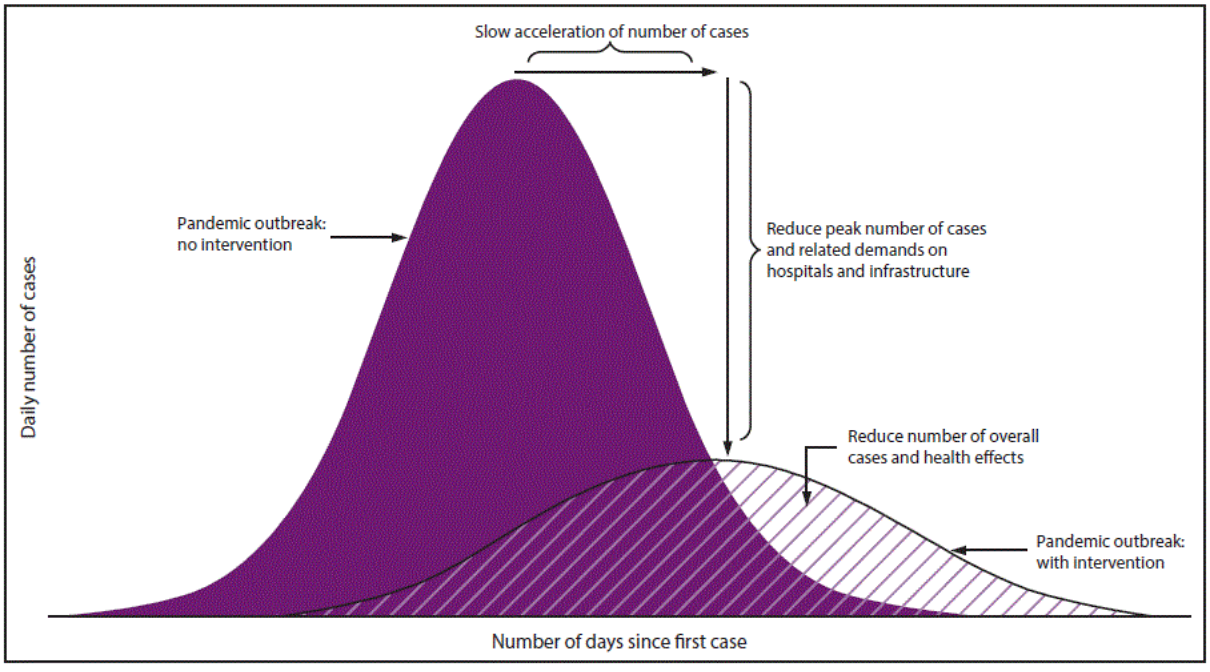

Figure 1: Describing "Flattening the Curve"

It is important to look at the spread of the virus data because it is essential in predicting how it spreads over time. This is useful because health care capacity is limited. If scientists are able to predict the spread of the virus in areas where health care capacities are at their limits, then necessary resources can be produced and allocated ahead of time so capacity is not exceeded.

Agencies like the Center for Disease and Control Prevention collect this information but hospitals might be interested in looking at the data. If they are able to see that over time cases will rise exponentially, then they can take measures to allocate resources so they do not exceed capacity. At the end of the day, health care workers know lives will be lost, yet the goal is to limit this. Therefore, the data gathered in predicting the spread of the virus can be very useful in limiting the death rate.

DATA UNDERSTANDING

DATA SET DESCRIPTION

The data sets we worked with broke down confirmed COVID-19 cases and deaths by each county in Texas. The data sets are discussed in more detail in the *Data Quality* section. This section describes the most important variables we used. The data types are also specified. A nominal data type means data that labels variables that provide no quantitative value. An ordinal data type means data that can be measured or ordered. Interval scales give us the order of values and the ability to quantify the difference between each one. Ratio scales give us order, interval values, and the ability to calculate ratios. Table 1 provides the necessary data set descriptions.

Note that this section *only* describes the most important variables featured in all of the graphs. The *Data Preparation* section further breaks down variables like median_income by providing info on every given income range. Another example of this would be the variable total_pop being broken down by age ranges for males and females 60 years old and up.

Table 1: The description and data types of each important feature

Feature	Data Type	Description
County_fips_code	Nominal	The individual zip code for each county in Texas
County_name	Nominal	The name of each county in Texas
Confirmed_cases	Ratio	The number of cases confirmed per date per county.
Deaths	Ratio	The number of deaths per date per county
State	Nominal	The state in which the data comes from (only Texas)
Total_pop	Ratio	The total population for each county in Texas
Median_age	Ordinal	The median age for each county in Texas
Median_income	Ratio	The median income for each county in Texas

Date	Nominal	The data set contains a year's worth of confirmed cases and deaths for each county. The *Date* variable indicates which day over that year period.

DATA QUALITY

In dealing with data sets, it is very important to be working with a clean and quality data set. If we are working with an incomplete set, then we are susceptible to skewed data because of outliers, duplicates, or NA values. This is a necessary step in data mining because we have to be able to understand the data in order to be able to present anything meaningful.

For this project, we pulled from the COVID-19_cases_TX data set and the COVID-19_cases_plus_census data set. The COVID-19_cases_TX data set describes confirmed cases and deaths for every county in Texas, which is outlined by county zip codes. The COVID-19_cases_plus_census data set gives us a specific breakdown of each county. For example, the data set breaks down confirmed cases and deaths by income ranges. This section describes the data quality of the most important variables we used.

County_fips_code:

The zip code by county was not missing any data because we are looking at every county in Texas and our data set has that available to us. However, the COVID-19_cases_TX set contained many duplicates for zip codes because this file is broken down over a time period of one year for every county. Therefore, a year's worth of data on confirmed cases and deaths by county will have duplicates. Yet, the file COVID-19_cases_plus_census set fixes this for us. The date on this file is the same for each county, so there are only 255 unique zip codes represented.

County_name:

The county name variable also contains duplicates, but it is also for the same reason that county_fips_code has duplicates. The census file only has 255 rows representing each county, so there are no duplicates in that file as each unique county is represented once.

Confirmed_cases:

This variable was mostly clean and accurate, therefore it did not need a lot of attention in terms of cleaning. However, some outliers do exist. For example, Loving County (total population of 74) only had 1 confirmed case as of January 19, 2021. On the other hand, Dallas County (total population of 2,552,213) had 234,625 confirmed cases on that same day. This outlier does not necessarily skew our data, but rather it gives us a scope into how covid affected small and large populations.

Deaths:

This variable is essentially the same as confirmed_cases. Using the same example, Loving County has had 0 deaths whereas Dallas County has had 2,453 deaths. Again, outliers like Loving County does not skew out data but rather gives us a better understanding of it.

State:

State contains duplicates only because the state is the same for every entry since we are only looking at Texas. This does not affect our data.

Total_pop:

Given that we have access to a census file, the total population variable per country is accurate. There are no missing values.

Median_age:

This variable represents the median age for each county in Texas. It is a rough estimate, but there are no missing values.

Date:

The date contains duplicates in the census file. This is because the file is showing us the total confirmed cases across an entire year. The date duplicates do not affect our data but give us a broader scope on confirmed cases and deaths per county.

STATISTICS

The following section provides a statistical summary of variables we looked to find correlations in. Comparing all of the data, it is important to look at the number of cases and the number of deaths. This data is extremely helpful in finding correlations between different data types. We chose to look at education levels, wealth, and age as it related to the number of cases and deaths. Some of these variables seemed to be connected. The percentage of wealthy people in a county are often correlated to the level of education in the county. This makes sense because people with a higher level of education typically make more money. Not only do they make more money, but it also allows them to live in areas with better healthcare if they do become infected. This higher level of healthcare allows them to be cured more easily because the facilities they are in are often better funded and have better equipment and treatment options. Concerning age, we assumed the older the population of the county, the more deaths per case. This is simply due to the fact that older people have weakened immune systems. They also tend to have more underlying conditions that decrease their ability to fight the virus.

As we analyzed the data, our initial hypothesis seemed to be correct. These variables proved to be effective in predicting the impact COVID would have on a county. Wealthier counties had fewer confirmed cases, which agrees with our hypothesis. Even in wealthy counties

with more cases, the death rate was much lower due to the higher quality medical facilities. The older the county was on average meant a higher number of cases and of deaths

Table 2: The statistical summary of various educational backgrounds (the ages for the various educational backgrounds are males 45-64)

Variable	Data Type	Range	Median	Mean	Variance	Std. Dev.	Max	Min
LowEdu%	Ratio	41.88	8.25	9.97	48.98	7.00	41.88	0
MidEdu%	Ratio	66.11	68.03	66.81	89.16	9.44	100.0	33.89
HighEdu%	Ratio	63.56	21.91	23.22	88.20	9.39	63.56	0
Case%	Ratio	16.94	7.39	7.80	6.94	2.63	18.29	1.35
Death%	Ratio	.6284	.1727	.1855	.0098	.0989	.6284	0
Associates_degree	Ratio	29,530	134	846	7,750,461	2784	29,530	0
Bachelors_degree	Ratio	96,857	210.5	2275.4	79,468,326	8914.5	96,857	0
Graduate_degree	Ratio	60,236	93	1337.5	30,451,095	5518.3	60,236	0
Less_than_9_grade	Ratio	67,074	227.5	1194	28,385,351	5327.8	67,074	0
Some_college	Ratio	95,642	513.5	2012.5	73,979,292.7	8501.1	3	0
Male_60_to_61	Ratio	46,922	242.5	1125.7	15,368,199.7	3920.2	46,922	0
Female_60_to_61	Ratio	48,638	247	1234.7	35.59	4241.1	48,638	0
Male_70_to_74	Ratio	49,831	390	1453	18,985,602	4357	49,831	0
Female_70_to_74	Ratio	57,421	392	1700.3	27,337,975.7	5228.6	57,421	0
Male_80_to_84	Ratio	19,416	186.5	629.4	3,146,740.6	1773.9	19.416	0
Female_80_to_84	Ratio	29,974	219.5	892.1	7,504,377.1	2739.4	29,974	0
Median_age	Ratio	31.70	38.55	39.02	35.59	5.97	57.50	25.80

INTERPRETING AND VISUALIZING THE DATA

After generating many different charts, relationships between different variables become very clear. The relationship between wealth and education level is very strong, and it is shown consistently in the graphs as well as the relationship between population density and the rate of the spread.

In looking to see the impacts different government orders have on the virus, we can look at a graph of the total number of cases in Texas.

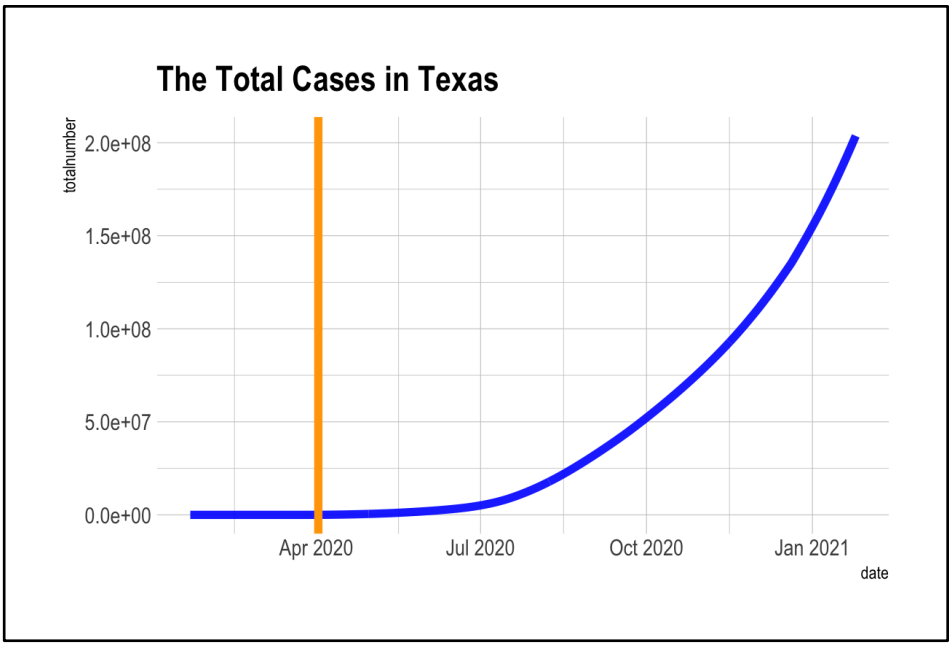

Figure 2: The Total Number of Cases in TX

You can see the orange line in Figure 2 marking when Gov. Abbott passed an executive order no longer allowing people to eat in restaurants. After this was passed, the number of cases remained low until the beginning of May when the governor began opening up restaurants and bars. As you can see by the blue line, around the beginning of May the number of cases began to rise. From then, no matter what the governor did, the case numbers continued to rise despite mask mandates and social distancing.

Population Density and Spread Rate

One important thing to note is the relationship between the population density and spread rate of the virus.

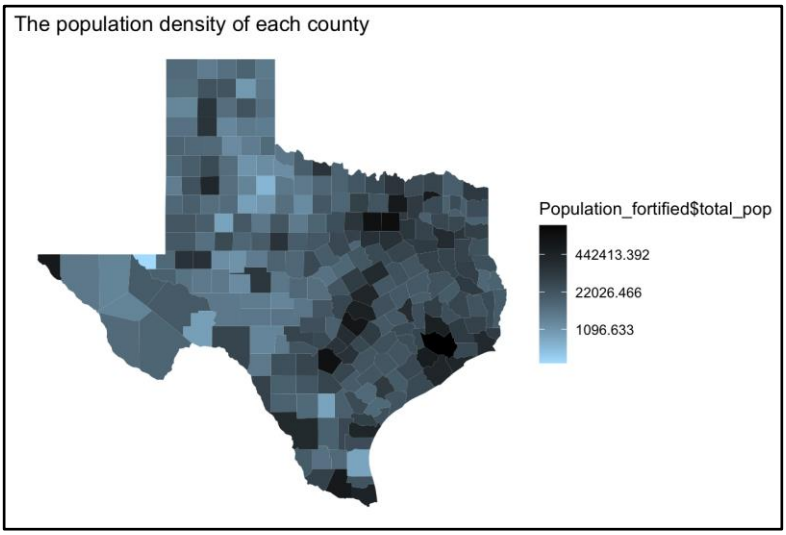

Figure 3: The Population Density of Each Texas County

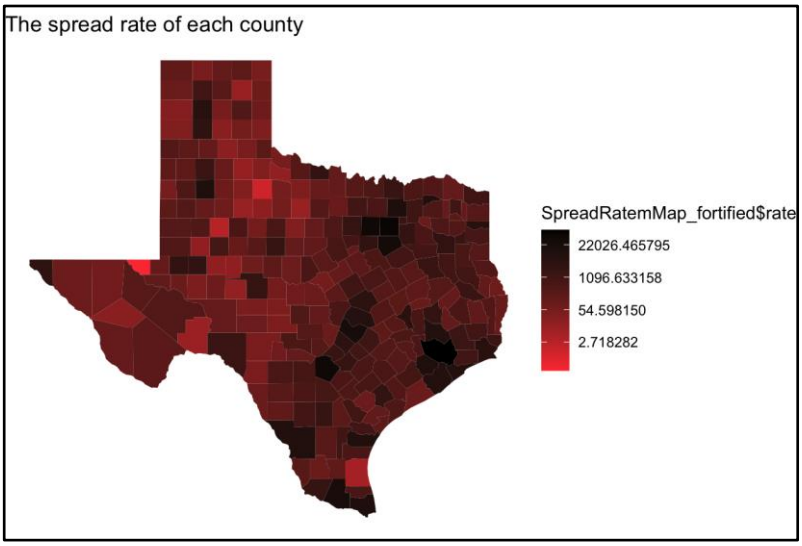

Figure 4: The Spread Rate of Each Texas County

In these graphs, it is easy to see that population density has an extremely strong correlation to the rate of spreading. In counties that contain large cities, such as Dallas, Houston, and Austin, the population density is larger and so is the spread rate. These are shown by darker counties on Figure 3 to show more dense populations, and darker red counties on Figure 4 to show a higher rate of spread. The figures are almost interchangeable. We see that the darker areas on Figure 3 correspond greatly to the darker areas on Figure 4.

COVID-19 vs. Wealth and Education

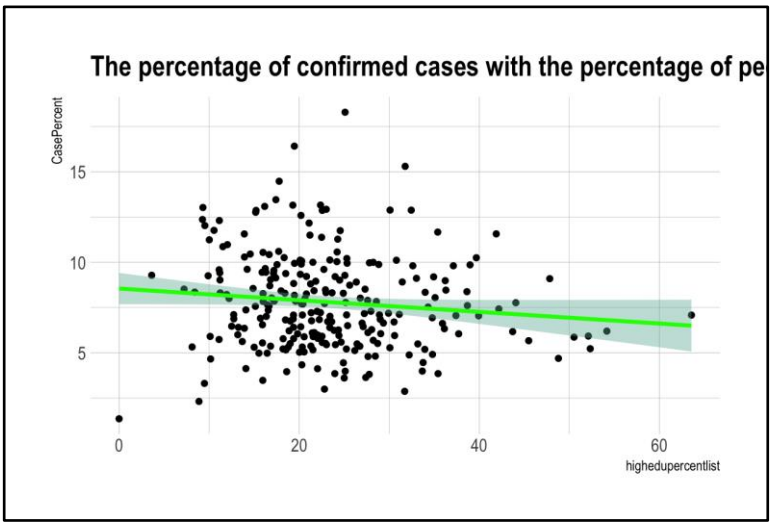

Figure 5: Percent of Confirmed Cases vs. Percent of Population with Higher Education

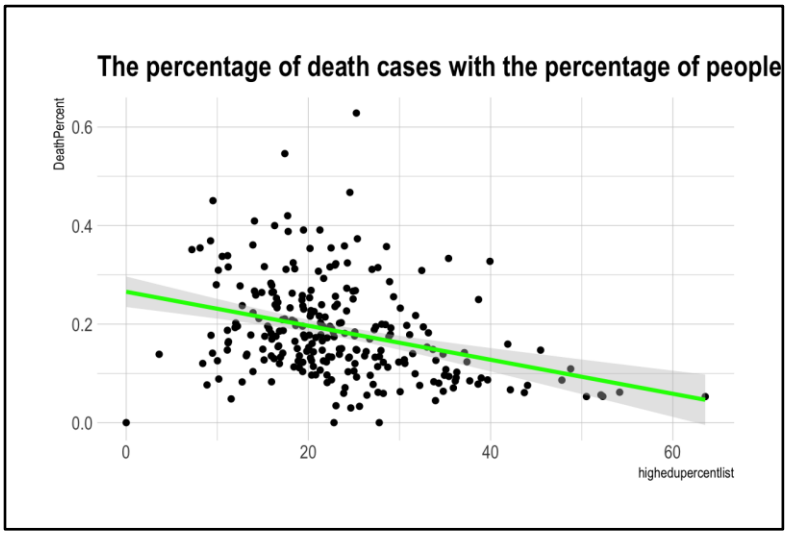

Figure 6: Percent of Deaths vs. Percent of Population with Higher Education

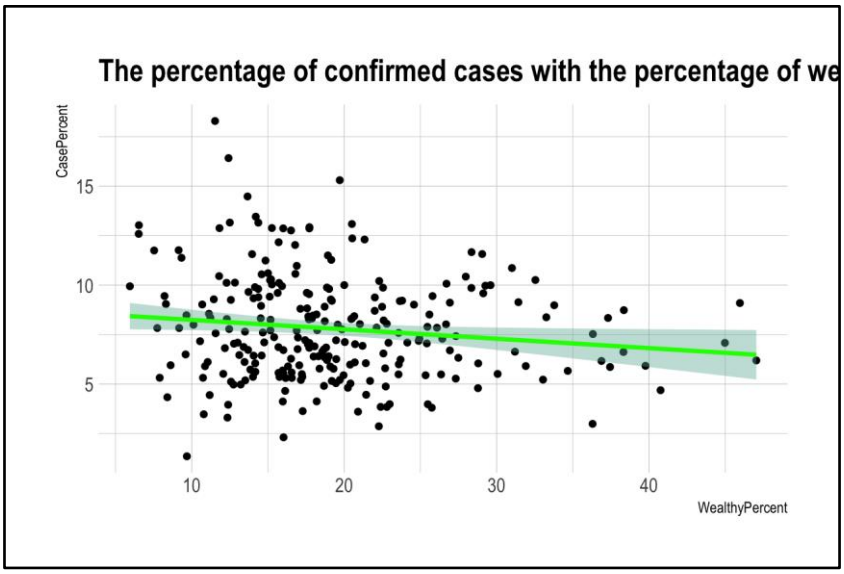

Figure 7: Percentage of Confirmed Cases vs. Percent of Population that is Wealthy

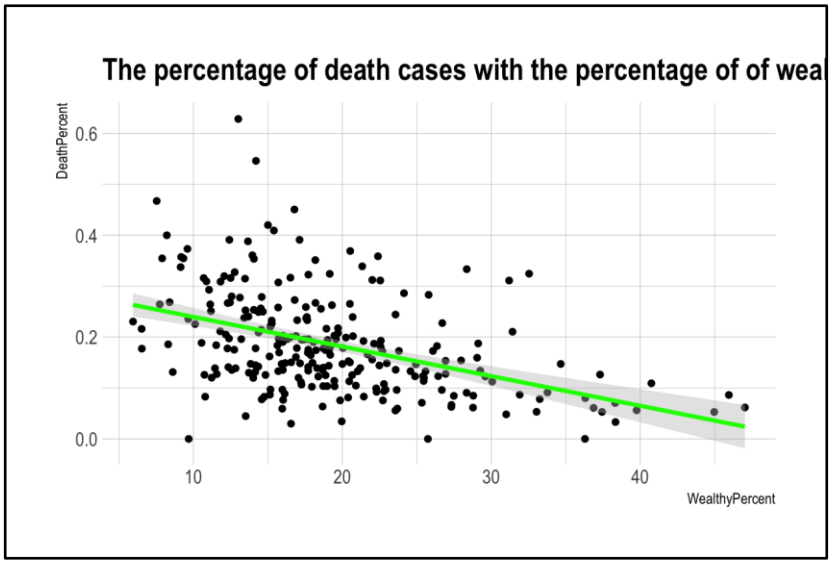

Figure 8: Percentage of Deaths vs. Percent of Population that is Wealthy

These charts are four of the most fascinating. It seems it could easily be inferred after thinking about the regular relationship between wealth and education, but it is interesting nonetheless. Looking at all four of these figures, Figure 5 and 6 look extremely similar to Figures 7 and 8. Looking at Figure 6, the higher the percentage of higher education in a county signifies a lower death percentage. This easily relates to Figure 7. This is expected for a few reasons. One reason is the higher the education level, the more income on average. These people tend to live in nicer places with more easily accessible healthcare. Not only is healthcare more accessible, it is also probably more cutting edge. This allows doctors to help patients even more. This means more aspirators and more doctors. These people likely have a better understanding of all of the different ways the virus spreads. This includes knowledge of how easily the virus spreads during

different activities. It also includes the knowledge of what lifestyle changes they can make to decrease their risk of getting COVID. Some of these things are only available to wealthier people. For example, grocery delivery and pickup and food delivery are great options to limit your exposure to other people and the virus. However, these options are not cheap. This means they are better suited to prevent their exposure, which leads to less infections and less death. This is portrayed in figures 5 through 8.

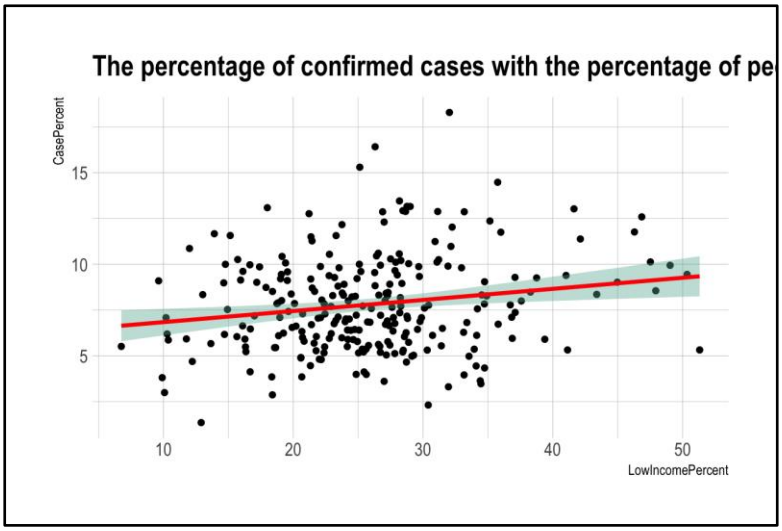

Figure 9: Percent of Confirmed Cases vs. Percent of Low Income Population

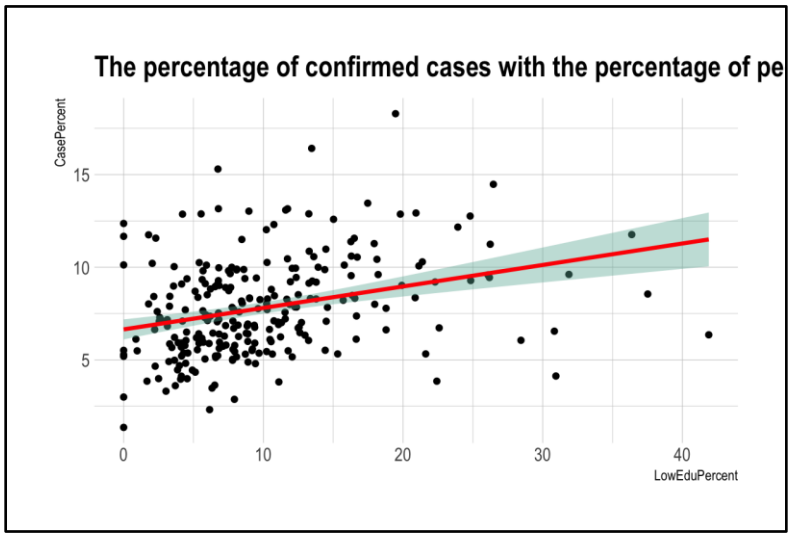

Figure 10: Percent of Confirmed Cases vs. Percent of Population with Low Education

As one would expect, all graphs relating to Wealth and Education follow this same pattern. Lower education typically corresponds to lower income, and the confirmed cases for each of these (shown in Figure 9 and Figure 10) look extremely similar.

COVID-19 vs. Age

One of the last comparisons we made compared cases and deaths to the median age of each county, as shown in the following figures.

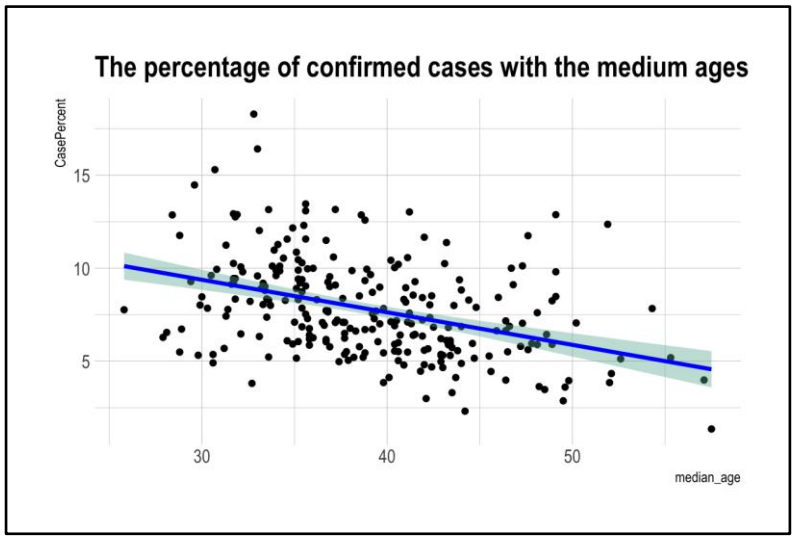

Figure 11: Percent of Confirmed Cases vs. Median Age of County

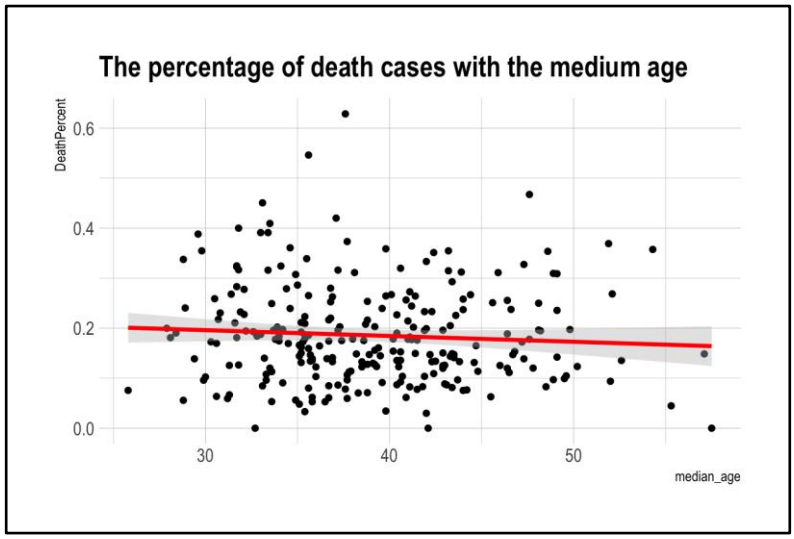

Figure 12: Percent of Death Cases vs. Median Age of the County

The data shown on these figures is initially shocking. Figure 11 exemplifies that counties with older median ages had less COVID cases and deaths. This is shocking because we believe the older populations are more at risk for catching the virus, yet they actually got the virus less often than counties with younger median ages. This makes sense when we look at the people's response to COVID. Many people stopped visiting elderly people in order to protect them from the virus. This means exposure to the virus was limited, and thus it made them less likely to catch COVID. Since they had less likelihood of getting COVID, Figure 12 shows that they had less deaths from COVID.

DATA PREPARATION

Source Code Introduction

There are six sections in the source code, which refer to all the sections in the report. The program will first read in "COVID-19_cases_TX.csv" as the data frame called TXCase. It will then read in "COVID-19_cases_plus_census.csv" as a data frame called CensusData.

Section 1: When did the first case happen in each county in Texas.

To find out the date of the first case in each county in Texas, it needs to use TXCase, which shows daily confirmed cases by date in each county. It will store the first date for each county that shows a confirmed case into a data frame called FirstCase. In that container, it will have a list of county names, a list of county codes, a list of dates with the first case, and how many cases in that day for each county. The project will create a curved graph with the date and the counties' names to visualize that dataset.

```
> summary(FirstCase)
 county_fips_code county_name          state           state_fips_code     date           confirmed_cases
 Min.   :48001    Length:254         Length:254         Min.   :48      Length:254         Min.   :1.000
 1st Qu.:48128    Class :character   Class :character   1st Qu.:48      Class :character   1st Qu.:1.000
 Median :48254    Mode  :character   Mode  :character   Median :48      Mode  :character   Median :1.000
 Mean   :48254                                          Mean   :48                         Mean   :1.232
 3rd Qu.:48381                                          3rd Qu.:48                         3rd Qu.:1.000
 Max.   :48507                                          Max.   :48                         Max.   :7.000
     deaths
 Min.   :0.000000
 1st Qu.:0.000000
 Median :0.000000
 Mean   :0.003937
 3rd Qu.:0.000000
 Max.   :1.000000
>
```

Figure 13: Statistical Summary of "FirstCase"

Figure 13 is the statistical summary of "FirstCase." It has seven columns, in which four of them are numeric. The data frame shows that the dates showing the first case in each county typically have one new case on that day since the mean and the median is all 1. However, the maximum number could reach 7, reflecting that a county could have seven new cases on its "first day." For the data of death cases, most counties do not have death cases on their "first day," but some counties do; it may be caused by some cases that are transported from other counties to those counties' hospitals for further treatment.

To find out how the COVID-19 spread in Texas, the project will keep analyzing the FirstCase; the project will create a new data frame called "FirstCaseByDate." It is created from FirstCase, but it uses a *ddply* function, which categorizes it by using date. Therefore, FirstCaseByDate will have a list of dates, and it also shows the accumulated number of counties, which already have confirmed cases. In a word, as time passes, how many counties have shown their first case will be reflected on the data frame.

```
> summary(FirstCaseByDate)
      date                number
 Min.   :2020-03-05   Min.   :  2.0
 1st Qu.:2020-03-30   1st Qu.:125.2
 Median :2020-04-21   Median :199.0
 Mean   :2020-05-05   Mean   :169.0
 3rd Qu.:2020-05-26   3rd Qu.:229.8
 Max.   :2020-11-17   Max.   :254.0
> |
```

Figure 14: Statistical Summary of "FirstCaseByDate"

	date	number
1	2020-03-05	2
2	2020-03-09	4
3	2020-03-10	7
4	2020-03-13	10
5	2020-03-14	16
6	2020-03-15	17
7	2020-03-17	19
8	2020-03-18	23
9	2020-03-19	27
10	2020-03-20	34
11	2020-03-21	40

Figure 15: Table of "FirstCaseByDate"

Section 2: How fast did the virus spread in Texas

In this section, the project will create a new data frame called SpreadRate, it has all-255 counties' names, and it has the total confirmed cases for each county, which is combined from TXCase. Moreover, it also has the total days that count the confirmed cases to get the average new cases per day for each county, which is the spread rate.

```
> summary(SpreadRate)
 county_fips_code   county_name        confirmed_cases        ndate          rate
 Length:254         Length:254         Min.   :      71   Min.   :370   Min.   :    0.19
 Class :character   Class :character   1st Qu.:   37608   1st Qu.:370   1st Qu.:  101.64
 Mode  :character   Mode  :character   Median :  115710   Median :370   Median :  312.73
                                       Mean   :  801816   Mean   :370   Mean   : 2167.07
                                       3rd Qu.:  341483   3rd Qu.:370   3rd Qu.:  922.93
                                       Max.   :32263458   Max.   :370   Max.   :87198.54
> |
```

Figure 16: Statistical Summary of "SpreadRate"

To further analyze the spread rate, the project will compare it with the city's density (the population of the county & the geographical size of the county). The first step is to get the

counties' total population, and it will be imported from CensusData. The population data frame has the counties' names with geo_id, and it also has the total confirmed case and the total population.

	county_fips_code	county_name	state	date	confirmed_cases	deaths	geo_id	total_pop
1	1	Anderson County	TX	2021/1/19	5575	75	48001	57747
2	2	Andrews County	TX	2021/1/19	1606	37	48003	17577
3	3	Angelina County	TX	2021/1/19	6765	193	48005	87700
4	4	Aransas County	TX	2021/1/19	895	26	48007	24832
5	5	Archer County	TX	2021/1/19	694	10	48009	8793
6	6	Armstrong County	TX	2021/1/19	128	6	48011	1929
7	7	Atascosa County	TX	2021/1/19	3781	90	48013	48139
8	8	Austin County	TX	2021/1/19	1404	18	48015	29292
9	9	Bailey County	TX	2021/1/19	742	15	48017	7098
10	10	Bandera County	TX	2021/1/19	820	20	48019	21316

Figure 17: Table of CensusData

The second step is to visualize the result by using cartograms. A cartogram is a map in which the geometry of regions is distorted to convey the information of an alternate variable. The region area will be inflated or deflated according to its numeric value. This project will use the map of Texas, "TX-48-texas-counties.geojson." [4] This *geojson* file is modified so that the county's list sorts in ascending order. The first map is about the geographical size and each county's population, and the second map is about how the geographical size relates to the spread rate.

Section 3: What is the social distancing response, and how long did it take after the first case?

To analyze the impact of social distancing policy in this section, the project uses April 2nd, 2020, which is when the Texas government announced a stay-at-home order and identify how it relates to the spread rate in Texas. The graph has another vertical curve (the x-intercept) with the date announcing the stay-at-home policy. Furthermore, to find its effect on the total number of cases in Texas, the project has created a new data frame called CasewithDate; it has all the dates that are recorded in the TXCase, but compared to FirstCaseByDate, it also has the cumulative number of new cases and total cases in Texas.

```
> summary(CasewithDate)
      date                casenumber        totalnumber
 Min.   :2020-01-22   Min.   :      0   Min.   :        0
 1st Qu.:2020-04-23   1st Qu.:  22156   1st Qu.:   328106
 Median :2020-07-24   Median : 378517   Median : 11506630
 Mean   :2020-07-24   Mean   : 550435   Mean   : 42170818
 3rd Qu.:2020-10-24   3rd Qu.: 873049   3rd Qu.: 71605164
 Max.   :2021-01-25   Max.   :2248927   Max.   :203661045
```

Figure 18: Statistical Summary of "CasewithDate"

Section 4: Does the spread of COVID-19 relate to ages?

In this section, the project will mainly focus on the CensusData; it has a DatawithAge data frame with a list of counties and with their COVID-19 conditions and civilians' age distribution. Using the total population, the total number of confirmed cases and deaths, and the population under age distribution, we can determine how age could relate to the spread of COVID-19. In the data frame, OldPercent refers to the percentage of older adults (age is greater than 60) in that county; it calculates the total number of people with ages greater than 60 in each county and divides it by the total population of that county. CasePercent simply refers to the percentage of confirmed cases with that country's total population, and the same is true for DeathPercent. The project will also analyze the connection between COVID-19 and age distribution with the data of median age in each county. It is an item from CensusData.

```
> summary(DatawithAge)
 county_fips_code county_name          state              date           confirmed_cases      deaths           geo_id      
 Min.   :48001    Length:254         Length:254         Length:254         Min.   :     1   Min.   :   0.00   Min.   :48001  
 1st Qu.:48128    Class :character   Class :character   Class :character   1st Qu.:   487   1st Qu.:  13.00   1st Qu.:48128  
 Median :48254    Mode  :character   Mode  :character   Mode  :character   Median :  1310   Median :  30.00   Median :48254  
 Mean   :48254                                                           Mean   :  8419   Mean   : 127.48   Mean   :48254  
 3rd Qu.:48381                                                           3rd Qu.:  3502   3rd Qu.:  78.75   3rd Qu.:48381  
 Max.   :48507                                                           Max.   :286356   Max.   :3825.00   Max.   :48507  
   total_pop         median_age      male_60_61        male_62_64      male_65_to_66     male_67_to_69     male_70_to_74    
 Min.   :     74   Min.   :25.80   Min.   :    0.0   Min.   :    0.0   Min.   :    0.0   Min.   :    0.0   Min.   :    0.0  
 1st Qu.:   7072   1st Qu.:34.90   1st Qu.:   82.0   1st Qu.:  110.0   1st Qu.:   72.0   1st Qu.:   96.5   1st Qu.:  135.8  
 Median :  18612   Median :38.55   Median :  242.5   Median :  313.0   Median :  206.5   Median :  294.0   Median :  390.0  
 Mean   : 107951   Mean   :39.02   Mean   : 1125.7   Mean   : 1510.6   Mean   :  905.3   Mean   : 1171.6   Mean   : 1452.6  
 3rd Qu.:  49295   3rd Qu.:42.90   3rd Qu.:  603.8   3rd Qu.:  852.2   3rd Qu.:  562.0   3rd Qu.:  729.8   3rd Qu.: 1028.0  
 Max.   :4525519   Max.   :57.50   Max.   :46922.0   Max.   :58153.0   Max.   :32938.0   Max.   :42601.0   Max.   :49831.0  
 male_75_to_79     male_80_to_84     male_85_and_over  female_60_to_61   female_62_to_64   female_65_to_66   female_67_to_69  
 Min.   :    0.0   Min.   :    0.00   Min.   :    0.00   Min.   :    0.0   Min.   :    0.0   Min.   :    0.0   Min.   :    0.0  
 1st Qu.:   97.0   1st Qu.:   63.25   1st Qu.:   42.25   1st Qu.:   73.5   1st Qu.:  119.5   1st Qu.:   73.0   1st Qu.:   93.5  
 Median :  260.5   Median :  186.50   Median :  145.50   Median :  247.0   Median :  354.0   Median :  224.0   Median :  317.5  
 Mean   :  968.4   Mean   :  629.44   Mean   :  492.45   Mean   : 1234.7   Mean   : 1650.9   Mean   :  999.5   Mean   : 1312.4  
 3rd Qu.:  659.2   3rd Qu.:  445.00   3rd Qu.:  324.00   3rd Qu.:  649.5   3rd Qu.:  888.2   3rd Qu.:  566.0   3rd Qu.:  792.8  
 Max.   :30103.0   Max.   :19416.00   Max.   :15822.00   Max.   :48638.0   Max.   :65231.0   Max.   :38209.0   Max.   :47785.0  
 female_70_to_74   female_75_to_79   female_80_to_84   female_85_and_over   OldPercent      CasePercent       DeathPercent     
 Min.   :    0.0   Min.   :    0.0   Min.   :    0.0   Min.   :    0.00   Min.   :11.07   Min.   : 1.351   Min.   :0.0000  
 1st Qu.:  151.5   1st Qu.:  115.8   1st Qu.:   90.5   1st Qu.:   81.25   1st Qu.:18.67   1st Qu.: 5.896   1st Qu.:0.1199  
 Median :  392.0   Median :  326.5   Median :  219.5   Median :  240.00   Median :22.43   Median : 7.394   Median :0.1727  
 Mean   : 1700.3   Mean   : 1212.6   Mean   :  892.1   Mean   :  924.21   Mean   :23.41   Mean   : 7.799   Mean   :0.1855  
 3rd Qu.: 1102.5   3rd Qu.:  780.5   3rd Qu.:  543.8   3rd Qu.:  587.50   3rd Qu.:27.65   3rd Qu.: 9.410   3rd Qu.:0.2394  
 Max.   :57421.0   Max.   :39285.0   Max.   :29974.0   Max.   :29344.00   Max.   :45.48   Max.   :18.290   Max.   :0.6284  
> 
```

Figure 19: Statistical Summary of "DatewithAge"

Section 5: Does the spread of COVID-19 relate to civilians' income?

In this section, instead of using the age distribution, the project will analyze the income condition in each county. The project has created a new data frame called *DatawithIncome*, which imported the income data from the CensusData. It has the total population, total confirmed cases and deaths, the number of employees, and income distribution in each county. The project will mainly analyze the income, but it will also collect the number of people in each class. Poor condition refers to the people whose income is smaller than 25000. The wealthy condition refers to the people whose income is higher than 100,000, and the middle class is the people in between.

```
> summary(DatawithIncome)
 county_fips_code county_name          state               date          confirmed_cases      deaths            geo_id
Min.   :48001    Length:254         Length:254         Length:254         Min.   :     1   Min.   :   0.00   Min.   :48001
1st Qu.:48128    Class :character   Class :character   Class :character   1st Qu.:   487   1st Qu.:  13.00   1st Qu.:48128
Median :48254    Mode  :character   Mode  :character   Mode  :character   Median :  1310   Median :  30.00   Median :48254
Mean   :48254                                                            Mean   :  8419   Mean   : 127.48   Mean   :48254
3rd Qu.:48381                                                            3rd Qu.:  3502   3rd Qu.:  78.75   3rd Qu.:48381
Max.   :48507                                                            Max.   :286356   Max.   :3825.00   Max.   :48507
   total_pop         median_age    median_income   income_less_10000 income_10000_14999 income_15000_19999 income_20000_24999
Min.   :     74   Min.   :25.80   Min.   :24794   Min.   :    0     Min.   :    0      Min.   :    0.0    Min.   :    0.0
1st Qu.:   7072   1st Qu.:34.90   1st Qu.:42327   1st Qu.:  164     1st Qu.:  135      1st Qu.:  152.2    1st Qu.:  144.2
Median :  18612   Median :38.55   Median :48311   Median :  506     Median :  408      Median :  390.0    Median :  372.5
Mean   : 107951   Mean   :39.02   Mean   :49894   Mean   : 2470     Mean   : 1715      Mean   : 1779.8    Mean   : 1877.7
3rd Qu.:  49295   3rd Qu.:42.90   3rd Qu.:55741   3rd Qu.: 1249     3rd Qu.: 1003      3rd Qu.:  934.2    3rd Qu.: 1104.8
Max.   :4525519   Max.   :57.50   Max.   :93645   Max.   :98715     Max.   :68337      Max.   :75648.0    Max.   :80275.0
income_25000_29999 income_30000_34999 income_35000_39999 income_40000_44999 income_45000_49999 income_50000_59999 income_60000_74999
Min.   :    2.0    Min.   :    0.0    Min.   :    2.0    Min.   :    0.0    Min.   :    0.00   Min.   :     3.0   Min.   :     2.0
1st Qu.:  130.0    1st Qu.:  117.2    1st Qu.:  106.2    1st Qu.:  113.5    1st Qu.:   96.25   1st Qu.:   162.5   1st Qu.:   214.8
Median :  362.0    Median :  374.0    Median :  326.0    Median :  346.0    Median :  263.00   Median :   529.5   Median :   653.0
Mean   : 1802.9    Mean   : 1825.7    Mean   : 1691.3    Mean   : 1707.5    Mean   : 1494.70   Mean   :  2945.2   Mean   :  3694.7
3rd Qu.:  985.5    3rd Qu.:  938.2    3rd Qu.:  903.5    3rd Qu.:  839.2    3rd Qu.:  765.00   3rd Qu.:  1455.5   3rd Qu.:  1725.2
Max.   :74710.0    Max.   :78091.0    Max.   :70427.0    Max.   :73216.0    Max.   :60928.00   Max.   :122390.0   Max.   :152567.0
income_75000_99999 income_100000_124999 income_125000_149999 income_150000_199999 income_200000_or_more  employed_pop
Min.   :    11.0   Min.   :     0.0     Min.   :    0.00     Min.   :    0.00     Min.   :     0.00     Min.   :     39
1st Qu.:   243.5   1st Qu.:   152.8     1st Qu.:   73.25     1st Qu.:   69.25     1st Qu.:    54.25     1st Qu.:   2521
Median :   765.0   Median :   482.0     Median :  232.50     Median :  218.00     Median :   165.00     Median :   7448
Mean   :  4456.9   Mean   :  3205.2     Mean   : 1997.91     Mean   : 2131.40     Mean   :  2332.56     Mean   :  49957
3rd Qu.:  1953.5   3rd Qu.:  1446.8     3rd Qu.:  761.50     3rd Qu.:  671.25     3rd Qu.:   570.00     3rd Qu.:  20850
Max.   :177981.0   Max.   :131467.0     Max.   :83137.00     Max.   :92872.00     Max.   :122052.00     Max.   :2180392
unemployed_pop     not_in_labor_force    poverty       WealthyPercent   MidClassPercent LowIncomePercent  CasePercent
Min.   :     0.0   Min.   :     28    Min.   :    10   Min.   : 5.939   Min.   :39.65   Min.   : 6.748   Min.   : 1.351
1st Qu.:   138.0   1st Qu.:   2387    1st Qu.:  1084   1st Qu.:14.236   1st Qu.:52.11   1st Qu.:20.928   1st Qu.: 5.896
Median :   481.5   Median :   6563    Median :  2739   Median :17.912   Median :55.38   Median :25.438   Median : 7.394
Mean   :  3090.1   Mean   :  29264    Mean   : 16895   Mean   :19.288   Mean   :54.85   Mean   :25.858   Mean   : 7.799
3rd Qu.:  1339.8   3rd Qu.:  17727    3rd Qu.:  7554   3rd Qu.:22.658   3rd Qu.:57.61   3rd Qu.:29.499   3rd Qu.: 9.410
Max.   :149192.0   Max.   :1099302    Max.   :751985   Max.   :47.030   Max.   :77.42   Max.   :51.316   Max.   :18.290
 DeathPercent
Min.   :0.0000
1st Qu.:0.1199
Median :0.1727
Mean   :0.1855
3rd Qu.:0.2394
Max.   :0.6284
```

Figure 20: Statistical Summary of "DatewithIncome"

This data frame also has three lines: WealthyPercent, MidClassPercent, and LowIncomePercent. These are the percentages of people in each class, and they are collected by dividing the numbers of people in each class with the total population in each county.

Section 6: Does the spread of COVID-19 relate to the educational background? (case select male 40-65)

In this last section, there is a new data frame called *DatawithEdu* and it collects the numbers of people between 40 and 65 with different educational backgrounds. This data also comes from CensusData, but three new lines are added to the data frame: LowEduPercent, MidEduPercent, and HighEduPercent. Like those lines in the *DatawithIncome*, LowEduPercent is the percentage of people with a primary school diploma or does not have any educational background. The HighEduPercent is the percentage of people with a college diploma.

```
> summary(DatawithEdu)
 county_fips_code county_name          state               date          confirmed_cases      deaths            geo_id
Min.   :48001    Length:254         Length:254         Length:254         Min.   :     1   Min.   :   0.00   Min.   :48001
1st Qu.:48128    Class :character   Class :character   Class :character   1st Qu.:   487   1st Qu.:  13.00   1st Qu.:48128
Median :48254    Mode  :character   Mode  :character   Mode  :character   Median :  1310   Median :  30.00   Median :48254
Mean   :48254                                                            Mean   :  8419   Mean   : 127.48   Mean   :48254
3rd Qu.:48381                                                            3rd Qu.:  3502   3rd Qu.:  78.75   3rd Qu.:48381
Max.   :48507                                                            Max.   :286356   Max.   :3825.00   Max.   :48507
  total_pop       male_45_64_associates_degree male_45_64_bachelors_degree male_45_64_graduate_degree male_45_64_less_than_9_grade
Min.   :     74   Min.   :    0.0             Min.   :    0.0             Min.   :    0.0             Min.   :    0.00
1st Qu.:   7072   1st Qu.:   38.0             1st Qu.:   75.5             1st Qu.:   29.0             1st Qu.:   72.25
Median :  18612   Median :  134.0             Median :  210.5             Median :   93.0             Median :  227.50
Mean   : 107951   Mean   :  846.0             Mean   : 2275.4             Mean   : 1337.5             Mean   : 1194.00
3rd Qu.:  49295   3rd Qu.:  443.2             3rd Qu.:  754.2             3rd Qu.:  306.2             3rd Qu.:  528.25
Max.   :4525519   Max.   :29530.0             Max.   :96857.0             Max.   :60236.0             Max.   :67074.00
male_45_64_grade_9_12 male_45_64_high_school male_45_64_some_college male_45_to_64      LowEduPercent    MidEduPercent
Min.   :    0.0       Min.   :    6         Min.   :    3.0         Min.   :    15.0   Min.   : 0.000   Min.   : 33.89
1st Qu.:   88.5       1st Qu.:  264         1st Qu.:  153.2         1st Qu.:   792.2   1st Qu.: 5.394   1st Qu.: 61.61
Median :  266.0       Median :  806         Median :  513.5         Median :  2389.0   Median : 8.249   Median : 68.03
Mean   : 1088.5       Mean   : 3260         Mean   : 2612.5         Mean   : 12613.6   Mean   : 9.970   Mean   : 66.81
3rd Qu.:  689.8       3rd Qu.: 2102         3rd Qu.: 1486.2         3rd Qu.:  6273.5   3rd Qu.:12.604   3rd Qu.: 72.78
Max.   :44727.0       Max.   :122562        Max.   :95645.0         Max.   :516631.0   Max.   :41.884   Max.   :100.00
 HighEduPercent   CasePercent      DeathPercent
Min.   : 0.00   Min.   : 1.351   Min.   :0.0000
1st Qu.:16.85   1st Qu.: 5.896   1st Qu.:0.1199
Median :21.91   Median : 7.394   Median :0.1727
Mean   :23.22   Mean   : 7.799   Mean   :0.1855
3rd Qu.:27.74   3rd Qu.: 9.410   3rd Qu.:0.2394
Max.   :63.56   Max.   :18.290   Max.   :0.6284
>
```

Figure 21: Statistical Summary of "DatewithEdu"

CONCLUSION

It is possible to predict the potential effect of the COVID-19 virus in a county by using the data regarding the county's demographics. In the report, we mined COVID-19 data in order to come up with the following conclusions:

- ❏ The time to prevent the spread of the virus was at the beginning, and no matter what the government did after reopening businesses could significantly reduce the spread
- ❏ The greater the wealth in a county means the less likely they were to have a large number of COVID cases and deaths, and vice versa
- ❏ The higher the education level in a county means the less likely they are to have a large number of COVID cases and deaths
- ❏ The lower the education level in a county means the more likely they are to have a large number of COVID cases and deaths
- ❏ The larger the population density in a county means the faster COVID is spread
- ❏ The smaller the population density means the slower COVID is spread
- ❏ The median age of a county could become a predictor of COVID-19's effects depending on the actions taken within the county

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