Analysis of the Social and Political Factors for Success/Failure in Tackling the Covid-19 Pandemic

## Introduction

The Coronavious pandemic has led to social and economic disruption on an unprecidented scale with every country in the world being affected in some way. COVID-19 has dominated business, trade, politics and the media, leading many to question exactly what factors of a nation’s governence have lead to fewer COVD-19 deaths. Some of the most prevelent beleifes sorounding this include:

* Richer countries do better or worse at handling the pandemic than poorer countries.
* Countries led by women more successful than those led by men.
* The success in dealing with the pandemic related the proportion of older people living in a country.
* Democratic countries more successful at dealting with the pandemic than autoritrian ones.

By using data from countries around the world, namely relating to; wealth, age, the gender of a nation’s leader and the strength of democratic institutions as well as statisitcal analysis of these varibles, I am able to further understand the effect these vairbles have on the total deaths per million in a country. This will help me in determining the validity of these hypothesis or if they have no effect on the level of COVID-19 deaths at all (This is known as the null hypothesis).

## Justification:

### Countries led by women more successful than those led by men:

Maybe it is the type of leader that has an effect on COVID-19 deaths in a country? The early success of high profile female world leaders has been studied by academics and widely publicized by prominent media outlets. This leads to the hypothesis, Countries led by women are more successful than those led by men, and if so why? The behavior of male and female world leaders have been compared, with some studies claiming that female leader are “more risk-averse than men” and are more likely to downplay the crisis. While on the overhand Female leaders such as Jacinda Ardern and Angela Merkle were observed taking stricter measures to stop COVID-19 spreading earlier in the countries they led.

### Richer countries do better or worse at handling the pandemic than poorer countries:

It is not outlandish to assume that a nation with a wealthier population is likely to have access to better medical resources. The United Kingdom or Norway for example have high GDP per capitas, strong service economies and and sizable government infrastructure to plan for and potentially mitigate the effects of a pandemic in it’s population. These factors should also mean that measure put in place by a government such as lockdowns and working from home will have less of a financial impact on the population compared to countries which do not have robust medical and telecommunications infrastructure as well as having economies that rely on manufacturing or agriculture.

### The success in dealing with the pandemic related the proportion of older people living in a country:

Pandemics often have higher cases in the young but have a higher mortality rate in the elderly. A country with a larger proportion of older people in the population may be more likely to take fewer risks with its population and bring in stricter measures to mitigate the effect of the pandemic on the most vulnerable in the country.

### Democratic countries more successful at dealting with the pandemic than autoritrian ones:

Effective measures to controls the spread of COIVD-19 may be more difficult or slow to implement in liberal, Democratic political regimes. Measures such as travel bans and the limiting of social gatherings may be seen as autocratic by some members of the public and politicians alike. On the other hand, actual authoritarian regimes “may suffer from a lack of transparency and over-stringent responses.” Examples of such responses include media censorship and the falsification of data to control the population as well as the image of the country to the rest of the world. Such issues my cause distrust for a less transparent government’s COVID-19 policies and cause more deaths.

## The Results:

To actually prove that these hypotheses do or don’t effect COVID-19 deaths in countries I first began by examining the variables most relevant to each hypothesis individually, the selected hypotheses can be found in Table 1. Firstly, I calculated the measure of central tendency and dispersion for the variables, for use in later analysis (also listed in Table 1).

Next, An important step to analyzing the data is to understand how the relevant variables are distributed. Visualizing distribution with plots helped me get some quick about the variables. these are found in figures 1 to 5.

After that I compared the relevant variables to the total COVID-19 deaths per million with conditional distribution plots (figures 7 to 9).

Lastly, using the means I worked out in the table. I will conduct two sample T-tests on the variables to test if the differences in the effect of the variables identified in the plots are statistically significant. A two sample T-test is a type of hypothesis test used to compare whether the difference between the means of two groups is statistically significant or if it due just to random chance. P-values and T-values are important to understanding how to interpret T-tests. The P-value tells us how likely it is to get a result like the one we get if the null hypothesis is true. A p-value of below 0.05 would be statistically significant. This means we reject the null hypothesis if it is below that number.

## Table

Understanding the

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Name of the Relevant MCT | Value of the MCT | Name of the Relevant MD | Value of the MD |
| Total Deaths Per Million | Continuous | 140.40 | variance and/or standard deviation | 209.88 |
| GDP Per Capita | Continuous | 14910.69 | variance and/or standard deviation | 16071.77 |
| Female Head of Government | Nominal | 0 (Male) = 107 1 (Female) = 9 | proportion in each category | 0 (Male) = 0.92 1 (Female) = 0.08 |
| V-Dem Polyarchy | Continuous | 0.56 | variance and/or standard deviation | 0.22 |

*Table 1. The Name of the Relevant Measure of Central Tendency (MCT) and Measure of Dispersion with their values*

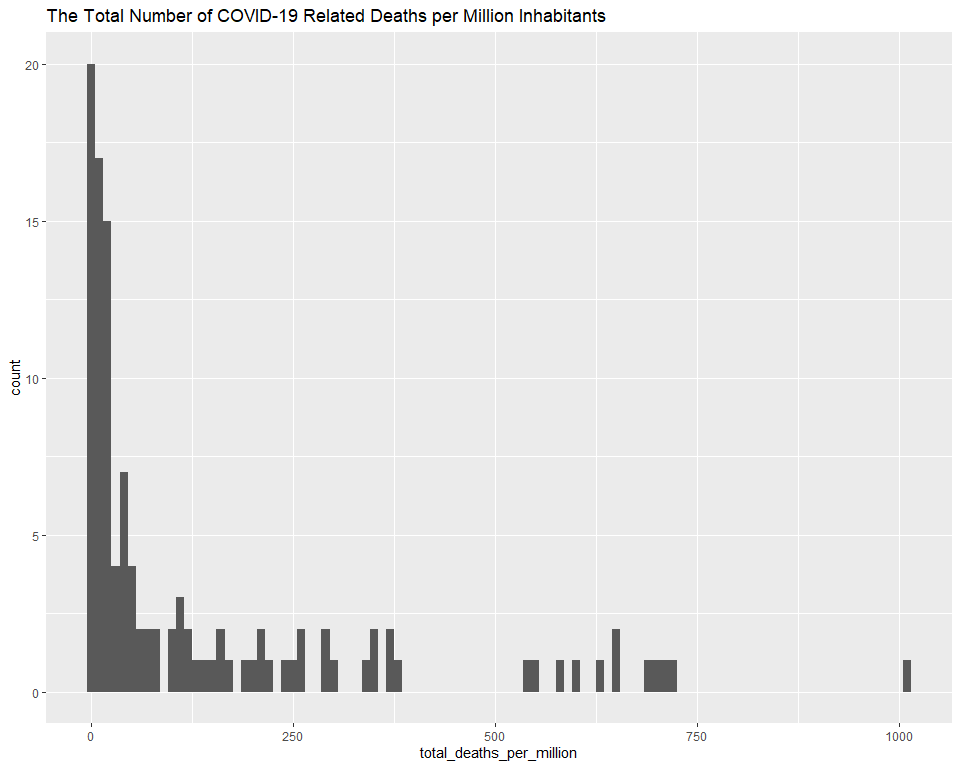


Figure 1.

From this distribution we can see that there is a group of countries with mostly low total COVID-19 deaths per million with the number of countries decreasing ans the total deaths per million rises. The lower, total deaths range between 0 and 375, another group of countries with deaths between 500 and 750 per million and one country with over 1000 total deaths per million.

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

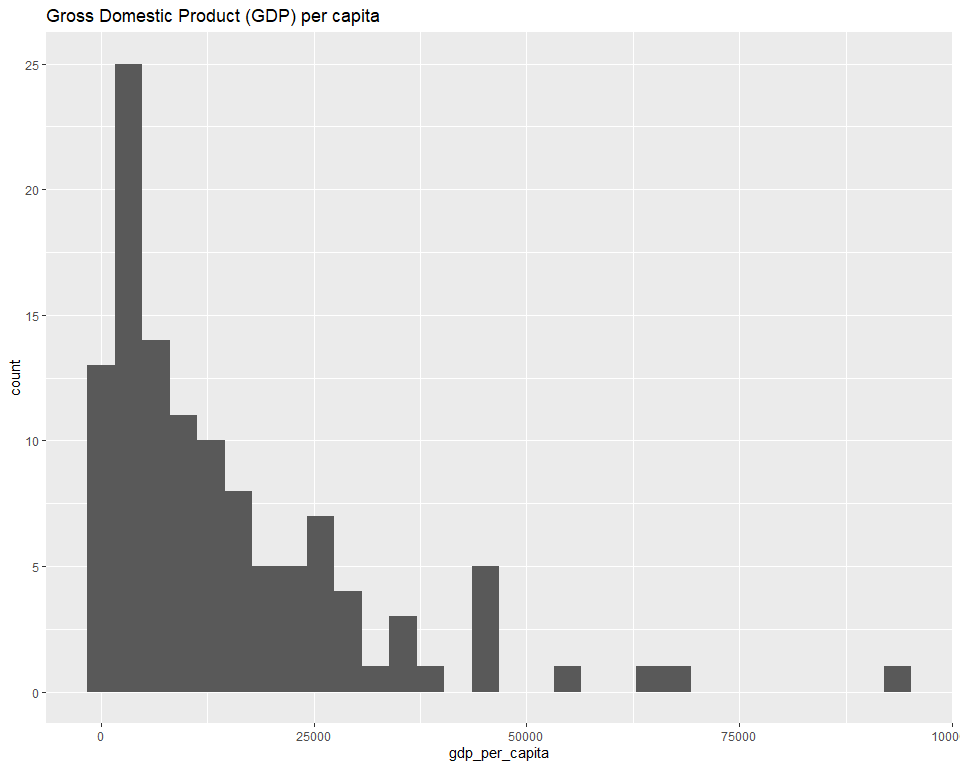


Figure 2.

There Are many more countries with a GDP per Capita below 25,000 Dollars than higher. There are some countries with GDP per capitas 25 and 60,000 Dollars some much wealthier countries with a GDP per capita of around 95,000 dollars.

## mapping: label = ~location   
## geom\_text: parse = FALSE, check\_overlap = FALSE, na.rm = FALSE  
## stat\_identity: na.rm = FALSE  
## position\_identity

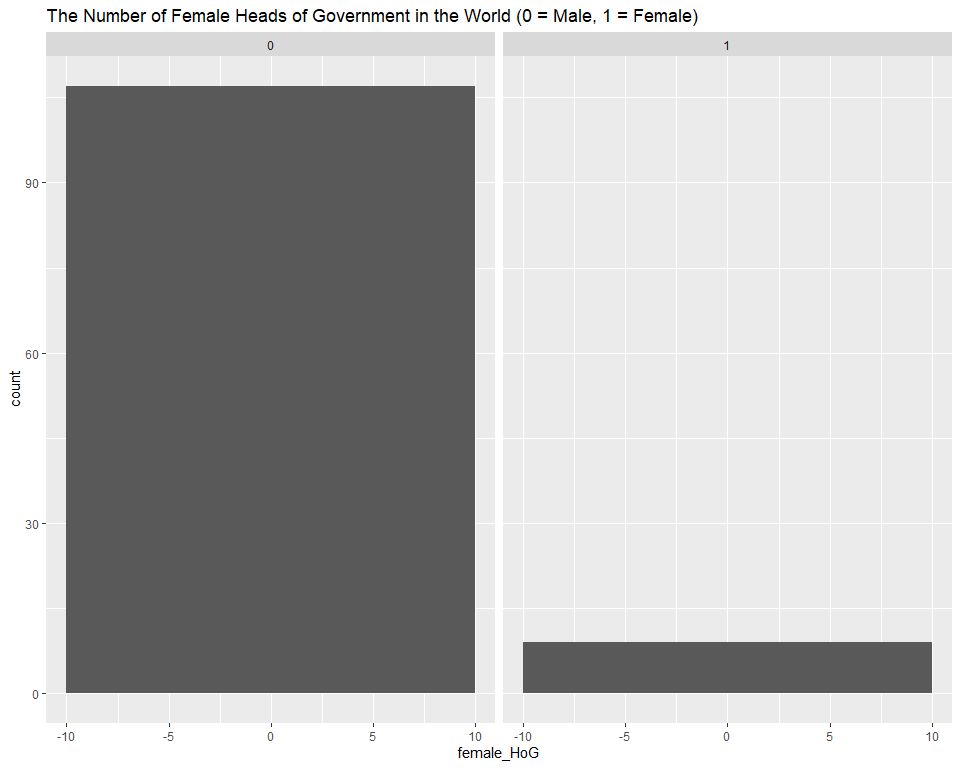


Figure 3.

The vast majority of heads of government in the world are male, with only 9 out of the 116 countries in the data set having female heads of government.

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

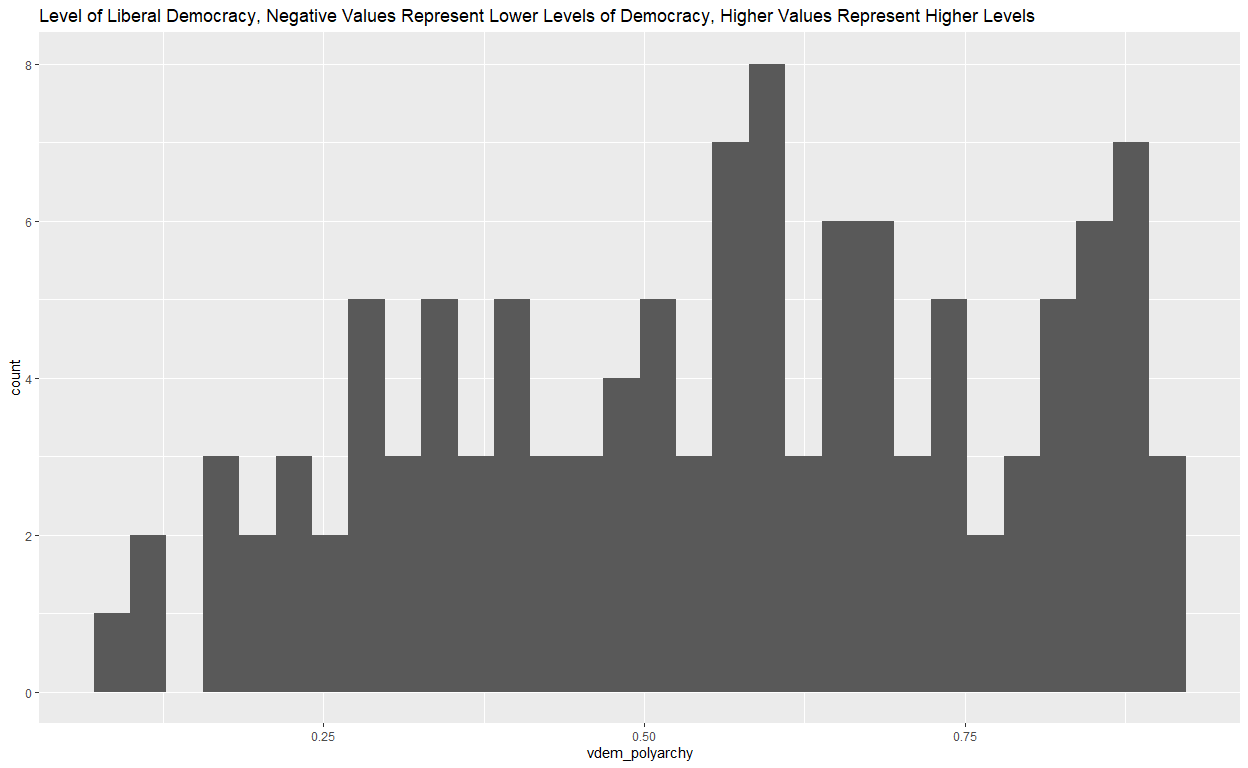


Figure 4.

This Histogram shows the level liberal democracy of the countries in the data set ranging from 0, meaning that a country has no democratic institutions to 1, meaning that the county has the strongest democratic institutions. The countries in this data set range from 0.09 to 0.9. The most common values being found around 0.6. unlike the other histograms, this one is skewed to the right. There are more countries considered to be democratic than not.

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.

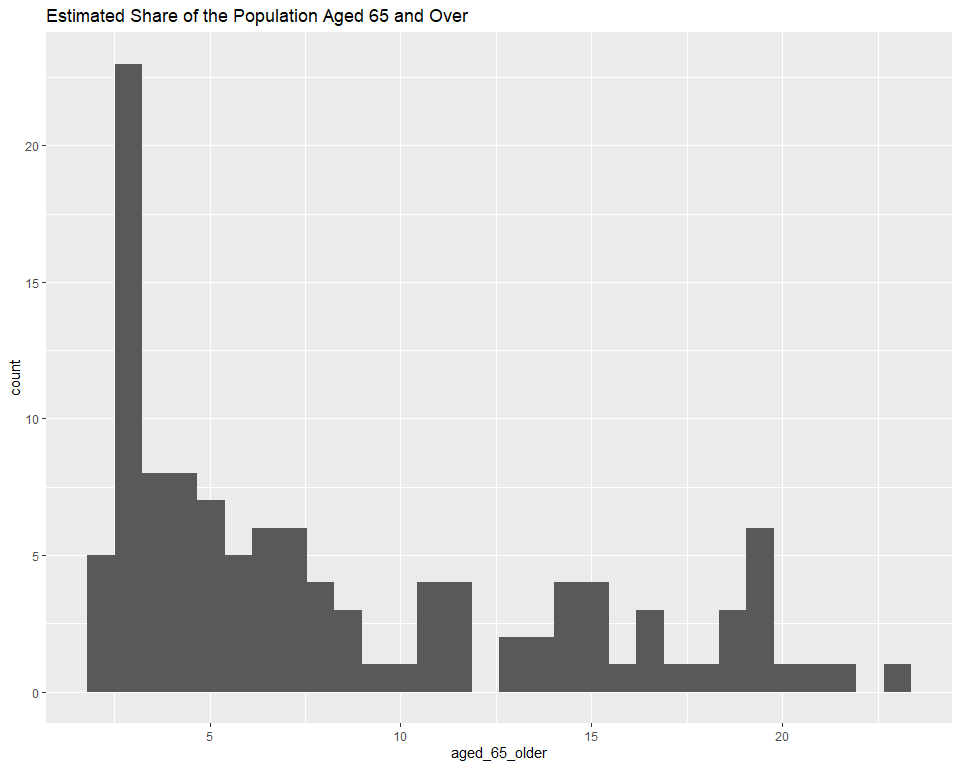


Figure 5.

The last histogram show the estimated share of a country’s population over the age of 65. the share ranges between 2% at the lowest and 23% at the highest. This graph is skewed to the left. The most common percentage of estimated share of the population being between 2% and 3%. There are more countries with lower estimated shares of 65s and over than higher estimated shares.

#### Richer Countries do better than Poorer countries.

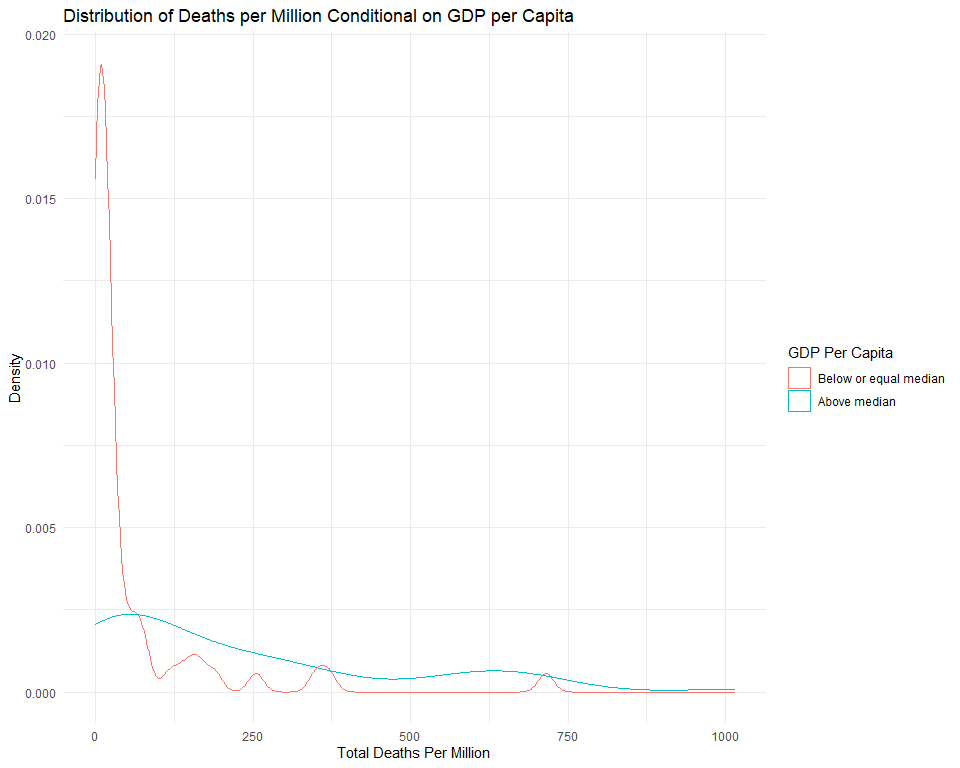


Figure 7.

There is a much wider spread of COVID-19 deaths per million in countries with above median GDP per capita compared to countries below the median. Countries with lower seem to have fewer COVID-19 deaths per million.

#### The success in dealing with the pandemic is related to the proportion of older people living in the country.

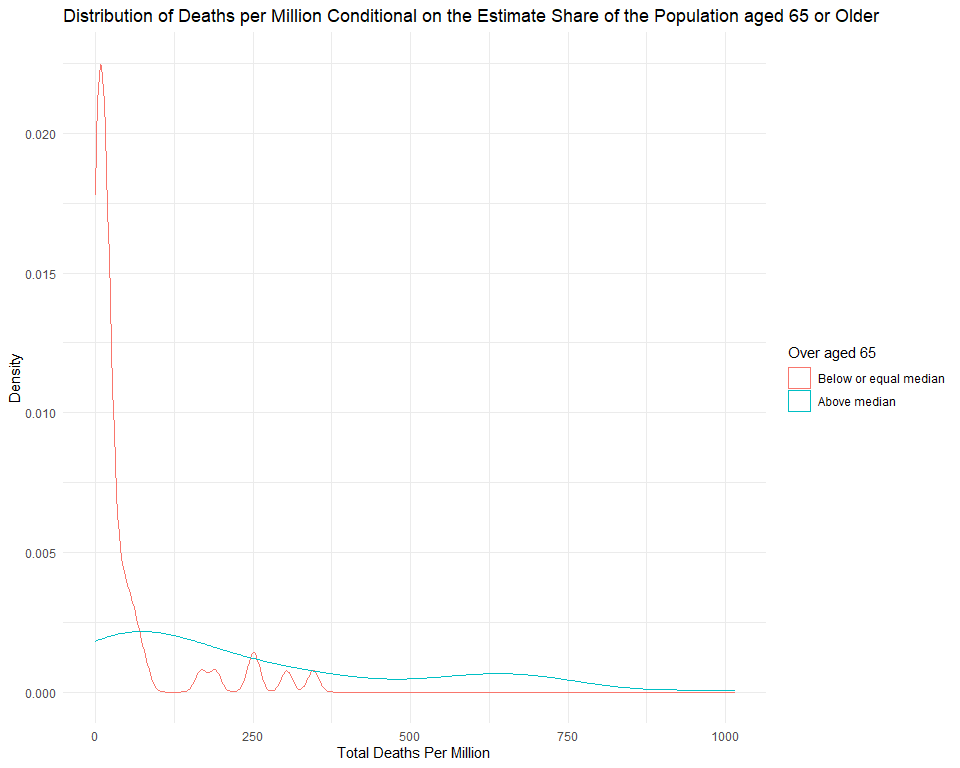


Figure 8.

Their is a wider spread of country’s COVID-19 deaths per million with populations over 65 comapared to countries with a smaller estimated share of the population over that age.

#### Democratic countries are more successful than authoritarian countries.

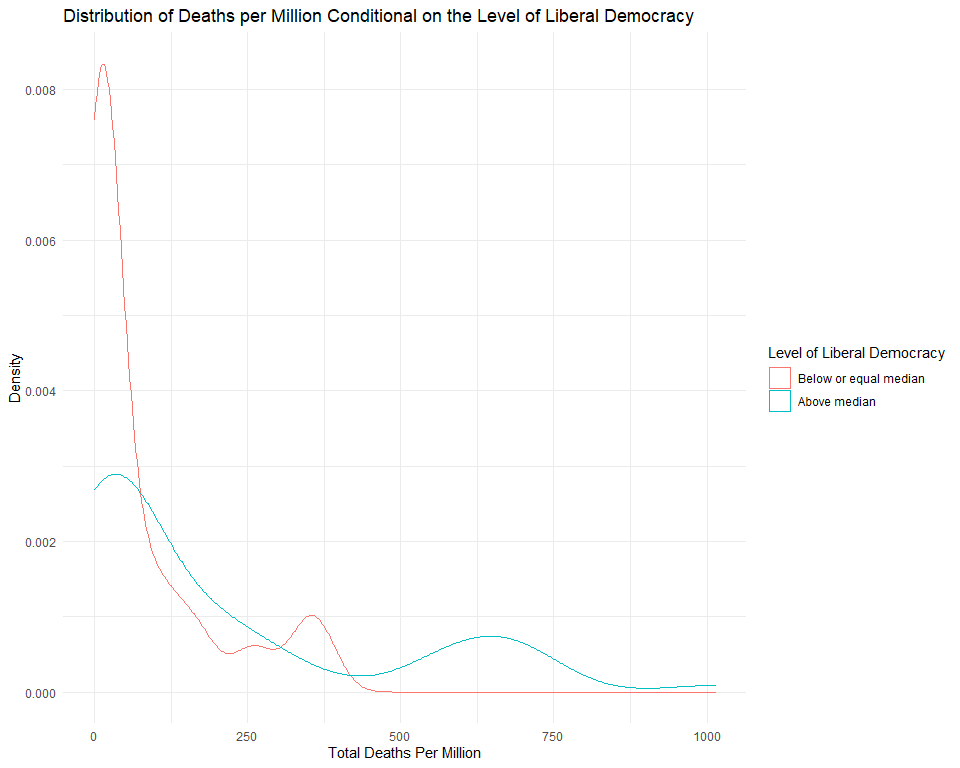


Figure 9.

Countries below or equal to the median level of liberal democracy have a lower spread of total COVID-19 deaths per million, however most countries above the median also have low COVID-19 deaths per million but have a larger distribution spread.

# TWO SAMPLE T-TESTS

#### Richer Countries do better than Poorer countries.

# T-Test: GDP

##   
## Welch Two Sample t-test  
##   
## data: total\_deaths\_per\_million by vdem\_var  
## t = -3.3834, df = 76.758, p-value = 0.00113  
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0  
## 95 percent confidence interval:  
## -200.56063 -51.94485  
## sample estimates:  
## mean in group 0 mean in group 1   
## 77.27481 203.52755

The null hypothesis is that countries with a GDP per capita higher than the average have a lower total COVID-19 deaths per million than countries with a lower GDP per capita.

From the result of the T-test I can observe that the p-value of 0.0013, below the 0.05 threshold. The average total deaths per million of countries with a GDP per capita below the average was 77.27 and the countries above the average GDP was 203.53. I can reject the null hypothesis. Richer countries on average do not do better than poorer countries.

#### The success in dealing with the pandemic is related to the proportion of older people living in the country.

# T-Test: Aged 65 Plus

##   
## Welch Two Sample t-test  
##   
## data: total\_deaths\_per\_million by sixty\_five\_var  
## t = -5.6498, df = 67.436, p-value = 3.509e-07  
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0  
## 95 percent confidence interval:  
## -264.5275 -126.4257  
## sample estimates:  
## mean in group 0 mean in group 1   
## 42.66288 238.13948

The null hypothesis is that countries with an population over 65 higher than average have lower total COVID-19 deaths per million than countries with a lower population ages.

From the result of the T-test I can observe that the p-value is 3.509e-07 (0.0000003509), below the 0.05 threshold. The average total deaths per million of countries with a below the average was 42.66 and the countries above the average population over 65 was 238.14. I can reject the null hypothesis. The success in dealing with the pandemic is not related to the proportion of older people living in the country.

#### Democratic countries are more successful than authoritarian countries.

# T-Test: VDEM Polyarchy

##   
## Welch Two Sample t-test  
##   
## data: total\_deaths\_per\_million by vdem\_var  
## t = -3.3834, df = 76.758, p-value = 0.00113  
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0  
## 95 percent confidence interval:  
## -200.56063 -51.94485  
## sample estimates:  
## mean in group 0 mean in group 1   
## 77.27481 203.52755

The null hypothesis is that countries with a level of liberal democracy higher than the average, have a total COVID-19 deaths per million lower than countries with a lower level of liberal democracy.

From the result of the T-test I can observe that the p-value is 0.00113, below the 0.05 threshold. The average total deaths per million of counties with a below average level of liberal democracy was 77.27 and the countries with an above average level of liberal democracy. I can reject the null hypothesis. Democratic countires are not more successful than authoritarian countries.

#### Countries led by women are more successful than those led by men.

# T-Test: Female HoG

## # A tibble: 2 x 3  
## female\_HoG mean n  
## <int> <dbl> <int>  
## 1 0 142. 107  
## 2 1 116. 9

##   
## Welch Two Sample t-test  
##   
## data: total\_deaths\_per\_million by female\_HoG  
## t = 0.34375, df = 9.1794, p-value = 0.7388  
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0  
## 95 percent confidence interval:  
## -149.8988 203.8073  
## sample estimates:  
## mean in group 0 mean in group 1   
## 142.4925 115.5382

The null hypothesis is that countries with a female head of government have lower total deaths per million than countries with a male head of government. The p value is 0.7388, above the 0.05 threshold. This means that the distribution is not statistically significant and I cannot reject the null hypothesis. While countries with a female head of government do have a lower total deaths per million, there are only 9 female leaders compared to 116 male heads of government.

## Conclusion:

## Code:

#### INSTALL LIBRARYS: ####  
library("ggplot2")  
library(tidyverse)  
library(tidyr)  
#### INPUT DATASET: ####  
dataset <- read.csv("https://raw.githubusercontent.com/QMUL-SPIR/Public\_files/master/datasets/Covid2020.csv")  
dataset\_omit <- read.csv("https://raw.githubusercontent.com/QMUL-SPIR/Public\_files/master/datasets/Covid2020.csv")  
dataset\_omit <- drop\_na(dataset\_omit, extreme\_poverty)  
head(dataset)  
  
#### EXAMINE THE RELEVENT VARIABLES: ####  
  
# Total Deaths Per Million:  
  
# MCT:  
   
tdm\_mean <- mean(dataset\_omit$total\_deaths\_per\_million)  
tdm\_mean  
  
# MD:  
  
sd(dataset\_omit$total\_deaths\_per\_million)  
  
# GDP Per Captia:  
# MCT:  
  
gdp\_per\_cap <- mean(dataset\_omit$gdp\_per\_capita)  
gdp\_per\_cap  
  
# MD:  
  
sd(dataset\_omit$gdp\_per\_capita)  
  
# Female Head of Government:   
  
# MCT:  
  
fem\_hog <- table(dataset\_omit$female\_HoG)  
fem\_hog  
  
# MD:  
  
fem\_hog\_dev <- prop.table(table(dataset\_omit$female\_HoG))  
fem\_hog\_dev  
  
# Aged 65 of Older:  
  
# MCT:  
  
old\_age <- mean(dataset\_omit$aged\_65\_older)  
old\_age  
  
# MD:  
  
sd(dataset\_omit$aged\_65\_older)  
  
# VDEM Polyarchy:  
  
# MCT:  
  
vdem <- mean(dataset\_omit$vdem\_polyarchy)  
vdem  
  
# MD:  
  
sd(dataset\_omit$vdem\_polyarchy)  
  
#### A TABLE WITH ALL THE VARIBALE AND MEASURE OF CENTRAL TENDENCY: ####  
  
# This will be added in Rmd  
  
#### A RELEVENT PLOT FOR EVERY VARIABLE ####  
  
# Total Deaths Per Million:  
gg\_total\_deaths\_per\_mil <- ggplot(dataset\_omit, aes(x = total\_deaths\_per\_million))  
gg\_total\_deaths\_per\_mil + geom\_histogram(binwidth = 10)  
  
# GDP Per Capita:  
gg\_gdp\_per\_cap <- ggplot(dataset\_omit, aes(x = gdp\_per\_capita))  
gg\_gdp\_per\_cap + geom\_histogram()  
  
# Female Head of Government:  
gg\_female\_HoG\_deaths <- ggplot(data = dataset\_omit, aes(x = female\_HoG)) +  
 geom\_histogram(binwidth = 20)  
  
geom\_text(size = 2,   
 colour = "red",   
 aes(label = location))  
  
gg\_female\_HoG\_deaths + facet\_wrap(~ female\_HoG)  
  
# Aged 65 or Older:  
gg\_aged\_65\_plus <- ggplot(data = dataset\_omit, aes(x = aged\_65\_older))  
gg\_aged\_65\_plus + geom\_histogram()  
  
# VDEM Polyarchy:  
gg\_vdem <- ggplot(data = dataset\_omit, aes(x = vdem\_polyarchy))  
gg\_vdem + geom\_histogram()  
  
#### RECODES FOR VARIBELS OF INTREST (BINARY)####  
  
# calculate median GDP Per Capita  
med\_gdp <- median(dataset\_omit$gdp\_per\_capita)  
  
# create new variable using case\_when()  
dataset\_omit <- dataset\_omit %>% # pipe the dataset  
 mutate( # create new variable  
 gdp\_var = # name the new variable  
 factor(case\_when(  
 gdp\_per\_capita > med\_gdp ~ 1,  
 gdp\_per\_capita <= med\_gdp ~ 0)))  
  
# calculate median 65 or Older  
med\_65\_plus <- median(dataset\_omit$aged\_65\_older)  
  
# create new variable using case\_when()  
dataset\_omit <- dataset\_omit %>% # pipe the dataset  
 mutate( # create new variable  
 sixty\_five\_var = # name the new variable  
 factor(case\_when(  
 aged\_65\_older > med\_65\_plus ~ 1,  
 aged\_65\_older <= med\_65\_plus ~ 0)))  
  
# calculate median vdem Polyarchy  
med\_vdem <- median(dataset\_omit$vdem\_polyarchy)  
  
# create new variable using case\_when()  
dataset\_omit <- dataset\_omit %>% # pipe the dataset  
 mutate( # create new variable  
 vdem\_var = # name the new variable  
 factor(case\_when(  
 vdem\_polyarchy > med\_vdem ~ 1,  
 vdem\_polyarchy <= med\_vdem ~ 0)))  
  
  
  
#### RELATIONSHP BETWEEN TOTAL COVID 19 DEATHS AND THE RELEVENT VARIABLES ####  
  
 #### CONDITIONAL DISTRIBUTION PLOTS ####  
  
# Distribution of Deaths per Million Conditional on GDP per Capita  
  
gdp\_dist <- ggplot(data = dataset\_omit, aes(total\_deaths\_per\_million, group = gdp\_var)) +   
 geom\_density(aes(colour = gdp\_var)) +  
 labs(x = "Total Deaths Per Million", # clearer x axis label  
 y = "Density", # clearer y axis label  
 title = "Distribution of Deaths per Million Conditional on GDP per Capita") + # title   
 scale\_color\_discrete(name = "GDP Per Capita", # change legend title  
 labels = c("Below or equal median", # change legend labels  
 "Above median")) +   
 theme\_minimal()  
  
gdp\_dist  
  
# Distribution of Deaths per Million Conditional on median 65 or Older  
  
sixtyfive\_dist <- ggplot(data = dataset\_omit, aes(aged\_65\_older, group = sixty\_five\_var)) +   
 geom\_density(aes(colour = sixty\_five\_var)) +  
 labs(x = "Total Deaths Per Million", # clearer x axis label  
 y = "Density", # clearer y axis label  
 title = "Distribution of Deaths per Million Conditional on the Estimate Share of the Population aged 65 or Older") + # title   
 scale\_color\_discrete(name = "Over aged 65", # change legend title  
 labels = c("Below or equal median", # change legend labels  
 "Above median")) +   
 theme\_minimal()  
  
sixtyfive\_dist  
  
# Distribution of Deaths per Million Conditional on median vdem Polyarchy  
  
vdem\_dist <- ggplot(data = dataset\_omit, aes(vdem\_polyarchy, group = vdem\_var)) +   
 geom\_density(aes(colour = vdem\_var)) +  
 labs(x = "Total Deaths Per Million", # clearer x axis label  
 y = "Density", # clearer y axis label  
 title = "Distribution of Deaths per Million Conditional on the Level of Liberal Democracy") + # title   
 scale\_color\_discrete(name = "Level of Liberal Democracy", # change legend title  
 labels = c("Below or equal median", # change legend labels  
 "Above median")) +   
 theme\_minimal()  
  
vdem\_dist  
  
 #### TWO SAMPLE T-TESTS ####  
  
# T-Test: GDP  
  
t.test(vdem\_polyarchy ~ vdem\_var, # formula y ~ x  
 data = dataset\_omit, # dataset where the variables are found  
 mu = 0, # difference under the null hypothesis  
 alt = "two.sided", # two sided test (difference in means could be smaller or larger than 0)  
 conf = 0.95) # confidence interval  
  
# T-Test: Aged 65 Plus  
  
t.test(aged\_65\_older ~ sixty\_five\_var, # formula y ~ x  
 data = dataset\_omit, # dataset where the variables are found  
 mu = 0, # difference under the null hypothesis  
 alt = "two.sided", # two sided test (difference in means could be smaller or larger than 0)  
 conf = 0.95) # confidence interval  
  
# T-Test: VDEM Polyarchy  
  
t.test(vdem\_polyarchy ~ vdem\_var, # formula y ~ x  
 data = dataset\_omit, # dataset where the variables are found  
 mu = 0, # difference under the null hypothesis  
 alt = "two.sided", # two sided test (difference in means could be smaller or larger than 0)  
 conf = 0.95) # confidence interval  
  
# T-Test: Female HoG  
  
fem\_means <- # assign to object  
 dataset\_omit %>% # pipe dataset  
 group\_by(female\_HoG) %>% # group by whether in there is a female head of government  
 summarise(mean = mean(total\_deaths\_per\_million), # get mean of total\_deaths\_per\_million for each group  
 n = n()) # also get number of observations in each group  
  
fem\_means  
  
t.test(total\_deaths\_per\_million ~ female\_HoG, # formula y ~ x  
 data = dataset\_omit, # dataset where the variables are found  
 mu = 0, # difference under the null hypothesis  
 alt = "two.sided", # two sided test (difference in means could be smaller or larger than 0)  
 conf = 0.95) # confidence interval