

# Assignment 1

```
library(readr)
library(tidyverse)
library(ggplot2)
library(splines)
```

```
cases <- readr::read_tsv("cases.tsv")
population <- readr::read_tsv("population.tsv")
```

```
##   agegroup      year      sex      n
## Length:1908   Min.    :1970 Length:1908   Min.    : 0.00
## Class :character 1st Qu.:1983 Class :character 1st Qu.: 4.00
## Mode  :character Median :1996 Mode  :character Median : 28.00
##                Mean   :1996 Mean   : 96.73
##                3rd Qu.:2009 3rd Qu.:177.25
##                Max.    :2022 Max.    :621.00
```

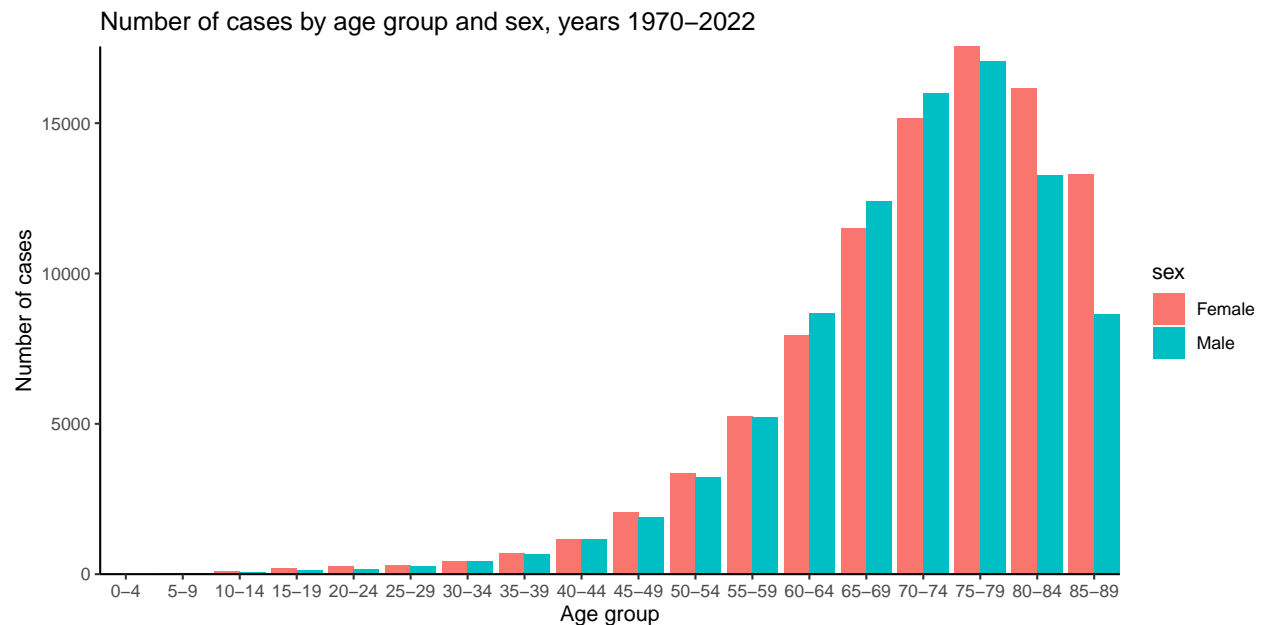
Dataset cases contains the yearly number of cancer cases (variable “n”) by age group (variable “agegroup”) and sex (variable “sex”), with variable “year” ranging from 1970 to 2022. Eighteen different age groups are defined, as:

```
## [1] 0-4 5-9 10-14 15-19 20-24 25-29 30-34 35-39 40-44 45-49 50-54 55-59
## [13] 60-64 65-69 70-74 75-79 80-84 85-89
## 18 Levels: 0-4 5-9 10-14 15-19 20-24 25-29 30-34 35-39 40-44 45-49 ... 85-89
```

Two sex groups are defined, as:

```
## [1] "Male" "Female"
```

## Question 1: plot the number of cases by age group and sex



The plot shows that:

- both for females and males separately, the total number of reported cases registered between 1970 and 2022 increases with age, reaches a peak at age group 75-79 and then decreases with age.

We have variables are below:

AgeGroup

Year

Sex

The number of cases

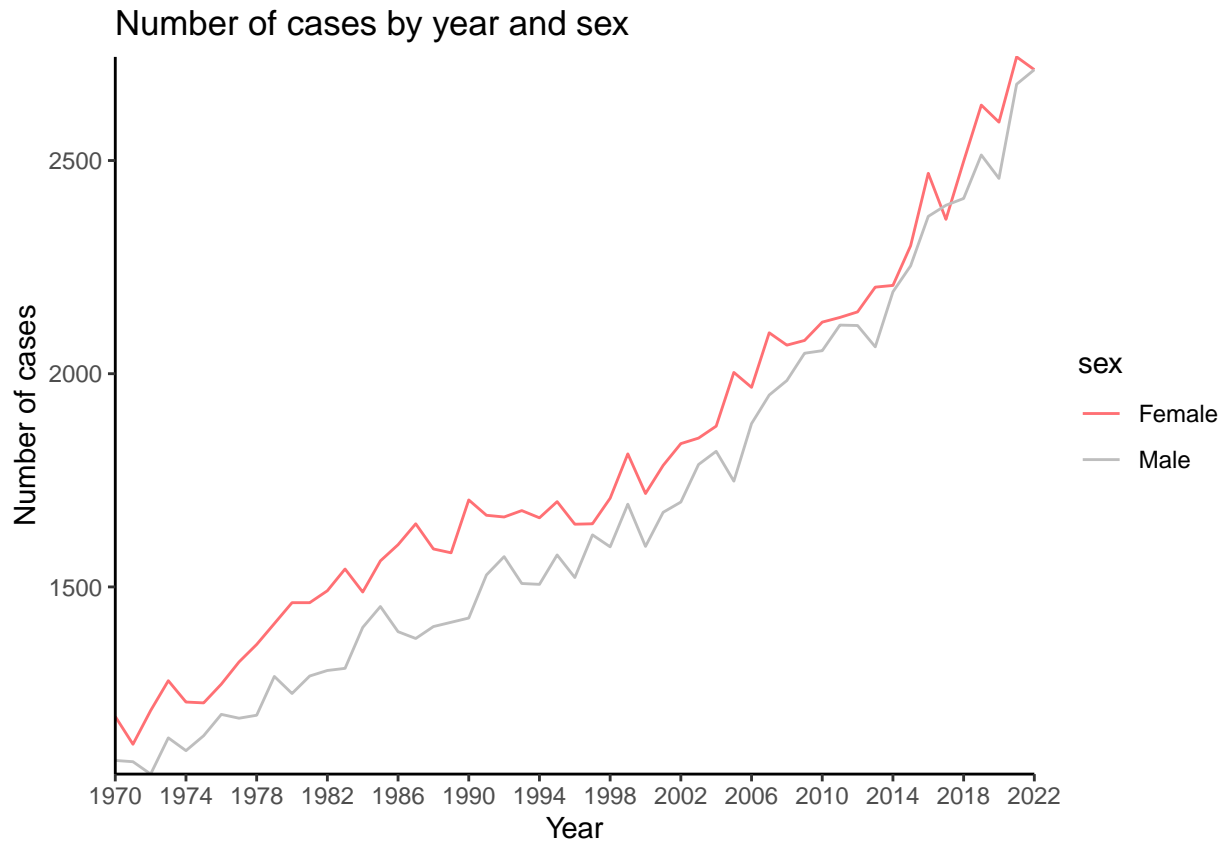
Conclusion : when age increases, the number of cancer cases are increasing too. Colon cancer tends to happen to the old aged group. We can guess age may be positively related to the colon cancer rate. In the plot, the age group 75-79 has the highest number of cases. And the age group over 80, the incidence rate tends to decrease.

## Question 2: total number of cases in each calendar year by males and females.

```
cases %>%
  group_by(year,sex) %>%
  summarize(n = sum(n)) %>%
  ungroup() %>%
  ggplot(aes(x = year, y = n, col = sex)) +
  #geom_point() +
  stat_summary(geom="line")+
  scale_color_manual(values=c("#FF7074",
                             "gray"))+

  theme_classic() +
  coord_cartesian(expand = FALSE) +
  scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4)))+
  # add labels and title
  ggtitle("Number of cases by year and sex") +
```

```
xlab("Year") + ylab("Number of cases")
```

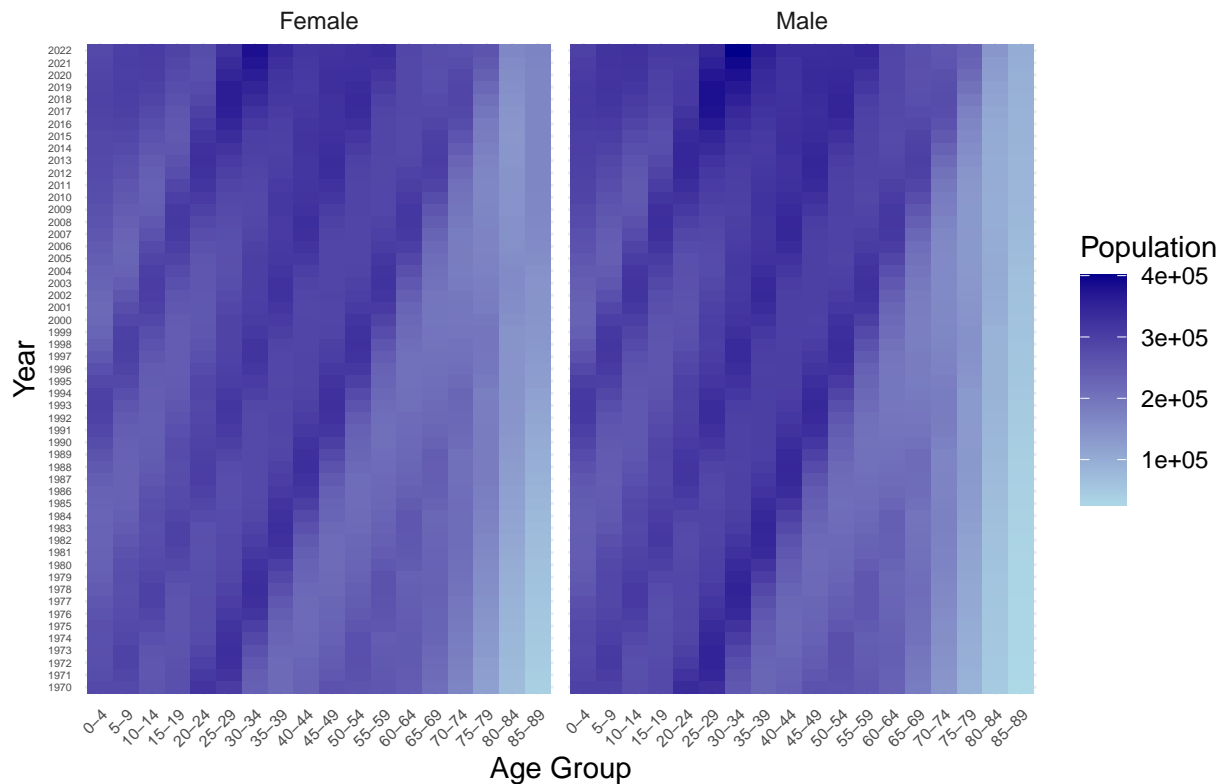


The graphs show an increasing trend in the yearly number of cases, both for females and males. The trend of the total cases of both sexes has continuously increased over the years. The total yearly number of reported cancer cases tends to be lower for males than for females.

### Question 3: population, and plot of population size over age groups and calendar year simultaneously, separately by males and females.

The dataset

#### Population Size by Age Group and Year



```
head(population)
```

```
## # A tibble: 6 x 4
##   agegroup sex    year  n_pop
##   <chr>    <chr> <dbl> <dbl>
## 1 0-4      Male   1970 296143
## 2 5-9      Male   1970 295092
## 3 10-14    Male   1970 272559
## 4 15-19    Male   1970 281997
## 5 20-24    Male   1970 336648
## 6 25-29    Male   1970 329316
```

```
summary(population)
```

```
##   agegroup      sex      year      n_pop
## Length:1908    Length:1908    Min.   :1970    Min.   : 26513
## Class :character Class :character 1st Qu.:1983    1st Qu.:215564
## Mode  :character Mode  :character Median :1996    Median :269226
##                                     Mean  :1996    Mean  :248347
##                                     3rd Qu.:2009    3rd Qu.:299042
##                                     Max.   :2022    Max.   :400939
```

```
# Compare age groups
```

```
all(unique(cases$agegroup) %in% unique(population$agegroup))
```

```
## [1] TRUE
```

```
# Compare calendar years
```

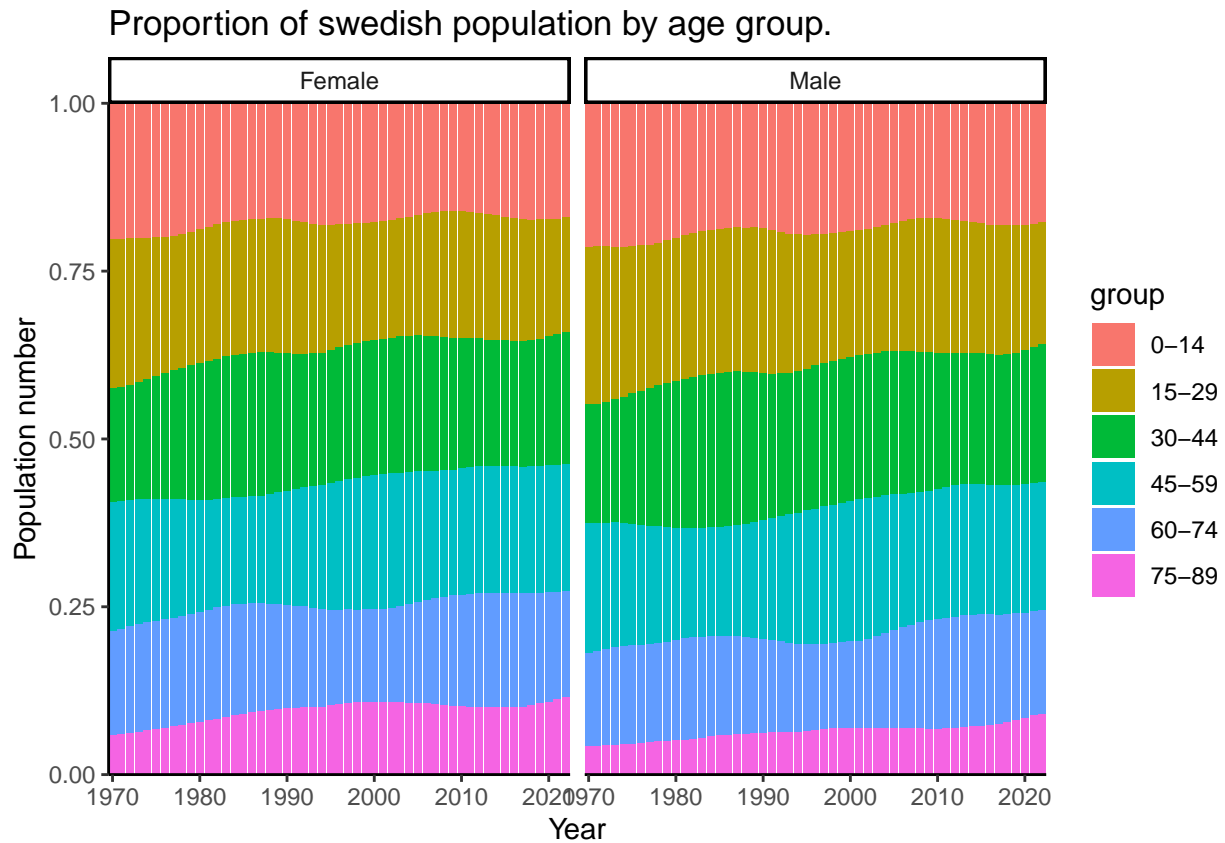
```
all(unique(cases$year) %in% unique(population$year))
```

```
## [1] TRUE
```

Dataset population includes the same age groups and calendar years as dataset cases.

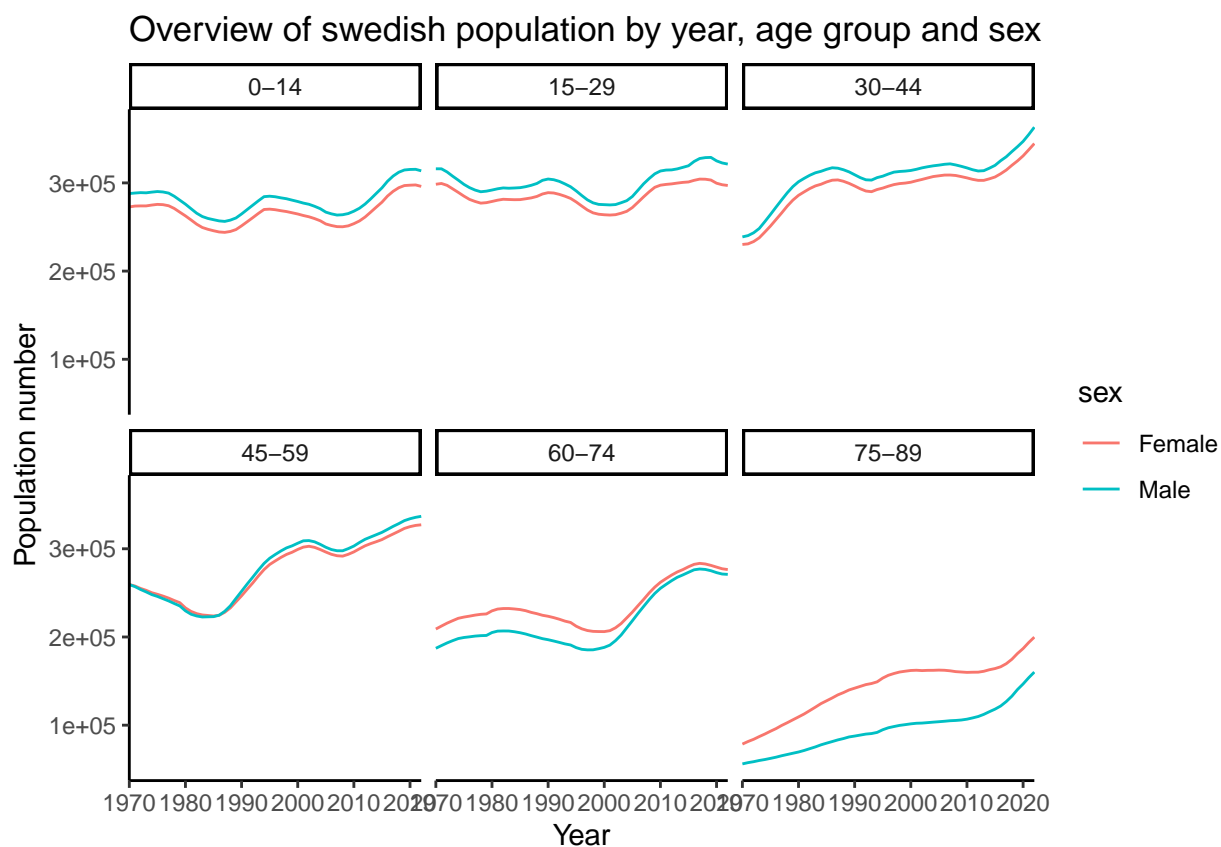
```
population <- population %>% mutate(agegroup = factor(agegroup, levels = factor_groups))
```

```
population %>%  
  mutate(group = case_when(  
    agegroup %in% factor_groups[1:3] ~ "0-14",  
    agegroup %in% factor_groups[4:6] ~ "15-29",  
    agegroup %in% factor_groups[7:9] ~ "30-44",  
    agegroup %in% factor_groups[10:12] ~ "45-59",  
    agegroup %in% factor_groups[13:15] ~ "60-74",  
    agegroup %in% factor_groups[16:18] ~ "75-89",  
    TRUE ~ NA  
  )  
  ) %>%  
  ggplot(aes(x = year, y = n_pop, fill = group)) +  
  facet_wrap(~sex, ncol = 2) +  
  geom_bar(position="fill", stat="identity") +  
  theme_classic() +  
  coord_cartesian(expand = FALSE) +  
  # add labels and title  
  ggtitle("Proportion of swedish population by age group.") +  
  xlab("Year") + ylab("Population number")
```



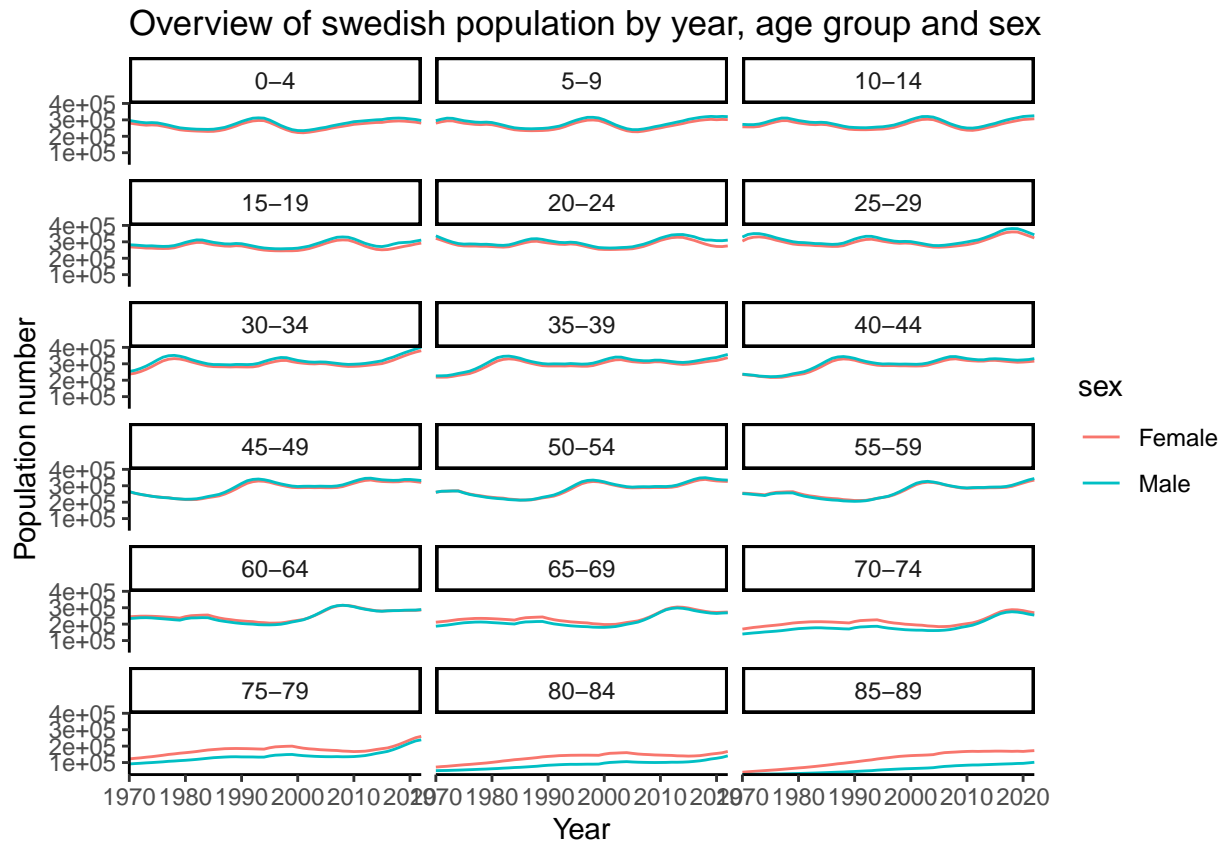
Plot, males and females bigger age groups

```
population %>%
  mutate(group = case_when(
    agegroup %in% factor_groups[1:3] ~ "0-14",
    agegroup %in% factor_groups[4:6] ~ "15-29",
    agegroup %in% factor_groups[7:9] ~ "30-44",
    agegroup %in% factor_groups[10:12] ~ "45-59",
    agegroup %in% factor_groups[13:15] ~ "60-74",
    agegroup %in% factor_groups[16:18] ~ "75-89",
    TRUE ~ NA
  )) %>%
  ggplot(aes(x = year, y = n_pop, color = sex)) +
  facet_wrap(~group, ncol = 3) +
  stat_summary(geom="line")+
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  # add labels and title
  ggtitle("Overview of swedish population by year, age group and sex") +
  xlab("Year") + ylab("Population number")
```



Plot, males and females

```
population %>%
  ggplot(aes(x = year, y = n_pop, color = sex)) +
  facet_wrap(~agegroup, ncol = 3) +
  stat_summary(geom="line")+
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  # add labels and title
  ggtitle("Overview of swedish population by year, age group and sex") +
  xlab("Year") + ylab("Population number")
```



Yes, the two datasets have the same age group and calendar years.

## Question 4: merge the datasets

merged dataframe, with age

```
# merging datasets
cases_pop <- cases %>% left_join(population)

## check
# cases %>% nrow() == cases_pop %>% nrow()
# population %>% nrow() == cases_pop %>% nrow()
cases_pop %>% head()
```

```
## # A tibble: 6 x 5
##   agegroup year sex      n  n_pop
##   <fct>    <dbl> <chr> <dbl> <dbl>
## 1 0-4      2022 Male     0 296183
## 2 5-9      2022 Male     0 319820
## 3 10-14    2022 Male     1 325003
## 4 15-19    2022 Male     8 310539
## 5 20-24    2022 Male     5 310354
## 6 25-29    2022 Male     4 342974
```



Cases and population datasets summarized. Will be merged in question 5

```
# cases by year and sex
cases_ys <- cases %>%
  group_by(year, sex) %>%
  summarize(n = sum(n)) %>%
  ungroup()

# population by year and sex
population_ys <- population %>%
  group_by(year, sex) %>%
  summarize(n_pop = sum(n_pop)) %>%
  ungroup()
```

### Question 5: Incidence rate

```
# rate per hundred thousand population, dataset with age
cases_pop <- cases_pop %>%
  # rate per 105 population
  mutate(rate = 105 * n/n_pop)

# rate per ten thousand population, dataset without age
# create dataset without age variable
cases_pop_ys <- cases_ys %>%
  left_join(population_ys) %>%
  # rate per 104 population
  mutate(rate = 104 * n/n_pop)
```

Interpretation:

Definition of incidence rate: “for a specific follow-up period, the number of new cases of the outcome divided by the total person-time at risk” (Adina Feldman, Lecture 2). In our case, for each period of one year, the number of new cases of cancer in that year, divided by the total person-time (1 year times population in that year).

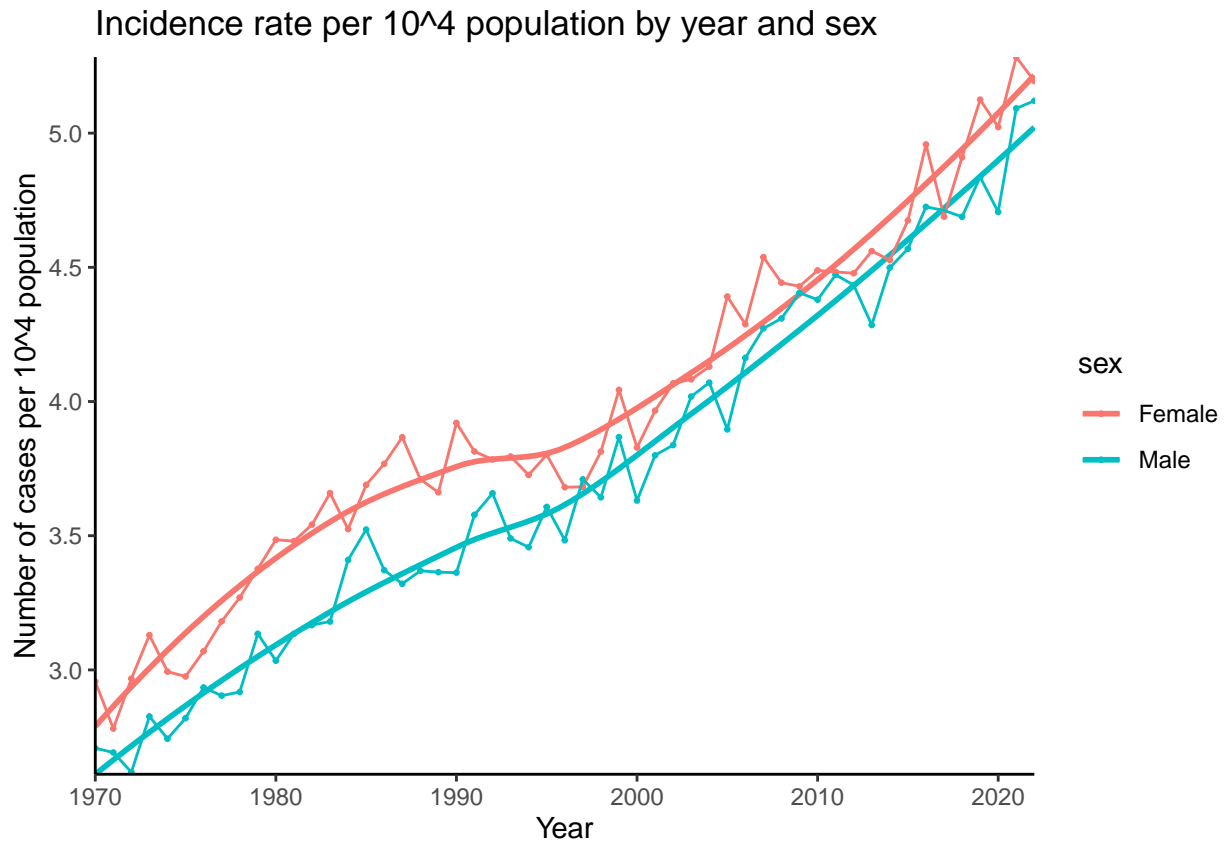
In this question, the definition of the incident rate = (total cases /total population) 100. (In the previous plots (total cases/total population) 10<sup>4</sup>) Yes, it’s a standard way to calculate the incidence rate, but it doesn’t not consider the age distribution since colon cancer risk varies by age.

**Question 6: Plot the incidence rate of colon cancer over calendar time and apply a smoother, separately by males and females (here you can use the incidence rate based on the total number of cases and the total population size). Describe what you can conclude from the graphs. Create a graph of incidence rates over calendar year by sex and age group, and apply smoothers, what can you conclude**

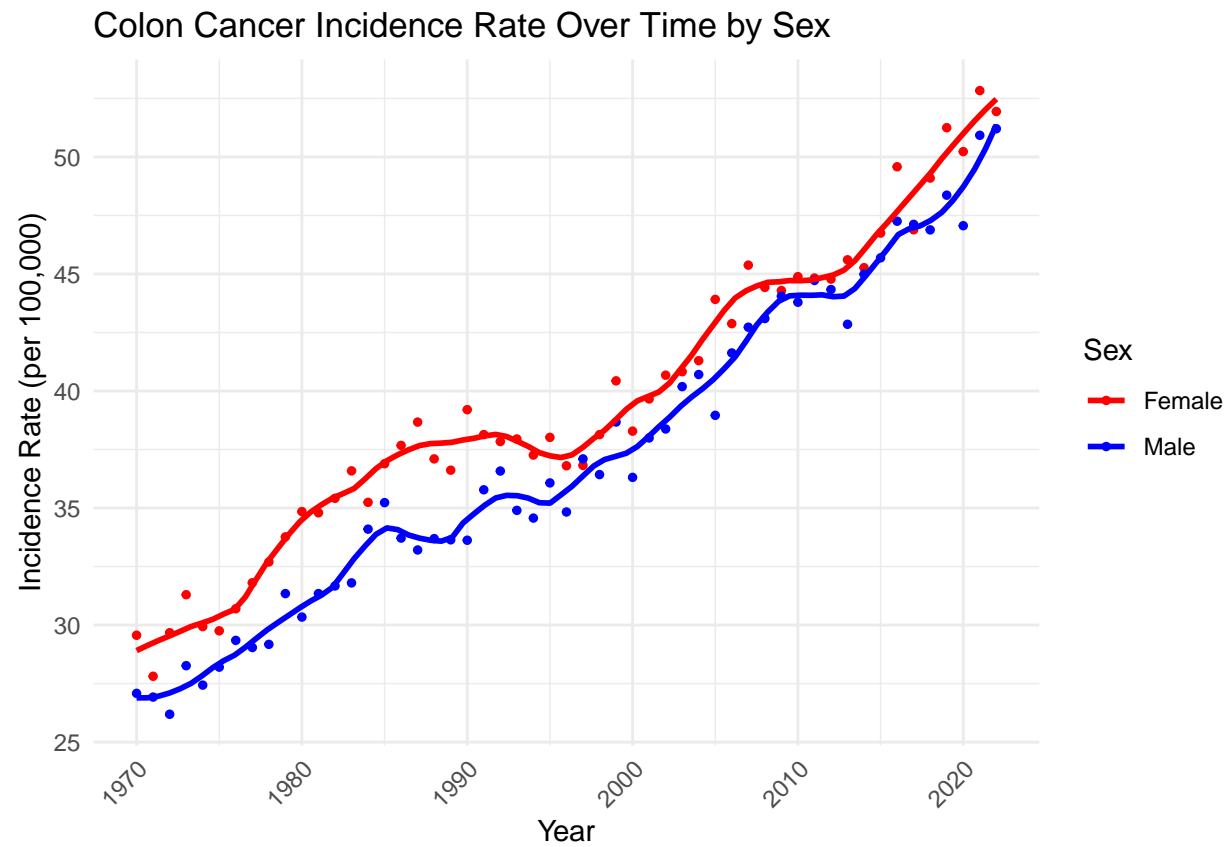
Summarized model

```
cases_pop_ys %>%
  ggplot(aes(x = year, y = rate, color = sex)) +
  # smooth the curve
  geom_smooth(se= FALSE) +
  # non smoothed data
```

```
geom_point(size = 0.5) +
stat_summary(geom="line") +
theme_classic() +
coord_cartesian(expand = FALSE) +
#scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
# add labels and title
ggtitle("Incidence rate per 10^4 population by year and sex") +
xlab("Year") + ylab("Number of cases per 10^4 population")
```



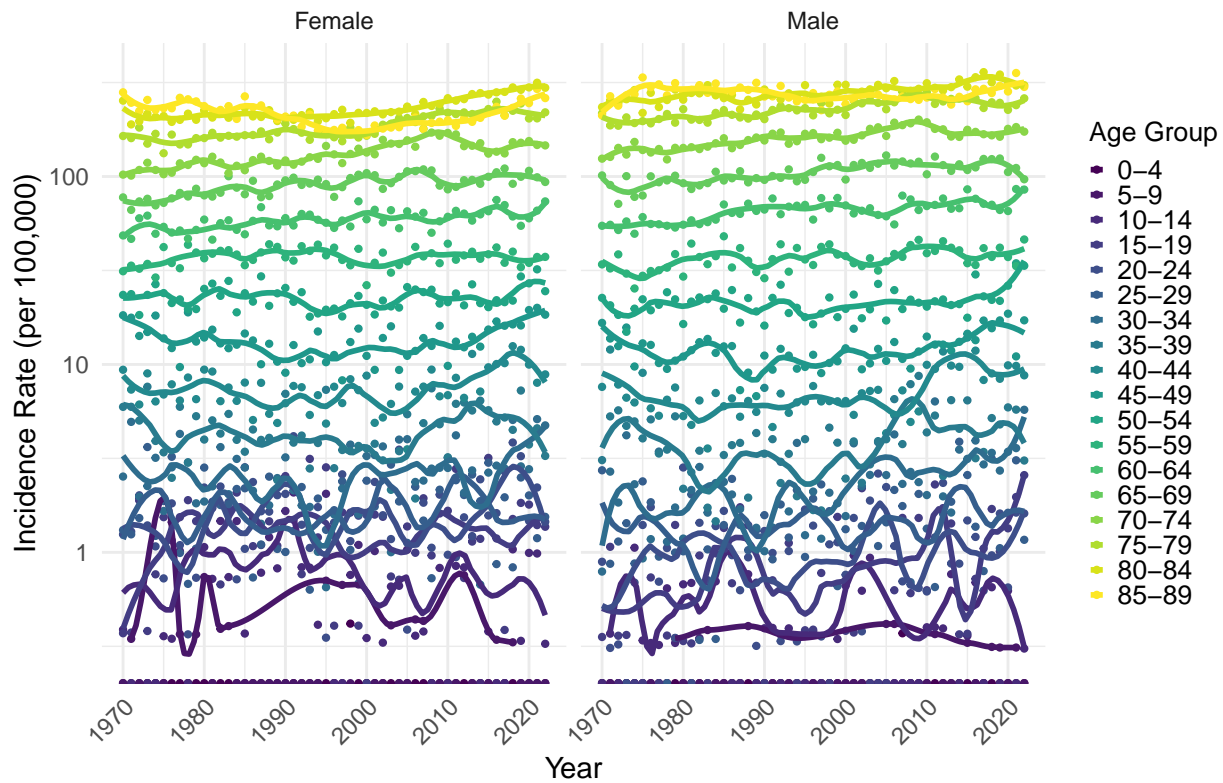
When I normalize by population size, I see that the incidence rate per ten thousand population shows an increasing trend in time, both for females and for males separately.



Yearly count per ten thousand population is lower for males than for females.\

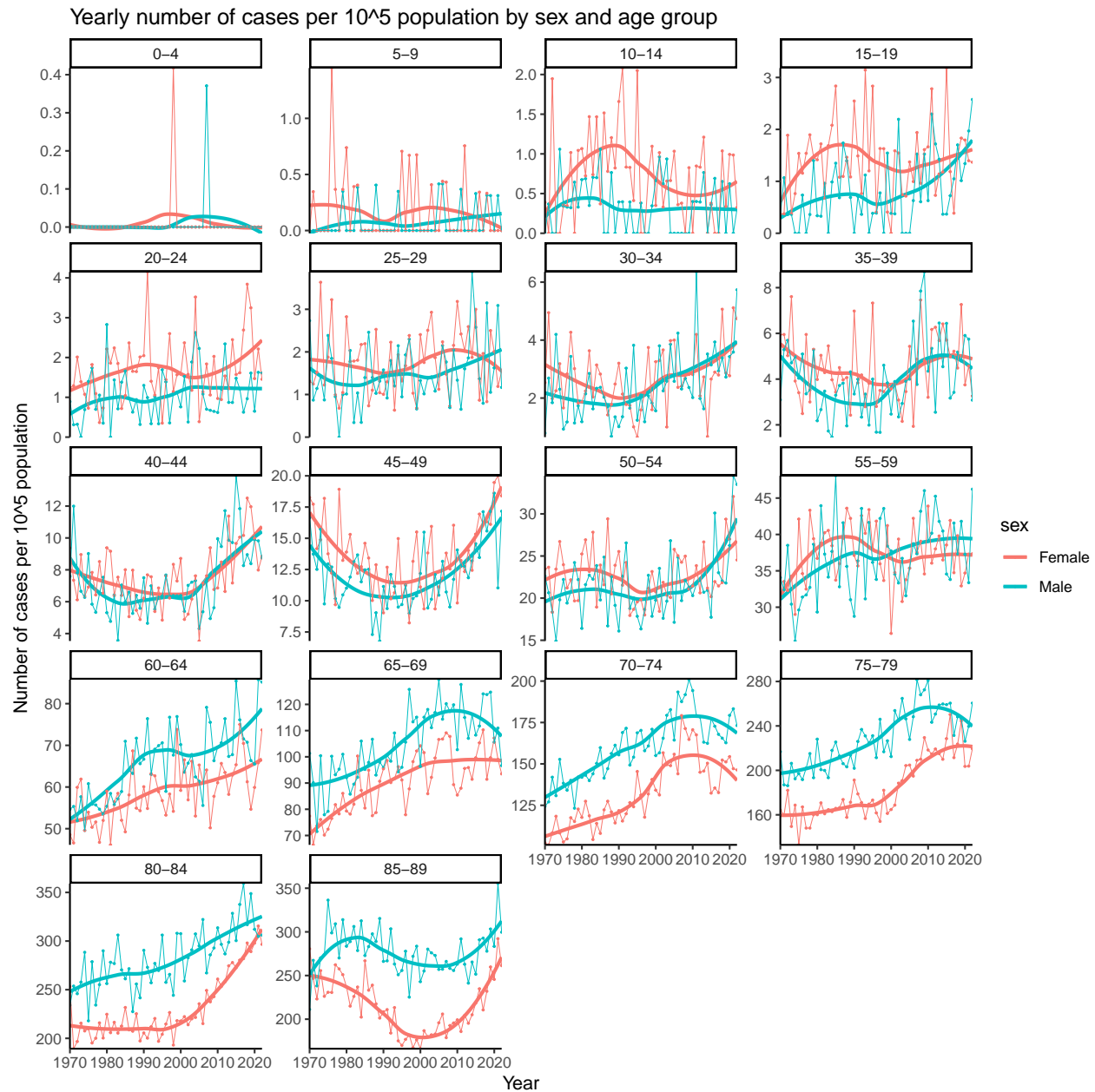
Age

## Colon Cancer Incidence Rate by Sex and Age Group Over Time



Facet plot with age groups, y scale free

```
cases_pop %>%
  ggplot(aes(x = year, y = rate, color = sex)) +
  facet_wrap(~ agegroup, ncol = 4, scales = "free_y") +
  # smooth the curve
  geom_smooth(se = FALSE) +
  # non smoothed data
  geom_point(size = 0.2) +
  stat_summary(geom="line", size = 0.05) +
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  #scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
  # add labels and title
  ggtitle(paste("Yearly number of cases per 10^5 population by sex and age group")) +
  xlab("Year") + ylab("Number of cases per 10^5 population")
```



- Comparing different ages, trends for age-specific incidence rates are different for different ages.
- Comparing females and males, while the crude incidence rate values tend to be higher for females than for males, the age-specific incidence rates have a tendency to be higher for females than for males, when age groups are s.t. age  $< 55$ . They tend to be lower for females than for males when age groups are s.t. age  $\geq 60$  years.

See different age structures in population for males and females: <https://www.healthknowledge.org.uk/e-learning/epidemiology/specialists/standardisation>

The incidence rate of colon cancer has steadily increased over calendar time for both males and females. Females consistently have a higher incidence rate of colon cancer compared to males throughout the period.

## Question 7: Poisson model

```
poisson_model <- cases_pop_ys %>%  
  glm(formula = n ~ year + sex + offset(log(n_pop)), family = "poisson")  
summary(poisson_model)
```

```
##  
## Call:  
## glm(formula = n ~ year + sex + offset(log(n_pop)), family = "poisson",  
##      data = .)  
##  
## Coefficients:  
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept) -2.969e+01  3.071e-01  -96.68  <2e-16 ***  
## year         1.094e-02  1.536e-04   71.25  <2e-16 ***  
## sexMale      -5.592e-02  4.658e-03  -12.01  <2e-16 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## (Dispersion parameter for poisson family taken to be 1)  
##  
##      Null deviance: 5505.07  on 105  degrees of freedom  
## Residual deviance:  222.81  on 103  degrees of freedom  
## AIC: 1211.4  
##  
## Number of Fisher Scoring iterations: 3  
  
 $\log(n/n\_pop) = -29.69415 + 0.01094 * year - 0.05592 * \delta_f(sex)$  with  $\delta_f(sex = "Female") = 0$ ,  
 $\delta_f(sex = "Male") = 1$ , since sex = “Male” was taken as a reference by the gml() function.
```

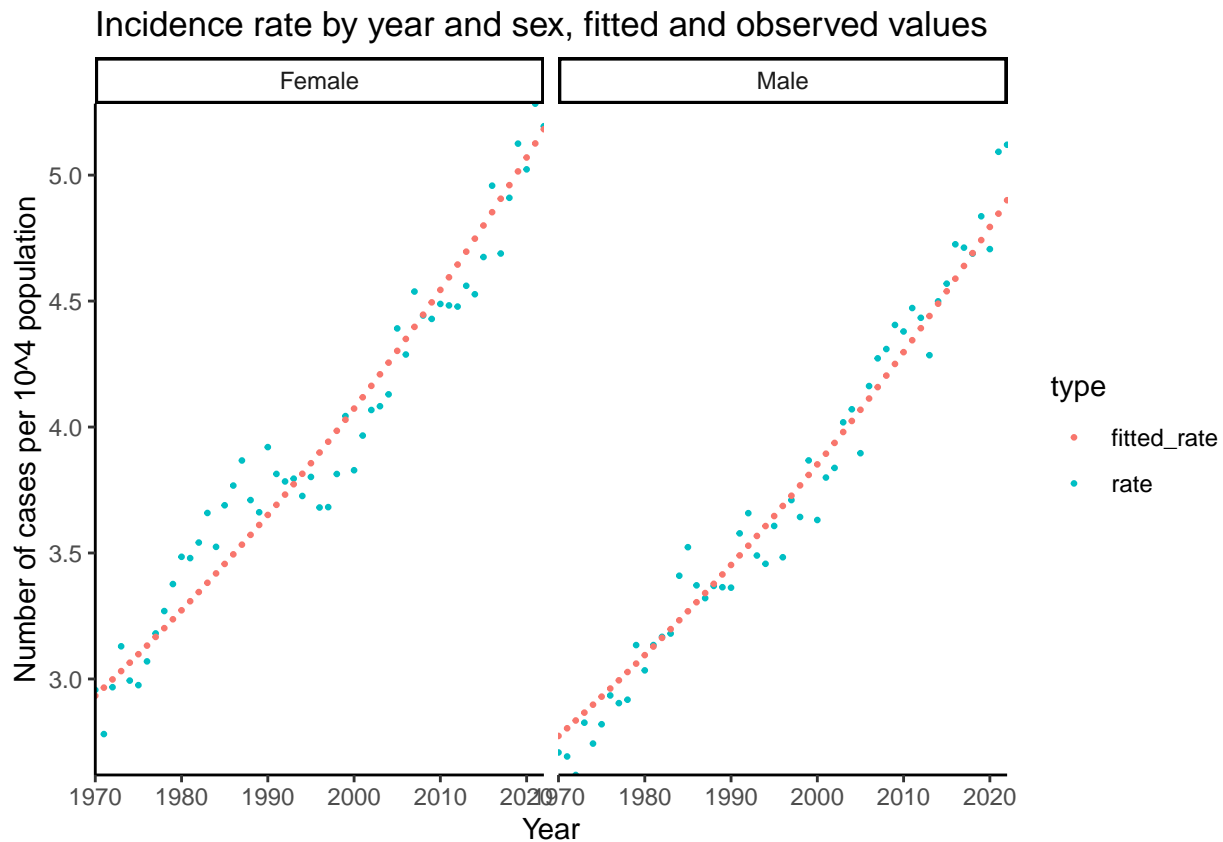
The Poisson model estimates the total number of cases as the dependent variable, using population size as an offset and calendar year and sex as independent variables.

The estimated intercept is -29.69, representing the baseline log-incidence rate when the year is 0 and the reference category for sex (likely Female). The coefficient for the variable year is 0.01094 ( $p < 0.001$ ), indicating a 1.1% annual increase in the incidence rate ( $(e^{(0.01094)} - 1) * 100$ ), holding sex constant. The coefficient for sex (Male) is -0.05592 ( $p < 0.001$ ), implying a 5.6% lower incidence rate for males compared to females, holding year constant.

$(e^{(0.01094)} - 1) * 100$  in dataset used for the regression, factor 100 is  $10^4$  instead

```
topplot <- cases_pop_ys %>%  
  add_column(fitted = poisson_model$fitted.values) %>%  
  mutate(fitted_rate = 10^4 * fitted/n_pop)  
  
topplot %>%  
  pivot_longer(cols = c(rate, fitted_rate), names_to = "type") %>%  
  ggplot(aes(x = year, y = value)) +  
  geom_point(aes(color = type), size = 0.5) +  
  facet_wrap(~sex, ncol = 2) +  
  theme_classic() +  
  coord_cartesian(expand = FALSE) +  
  #scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +  
  # add labels and title
```

```
ggtitle("Incidence rate by year and sex, fitted and observed values") +
xlab("Year") + ylab("Number of cases per 10^4 population")
```



### Question 8:

```
# Extract model coefficients
coefficients <- coef(poisson_model)
intercept <- coefficients["(Intercept)"]
year_coeff <- coefficients["year"]
sex_coeff <- coefficients["sexMale"]

# Calculate log incidence rate and incidence rate for 1970 and 2020
incidence_1970_male <- exp(intercept + year_coeff * 1970 + sex_coeff)
incidence_1970_female <- exp(intercept + year_coeff * 1970 )
incidence_2020_male <- exp(intercept + year_coeff * 2020 + sex_coeff)
incidence_2020_female <- exp(intercept + year_coeff * 2020)

# Print results
incidence_1970_male
```

```
## (Intercept)
## 0.0002773751
```

```
incidence_1970_female
```

```
## (Intercept)
## 0.0002933271
```

```
incidence_2020_male
```

```
## (Intercept)  
## 0.0004794199
```

```
incidence_2020_female
```

```
## (Intercept)  
## 0.0005069918
```

Based on the model output, the estimated incidence rates in 1970 are 0.0002933 for females and 0.0002774 for males. In 2020, the incidence rates are 0.0005070 for females and 0.0004794 for males.

### 3. Assumptions made regarding how the incidence rate changes over calendar years and difference between males and females

- Rates for males and females have the same time dependence, and differ just by a constant term (multiplicative).
- Repeat with mixing year\*sex
- The model assumes that the log-incidence rate changes linearly with the calendar year, leading to an annual incidence rate increase of 1.1%  $((e^{(0.01094)} - 1) * 100)$ .  $//10^4$  in the dataset used here

The key assumptions made in this model:

- A linear relationship between year and log-incidence rate:  $\log(\ ) = \_0 + \_1(\text{year}) + \_2(\text{sex})$
- A constant difference between males and females:  $\_2 = -0.0559$ , males have 5.5% lower incidence rates than females
- No interactions among year, sex, age group.
- Accurate population size as an offset: the population size is accurately measured and representative of the population at risk for both sexes and years.
- Poisson distribution of the dependent variable: the variance in the number of cases increases with the expected number of cases.
- A constant difference in  $\log(\ )$  between males and females:  $\_2 = -0.0559$ , males have 5.5% lower incidence rates than females  $((\mu_{\text{males}} - \mu_{\text{females}}) / \mu_{\text{females}} = \exp(-0.0559) - 1 = -0.054)$

## Question 9

```
poisson_model_age <- cases_pop %>%  
  mutate(agegroup = factor(agegroup, levels = factor_groups)) %>%  
  glm(formula = n ~ year*sex + year*agegroup + agegroup * sex + offset(log(n_pop)), family = "poisson")  
  
# View the summary of the model  
summary(poisson_model_age)
```

```
##  
## Call:  
## glm(formula = n ~ year * sex + year * agegroup + agegroup * sex +  
##      offset(log(n_pop)), family = "poisson", data = .)  
##  
## Coefficients:  
##  
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept)    -6.879e+01  9.627e+01  -0.715   0.4749
```



## year	2.618e-02	4.807e-02	0.545	0.5860
## sexMale	1.086e+00	1.545e+00	0.703	0.4819
## agegroup5-9	5.897e+01	9.865e+01	0.598	0.5500
## agegroup10-14	7.020e+01	9.684e+01	0.725	0.4685
## agegroup15-19	3.521e+01	9.654e+01	0.365	0.7153
## agegroup20-24	4.121e+01	9.648e+01	0.427	0.6693
## agegroup25-29	4.711e+01	9.643e+01	0.489	0.6252
## agegroup30-34	3.562e+01	9.637e+01	0.370	0.7117
## agegroup35-39	4.877e+01	9.634e+01	0.506	0.6127
## agegroup40-44	4.329e+01	9.631e+01	0.449	0.6531
## agegroup45-49	5.194e+01	9.629e+01	0.539	0.5897
## agegroup50-54	5.354e+01	9.628e+01	0.556	0.5782
## agegroup55-59	5.598e+01	9.628e+01	0.581	0.5609
## agegroup60-64	4.976e+01	9.628e+01	0.517	0.6053
## agegroup65-69	4.985e+01	9.627e+01	0.518	0.6046
## agegroup70-74	4.853e+01	9.627e+01	0.504	0.6142
## agegroup75-79	4.823e+01	9.627e+01	0.501	0.6164
## agegroup80-84	4.867e+01	9.627e+01	0.505	0.6132
## agegroup85-89	6.130e+01	9.627e+01	0.637	0.5243
## year:sexMale	-5.696e-04	3.104e-04	-1.835	0.0665
## year:agegroup5-9	-2.792e-02	4.927e-02	-0.567	0.5710
## year:agegroup10-14	-3.283e-02	4.836e-02	-0.679	0.4972
## year:agegroup15-19	-1.496e-02	4.821e-02	-0.310	0.7563
## year:agegroup20-24	-1.788e-02	4.818e-02	-0.371	0.7106
## year:agegroup25-29	-2.080e-02	4.815e-02	-0.432	0.6658
## year:agegroup30-34	-1.484e-02	4.812e-02	-0.308	0.7578
## year:agegroup35-39	-2.117e-02	4.811e-02	-0.440	0.6599
## year:agegroup40-44	-1.816e-02	4.809e-02	-0.378	0.7056
## year:agegroup45-49	-2.220e-02	4.808e-02	-0.462	0.6443
## year:agegroup50-54	-2.274e-02	4.808e-02	-0.473	0.6362
## year:agegroup55-59	-2.372e-02	4.808e-02	-0.493	0.6217
## year:agegroup60-64	-2.037e-02	4.807e-02	-0.424	0.6717
## year:agegroup65-69	-2.020e-02	4.807e-02	-0.420	0.6743
## year:agegroup70-74	-1.935e-02	4.807e-02	-0.403	0.6873
## year:agegroup75-79	-1.904e-02	4.807e-02	-0.396	0.6921
## year:agegroup80-84	-1.914e-02	4.807e-02	-0.398	0.6905
## year:agegroup85-89	-2.552e-02	4.807e-02	-0.531	0.5956
## sexMale:agegroup5-9	-7.823e-01	1.460e+00	-0.536	0.5921
## sexMale:agegroup10-14	-6.568e-01	1.424e+00	-0.461	0.6447
## sexMale:agegroup15-19	-4.856e-01	1.419e+00	-0.342	0.7322
## sexMale:agegroup20-24	-4.125e-01	1.418e+00	-0.291	0.7711
## sexMale:agegroup25-29	-1.100e-01	1.417e+00	-0.078	0.9381
## sexMale:agegroup30-34	-3.506e-02	1.416e+00	-0.025	0.9802
## sexMale:agegroup35-39	-7.101e-02	1.415e+00	-0.050	0.9600
## sexMale:agegroup40-44	1.914e-02	1.415e+00	0.014	0.9892
## sexMale:agegroup45-49	-5.963e-02	1.415e+00	-0.042	0.9664
## sexMale:agegroup50-54	-4.559e-04	1.414e+00	0.000	0.9997
## sexMale:agegroup55-59	4.903e-02	1.414e+00	0.035	0.9723
## sexMale:agegroup60-64	1.673e-01	1.414e+00	0.118	0.9058
## sexMale:agegroup65-69	1.981e-01	1.414e+00	0.140	0.8886
## sexMale:agegroup70-74	2.426e-01	1.414e+00	0.172	0.8638
## sexMale:agegroup75-79	2.643e-01	1.414e+00	0.187	0.8517
## sexMale:agegroup80-84	2.516e-01	1.414e+00	0.178	0.8588
## sexMale:agegroup85-89	3.263e-01	1.414e+00	0.231	0.8175

```

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 406971.1  on 1907  degrees of freedom
## Residual deviance:   2749.5   on 1853  degrees of freedom
## AIC: 11967
##
## Number of Fisher Scoring iterations: 6

# Extract model coefficients
coefficients <- coef(poisson_model_age)

# males
rate_1970_male <- exp(
  #intercept
  coefficients["(Intercept)"] +
  #year
  coefficients["year"] * 1970 +
  #male
  coefficients["sexMale"] * 1 +
  #age 70-74
  coefficients["agegroup70-74"] * 1 +
  # year*sex
  coefficients["year:sexMale"] * 1970 * 1 +
  # year*age 70-74
  coefficients["year:agegroup70-74"] * 1970 * 1 +
  # sex*age 70-74
  coefficients["sexMale:agegroup70-74"] * 1 * 1)

rate_1970_female <- exp(
  #intercept
  coefficients["(Intercept)"] +
  #year
  coefficients["year"] * 1970 +
  #female
  coefficients["sexMale"] * 0 +
  #age 70-74
  coefficients["agegroup70-74"] * 1 +
  # year*sex
  coefficients["year:sexMale"] * 1970 * 0 +
  # year*age 70-74
  coefficients["year:agegroup70-74"] * 1970 * 1 +
  # sex*age 70-74
  coefficients["sexMale:agegroup70-74"] * 0 * 1)

rate_2020_male <- exp(
  #intercept
  coefficients["(Intercept)"] +
  #year
  coefficients["year"] * 2020 +
  #male
  coefficients["sexMale"] * 1 +

```

```

#age 70-74
coefficients["agegroup70-74"] * 1 +
# year*sex
coefficients["year:sexMale"] * 2020 * 1 +
# year*age 70-74
coefficients["year:agegroup70-74"] * 2020 * 1 +
# sex*age 70-74
coefficients["sexMale:agegroup70-74"] * 1 * 1)

rate_2020_female <- exp(
  #intercept
  coefficients["(Intercept)"] +
  #year
  coefficients["year"] * 2020 +
  #female
  coefficients["sexMale"] * 0 +
  #age 70-74
  coefficients["agegroup70-74"] * 1 +
  # year*sex
  coefficients["year:sexMale"] * 2020 * 0 +
  # year*age 70-74
  coefficients["year:agegroup70-74"] * 2020 * 1 +
  # sex*age 70-74
  coefficients["sexMale:agegroup70-74"] * 0 * 1)

```

```
rate_1970_male
```

```
## (Intercept)
## 0.001349865
```

```
rate_1970_female
```

```
## (Intercept)
## 0.001097564
```

```
rate_2020_male
```

```
## (Intercept)
## 0.001845669
```

```
rate_2020_female
```

```
## (Intercept)
## 0.001544049
```

Colon cancer is more common in older age groups, and the age distribution has shifted over time. To better estimate incidence rates, we refit the Poisson model by including interaction terms: “year \* sex,” “year \* age group,” and “sex \* age group.”

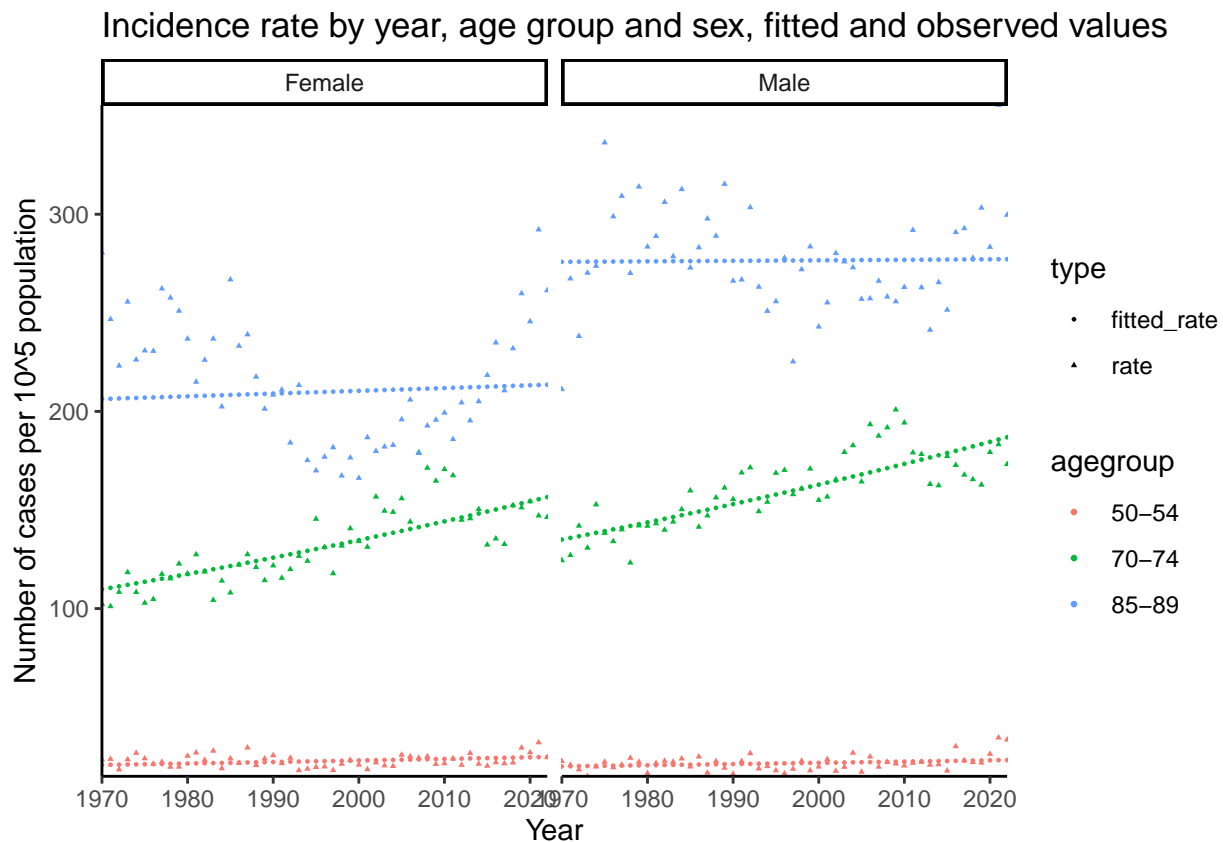
Based on the updated model output, the estimated incidence rates in 1970 for the 70-74 age group are 0.001350 for males and 0.001098 for females. In 2020, the incidence rates for the same age group are 0.001846 for males and 0.001544 for females.

- For 70-74 age group, the estimated incidence rates for females are lower than the estimated incidence rates for males

## Plot of the fit

```
topplot <- cases_pop %>%
  add_column(fitted = poisson_model_age$fitted.values) %>%
  mutate(fitted_rate = 10^5 * fitted/n_pop)

topplot %>%
  pivot_longer(cols = c(rate, fitted_rate), names_to = "type") %>%
  filter(agegroup %in% c("50-54", "70-74", "85-89")) %>%
  ggplot(aes(x = year, y = value, color = agegroup)) +
  geom_point(aes(shape = type), size = 0.5) +
  facet_wrap(~sex, ncol = 2) +
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  #scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
  # add labels and title
  ggtitle("Incidence rate by year, age group and sex, fitted and observed values") +
  xlab("Year") + ylab("Number of cases per 10^5 population")
```



## Question 10

```
# Merge cases and population data frames
merged_data <- merge(cases, population, by = c("agegroup", "sex", "year"))
print(head(merged_data, n=5))
```

```
##   agegroup    sex year  n  n_pop
```

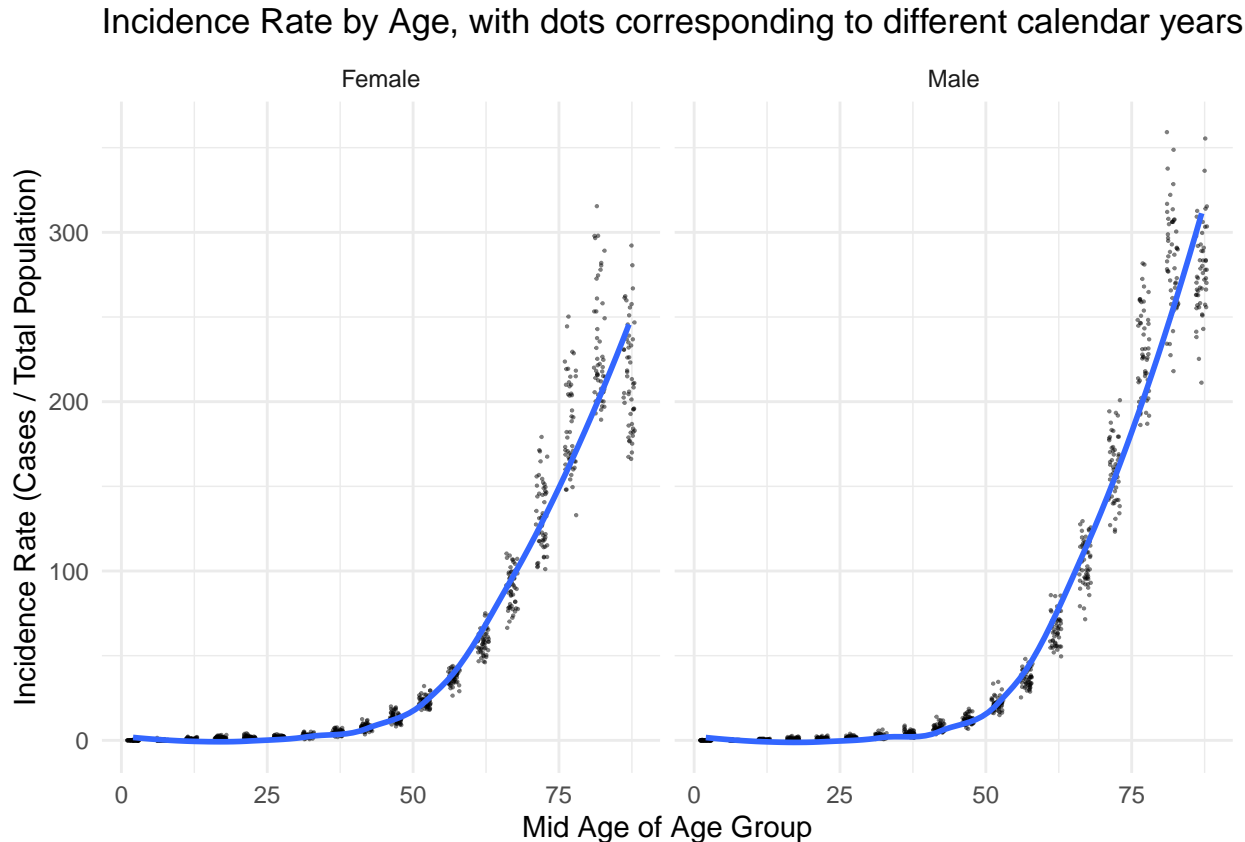
```
## 1      0-4 Female 1970 0 280468
## 2      0-4 Female 1971 0 275596
## 3      0-4 Female 1972 0 270765
## 4      0-4 Female 1973 0 267532
## 5      0-4 Female 1974 0 269260
```

```
merged_data <- merged_data %>%
  mutate(
    incidence_rate = (n / n_pop) * 100000,
    age_midpoint = as.numeric(sub("-", ".", agegroup)) + 2,
    sex = factor(sex)
  )
```

```
# Print column names to verify
print(colnames(merged_data))
```

```
## [1] "agegroup"      "sex"           "year"          "n"
## [5] "n_pop"         "incidence_rate" "age_midpoint"
```

```
# Plotting the relationship between mid age and incidence rate
ggplot(merged_data, aes(x = age_midpoint, y = incidence_rate)) +
  geom_point(alpha = 0.5, size = .1, position = position_jitter(w = 1, h = 0)) +
  geom_smooth(method = "loess", se = FALSE) +
  facet_wrap(~ sex) +
  labs(title = "Incidence Rate by Age, with dots corresponding to different calendar years",
       x = "Mid Age of Age Group",
       y = "Incidence Rate (Cases / Total Population)") +
  theme_minimal()
```



```

# Fitting a generalized linear model using splines
splines_model <- glm(
  formula = n ~ bs(year, df = 4)*bs(age_midpoint, df = 4) * sex + offset(log(n_pop)),
  data = merged_data,
  family = poisson()
)

summary(splines_model)

##
## Call:
## glm(formula = n ~ bs(year, df = 4) * bs(age_midpoint, df = 4) *
##      sex + offset(log(n_pop)), family = poisson(), data = merged_data)
##
## Coefficients:
##
##              Estimate Std. Error
## (Intercept)      -14.569275    0.748865
## bs(year, df = 4)1         2.501508    1.390446
## bs(year, df = 4)2         2.037596    1.019856
## bs(year, df = 4)3        -0.494946    1.326696
## bs(year, df = 4)4         0.284297    0.956309
## bs(age_midpoint, df = 4)1    2.803894    0.959586
## bs(age_midpoint, df = 4)2    5.501598    0.698437
## bs(age_midpoint, df = 4)3    7.992804    0.775120
## bs(age_midpoint, df = 4)4    8.585834    0.745947
## sexMale              -3.346662    1.545262
## bs(year, df = 4)1:bs(age_midpoint, df = 4)1    -2.558816    1.807307
## bs(year, df = 4)2:bs(age_midpoint, df = 4)1    -2.906208    1.344734
## bs(year, df = 4)3:bs(age_midpoint, df = 4)1     2.492452    1.692620
## bs(year, df = 4)4:bs(age_midpoint, df = 4)1     0.560981    1.213426
## bs(year, df = 4)1:bs(age_midpoint, df = 4)2    -2.409901    1.302262
## bs(year, df = 4)2:bs(age_midpoint, df = 4)2    -2.599417    0.959793
## bs(year, df = 4)3:bs(age_midpoint, df = 4)2    -1.518627    1.236974
## bs(year, df = 4)4:bs(age_midpoint, df = 4)2    -0.820693    0.892561
## bs(year, df = 4)1:bs(age_midpoint, df = 4)3    -2.427657    1.440452
## bs(year, df = 4)2:bs(age_midpoint, df = 4)3    -1.326466    1.055886
## bs(year, df = 4)3:bs(age_midpoint, df = 4)3     1.882810    1.368446
## bs(year, df = 4)4:bs(age_midpoint, df = 4)3     0.350943    0.985957
## bs(year, df = 4)1:bs(age_midpoint, df = 4)4    -2.382935    1.385469
## bs(year, df = 4)2:bs(age_midpoint, df = 4)4    -2.578386    1.016811
## bs(year, df = 4)3:bs(age_midpoint, df = 4)4     0.301665    1.322407
## bs(year, df = 4)4:bs(age_midpoint, df = 4)4    -0.119462    0.953222
## bs(year, df = 4)1:sexMale      3.875116    2.704734
## bs(year, df = 4)2:sexMale      0.421600    1.861218
## bs(year, df = 4)3:sexMale      3.127299    2.382851
## bs(year, df = 4)4:sexMale      3.666262    1.731212
## bs(age_midpoint, df = 4)1:sexMale    3.933159    1.879343
## bs(age_midpoint, df = 4)2:sexMale    2.504288    1.444037
## bs(age_midpoint, df = 4)3:sexMale    3.918359    1.586555
## bs(age_midpoint, df = 4)4:sexMale    3.375753    1.538658
## bs(year, df = 4)1:bs(age_midpoint, df = 4)1:sexMale -5.465763    3.346095
## bs(year, df = 4)2:bs(age_midpoint, df = 4)1:sexMale -1.040530    2.353886
## bs(year, df = 4)3:bs(age_midpoint, df = 4)1:sexMale -3.969268    2.936333
## bs(year, df = 4)4:bs(age_midpoint, df = 4)1:sexMale -4.775214    2.122510

```

```

## bs(year, df = 4)1:bs(age_midpoint, df = 4)2:sexMale -3.315179 2.533808
## bs(year, df = 4)2:bs(age_midpoint, df = 4)2:sexMale 0.186232 1.747198
## bs(year, df = 4)3:bs(age_midpoint, df = 4)2:sexMale -2.131003 2.225754
## bs(year, df = 4)4:bs(age_midpoint, df = 4)2:sexMale -2.572030 1.618188
## bs(year, df = 4)1:bs(age_midpoint, df = 4)3:sexMale -4.184404 2.781225
## bs(year, df = 4)2:bs(age_midpoint, df = 4)3:sexMale -0.638061 1.915849
## bs(year, df = 4)3:bs(age_midpoint, df = 4)3:sexMale -3.674431 2.446820
## bs(year, df = 4)4:bs(age_midpoint, df = 4)3:sexMale -4.133885 1.777236
## bs(year, df = 4)1:bs(age_midpoint, df = 4)4:sexMale -3.700081 2.693826
## bs(year, df = 4)2:bs(age_midpoint, df = 4)4:sexMale -0.001042 1.854556
## bs(year, df = 4)3:bs(age_midpoint, df = 4)4:sexMale -2.878592 2.373886
## bs(year, df = 4)4:bs(age_midpoint, df = 4)4:sexMale -3.586707 1.724491
##
## z value Pr(>|z|)
## (Intercept) -19.455 < 2e-16 ***
## bs(year, df = 4)1 1.799 0.07201 .
## bs(year, df = 4)2 1.998 0.04572 *
## bs(year, df = 4)3 -0.373 0.70910
## bs(year, df = 4)4 0.297 0.76625
## bs(age_midpoint, df = 4)1 2.922 0.00348 **
## bs(age_midpoint, df = 4)2 7.877 3.35e-15 ***
## bs(age_midpoint, df = 4)3 10.312 < 2e-16 ***
## bs(age_midpoint, df = 4)4 11.510 < 2e-16 ***
## sexMale -2.166 0.03033 *
## bs(year, df = 4)1:bs(age_midpoint, df = 4)1 -1.416 0.15683
## bs(year, df = 4)2:bs(age_midpoint, df = 4)1 -2.161 0.03068 *
## bs(year, df = 4)3:bs(age_midpoint, df = 4)1 1.473 0.14087
## bs(year, df = 4)4:bs(age_midpoint, df = 4)1 0.462 0.64386
## bs(year, df = 4)1:bs(age_midpoint, df = 4)2 -1.851 0.06423 .
## bs(year, df = 4)2:bs(age_midpoint, df = 4)2 -2.708 0.00676 **
## bs(year, df = 4)3:bs(age_midpoint, df = 4)2 -1.228 0.21956
## bs(year, df = 4)4:bs(age_midpoint, df = 4)2 -0.919 0.35784
## bs(year, df = 4)1:bs(age_midpoint, df = 4)3 -1.685 0.09192 .
## bs(year, df = 4)2:bs(age_midpoint, df = 4)3 -1.256 0.20902
## bs(year, df = 4)3:bs(age_midpoint, df = 4)3 1.376 0.16886
## bs(year, df = 4)4:bs(age_midpoint, df = 4)3 0.356 0.72188
## bs(year, df = 4)1:bs(age_midpoint, df = 4)4 -1.720 0.08544 .
## bs(year, df = 4)2:bs(age_midpoint, df = 4)4 -2.536 0.01122 *
## bs(year, df = 4)3:bs(age_midpoint, df = 4)4 0.228 0.81955
## bs(year, df = 4)4:bs(age_midpoint, df = 4)4 -0.125 0.90027
## bs(year, df = 4)1:sexMale 1.433 0.15194
## bs(year, df = 4)2:sexMale 0.227 0.82080
## bs(year, df = 4)3:sexMale 1.312 0.18938
## bs(year, df = 4)4:sexMale 2.118 0.03420 *
## bs(age_midpoint, df = 4)1:sexMale 2.093 0.03636 *
## bs(age_midpoint, df = 4)2:sexMale 1.734 0.08288 .
## bs(age_midpoint, df = 4)3:sexMale 2.470 0.01352 *
## bs(age_midpoint, df = 4)4:sexMale 2.194 0.02824 *
## bs(year, df = 4)1:bs(age_midpoint, df = 4)1:sexMale -1.633 0.10237
## bs(year, df = 4)2:bs(age_midpoint, df = 4)1:sexMale -0.442 0.65845
## bs(year, df = 4)3:bs(age_midpoint, df = 4)1:sexMale -1.352 0.17645
## bs(year, df = 4)4:bs(age_midpoint, df = 4)1:sexMale -2.250 0.02446 *
## bs(year, df = 4)1:bs(age_midpoint, df = 4)2:sexMale -1.308 0.19075
## bs(year, df = 4)2:bs(age_midpoint, df = 4)2:sexMale 0.107 0.91511
## bs(year, df = 4)3:bs(age_midpoint, df = 4)2:sexMale -0.957 0.33835

```

```

## bs(year, df = 4)4:bs(age_midpoint, df = 4)2:sexMale -1.589 0.11196
## bs(year, df = 4)1:bs(age_midpoint, df = 4)3:sexMale -1.505 0.13245
## bs(year, df = 4)2:bs(age_midpoint, df = 4)3:sexMale -0.333 0.73910
## bs(year, df = 4)3:bs(age_midpoint, df = 4)3:sexMale -1.502 0.13317
## bs(year, df = 4)4:bs(age_midpoint, df = 4)3:sexMale -2.326 0.02002 *
## bs(year, df = 4)1:bs(age_midpoint, df = 4)4:sexMale -1.374 0.16958
## bs(year, df = 4)2:bs(age_midpoint, df = 4)4:sexMale -0.001 0.99955
## bs(year, df = 4)3:bs(age_midpoint, df = 4)4:sexMale -1.213 0.22528
## bs(year, df = 4)4:bs(age_midpoint, df = 4)4:sexMale -2.080 0.03754 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
## Null deviance: 406971.1 on 1907 degrees of freedom
## Residual deviance: 2572.3 on 1858 degrees of freedom
## AIC: 11780
##
## Number of Fisher Scoring iterations: 6
# Assuming you have your merged data as 'merged_data' and fitted model as 'model'
# Create a new data frame for predictions
age_groups <- c(52, 72, 87)
sex_groups <- c("Female", "Male")
years <- unique(merged_data$year) # Get all unique years from your data

# Create an empty data frame to store predictions
prediction_data <- expand.grid(
  year = years,
  age_midpoint = age_groups,
  sex = sex_groups
)

# Add population to avoid warnings (use dummy values as predictions will standardize population)
prediction_data$n_pop <- 1

# Use the predict() function to generate predicted values
prediction_data$predicted_incidence <- predict(splines_model, newdata = prediction_data, type = "response")

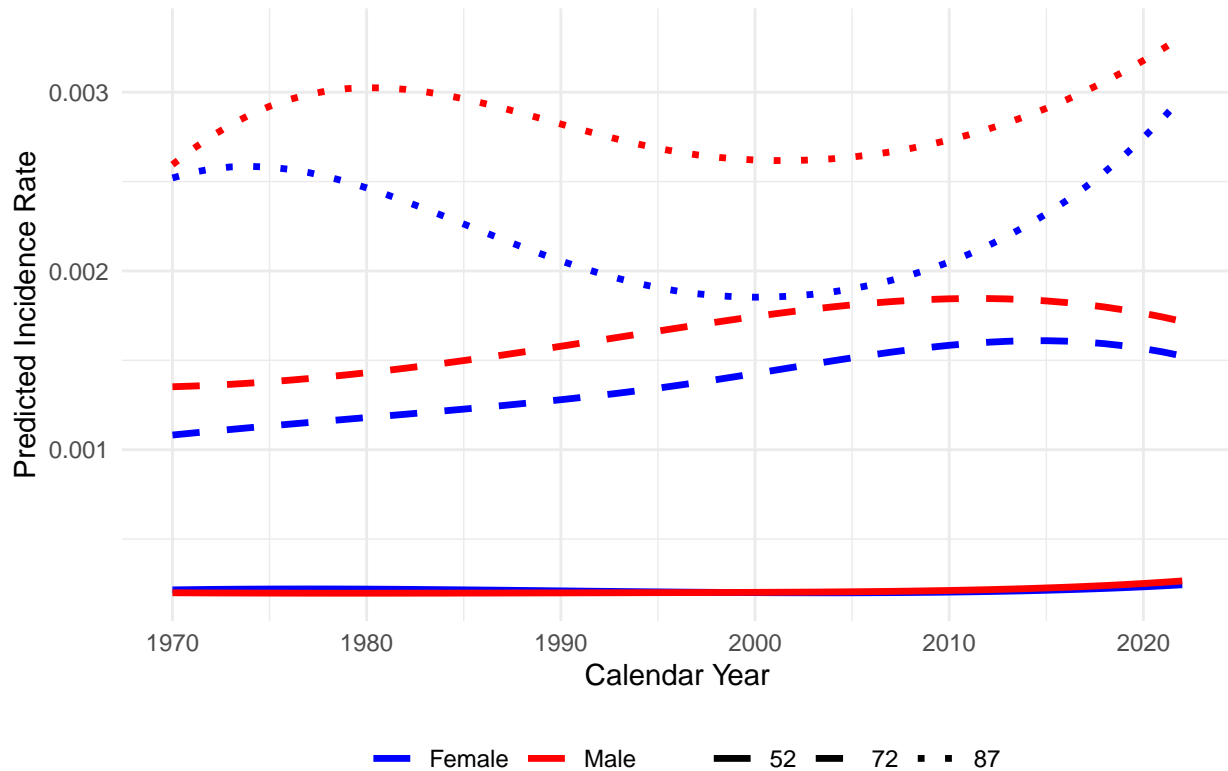
# Plotting the incidence rates over time for each sex at ages 52, 72, and 87
library(ggplot2)

ggplot(prediction_data, aes(x = year, y = predicted_incidence, color = sex, linetype = as.factor(age_midpoint))) +
  geom_line(size = 1.2) +
  labs(title = "Predicted Incidence Rates Across Calendar Time",
       x = "Calendar Year",
       y = "Predicted Incidence Rate") +
  scale_color_manual(values = c("blue", "red")) +
  scale_linetype_manual(values = c("solid", "dashed", "dotted")) +
  theme_minimal() +
  theme(legend.title = element_blank()) +
  theme(legend.position = "bottom")

```



## Predicted Incidence Rates Across Calendar Time

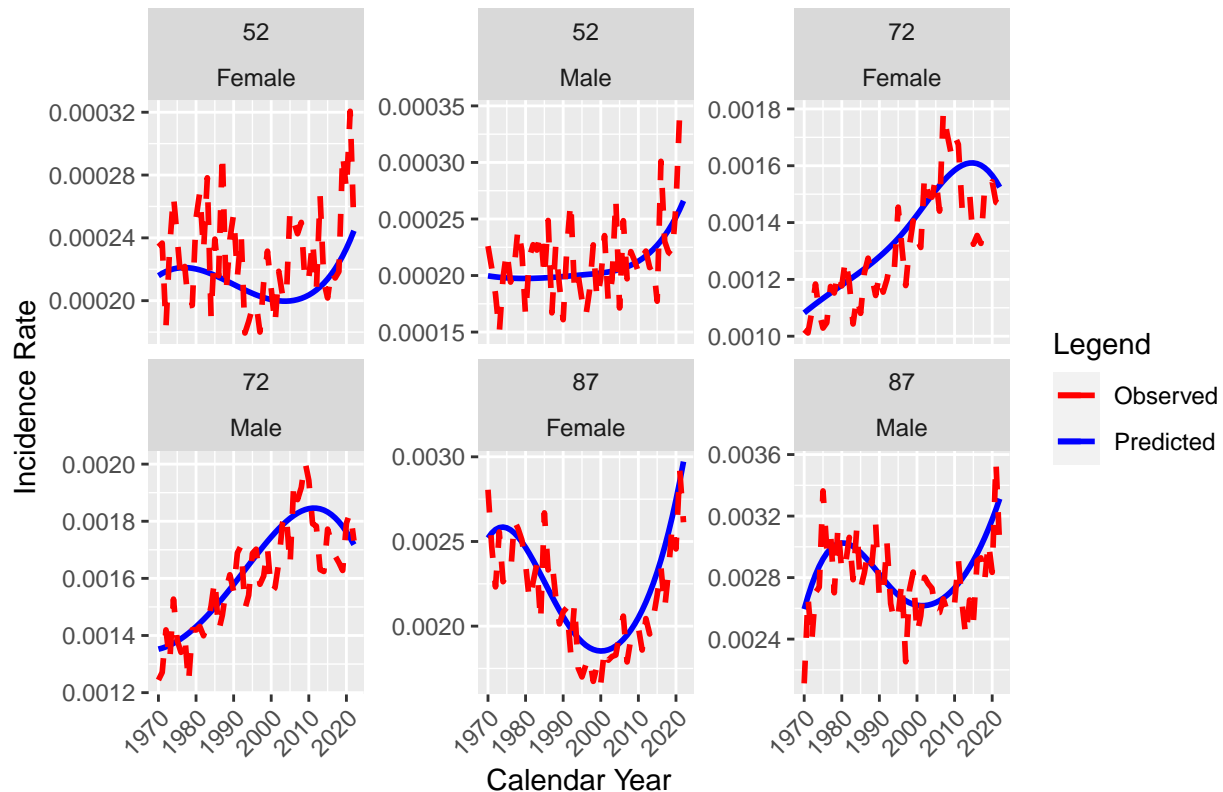


```
# Compare with observed values
observed_data <- merged_data %>%
  filter(age_midpoint %in% c(52, 72, 87)) %>%
  group_by(year, age_midpoint, sex) %>%
  summarize(observed_rate = sum(n) / sum(n_pop))

# Combine predicted and observed data
comparison_data <- left_join(prediction_data, observed_data, by = c("year", "age_midpoint", "sex"))

ggplot(comparison_data, aes(x = year)) +
  geom_line(aes(y = predicted_incidence, color = "Predicted"), size = 1) +
  geom_line(aes(y = observed_rate, color = "Observed"), size = 1, linetype = "dashed") +
  facet_wrap(~ age_midpoint + sex, scales = "free_y") +
  labs(
    title = "Comparison of Predicted and Observed Incidence Rates",
    x = "Calendar Year",
    y = "Incidence Rate",
    color = "Legend"
  ) +
  scale_color_manual(values = c("Predicted" = "blue", "Observed" = "red")) +
  theme(axis.text.x = element_text(angle=45, hjust=1))
```

## Comparison of Predicted and Observed Incidence Rates



The blue interpolation might be misleading near the endpoints, as one could make the argument that the curve should follow a flatter or even negative curvature at that point. This may just be an effect of the smoother applied.

## Question 11: direct age standardised rate

```
# reference values for male and female population
standard_pop <- population %>%
  filter(year == 2022) %>%
  rename(ref_pop = n_pop) %>%
  select(-year)

# reference value for total male population
tot_male <- standard_pop %>%
  filter(sex == "Male") %>%
  pull(ref_pop) %>% sum()

# reference value for total female population
tot_female <- standard_pop %>%
  filter(sex == "Female") %>%
  pull(ref_pop) %>% sum()
```

Standardised incidence rates:

```

age_standardised_rates <- cases_pop %>%
  select(-rate) %>%
  left_join(standard_pop) %>%
  # add number of cases obtained if population number was ref_pop
  mutate(cases_ref_pop = ref_pop * n/n_pop) %>%
  # for each year, compute total (sum over agegroups) and divide by total reference population
  # keep male and female categories
  group_by(year, sex) %>%
  # sum over agegroups
  summarize(sum_ages = sum(cases_ref_pop, na.rm = TRUE)) %>%
  mutate(standardised_rate = case_when(sex == "Female" ~ sum_ages/tot_female,
                                       sex == "Male" ~ sum_ages/tot_male,
                                       TRUE ~ NA)
        ) %>%
  select(-sum_ages) %>%
  # rescale
  mutate(standardised_rate = 10^4 * standardised_rate)

```

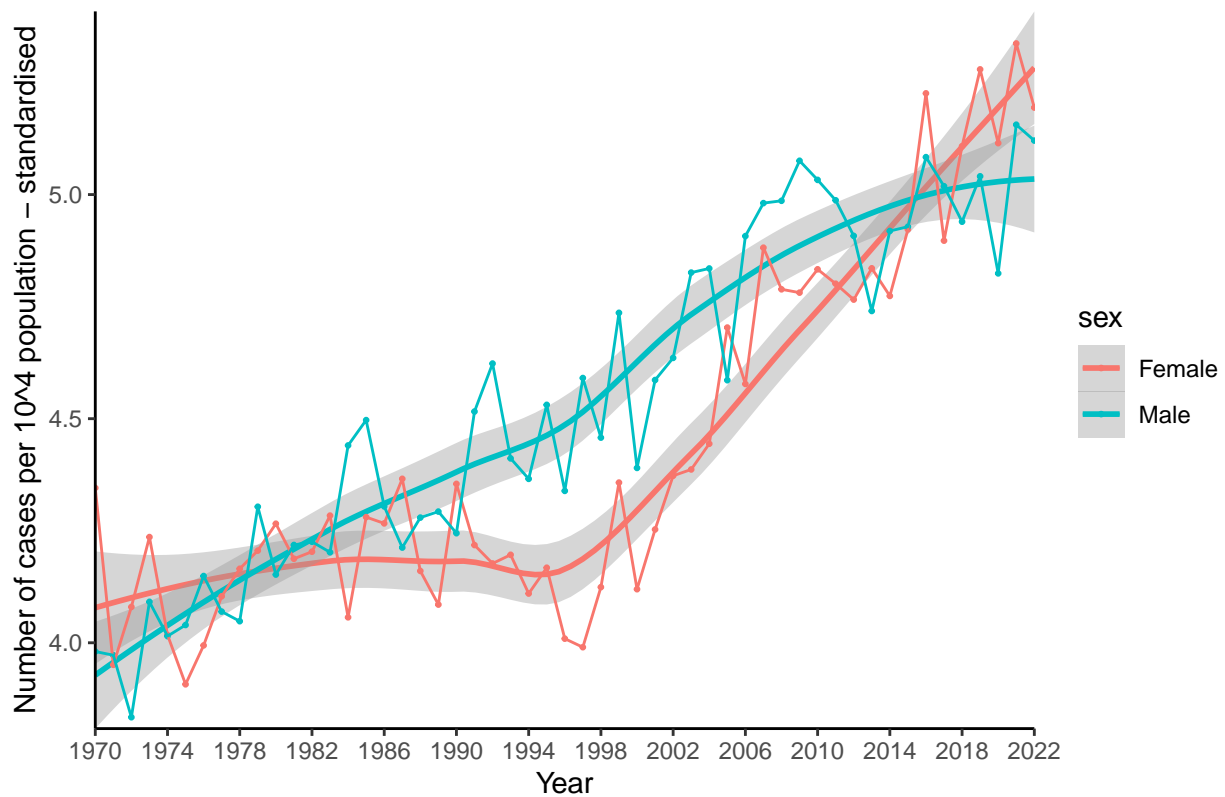
### Plot of age standardised rates

```

age_standardised_rates %>%
  ggplot(aes(x = year, y = standardised_rate, color = sex)) +
  # smooth the curve
  geom_smooth() +
  # non smoothed data
  geom_point(size = 0.5) +
  stat_summary(geom="line") +
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
  # add labels and title
  ggtitle("Standardised incidence rate: cases per 10^4 population by year and sex") +
  xlab("Year") + ylab("Number of cases per 10^4 population - standardised")

```

## Standardised incidence rate: cases per 10<sup>4</sup> population by year and sex

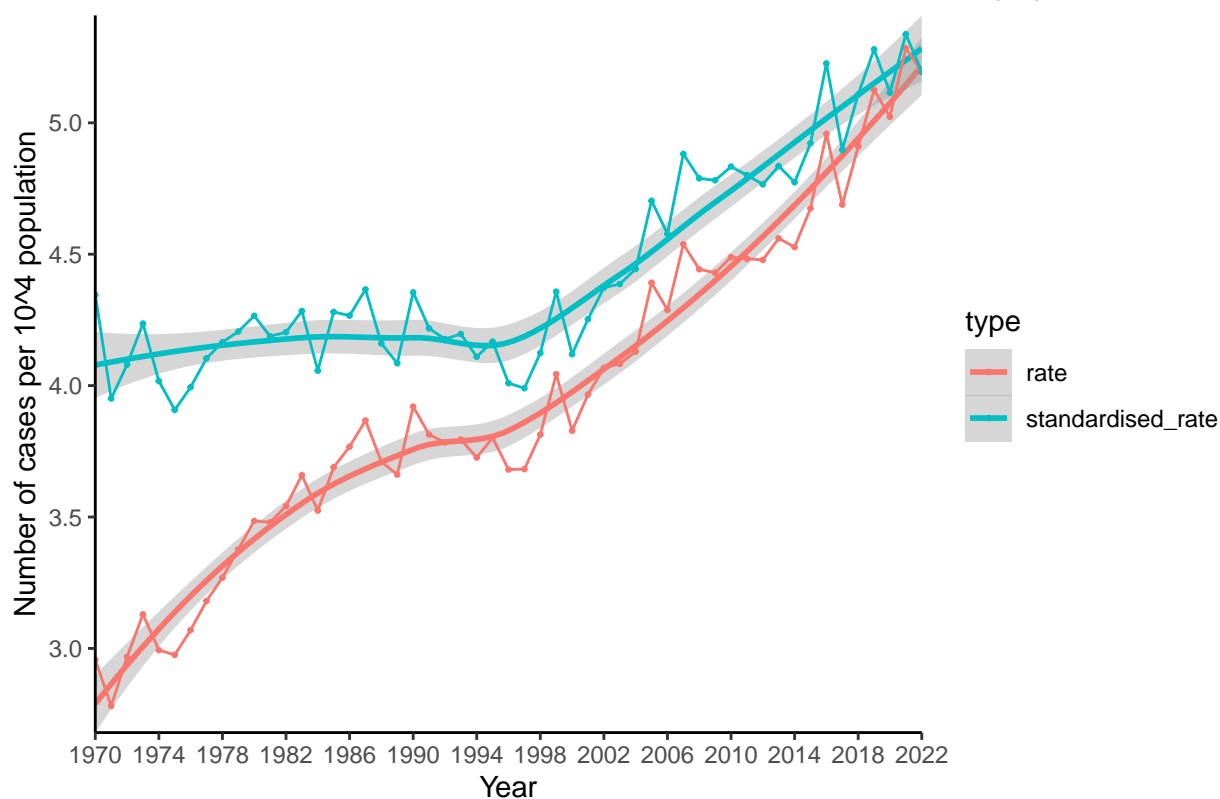


## Comparison with non standardised rates

Females:

```
cases_pop_ys %>%
  filter(sex == "Female") %>%
  left_join(age_standardised_rates) %>%
  select(year, sex, rate, standardised_rate) %>%
  pivot_longer(cols = c(rate, standardised_rate), names_to = "type") %>%
  ggplot(aes(x = year, y = value, color = type)) +
  # smooth the curve
  geom_smooth() +
  # non smoothed data
  geom_point(size = 0.5) +
  stat_summary(geom="line") +
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
  # add labels and title
  ggtitle("Standardised vs non standardised incidence rate - female population") +
  xlab("Year") + ylab("Number of cases per 10^4 population")
```

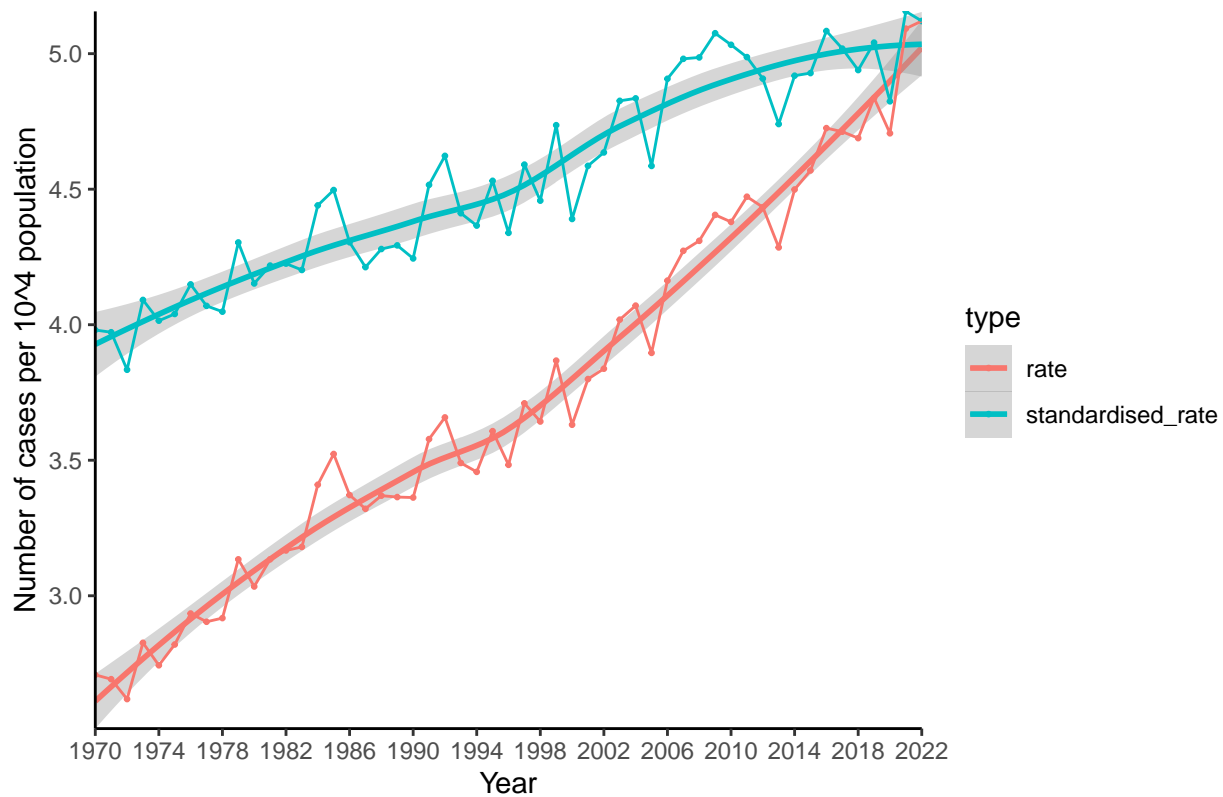
## Standardised vs non standardised incidence rate – female population



## Males

```
cases_pop_ys %>%
  filter(sex == "Male") %>%
  left_join(age_standardised_rates) %>%
  select(year, sex, rate, standardised_rate) %>%
  pivot_longer(cols = c(rate, standardised_rate), names_to = "type") %>%
  ggplot(aes(x = year, y = value, color = type)) +
  # smooth the curve
  geom_smooth() +
  # non smoothed data
  geom_point(size = 0.5) +
  stat_summary(geom="line") +
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
  # add labels and title
  ggtitle("Standardised vs non standardised incidence rate - male population") +
  xlab("Year") + ylab("Number of cases per 104 population")
```

## Standardised vs non standardised incidence rate – male population



## Question 12: direct age standardised rate on predicted data

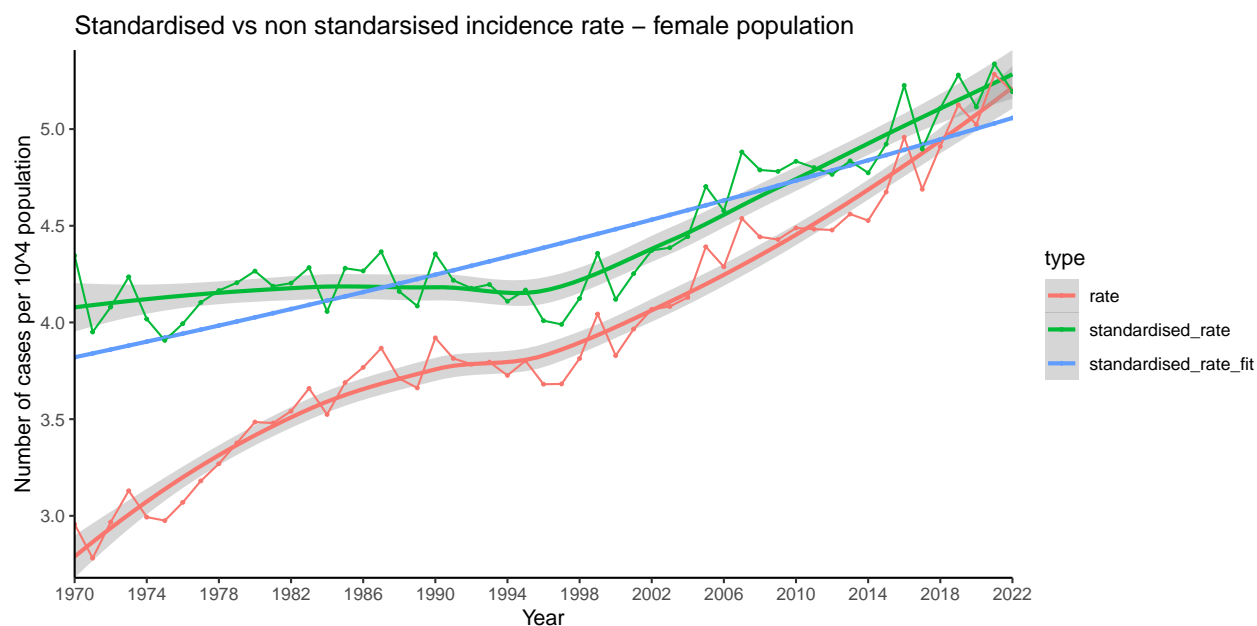
```
cases_pop_fit <- cases_pop %>%
  select(-rate, -n) %>%
  # replace number of cases with fitted number of cases, which should already be in the right order
  add_column(n_fit = poisson_model_age$fitted.values)

# repeat question 11
age_standardised_rates_fit <- cases_pop_fit %>%
  left_join(standard_pop) %>%
  # add number of cases obtained if population number was ref_pop
  mutate(cases_ref_pop = ref_pop * n_fit/n_pop) %>%
  # for each year, compute total (sum over agegroups) and divide by total reference population
  # keep male and female categories
  group_by(year, sex) %>%
  # sum over agegroups
  summarize(sum_ages = sum(cases_ref_pop, na.rm = TRUE)) %>%
  ungroup() %>%
  mutate(standardised_rate_fit = case_when(sex == "Female" ~ sum_ages/tot_female,
                                           sex == "Male" ~ sum_ages/tot_male,
                                           TRUE ~ NA)
  ) %>%
  select(-sum_ages) %>%
  # rescale
  mutate(standardised_rate_fit = 10^4 * standardised_rate_fit)
```

Comparison of standardised rates obtained with fitted data, with standardised rates from the original dataset.

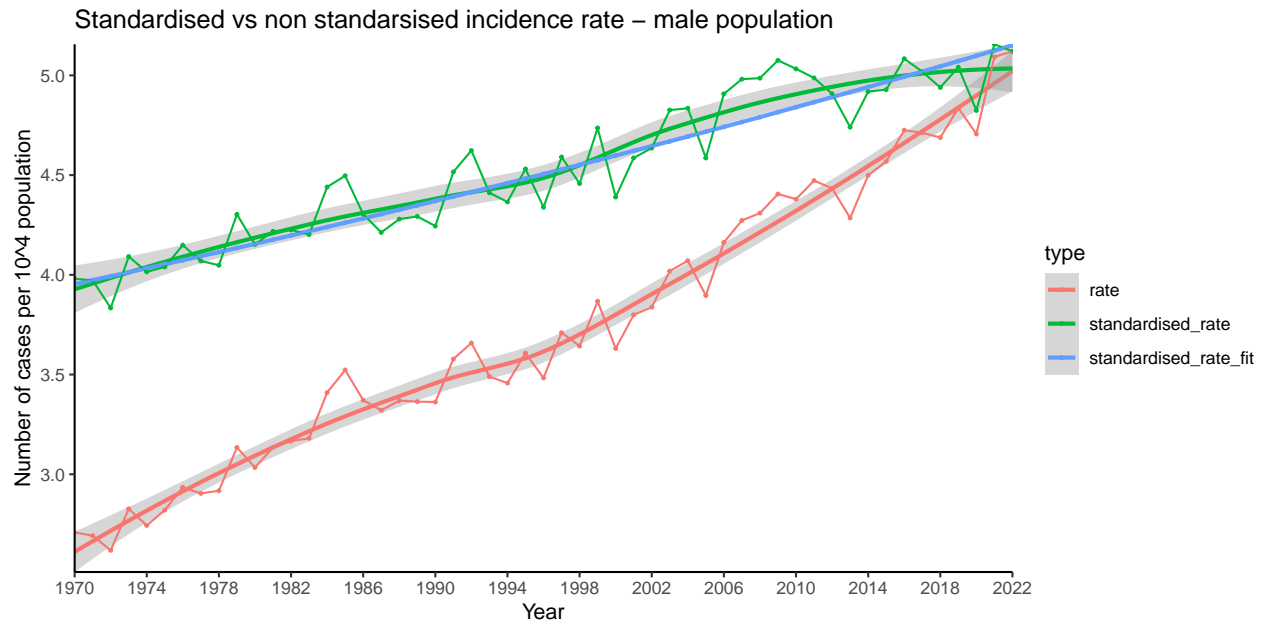
Females:

```
cases_pop_ys %>%
  filter(sex == "Female") %>%
  left_join(age_standardised_rates) %>%
  left_join(age_standardised_rates_fit) %>%
  select(year, sex, rate, standardised_rate, standardised_rate_fit) %>%
  pivot_longer(cols = c(rate, standardised_rate, standardised_rate_fit), names_to = "type") %>%
  #filter(type == "standardised_rate_fit") %>%
  ggplot(aes(x = year, y = value, color = type)) +
  # smooth the curve
  geom_smooth() +
  # non smoothed data
  geom_point(size = 0.5) +
  stat_summary(geom="line") +
  theme_classic() +
  coord_cartesian(expand = FALSE) +
  scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
  # add labels and title
  ggtitle("Standardised vs non standardised incidence rate - female population") +
  xlab("Year") + ylab("Number of cases per 10^4 population")
```



```
cases_pop_ys %>%
  filter(sex == "Male") %>%
  left_join(age_standardised_rates) %>%
  left_join(age_standardised_rates_fit) %>%
  select(year, sex, rate, standardised_rate, standardised_rate_fit) %>%
  pivot_longer(cols = c(rate, standardised_rate, standardised_rate_fit), names_to = "type") %>%
  # smooth the curve
  geom_smooth() +
  # non smoothed data
```

```
geom_point(size = 0.5) +
stat_summary(geom="line") +
theme_classic() +
coord_cartesian(expand = FALSE) +
scale_x_continuous(lim = c(1970, 2022), breaks = c(seq(1970, 2022, by = 4))) +
# add labels and title
ggtitle("Standardised vs non standardised incidence rate - male population") +
xlab("Year") + ylab("Number of cases per 10^4 population")
```



Both for females and for males, compared to the original rates, the curve for the standardised rates has a greater value at the intercept and a smaller slope, especially initially. However, as time is increased, the slopes tend to align. The Standardized rates are consistently higher than the original rates, with the difference decreasing monotonely over time.

This can be explained by the different structure in the population over the years and the proportional increase in population aged 75 and older, where cancer rates are in general the highest.

For males the fit is almost completely within the confidence band, whereas for the female group the fit is not. This might just be a consequence of the more constant curvature for males than for females, as the female fit fluctuates more.

## Question 13: conclusions

Incidence rates of colon cancer vary significantly across age groups, with older age groups generally having higher incidence rates as seen in the plot “Colon Cancer Incidence Rate by Sex and Age Group Over Time” in question 6. 1. For age group 0-4 and 85-89 the incidence rate is more constant over the time period 1970- 2020 for males than for females. 2. For age group 40-44 there was an increase by a factor of ten or so between the years 2000 and 2020 whereas there was no such change for females.

Over time, there is an overall increase in incidence rates for most age groups, particularly for middle-aged and older adults.

The overall incidence rates of colon cancer have increased steadily for both males and females over the years.



Females consistently show slightly higher crude incidence rates compared to males throughout the observed time period.

When we take age into account females tend to have lower incidence rate than males (agegroup 75 up): this could be related to the fact, that, for these agegroups the female population is more numerous than men population