Mortality in Ontario: An Analysis of Daily Mortality by Age, Pre- and Current COVID Era

Vinky Wang

02/01/2021

Introduction

As the total number of daily mortality counts in Ontario continue to rise, the cases for the older demographic (over 85 years old) appear to be aligning with historical averages whereas cases for the younger demographic (under 45 years old) are steadily increasing. It is believed that the younger population are mainly responsible for the second wave of the COVID-19 pandemic (September to present) as the first wave (March to May) primarily affected the older population and various public health measures have been put in place since then. This report aims to investigate daily mortality counts among the younger and older demographics comparing the first and second wave of the COVID-19 pandemic.

Methods

The data is available through Statistics Canada Table: 13-10-0768-01 which is a table of the weekly number of deaths from January 1st, 2010 to October 31st, 2020. Anytime before March 1st, 2020 is referred to as pre-COVID era and anytime after is the present COVID-era for the purposes of this analysis.

Through an exploratory analysis in Figure 1 of the daily mortality counts, an overall increasing trend is observed which may correspond to an increasing and/or aging population in Ontario. Additionally, there appears to be an annual cyclical pattern and a seasonal trend with higher deaths during the winter months (around week 1) likely due to the flu season and lower during the summer months (around week 30).

A seasonally adjusted poisson regression model was fit to the positive, count response of daily mortality. The seasonal adjustment captures the winter and summer month variation and sinusoidal basis functions of $sin(2\pi x_i)$ and $cos(2\pi x_i)$ corresponding to the annual fluctuations and $sin(4\pi x_i)$ and $cos(4\pi x_i)$ to the bi-annual captures the cyclical pattern. The model was implemented in the INLA, or Integrated Nested Laplace Approximation software in R which is a computationally efficient method for implementing Bayesian inferences.[1]

Model

$$Y_i \sim Poisson(\lambda_i)$$

$$log(\lambda_i) = X_i^T \beta + f_i(t_i) + V_i$$

$$V_i \sim N(0, \tau^2)$$

$$f_i(t+1) - 2f(t) + f(t-1) \sim N(0, \sigma^2)$$

$$\beta \sim MVN(0, \kappa I)$$

$$\tau \sim \text{Exponential prior such that } Pr(\tau^2 > log(1.2)) = 0.5$$

$$\sigma \sim \text{Exponential prior such that} Pr(\sigma^2 > 0.01) = 0.5$$

- Y_i: Daily mortality counts
- λ_i: Mean of deaths
- $f_i(t_i)$: Seasonally adjusted trend following a second order Random Walk
- V_i: Overdispersion

Prior Specification

A default weakly informative zero-mean Gaussian prior was assigned to the regression parameters β. By the favoured model principle of penalized least squares with a second derivative penalty, a second order random walk was assigned to the seasonally adjusted trend to encourage straight lines for achieving lower bias.[2] A penalized complexity prior was used on the second order random walk to control the strength of the constraint to the favoured model.[3] The prior of $Pr(\tau^2 > log(1.2)) = 0.5$ encodes our belief that the weekly variability should be no greater than 20% as the prior median. The prior of $Pr(\sigma^2 > 0.01) = 0.5$ encodes our belief that the yearly change in slope should be no greater than 0.01 as the prior median. As the simulated posterior samples by the fitted model with the above prior specifications follow closely with the observed data, this suggests that our priors are on the appropriate order of magnitude.
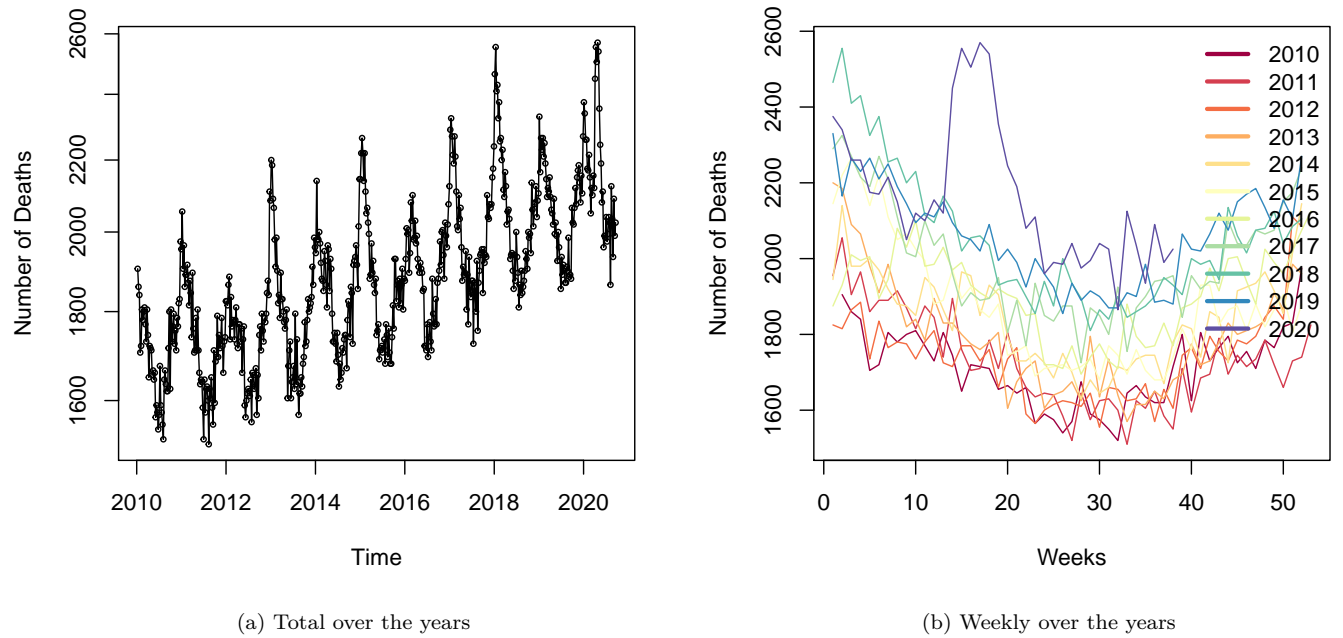
Results

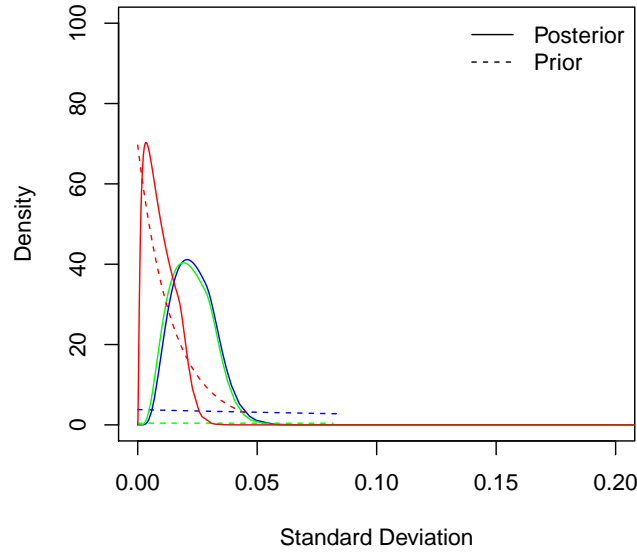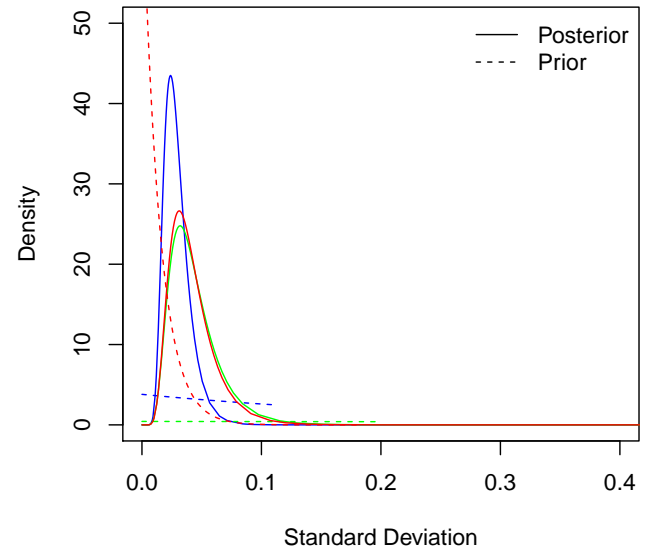(a) Total over the years

(b) Weekly over the years

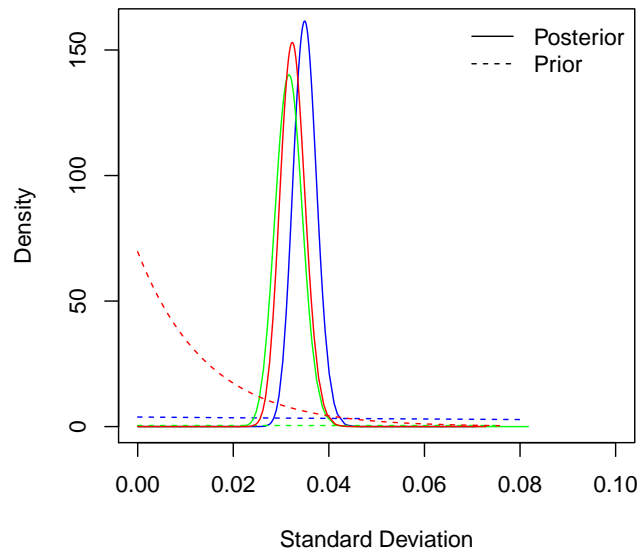Figure 1: Number of Deaths in Ontario
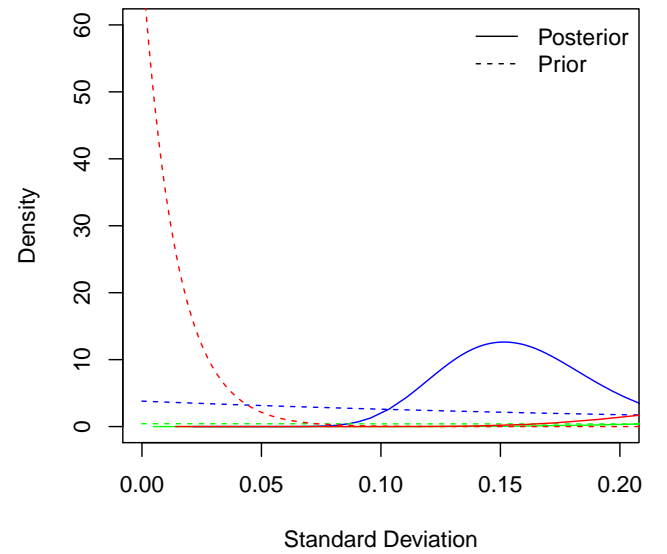
(a) by Weekly

(b) by Yearly

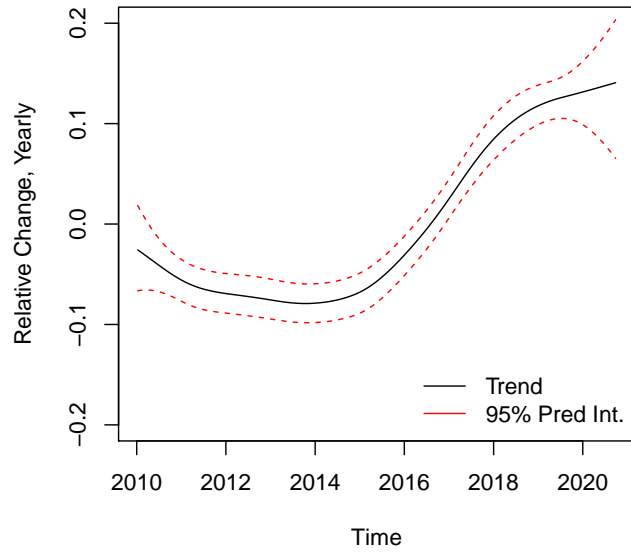Figure 2: Prior Sensitivity Analysis for Deaths Under 45 Years Old. Prior and Posterior Distributions.
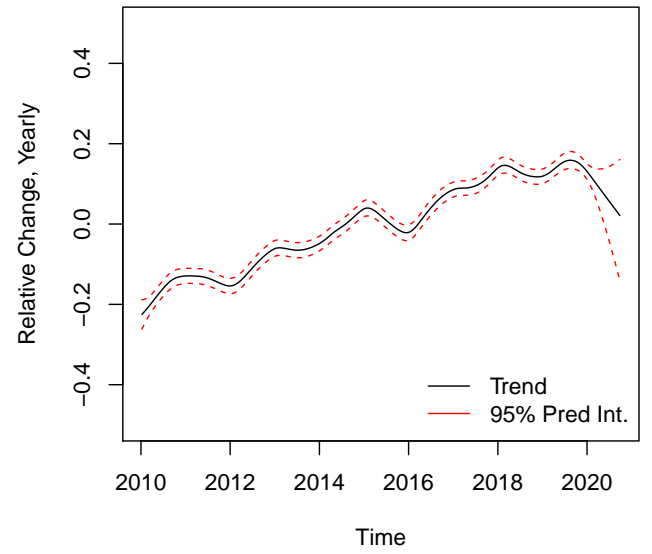

(a) by Weekly

(b) by Yearly

Figure 3: Prior Sensitivity Analysis for Deaths over 85 Years Old. Prior and Posterior Distributions.

(a) Under 45 Years Old

(b) Over 85 Years Old

Figure 4: Random Effect. Yearly Change in Slope.
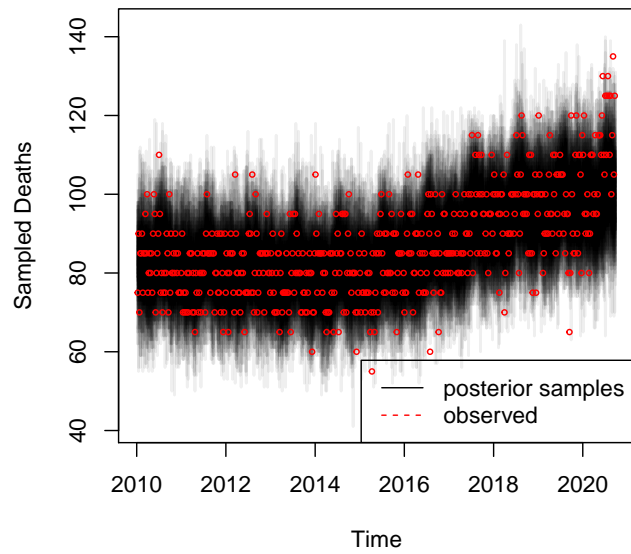
(a) Under 45 Years Old
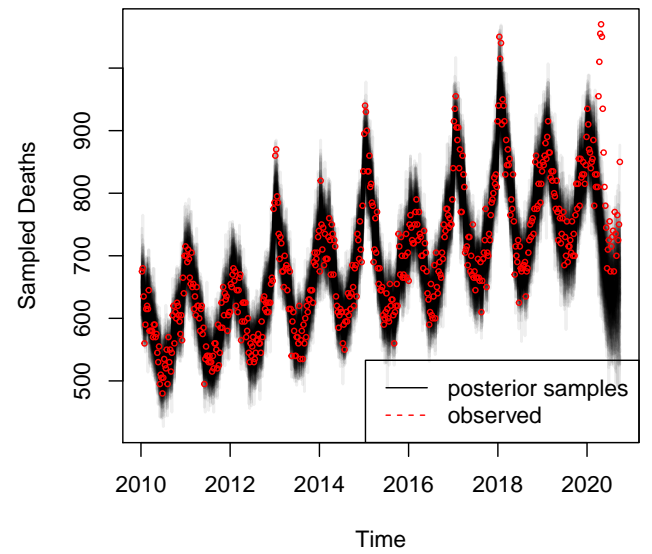
(b) Over 85 Years Old

Figure 5: Simulated Posterior Samples for Daily Mortality Counts.
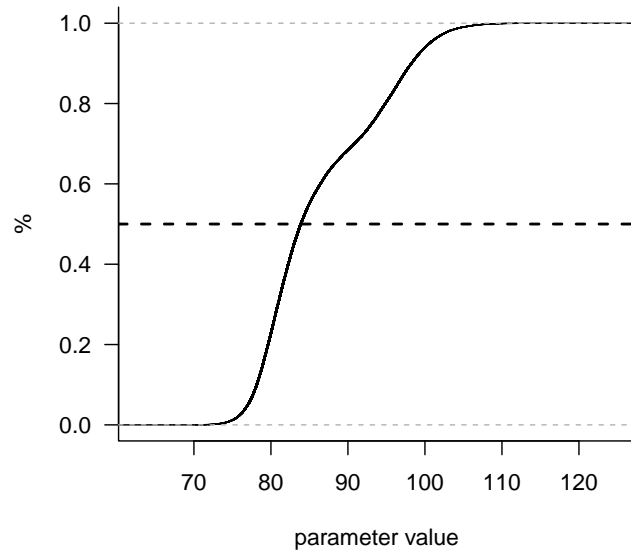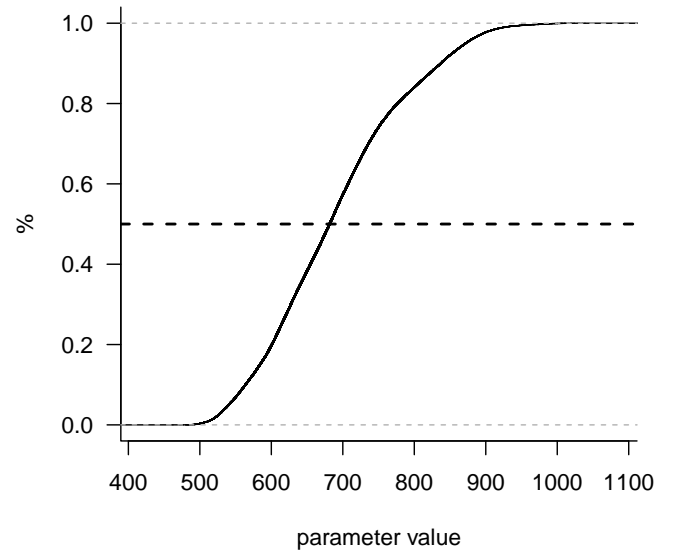
(a) Under 45 Years Old

(b) Over 85 Years Old

Figure 6: Empirical Cumulative Distribution Function of Sampled Daily Mortality Counts.
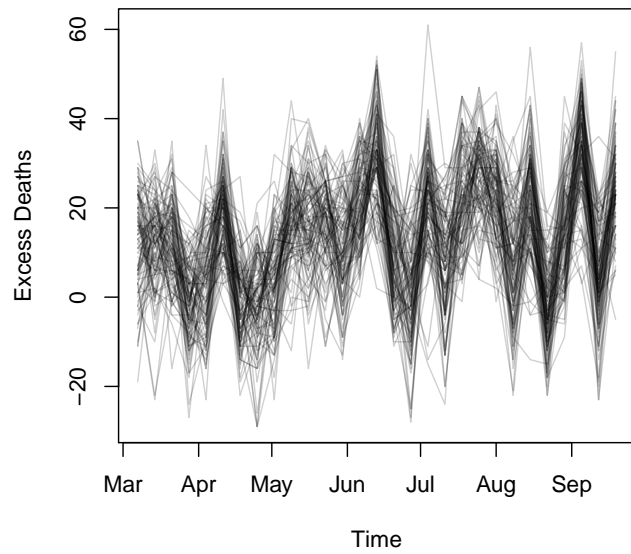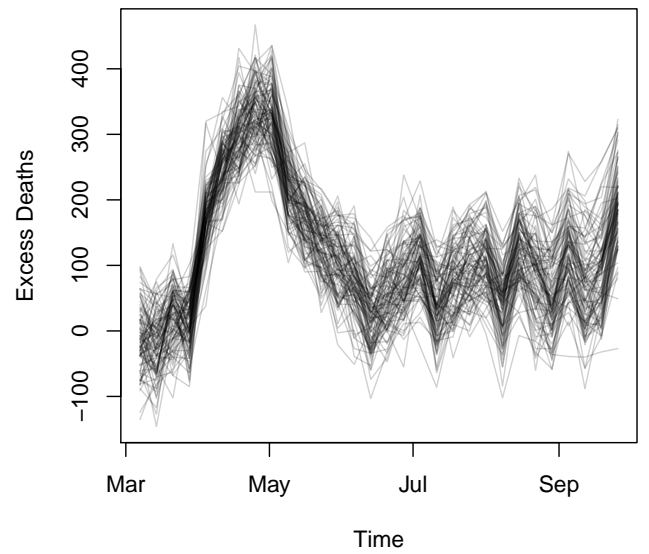
(a) Under 45 Years Old

(b) Over 85 Years Old

Figure 7: Plot of Excess Mortality Counts.

(a) First Wave (March to May)

(b) Second Wave (September to Present)

Figure 8: Histogram Of Excess Daily Mortality Counts For Under 45 Years Old
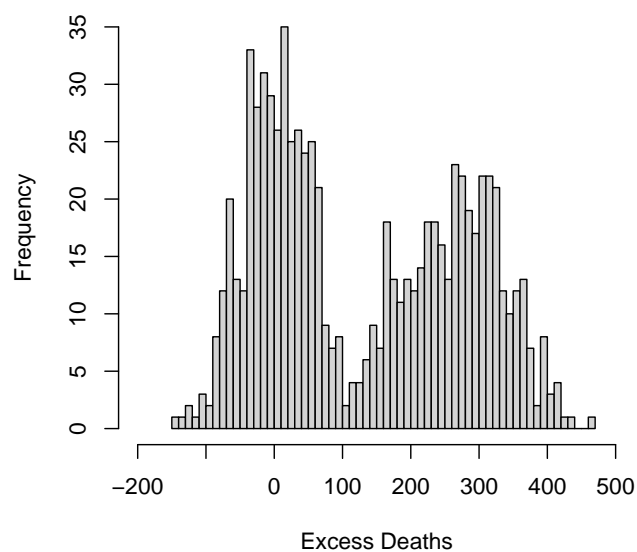
(a) First Wave (March to May)
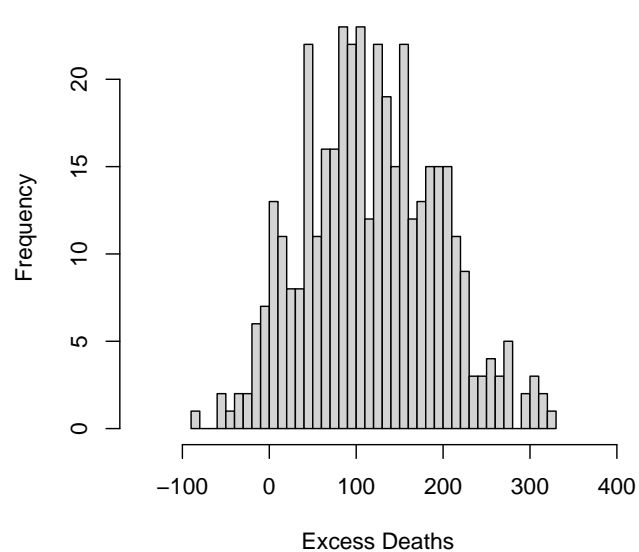
(b) Second Wave (September to Present)

Figure 9: Histogram Of Excess Daily Mortality Counts For over 85 Years Old

Table 1: Summary outputs and Posterior Standard Deviations for Deaths Under 45 Years Old

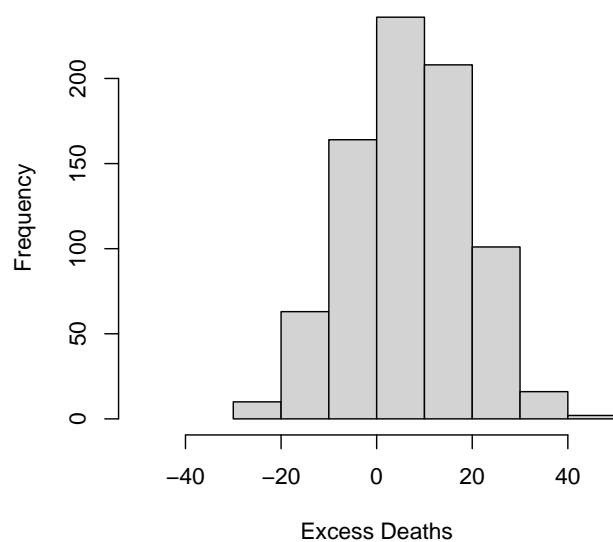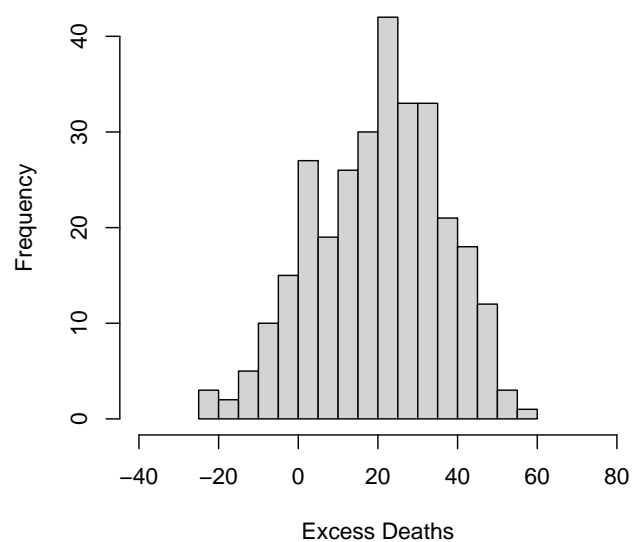|	0.5quant	0.025quant	0.975quant
(Intercept)	4.4542492	4.4443323	4.4640506
sin12	-0.0160763	-0.0295909	-0.0025759
sin6	0.0128190	-0.0004866	0.0261218
cos12	-0.0156371	-0.0289598	-0.0023263
cos6	0.0154897	0.0021178	0.0288461
SD weekly	0.0229571	0.0086060	0.0425519
SD yearly	0.0274636	0.0137105	0.0566550

Table 2: Summary outputs and Posterior Standard Deviations for Deaths Over 85 Years Old

	0.5quant	0.025quant	0.975quant
(Intercept)	6.5261105	6.5193618	6.5325422
sin12	0.0511834	0.0438006	0.0585734
sin6	0.0104110	0.0040204	0.0167837
cos12	0.1177758	0.1103814	0.1252188
cos6	0.0000995	-0.0062919	0.0064695
SD weekly	0.0349964	0.0303632	0.0400721
SD yearly	0.1564106	0.1034152	0.2308293

Table 3: Summary of Excess Deaths for Under 45 Years Old

	2.5%	50%	97.5%
First Wave (March to May)	-12	8	25
Second Wave (September to Present)	-2	21	39

Table 4: Summary of Excess Deaths for Over 85 Years Old

	2.5%	50%	97.5%
First Wave (March to May)	51	133	217
Second Wave (September to Present)	12	120	239

Discussion

The following additional prior specifications were explored for a prior sensitivity analysis of both deaths under 45 years old and over 85 years old :

(1)

$\tau \sim$ Exponential prior such that $Pr(\tau^2 > log(5)) = 0.5$ and $\sigma \sim$ Exponential prior such that $Pr(\sigma^2 > 10) = 0.5$

(2)

$\tau \sim$ Exponential prior such that $Pr(\tau^2 > log(1.01)) = 0.5$ and $\sigma \sim$ Exponential prior such that $Pr(\sigma^2 > 0.1) = 0.5$

Model (1) represents the prior belief that the weekly variability should be no greater than by a factor of 4 as the prior median and the yearly change in slope should be no greater than 10 as the prior median. Model (2) represents the prior belief that the weekly variability should be no greater than 1% as the prior median and the yearly change in slope should be no greater than 0.1 as the prior median. As the posterior distributions of the fitted model closely overlaps with model (1) and model (2) for both the weekly and yearly variability of the under 45 years old and over 85 years old deaths, this suggests that the priors are not sensitive and the data is mainly informing the posteriors rather than the priors.

The posterior median for the weekly variability of deaths under 45 years old is 0.023 and yearly variability is 0.027 with relatively wide 95% credible intervals of (0.009, 0.043) and (0.014, 0.057) respectively. The posterior median for the weekly variability of deaths over 85 years old is 0.035 and yearly variability is 0.156 with relatively narrower 95% credible intervals of (0.030, 0.040) and (0.103, 0.231) respectively. There appears to be a slightly greater difference in deaths from year to year than week to week.

The yearly change in slope plot in Figure 4 indicates that the seasonal trend is quite visible for the over 85 years old age group and less strong for the under 45 years old age group. Additionally, there appears to be a steady increase in mortality counts since 2015 for ages under 45 years old and a steady increase since 2010 for ages over 85 years old.

The recently observed deaths in both age groups tends to be higher than the forecasted deaths based on historical, pre-COVID era data shown in Figure 5. The excess deaths, that is, the difference in the number of deaths in the present COVID era and the forecasted deaths based on historical, pre-COVID era data is shown in Figure 7 to 9. The excess deaths for the under 45 years old age group fluctuates dramatically between about 10 fewer deaths to 40 excess deaths. In contrast, the over 85 years old age group tend to consistently have about 100 excess deaths since June with a dramatic spike to an upwards of 400 excess deaths in May.

The median number of excess deaths in the first wave (March to May) for the under 45 years old age group is 9 with a 95% CI of 10 fewer deaths to 27 excess deaths. The median number of excess deaths in the second wave (September to present) is 22 with a 95% CI of 0 fewer deaths and 42 excess deaths. The median number of excess deaths in the first wave (March to May) for the over 85 years old age group is 128 with a 95% CI of 47 to 206 excess deaths. The median number of excess deaths in the second wave (September to present) is 118 with a 95% CI of 22 to 241 excess deaths. It appears that the younger population has been more affected in the second wave than first whereas this is the converse for the elderly. Although there is greater variability in excess deaths among the elderly, it is apparent that those over the age of 85 years old are consistently at higher risk than those under the age of 45 years old.

Conclusion

The under 45 years old age group have been more affected in the second wave (September to present) than the first wave (March to May) of the current COVID era whereas the converse is true for the over 85 years old age group. Although there is greater variability in excess deaths for the over 85 years old age group, the elderly population are consistently at higher risk.

References

[1] Bayesian computing. (2015). Spatial and Spatio-temporal Bayesian Models with R-INLA, 75-126. doi: 10.1002/9781118950203.ch4

[2] Heckman, Nancy E. and James O. Ramsay (2000). "Penalized Regression with Model-Based Penalties". In: The Canadian Journal of Statistics / La Revue Canadienne de Statistique 28.2, pp. 241–258. url: http://www.jstor.org/stable/3315976.

[3] Simpson, Daniel, Haavard Rue, Andrea Riebler, Thiago G. Martins, and Sigrunn H. Sorbye (Feb. 2017). "Penalising Model Component Complexity: A Principled, Practical Approach to Constructing Priors". In: Statistical Science 32.1, pp. 1–28. doi: 10.1214/16-STS576

Appendix

(a) by Weekly

(b) by Yearly

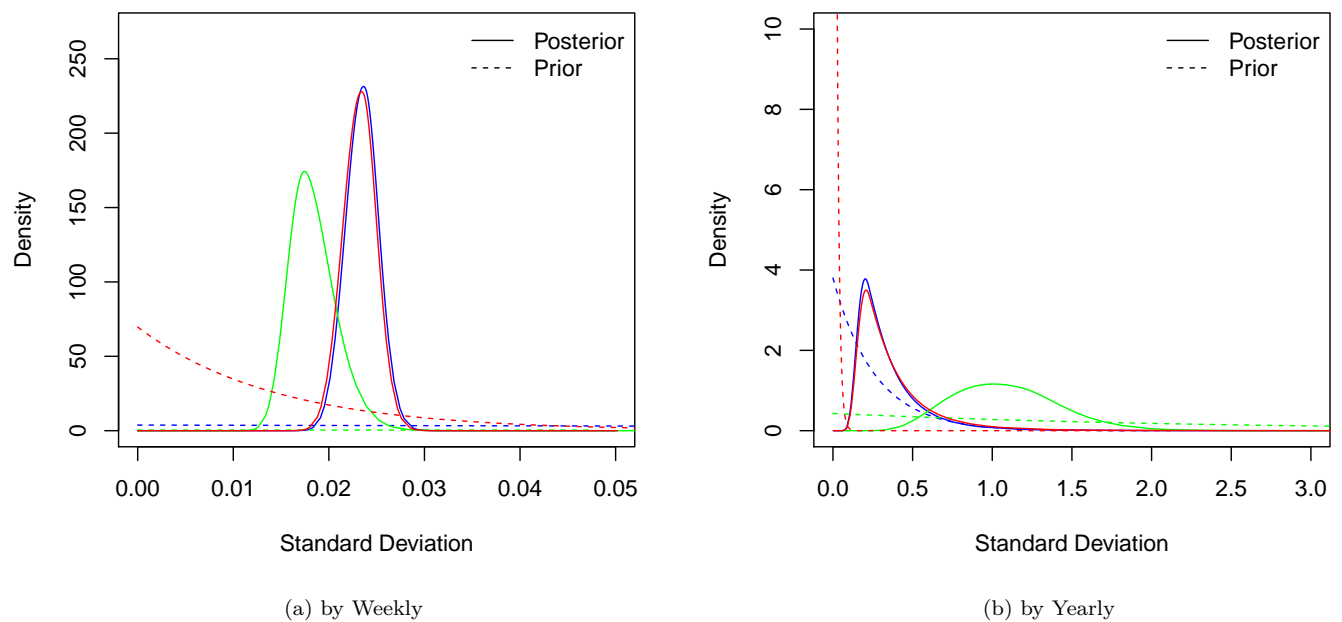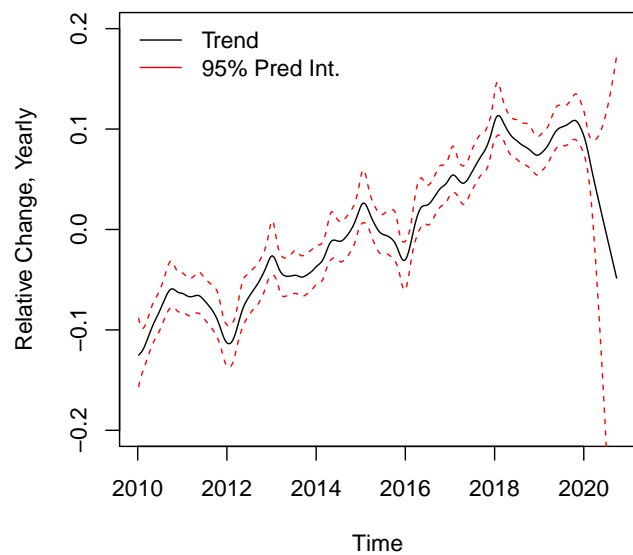Figure 10: Prior Sensitivity Analysis for Total Deaths. Prior and Posterior Distributions.

Figure 11: Random Effect of Total Population. Yearly Change in Slope.
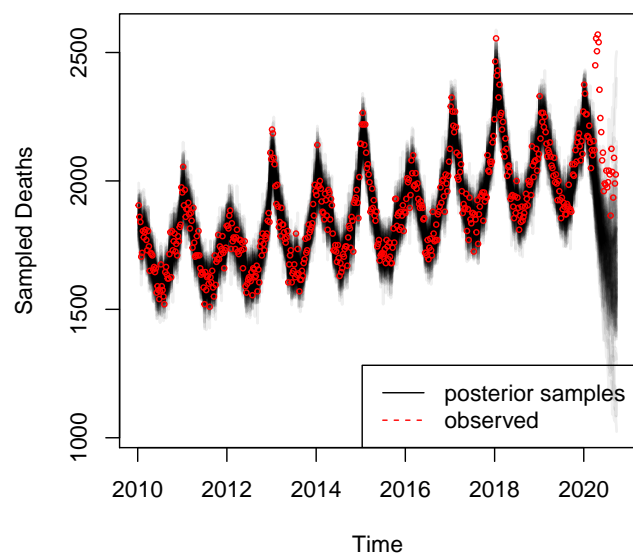
Figure 12: Simulated Posterior Samples for Daily Mortality Counts of Total Population.

11
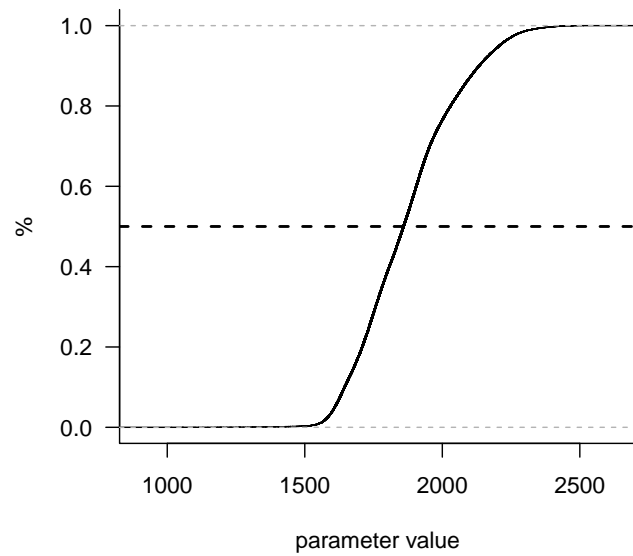
Figure 13: Empirical Cumulative Distribution Function of Sampled Daily Mortality Counts of Total Population.
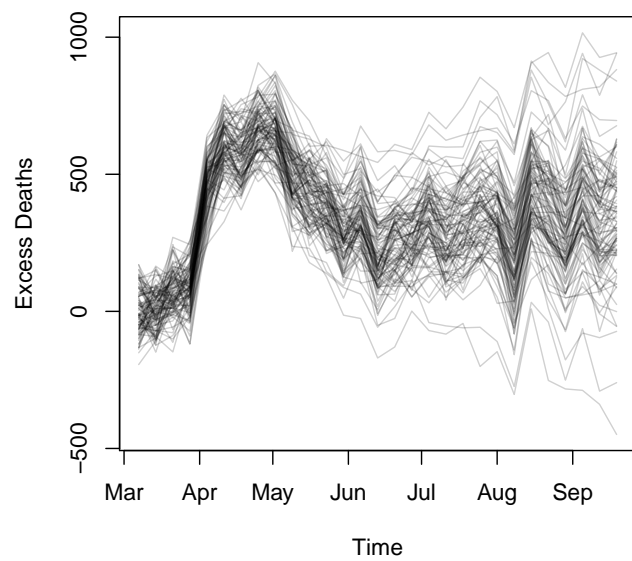
Figure 14: Plot of Excess Mortality Counts for Total Population.

Table 5: Summary outputs and Posterior Standard Deviations for Total Deaths

	0.5quant	0.025quant	0.975quant
(Intercept)	7.5304584	7.5196794	7.5372954
sin12	0.0376553	0.0272459	0.0483386
sin6	0.0070023	0.0024123	0.0116390
cos12	0.0811011	0.0706635	0.0918431
cos6	0.0049797	0.0003680	0.0095534
SD weekly	0.0234903	0.0201248	0.0268142
SD yearly	0.2829581	0.1294236	0.9274931

Table 6: Summary of Excess Deaths for Total Population

	2.5%	50%	97.5%
First Wave (March to May)	145	306	462
Second Wave (September to Present)	-51	357	845
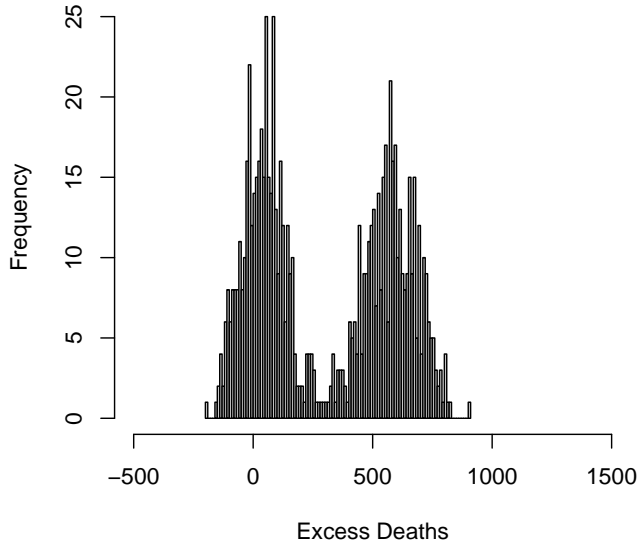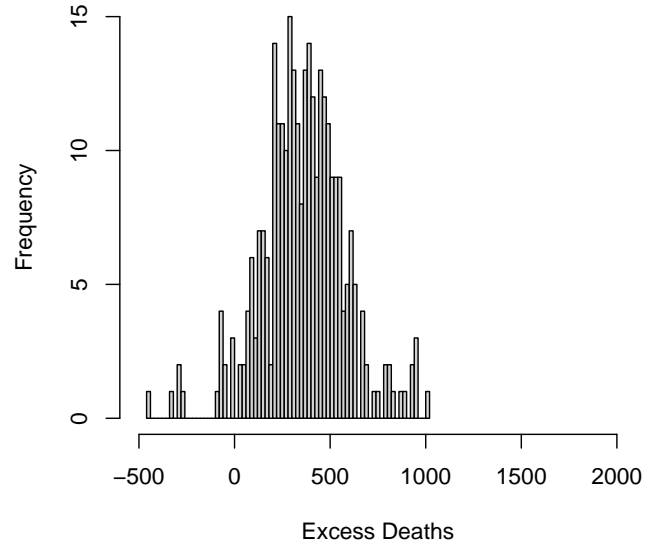
(a) First Wave (March to May) (b) Second Wave (September to Present)

Figure 15: Histogram Of Excess Daily Mortality Counts For Total

```r
#load library
library(cansim)
library(dplyr)
library(lubridate)
library(INLA, verbose=FALSE)
library(knitr)
library(bookdown)
library(kableExtra)
```

```r
library(LDATS)


#load data
deaths = get_cansim("13-10-0768-01")

deaths <- deaths %>%
  filter(GEO == "Ontario, place of occurrence", Sex == "Both sexes") %>%
  rename(age = "Age at time of death", dead = "VALUE")

#create dataframe
x = deaths[,c("REF_DATE", "age", "dead")]
x$time = as.Date(x$REF_DATE)
x$week = week(x$REF_DATE)
x$year = year(x$REF_DATE)


x = x[!is.na(x$dead), ]

#view dataframe
str(x)
head(x)

#plots
#spikes correspond to flu season (winter months)
plot(x[x$age == "Age at time of death, all ages", c("time", "dead")], type = "o",
log = "y", ylab="Number of Deaths", xlab="Time", cex=0.5)

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

{matplot(xWide2[xWide2$age == "Age at time of death, all ages", Syear], type = "l",
lty = 1, col = Scol, xlab="Weeks", ylab="Number of Deaths")
legend("topright", col = Scol, legend = Syear, bty = "n",
lty = 1, lwd = 3)}


#divide the data into pre and post covid, add extra dates for forecasting in INLA
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),
]

#create some time variables, including sines and cosines. Time in years and centred so numerically stab
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)
```

```r
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)

#select age groups of interest
xForInla45= xForInla[xForInla$age == 'Age at time of death, 0 to 44 years', ]
xForInla85= xForInla[xForInla$age == 'Age at time of death, 85 years and over', ]

#fit INLA on <45 year old
underres = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(1.20), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(0.01, 0.5)),
data=xForInla45,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')


#fit INLA on >85 year old
overres = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(1.20), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(0.01, 0.5)),
data=xForInla85,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')


#prior sensitivity analysis
under2 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(5), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(10, 0.5)),
data=xForInla45,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')

under3 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(1.01), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(0.1, 0.5)),
data=xForInla45,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')

#prior and posteriors of SD for each model
theSd_underres= Pmisc::priorPost(underres)
```

```r
theSd_under2= Pmisc::priorPost(under2)
theSd_under3= Pmisc::priorPost(under3)

#prior and posterior distbns
#prior density shows a flat exponential (recall set sigma to to 0.2)
{plot(theSd_underres$`sd for timeIid`$posterior, type='l', xlab='Standard Deviation', ylab='Density', co
lines(theSd_underres$`sd for timeIid`$prior, col='blue', lty=2)

lines(theSd_under2$`sd for timeIid`$posterior, col='green')
lines(theSd_under2$`sd for timeIid`$prior, col='green', lty=2)

lines(theSd_under3$`sd for timeIid`$posterior, col='red')
lines(theSd_under3$`sd for timeIid`$prior, col='red', lty=2)


legend('topright',
lty=1:2, lwd=1, legend = c('Posterior','Prior'),
bty='n')
}

{plot(theSd_underres$`sd for timeForInla`$posterior, type='l', xlab='Standard Deviation', ylab='Density'
lines(theSd_underres$`sd for timeForInla`$prior, col='blue', lty=2)

lines(theSd_under2$`sd for timeForInla`$posterior, col='green')
lines(theSd_under2$`sd for timeForInla`$prior, col='green', lty=2)

lines(theSd_under3$`sd for timeForInla`$posterior, col='red')
lines(theSd_under3$`sd for timeForInla`$prior, col='red', lty=2)


legend('topright',
lty=1:2, lwd=1, legend = c('Posterior','Prior'),
bty='n')
}



#prior sensitivity analysis
over2 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(5), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(10, 0.5)),
data=xForInla85,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')

over3 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(1.01), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(0.1, 0.5)),
data=xForInla85,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
```

```
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')

#prior and posteriors of SD for each model
theSd_overres= Pmisc::priorPost(overres)
theSd_over2= Pmisc::priorPost(over2)
theSd_over3= Pmisc::priorPost(over3)

#prior and posterior distbns
#prior density shows a flat exponential (recall set sigma to to 0.2)
{plot(theSd_overres$`sd for timeIid`$posterior, type='l', xlab='Standard Deviation', ylab='Density', col
lines(theSd_overres$`sd for timeIid`$prior, col='blue', lty=2)

lines(theSd_over2$`sd for timeIid`$posterior, col='green')
lines(theSd_over2$`sd for timeIid`$prior, col='green', lty=2)

lines(theSd_over3$`sd for timeIid`$posterior, col='red')
lines(theSd_over3$`sd for timeIid`$prior, col='red', lty=2)


legend('topright',
lty=1:2, lwd=1, legend = c('Posterior','Prior'),
bty='n')
}

{plot(theSd_overres$`sd for timeForInla`$posterior, type='l', xlab='Standard Deviation', ylab='Density'
lines(theSd_overres$`sd for timeForInla`$prior, col='blue', lty=2)

lines(theSd_over2$`sd for timeForInla`$posterior, col='green')
lines(theSd_over2$`sd for timeForInla`$prior, col='green', lty=2)

lines(theSd_over3$`sd for timeForInla`$posterior, col='red')
lines(theSd_over3$`sd for timeForInla`$prior, col='red', lty=2)


legend('topright',
lty=1:2, lwd=1, legend = c('Posterior','Prior'),
bty='n')
}


#random effect under 45
{matplot(xForInla45$time, underres$summary.random$timeForInla[,
c("0.5quant", "0.975quant", "0.025quant")], type = "l",
lty = c(1, 2, 2), col = c("black", 'red', 'red'), ylim = c(-0.5, 0.5) *
0.4, ylab="Relative Change, Yearly", xlab="Time")
legend("bottomright", col=c('black','red', 'red'), legend=c("Trend", "95% Pred Int."), bty="n", lty=1, l

}

#random effect over 85
{matplot(xForInla85$time, overres$summary.random$timeForInla[,
c("0.5quant", "0.975quant", "0.025quant")], type = "l",
```

```r
lty = c(1, 2, 2), col = c("black", 'red', 'red'), ylim = c(-0.5, 0.5), ylab="Relative Change, Yearly",
legend("bottomright", col=c('black','red', 'red'), legend=c("Trend", "95% Pred Int."), bty="n", lty=1,
}


#under 45
#first wave (Mar-May)
#posterior samples
#100 posterior samples of (log lambda)
set.seed(442)
sampleList_under = INLA::inla.posterior.sample(100, underres, selection = list(Predictor = 0))
#exponentiate (lambda)
sampleIntensity_under = exp(do.call(cbind, Biobase::subListExtract(sampleList_under,
"latent")))
#y (poisson(lambda))
sampleDeaths_under = matrix(rpois(length(sampleIntensity_under),
sampleIntensity_under), nrow(sampleIntensity_under), ncol(sampleIntensity_under))


{matplot(xForInla45$time, sampleDeaths_under, col = "#00000010",
lwd = 2, lty = 1, type = "l", ylab="Sampled Deaths", xlab="Time")
points(x[x$age == "Age at time of death, 0 to 44 years", c("time", "dead")], col = "red",
cex = 0.5, ylim=c(20, 160))
legend("bottomright",legend=c("posterior samples", "observed"), col=c("black","red"), lty=1:2)
}

#over 85
#first wave (Mar-May)
#posterior samples
#100 posterior samples of (log lambda)
set.seed(442)
sampleList_over = INLA::inla.posterior.sample(100, overres, selection = list(Predictor = 0))
#exponentiate (lambda)
sampleIntensity_over = exp(do.call(cbind, Biobase::subListExtract(sampleList_over,
"latent")))
#y (poisson(lambda))
sampleDeaths_over = matrix(rpois(length(sampleIntensity_over),
sampleIntensity_over), nrow(sampleIntensity_over), ncol(sampleIntensity_over))


{matplot(xForInla85$time, sampleDeaths_over, col = "#00000010",
lwd = 2, lty = 1, type = "l", ylab="Sampled Deaths", xlab="Time")
points(x[x$age == "Age at time of death, 85 years and over", c("time", "dead")], col = "red",
cex = 0.5, ylim=c(0,150))
legend("bottomright",legend=c("posterior samples", "observed"), col=c("black","red"), lty=1:2)
}

#ecdf

ecdf_plot(sampleIntensity_under)
ecdf_plot(sampleIntensity_over)

#under 45
```

```r
xPostCovid_under = xPostCovid[xPostCovid$age == "Age at time of death, 0 to 44 years",
]
xPostCovidForecast_under = sampleDeaths_under[match(xPostCovid_under$time,
xForInla45$time), ]


excessDeaths_under = xPostCovid_under$dead - xPostCovidForecast_under


{matplot(xPostCovid_under$time, excessDeaths_under, type = "l",
lty = 1, col = "#00000030", xlab="Time", ylab="Excess Deaths")
}

#over 85
xPostCovid_over = xPostCovid[xPostCovid$age == "Age at time of death, 85 years and over",]
xPostCovidForecast_over = sampleDeaths_over[match(xPostCovid_over$time,
xForInla85$time), ]

excessDeaths_over = xPostCovid_over$dead - xPostCovidForecast_over


{matplot(xPostCovid_over$time, excessDeaths_over, type = "l",
lty = 1, col = "#00000030", xlab="Time", ylab="Excess Deaths")
}


#under 45
excessDeathsunder_wave1 = excessDeaths_under[xPostCovid_under$time >
as.Date("2020/03/01") & xPostCovid_under$time <
as.Date("2020/05/01"), ]

excessDeathsunder_wave2 = excessDeaths_under[xPostCovid_under$time >
as.Date("2020/09/01") & xPostCovid_under$time <
as.Date("2020/11/01"), ]

hist(excessDeathsunder_wave1, xlab="Excess Deaths", xlim=c(-50,50),main="", breaks = 10)
hist(excessDeathsunder_wave2, xlab="Excess Deaths", xlim=c(-40,80),main="", breaks = 12)



#over 85
excessDeathsover_wave1 = excessDeaths_over[xPostCovid_over$time >
as.Date("2020/03/01") & xPostCovid_over$time <
as.Date("2020/05/01"), ]

excessDeathsover_wave2 = excessDeaths_over[xPostCovid_over$time >
as.Date("2020/09/01") & xPostCovid_over$time <
as.Date("2020/11/01"), ]

hist(excessDeathsover_wave1, xlab="Excess Deaths", xlim=c(-200,500),main="", breaks = 70)
hist(excessDeathsover_wave2, xlab="Excess Deaths", xlim=c(-150,400),main="", breaks = 55)

qCols = c('0.5quant','0.025quant','0.975quant')
```

```r
#Under
theSdunder = Pmisc::priorPost(underres)$summary[,qCols]

rownames(theSdunder) = c("SD weekly", "SD yearly")
knitr::kable(round(rbind(underres$summary.fixed[, qCols], theSdunder),3), caption = "Summary outputs and

#Over
theSdover = Pmisc::priorPost(overres)$summary[,qCols]

rownames(theSdover) = c("SD weekly", "SD yearly")
knitr::kable(round(rbind(overres$summary.fixed[, qCols], theSdover),3), caption = "Summary outputs and

#under 45
excessDeathsunder_wave1q = apply(excessDeathsunder_wave1, 1, quantile, probs = c(0.025,0.5, 0.975))
excessDeathsunder_wave1avg = apply(excessDeathsunder_wave1q, 1, mean)
excessDeathsunder_wave2q = apply(excessDeathsunder_wave2, 1, quantile, probs = c(0.025,0.5, 0.975))
excessDeathsunder_wave2avg = apply(excessDeathsunder_wave2q, 1, mean)

excessdeathsunder_quant = rbind(excessDeathsunder_wave1avg, excessDeathsunder_wave2avg)
rownames(excessdeathsunder_quant) = c("First Wave (March to May)", "Second Wave (September to Present)")

kable(round(excessdeathsunder_quant, 0), caption="Summary of Excess Deaths for Under 45 Years Old")


#over 85
excessDeathsover_wave1q = apply(excessDeathsover_wave1, 1, quantile, probs = c(0.025,0.5, 0.975))
excessDeathsover_wave1avg = apply(excessDeathsover_wave1q, 1, mean)
excessDeathsover_wave2q = apply(excessDeathsover_wave2, 1, quantile, probs = c(0.025,0.5, 0.975))
excessDeathsover_wave2avg = apply(excessDeathsover_wave2q, 1, mean)

excessdeathsover_quant = rbind(excessDeathsover_wave1avg, excessDeathsover_wave2avg)
rownames(excessdeathsover_quant) = c("First Wave (March to May)", "Second Wave (September to Present)")

kable(round(excessdeathsover_quant, 0), caption="Summary of Excess Deaths for Over 85 Years Old")

#total

#fit INLA on total deaths
totalres = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(1.20), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(0.1, 0.5)),
data=xForInlaTotal,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')


#prior sensitivity analysis
total2 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(5), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(10, 0.5)),
data=xForInlaTotal,
```

```r
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')

total3 = inla(dead ~ sin12 + sin6 + cos12 + cos6 +
f(timeIid, prior='pc.prec', param= c(log(1.01), 0.5)) +
f(timeForInla, model = 'rw2', prior='pc.prec', param= c(0.1, 0.5)),
data=xForInlaTotal,
control.predictor = list(compute=TRUE, link=1),
control.compute = list(config=TRUE),
# control.inla = list(fast=FALSE, strategy='laplace'),
family='poisson')

#prior and posteriors of SD for each model
theSd_totalres= Pmisc::priorPost(totalres)
theSd_total2= Pmisc::priorPost(total2)
theSd_total3= Pmisc::priorPost(total3)


#prior and posterior distbns
#prior density shows a flat exponential (recall set sigma to to 0.2)
{plot(theSd_totalres$`sd for timeIid`$posterior, type='l', xlab='Standard Deviation', ylab='Density', c
lines(theSd_totalres$`sd for timeIid`$prior, col='blue', lty=2)

lines(theSd_total2$`sd for timeIid`$posterior, col='green')
lines(theSd_total2$`sd for timeIid`$prior, col='green', lty=2)

lines(theSd_total3$`sd for timeIid`$posterior, col='red')
lines(theSd_total3$`sd for timeIid`$prior, col='red', lty=2)


legend('topright',
lty=1:2, lwd=1, legend = c('Posterior','Prior'),
bty='n')
}

{plot(theSd_totalres$`sd for timeForInla`$posterior, type='l', xlab='Standard Deviation', ylab='Density
lines(theSd_totalres$`sd for timeForInla`$prior, col='blue', lty=2)

lines(theSd_total2$`sd for timeForInla`$posterior, col='green')
lines(theSd_total2$`sd for timeForInla`$prior, col='green', lty=2)

lines(theSd_total3$`sd for timeForInla`$posterior, col='red')
lines(theSd_total3$`sd for timeForInla`$prior, col='red', lty=2)


legend('topright',
lty=1:2, lwd=1, legend = c('Posterior','Prior'),
bty='n')
}


#random effect for total
```

```r
{matplot(xForInlaTotal$time, totalres$summary.random$timeForInla[,
c("0.5quant", "0.975quant", "0.025quant")], type = "l",
lty = c(1, 2, 2), col = c("black", 'red', 'red'), ylim = c(-0.5, 0.5) *
0.4, ylab="Relative Change, Yearly", xlab="Time")
legend("topleft", col=c('black','red', 'red'), legend=c("Trend", "95% Pred Int."), bty="n", lty=1, lwd=

}


#first wave (Mar-May)
#posterior samples
#total
#100 posterior samples of (log lambda)
set.seed(442)
sampleList_total = INLA::inla.posterior.sample(100, totalres, selection = list(Predictor = 0))
#exponentiate (lambda)
sampleIntensity_total = exp(do.call(cbind, Biobase::subListExtract(sampleList_total,
"latent")))
#y (poisson(lambda))
sampleDeaths_total = matrix(rpois(length(sampleIntensity_total),
sampleIntensity_total), nrow(sampleIntensity_total), ncol(sampleIntensity_total))


{matplot(xForInlaTotal$time, sampleDeaths_total, col = "#00000010",
lwd = 2, lty = 1, type = "l", ylab="Sampled Deaths", xlab="Time")
points(x[x$age == "Age at time of death, all ages", c("time", "dead")], col = "red",
cex = 0.5)
legend("bottomright",legend=c("posterior samples", "observed"), col=c("black","red"), lty=1:2)
}

ecdf_plot(sampleIntensity_total)


#total
xPostCovid_total = xPostCovid[xPostCovid$age == "Age at time of death, all ages",]
xPostCovidForecast_total = sampleDeaths_total[match(xPostCovid_total$time,
xForInlaTotal$time), ]

excessDeaths_total = xPostCovid_total$dead - xPostCovidForecast_total


{matplot(xPostCovid_total$time, excessDeaths_total, type = "l",
lty = 1, col = "#00000030", xlab="Time", ylab="Excess Deaths")
}

#total
excessDeathstotal_wave1 = excessDeaths_total[xPostCovid_total$time >
as.Date("2020/03/01") & xPostCovid_total$time <
as.Date("2020/05/01"), ]

excessDeathstotal_wave2 = excessDeaths_total[xPostCovid_total$time >
as.Date("2020/09/01") & xPostCovid_total$time <
as.Date("2020/11/01"), ]
```

```r
hist(excessDeathstotal_wave1, xlab="Excess Deaths", xlim=c(-500,1500),main="", breaks = 90)
hist(excessDeathstotal_wave2, xlab="Excess Deaths", xlim=c(-500,2000),main="", breaks = 70)

#total
theSdtotal = Pmisc::priorPost(totalres)$summary[,qCols]

rownames(theSdtotal) = c("SD weekly", "SD yearly")
knitr::kable(rbind(totalres$summary.fixed[, qCols], theSdtotal), caption = "Summary outputs and Posteri

#total
excessDeathstotal_wave1q = apply(excessDeathstotal_wave1, 1, quantile, probs = c(0.025,0.5, 0.975))
excessDeathstotal_wave1avg = apply(excessDeathstotal_wave1q, 1, mean)
excessDeathstotal_wave2q = apply(excessDeathstotal_wave2, 1, quantile, probs = c(0.025,0.5, 0.975))
excessDeathstotal_wave2avg = apply(excessDeathstotal_wave2q, 1, mean)

excessdeathstotal_quant = rbind(excessDeathstotal_wave1avg, excessDeathstotal_wave2avg)
rownames(excessdeathstotal_quant) = c("First Wave (March to May)", "Second Wave (September to Present)")

kable(round(excessdeathstotal_quant, 0), caption="Summary of Excess Deaths for Total Population")
```