# Top 10 Mortality Causes for Republic of Korea of the years 2000, 2010, 2015, 2019*

**Poisson and Negative Bionimal Modelling of Annual Death Number and its Cause**

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First sentence. Second sentence. Third sentence. Fourth sentence.

## Table of contents

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*Code and data are available at: https://github.com/anggimude/Top-Mortality-Causes-of-South-Korea

# 1 Introduction

The remainder of this paper is structured as follows. Section 2….

# 2 Data

## 2.1 Raw Data

The data used in this paper is derived from WHO(WHO) and was downloaded from the WHO Mortality Database. WHO(WHO) provides data for years country-level Global Health Estimates(GHE2019) for the years 2000-2019. Because the years that have estimates of a list provided of the cause of death categories in terms of International Classification of Diseases, Tenth Revision(ICD-10) in terms of a summary table of number of deaths by cause, age, and sex for WHO(WHO) member states for the years are 2000, 2010, 2015, 2019; the data for these four years are cleaned and analyzed for this paper. The analysis of deaths by cause of the raw data is executed for the age groups from 5 to 85+. This paper looks into the data for Republic of Korea as the author is South Korean but also because WHO methods and data sources(citation) certifies a high quality of data. The raw data includes columns such as code, cause, IS03, year, sex, age group, population, deaths, death rate per 100000 population, DALY, DALY rate per 100000 population.

The cleaning, testing, and modelling of the data for this paper was done through R (R Core Team 2023) with the aid of the following packages: tidyverse (Wickham et al. 2019), dplyr (Wickham et al. 2023), rstanarm (Goodrich et al. 2020), ggplot2 (Wickham 2016), modelsummary (Arel-Bundock 2022), bayesplot (Gabry and Mahr 2024), parameters (Lüdecke et al. 2020), broom (Robinson, Hayes, and Couch 2023), kableExtra (Zhu 2021), gt (Iannone et al. 2024), readr (Wickham, Hester, and Bryan 2024), broom.mixed (Bolker and Robinson 2022).

## 2.2 Cleaned Data

The data that is needed for this paper is year, cause, and number of deaths, so the raw data is cleaned to contain only the three columns we need. Because we are looking into the top 10 mortality in this paper, we rank the causes based on its number of deaths and merge it into Table 1. Now that the cleaning is done we can see the top 10 causes of deaths for the years 2000, 2010, 2015, and 2019, however, this isn't enough because to make a graph and create a poisson and negative binomial model, we must find the causes that are common in all of the years. Table 2 represents the table in which only the causes that appear among all the years descending order of ranking. Now we can recognize the six main causes of death in South Korea is stroke, Ischaemic Heart Disease, Stomach Cancer, Trachea Bronchus Lung Cancer, Liver Cancer, and Self Harm. Looking at Figure 1, we can see some interesting trends.

For example, there is a plunge in the annual number of deaths from stroke over the 9 year span. On the other hand, there has been increases for the causes of Ischaemic heart disease and Trachea, Bronchus, Lung cancer. There is a slight decrease in stomach cancer while liver cancer didn't fluctuate as much. Self harm is interesting because Korea is known to have the highest suicide rates out of all the OECD countries(Citation), and we see an increase in the number deaths from self harm has increased rapidly from 2000 to 2010 and a small decrease from 2010 to 2015. It seems like the death numbers from self harm has plateaued with a very slow rate of increase. In general, the top 10 most common causes of deaths are stroke, heart disease, stomach cancer, lung cancer, road injury, liver cancer, diabetes, Cirrhosis of the liver(liver damage), and self harm.

Table 1: Top 10 Mortality Rates of South Korea

| Year | Cause | Deaths | Death Rate | Ranking |
|------|-------|--------|------------|---------|
| 2000 | Stroke | 44109 | 93 | 1 |
| 2000 | Ischaemic heart disease | 18837 | 39 | 2 |
| 2000 | Stomach cancer | 13205 | 27 | 3 |
| 2000 | Trachea, bronchus, lung cancers | 12879 | 27 | 4 |
| 2000 | Road injury | 12141 | 25 | 5 |
| 2000 | Liver cancer | 10893 | 22 | 6 |
| 2000 | Diabetes mellitus | 10414 | 21 | 7 |
| 2000 | Cirrhosis of the liver | 9968 | 21 | 8 |
| 2000 | Self-harm | 6860 | 14 | 9 |
| 2000 | Chronic obstructive pulmonary disease | 6783 | 14 | 10 |
| 2010 | Stroke | 31934 | 64 | 1 |
| 2010 | Ischaemic heart disease | 23696 | 47 | 2 |
| 2010 | Trachea, bronchus, lung cancers | 17121 | 34 | 3 |
| 2010 | Self-harm | 16852 | 34 | 4 |
| 2010 | Liver cancer | 12204 | 24 | 5 |
| 2010 | Stomach cancer | 11507 | 23 | 6 |
| 2010 | Diabetes mellitus | 9225 | 18 | 7 |
| 2010 | Lower respiratory infections | 9013 | 18 | 8 |
| 2010 | Colon and rectum cancers | 8886 | 17 | 9 |
| 2010 | Chronic obstructive pulmonary disease | 7904 | 15 | 10 |
| 2015 | Stroke | 28655 | 56 | 1 |
| 2015 | Ischaemic heart disease | 27336 | 53 | 2 |
| 2015 | Trachea, bronchus, lung cancers | 18806 | 37 | 3 |
| 2015 | Lower respiratory infections | 17164 | 33 | 4 |
| 2015 | Self-harm | 14255 | 28 | 5 |
| 2015 | Liver cancer | 12217 | 24 | 6 |
| 2015 | Alzheimer disease and other dementias | 11164 | 21 | 7 |
| 2015 | Stomach cancer | 9534 | 18 | 8 |

| Year | Cause | Deaths | Death Rate | Ranking |
|---|---|---|---|---|
| 2015 | Colon and rectum cancers | 9405 | 18 | 9 |
| 2015 | Kidney diseases | 9188 | 18 | 10 |
| 2019 | Ischaemic heart disease | 28042 | 54 | 1 |
| 2019 | Lower respiratory infections | 26649 | 52 | 2 |
| 2019 | Stroke | 25596 | 49 | 3 |
| 2019 | Trachea, bronchus, lung cancers | 20293 | 39 | 4 |
| 2019 | Self-harm | 14635 | 28 | 5 |
| 2019 | Alzheimer disease and other dementias | 12144 | 23 | 6 |
| 2019 | Liver cancer | 11589 | 22 | 7 |
| 2019 | Colon and rectum cancers | 10180 | 19 | 8 |
| 2019 | Kidney diseases | 10107 | 19 | 9 |
| 2019 | Stomach cancer | 8624 | 16 | 10 |

Table 2: Common Mortality Causes of All Four Years 2000, 2010, 2015, 2019

| Year | Cause | Deaths |
|---|---|---|
| 2000 | Stroke | 44109 |
| 2000 | Ischaemic heart disease | 18837 |
| 2000 | Stomach cancer | 13205 |
| 2000 | Trachea, bronchus, lung cancers | 12879 |
| 2000 | Liver cancer | 10893 |
| 2000 | Self-harm | 6860 |
| 2010 | Stroke | 31934 |
| 2010 | Ischaemic heart disease | 23696 |
| 2010 | Trachea, bronchus, lung cancers | 17121 |
| 2010 | Self-harm | 16852 |
| 2010 | Liver cancer | 12204 |
| 2010 | Stomach cancer | 11507 |
| 2015 | Stroke | 28655 |
| 2015 | Ischaemic heart disease | 27336 |
| 2015 | Trachea, bronchus, lung cancers | 18806 |
| 2015 | Self-harm | 14255 |
| 2015 | Liver cancer | 12217 |
| 2015 | Stomach cancer | 9534 |
| 2019 | Ischaemic heart disease | 28042 |
| 2019 | Stroke | 25596 |
| 2019 | Trachea, bronchus, lung cancers | 20293 |
| 2019 | Self-harm | 14635 |
| 2019 | Liver cancer | 11589 |
| 2019 | Stomach cancer | 8624 |

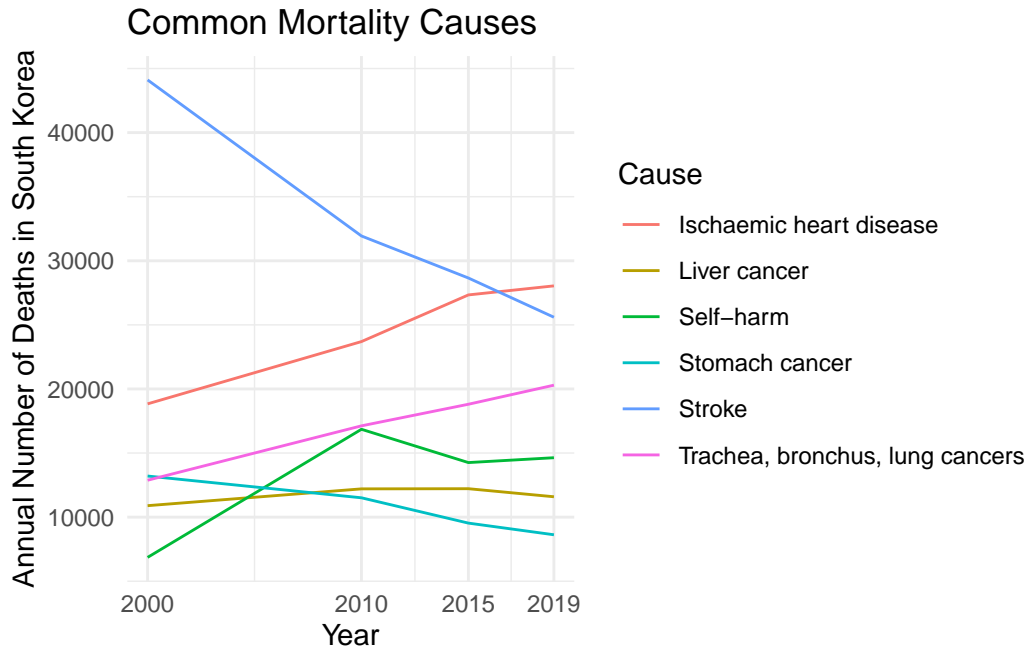| Year | Cause | Deaths |
|------|-------|--------|



Figure 1: Line Graph of Common Mortality Causes of South Korea

## 2.3 Basic Summary Statistics

Table 3 is a representation of the Table 2 showing its minimum, mean, maximum, standard deviation, variance, and sample size. The summary statistics shows that the mean of the number of deaths are 18320, with a minimum of 6860, and a maximum of 44109 for a sample size of 24 as the data selected is from Table 2. The standard deviation and variance may be abnormally high because the range of the data is large, in other words, because the mean is 18320, and the maximum is 44109, there is likely a few outliers in the data creating such a high standard deviation and variance.

Table 3: Summary statistics of the number of yearly deaths, by cause, in South Korea

|        | Min  | Mean   | Max    | SD   | Var        | N  |
|--------|------|--------|--------|------|------------|----|
| Deaths | 6860 | 18 320 | 44 109 | 8927 | 79 687 233 | 24 |

# 3 Model

The goal the Bayesian model is to incorporate prior knowledge such as previous studies or analysis into the choice of model. In this paper we use poisson and negative binomial model because both of these models is often used when there occurs a certain number of events in a certain time period or intervals. The poisson distribution is efficient when used for situations where events occur independently over intervals of time. The data represents the cause and the annual number of death for the selected years, the poisson distribution is a measure that is appropriate. However, the poisson distribution is not the perfect fit because it assumes that the mean and the variance are the same whilst Table 3 shows us there is a significant difference in the mean and standard deviation. Negative binomial distribution is a perfect for situations like this. The negative binomial distribution accounts for additional variability when the data shows evidence of over dispersion. In addition, the negative binomial distribution has an extra parameter that considers the variance being larger than the mean. Thus, executing both models and comparing the results will determine the goodness of the fit.

## 3.1 Model set-up

The two models that are used in this paper are poisson and negative binomial which are both run in R (R Core Team 2023) using the `rstanarm` package of (**rstanarm?**). We use the default priors from `rstanarm`. Both models define $y_i$ as the number of deaths to a specific cause. For the poisson model it is followed by the mean parameter $\gamma_i$. The mean parameter $\gamma_i$ is modeled as an exponential of a linear combination of the intercept $\alpha_i$, regression coefficient $\beta_i$ where $i$ is the predictor, and an extra coefficient $\gamma_i$. All three $\alpha_i$, $\beta_i$, and $\gamma_i$ follows a normal distribution with mean 0 and standard deviation of 2.5 as the prior. The negative Binomial model has a mean parameter $\mu_i$ and a dispersion parameter $\phi$. $\mu_i$ is modeled as the exponential of a lienar combination of an intercept $\alpha_i$, coefficients $\beta_i$ which represents the effects of each cause on the number of deaths, and $\gamma_i$ will account for any extra variability in our scenario. The intercept $\alpha_i$ and coefficient of cause $\beta_i$ follow a normal distribution with mean 0 and a standard deviation of 2.5. The dispersion parameter $\phi$ follows an exponential distribution with a rate parameter of 1. In summary, both poisson and negative binomial models work towards predicting the number of deaths based on the different causes assuming each cause has a coefficient affecting the number of deaths.

$$y_i \sim \text{Poisson}(\lambda_i) \quad (1) \tag{1}$$
$$\lambda_i = \exp(\alpha + \beta_i + \gamma_i) \quad (2) \tag{2}$$
$$\alpha \sim \text{Normal}(0, 2.5) \quad (3) \tag{3}$$
$$\beta_i \sim \text{Normal}(0, 2.5) \quad (4) \tag{4}$$
$$\gamma_i \sim \text{Normal}(0, 2.5) \quad (5) \tag{5}$$
$$\tag{6}$$

$$y_i \sim \text{NegBinomial}(\mu_i, \phi) \quad (1) \tag{7}$$
$$\mu_i = \exp(\alpha + \beta_i + \gamma_i) \quad (2) \tag{8}$$
$$\alpha \sim \text{Normal}(0, 2.5) \quad (3) \tag{9}$$
$$\beta_i \sim \text{Normal}(0, 2.5) \quad (4) \tag{10}$$
$$\gamma_i \sim \text{Normal}(0, 2.5) \quad (5) \tag{11}$$
$$\phi \sim \text{Exponential}(1) \quad (6) \tag{12}$$

## 3.2 Model justification

Applying the information from Table 2, it is difficult to generalize whether there would be a positive or negative correlation between the number of deaths and its cause. This is because every year there is a different number of deaths from the same cause. For example, from Figure 1, we can expect that stroke would have negative correlation coefficient because the annual number of deaths has decreased significantly over the 9 years period. On the other hand, we may predict a positive correlation coefficient for the causes like heart disease and lung cancer as they have been showing an increase trend in the number of deaths since 2000 to 2019. It may be difficult to exactly predict how self harm, liver cancer, and stomach cancer without the actual calculations being done due to the ambiguity the data shows.

# 4 Results

## 4.1 Overview of models

Our results are summarized in Table 4 and Table 5. We are primarily interested how each cause of death correlates to the annual number of deaths in South Korea. The two models provides us with th estimates for the intercept and coefficient for the causes such as liver cancer, self harm, stomach cancer, stroke, and trachea bronchus lung cancer. The intercept represents the expected log count of deaths when the cause variable is zero. However, with our data set,

the cause variable cannot be zero, which makes the interpretation of this quite unclear. The coefficients for the different causes imply the log rate ratio for each cause compared to the reference category. In other words, the coefficient shows the rate at which each cause effects the log count of deaths. Num.Obs represents the number of observations made in the model, Log.lik is the log-likelihood measuring the fitness of the model, where the lower, the better fit it is. ELPD and ELPD s.e. explains the log predictive density and its standard error. LOOIC is an acronym for leave-one-out information criterion which is a measure of model fit. Lower values are better, and the standard error shows the uncertainty of the estimate. WAIC stands for watanabe-akaike information criterion which is another measure of good fit; lower values are better fit. RMSE is the room mean squared error measuring the model's predictive performance where the lower values mean more accurate predicts.

## 4.2 Poisson model results

Table 4 represents the summary of the poisson model. It has an intercept of 10.105 which we can interpret as there will be 10 deaths annually from other factors. Stomach and liver cancer display a strong negative correlation coefficient each -0.826, and -0.736 respectively. Self harm also has a quite strong negative correlation coefficient -0.621. This implies that the model predicts that there will be a decrease in the log count of deaths for these causes, in short, there will be a decrease in the annual number of deaths for causes with a negative correlation coefficient when all else is held the same. Trachea, bronchus, lung(TBL) cancer has a relatively weaker negative coefficient compared to the other causes mentioned above but it is not a negligible number -0.349. Stroke is interesting because from Figure 1, we expected the coefficient to be strongly negative but it turns out to be slightly positive 0.286. For an unknown reason, the model is predicting that there will be an increase in the annual number of deaths from stroke in the near future. The poisson model has a very low log likelihood of -8157.665 implying the model may be a good fit. However, when we look at the values for LOOIC, WAIC, and RMSE, the values are extremely high each 17671.3, 22572.8, and 3830.21 which makes this model results quite unreliable.

## 4.3 Negative binomial model results

Table 4: Poisson model of most prevalent cause of deaths in South Korea 2000, 2010, 2015, 2019

|                | Poisson    |
|----------------|------------|
| Intercept      | 10.105     |
| Liver Cancer   | −0.736     |
| Self Harm      | −0.621     |
| Stomach Cancer | −0.826     |
| Stroke         | 0.286      |
| TBL Cancer     | −0.349     |
| Num.Obs.       | 24         |
| Log.Lik.       | −8157.665  |
| ELPD           | −8835.6    |
| ELPD s.e.      | 2653.7     |
| LOOIC          | 17 671.3   |
| LOOIC s.e.     | 5307.3     |
| WAIC           | 22 572.8   |
| RMSE           | 3830.21    |

Table 5 displays the results of the negative binomial test. Looking into the results, there is one thing different compared to what saw from Table 4. The negative binomial model includes the standard error in parentheses which indicates uncertainty or variability and smaller standard error implies more precision. The intercept is 10.102 with a standard error of 0.190 suggesting the intercept is accurate. Liver cancer, self harm, stomach cancer, and TBL cancer is showing a negative correlation coefficient each of which is -0.726, -0.610, -0.814, and -0.314. Each has a standard error of 0.266, 0.268, 0.276, 0.272. Liver cancer, self harm, and stomach cancer exhibit the strongest negative correlation coefficient in which we can interpret as in the future, there will be a significant decrease in the number of deaths from these causes if all else is equal. TBL cancer show a relatively weaker correlation coefficient which implies that it is likely that there will be a small decrease in the number of deaths in the future. Stroke is the only cause that has a positive correlation coefficient 0.296 with a standard error of 0.274. We can say that there is a high probability that there will be a slight increase in the number of deaths caused by stroke in the future. The log likelihood is -237.44 suggesting the results of this model is accurate. The LOOIC and WAIC are relatively lower than the ones from Table 4 encourages that the negative binomial model is a better fit than the poisson model. Since the RMSE is quite similar, we can think that the negative binomial model is a better fit than the poisson model which makes the results from the negative binomial more accurate.

Table 5: Negative Binomial model of most prevalent cause of deaths in South Korea 2000, 2010, 2015, 2019

|  | Negative Binomial |
|---|---|
| Intercept | 10.102 |
|  | (0.190) |
| Liver Cancer | −0.726 |
|  | (0.266) |
| Self Harm | −0.610 |
|  | (0.268) |
| Stomach Cancer | −0.814 |
|  | (0.276) |
| Stroke | 0.296 |
|  | (0.274) |
| TBL Cancer | −0.341 |
|  | (0.272) |
| Num.Obs. | 24 |
| Log.Lik. | −237.440 |
| ELPD | −240.6 |
| ELPD s.e. | 2.4 |
| LOOIC | 481.2 |
| LOOIC s.e. | 4.8 |
| WAIC | 481.0 |
| RMSE | 3832.16 |

## 4.4 Model results summary

Comparing the values of the two data sets, and the goodness of fit of the models, we can confirm the validity of our model results. Looking at the two values we from each model for each cause, all causes are in very close proximity. Through this we can see that the results from Table 4 and Table 5 are credible. Thus, we can confidently say that liver cancer has a negative correlation coefficient of -0.73, self harm's coefficient is around -0.61, stomach cancer is around -0.82, stroke is around 0.29, lung cancer is around -0.341 all of which have a standard error around 0.27. These results suggest that the model estimates that liver cancer, self harm, stomach cancer, and lung cancer will have a decrease in the log number of deaths while stroke will have an increase in the log number of deaths.

## 4.5 Other model results

Figure 2 is posterior predictive check and Figure 3 is a leave-one-out cross validation. These will be further discussed in Section B.1.
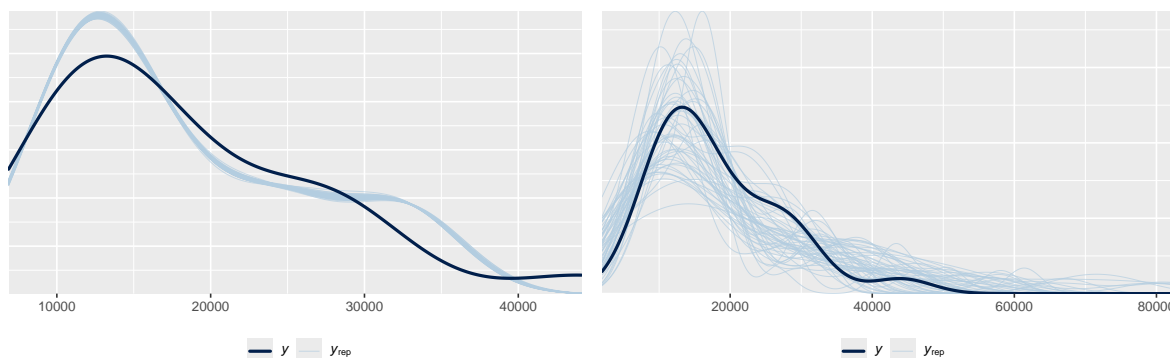


(a) Posterior prediction check   (b) Comparing the posterior with the prior

Figure 2: Examining how the model fits, and is affected by, the data

```
                                        elpd_diff se_diff
cause_of_death_south_korea_neg_binomial      0.0     0.0
cause_of_death_south_korea_poisson       -8595.0  2652.1
```

Figure 3: Checking the convergence of the MCMC algorithm

12

# 5 Discussion

## 5.1 First discussion point

In Figure 1, we have observed that the number of deaths from stroke has decreased while lung cancer and heart disease has increased. In this section we are interested in why these trends may have occurred. Stroke is known to be a brain attack occurring when something blocks the blood supply to the brain or when a blood vessel in the brain bursts. Stroke has been known to be one of the leading causes of deaths in many countries over the past decade. This is because some can fully recover but the median survival after stoke is approximately 5 to 10 years. Over the 9 year period of our data, there has been significant improvements in healthcare, stroke rehabilitation, and advances in the acute stroke treatment globally has led to a remarkable decrease in the mortality from stroke. However, as we see in Section 4.4, the model expects an increase in the number of deaths from stroke, this could so because stroke is also caused due to stress and other unknown factors which is why despite the improvement in technology, it is still a leading factor of mortality globally.

TBL cancer is known to be the second most common cancer globally. Trachea refers to the windpipe and bronchi are the two large tubes that carry air from the trachea to each lungs. TBL cancer refers to any cancer that is caused in these areas of the human body. Smoking is known to be the most important risk factors of lung cancer and thankfully there has been a decrease in the number of smokers over time. This is maybe why the in Section 4.4, the two models expect a decrease in mortality in from TBL cancer. Then why may Figure 1 display an increasing trend. This could be due to the aging population and because of treatment delays. Lung cancer can be cured when found in its early stages, but when found in the later stages, it becomes much more difficult to cure and is likely to lead to death. Such reasons may be why the mortality from lung cancer is one of the highest even within the category of all cancer types not only any mortality causes.

## 5.2 Second discussion point

It is always interesting to look deep into the self harm numbers of South Korea as it is notorious around the world. One of the main reasons this trend occurs is due to the high social pressure from the competitive and success oriented society. We expect that students may have be the leading cause of this high self harm rates, but also it is because of poverty among elderly citizens. While looking at the raw data, we could observe some interesting trends between road injuries and self harm. Figure 4 represents this data and the trend. Initially in 2000, number of deaths from car injuries were twice the number of self harm, but as time passed, self harm exceeded car injuries by more than twice now. While deaths from car injuries has decreased significantly over the 9 years likely thanks to the improvement of technology, health care, and social consciousness. On the other hand, the increase in deaths from self harm is presumably from socio-economical disparities, aging population, and decreases in birth rates.

For some reason, despite the governments effort and policies, it has been possible to decrease deaths from car injuries but not from self harm. This is crucial to mention because the number of deaths from self harm is not high only among a certain gender or age group. It is not just among high school students nor elderly nor men nor female, it is the whole society that is not doing well mentally leading to such painful results. Some methods that can be implemented in decreasing the number of deaths could be by government advertisement on getting therapy. This is because in Korea, people find it difficult to talk and go to therapists and get counselling due to social pressures and negative views towards people going to therapy.
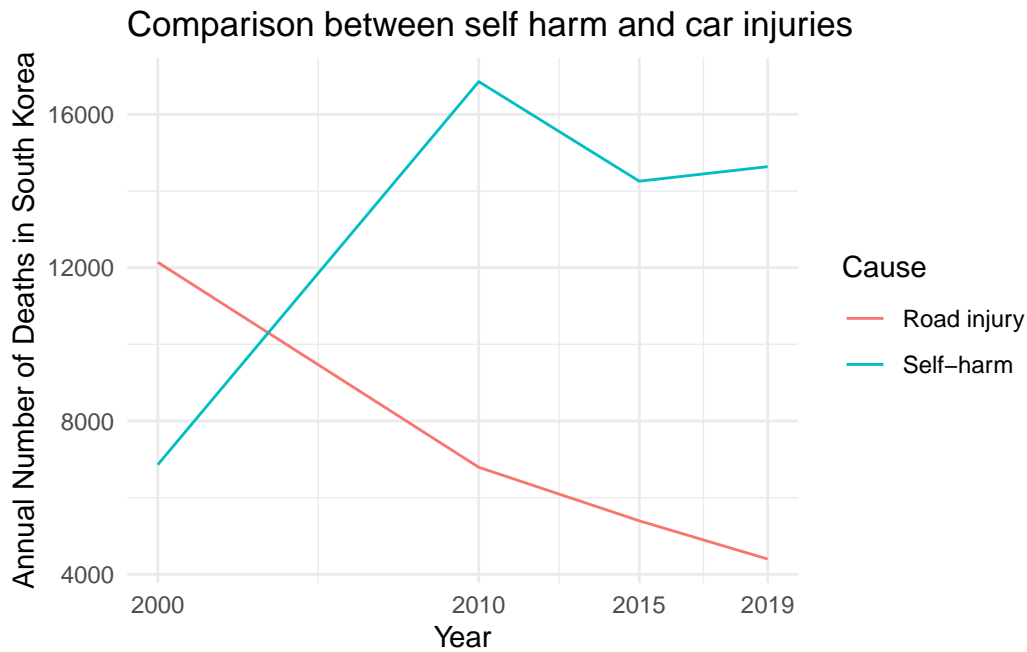


Figure 4: Comparing the sequel of car injuries and self harm numbers

## 5.3 Third discussion point

talk about less common data

## 5.4 Weaknesses and next steps

Weaknesses and next steps should also be included. next step talking about how the relseae of this paper may let people understand and be shocked from the data because normally people don't get to see a graph will lots of the top causes of death plotted over time and thus don't realize it is more serious than what people think and be more aware of their health and surroundings.
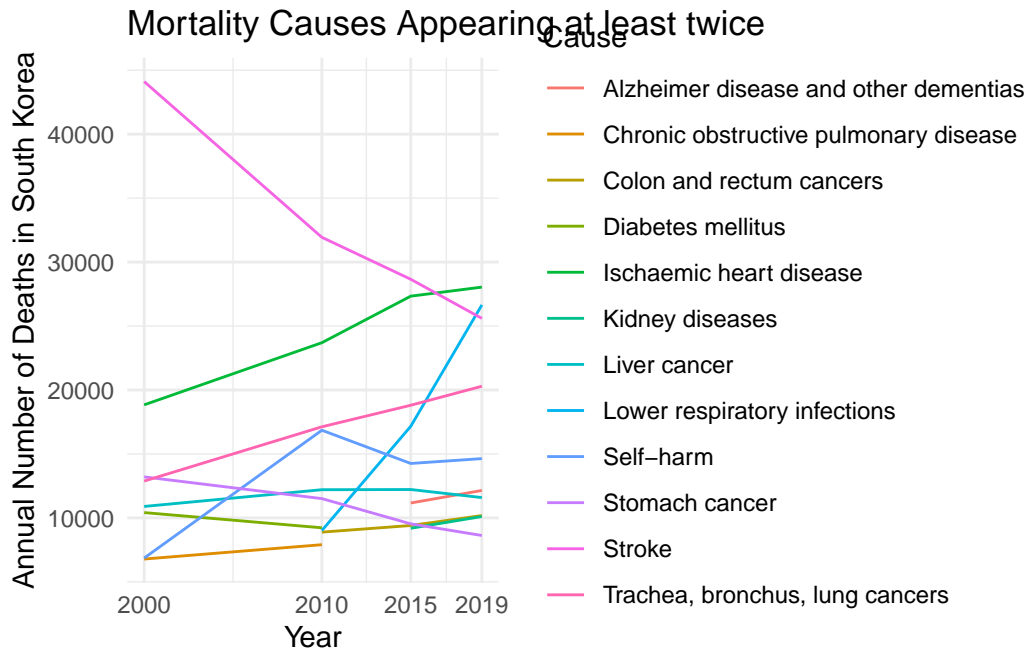
Figure 5: Mortality causes that appear in at least two years

# Appendix

# A  Additional data details

# B  Model details

## B.1  Posterior predictive check

In **?@fig-ppcheckandposteriorvsprior-1** we implement a posterior predictive check. This shows...

In **?@fig-ppcheckandposteriorvsprior-2** we compare the posterior with the prior. This shows...

## B.2  Diagnostics

**?@fig-stanareyouokay-1** is a trace plot. It shows... This suggests...

**?@fig-stanareyouokay-2** is a Rhat plot. It shows... This suggests...

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