

Assignment 2: Risk Adjustment

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Introduction

This analysis will show how much different variables influence the healthcare costs of an individual. My findings in short:

- Increased age category has on average the result that you have more health costs.
- When you are male you will on average have more health costs.
- The different income sources have different sized effects on the health costs.
- Whether or not you have limited coverage on your insurance has a large effect. When you have limited coverage on your insurance you have on average less health costs compared to someone who has full coverage.
- Whether or not you live in an unhealthy region also has a large effect on your health costs. When you live in an unhealthy region you have on average more health costs than someone who does not live in an unhealthy region.

Assignment

Reading in libraries and data

```
library(tidyverse)
library(ggplot2); theme_set(theme_bw())
library(patchwork)
library(mlogit)
```

```
data <- read.csv('data_assignment2.csv', sep = ',')
```

Exploratory data analysis

```
head(data)
```

##	ID	Gender	Age_category	Insurer	Order_age	Income_source	Limited_coverage
## 1	20824	Male	[0,5]	Insurer A	1	Child	0
## 2	49573	Male	[0,5]	Insurer A	1	Child	0
## 3	71451	Male	[0,5]	Insurer B	1	Child	0
## 4	76844	Male	[0,5]	Insurer A	1	Child	0

```
## 5 179479 Male [0,5] Insurer D 1 Child 0
## 6 304970 Male [0,5] Insurer A 1 Child 0
## Unhealthy_region Healthcare_cost Population_density
## 1 0 0 3
## 2 1 0 4
## 3 0 0 4
## 4 0 0 1
## 5 1 0 3
## 6 0 0 2
```

Before I summarize the data I first set the categorical variables to categorical data type.

```
categorical_cols <- c("Gender", "Age_category", "Insurer", "Income_source")
data[categorical_cols] <- lapply(data[categorical_cols], factor)
summary(data)
```

```
## ID Gender Age_category Insurer
## Min. : 1 Female:519359 (35,40]:105892 Insurer A:298515
## 1st Qu.: 250007 Male :476949 (40,45]:104025 Insurer B:249245
## Median : 500016 (30,35]: 99326 Insurer C:229069
## Mean : 500009 (45,50]: 95418 Insurer D:169819
## 3rd Qu.: 750011 (25,30]: 86222 Insurer E: 49660
## Max. :1000000 (50,55]: 82777
## (Other):422648
## Order_age Income_source Limited_coverage
## Min. : 1.000 Child : 63984 Min. :0.00000
## 1st Qu.: 7.000 Pension :139614 1st Qu.:0.00000
## Median : 9.000 Student : 34282 Median :0.00000
## Mean : 9.451 Unemployment Benefits: 36790 Mean :0.07059
## 3rd Qu.:12.000 Working :721638 3rd Qu.:0.00000
## Max. :24.000 Max. :1.00000
##
## Unhealthy_region Healthcare_cost Population_density
## Min. :0.0000 Min. : 0 Min. :1
## 1st Qu.:0.0000 1st Qu.: 0 1st Qu.:2
## Median :0.0000 Median : 9696 Median :3
## Mean :0.1495 Mean : 8145 Mean :3
## 3rd Qu.:0.0000 3rd Qu.:12451 3rd Qu.:4
## Max. :1.0000 Max. :27030 Max. :5
##
```

```
dim(data)
```

```
## [1] 996308 10
```

The data summary shows that we have data of 996.308 people of which we know:

- ID: id of person
- Gender: gender of person (male/female)
- Age_category: in which age category the person falls, see below a summary of age categories and distribution of age.
- Order_age: the age_category ordered from low to high

- Insurer: Which insurer the person has
- Income_source: the source of income
- Limited_coverage: whether the person has limited coverage (yes/no)
- Unhealthy_region: whether the person lives in an unhealthy region (yes/no)
- Healthcare_cost: The healthcare cost
- Population_density: how densely populated the area where the person lives is measured on a scale of 1 to 5

To check whether there are missing values:

```
sapply(data, function(x) sum(is.na(x)))
```

```
##           ID           Gender      Age_category           Insurer
##           0             0             0             0
##      Order_age      Income_source      Limited_coverage      Unhealthy_region
##           0             0             0             0
##      Healthcare_cost      Population_density
##           0             0
```

There are no missing values.

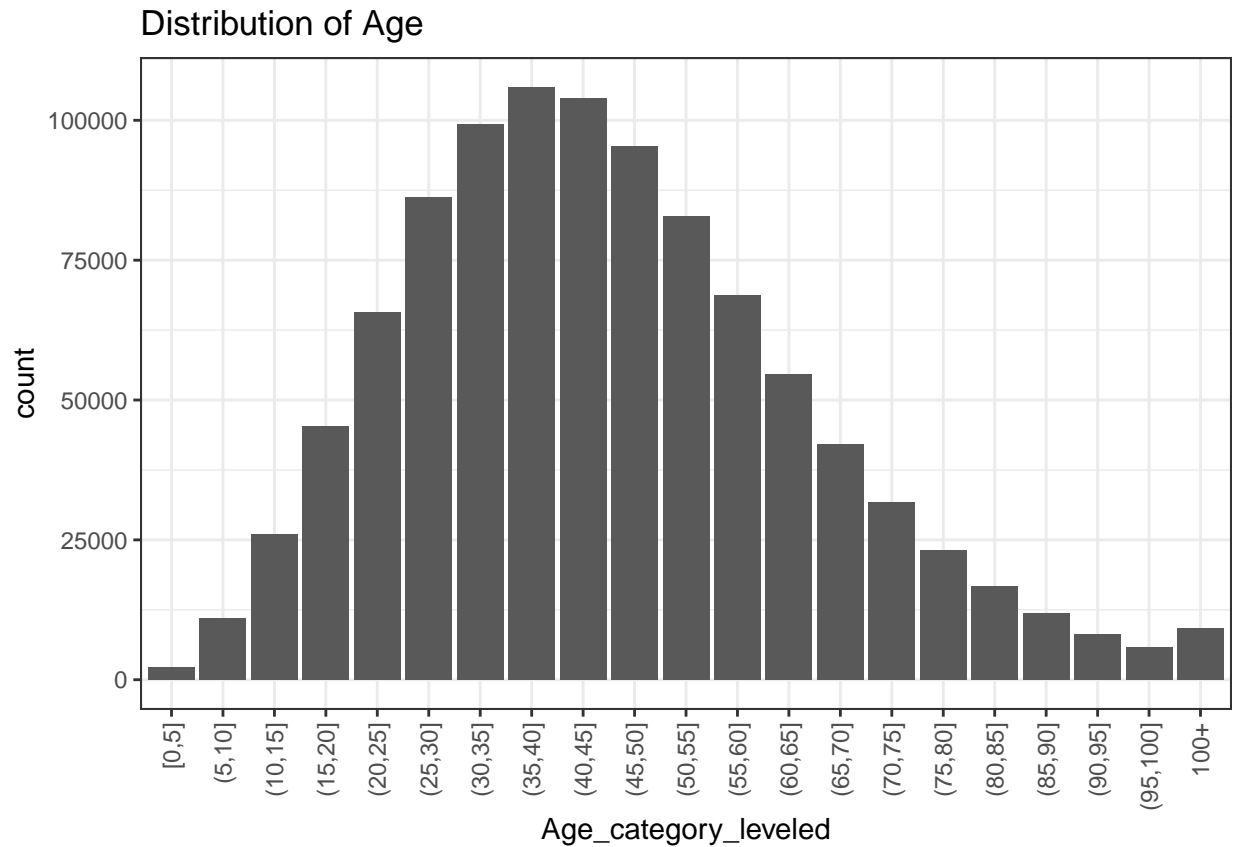
For visualization and clarity purposes i set the age_category levels to increasing categories starting from category [0,5]

```
age_levels <- c( "[0,5]", "(5,10]", "(10,15]", "(15,20]", "(20,25]", "(25,30]", "(30,35]", "(35,40]",
  "(40,45]", "(45,50]", "(50,55]", "(55,60]", "(60,65]",
  "(65,70]", "(70,75]", "(75,80]", "(80,85]", "(85,90]", "(90,95]",
  "(95,100]", "100+")
data$Age_category_levelled <- factor(data$Age_category, levels = age_levels)
```

Data visualisation

Basic graphs

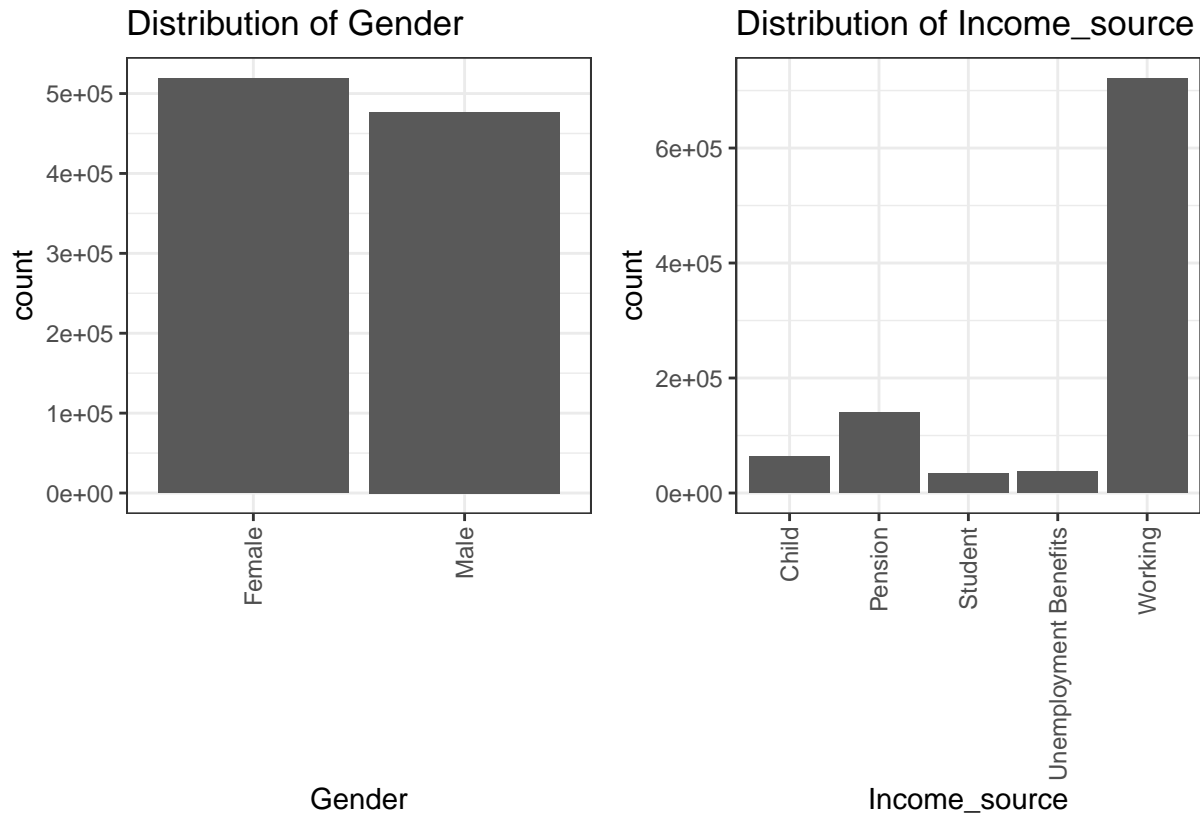
```
ggplot(data = data, aes( x = Age_category_levelled))+
  geom_bar()+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Distribution of Age")
```



```
Gender_dist <- ggplot(data = data, aes( x = Gender))+  
  geom_bar()+  
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+  
  ggtitle("Distribution of Gender")
```

```
Income_dist <- ggplot(data = data, aes( x = Income_source))+  
  geom_bar()+  
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+  
  ggtitle("Distribution of Income_source")
```

```
Gender_dist + Income_dist
```



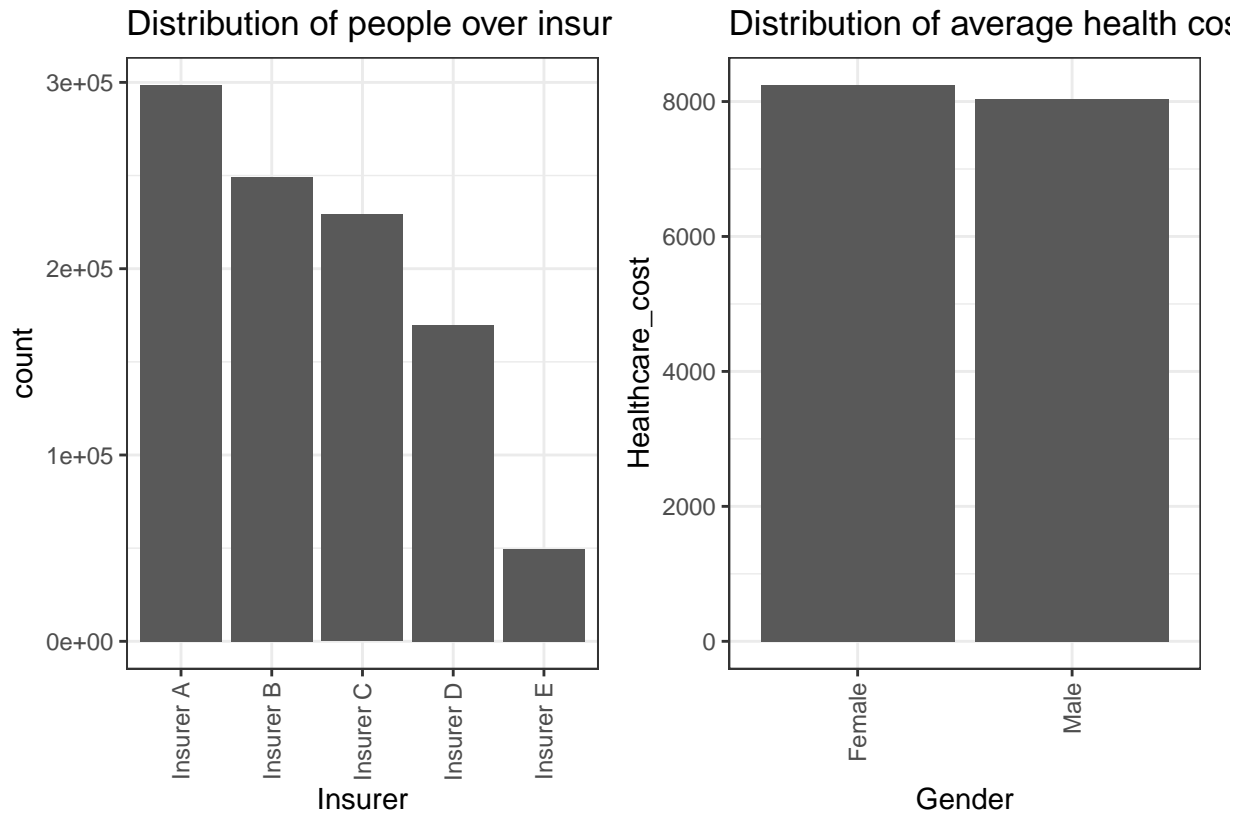
```
Insurer_dist <- ggplot(data = data, aes( x = Insurer))+
  geom_bar()+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Distribution of people over insurers")
```

```
mean_cost_insurer <- ggplot(data )+
  geom_bar(aes( x = Gender, y = Healthcare_cost ),stat = "summary", fun.y = "mean")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Distribution of average health cost epr insurer")
```

```
## Warning: Ignoring unknown parameters: fun.y
```

```
Insurer_dist + mean_cost_insurer
```

```
## No summary function supplied, defaulting to 'mean_se()'
```



The above graphs show that insurer A,B,C,D all have the same average costs. However insurer E has a higher cost than the rest. This can be explained by the small market power (and number of insured) Insurer E has.

Basic numbers

```
data%>%
  group_by(Insurer)%>%
  summarise_at(vars(Limited_coverage), funs(mean(.)))
```

```
## Warning: 'funs()' was deprecated in dplyr 0.8.0.
## Please use a list of either functions or lambdas:
##
##   # Simple named list:
##   list(mean = mean, median = median)
##
##   # Auto named with 'tibble::lst()':
##   tibble::lst(mean, median)
##
##   # Using lambdas
##   list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
## This warning is displayed once every 8 hours.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was generated.
```

```
## # A tibble: 5 x 2
```

```
##   Insurer   Limited_coverage
##   <fct>         <dbl>
## 1 Insurer A         0.0704
## 2 Insurer B         0.0707
## 3 Insurer C         0.0703
## 4 Insurer D         0.0708
## 5 Insurer E         0.0717
```

These results show that each insurer has around the same share of people who have limited coverage, all have around 7%.

```
data%>%
  group_by(Insurer)%>%
  summarise_at(vars(Unhealthy_region), funs(mean(.)))
```

```
## # A tibble: 5 x 2
##   Insurer   Unhealthy_region
##   <fct>         <dbl>
## 1 Insurer A         0.149
## 2 Insurer B         0.150
## 3 Insurer C         0.148
## 4 Insurer D         0.151
## 5 Insurer E         0.150
```

These results show that the number of people who live in an unhealthy region as a share per insurer is quite balanced. Each insurer has around 15% which live in an unhealthy region.

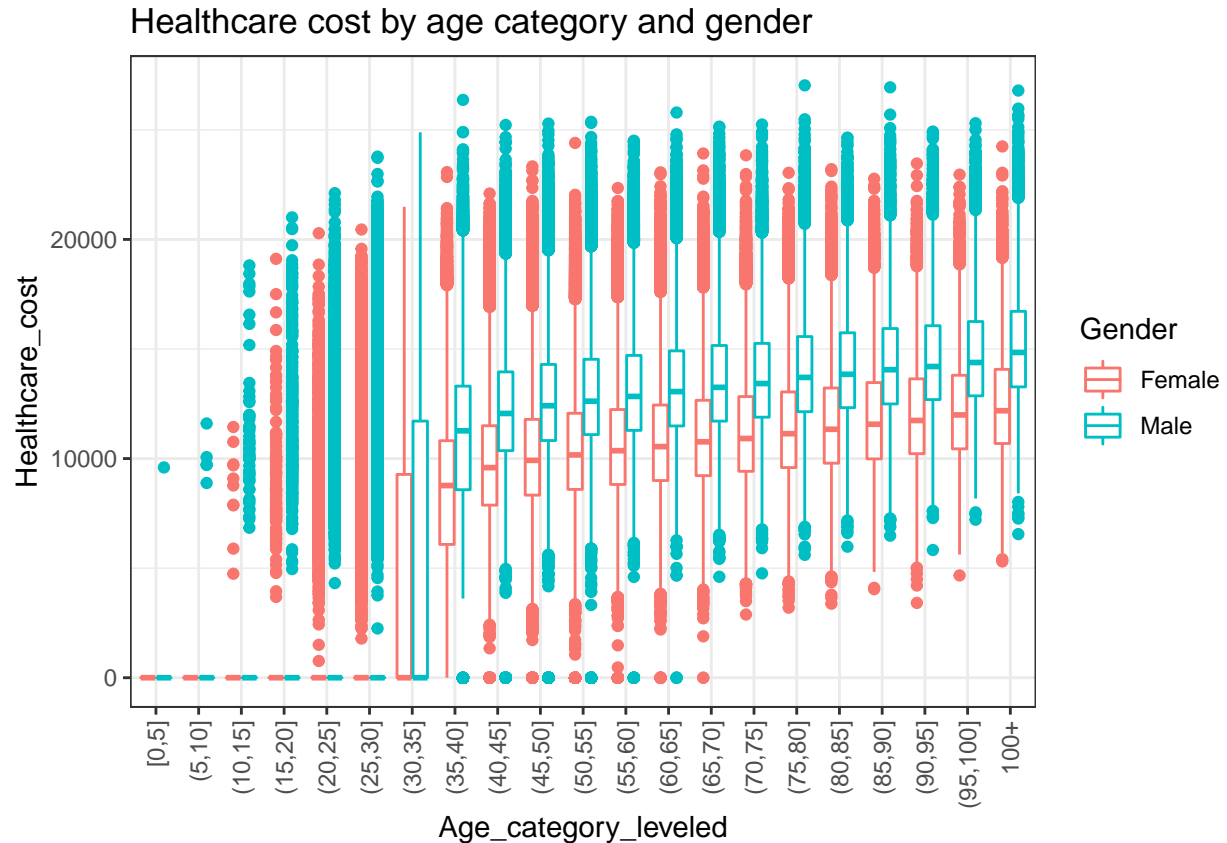
```
data%>%
  group_by(Limited_coverage)%>%
  summarise_at(vars(Healthcare_cost), funs(mean(.)))
```

```
## # A tibble: 2 x 2
##   Limited_coverage Healthcare_cost
##           <int>         <dbl>
## 1             0         8763.
## 2             1             0
```

These results show that the mean healthcare costs of people with limited coverage are 0 and the mean healthcare costs of people without limited coverage is 8763.

Exploratory Graphs

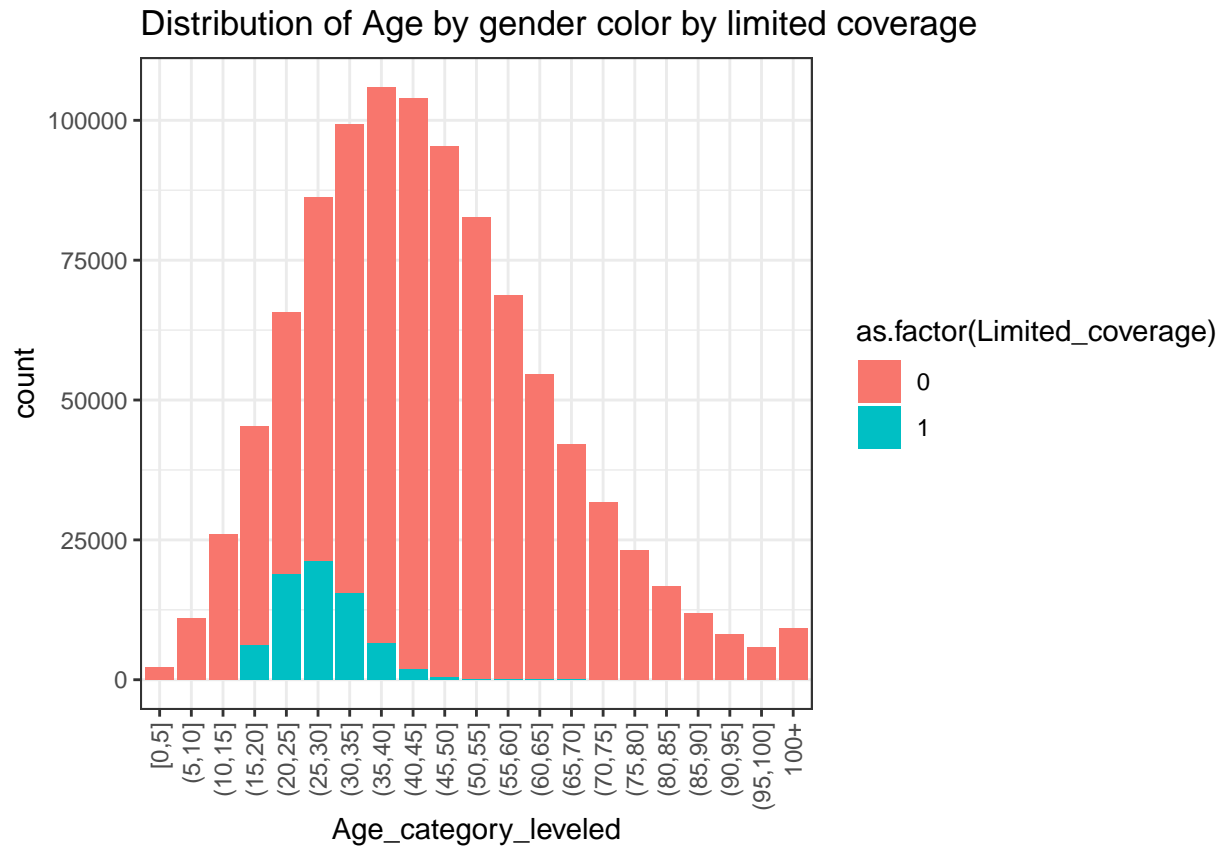
```
ggplot(data = data, aes( x = Age_category_ leveled, y = Healthcare_cost, color = Gender))+
  geom_boxplot()+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Healthcare cost by age category and gender")
```



This boxplot shows that healthcare costs are increasing over age category and that overall the female healthcare costs are lower than the male healthcare costs. The below line graph shows the difference by gender.

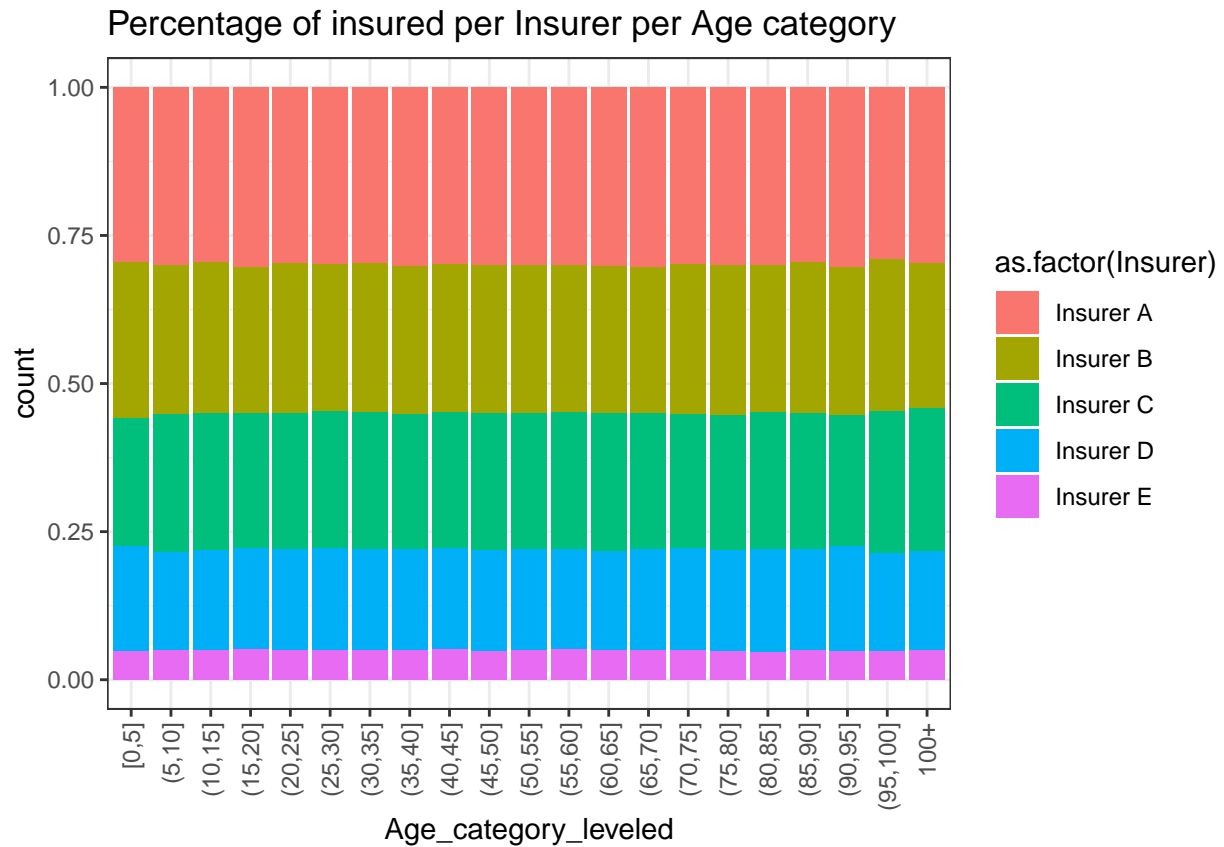
The below graph shows that most of the people who have limited coverage are in the younger age groups. Up to the age group of 15 it can be expected that people do not have limited coverage as they probably fall under full coverage for the government (such as the case in the Netherlands).

```
ggplot(data = data, aes( x = Age_category_levelled, fill = as.factor(Limited_coverage)))+
  geom_bar()+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Distribution of Age by gender color by limited coverage")
```

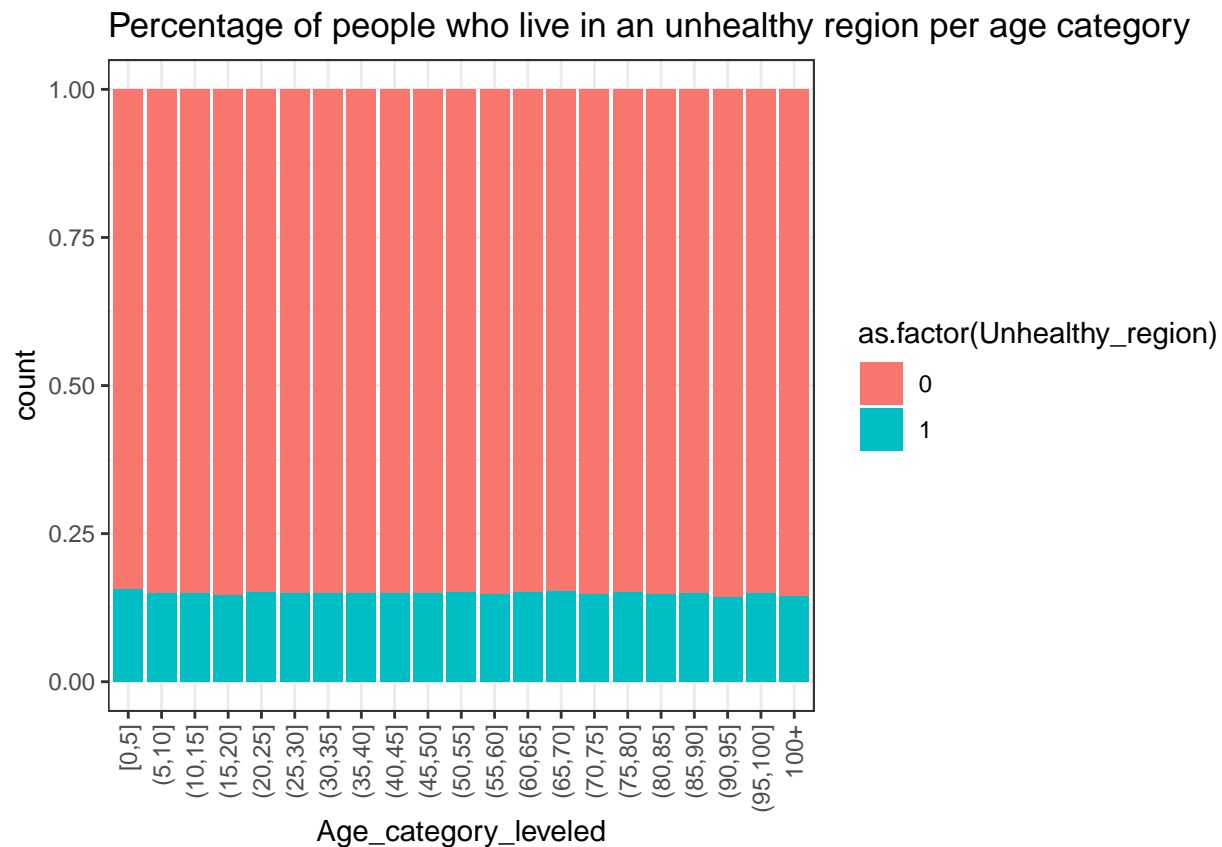
The below graph shows that the distribution of people who are with a certain insurer does not change over age categories.

```
ggplot(data = data, aes( x = Age_category_levelled, fill = as.factor(Insurer)))+
  geom_bar(position = "fill")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Percentage of insured per Insurer per Age category")
```



The Below graph shows that the percentage of people who live in an unhealthy region does not change over age categories.

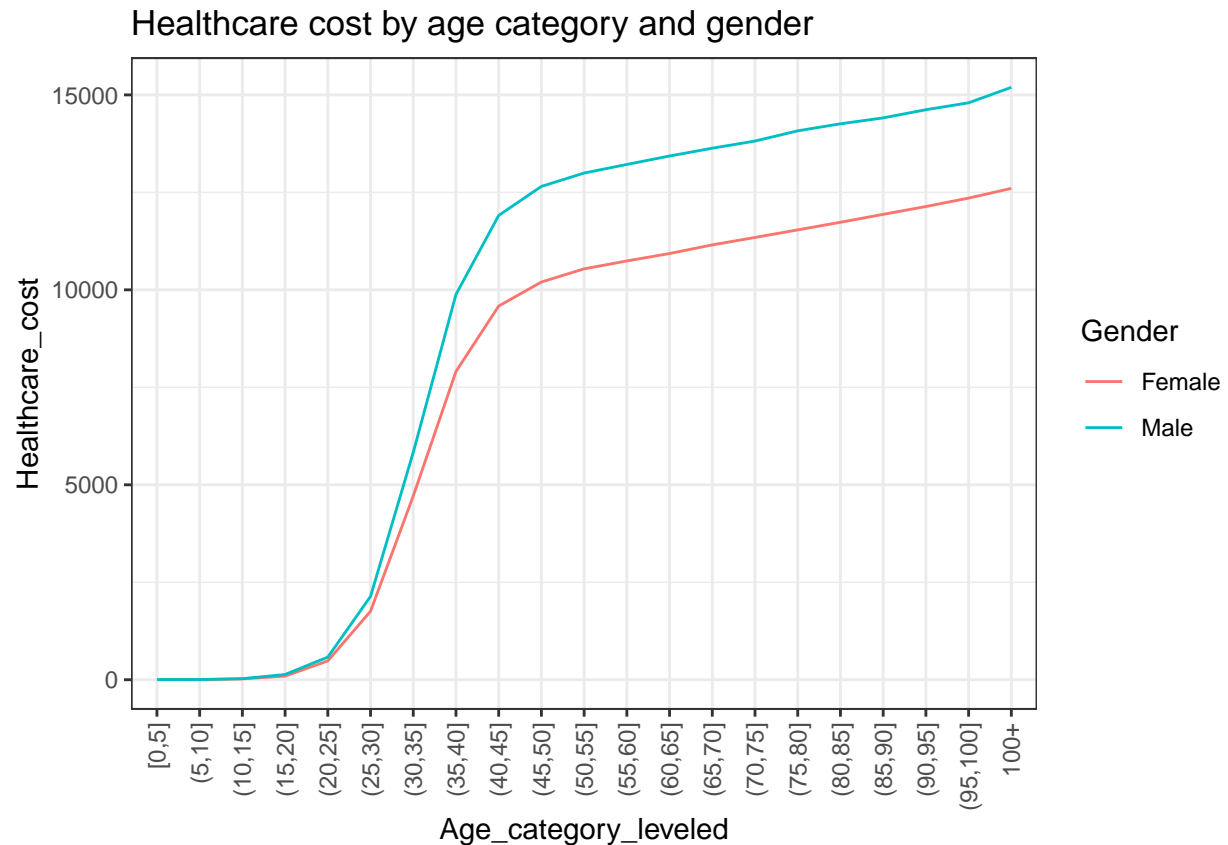
```
ggplot(data = data, aes( x = Age_category_leveled, fill = as.factor(Unhealthy_region)))+
  geom_bar(position = "fill")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Percentage of people who live in an unhealthy region per age category")
```



This graph shows that on average over all age groups the male healthcare costs are higher.

```
ggplot(data = data, aes( x = Age_category_ leveled, y = Healthcare_cost, colour = Gender))+
  stat_summary(aes(y = Healthcare_cost, group = Gender), fun.y = mean, geom = "line")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Healthcare cost by age category and gender")
```

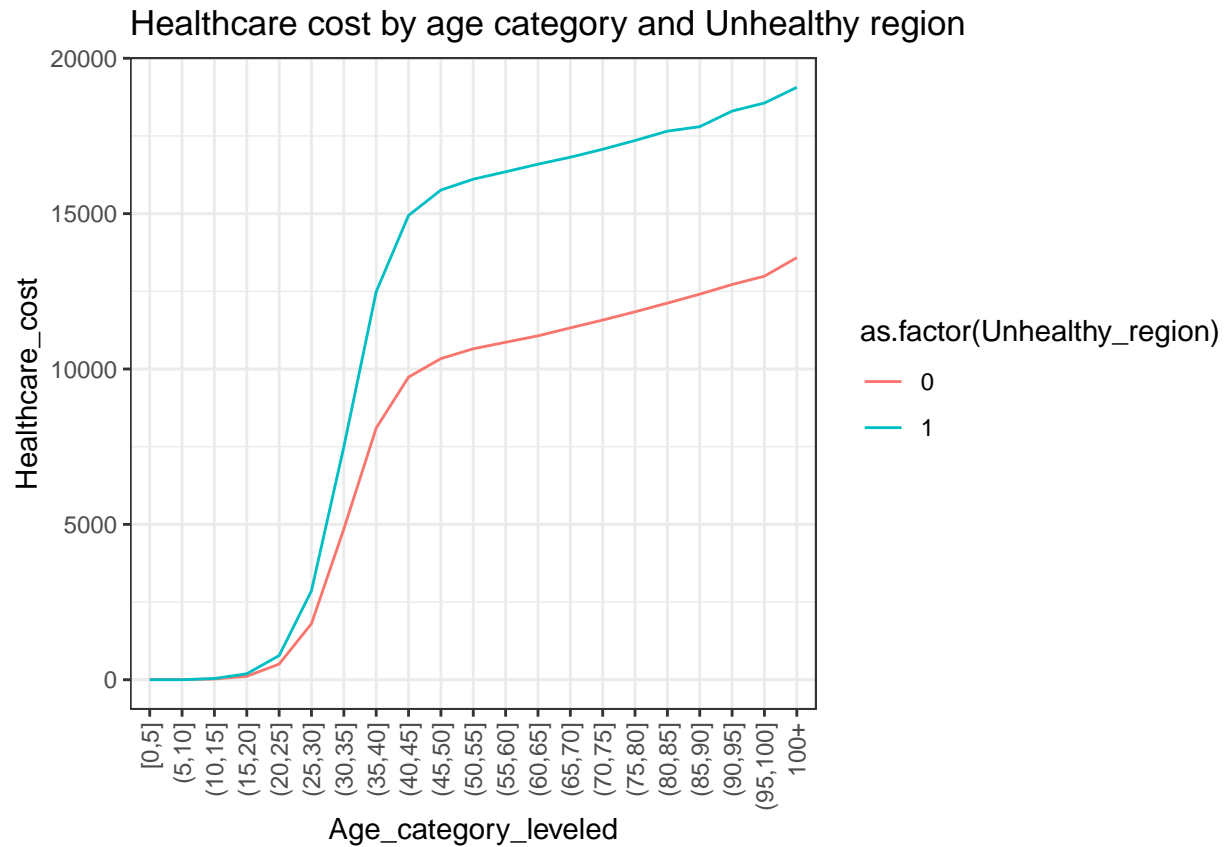
Warning: 'fun.y' is deprecated. Use 'fun' instead.



This graph shows that people who live in an unhealthy region have on average per age category higher healthcare costs.

```
ggplot(data = data, aes( x = Age_category_levelled, y = Healthcare_cost, colour = as.factor(Unhealthy_region))) +
  stat_summary(aes(y = Healthcare_cost, group = as.factor(Unhealthy_region)), fun.y = mean, geom = "line") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1)) +
  ggtitle("Healthcare cost by age category and Unhealthy region")
```

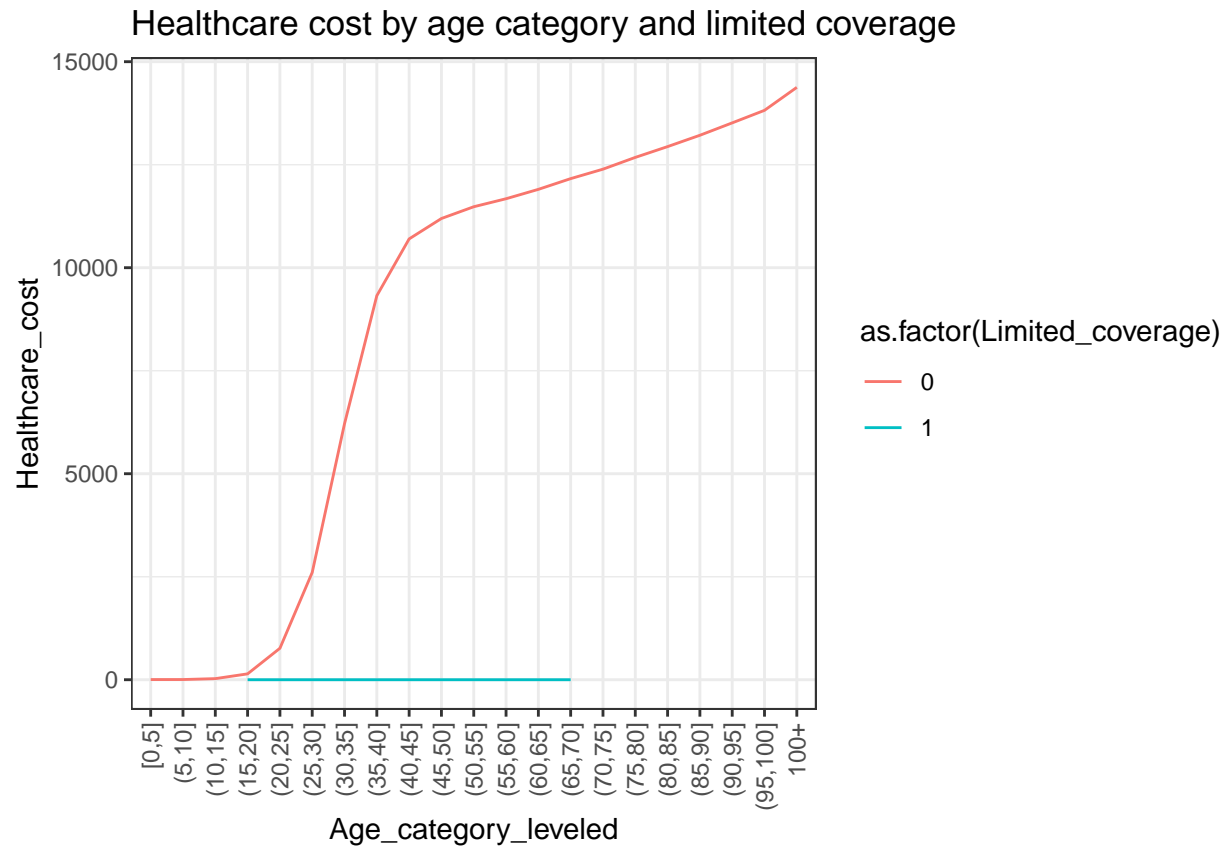
Warning: 'fun.y' is deprecated. Use 'fun' instead.



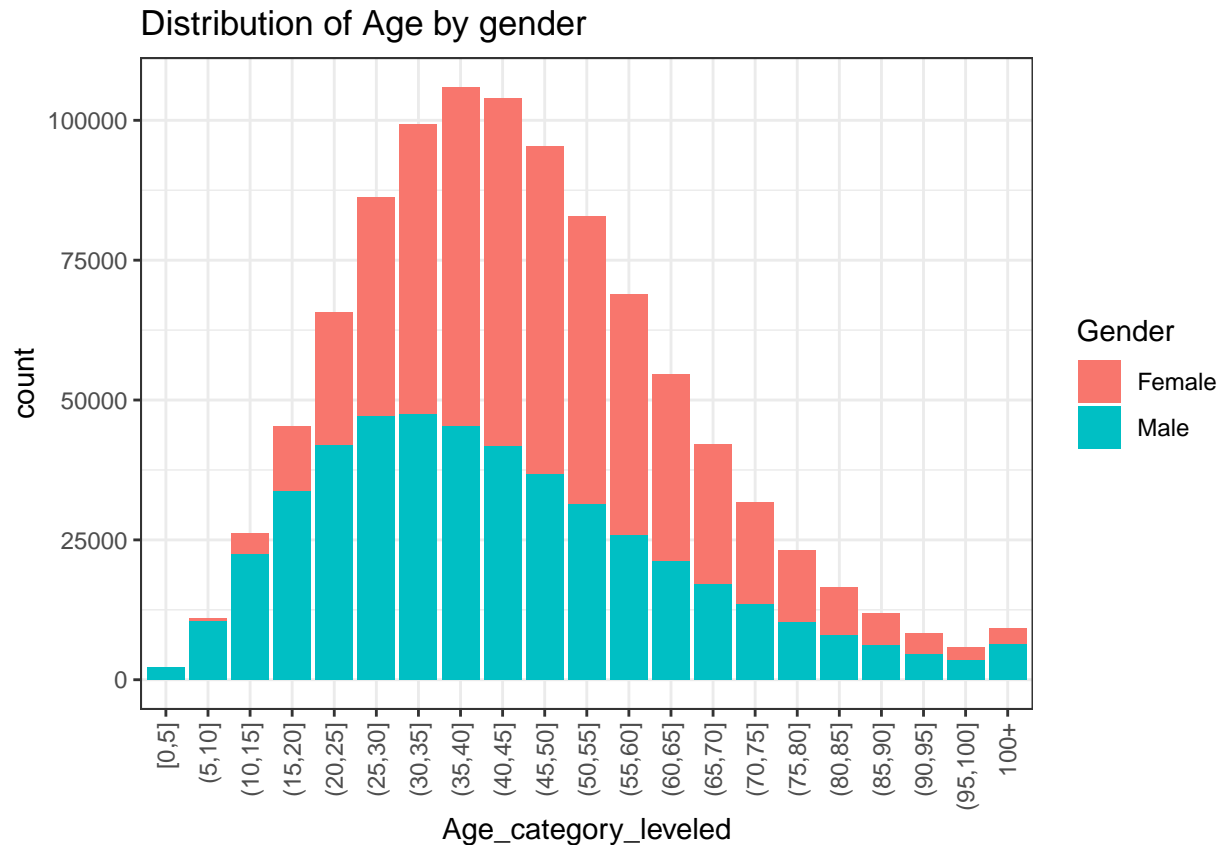
This graph shows that people with limited coverage have no healthcare costs.

```
ggplot(data = data, aes( x = Age_category_levelled, y = Healthcare_cost, colour = as.factor(Limited_coverage))) +
  stat_summary(aes(y = Healthcare_cost, group = as.factor(Limited_coverage)), fun.y = mean, geom = "line") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1)) +
  ggtitle("Healthcare cost by age category and limited coverage")
```

Warning: 'fun.y' is deprecated. Use 'fun' instead.



```
ggplot(data = data, aes( x = Age_category_ leveled, fill = Gender))+
  geom_bar()+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Distribution of Age by gender")
```



In the graph above we can see that the share of males in the youngest categories is very large, also in the oldest categories this difference can be observed.

Estimating model based on Age and Gender

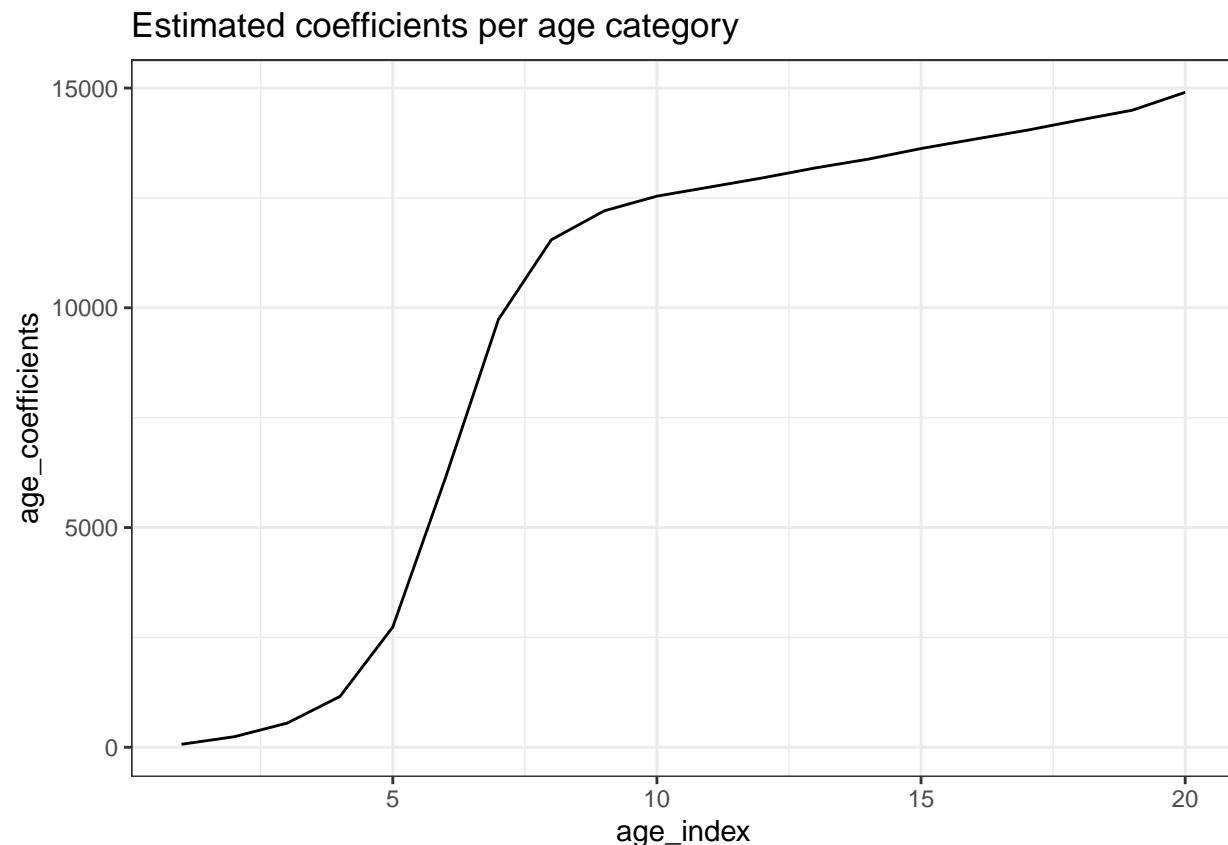
```
model1 <- lm(Healthcare_cost ~ Age_category_levelled + Gender, data = data)
summary(model1)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Age_category_levelled + Gender,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12991.0  -1960.4   -388.5   1644.3  21003.6
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -1745.620     79.094  -22.070 < 2e-16 ***
## Age_category_levelled(5,10]      67.637     86.357   0.783  0.43350
## Age_category_levelled(10,15]    240.471     82.041   2.931  0.00338 **
## Age_category_levelled(15,20]    548.903     80.669   6.804 1.02e-11 ***
## Age_category_levelled(20,25]   1156.457     80.102  14.437 < 2e-16 ***
```

```
## Age_category_leveled(25,30]    2737.504    79.815  34.298 < 2e-16 ***
## Age_category_leveled(30,35]    6141.315    79.706  77.050 < 2e-16 ***
## Age_category_leveled(35,40]    9735.011    79.672 122.189 < 2e-16 ***
## Age_category_leveled(40,45]   11547.458    79.698 144.890 < 2e-16 ***
## Age_category_leveled(45,50]   12205.643    79.780 152.991 < 2e-16 ***
## Age_category_leveled(50,55]   12541.077    79.922 156.917 < 2e-16 ***
## Age_category_leveled(55,60]   12747.848    80.137 159.077 < 2e-16 ***
## Age_category_leveled(60,65]   12956.523    80.457 161.037 < 2e-16 ***
## Age_category_leveled(65,70]   13183.380    80.917 162.925 < 2e-16 ***
## Age_category_leveled(70,75]   13382.899    81.568 164.070 < 2e-16 ***
## Age_category_leveled(75,80]   13624.450    82.554 165.036 < 2e-16 ***
## Age_category_leveled(80,85]   13834.795    83.951 164.795 < 2e-16 ***
## Age_category_leveled(85,90]   14039.950    85.920 163.407 < 2e-16 ***
## Age_category_leveled(90,95]   14272.745    88.863 160.615 < 2e-16 ***
## Age_category_leveled(95,100]  14497.314    92.662 156.453 < 2e-16 ***
## Age_category_leveled100+      14903.376    87.791 169.759 < 2e-16 ***
## GenderMale                    1780.134     7.731 230.257 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3724 on 996286 degrees of freedom
## Multiple R-squared:  0.6076, Adjusted R-squared:  0.6076
## F-statistic: 7.346e+04 on 21 and 996286 DF,  p-value: < 2.2e-16
```

The simple model with age and gender above shows that, just like in the graphs, the costly individuals are older individuals and males in general. Males have on average 1780 more healthcost. The older the individual the more healthcosts you will on average have, this can be observed from the increasing coefficient of the age_categories. The older the category the higher the coefficient estimate of the age_category, meaning that on average an individual will have higher health costs when they fall in a higher age category.

```
age_coefficients <- model1$coefficients[2:21]
age_index <- seq(20)
data_age_coeff <- data.frame(age_index, age_coefficients)
ggplot(data_age_coeff, aes(x = age_index, y = age_coefficients))+
  geom_line()+
  ggtitle("Estimated coefficients per age category")
```

Simple model with split gender per age category

Below I create a model where each age category is also split by gender to see whether the gender costs coefficient change over age categories. (Here I set the intercept to 0 to make the coefficients positive)

```
model_Split_gender <- lm(Healthcare_cost ~ (Age_category_levleled:Gender) -1, data = data)
summary(model_Split_gender)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ (Age_category_levleled:Gender) -
##     1, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13433  -1940   -288    1610   21639
##
## Coefficients:
##                                     Estimate Std. Error t value Pr(>|t|)
## Age_category_levleled[0,5]:GenderFemale      0.000     599.922   0.000  1.00000
## Age_category_levleled(5,10):GenderFemale      0.000     150.476   0.000  1.00000
## Age_category_levleled(10,15):GenderFemale     23.577      61.271   0.385  0.70038
## Age_category_levleled(15,20):GenderFemale     92.541      34.157   2.709  0.00674
## Age_category_levleled(20,25):GenderFemale    483.010      23.938  20.178 < 2e-16
```

```

## Age_category_ leveled(25,30]:GenderFemale    1756.311    18.697  93.934 < 2e-16
## Age_category_ leveled(30,35]:GenderFemale    4712.029    16.250 289.967 < 2e-16
## Age_category_ leveled(35,40]:GenderFemale    7904.984    15.035 525.783 < 2e-16
## Age_category_ leveled(40,45]:GenderFemale    9583.533    14.809 647.125 < 2e-16
## Age_category_ leveled(45,50]:GenderFemale   10200.507    15.276 667.743 < 2e-16
## Age_category_ leveled(50,55]:GenderFemale   10538.160    16.323 645.619 < 2e-16
## Age_category_ leveled(55,60]:GenderFemale   10741.101    17.848 601.814 < 2e-16
## Age_category_ leveled(60,65]:GenderFemale   10931.603    20.212 540.842 < 2e-16
## Age_category_ leveled(65,70]:GenderFemale   11153.590    23.396 476.734 < 2e-16
## Age_category_ leveled(70,75]:GenderFemale   11343.497    27.332 415.031 < 2e-16
## Age_category_ leveled(75,80]:GenderFemale   11537.830    32.745 352.353 < 2e-16
## Age_category_ leveled(80,85]:GenderFemale   11733.523    39.674 295.751 < 2e-16
## Age_category_ leveled(85,90]:GenderFemale   11935.467    48.881 244.176 < 2e-16
## Age_category_ leveled(90,95]:GenderFemale   12137.748    61.146 198.506 < 2e-16
## Age_category_ leveled(95,100]:GenderFemale  12353.181    76.565 161.343 < 2e-16
## Age_category_ leveled100+:GenderFemale      12601.902    68.614 183.663 < 2e-16
## Age_category_ leveled[0,5]:GenderMale         4.362    78.845  0.055 0.95588
## Age_category_ leveled(5,10]:GenderMale        4.801    36.244  0.132 0.89461
## Age_category_ leveled(10,15]:GenderMale       26.926    24.681  1.091 0.27529
## Age_category_ leveled(15,20]:GenderMale       134.102    20.165  6.650 2.93e-11
## Age_category_ leveled(20,25]:GenderMale       580.241    18.067  32.117 < 2e-16
## Age_category_ leveled(25,30]:GenderMale      2137.072    17.040 125.413 < 2e-16
## Age_category_ leveled(30,35]:GenderMale      5831.173    16.962 343.776 < 2e-16
## Age_category_ leveled(35,40]:GenderMale      9882.043    17.359 569.286 < 2e-16
## Age_category_ leveled(40,45]:GenderMale     11908.695    18.117 657.307 < 2e-16
## Age_category_ leveled(45,50]:GenderMale     12653.333    19.275 656.458 < 2e-16
## Age_category_ leveled(50,55]:GenderMale     12995.633    20.855 623.131 < 2e-16
## Age_category_ leveled(55,60]:GenderMale     13215.982    22.999 574.625 < 2e-16
## Age_category_ leveled(60,65]:GenderMale     13432.829    25.421 528.420 < 2e-16
## Age_category_ leveled(65,70]:GenderMale     13632.678    28.266 482.304 < 2e-16
## Age_category_ leveled(70,75]:GenderMale     13816.712    31.864 433.612 < 2e-16
## Age_category_ leveled(75,80]:GenderMale     14078.553    36.323 387.594 < 2e-16
## Age_category_ leveled(80,85]:GenderMale     14258.706    41.513 343.474 < 2e-16
## Age_category_ leveled(85,90]:GenderMale     14410.051    47.269 304.853 < 2e-16
## Age_category_ leveled(90,95]:GenderMale     14619.478    54.753 267.007 < 2e-16
## Age_category_ leveled(95,100]:GenderMale    14797.693    62.537 236.622 < 2e-16
## Age_category_ leveled100+:GenderMale      15193.429    46.522 326.583 < 2e-16
##
## Age_category_ leveled[0,5]:GenderFemale
## Age_category_ leveled(5,10]:GenderFemale
## Age_category_ leveled(10,15]:GenderFemale
## Age_category_ leveled(15,20]:GenderFemale **
## Age_category_ leveled(20,25]:GenderFemale ***
## Age_category_ leveled(25,30]:GenderFemale ***
## Age_category_ leveled(30,35]:GenderFemale ***
## Age_category_ leveled(35,40]:GenderFemale ***
## Age_category_ leveled(40,45]:GenderFemale ***
## Age_category_ leveled(45,50]:GenderFemale ***
## Age_category_ leveled(50,55]:GenderFemale ***
## Age_category_ leveled(55,60]:GenderFemale ***
## Age_category_ leveled(60,65]:GenderFemale ***
## Age_category_ leveled(65,70]:GenderFemale ***
## Age_category_ leveled(70,75]:GenderFemale ***
## Age_category_ leveled(75,80]:GenderFemale ***

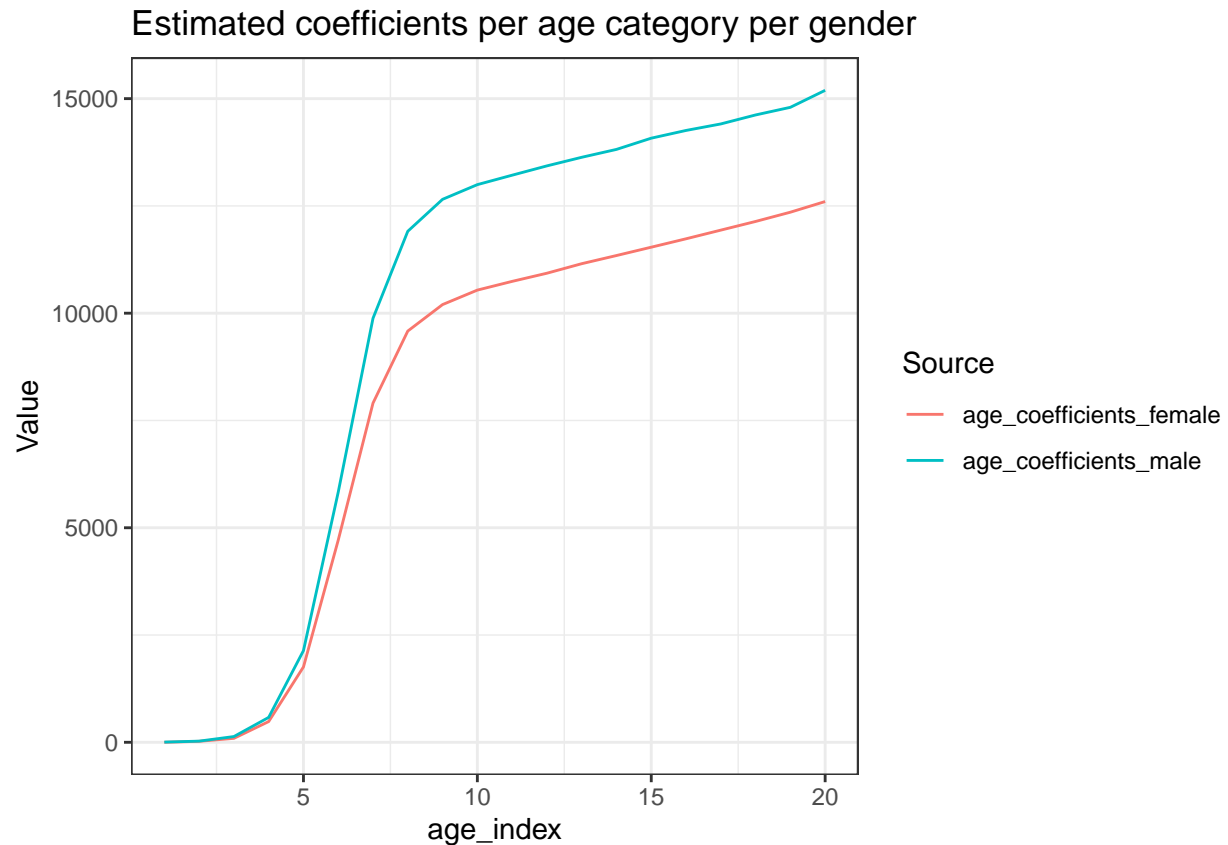
```

```
## Age_category_ leveled(80,85]:GenderFemale ***
## Age_category_ leveled(85,90]:GenderFemale ***
## Age_category_ leveled(90,95]:GenderFemale ***
## Age_category_ leveled(95,100]:GenderFemale ***
## Age_category_ leveled100+:GenderFemale ***
## Age_category_ leveled[0,5]:GenderMale
## Age_category_ leveled(5,10]:GenderMale
## Age_category_ leveled(10,15]:GenderMale
## Age_category_ leveled(15,20]:GenderMale ***
## Age_category_ leveled(20,25]:GenderMale ***
## Age_category_ leveled(25,30]:GenderMale ***
## Age_category_ leveled(30,35]:GenderMale ***
## Age_category_ leveled(35,40]:GenderMale ***
## Age_category_ leveled(40,45]:GenderMale ***
## Age_category_ leveled(45,50]:GenderMale ***
## Age_category_ leveled(50,55]:GenderMale ***
## Age_category_ leveled(55,60]:GenderMale ***
## Age_category_ leveled(60,65]:GenderMale ***
## Age_category_ leveled(65,70]:GenderMale ***
## Age_category_ leveled(70,75]:GenderMale ***
## Age_category_ leveled(75,80]:GenderMale ***
## Age_category_ leveled(80,85]:GenderMale ***
## Age_category_ leveled(85,90]:GenderMale ***
## Age_category_ leveled(90,95]:GenderMale ***
## Age_category_ leveled(95,100]:GenderMale ***
## Age_category_ leveled100+:GenderMale ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3698 on 996266 degrees of freedom
## Multiple R-squared:  0.8655, Adjusted R-squared:  0.8655
## F-statistic: 1.527e+05 on 42 and 996266 DF,  p-value: < 2.2e-16
```

The coefficients show that there is a difference between genders and that there is an increasing trend over age categories, meaning that just as in the graph above the health costs are increasing the older someone is. To make visible the difference between gender per age category I again plotted the coefficients below, but then split per gender. The graph shows the same trend as the earlier graph on average health costs shows above (see the graph with title: Healthcare cost by age category and gender).

```
age_coefficients_female <- model_Split_gender$coefficients[2:21]
age_coefficients_male <- model_Split_gender$coefficients[23:42]
age_index <- seq(20)
data_age_coeff_gender <- data.frame(age_index, age_coefficients_female, age_coefficients_male)
data_age_coeff_gender_long <- pivot_longer(data_age_coeff_gender, cols = c(age_coefficients_female, age_coefficients_male),
                                           names_to = "Source", values_to = "Value")

ggplot(data_age_coeff_gender_long, aes(x = age_index, y = Value, color = Source))+
  geom_line()+
  ggtitle("Estimated coefficients per age category per gender")
```



A second model based on the ordered age:

Order_age is a variable ranging from 1 to 24 depending on the age category, the higher the number the higher the age category. a one increase in the Order_age means one higher age category. For most of the data (except above age 100) this means that a person is in an age class of 5 years higher. See below for a table of Order_age values per Age category.

```
age_table <- data %>%
  group_by(Order_age)%>%
  distinct(Age_category)
colnames(age_table) <- c("Age_category", "age_index")
age_table$age_index = age_table$age_index - 1
age_table <- age_table[0:21,]
age_table
```

```
## # A tibble: 21 x 2
## # Groups:   age_index [21]
##   Age_category age_index
##   <fct>         <dbl>
## 1 [0,5]         0
## 2 (5,10]        1
## 3 (10,15]       2
## 4 (15,20]       3
## 5 (20,25]       4
```

```
## 6 (25,30]          5
## 7 (30,35]          6
## 8 (35,40]          7
## 9 (40,45]          8
## 10 (45,50]         9
## # ... with 11 more rows
```

```
model2 <- lm(Healthcare_cost ~ Order_age + Gender, data = data)
summary(model2)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Order_age + Gender, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16385  -3750   -326    3139   19239
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2058.339     12.895  -159.6  <2e-16 ***
## Order_age    1032.626       1.139   906.9  <2e-16 ***
## GenderMale    926.755       8.912   104.0  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4400 on 996305 degrees of freedom
## Multiple R-squared:  0.4524, Adjusted R-squared:  0.4524
## F-statistic: 4.115e+05 on 2 and 996305 DF,  p-value: < 2.2e-16
```

The outcome of this regression shows that on average when you increase Order_age by 1, so fall in an age category higher, you will have 1032.6 increased health costs. The outcome from this regression also shows that you will on average have 926.8 increased health costs when you are male instead of female.

To conclude from both regressions the groups that are likely to be profitable and the groups that are likely to be loss-making:

- Profitable:
 - Females on average have lower healthcare costs.
 - The older people are the more the healthcare costs. To get insight in how this changes over time I have plotted the coefficients in the graph above. There is a large jump between age category [25-30] with a value 2737 and age category [30-35] with a value 6141. See the graph for the exact change in coefficient. But it depends on the premium of the individuals at what age the individuals become loss-making on average.
- Loss-making:
 - Males on average have higher healthcare costs.
 - Older individuals have increased healthcare costs (see the coefficients per age category graph above). Older people are more likely to be loss making.

Model Extension

I will now extend the model using other available data and analyze whether this extra data increases the accuracy of the model.

```
summary(model1)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Age_category_levleled + Gender,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12991.0  -1960.4   -388.5   1644.3  21003.6
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -1745.620     79.094  -22.070 < 2e-16 ***
## Age_category_levleled(5,10]      67.637     86.357   0.783  0.43350
## Age_category_levleled(10,15]    240.471     82.041   2.931  0.00338 **
## Age_category_levleled(15,20]    548.903     80.669   6.804 1.02e-11 ***
## Age_category_levleled(20,25]   1156.457     80.102  14.437 < 2e-16 ***
## Age_category_levleled(25,30]   2737.504     79.815  34.298 < 2e-16 ***
## Age_category_levleled(30,35]   6141.315     79.706  77.050 < 2e-16 ***
## Age_category_levleled(35,40]   9735.011     79.672 122.189 < 2e-16 ***
## Age_category_levleled(40,45]  11547.458     79.698 144.890 < 2e-16 ***
## Age_category_levleled(45,50]  12205.643     79.780 152.991 < 2e-16 ***
## Age_category_levleled(50,55]  12541.077     79.922 156.917 < 2e-16 ***
## Age_category_levleled(55,60]  12747.848     80.137 159.077 < 2e-16 ***
## Age_category_levleled(60,65]  12956.523     80.457 161.037 < 2e-16 ***
## Age_category_levleled(65,70]  13183.380     80.917 162.925 < 2e-16 ***
## Age_category_levleled(70,75]  13382.899     81.568 164.070 < 2e-16 ***
## Age_category_levleled(75,80]  13624.450     82.554 165.036 < 2e-16 ***
## Age_category_levleled(80,85]  13834.795     83.951 164.795 < 2e-16 ***
## Age_category_levleled(85,90]  14039.950     85.920 163.407 < 2e-16 ***
## Age_category_levleled(90,95]  14272.745     88.863 160.615 < 2e-16 ***
## Age_category_levleled(95,100] 14497.314     92.662 156.453 < 2e-16 ***
## Age_category_levleled100+    14903.376     87.791 169.759 < 2e-16 ***
## GenderMale           1780.134       7.731 230.257 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3724 on 996286 degrees of freedom
## Multiple R-squared:  0.6076, Adjusted R-squared:  0.6076
## F-statistic: 7.346e+04 on 21 and 996286 DF,  p-value: < 2.2e-16
```

```
model3 <- lm(Healthcare_cost ~ Age_category_levleled + Gender + Income_source + Limited_coverage + Unhea
summary(model3)
```

```
##
## Call:
```

```

## lm(formula = Healthcare_cost ~ Age_category_ leveled + Gender +
##      Income_source + Limited_coverage + Unhealthy_region + Population_density,
##      data = data)
##
## Residuals:
##      Min        1Q      Median        3Q        Max
## -16078.5  -1727.1      80.4    1934.7   17612.1
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -2345.061      71.214  -32.930 < 2e-16 ***
## Age_category_ leveled(5,10]         90.585      77.356    1.171 0.241594
## Age_category_ leveled(10,15]        266.038      73.489    3.620 0.000294 ***
## Age_category_ leveled(15,20]        487.520      73.670    6.618 3.65e-11 ***
## Age_category_ leveled(20,25]        932.276      78.329   11.902 < 2e-16 ***
## Age_category_ leveled(25,30]       2353.064      78.637   29.923 < 2e-16 ***
## Age_category_ leveled(30,35]       5408.188      78.567   68.835 < 2e-16 ***
## Age_category_ leveled(35,40]       8633.811      78.583  109.869 < 2e-16 ***
## Age_category_ leveled(40,45]      10274.548      78.633  130.665 < 2e-16 ***
## Age_category_ leveled(45,50]      10879.236      78.708  138.222 < 2e-16 ***
## Age_category_ leveled(50,55]      11197.633      78.826  142.055 < 2e-16 ***
## Age_category_ leveled(55,60]      11413.486      79.001  144.473 < 2e-16 ***
## Age_category_ leveled(60,65]      11609.820      79.262  146.474 < 2e-16 ***
## Age_category_ leveled(65,70]      11769.217      85.422  137.778 < 2e-16 ***
## Age_category_ leveled(70,75]      11967.433      89.353  133.934 < 2e-16 ***
## Age_category_ leveled(75,80]      12196.587      90.077  135.401 < 2e-16 ***
## Age_category_ leveled(80,85]      12421.364      91.108  136.336 < 2e-16 ***
## Age_category_ leveled(85,90]      12619.808      92.570  136.327 < 2e-16 ***
## Age_category_ leveled(90,95]      12879.083      94.775  135.892 < 2e-16 ***
## Age_category_ leveled(95,100]     13077.553      97.651  133.921 < 2e-16 ***
## Age_category_ leveled100+         13501.194      93.973  143.670 < 2e-16 ***
## GenderMale          1784.937        6.926  257.721 < 2e-16 ***
## Income_sourcePension    1445.198       51.461   28.083 < 2e-16 ***
## Income_sourceStudent    1353.378       34.663   39.043 < 2e-16 ***
## Income_sourceUnemployment Benefits  1430.432       37.271   38.379 < 2e-16 ***
## Income_sourceWorking    1365.035       33.049   41.303 < 2e-16 ***
## Limited_coverage      -3909.255       14.214 -275.026 < 2e-16 ***
## Unhealthy_region        3862.047        9.374  411.977 < 2e-16 ***
## Population_density      -1.951        2.363   -0.826 0.408921
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3336 on 996279 degrees of freedom
## Multiple R-squared:  0.6852, Adjusted R-squared:  0.6851
## F-statistic: 7.743e+04 on 28 and 996279 DF,  p-value: < 2.2e-16

```

Population density will be left out of the model as the estimated effect size is very small and the coefficient is not significant. The other variables I will leave in the model, in the appendix summaries can be found on the models with and without the other variables. From those I conclude that model fit (R-squared) and statistical significance are optimal when I leave in all the variables except population density. The other added variables do seem to have a significant effect on the health costs based on the estimated coefficients and the statistical significance of these coefficients. Another important measure to check whether the model has become more accurate with the added variables is the value of the R-squared of the model. Compared to the model without the added variables we see an increase in the R-squared. R-squared value of the basic

age and gender model: 0.6076 R-squared value of the model with added variables: 0.6852

When we remove the population density variable from the model we are left with the following model:

```
model4 <- lm(Healthcare_cost ~ Age_category_ leveled + Gender + Income_source + Limited_coverage + Unheal
summary(model4)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Age_category_ leveled + Gender +
##     Income_source + Limited_coverage + Unhealthy_region, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16074.6  -1727.2    78.5   1935.0  17614.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -2350.873     70.865  -33.174 < 2e-16 ***
## Age_category_ leveled(5,10]      90.534     77.356    1.170 0.241855
## Age_category_ leveled(10,15]     266.000     73.489    3.620 0.000295 ***
## Age_category_ leveled(15,20]     487.475     73.670    6.617 3.67e-11 ***
## Age_category_ leveled(20,25]     932.276     78.329   11.902 < 2e-16 ***
## Age_category_ leveled(25,30]    2353.053     78.637   29.923 < 2e-16 ***
## Age_category_ leveled(30,35]    5408.182     78.567   68.835 < 2e-16 ***
## Age_category_ leveled(35,40]    8633.808     78.583  109.869 < 2e-16 ***
## Age_category_ leveled(40,45]   10274.535     78.633  130.665 < 2e-16 ***
## Age_category_ leveled(45,50]   10879.234     78.708  138.222 < 2e-16 ***
## Age_category_ leveled(50,55]   11197.634     78.826  142.055 < 2e-16 ***
## Age_category_ leveled(55,60]   11413.468     79.001  144.473 < 2e-16 ***
## Age_category_ leveled(60,65]   11609.804     79.262  146.474 < 2e-16 ***
## Age_category_ leveled(65,70]   11769.253     85.422  137.778 < 2e-16 ***
## Age_category_ leveled(70,75]   11967.492     89.353  133.935 < 2e-16 ***
## Age_category_ leveled(75,80]   12196.640     90.077  135.402 < 2e-16 ***
## Age_category_ leveled(80,85]   12421.407     91.108  136.337 < 2e-16 ***
## Age_category_ leveled(85,90]   12619.849     92.570  136.327 < 2e-16 ***
## Age_category_ leveled(90,95]   12879.102     94.775  135.892 < 2e-16 ***
## Age_category_ leveled(95,100]  13077.584     97.651  133.921 < 2e-16 ***
## Age_category_ leveled100+    13501.266     93.973  143.671 < 2e-16 ***
## GenderMale        1784.935        6.926  257.720 < 2e-16 ***
## Income_sourcePension    1445.114     51.461   28.082 < 2e-16 ***
## Income_sourceStudent    1353.337     34.663   39.042 < 2e-16 ***
## Income_sourceUnemployment Benefits 1430.392     37.271   38.378 < 2e-16 ***
## Income_sourceWorking    1365.002     33.049   41.302 < 2e-16 ***
## Limited_coverage     -3909.250     14.214  -275.025 < 2e-16 ***
## Unhealthy_region      3862.047      9.374  411.977 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3336 on 996280 degrees of freedom
## Multiple R-squared:  0.6852, Adjusted R-squared:  0.6851
## F-statistic: 8.03e+04 on 27 and 996280 DF, p-value: < 2.2e-16
```

Compared to the previous model the R-squared has not changed, which also indicates that the population density did not add accuracy to the model.

Model analysis

From the estimated coefficients of the final model we can observe the following:

- Increased age category has on average the result that you have more health costs.
- When you are male you will on average have 1785 more health costs.
- The different income sources have different sized effects on the health costs. It can be expected that someone who has unemployment benefits have on average a higher health cost than someone who works and it can be expected that students (often young and healthy) will have lower health costs than people who live on a pension. This reasoning can be seen in the estimated coefficients:
 - Income_sourcePension: 1445.114
 - Income_sourceStudent: 1353.337
 - Income_sourceUnemployment Benefits: 1430.392
 - Income_sourceWorking: 1365.002
- Whether or not you have limited coverage on your insurance has a large effect. When you have limited coverage on your insurance you have on average 3909.3 less health costs compared to someone who has full coverage.
- Whether or not you live in an unhealthy region also has a large effect on your health costs. When you live in an unhealthy region you have on average 3862.0 more health costs than someone who does not live in an unhealthy region.

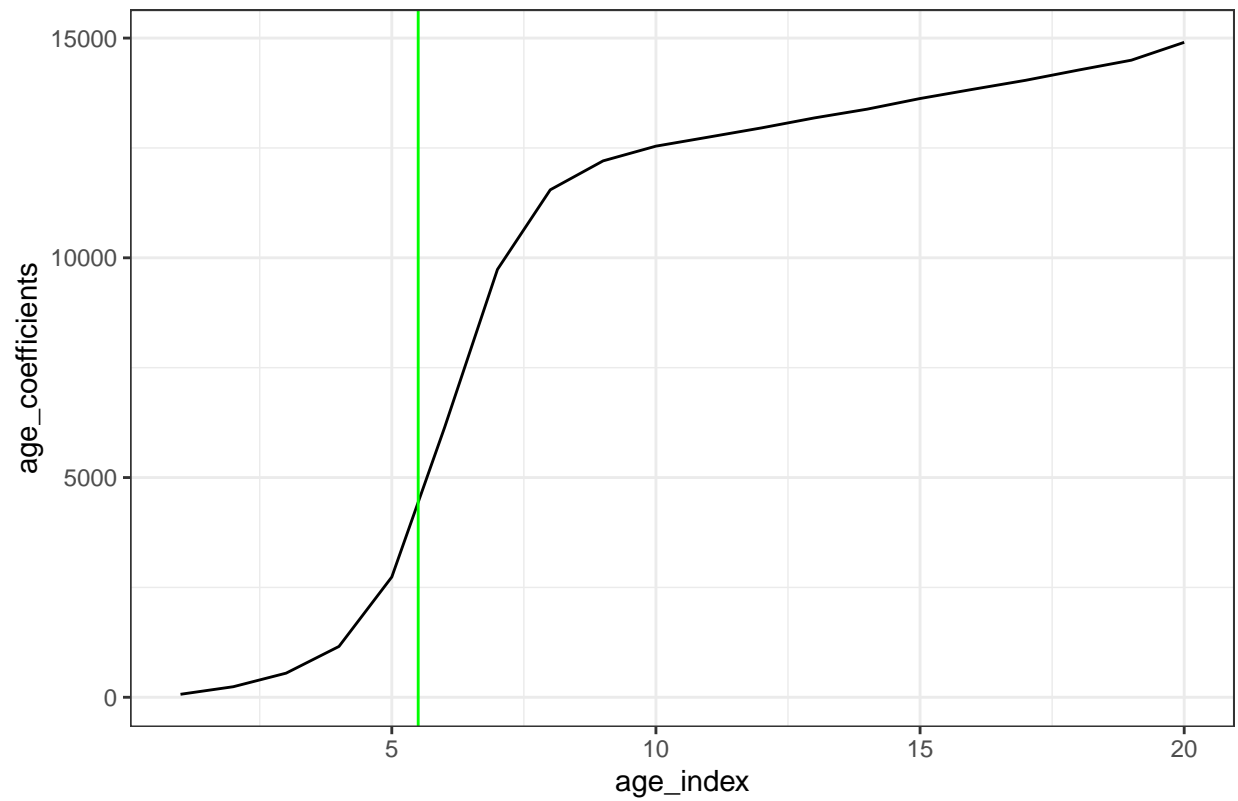
Further analysis using graphs

As we concluded above the individuals who are in the category [30-35] and above have a much higher health cost than those younger than them. So for analysis I split this group in two where one group is everyone under 30 and one group is everyone above 30. In the graph below this shows that I will include everyone up to the green line.

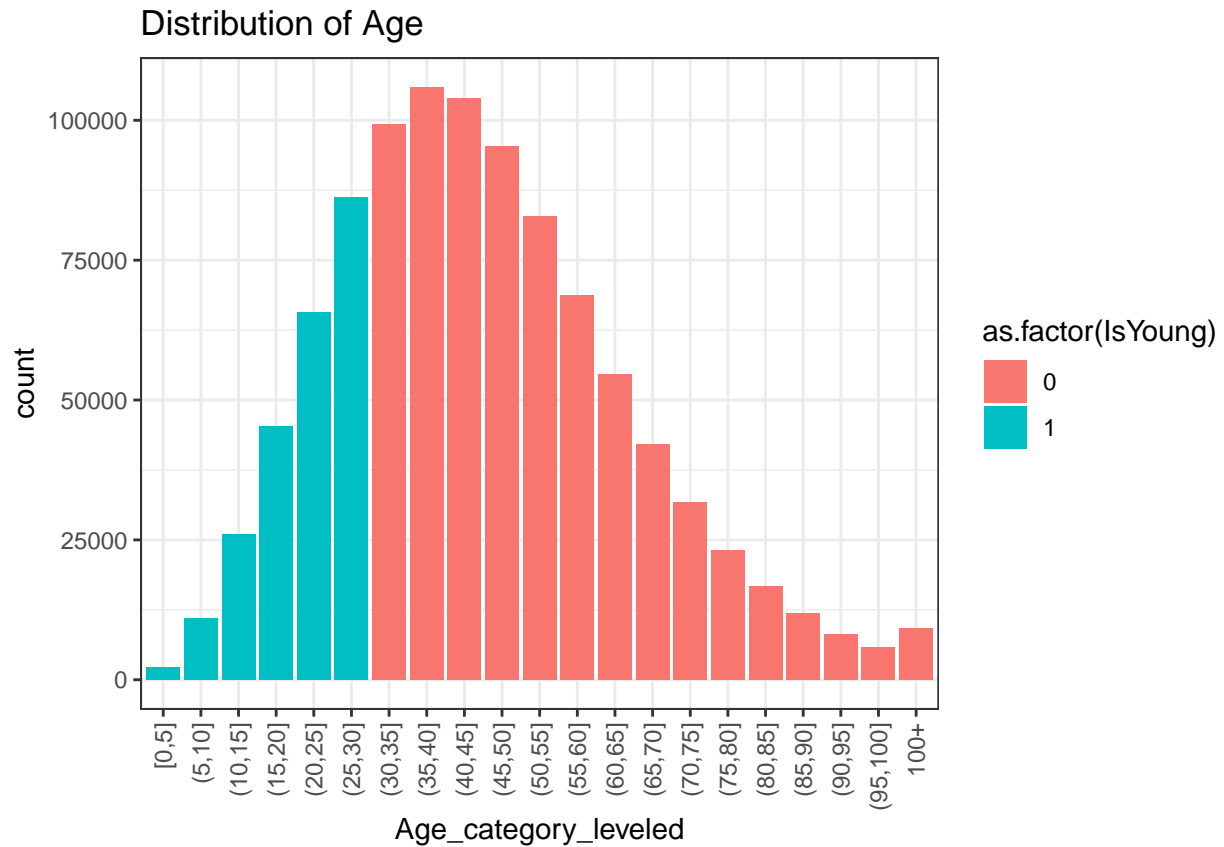
```
data$IsYoung <- ifelse(data$Order_age <= 6, 1, 0)
```

```
ggplot(data_age_coeff, aes(x = age_index, y = age_coefficients))+  
  geom_line()+  
  ggtitle("Estimated coefficients per age category")+  
  geom_vline(xintercept = 5.5, colour = 'green')
```

Estimated coefficients per age category

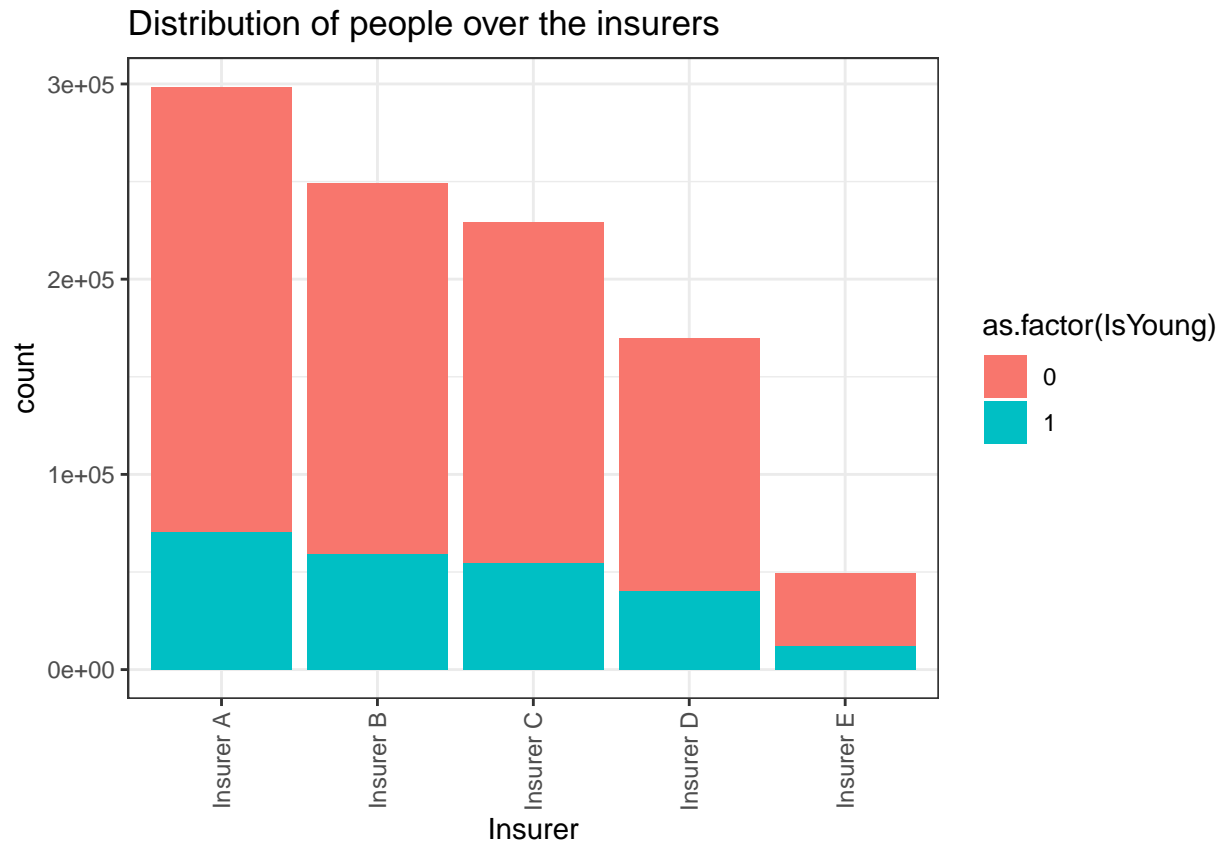


```
ggplot(data = data, aes( x = Age_category_ leveled, fill = as.factor(IsYoung)))+  
  geom_bar()+  
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+  
  ggtitle("Distribution of Age")
```



Using this split I can now visualize which insurer has the most profitable individuals.

```
ggplot(data = data, aes( x = Insurer, fill = as.factor(IsYoung)))+
  geom_bar()+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))+
  ggtitle("Distribution of people over the insurers")
```



```
data%>%
  group_by(Insurer)%>%
  summarise_at(vars(IsYoung), funs(mean(.)))
```

```
## # A tibble: 5 x 2
##   Insurer  IsYoung
##   <fct>      <dbl>
## 1 Insurer A  0.237
## 2 Insurer B  0.238
## 3 Insurer C  0.238
## 4 Insurer D  0.238
## 5 Insurer E  0.239
```

From this analysis we can observe that Insurer E has the highest share of people under 30, namely 23.9%. However the percentages between insurers do not differ much. The lowest percentage is 23.67%, while the highest (from insurer E) is 23.91%

Appendix

```
model_A1 <- lm(Healthcare_cost ~ Age_category_ leveled + Gender + Limited_coverage + Unhealthy_region +
summary(model_A1)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Age_category_levleled + Gender +
##     Limited_coverage + Unhealthy_region + Population_density,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16078.6  -1703.5    77.4   1936.6  17626.5
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -2341.500     71.280   -32.849 < 2e-16 ***
## Age_category_levleled(5,10]      90.426     77.428     1.168 0.242856
## Age_category_levleled(10,15]    265.540     73.557     3.610 0.000306 ***
## Age_category_levleled(15,20]   1097.774     72.353    15.173 < 2e-16 ***
## Age_category_levleled(20,25]   2269.503     71.933    31.550 < 2e-16 ***
## Age_category_levleled(25,30]   3699.819     71.646    51.640 < 2e-16 ***
## Age_category_levleled(30,35]   6761.831     71.498    94.574 < 2e-16 ***
## Age_category_levleled(35,40]   9994.904     71.438   139.909 < 2e-16 ***
## Age_category_levleled(40,45]  11639.102     71.458   162.881 < 2e-16 ***
## Age_category_levleled(45,50]  12244.864     71.531   171.183 < 2e-16 ***
## Age_category_levleled(50,55]  12563.459     71.658   175.326 < 2e-16 ***
## Age_category_levleled(55,60]  12779.320     71.850   177.861 < 2e-16 ***
## Age_category_levleled(60,65]  12975.723     72.137   179.876 < 2e-16 ***
## Age_category_levleled(65,70]  13195.423     72.550   181.881 < 2e-16 ***
## Age_category_levleled(70,75]  13410.381     73.134   183.368 < 2e-16 ***
## Age_category_levleled(75,80]  13639.634     74.018   184.275 < 2e-16 ***
## Age_category_levleled(80,85]  13864.525     75.271   184.196 < 2e-16 ***
## Age_category_levleled(85,90]  14063.128     77.036   182.553 < 2e-16 ***
## Age_category_levleled(90,95]  14322.552     79.675   179.763 < 2e-16 ***
## Age_category_levleled(95,100] 14521.206     83.081   174.784 < 2e-16 ***
## Age_category_levleled100+    14945.190     78.714   189.868 < 2e-16 ***
## GenderMale        1780.921       6.932   256.926 < 2e-16 ***
## Limited_coverage   -3828.769     14.103  -271.488 < 2e-16 ***
## Unhealthy_region    3861.618       9.383   411.549 < 2e-16 ***
## Population_density    -1.799       2.365    -0.761 0.446856
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3339 on 996283 degrees of freedom
## Multiple R-squared:  0.6846, Adjusted R-squared:  0.6846
## F-statistic: 9.009e+04 on 24 and 996283 DF,  p-value: < 2.2e-16
```

```
model_A2 <- lm(Healthcare_cost ~ Age_category_levleled + Gender + Income_source + Unhealthy_region + Population_density, data = data)
summary(model_A2)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Age_category_levleled + Gender +
##     Income_source + Unhealthy_region + Population_density, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -16074 -1802 41 1735 18570
##
## Coefficients:
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2341.199 73.867 -31.695 < 2e-16 ***
## Age_category_leveld(5,10] 90.403 80.239 1.127 0.259880
## Age_category_leveld(10,15] 265.471 76.228 3.483 0.000497 ***
## Age_category_leveld(15,20] 486.538 76.416 6.367 1.93e-10 ***
## Age_category_leveld(20,25] 961.099 81.248 11.829 < 2e-16 ***
## Age_category_leveld(25,30] 2549.378 81.564 31.256 < 2e-16 ***
## Age_category_leveld(30,35] 5956.546 81.469 73.114 < 2e-16 ***
## Age_category_leveld(35,40] 9551.568 81.438 117.287 < 2e-16 ***
## Age_category_leveld(40,45] 11363.316 81.459 139.497 < 2e-16 ***
## Age_category_leveld(45,50] 12018.729 81.528 147.418 < 2e-16 ***
## Age_category_leveld(50,55] 12350.828 81.648 151.270 < 2e-16 ***
## Age_category_leveld(55,60] 12568.537 81.829 153.595 < 2e-16 ***
## Age_category_leveld(60,65] 12765.476 82.100 155.487 < 2e-16 ***
## Age_category_leveld(65,70] 12924.858 88.498 146.047 < 2e-16 ***
## Age_category_leveld(70,75] 13123.143 92.580 141.749 < 2e-16 ***
## Age_category_leveld(75,80] 13352.410 93.333 143.063 < 2e-16 ***
## Age_category_leveld(80,85] 13577.315 94.403 143.823 < 2e-16 ***
## Age_category_leveld(85,90] 13775.940 95.921 143.617 < 2e-16 ***
## Age_category_leveld(90,95] 14035.382 98.210 142.912 < 2e-16 ***
## Age_category_leveld(95,100] 14234.062 101.197 140.658 < 2e-16 ***
## Age_category_leveld100+ 14658.093 97.378 150.528 < 2e-16 ***
## GenderMale 1780.384 7.184 247.829 < 2e-16 ***
## Income_sourcePension 286.935 53.199 5.394 6.91e-08 ***
## Income_sourceStudent 212.817 35.697 5.962 2.50e-09 ***
## Income_sourceUnemployment Benefits 275.577 38.414 7.174 7.30e-13 ***
## Income_sourceWorking 206.096 34.001 6.061 1.35e-09 ***
## Unhealthy_region 3861.457 9.724 397.115 < 2e-16 ***
## Population_density -1.715 2.451 -0.700 0.484182
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3461 on 996280 degrees of freedom
## Multiple R-squared: 0.6613, Adjusted R-squared: 0.6612
## F-statistic: 7.203e+04 on 27 and 996280 DF, p-value: < 2.2e-16
```

```
model_A3 <- lm(Healthcare_cost ~ Age_category_leveld + Gender + Income_source + Limited_coverage + Population_density, data = data)
summary(model_A3)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Age_category_leveld + Gender +
## Income_source + Limited_coverage + Population_density, data = data)
##
## Residuals:
## Min 1Q Median 3Q Max
## -12993.9 -2093.8 -277.6 1884.7 20508.9
##
## Coefficients:
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1744.926 77.025 -22.654 < 2e-16 ***
```

```
## Age_category_ leveled(5,10]          67.879      83.686      0.811  0.41730
## Age_category_ leveled(10,15]         241.134      79.503      3.033  0.00242 **
## Age_category_ leveled(15,20]         459.375      79.699      5.764 8.22e-09 ***
## Age_category_ leveled(20,25]          929.384      84.739     10.968 < 2e-16 ***
## Age_category_ leveled(25,30]        2347.782      85.072     27.598 < 2e-16 ***
## Age_category_ leveled(30,35]        5399.785      84.997     63.529 < 2e-16 ***
## Age_category_ leveled(35,40]         8624.198      85.013    101.445 < 2e-16 ***
## Age_category_ leveled(40,45]       10265.673      85.067    120.677 < 2e-16 ***
## Age_category_ leveled(45,50]       10873.078      85.149    127.695 < 2e-16 ***
## Age_category_ leveled(50,55]       11194.866      85.276    131.278 < 2e-16 ***
## Age_category_ leveled(55,60]       11399.811      85.465    133.385 < 2e-16 ***
## Age_category_ leveled(60,65]       11607.865      85.748    135.372 < 2e-16 ***
## Age_category_ leveled(65,70]       11767.360      92.412    127.336 < 2e-16 ***
## Age_category_ leveled(70,75]       11948.138      96.665    123.604 < 2e-16 ***
## Age_category_ leveled(75,80]       12189.570      97.449    125.087 < 2e-16 ***
## Age_category_ leveled(80,85]       12399.776      98.564    125.804 < 2e-16 ***
## Age_category_ leveled(85,90]       12604.733     100.146    125.864 < 2e-16 ***
## Age_category_ leveled(90,95]       12837.355     102.530    125.206 < 2e-16 ***
## Age_category_ leveled(95,100]      13061.682     105.642    123.641 < 2e-16 ***
## Age_category_ leveled100+          13467.268     101.663    132.469 < 2e-16 ***
## GenderMale                          1785.240       7.493    238.267 < 2e-16 ***
## Income_sourcePension                 1437.640      55.672     25.823 < 2e-16 ***
## Income_sourceStudent                 1347.327      37.500     35.929 < 2e-16 ***
## Income_sourceUnemployment Benefits  1401.408      40.321     34.756 < 2e-16 ***
## Income_sourceWorking                 1349.507      35.754     37.745 < 2e-16 ***
## Limited_coverage                    -3907.915      15.377   -254.135 < 2e-16 ***
## Population_density                   -1.917       2.556     -0.750  0.45317
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3609 on 996280 degrees of freedom
## Multiple R-squared:  0.6315, Adjusted R-squared:  0.6315
## F-statistic: 6.324e+04 on 27 and 996280 DF,  p-value: < 2.2e-16
```

```
model_A4 <- lm(Healthcare_cost ~ Age_category_ leveled + Gender + Income_source + Limited_coverage + Unh
summary(model_A4)
```

```
##
## Call:
## lm(formula = Healthcare_cost ~ Age_category_ leveled + Gender +
##     Income_source + Limited_coverage + Unhealthy_region, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16074.6  -1727.2    78.5   1935.0  17614.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -2350.873     70.865   -33.174 < 2e-16 ***
## Age_category_ leveled(5,10]         90.534     77.356    1.170 0.241855
## Age_category_ leveled(10,15]        266.000     73.489    3.620 0.000295 ***
## Age_category_ leveled(15,20]        487.475     73.670    6.617 3.67e-11 ***
## Age_category_ leveled(20,25]        932.276     78.329   11.902 < 2e-16 ***
## Age_category_ leveled(25,30]       2353.053     78.637   29.923 < 2e-16 ***
```

```

## Age_category_leveled(30,35]          5408.182    78.567    68.835 < 2e-16 ***
## Age_category_leveled(35,40]          8633.808    78.583   109.869 < 2e-16 ***
## Age_category_leveled(40,45]         10274.535    78.633   130.665 < 2e-16 ***
## Age_category_leveled(45,50]         10879.234    78.708   138.222 < 2e-16 ***
## Age_category_leveled(50,55]         11197.634    78.826   142.055 < 2e-16 ***
## Age_category_leveled(55,60]         11413.468    79.001   144.473 < 2e-16 ***
## Age_category_leveled(60,65]         11609.804    79.262   146.474 < 2e-16 ***
## Age_category_leveled(65,70]         11769.253    85.422   137.778 < 2e-16 ***
## Age_category_leveled(70,75]         11967.492    89.353   133.935 < 2e-16 ***
## Age_category_leveled(75,80]         12196.640    90.077   135.402 < 2e-16 ***
## Age_category_leveled(80,85]         12421.407    91.108   136.337 < 2e-16 ***
## Age_category_leveled(85,90]         12619.849    92.570   136.327 < 2e-16 ***
## Age_category_leveled(90,95]         12879.102    94.775   135.892 < 2e-16 ***
## Age_category_leveled(95,100]        13077.584    97.651   133.921 < 2e-16 ***
## Age_category_leveled100+           13501.266    93.973   143.671 < 2e-16 ***
## GenderMale                          1784.935      6.926   257.720 < 2e-16 ***
## Income_sourcePension                 1445.114    51.461    28.082 < 2e-16 ***
## Income_sourceStudent                 1353.337    34.663    39.042 < 2e-16 ***
## Income_sourceUnemployment Benefits  1430.392    37.271    38.378 < 2e-16 ***
## Income_sourceWorking                 1365.002    33.049    41.302 < 2e-16 ***
## Limited_coverage                    -3909.250    14.214  -275.025 < 2e-16 ***
## Unhealthy_region                     3862.047      9.374   411.977 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3336 on 996280 degrees of freedom
## Multiple R-squared:  0.6852, Adjusted R-squared:  0.6851
## F-statistic: 8.03e+04 on 27 and 996280 DF,  p-value: < 2.2e-16

```