Study of COVID-19 Impact in Scandinavia

Intro

The Nordic countries are a unique region for analyzing the COVID-19 pandemic because of the different approaches to controlling the virus. In my study, I focused on the differences between the strategies of **Sweden** and its neighbors **Finland**, **Denmark**, and **Norway**.

Sweden has chosen the path of minimal restrictions, relying on recommendations and voluntary compliance. The authorities left schools, restaurants and stores open, focusing on protecting vulnerable groups and maintaining public health. This approach has generated much controversy and debate in the international community.

When the pandemic first started, the Swedish government developed measures that were not very strict compared to those introduced by the governments of Finland, Denmark, and Norway. These countries closed educational institutions and public facilities, introduced quarantine measures and restrictions on public gatherings. Borders were also closed to entry for most of the countries. Thus, the spread of the virus was controlled in these countries. And quarantine measures were enforced by digital tools.

For example, Finland imposed a two-month quarantine at the start of the pandemic, closing schools, restaurants and banning travel in and around Helsinki. The rapid deployment of a contact-tracking application and the high level of public confidence in the government's measures also contributed to compliance.

Denmark used a strategy of mass testing and contact tracing to detect and isolate cases early. Norway also introduced stringent early measures, including border closures and local restrictions depending on the level of infection in different regions.

Vaccination strategies also varied. While all countries were aggressive in their vaccination campaigns, the pace and methods differed. For example, Norway and Finland focused on protecting the elderly and vulnerable, while Denmark and Sweden also focused on vaccinating young people and critical workers.

The aim of my study is to provide an overall analysis of the COVID-19 situation and mortality in the Nordic countries and to compare different approaches and their consequences. I want to find out how different pandemic control strategies have affected morbidity and mortality and what can be learned from these differences for future epidemiologic strategies.

Loading Data

```r
library(tidyverse)
library(dplyr)
library(lubridate)
library(ggplot2)
```

```
url_in <- "https://raw.githubusercontent.com/CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covi
cases <- read_csv(str_c(url_in, "time_series_covid19_confirmed_global.csv"))
deaths <- read_csv(str_c(url_in, "time_series_covid19_deaths_global.csv"))
```

Data preprocessing and cleaning

The following steps were performed to pre-process and clean the data: rows for the Nordic countries (Finland, Sweden, Denmark, Norway) were selected from the global data on confirmed cases and deaths from COVID-19, unnecessary columns such as geo-coordinates were removed as they are not required for the analysis. Danish island data were also excluded to avoid bias in the analysis. Key columns were renamed and dates were converted to date format. Dataset was converted from wide format to long format, then case and death data were aggregated by country and date, and a column with the population of each country was added for further analysis. The data were then grouped by country, year and month, cumulative and new cases and deaths were calculated, and a new dataframe was created for further analysis. This resulted in two dataframes, one with raw data and one with aggregated data by month.

```
population <- data.frame(
  Country = c("Finland", "Sweden", "Denmark", "Norway"),
  Population = c(5530719, 10379295, 5831404, 5421241)
)

cases <- cases %>%
  rename(Country = `Country/Region`) %>%
  filter(Country %in% population$Country & is.na(`Province/State`)) %>%
  select(-c(`Province/State`, Lat, Long)) %>%
  pivot_longer(cols = -Country, names_to = "Date", values_to = "Cases") %>%
  mutate(Date = mdy(Date))

deaths <- deaths %>%
  rename(Country = `Country/Region`) %>%
  filter(Country %in% population$Country & is.na(`Province/State`)) %>%
  select(-c(`Province/State`, Lat, Long)) %>%
    pivot_longer(cols = -Country, names_to = "Date", values_to = "Deaths") %>%
    mutate(Date = mdy(Date))

data <- cases %>%
  full_join(deaths, by=join_by("Country", "Date")) %>%
  mutate(Year = year(Date), Month = month(Date)) %>%
  full_join(population, by="Country")

summary(data)
```

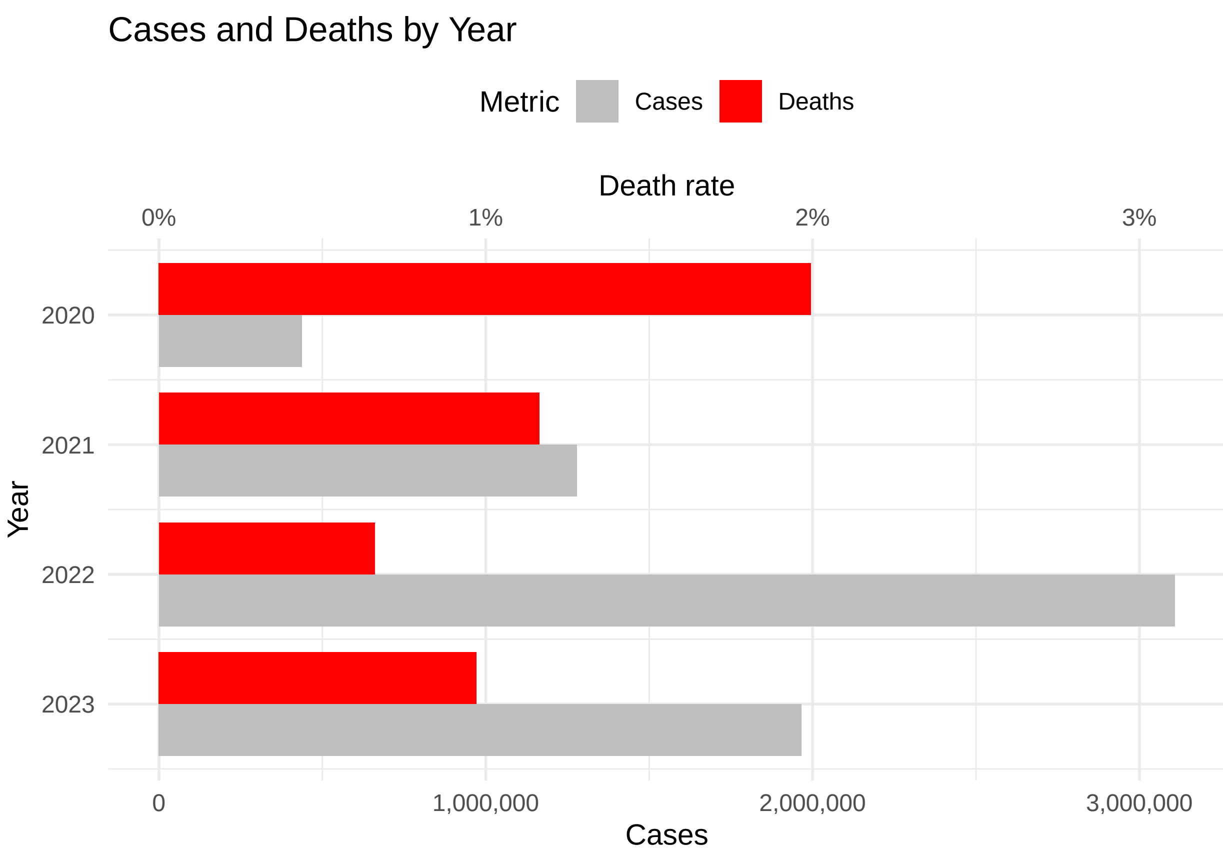
```
##    Country                 Date                Cases            Deaths     
##  Length:4572        Min.   :2020-01-22   Min.   :      0   Min.   :    0  
##  Class :character   1st Qu.:2020-11-02   1st Qu.:  46982   1st Qu.:  673  
##  Mode  :character   Median :2021-08-15   Median : 316438   Median : 2616  
##                     Mean   :2021-08-15   Mean   : 894303   Mean   : 5166  
##                     3rd Qu.:2022-05-28   3rd Qu.:1446439   3rd Qu.: 6893  
##                     Max.   :2023-03-09   Max.   :3404407   Max.   :23777  
##       Year          Month          Population      
##  Min.   :2020   Min.   : 1.000   Min.   : 5421241  
##  1st Qu.:2020   1st Qu.: 3.000   1st Qu.: 5503350  
##  Median :2021   Median : 6.000   Median : 5681062  
##  Mean   :2021   Mean   : 6.335   Mean   : 6790665  
##  3rd Qu.:2022   3rd Qu.: 9.000   3rd Qu.: 6968377  
##  Max.   :2023   Max.   :12.000   Max.   :10379295  
```

```r
data_grouped <- data %>%
  group_by(Country, Year, Month) %>%
  summarise(
    CasesCum = max(Cases),
    DeathsCum = max(Deaths),
    CasesNew = max(Cases) - min(Cases),
    DeathsNew = max(Deaths) - min(Deaths),
    Population = first(Population),
    .groups = "drop")

summary(data_grouped)
```

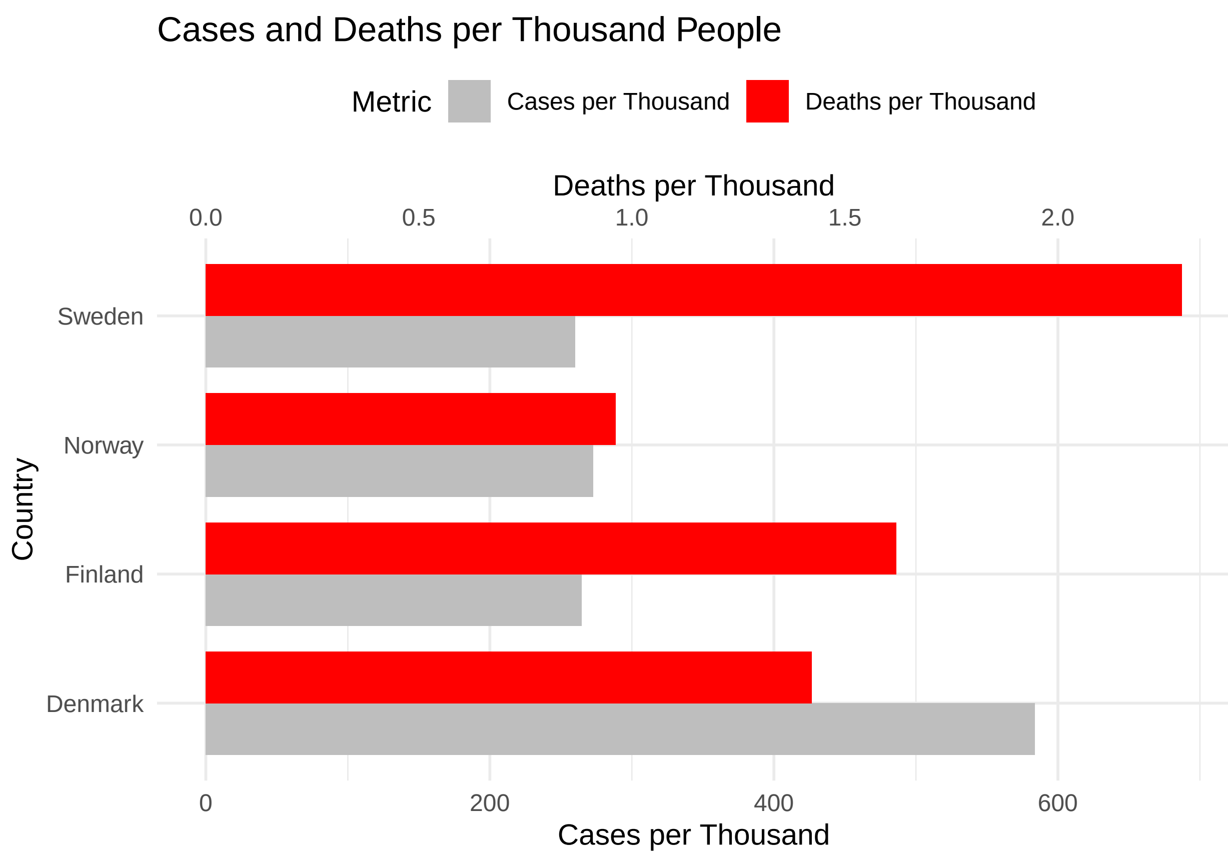
```
##    Country               Year          Month           CasesCum      
##  Length:156         Min.   :2020   Min.   : 1.000   Min.   :      0  
##  Class :character   1st Qu.:2020   1st Qu.: 3.000   1st Qu.:  48763  
##  Mode  :character   Median :2021   Median : 6.000   Median : 352244  
##                     Mean   :2021   Mean   : 6.154   Mean   : 932689  
##                     3rd Qu.:2022   3rd Qu.: 9.000   3rd Qu.:1460638  
##                     Max.   :2023   Max.   :12.000   Max.   :3404407  
##    DeathsCum          CasesNew         DeathsNew          Population      
##  Min.   :    0.0   Min.   :     0   Min.   :   0.0   Min.   : 5421241  
##  1st Qu.:  695.5   1st Qu.:  4299   1st Qu.:  39.0   1st Qu.: 5503350  
##  Median : 2685.0   Median : 16240   Median : 138.5   Median : 5681062  
##  Mean   : 5336.0   Mean   : 55433   Mean   : 287.9   Mean   : 6790665  
##  3rd Qu.: 7121.8   3rd Qu.: 33223   3rd Qu.: 375.2   3rd Qu.: 6968377  
##  Max.   :23777.0   Max.   :976903   Max.   :2864.0   Max.   :10379295  
```

Analysis through years and countries

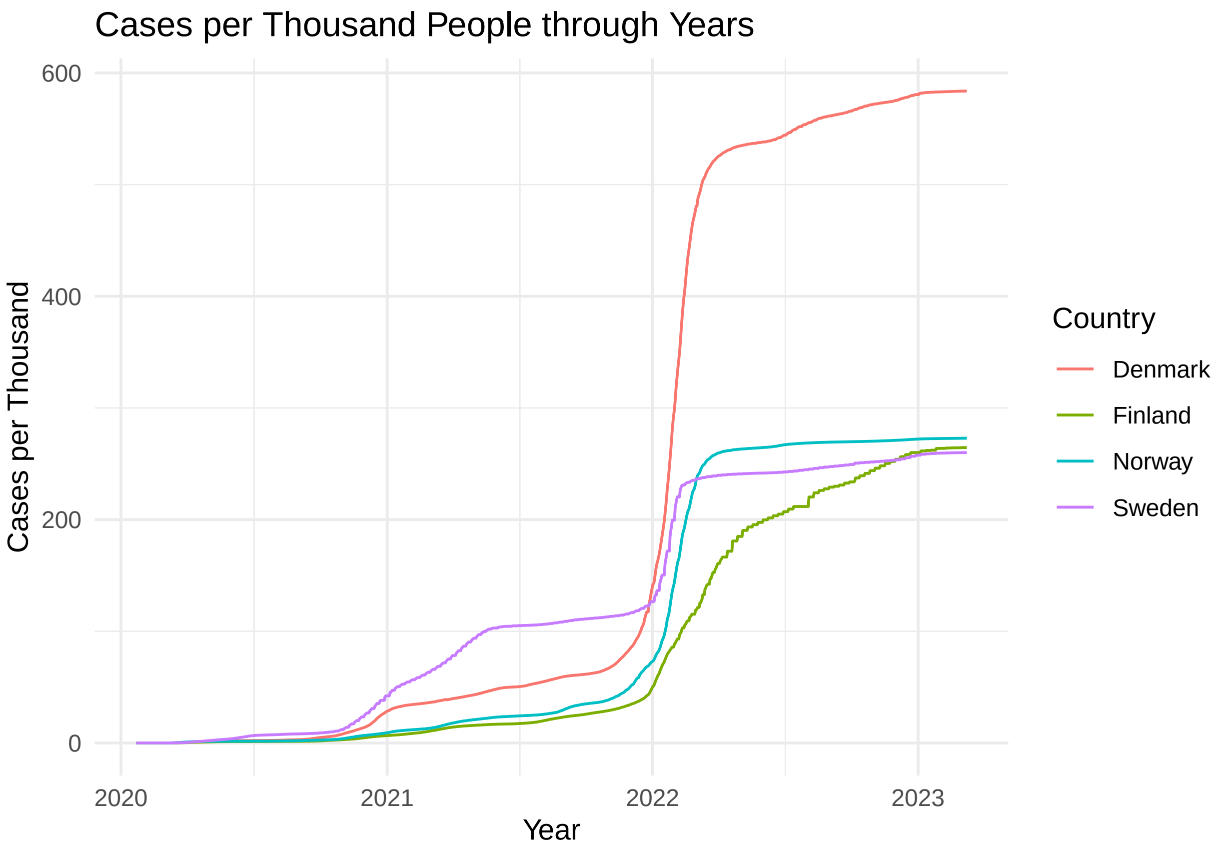
```r
data %>%
  group_by(Year) %>%
  summarise(
    Cases = max(Cases)-min(Cases),
    Deaths = (max(Deaths)-min(Deaths))/Cases,
    .groups = "drop") %>%
  mutate(Deaths = Deaths * 100000000) %>%
  pivot_longer(cols = c("Cases", "Deaths"),
               names_to = "metric", values_to = "value") %>%

ggplot(aes(x = Year, y = value, fill = metric)) +
  geom_bar(stat = "identity", position = "dodge", width = 0.8) +
  scale_y_continuous(
    name = "Cases",
    labels = scales::comma,
    sec.axis = sec_axis(~ . / 100000000, name = "Death rate",
                        labels = scales::percent)) +
  scale_fill_manual(values = c("Cases" = "gray", "Deaths" = "red")) +
  labs(title = "Cases and Deaths by Year",
       x = "Year",
       y = "Value",
       fill = "Metric") +
  theme_minimal() +
  scale_x_reverse() +
  coord_flip() +
  theme(legend.position = "top")
```



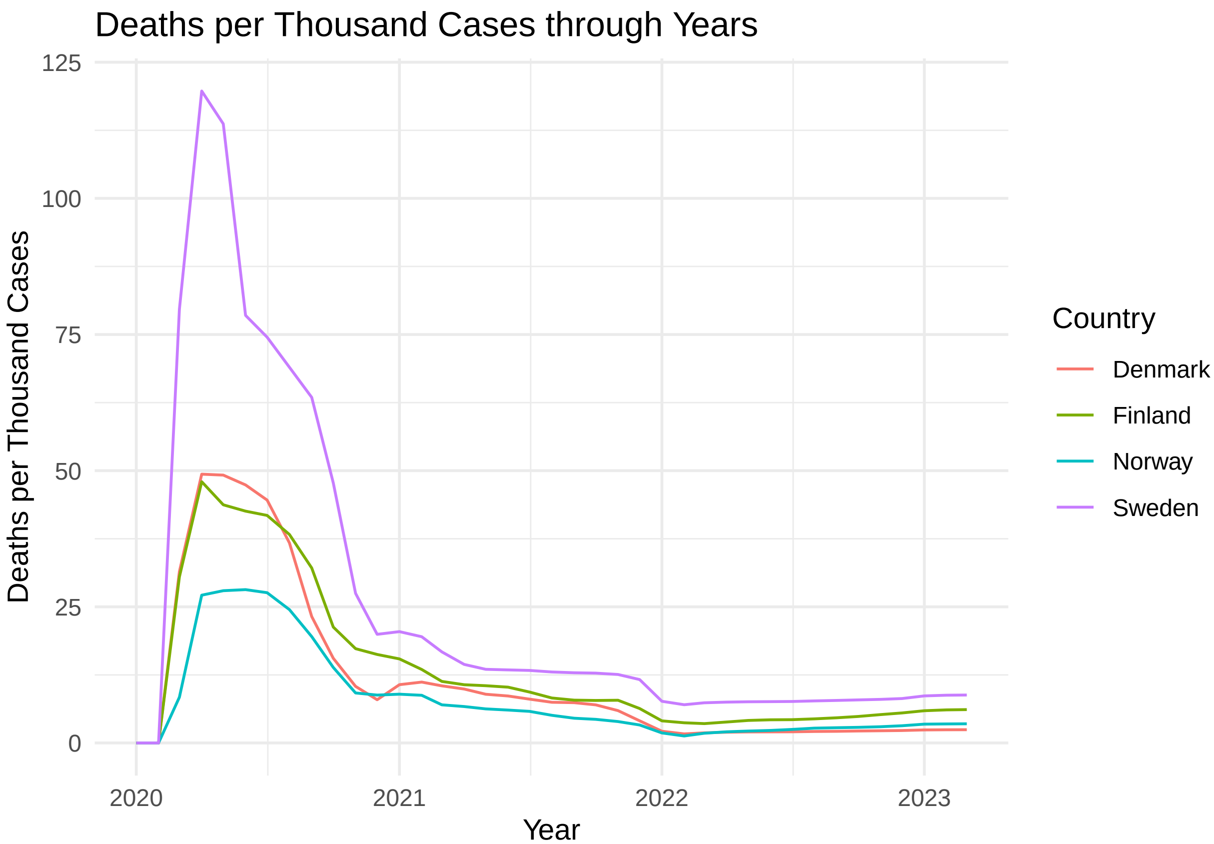

```r
data %>% group_by(Country, Population) %>%
  summarise(Cases = max(Cases), Deaths = max(Deaths), .groups = "drop") %>%
  mutate(`Cases per Thousand` = Cases * 1000 / Population,
         `Deaths per Thousand` = Deaths * 300 * 1000 / Population) %>%
  pivot_longer(cols = c("Cases per Thousand", "Deaths per Thousand"),
               names_to = "metric", values_to = "value") %>%

ggplot(aes(x = Country, y = value, fill = metric)) +
  geom_bar(stat = "identity", position = "dodge", width = 0.8) +
  scale_y_continuous(name = "Cases per Thousand",
    sec.axis = sec_axis(~ . / 300, name = "Deaths per Thousand")) +
  scale_fill_manual(values = c("Cases per Thousand" = "gray",
                               "Deaths per Thousand" = "red")) +
  labs(title = "Cases and Deaths per Thousand People",
       x = "Country",
       y = "Value",
       fill = "Metric") +
  theme_minimal() +
  coord_flip() +
  theme(legend.position = "top")
```




```
data %>%
  mutate(Cases = Cases * 1000 / Population,
         Deaths = Deaths * 1000 / Population ) %>%
  ggplot() +
  geom_line(aes(x = Date, y = Cases, color=Country)) +
  labs(
    title = "Cases per Thousand People through Years",
       x = "Year",
       y = "Cases per Thousand",
       color = "Country") +
  theme_minimal()
```




```r
data_grouped %>%
  mutate(DeathsCum = ifelse(CasesCum == 0, 0, DeathsCum * 1000 / CasesCum) ) %>%
  mutate(Date = as.Date(paste(Year, Month, "01", sep = "-"))) %>%

  ggplot(aes(x = Date, y = DeathsCum, color=Country)) +
  geom_line()+
  labs(
    title = "Deaths per Thousand Cases through Years",
       x = "Year",
       y = "Deaths per Thousand Cases",
       color = "Country") +
  theme_minimal()
```



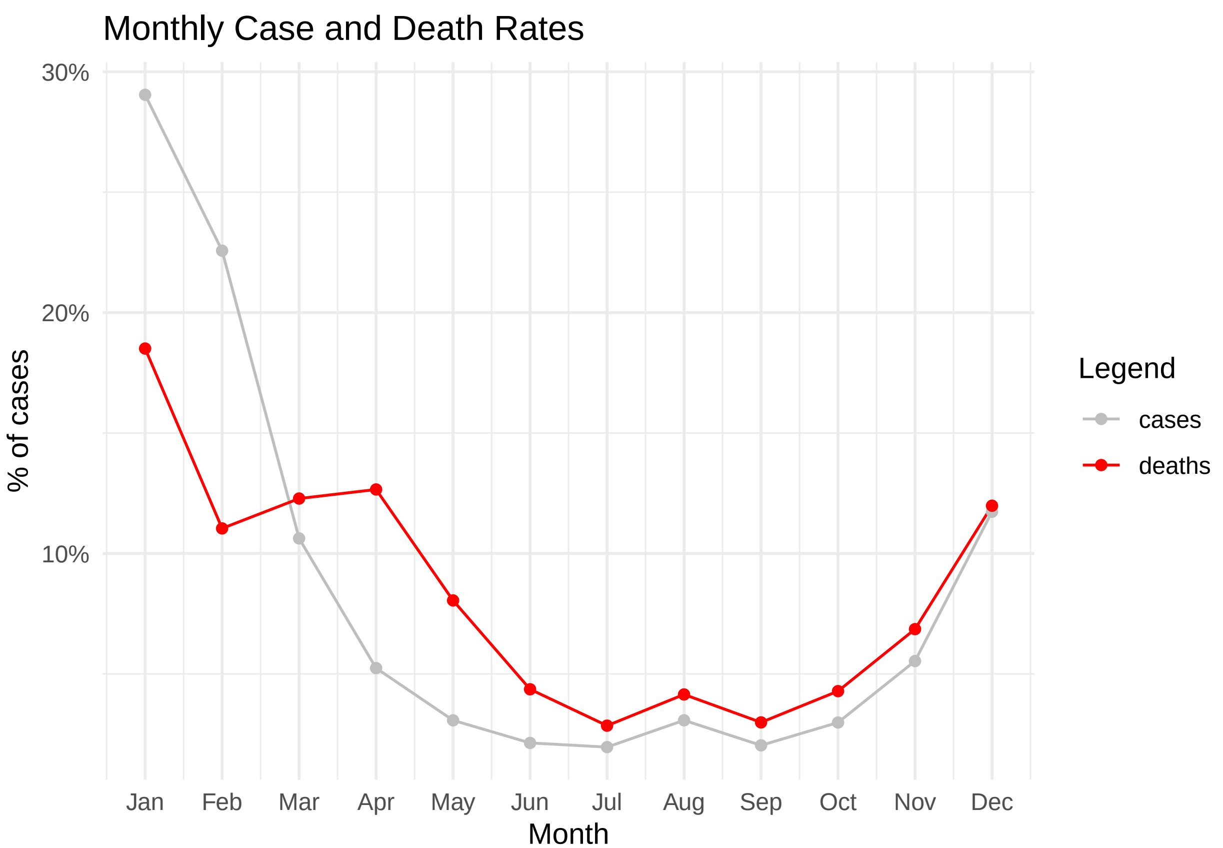
Analysis The COVID-19 incidence in the study countries and post-COVID-19 mortality showed significant discrepancies of pandemic effect to a population and efficiency of measures. The study was carried out in the 2020 to 2023 period. The results showed a significant spike in levels of detection, especially in 2022, when the level was the highest. It also suggests a wide dissemination of much more contagious strains, like Omicron.

On a per-population basis, how ever paints a different picture of the patterns across countries. Of the Nordics, Sweden has by far had the most people die per thousand inhabitants. In contrast, we observed lower mortality rates in Denmark and Norway despite of the highest numbers of cases globally implying better public health interventions and also likely a more stricter protocols. In both the cases and deaths per thousand, Finland appears with a relatively moderate impact — suggesting that it has taken something of an evenhanded approach to pandemic control.

The cumulative number of cases per thousand people in Denmark and Sweden also start to rise sharply, as we would expect with higher rate. Yet, in every country deaths per thousand cases have fallen dramatically — testament to better treatment and the beneficial results of their vaccination programmes.

Monthly Trends Analysis

```
data_grouped %>%
  group_by(Month) %>% summarise(Cases = sum(CasesNew),
                                Deaths = sum(DeathsNew), .groups = "drop") %>%
  mutate(Cases = Cases/sum(Cases), Deaths = Deaths/sum(Deaths)) %>%

  ggplot(aes(x = Month)) +
  geom_line(aes(y = Cases, color = "cases")) +
  geom_line(aes(y = Deaths, color = "deaths")) +
  geom_point(aes(y = Cases, color = "cases")) +
  geom_point(aes(y = Deaths, color = "deaths")) +
  scale_color_manual(values = c("cases" = "gray", "deaths" = "red")) +
  scale_y_continuous(labels = scales::percent) +
  labs(
    title = "Monthly Case and Death Rates",
       x = "Month",
       y = "% of cases",
       color = "Legend") +
  theme_minimal() +
  scale_x_continuous(breaks = 1:12, labels = month.abb)
```

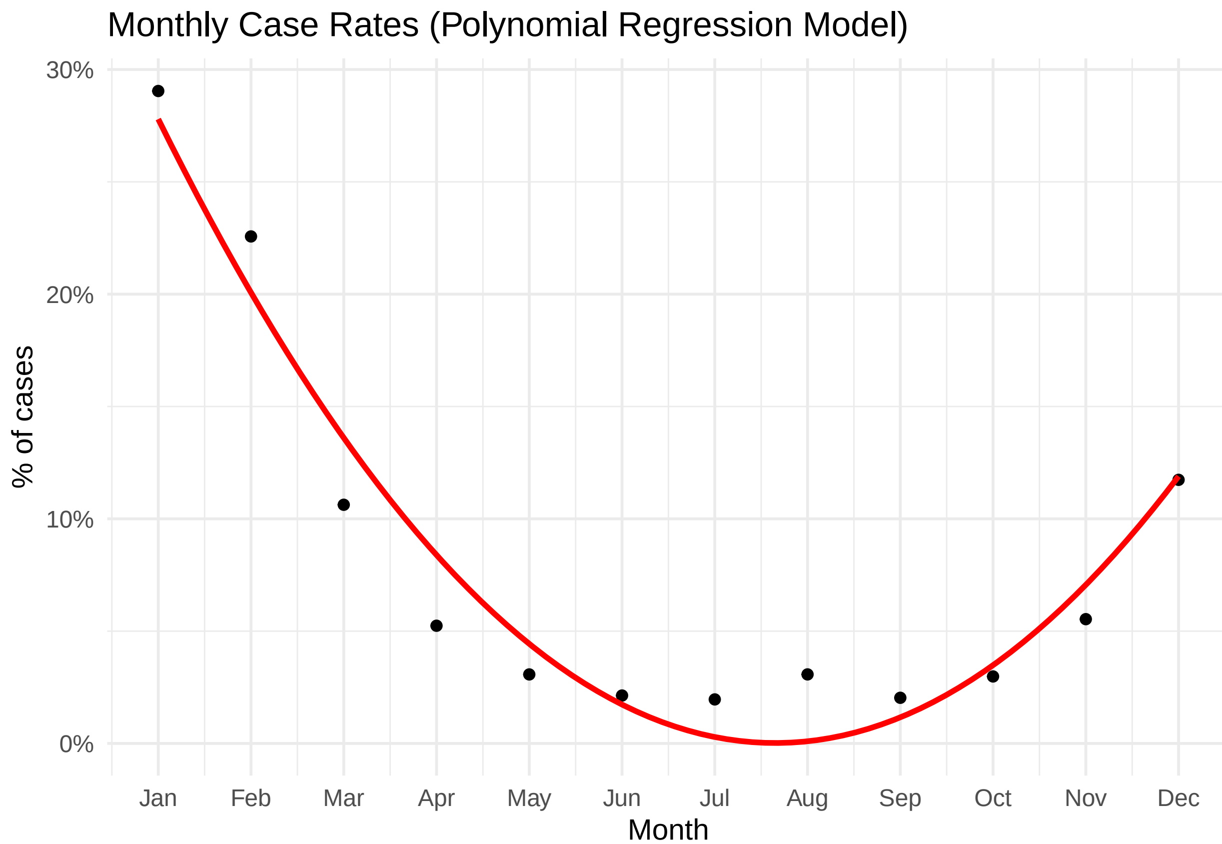


Analysis The percentage of cases by month is also displayed and follows a pattern, which may suggest that COVID-19 seasonality: the highest percent occurring in January, continually decreasing through June with a drop before May then tapering off again to increase at year end now numbering four for November. Mortality traces a similar curve but then plateaus at mid-year before both rates begin increasing again around December. The pattern highlights how the change of seasons will form cases in transmission and severity that higher than for COVID-19 during colder months.

Polynomial Regression Model

Model description Obviously, the correlation between month and number of cases does not seemto be linear, so I used a polynomial function for the model. Overall, the resulting model does a good job of simulating the average number of cases, given the wide variation across months.

```
data_montly <- data_grouped %>%
  group_by(Month) %>% summarise(Cases = sum(CasesNew), .groups = "drop") %>%
  mutate(Cases = Cases/sum(Cases))

  ggplot(data_montly, aes(x = Month, y = Cases)) +
  geom_point() +
  geom_smooth(method = "lm", formula = y ~ poly(x, 2), se = FALSE, color = "red") +
  scale_y_continuous(labels = scales::percent) +
  labs(
    title = "Monthly Case Rates (Polynomial Regression Model)",
       x = "Month",
       y = "% of cases") +
  theme_minimal() +
  scale_x_continuous(breaks = 1:12, labels = month.abb)
```




```r
summary(lm(Cases ~ poly(Month, 2), data = data_montly))
```

```
##
## Call:
## lm(formula = Cases ~ poly(Month, 2), data = data_montly)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.031499 -0.014020  0.001219  0.013555  0.029776
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.083333   0.006357   13.11 3.61e-07 ***
## poly(Month, 2)1 -0.172871   0.022020   -7.85 2.57e-05 ***
## poly(Month, 2)2  0.229367   0.022020   10.42 2.55e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02202 on 9 degrees of freedom
## Multiple R-squared:  0.9498, Adjusted R-squared:  0.9386
## F-statistic: 85.06 on 2 and 9 DF,  p-value: 1.428e-06
```

Potential Bias in Data

This study may be susceptible to bias in multiple areas. The most important source of bias was the variation in testing and reporting procedures among Nordic countries. If a country has higher rate of testing, it would show more number of cases as compared to the ones which is not performing this test. This difference would not establish a higher incidence of actual infection, but simply variable capacity to detect the outbreak. Moreover, differences in criteria for counting COVID-19 deaths may also result to a varied toll of death counts and this could affect the comparative analysis.

Seasonal trends might also add bias to the data. The data does reveal seasonal patterns with numbers of cases and deaths peaking in cooler weather. But that analysis might not capture other intervening events — holiday gatherings, changes in travel patterns, or shifts in public health policies, which also can have a big impact on transmission. Seasonal effects may be distorted by these if they are not sufficiently controlled for.

Also, using solely cumulative data could ignore key temporal regimes. In this case, no information will be received as to the appearance of new options and how population behavior has evolved over time. If our analysis was carried out based on monthly or annual means, we would overlook short-term spikes/declines related to outbreaks/interventions. As a result, it creates an incomplete portrait of the course and control measures.