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1. CO2 Report: Did the fall of the Berlin wall and the global lockdown during the COVID-19 pandemic affect the global economy?

Summary

We used data about the Hawaii atmospheric Carbon Dioxide concentrations collected from the Scripps CO2 Program by Scripps Institution of Oceanography to determine whether the CO2 concentrations are affected by the fall of the Berlin wall in November 1989 and the global lockdown during the COVID-19 pandemic starting in February 2020. We found that the carbon dioxide concentration was affected by the fall of the Berlin Wall, resulting in a three-year slowdown in growth, while it seems like the carbon dioxide concentration was not affected significantly by the global COVID-19 pandemic.

Introduction

We used data collected from the Scripps CO2 Program by Scripps Institution of Oceanography which is about the atmospheric Carbon Dioxide concentrations observed in Hawaii since 1960 to analyze the trend of CO2. We wanted to figure out whether the fall of the Berlin wall and the global lockdown during the COVID-19 pandemic affect the global industrial production.

Method

First, we plotted the overall trend about Carbon Dioxide concentrations in terms of the time as well as the histogram of Carbon Dioxide concentrations.

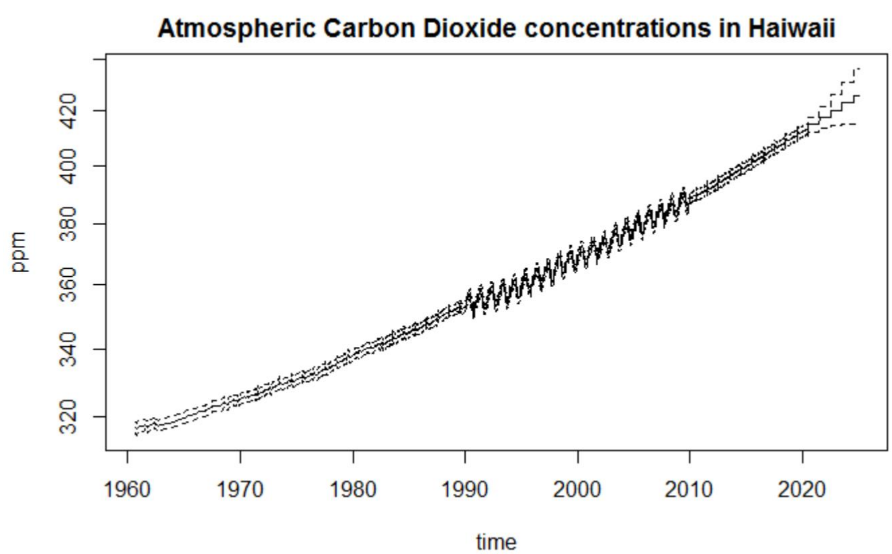

Figure 1: The plot of atmospheric Carbon Dioxide concentrations in Haiwaii.

According to Figure 1, we can clearly see that the Carbon Dioxide concentrations are increasing with a seasonal trend. Thus, a linear mixed model is not a good choice to do analysis. We used the generalized additive model since the plot shows non-linear effects of the covariate on the dependent variable. We defined a new variable *timeInla* which represents the difference between the date observed and the first day of 2000 in years. Based on that, we set two sine functions and two cosine functions to illustrate the seasonal trend. In addition, we set *timeInla* as the random effect with the second-order random walk since our data are related in time.

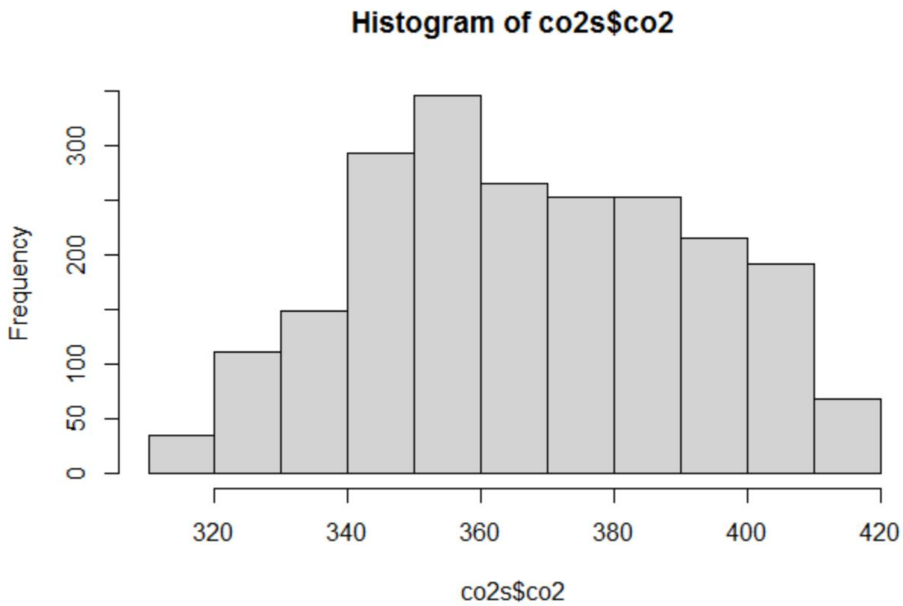

Figure 2: The histogram of atmospheric Carbon Dioxide concentrations in Haiwaii.

According to Figure 2, we can see that values of Carbon Dioxide concentrations are all positive. Since values are continuous and its distribution looks like a Gamma distribution, our model would be

$$
\begin{aligned}
Y_i &\sim \Gamma(\lambda_i, \theta_i) \\
log(\lambda_i \theta_i) &= X_i \boldsymbol{\beta} + U(t_i) \\
[U_1 \ldots U_T]^T &\sim \text{RW2}(0, \tau_U^2)
\end{aligned}
$$

with priors

$$
\begin{aligned}
\lambda_i &\sim PC.param(0.1, 0.5) \text{ where } Pr(\frac{1}{\sqrt{\lambda_i}} > 0.1) = 0.5 \\
\tau_U &\sim PC.param(0.1, 0.5) \text{ where } Pr(\frac{1}{\tau_U} > 0.1) = 0.5
\end{aligned}
$$

- Y_i indicates the Hawaii Carbon Dioxide concentration observed in i^{th} day;
- λ_i is the shape parameter of the Gamma distribution for the Carbon Dioxide concentration in the i^{th} day;
- θ_i is the scale parameter of the Gamma distribution for the Carbon Dioxide concentration in the i^{th} day; hence,
- $\lambda_i \theta_i$ represents the expectation of the Carbon Dioxide concentration observed in i^{th} day;
- X_i represents a collection of the values for four trigonometric functions $\sin 12$, $\cos 12$, $\sin 6$, and $\cos 6$ which are seasonal effects of the observation i with a 12 month and a 6 month frequency in the i^{th} day;
- $\boldsymbol{\beta}$ are coefficients for all covariates X_i and the intercept, which revels the influences of each factor;
- t_i represents the random effect of the i^{th} day.
- $U(t_i)$ is a second-order random walk with variance τ_U^2.

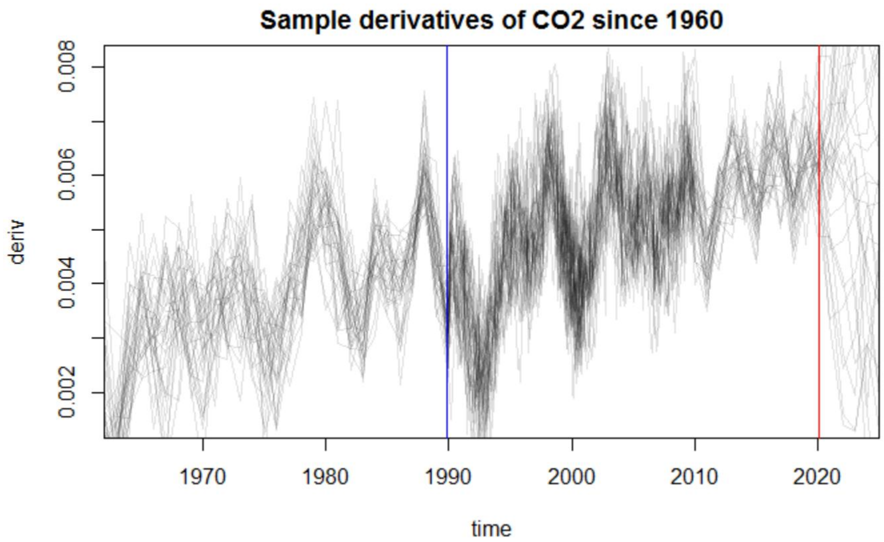

Figure 3: The sample derivatives of CO2 data since 1960.

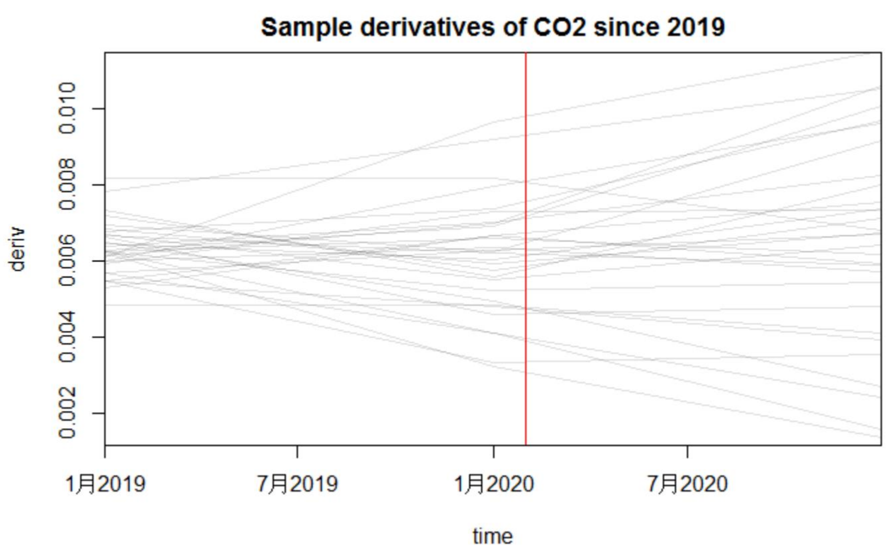

Figure 4: The sample derivatives of CO2 data since 2019.

Result

Figure 3 and 4 show the sample derivatives of the carbon dioxide data, which is sufficient to see the change in growth rate. The blue vertical line is the time spot of the falling of Berlin wall. We chose the date, November 9, 1989 according to Wikipedia. In general, the atmospheric carbon dioxide concentration in Hawaii is increasing during that period. However, the growth rate began to decline in 1988, increased briefly in several months in 1989, and then continued to decline until 1992. Although there is a slightly increasing trend right after the falling of Berlin wall, the overall trend is decreasing compared with the same period in other years. Thus, we can conclude that the reason for the low carbon dioxide concentration in Hawaii in 1989 might be affected by the collapse of a large number of industrial factories in the Soviet Union and Eastern Europe due to the fall of the Berlin wall.
The red vertical lines in both graphs indicate the time spot of the global lockdown caused by the

COVID-19 pandemic. We chose the date, February 1, 2020 according to the time of the beginning of epidemic around the world. Since Figure 3 is a little bit messy after that time, we used Figure 4 for our analysis. In general, the atmospheric carbon dioxide concentration in Hawaii is increasing. The growth rate is not visible decreasing; however, it is more like constant within a reasonable range compared with the same period in other years. Although the epidemic has caused many factories to shut down, resulting in the reduction of carbon dioxide emissions, atmospheric carbon dioxide concentrations in Hawaii did not have significant changes. Therefore, we can conclude that the atmospheric carbon dioxide concentrations in Hawaii did not affected by the shutdown of the world economy through these data.

Appendix

We used R to built the models, which can be accessed in Appendix 1.

2. Death Report: Which part of groups in age are affected during two waves of the COVID-19 epidemic between March and May, and in September, respectively?

Summary

We used the data about daily mortality counts to analyze how two waves of COVID-19 pandemic affected younger and elder people in Quebec. We found that the first wave of the COVID-19 epidemic caused dramatic high deaths of the elderly, and the second wave continuously affected the elderly, making the highest mortality compared to the same period in a decade. For Quebec people who are under 50, there is no significant impact by two waves of the COVID-19 epidemic. It is not certain that the second wave is caused by irresponsible young people.

Introduction

We used the data about daily mortality counts in Quebec collected from institution of statistics of Quebec to analyze how two waves of COVID-19 pandemic affected elder people. We also wanted to figure out whether the activities of young people due to the start of school influenced the second wave of epidemics in September.

Method

In order to do these analysis, we built two models using the death dataset for people over 70, and people under 50, respectively. We eliminated data before 2010 to get a better comparison. First, we plotted the overall trend about death counts in time.

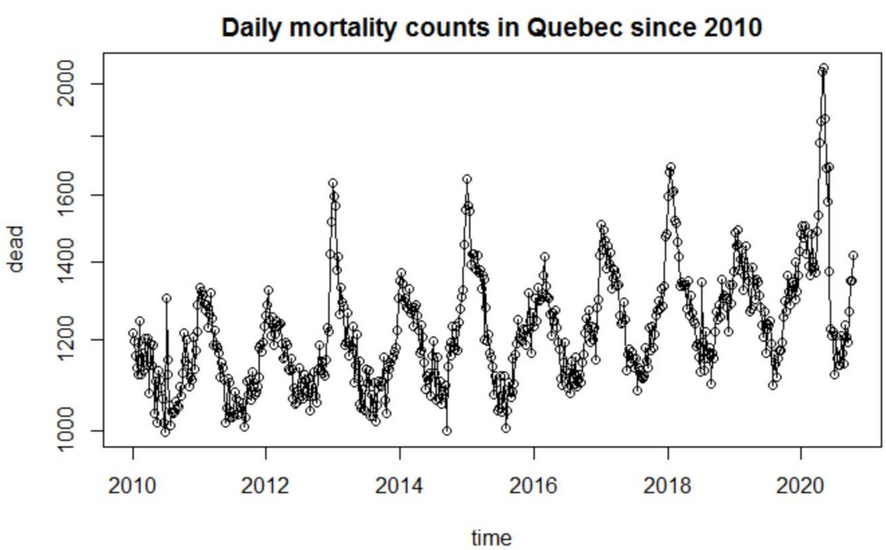

Figure 5: The plot of atmospheric Carbon Dioxide concentrations in Haiwaii.

Since death mortality data are counted number related to time and the plot showed non-linear effects of the covariate on the dependent variable, we preferred to use the generalized additive mixed model with Poisson distribution. We defined two parameters, $timeIid$, and $timeForInla$ as our semi-parametric Bayes. $timeIid$ is another representatives of the date. $timeForInla$ represents the difference between the date observed and the first day of 2015 in years. Based on that, we set two sine functions and two cosine functions to illustrate the seasonal trend. In addition, we set $timeForInla$ as the random effect with the second-order random walk since our data are related in time. In addition, we set $timeIid$ as the independent and identically distributed random effect. Thus, our model would be

$$\begin{aligned} Y_i &\sim \text{Poisson}(\lambda_i) \\ \log(\lambda_i) &= X_i\beta + U(t_i) + V_i \\ [U_1 \ldots U_T]^T &\sim \text{RW2}(0, \tau_U^2) \\ V_i &\sim \mathcal{N}(0, \tau_V^2) \end{aligned}$$

with priors

$$\tau_U \sim PC.param(\log(1.2), 0.5) \text{ where } Pr(\frac{1}{\tau_U} > \log(1.2)) = 0.5$$

$$\tau_V \sim PC.param(0.01, 0.5) \text{ where } Pr(\frac{1}{\tau_V} > 0.01) = 0.5$$

- Y_i indicates Quebec death counts in i^{th} day; the first model used the number for people who are 70 years old and over, the second model used the number for people who are under 50;
- λ_i is the proportion of the Quebec mortality in i^{th} day among elder people and young people respectively;
- X_i represents a collection of the values for four trigonometric functions $\sin 12$, $\sin 6$, $\cos 12$, and $\cos 6$ which are seasonal effects of the observation i with a 12 month and a 6 month frequency in the i^{th} day;
- β are coefficients for all covariates X_i, which revels the influences of each factor;
- t_i represents the random effect of the i^{th} day;
- $U(t_i)$ is a second-order random walk with variance τ_U^2;
- V_i represents the random effect of the i^{th} day which covers independent variation or over-dispersion.

According to Figure 5, we can see that death counts are usually high in the first few months of each year. Then, it decreased continuously when it closed to the end of the year, started to increase in the last few months of each year. Thus, we set the prior for $timeIid$ to $Pr(\sigma_V > \log(1.2)) = 0.5$ which means that the odds ratio of the IQR is a 20% increase since the median of the death counts is reached near the first half of the year in general. Since the death counts in the first few months are high, we set the prior for $timeForInla$ to $Pr(\sigma_U > 0.01) = 0.5$ which means that the median is reached in the first few months. The prior and the posterior distribution for the $timeIid$ and $timeForInla$ are shown in Figure 6 and 7.

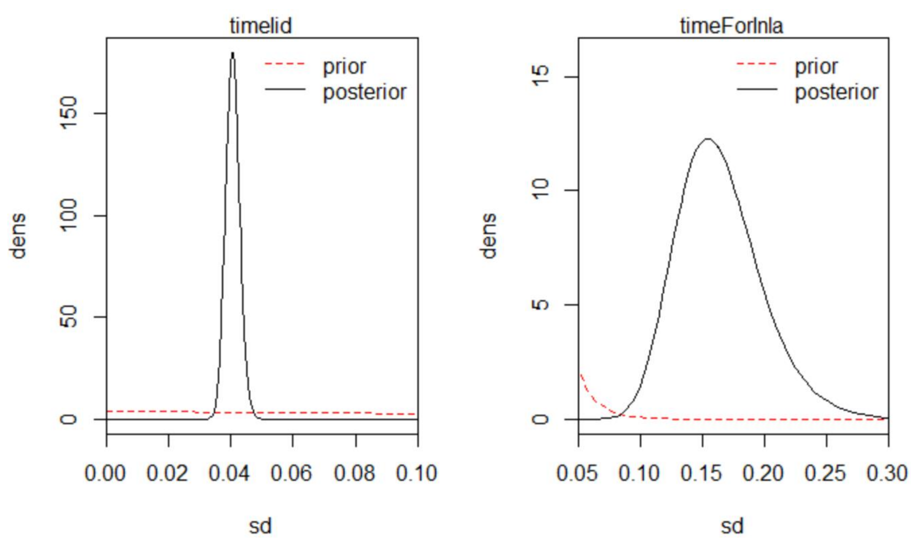

Figure 6: The priors of the $timeIid$ and $timeForInla$ for the model about elder people.

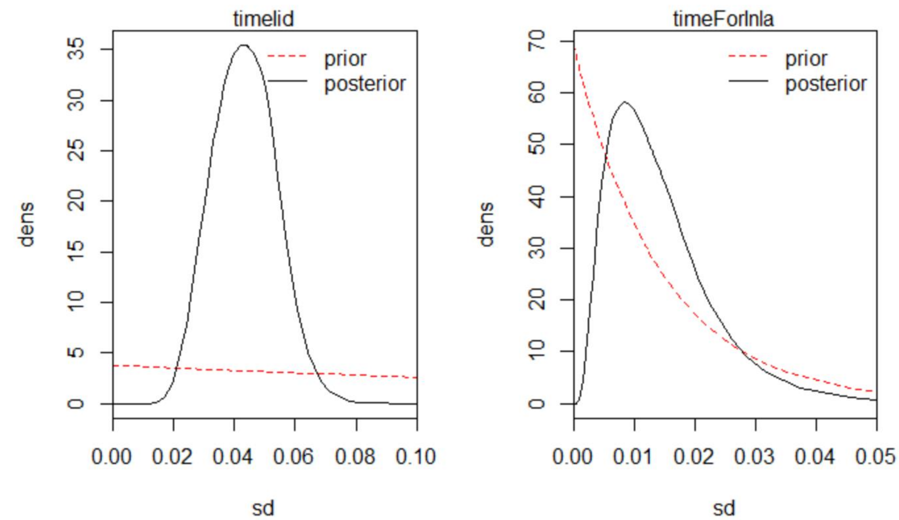

Figure 7: The priors of the $timeIid$ and $timeForInla$ for the model about young people.

Result

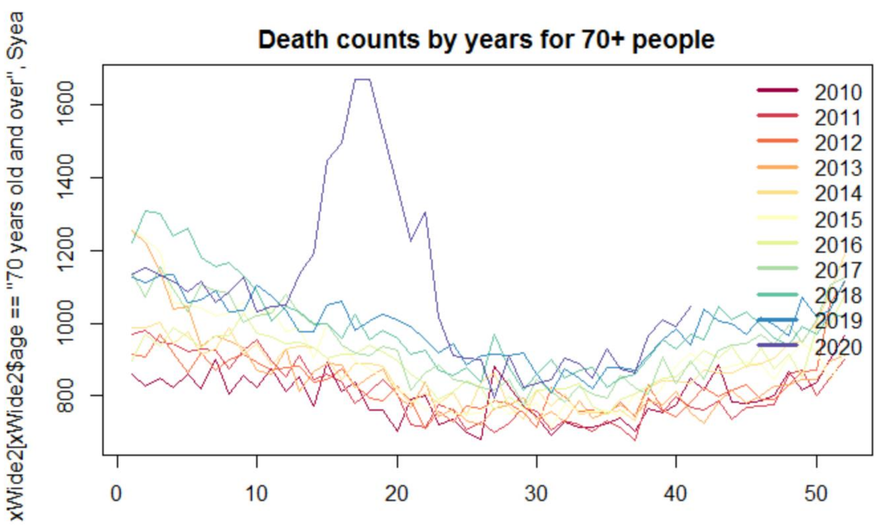

Figure 8: Death counts for 70+ people since 2010.

First, let's consider people who are 70 years old and over. Figure 8 shows death counts by weeks in different years from 2010 to 2020. We can clearly see that the number of deaths among the elder people in 2020 is much higher in the range of the 10^{th} to the 30^{th} week than those in other years, and reached in the highest since the 35^{th} week. According to Figure 9, it is obvious that the mortality of elder people is abnormal in March, April, May and June in 2020 since the difference between the real deaths and the predicted deaths gradually expands, reaches the peak, approximately 800, in May, and returns to normal until July. Figure 10 and 11 illustrate the quantiles of the additional unpredicted deaths of the first and the second wave of pandemic. We can get that the first wave of the epidemic was more serious than expected, reaching four thousand unpredicted deaths at the 40% quantile. For the second wave, it reached 500 extra deaths at the 40% quantile. Thus, we can conclude that the first wave of the COVID-19 epidemic had a great impact on Quebec people who are 70 years old or over, resulting

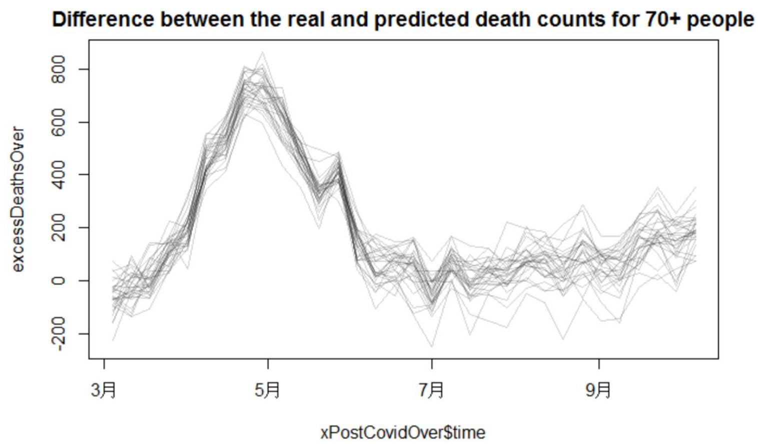

Figure 9: Differences between the real mortality and the predicted mortality during the COVID-19 pandemic for 70+ people.

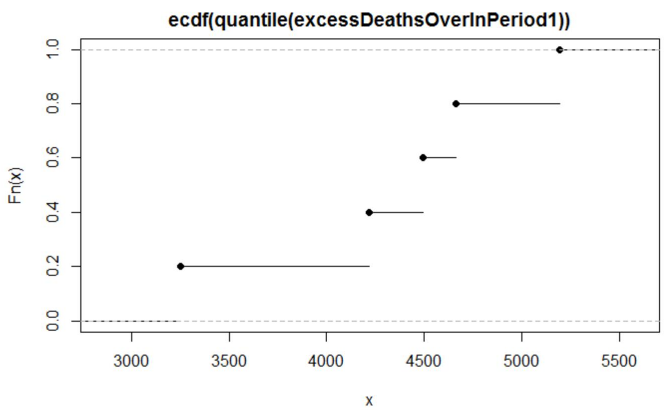

Figure 10: Quantiles of the differences between the real count and the predicted count for 70+ people in the first wave of the pandemic.

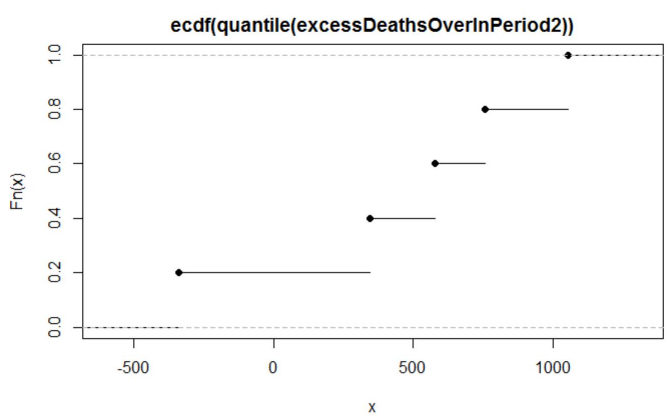

Figure 11: Quantiles of the differences between the real count and the predicted count for 70+ people in the second wave of the pandemic.

in a three-month high mortality. The second wave still affected elder people, which caused a relatively higher mortality than that in previous several years.

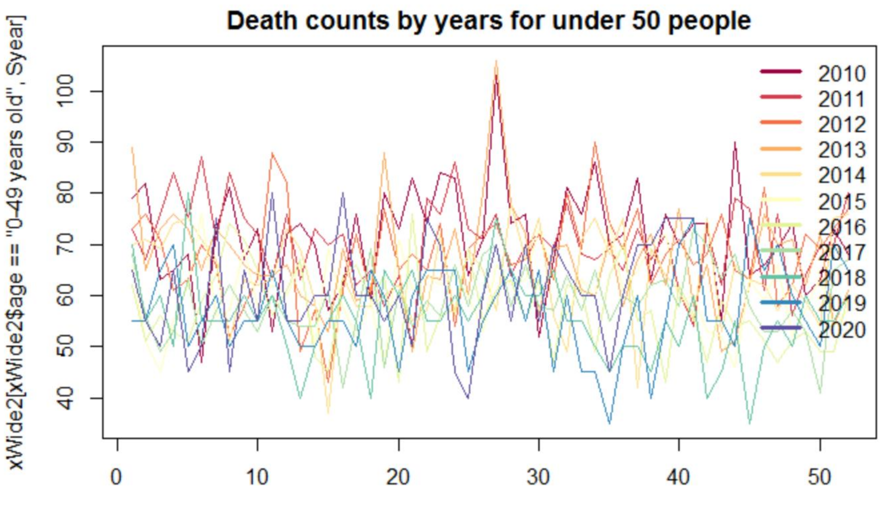

Figure 12: Death counts for under 50 people since 2010.

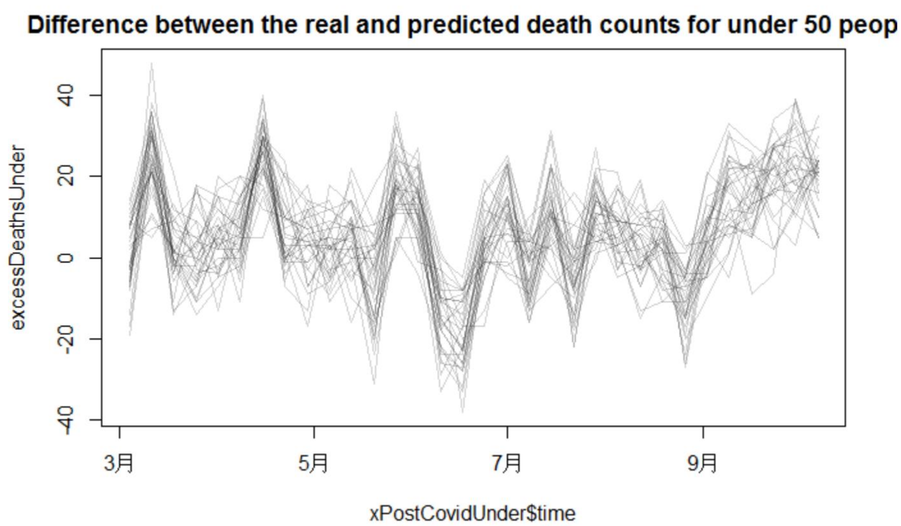

Figure 13: Differences between the real mortality and the predicted mortality during the COVID-19 pandemic for under 50 people.

Turning to people who are under 50. According to Figure 12, We can see that the number of deaths among young people in 2020 does not have significant difference with those in other years, since the mortality in each year is similar in general. According to Figure 13, it is obvious that the mortality of young people is higher than the prediction in March, April and September in 2020, while the mortality in other months maintained the normal changes. Figure 14 and 15 illustrate the quantiles of the additional unpredicted deaths of the first and the second wave of pandemic. We can see that the impact of the first wave was similar to that of the second wave, since at each quantile, the unpredicted death counts are similar, from about 45 at the 20% quantile to under 150 at the 100% quantile. Thus, we can conclude that the first wave of the COVID-19 epidemic affected Quebec people who are under 50, resulting in a small increasing deaths. Although the actual number of deaths is greater than the predicted number since September, we cannot certainly conclude that behaviours of irresponsible young people are the cause of the second wave of epidemics.

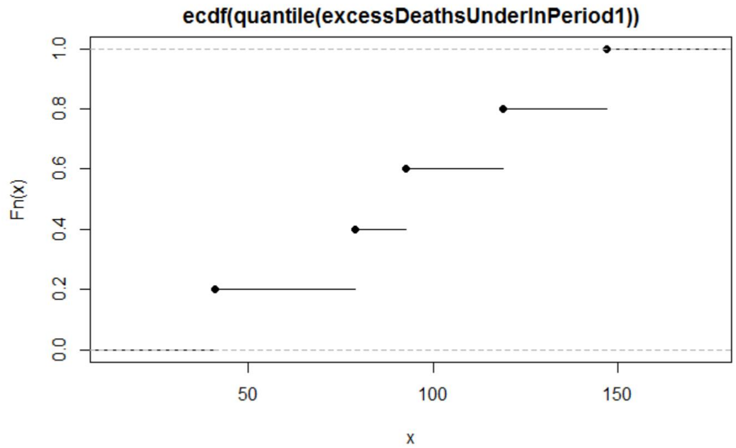

Figure 14: Quantiles of the differences between the real count and the predicted count for under 50 people in the first wave of the pandemic.

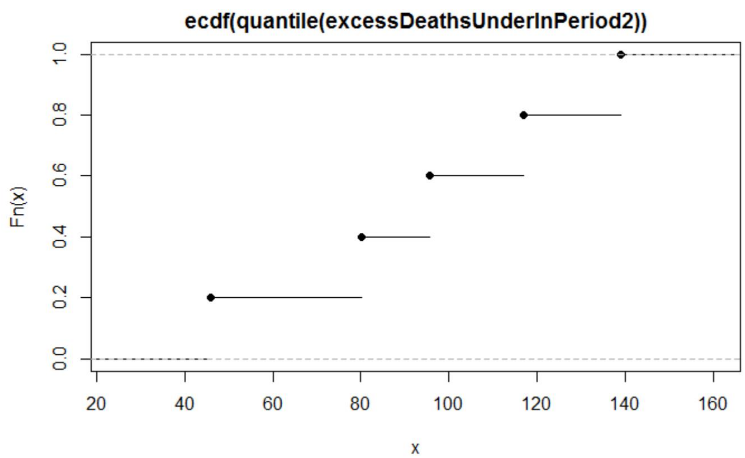

Figure 15: Quantiles of the differences between the real count and the predicted count for under 50 people in the second wave of the pandemic.

Appendix

We used R to built the models, which can be accessed in Appendix 2.

Appendix

Appendix 1 R code for Question 1

```r
library("Pmisc")
library("INLA")
cUrl = paste0("http://scrippsco2.ucsd.edu/assets/data/atmospheric/", "stations/flask_co2/daily/daily_flask_co2_mlo.csv")
cFile = basename(cUrl)
if (!file.exists(cFile)) download.file(cUrl, cFile)
co2s = read.table(cFile, header = FALSE, sep = ",",
                  skip = 69, stringsAsFactors = FALSE, col.names =
                    c("day", "time", "junk1", "junk2", "Nflasks", "quality", "co2"))
co2s$date = strptime(paste(co2s$day, co2s$time), format = "%Y-%m-%d %H:%M",
                     tz = "UTC")
# remove low-quality measurements
co2s = co2s[co2s$quality == 0, ]

plot(co2s$date, co2s$co2, log = "y", cex = 0.3, col = "#00000040",
     xlab = "time", ylab = "ppm")
plot(co2s[co2s$date > ISOdate(2015, 3, 1, tz = "UTC"),
          c("date", "co2")], log = "y", type = "o", xlab = "time",
     ylab = "ppm", cex = 0.5)

co2s$day = as.Date(co2s$date)
toAdd = data.frame(day = seq(max(co2s$day) + 3, as.Date("2025/1/1"), by = "10 days"),
                   co2 = NA)
co2ext = rbind(co2s[, colnames(toAdd)], toAdd)
timeOrigin = as.Date("2000/1/1")
co2ext$timeInla = signif(as.numeric(co2ext$day - timeOrigin)/365.25, 2)
co2ext$cos12 = cos(2 * pi * co2ext$timeInla)
co2ext$sin12 = sin(2 * pi * co2ext$timeInla)
co2ext$cos6 = cos(2 * 2 * pi * co2ext$timeInla)
co2ext$sin6 = sin(2 * 2 * pi * co2ext$timeInla)

hist(co2ext$co2)

library('INLA', verbose=FALSE)
# disable some error checking in INLA
mm = get("inla.models", INLA:::inla.get.inlaEnv())
if(class(mm) == 'function') mm = mm()
mm$latent$rw2$min.diff = NULL
assign("inla.models", mm, INLA:::inla.get.inlaEnv())

co2res = inla(co2 ~ sin12 + cos12 + sin6 + cos6 +
                f(timeInla, model = 'rw2', prior='pc.prec', param = c(0.1, 0.5)),
              data = co2ext, family='gamma',
              control.family = list(hyper=list(prec=list(prior='pc.prec',
                                                           param=c(0.1, 0.5)))),
              # add this line if your computer has trouble
              # control.inla = list(strategy='gaussian'),
              control.predictor = list(compute=TRUE, link=1),
              control.compute = list(config=TRUE), verbose=FALSE)
qCols = c('0.5quant','0.025quant','0.975quant')
Pmisc::priorPost(co2res)$summary[,qCols]

sampleList = INLA::inla.posterior.sample(30, co2res,
                                         selection = list(timeInla = 0))
sampleMean = do.call(cbind, Biobase::subListExtract(sampleList,
"latent"))
sampleDeriv = apply(sampleMean, 2, diff)/diff(co2res$summary.random$timeInla$ID)

matplot(co2ext$day, co2res$summary.fitted.values[, qCols],
        type = "l", col = "black", lty = c(1, 2, 2), log = "y",
        xlab = "time", ylab = "ppm",
        main="Atmospheric Carbon Dioxide concentrations in Haiwaii")
Stime = timeOrigin + round(365.25 * co2res$summary.random$timeInla$ID)
```

```r
matplot(Stime, co2res$summary.random$timeInla[, qCols], type = "l",
        col = "black", lty = c(1, 2, 2), xlab = "time", ylab = "y")
matplot(Stime[-1], sampleDeriv, type = "l", lty = 1, xaxs = "i",
        col = "#00000020", xlab = "time", ylab = "deriv",
        ylim = quantile(sampleDeriv, c(0.01, 0.995)),
        main="Sample derivatives of CO2 since 1960")
abline(v=as.Date("1989/11/9"), col="blue")
abline(v=as.Date("2020/2/1"), col="red")
forX = as.Date(c("2018/1/1", "2021/1/1"))
forX = seq(forX[1], forX[2], by = "6 months")
toPlot = which(Stime > min(forX) & Stime < max(forX))
matplot(Stime[toPlot], sampleDeriv[toPlot, ], type = "l", lty = 1,
        xaxs = "i", col = "#00000020", xlab = "time", ylab = "deriv",
        xaxt = "n", ylim = quantile(sampleDeriv[toPlot, ], c(0.01, 0.995)),
        main="Sample derivatives of CO2 since 2019")
abline(v=as.Date("2020/2/1"), col="red")
axis(1, as.numeric(forX), format(forX, "%b%Y"))
```

Appendix 2 R code for Question 2

```r
xUrl = paste0("https://www.stat.gouv.qc.ca/statistiques/population-demographie/deces-mortalite/WeeklyDeaths_QC_2010-2020_AgeGr.csv")
xFile = basename(xUrl)
if (!file.exists(xFile)) download.file(xUrl, xFile)
xWide = read.table(xFile, sep = ";", skip = 7, col.names = c("year", "junk", "age",
                                                   paste0("w", 1:53)))
xWide = xWide[grep("^[[:digit:]]+$", xWide$year), ]
x = reshape2::melt(xWide, id.vars = c("year", "age"),
                   measure.vars = grep("^w[[:digit:]]+$", colnames(xWide)))
x$dead = as.numeric(gsub("[[:space:]]", "", x$value))
x$week = as.numeric(gsub("w", "", x$variable))
x$year = as.numeric(x$year)
x = x[order(x$year, x$week, x$age), ]

newYearsDay = as.Date(ISOdate(x$year, 1, 1))
x$time = newYearsDay + 7 * (x$week - 1)
x = x[!is.na(x$dead), ]
x = x[x$week < 53, ]

plot(x[x$age == "Total", c("time", "dead")], type = "o", log = "y", main="Daily mortality counts in Quebec since 2010")

xWide2 = reshape2::dcast(x, week + age ~ year, value.var = "dead")
Syear = grep("[[:digit:]]", colnames(xWide2), value = TRUE)
Scol = RColorBrewer::brewer.pal(length(Syear), "Spectral")

dateCutoff = as.Date("2020/3/1")
xPreCovid = x[x$time < dateCutoff, ]
xPostCovid = x[x$time >= dateCutoff, ]
toForecast = expand.grid(age = unique(x$age), time = unique(xPostCovid$time),
                         dead = NA)
xForInla = rbind(xPreCovid[, colnames(toForecast)], toForecast)
xForInla = xForInla[order(xForInla$time, xForInla$age), ]

xForInla$timeNumeric = as.numeric(xForInla$time)
xForInla$timeForInla = (xForInla$timeNumeric -
                        as.numeric(as.Date("2015/1/1")))/365.25
xForInla$timeIid = xForInla$timeNumeric
xForInla$sin12 = sin(2 * pi * xForInla$timeNumeric/365.25)
xForInla$sin6 = sin(2 * pi * xForInla$timeNumeric * 2/365.25)
xForInla$cos12 = cos(2 * pi * xForInla$timeNumeric/365.25)
xForInla$cos6 = cos(2 * pi * xForInla$timeNumeric * 2/365.25)

plot(x[x$age == "70 years old and over", c("time", "dead")], type = "o", log = "y")
matplot(xWide2[xWide2$age == "70 years old and over", Syear],
        type = "l", lty = 1, col = Scol, main="Death counts by years for 70+ people")
```

```r
legend("topright", col = Scol, legend = Syear, bty = "n", lty = 1, lwd = 3)

# the model for people who are 70 years old and over
xForInlaOver70= xForInla[xForInla$age == '70 years old and over', ]
library(INLA, verbose=FALSE)

res2 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
                    f(timeIid, prior='pc.prec', param= c(log(1.2), 0.5)) +
                    f(timeForInla, model = 'rw2', prior='pc.prec',
                      param= c(0.01, 0.5)), data=xForInlaOver70,
            control.predictor = list(compute=TRUE, link=1),
            control.compute = list(config=TRUE),
            # control.inla = list(fast=FALSE, strategy='laplace'),
            family='poisson')

qCols = paste0(c(0.5, 0.025, 0.975), "quant")
rbind(res2$summary.fixed[, qCols], Pmisc::priorPostSd(res2)$summary[, qCols])

matplot(xForInlaOver70$time, res2$summary.fitted.values[, qCols], type = "l",
        ylim = c(500, 1800), lty = c(1, 2, 2), col = "black", log = "y")
points(x[x$age == "70 years old and over", c("time", "dead")], cex = 0.4, col = "red")

matplot(xForInlaOver70$time,
        res2$summary.random$timeForInla[, c("0.5quant", "0.975quant", "0.025quant")],
        type = "l", lty = c(1, 2, 2), col = "black")

sampleListOver = INLA::inla.posterior.sample(30, res2, selection = list(Predictor = 0))
sampleIntensityOver = exp(do.call(cbind, Biobase::subListExtract(sampleListOver,
                                                                  "latent")))
sampleDeathsOver = matrix(rpois(length(sampleIntensityOver), sampleIntensityOver),
                          nrow(sampleIntensityOver), ncol(sampleIntensityOver))

matplot(xForInlaOver70$time, sampleDeathsOver, col = "#00000010",
        lwd = 2, lty = 1, type = "l", log = "y", ylim=c(500, 2200))
points(x[x$age == "70 years old and over", c("time", "dead")], col = "red", cex = 0.5)
matplot(xForInlaOver70$time, sampleDeathsOver, col = "#00000010", lwd = 2,
        lty = 1, type = "l", log = "y", xlim = as.Date(c("2019/6/1", "2020/11/1")),
        ylim = c(0.5, 2.3) * 1000)

points(x[x$age == "70 years old and over", c("time", "dead")], col = "red", cex = 0.5)

xPostCovidOver = xPostCovid[xPostCovid$age == "70 years old and over", ]
xPostCovidForecastOver = sampleDeathsOver[match(xPostCovidOver$time,
                                                 xForInlaOver70$time), ]
excessDeathsOver = xPostCovidOver$dead - xPostCovidForecastOver

matplot(xPostCovidOver$time, xPostCovidForecastOver, type = "l",
        ylim = c(500, 2200), col = "black")
points(xPostCovidOver[, c("time", "dead")], col = "red")
matplot(xPostCovidOver$time, excessDeathsOver, type = "l", lty = 1, col = "#00000030",
        main="Difference between the real and predicted death counts for 70+ people")

excessDeathsOverSub1 = excessDeathsOver[xPostCovidOver$time > as.Date("2020/03/01") &
                                        xPostCovidOver$time < as.Date("2020/06/01"),
                                        ]
excessDeathsOverInPeriod1 = apply(excessDeathsOverSub1, 2, sum)
round(quantile(excessDeathsOverInPeriod1))

round(quantile(excessDeathsOver[nrow(excessDeathsOver), ]))

excessDeathsOverSub2 = excessDeathsOver[xPostCovidOver$time > as.Date("2020/09/01") &
                                        xPostCovidOver$time < as.Date("2020/10/01"),
                                        ]
excessDeathsOverInPeriod2 = apply(excessDeathsOverSub2, 2, sum)
round(quantile(excessDeathsOverInPeriod2))

round(quantile(excessDeathsOver[nrow(excessDeathsOver), ]))
plot(ecdf(quantile(excessDeathsOverInPeriod1)))
```

```r
plot(ecdf(quantile(excessDeathsOverInPeriod2)))
plot(ecdf(quantile(excessDeathsOver[nrow(excessDeathsOver), ])))

# the model for people who are under 50
plot(x[x$age == "0-49 years old", c("time", "dead")], type = "o", log = "y")
matplot(xWide2[xWide2$age == "0-49 years old", Syear], type = "l", lty = 1,
        col = Scol, main="Death counts by years for under 50 people")
legend("topright", col = Scol, legend = Syear, bty = "n", lty = 1, lwd = 3)

xForInlaUnder50= xForInla[xForInla$age == '0-49 years old', ]
library(INLA, verbose=FALSE)

res3 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
                   f(timeIid, prior='pc.prec', param= c(log(1.2), 0.5)) +
                   f(timeForInla, model = 'rw2', prior='pc.prec',
                     param= c(0.01, 0.5)), data=xForInlaUnder50,
            control.predictor = list(compute=TRUE, link=1),
            control.compute = list(config=TRUE),
           # control.inla = list(fast=FALSE, strategy='laplace'),
            family='poisson')

qCols = paste0(c(0.5, 0.025, 0.975), "quant")
rbind(res3$summary.fixed[, qCols], Pmisc::priorPostSd(res3)$summary[, qCols])

matplot(xForInlaUnder50$time, res3$summary.fitted.values[, qCols], type = "l",
        lty = c(1, 2, 2), col = "black", log = "y")
points(x[x$age == "0-49 years old", c("time", "dead")], cex = 0.4, col = "red")

matplot(xForInlaUnder50$time,
        res3$summary.random$timeForInla[, c("0.5quant", "0.975quant", "0.025quant")],
        type = "l", lty = c(1, 2, 2), col = "black")

sampleListUnder = INLA::inla.posterior.sample(30, res3, selection = list(Predictor = 0))
sampleIntensityUnder = exp(do.call(cbind, Biobase::subListExtract(sampleListUnder,
                                                                   "latent")))
sampleDeathsUnder = matrix(rpois(length(sampleIntensityUnder), sampleIntensityUnder),
                           nrow(sampleIntensityUnder), ncol(sampleIntensityUnder))

matplot(xForInlaUnder50$time, sampleDeathsUnder, col = "#00000010",
        lwd = 2, lty = 1, type = "l", log = "y")
points(x[x$age == "0-49 years old", c("time", "dead")], col = "red", cex = 0.5)
matplot(xForInlaUnder50$time, sampleDeathsUnder, col = "#00000010", lwd = 2,
        lty = 1, type = "l", log = "y", xlim = as.Date(c("2019/6/1", "2020/11/1")))

points(x[x$age == "0-49 years old", c("time", "dead")], col = "red", cex = 0.5)

xPostCovidUnder = xPostCovid[xPostCovid$age == "0-49 years old", ]
xPostCovidForecastUnder = sampleDeathsUnder[match(xPostCovidUnder$time,
                                              xForInlaUnder50$time), ]
excessDeathsUnder = xPostCovidUnder$dead - xPostCovidForecastUnder

matplot(xPostCovidUnder$time, xPostCovidForecastUnder, type = "l", col = "black")
points(xPostCovidUnder[, c("time", "dead")], col = "red")
matplot(xPostCovidUnder$time, excessDeathsUnder, type = "l", lty = 1, col = "#00000030",
        main="Difference between the real and predicted death counts for under 50 people")

excessDeathsUnderSub1 = excessDeathsUnder[xPostCovidUnder$time > as.Date("2020/03/01") &
                                         xPostCovidUnder$time < as.Date("2020/06/01"),
                                    ]
excessDeathsUnderInPeriod1 = apply(excessDeathsUnderSub1, 2, sum)
round(quantile(excessDeathsUnderInPeriod1))

round(quantile(excessDeathsUnder[nrow(excessDeathsUnder), ]))

```

```
excessDeathsUnderSub2 = excessDeathsUnder[xPostCovidUnder$time > as.Date("2020/09/01")
    &
                                          xPostCovidUnder$time < as.Date("2020/11/01"),
                                  ]
excessDeathsUnderInPeriod2 = apply(excessDeathsUnderSub2, 2, sum)
round(quantile(excessDeathsUnderInPeriod2))

round(quantile(excessDeathsUnder[nrow(excessDeathsUnder), ]))

plot(ecdf(quantile(excessDeathsUnderInPeriod1)))
plot(ecdf(quantile(excessDeathsUnderInPeriod2)))
plot(ecdf(quantile(excessDeathsUnder[nrow(excessDeathsUnder), ])))
```