JACC study Milk intake and stroke mortality analysis

Chaochen Wang

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Contents

1 Read in the data

```
library(readr)
library(tidyverse)
```

```
## -- Attaching packages ------------------ tidyverse 1.3.0 --

## v ggplot2 3.3.2     v dplyr   1.0.2
## v tibble  3.0.3     v stringr 1.4.0
## v tidyr   1.1.1     v forcats 0.5.0
## v purrr   0.3.4

## -- Conflicts --------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(lubridate) # for dealing with date time data
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
MILK <- read_csv("../data/StrokeMilk.csv",
                     progress = show_progress(),
                     col_types = cols(.default = "c"))

MILK %>%
  filter(tr_age > 39 & tr_age < 80) %>%
  group_by(tr_sex) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 2 x 3
##   tr_sex      n rel.freq
##   <chr>   <int> <chr>
## 1 1       46395 41.95%
## 2 2       64190 58.05%
```

2 delete subjects outside of age range ——————————————————

```r
MILK_0 <- MILK %>%
  filter(tr_age > 39 & tr_age < 80)
```

3 define total stroke mortality ——————————————————

```r
MILK_0 <- MILK_0 %>%
  mutate(Tot_Stroke = if_else(grepl("I6[0-9][0-9]|I6[0-9]",
                                    ICD10), "I60_9",
                      if_else(!is.na(ICD10), "other_death",
                                      "Alive/Censor")))
MILK_0%>%
  group_by(tr_sex, Tot_Stroke) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex Tot_Stroke       n rel.freq
##   <chr>  <chr>        <int> <chr>
## 1 1      Alive/Censor 31110 67.05%
## 2 1      I60_9         1825 3.93%
## 3 1      other_death  13460 29.01%
## 4 2      Alive/Censor 52347 81.55%
## 5 2      I60_9         1777 2.77%
## 6 2      other_death  10066 15.68%
```

4 define different type of stroke mortality/CVD ?——————————————————

I60 Nontraumatic subarachnoid hemorrhage

I61 Nontraumatic intracerebral hemorrhage

I62 Other and unspecified nontraumatic intracranial hemorrhage

I63 Cerebral infarction

I65 Occlusion and stenosis of precerebral arteries, not resulting in cerebral infarction

I66 Occlusion and stenosis of cerebral arteries, not resulting in cerebral infarction

I67 Other cerebrovascular diseases

I68 Cerebrovascular disorders in diseases classified elsewhere

I69 Sequelae of cerebrovascular disease

```
MILK_0 <- MILK_0 %>%
  mutate(HemoStroke = if_else(grepl("I6[0-2][0-9]|I6[0-2]",
                                    ICD10), "I60_2",
                              if_else(!is.na(ICD10), "other_death",
                                      "Alive/Censor"))) %>%
  mutate(IscheStroke = if_else(grepl("I63[0-9]|I63",
                                    ICD10), "I63",
                              if_else(!is.na(ICD10), "other_death",
                                      "Alive/Censor"))) %>%
  mutate(CHD = if_else(grepl("I2[0-5][0-9]|I2[0-5]",
                                     ICD10), "I20_5",
                               if_else(!is.na(ICD10), "other_death",
                                       "Alive/Censor"))) %>%
  mutate(HeartF = if_else(grepl("I50[0-9]|I50",
                                     ICD10), "I50",
                               if_else(!is.na(ICD10), "other_death",
                                       "Alive/Censor")))



MILK_0%>%
  group_by(tr_sex, HemoStroke) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex HemoStroke       n rel.freq
##   <chr>  <chr>        <int> <chr>
## 1 1      Alive/Censor 31110 67.05%
## 2 1      I60_2          556 1.2%
## 3 1      other_death  14729 31.75%
## 4 2      Alive/Censor 52347 81.55%
## 5 2      I60_2          666 1.04%
## 6 2      other_death  11177 17.41%
```

```
MILK_0%>%
  group_by(tr_sex, IscheStroke) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex IscheStroke      n rel.freq
##   <chr>  <chr>        <int> <chr>
## 1 1      Alive/Censor 31110 67.05%
## 2 1      I63            705 1.52%
## 3 1      other_death  14580 31.43%
## 4 2      Alive/Censor 52347 81.55%
## 5 2      I63            600 0.93%
## 6 2      other_death  11243 17.52%
```

```
MILK_0%>%
  group_by(tr_sex, CHD) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex CHD              n rel.freq
##   <chr>  <chr>        <int> <chr>
## 1 1      Alive/Censor 31110 67.05%
## 2 1      I20_5         1003 2.16%
## 3 1      other_death  14282 30.78%
## 4 2      Alive/Censor 52347 81.55%
## 5 2      I20_5          758 1.18%
## 6 2      other_death  11085 17.27%
```

```
MILK_0%>%
  group_by(tr_sex, HeartF) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex HeartF           n rel.freq
##   <chr>  <chr>        <int> <chr>
## 1 1      Alive/Censor 31110 67.05%
## 2 1      I50            711 1.53%
## 3 1      other_death  14574 31.41%
## 4 2      Alive/Censor 52347 81.55%
## 5 2      I50            799 1.24%
## 6 2      other_death  11044 17.21%
```

5 Define milk intake

```r
MILK_0 <- MILK_0 %>%
  mutate(Milk_fre = as.numeric(MILK)) %>%
  mutate(Milk_fre = as.factor(Milk_fre)) %>%
  mutate(Mlkfre = fct_collapse(Milk_fre,
                               Never = "1",
                               Mon1_2 = "2",
                               Wek1_2 = "3",
                               Wek3_4 = "4",
                               Daily  = "5")) %>%
  mutate(MlkLogi = fct_collapse(Mlkfre,
                                Never = "Never",
                                Drinker = c("Mon1_2", "Wek1_2", "Wek3_4", "Daily")))
```

```
## Warning: Problem with `mutate()` input `Milk_fre`.
## i NAs introduced by coercion
## i Input `Milk_fre` is `as.numeric(MILK)`.
```

```
## Warning in mask$eval_all_mutate(dots[[i]]): NAs introduced by coercion
```

```r
MILK_0 %>%
  group_by(tr_sex, Mlkfre) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 12 x 4
## # Groups:   tr_sex [2]
##    tr_sex Mlkfre     n rel.freq
##    <chr>  <fct>  <int> <chr>
##  1 1      Never   8961 19.31%
##  2 1      Mon1_2  3691 7.96%
##  3 1      Wek1_2  6228 13.42%
##  4 1      Wek3_4  5862 12.63%
##  5 1      Daily  17110 36.88%
##  6 1      <NA>    4543 9.79%
##  7 2      Never  10960 17.07%
##  8 2      Mon1_2  3830 5.97%
##  9 2      Wek1_2  7975 12.42%
## 10 2      Wek3_4  8516 13.27%
## 11 2      Daily  26957 42%
## 12 2      <NA>    5952 9.27%
```

```r
MILK_0 %>%
  group_by(tr_sex, MlkLogi) %>%
  summarise(n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex MlkLogi     n rel.freq
##   <chr>  <fct>   <int> <chr>
## 1 1      Never    8961 19.31%
## 2 1      Drinker 32891 70.89%
## 3 1      <NA>     4543 9.79%
## 4 2      Never   10960 17.07%
## 5 2      Drinker 47278 73.65%
## 6 2      <NA>     5952 9.27%
```

6 Calculate person-years

```
MILK_0 <- MILK_0 %>%
  mutate(Age = as.numeric(tr_age)) %>%
  mutate(Agegrp = cut(as.numeric(tr_age), c(30, 45, 55, 65, 75, 80), right = FALSE)) %>%
  mutate(followpy = as.numeric(actual)/365.25)
```

7 Identify potential confounders: smoking, alcohol intake, BMI, DM/HYT/MI/APO/Cancer history, Exercise, Energy intake, Sleep duration, vegetable/fru/gretea/cofe intake, school education

```
MILK_0 <-  MILK_0 %>%
  mutate(Smoking = replace_na(SM1, "unknown")) %>%
  mutate(Smoking = as_factor(Smoking)) %>%
  mutate(Smoking = fct_recode(Smoking, Never = "3", Past = "2", Current = "1")) %>%
  mutate(Smoking = factor(Smoking, levels = c("Never", "Past", "Current", "unknown"))) %>%  # Smoking
  mutate(Alc_Fre = if_else(as.numeric(DR1) >= 2, "Never or past",
                          if_else(as.numeric(DR1F) == 1, "Daily",
                                  if_else(as.numeric(DR1F) == 4, "< 1/week",
                                          if_else((as.numeric(DR1F) == 2) | (as.numeric(DR1F) == 3),
                                                  "1-4 /week", "Unknown"))))) %>%
  mutate(Alc_Fre = fct_explicit_na(Alc_Fre, na_level = "unknown")) %>%
  mutate(BMI = as.numeric(wt10)/(as.numeric(ht10)^2) * 100000) %>% # define BMI groups
  mutate(BMIgrp = cut(BMI, breaks = c(14, 18.5, 25, 30, 40), right = FALSE)) %>%
  mutate(BMIgrp = as.character(BMIgrp)) %>%
  replace_na(list(BMIgrp = "unknown")) %>%
  mutate(BMIgrp = factor(BMIgrp, levels = c("[18.5,25)",
                                            "[14,18.5)",
                                            "[25,30)",
                                            "[30,40)", "unknown"))) %>%
  mutate(DM_hist = if_else(as.numeric(p_DM) > 1, TRUE, FALSE)) %>%
  replace_na(list(DM_hist = "unknown")) %>% # recode DM history status
  mutate(HT_hist = if_else(as.numeric(p_HT) > 1, TRUE, FALSE)) %>%
  replace_na(list(HT_hist = "unknown")) %>% # recode hyt history status
  mutate(MI_hist = if_else(as.numeric(p_MI) > 1, TRUE, FALSE)) %>%
```

```
replace_na(list(MI_hist = "unknown")) %>% # recode MI history status
mutate(APO_hist = if_else(as.numeric(p_APO) > 1, TRUE, FALSE)) %>%
replace_na(list(APO_hist = "unknown")) %>% # recode APO history status
mutate(KID_hist = if_else(as.numeric(p_KID) > 1, TRUE, FALSE)) %>%
replace_na(list(KID_hist = "unknown")) %>% # recode KID history status
mutate(LIV_hist = if_else(as.numeric(p_LIV) > 1, TRUE, FALSE)) %>%
replace_na(list(LIV_hist = "unknown")) %>% # recode LIV history status
mutate(Can_hist = if_else(as.numeric(p_can1) > 1 |
                          as.numeric(p_can2) > 1, TRUE, FALSE)) %>%
replace_na(list(Can_hist = "unknown")) %>% # recode LIV history status
mutate(Exercise = as.numeric(sport) != 4) %>% # define exercise habits
mutate(Exercise = as.character(Exercise)) %>%
replace_na(list(Exercise = "unknown")) %>%
mutate(Exercise = factor(Exercise, levels = c("FALSE", "TRUE", "unknown"))) %>%
mutate(Exercise = fct_recode(Exercise,
                             "> 1h/w" = "TRUE",
                             "Almost0" = "FALSE",
                             unknown   = "unknown")) %>%
mutate(Engy = log(as.numeric(ENERGY))) %>%
mutate(Sleep = as.numeric(SLEEP)/10) %>%
mutate(Slepgrp = cut(Sleep, breaks = c(0, 6.9, 7.9, 8.9, 23), right = FALSE)) %>%
mutate(Slepgrp = as.character(Slepgrp)) %>%
replace_na(list(Slepgrp = "unknown")) %>%
mutate(Slepgrp = factor(Slepgrp, levels = c("[0,6.9)",
                                            "[6.9,7.9)",
                                            "[7.9,8.9)",
                                            "[8.9,23)", "unknown"))) %>%
mutate(Spi = as.factor(SPI)) %>% # define vegetable intake
mutate(Spi = fct_collapse(Spi,
                          unknown = "X",
                          daily = "5",
                          Thre4tw = "4",
                          One2tw = "3",
                          Less1tm = c("1", "2"))) %>%
mutate(Spi = fct_explicit_na(Spi, na_level = "unknown")) %>%
mutate(Fru = as.factor(FRU)) %>% # define fruit intake
mutate(Fru = fct_collapse(Fru,
                          unknown = "X",
                          daily = "5",
                          Thre4tw = "4",
                          One2tw = "3",
                          Less1tm = c("1", "2"))) %>%
mutate(Fru = fct_explicit_na(Fru, na_level = "unknown")) %>%
mutate(Gretea = as.factor(GreTEA1)) %>% # define greentea intake
mutate(Gretea = fct_collapse(Gretea,
                             unknown = "X",
                             Thre3tw = "2",
                             Thre3tw = "3",
                             Thre3tw = "4",
                             Never = "5",
                             daily = "1")) %>%
mutate(Gretea = fct_explicit_na(Gretea, na_level = "unknown"))  %>%
mutate(Cofe = as.factor(COFE)) %>% # define greentea intake
```

```r
mutate(Cofe = fct_collapse(Cofe,
                            unknown = "X",
                            Thre3tw = "2",
                            Thre3tw = "3",
                            Thre3tw = "4",
                            Never = "5",
                            daily = "1")) %>%
mutate(Cofe = fct_explicit_na(Cofe, na_level = "unknown"))  %>%
mutate(Educ = as.numeric(MILK_0$SCHOOL)) %>%
mutate(Educgrp = cut(Educ, breaks = c(0, 18, 70), right = FALSE)) %>%
mutate(Educgrp = as.character(Educgrp)) %>%
replace_na(list(Educgrp = "unknown")) %>%
mutate(Educgrp = factor(Educgrp, levels = c("[0,18)",
                                            "[18,70)",
                                            "unknown"))) %>% # Define menopause for women
mutate(Menopause = if_else(!is.na(MENO_AGE)& tr_sex == "2", TRUE,  # define menopause
                          if_else(as.numeric(tr_age) >= 50 & tr_sex == "2",
                                  TRUE, FALSE)))
```

```
## Warning: Problem with `mutate()` input `Alc_Fre`.
## i NAs introduced by coercion
## i Input `Alc_Fre` is `if_else(...)`.

## Warning in if_else(as.numeric(DR1F) == 1, "Daily", if_else(as.numeric(DR1F) == :
## NAs introduced by coercion

## Warning: Problem with `mutate()` input `Alc_Fre`.
## i NAs introduced by coercion
## i Input `Alc_Fre` is `if_else(...)`.

## Warning in if_else(as.numeric(DR1F) == 4, "< 1/week", if_else((as.numeric(DR1F)
## == : NAs introduced by coercion

## Warning: Problem with `mutate()` input `Alc_Fre`.
## i NAs introduced by coercion
## i Input `Alc_Fre` is `if_else(...)`.

## Warning in if_else((as.numeric(DR1F) == 2) | (as.numeric(DR1F) == 3), "1-4 /
## week", : NAs introduced by coercion

## Warning: Problem with `mutate()` input `Alc_Fre`.
## i NAs introduced by coercion
## i Input `Alc_Fre` is `if_else(...)`.

## Warning in if_else((as.numeric(DR1F) == 2) | (as.numeric(DR1F) == 3), "1-4 /
## week", : NAs introduced by coercion

## Warning: Problem with `mutate()` input `KID_hist`.
## i NAs introduced by coercion
## i Input `KID_hist` is `if_else(as.numeric(p_KID) > 1, TRUE, FALSE)`.
```

```
## Warning in if_else(as.numeric(p_KID) > 1, TRUE, FALSE): NAs introduced by
## coercion

## Warning: Problem with `mutate()` input `LIV_hist`.
## i NAs introduced by coercion
## i Input `LIV_hist` is `if_else(as.numeric(p_LIV) > 1, TRUE, FALSE)`.

## Warning in if_else(as.numeric(p_LIV) > 1, TRUE, FALSE): NAs introduced by
## coercion

## Warning: Problem with `mutate()` input `Can_hist`.
## i NAs introduced by coercion
## i Input `Can_hist` is `if_else(...)`.

## Warning in if_else(as.numeric(p_can1) > 1 | as.numeric(p_can2) > 1, TRUE, : NAs
## introduced by coercion

## Warning: Problem with `mutate()` input `Can_hist`.
## i NAs introduced by coercion
## i Input `Can_hist` is `if_else(...)`.

## Warning in if_else(as.numeric(p_can1) > 1 | as.numeric(p_can2) > 1, TRUE, : NAs
## introduced by coercion

## Warning: Problem with `mutate()` input `Exercise`.
## i NAs introduced by coercion
## i Input `Exercise` is `as.numeric(sport) != 4`.

## Warning in mask$eval_all_mutate(dots[[i]]): NAs introduced by coercion

## Warning: Problem with `mutate()` input `Sleep`.
## i NAs introduced by coercion
## i Input `Sleep` is `as.numeric(SLEEP)/10`.

## Warning in mask$eval_all_mutate(dots[[i]]): NAs introduced by coercion

## Warning: Problem with `mutate()` input `Educ`.
## i NAs introduced by coercion
## i Input `Educ` is `as.numeric(MILK_0$SCHOOL)`.

## Warning in mask$eval_all_mutate(dots[[i]]): NAs introduced by coercion
```

```r
MILK_0 %>%
  group_by(tr_sex, Smoking) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 8 x 4
## # Groups:   tr_sex [2]
##   tr_sex Smoking     n rel.freq
##   <chr>  <fct>   <int> <chr>
## 1 1      Never    9027 19.46%
## 2 1      Past    11668 25.15%
## 3 1      Current 23444 50.53%
## 4 1      unknown  2256 4.86%
## 5 2      Never   51457 80.16%
## 6 2      Past      963 1.5%
## 7 2      Current  3066 4.78%
## 8 2      unknown  8704 13.56%
```

```
MILK_0 %>%
  group_by(tr_sex, Alc_Fre) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 10 x 4
## # Groups:   tr_sex [2]
##    tr_sex Alc_Fre            n rel.freq
##    <chr>  <fct>          <int> <chr>
##  1 1      < 1/week        2027 4.37%
##  2 1      1-4 /week       7251 15.63%
##  3 1      Daily          22178 47.8%
##  4 1      Never or past 11118 23.96%
##  5 1      unknown         3821 8.24%
##  6 2      < 1/week        4106 6.4%
##  7 2      1-4 /week       6142 9.57%
##  8 2      Daily           2901 4.52%
##  9 2      Never or past 43908 68.4%
## 10 2      unknown         7133 11.11%
```

```
MILK_0 %>%
  group_by(tr_sex, BMIgrp) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 10 x 4
## # Groups:   tr_sex [2]
##    tr_sex BMIgrp        n rel.freq
##    <chr>  <fct>     <int> <chr>
##  1 1      [18.5,25) 33340 71.86%
##  2 1      [14,18.5)  2443 5.27%
##  3 1      [25,30)    7670 16.53%
##  4 1      [30,40)     451 0.97%
```

```
##   5 1      unknown    2491 5.37%
##   6 2      [18.5,25) 42523 66.25%
##   7 2      [14,18.5)  3774 5.88%
##   8 2      [25,30)   12391 19.3%
##   9 2      [30,40)    1271 1.98%
## 10 2      unknown    4231 6.59%
```

```
MILK_0 %>%
  group_by(tr_sex, DM_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex DM_hist     n rel.freq
##   <chr>  <chr>   <int> <chr>
## 1 1      FALSE   37631 81.11%
## 2 1      TRUE     2879 6.21%
## 3 1      unknown  5885 12.68%
## 4 2      FALSE   53167 82.83%
## 5 2      TRUE     2404 3.75%
## 6 2      unknown  8619 13.43%
```

```
MILK_0 %>%
  group_by(tr_sex, HT_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex HT_hist     n rel.freq
##   <chr>  <chr>   <int> <chr>
## 1 1      FALSE   32476 70%
## 2 1      TRUE     8990 19.38%
## 3 1      unknown  4929 10.62%
## 4 2      FALSE   43772 68.19%
## 5 2      TRUE    13541 21.1%
## 6 2      unknown  6877 10.71%
```

```
MILK_0 %>%
  group_by(tr_sex, MI_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex MI_hist     n rel.freq
##   <chr>  <chr>   <int> <chr>
## 1 1      FALSE   39063 84.2%
## 2 1      TRUE     1310 2.82%
## 3 1      unknown  6022 12.98%
## 4 2      FALSE   53826 83.85%
## 5 2      TRUE     1684 2.62%
## 6 2      unknown  8680 13.52%
```

```
MILK_0 %>%
  group_by(tr_sex, APO_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex APO_hist     n rel.freq
##   <chr>  <chr>    <int> <chr>
## 1 1      FALSE    39336 84.78%
## 2 1      TRUE       915 1.97%
## 3 1      unknown   6144 13.24%
## 4 2      FALSE    54642 85.13%
## 5 2      TRUE       581 0.91%
## 6 2      unknown   8967 13.97%
```

```
MILK_0 %>%
  group_by(tr_sex, KID_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex KID_hist     n rel.freq
##   <chr>  <chr>    <int> <chr>
## 1 1      FALSE    34759 74.92%
## 2 1      TRUE      1603 3.46%
## 3 1      unknown  10033 21.63%
## 4 2      FALSE    47752 74.39%
## 5 2      TRUE      2668 4.16%
## 6 2      unknown  13770 21.45%
```

```
MILK_0 %>%
  group_by(tr_sex, LIV_hist) %>%
  summarise (n= n()) %>%
```

```r
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex LIV_hist     n rel.freq
##   <chr>  <chr>    <int> <chr>
## 1 1      FALSE    33549 72.31%
## 2 1      TRUE      3077 6.63%
## 3 1      unknown   9769 21.06%
## 4 2      FALSE    47674 74.27%
## 5 2      TRUE      2992 4.66%
## 6 2      unknown  13524 21.07%
```

```r
MILK_0 %>%
  group_by(tr_sex, Can_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex Can_hist     n rel.freq
##   <chr>  <chr>    <int> <chr>
## 1 1      FALSE     5899 12.71%
## 2 1      TRUE       411 0.89%
## 3 1      unknown  40085 86.4%
## 4 2      FALSE     8453 13.17%
## 5 2      TRUE      1050 1.64%
## 6 2      unknown  54687 85.2%
```

```r
MILK_0 %>%
  group_by(tr_sex, Exercise) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex Exercise     n rel.freq
##   <chr>  <fct>    <int> <chr>
## 1 1      Almost0  25559 55.09%
## 2 1      > 1h/w   11697 25.21%
## 3 1      unknown   9139 19.7%
## 4 2      Almost0  38842 60.51%
## 5 2      > 1h/w   12172 18.96%
## 6 2      unknown  13176 20.53%
```

```r
MILK_0 %>%
  group_by(tr_sex, Slepgrp) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 10 x 4
## # Groups:   tr_sex [2]
##    tr_sex Slepgrp       n rel.freq
##    <chr>  <fct>     <int> <chr>
##  1 1      [0,6.9)    7804 16.82%
##  2 1      [6.9,7.9) 14248 30.71%
##  3 1      [7.9,8.9) 16512 35.59%
##  4 1      [8.9,23)   5384 11.6%
##  5 1      unknown    2447 5.27%
##  6 2      [0,6.9)   17064 26.58%
##  7 2      [6.9,7.9) 22008 34.29%
##  8 2      [7.9,8.9) 16749 26.09%
##  9 2      [8.9,23)   4307 6.71%
## 10 2      unknown    4062 6.33%
```

```r
MILK_0 %>%
  group_by(tr_sex, Spi) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 10 x 4
## # Groups:   tr_sex [2]
##    tr_sex Spi         n rel.freq
##    <chr>  <fct>   <int> <chr>
##  1 1      Less1tm  3977 8.57%
##  2 1      One2tw  11352 24.47%
##  3 1      Thre4tw 10688 23.04%
##  4 1      daily   11008 23.73%
##  5 1      unknown  9370 20.2%
##  6 2      Less1tm  3670 5.72%
##  7 2      One2tw  14111 21.98%
##  8 2      Thre4tw 15711 24.48%
##  9 2      daily   18067 28.15%
## 10 2      unknown 12631 19.68%
```

```r
MILK_0 %>%
  group_by(tr_sex, Fru) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 10 x 4
## # Groups:   tr_sex [2]
##    tr_sex Fru         n rel.freq
##    <chr>  <fct>   <int> <chr>
##  1 1      Less1tm  6511 14.03%
##  2 1      One2tw   9449 20.37%
##  3 1      Thre4tw  8221 17.72%
##  4 1      daily    9099 19.61%
##  5 1      unknown 13115 28.27%
##  6 2      Less1tm  5168 8.05%
##  7 2      One2tw   9534 14.85%
##  8 2      Thre4tw 11900 18.54%
##  9 2      daily   20390 31.77%
## 10 2      unknown 17198 26.79%
```

```
MILK_0 %>%
  group_by(tr_sex, Gretea) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 8 x 4
## # Groups:   tr_sex [2]
##   tr_sex Gretea      n rel.freq
##   <chr>  <fct>   <int> <chr>
## 1 1      daily   35374 76.25%
## 2 1      Thre3tw  4112 8.86%
## 3 1      Never    2765 5.96%
## 4 1      unknown  4144 8.93%
## 5 2      daily   47366 73.79%
## 6 2      Thre3tw  6185 9.64%
## 7 2      Never    4505 7.02%
## 8 2      unknown  6134 9.56%
```

```
MILK_0 %>%
  group_by(tr_sex, Cofe) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 8 x 4
## # Groups:   tr_sex [2]
##   tr_sex Cofe        n rel.freq
##   <chr>  <fct>   <int> <chr>
## 1 1      daily   21804 47%
## 2 1      Thre3tw 12264 26.43%
```

```
## 3 1      Never    9642 20.78%
## 4 1      unknown  2685 5.79%
## 5 2      daily   28693 44.7%
## 6 2      Thre3tw 16977 26.45%
## 7 2      Never   15026 23.41%
## 8 2      unknown  3494 5.44%
```

```
MILK_0 %>%
  group_by(tr_sex, Educgrp) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex Educgrp     n rel.freq
##   <chr>  <fct>   <int> <chr>
## 1 1      [0,18)  19209 41.4%
## 2 1      [18,70) 14470 31.19%
## 3 1      unknown 12716 27.41%
## 4 2      [0,18)  29683 46.24%
## 5 2      [18,70) 17917 27.91%
## 6 2      unknown 16590 25.85%
```

```
MILK_0 %>%
  group_by(tr_sex, Menopause) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 3 x 4
## # Groups:   tr_sex [2]
##   tr_sex Menopause     n rel.freq
##   <chr>  <lgl>     <int> <chr>
## 1 1      FALSE     46395 100%
## 2 2      FALSE     13456 20.96%
## 3 2      TRUE      50734 79.04%
```

```
# 02-04 AREA  (  +  )
# - touhoku: (1, 2, 3, 4, 17, 29)
# - kanto: (5, 6, 8, 9, 11, 13, 31)
# - chubu: (15, 18)
# - kinki: (10, 20, 21, 22, 24)
# - chugoku: (25, 26)
# - kyushiu: (27, 30)

MILK_0 <- MILK_0 %>%
  mutate(areano = as.numeric(areano)) %>%
```

```
  mutate(Area = if_else(areano %in% c(11, 22, 23, 24, 41, 30,
                                      170, 178, 179, 298, 299), "Touhoku",
                if_else(areano %in% c(51, 61, 81, 91, 92, 93,
                                      110, 130, 311), "Kanto",
                 if_else(areano %in% c(151, 181), "Chubu",
                  if_else(areano %in% c(100, 108, 109, 201, 211, 212, 213,
                                   214, 221, 241, 242, 243), "Kinki",
                   if_else(areano %in% c(250, 261), "Chugoku",
                    if_else(areano %in% c(271, 272, 273, 274, 300, 301, 302, 303, 304,
                     305, 306, 307, 308, 309), "Kyushiu", "else"))))))) %>%
  mutate(Area = factor(Area))
```

8 Exclusion: history of stroke, cancer, MI, angina pectoris, other ischemic heart disease (ICD9)

410-414 Ischemic Heart Disease

415-417 Diseases Of Pulmonary Circulation

420-429 Other Forms Of Heart Disease

```
MILK_0 %>%
  group_by(tr_sex, APO_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex APO_hist     n rel.freq
##   <chr>  <chr>    <int> <chr>
## 1 1      FALSE    39336 84.78%
## 2 1      TRUE       915 1.97%
## 3 1      unknown   6144 13.24%
## 4 2      FALSE    54642 85.13%
## 5 2      TRUE       581 0.91%
## 6 2      unknown   8967 13.97%
```

```
MILK_0 %>%
  group_by(tr_sex, Can_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
```

```
##   tr_sex Can_hist     n rel.freq
##   <chr>  <chr>    <int> <chr>
## 1 1      FALSE     5899 12.71%
## 2 1      TRUE       411 0.89%
## 3 1      unknown  40085 86.4%
## 4 2      FALSE     8453 13.17%
## 5 2      TRUE      1050 1.64%
## 6 2      unknown  54687 85.2%
```

```
MILK_0 %>%
  group_by(tr_sex, MI_hist) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)
```

```
## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex MI_hist     n rel.freq
##   <chr>  <chr>   <int> <chr>
## 1 1      FALSE   39063 84.2%
## 2 1      TRUE     1310 2.82%
## 3 1      unknown  6022 12.98%
## 4 2      FALSE   53826 83.85%
## 5 2      TRUE     1684 2.62%
## 6 2      unknown  8680 13.52%
```

```
MILK_0 <- MILK_0 %>%
  mutate(p_Oth1 = as.numeric(p_oth1c)) %>%
  mutate(p_Oth2 = as.numeric(p_oth2c)) %>%
  mutate(IscheHeart = if_else((p_Oth1 >=410 & p_Oth1 <=414) |
                              (p_Oth2 >=410 & p_Oth2 <=414), TRUE, FALSE)) %>%
  replace_na(list(IscheHeart = "unknown")) %>% # recode IscheHeart history status
  mutate(OtheHeart = if_else((p_Oth1 >=420 & p_Oth1 <=429) |
                              (p_Oth2 >=420 & p_Oth2 <=429), TRUE, FALSE)) %>%
  replace_na(list(OtheHeart = "unknown")) #%>% # recode Otherheart history status
```

```
## Warning: Problem with `mutate()` input `p_Oth1`.
## i NAs introduced by coercion
## i Input `p_Oth1` is `as.numeric(p_oth1c)`.
```

```
## Warning in mask$eval_all_mutate(dots[[i]]): NAs introduced by coercion
```

```
## Warning: Problem with `mutate()` input `p_Oth2`.
## i NAs introduced by coercion
## i Input `p_Oth2` is `as.numeric(p_oth2c)`.
```

```
## Warning in mask$eval_all_mutate(dots[[i]]): NAs introduced by coercion
```

```
MILK_0 %>%
  group_by(tr_sex, IscheHeart) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex IscheHeart     n rel.freq
##   <chr>  <chr>      <int> <chr>
## 1 1      FALSE       1774 3.82%
## 2 1      TRUE          91 0.2%
## 3 1      unknown    44530 95.98%
## 4 2      FALSE       2614 4.07%
## 5 2      TRUE          95 0.15%
## 6 2      unknown    61481 95.78%
```

```
MILK_0 %>%
  group_by(tr_sex, OtheHeart) %>%
  summarise (n= n()) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))  %>%
  print(n=Inf)
```

```
## `summarise()` regrouping output by 'tr_sex' (override with `.groups` argument)

## # A tibble: 6 x 4
## # Groups:   tr_sex [2]
##   tr_sex OtheHeart     n rel.freq
##   <chr>  <chr>     <int> <chr>
## 1 1      FALSE      1743 3.76%
## 2 1      TRUE        204 0.44%
## 3 1      unknown   44448 95.8%
## 4 2      FALSE      2566 4%
## 5 2      TRUE        314 0.49%
## 6 2      unknown   61310 95.51%
```

```
MData <- MILK_0 %>%
  filter(APO_hist != "TRUE" & IscheHeart != "TRUE" &
           OtheHeart != "TRUE" & Can_hist != "TRUE" & MI_hist != "TRUE" & !is.na(Mlkfre)) %>%
  select(Area, Age, Agegrp, tr_sex, ICD10, T_DX, Tot_Stroke, HemoStroke, IscheStroke, CHD, HeartF, MlkL
         Mlkfre, followpy, Smoking, Alc_Fre, BMI, BMIgrp, DM_hist, HT_hist, KID_hist,
         LIV_hist, Exercise, Engy, ENERGY, Sleep, Slepgrp, Spi, Fru, Gretea, Cofe, Educ,
         Educgrp, Menopause)

# data preparation done

MData_men <- MData %>%
  filter(tr_sex == "1")
MData_fem <- MData %>%
  filter(tr_sex == "2")
```

8.1 before entering the analyses ordered, we need to explore by preliminary analyses

```
# Number of subjects, number of cases, person years
# by frequency

MData_men %>%
  group_by(Mlkfre) %>%
  summarise(pyear = sum(followpy), n = n()) %>%
  mutate_if(is.numeric, format, 2)
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 5 x 3
##   Mlkfre pyear     n
##   <fct>  <chr>     <chr>
## 1 Never  135703.69 8508
## 2 Mon1_2 56550.58  3522
## 3 Wek1_2 97098.38  5928
## 4 Wek3_4 92152.69  5563
## 5 Daily  252364.31 15865
```

```
MData_fem %>%
  group_by(Mlkfre) %>%
  summarise(pyear = sum(followpy), n = n()) %>%
  mutate_if(is.numeric, format, 2)
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 5 x 3
##   Mlkfre pyear     n
##   <fct>  <chr>     <chr>
## 1 Never  173222.04 10407
## 2 Mon1_2 59904.18  3640
## 3 Wek1_2 129233.13 7590
## 4 Wek3_4 139919.21 8108
## 5 Daily  418924.60 25254
```

```
epiDisplay::tabpct(MData_men$Mlkfre, MData_men$Tot_Stroke,
                   percent = "row", graph = FALSE)
```

```
##
## Row percent
##                    MData_men$Tot_Stroke
## MData_men$Mlkfre  Alive/Censor  I60_9  other_death  Total
##           Never           5742    326         2440   8508
##                         (67.5)  (3.8)       (28.7)  (100)
##           Mon1_2          2582    122          818   3522
##                         (73.3)  (3.5)       (23.2)  (100)
##           Wek1_2          4292    181         1455   5928
```

```
##                       (72.4)  (3.1)       (24.5)  (100)
##           Wek3_4        4044    177         1342   5563
##                       (72.7)  (3.2)       (24.1)  (100)
##           Daily        10741    546         4578  15865
##                       (67.7)  (3.4)       (28.9)  (100)
```

```
epiDisplay::tabpct(MData_fem$Mlkfre, MData_fem$Tot_Stroke,
                   percent = "row", graph = FALSE)
```

```
##
## Row percent
##                  MData_fem$Tot_Stroke
## MData_fem$Mlkfre  Alive/Censor  I60_9  other_death  Total
##           Never           8322    300         1785  10407
##                           (80)  (2.9)       (17.2)  (100)
##           Mon1_2          3065     84          491   3640
##                         (84.2)  (2.3)       (13.5)  (100)
##           Wek1_2          6403    182         1005   7590
##                         (84.4)  (2.4)       (13.2)  (100)
##           Wek3_4          6931    172         1005   8108
##                         (85.5)  (2.1)       (12.4)  (100)
##           Daily          20951    585         3718  25254
##                           (83)  (2.3)       (14.7)  (100)
```

```
##########################################################################################################
## survival object
##########################################################################################################
library(survival)
library(ggplot2)
library(survminer)
```

```
## Loading required package: ggpubr
```

```
library(cowplot)
```

```
##
## ********************************************************

## Note: As of version 1.0.0, cowplot does not change the

##   default ggplot2 theme anymore. To recover the previous

##   behavior, execute:
##   theme_set(theme_cowplot())

## ********************************************************

##
## Attaching package: 'cowplot'
```

```
## The following object is masked from 'package:ggpubr':
##
##     get_legend

## The following object is masked from 'package:lubridate':
##
##     stamp
```

```
library(ggsci)

# In all
su_obj <- Surv(MData$followpy, MData$Tot_Stroke == "I60_9")

# in Men
su_obj_men <- Surv(MData_men$followpy, MData_men$Tot_Stroke == "I60_9")
# in Women
su_obj_fem <- Surv(MData_fem$followpy, MData_fem$Tot_Stroke == "I60_9")


###################################################################################################
## Kaplan-Meier plots and log rank tests for TotStroke and Milk intake  (frequency)
###################################################################################################
```

9 In ALL

9.1 Model0

```
SurvM0 <-  coxph(su_obj ~ Mlkfre,
                 data = MData)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.8813897	0.0803831	-1.570671	0.1162591	0.7529146	1.0317874
MlkfreWek1_2	0.7867064	0.0659815	-3.635868	0.0002770	0.6912722	0.8953159
MlkfreWek3_4	0.7314994	0.0668095	-4.679857	0.0000029	0.6417200	0.8338392
MlkfreDaily	0.8350038	0.0498459	-3.617533	0.0002974	0.7572854	0.9206982

```
epiDisplay::tabpct(MData$Mlkfre, MData$Tot_Stroke, graph = FALSE)
```

```
##
## Original table
##               MData$Tot_Stroke
## MData$Mlkfre  Alive/Censor  I60_9  other_death  Total
##       Never          14064    626         4225  18915
```

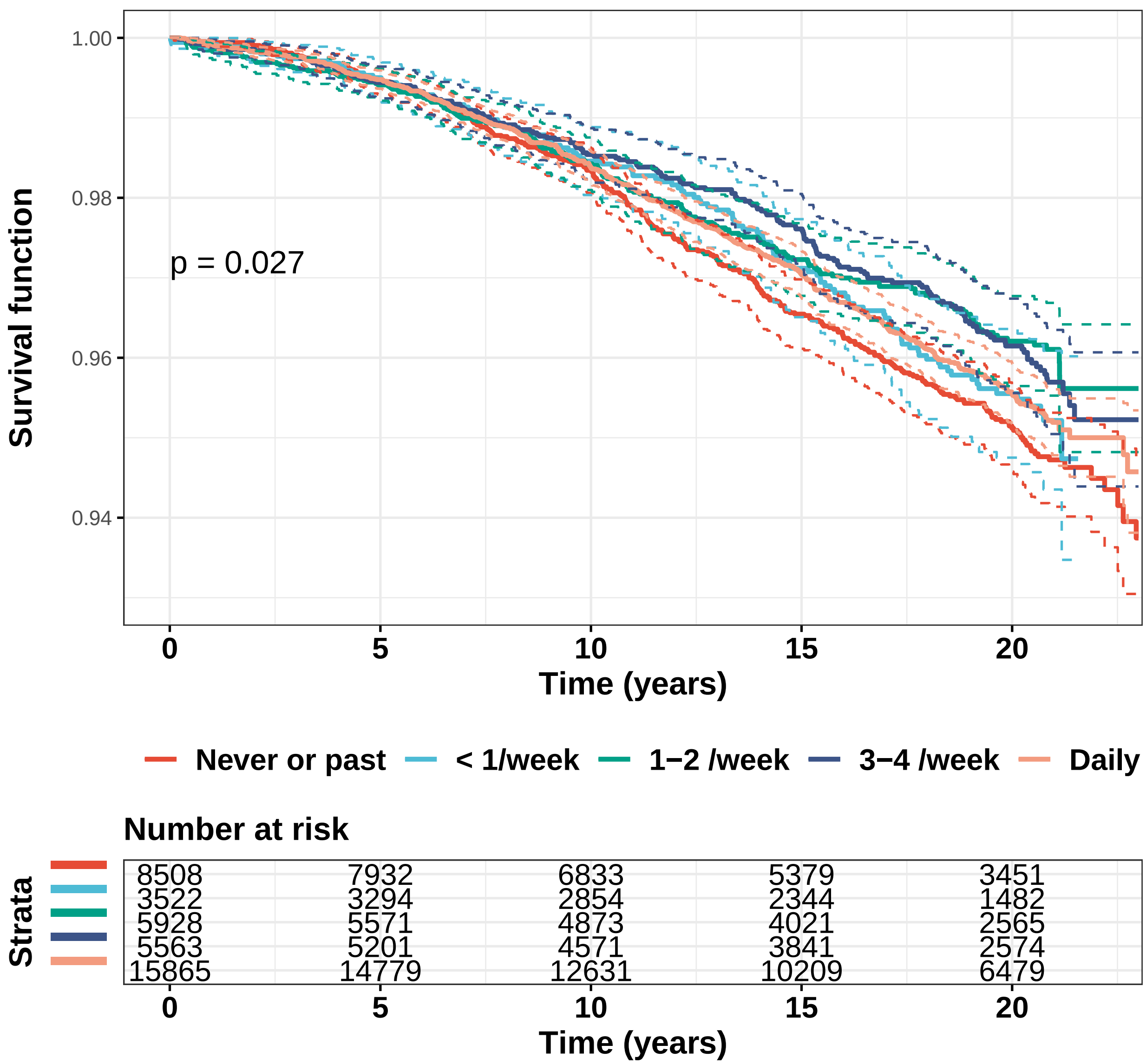


Figure 1: Kaplan-Meier survival curves for total stroke mortality by drinking frequency (P value was obtained from log-rank tests) in Men.

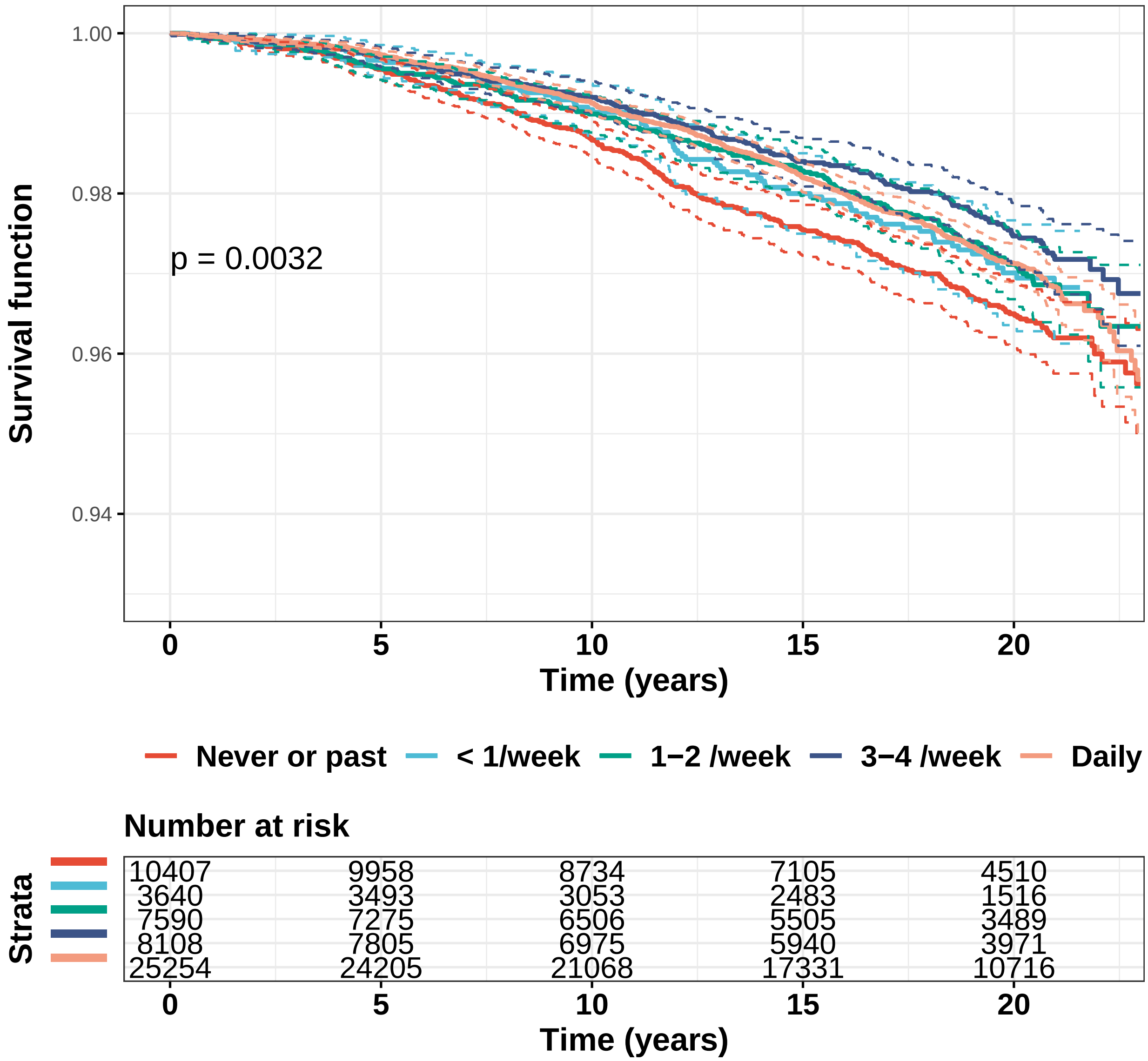


Figure 2: Kaplan-Meier survival curves for total stroke mortality by drinking frequency (P value was obtained from log-rank tests) in Women.

```
##        Mon1_2          5647    206          1309   7162
##        Wek1_2         10695    363          2460  13518
##        Wek3_4         10975    349          2347  13671
##        Daily          31692   1131          8296  41119
##        Total          73073   2675         18637  94385
##
## Row percent
##              MData$Tot_Stroke
## MData$Mlkfre  Alive/Censor  I60_9  other_death  Total
##        Never         14064    626          4225  18915
##                     (74.4)  (3.3)        (22.3)  (100)
##        Mon1_2         5647    206          1309   7162
##                     (78.8)  (2.9)        (18.3)  (100)
##        Wek1_2        10695    363          2460  13518
##                     (79.1)  (2.7)        (18.2)  (100)
##        Wek3_4        10975    349          2347  13671
##                     (80.3)  (2.6)        (17.2)  (100)
##        Daily         31692   1131          8296  41119
##                     (77.1)  (2.8)        (20.2)  (100)
##
## Column percent
##              MData$Tot_Stroke
## MData$Mlkfre  Alive/Censor       %  I60_9       %  other_death       %
##        Never         14064  (19.2)    626  (23.4)         4225  (22.7)
##        Mon1_2         5647   (7.7)    206   (7.7)         1309   (7.0)
##        Wek1_2        10695  (14.6)    363  (13.6)         2460  (13.2)
##        Wek3_4        10975  (15.0)    349  (13.0)         2347  (12.6)
##        Daily         31692  (43.4)   1131  (42.3)         8296  (44.5)
##        Total         73073   (100)   2675   (100)        18637   (100)
```

```
MData %>%
  group_by(Mlkfre) %>%
  summarise(TotPY = sum(followpy))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 5 x 2
##   Mlkfre   TotPY
##   <fct>    <dbl>
## 1 Never  308926.
## 2 Mon1_2 116455.
## 3 Wek1_2 226332.
## 4 Wek3_4 232072.
## 5 Daily  671289.
```

9.2 Model1

```
SurvM1 <-  coxph(su_obj ~ Mlkfre + Age + strata(Agegrp) + as.factor(tr_sex),
                 data = MData)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.9974010	0.0804620	-0.0323430	0.9741985	0.8518838	1.1677751
MlkfreWek1_2	0.9379351	0.0660501	-0.9700901	0.3320016	0.8240449	1.0675659
MlkfreWek3_4	0.8876175	0.0668806	-1.7824951	0.0746685	0.7785687	1.0119400
MlkfreDaily	0.8076188	0.0498561	-4.2856324	0.0000182	0.7324345	0.8905208
Age	1.1516143	0.0075195	18.7730675	0.0000000	1.1347662	1.1687124
as.factor(tr_sex)2	0.5786670	0.0388684	-14.0738661	0.0000000	0.5362211	0.6244728

9.3 Model2

```r
SurvM2 <-  coxph(su_obj ~ Mlkfre + Age + strata(Agegrp)+ as.factor(tr_sex) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
                 data = MData)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0349003	0.0812306	0.4223171	0.6727935	0.8825816	1.2135066
MlkfreWek1_2	1.0025875	0.0667232	0.0387294	0.9691062	0.8796854	1.1426604
MlkfreWek3_4	0.9807062	0.0679585	-0.2866800	0.7743574	0.8584057	1.1204314
MlkfreDaily	0.9269250	0.0517378	-1.4666773	0.1424639	0.8375395	1.0258500
Age	1.1398322	0.0075856	17.2539618	0.0000000	1.1230112	1.1569052
as.factor(tr_sex)2	0.5911321	0.0588325	-8.9357992	0.0000000	0.5267520	0.6633808
SmokingPast	0.8819262	0.0734587	-1.7104431	0.0871840	0.7636672	1.0184985
SmokingCurrent	1.2864300	0.0611140	4.1213304	0.0000377	1.1412107	1.4501285
Smokingunknown	1.0303859	0.0767867	0.3898250	0.6966659	0.8864188	1.1977352
Alc_Fre1-4 /week	1.0599396	0.1225933	0.4748377	0.6349027	0.8335459	1.3478225
Alc_FreDaily	1.1829152	0.1135827	1.4789392	0.1391566	0.9468296	1.4778671
Alc_FreNever or past	1.1978336	0.1090668	1.6550825	0.0979078	0.9672943	1.4833181
Alc_Freunknown	1.4322029	0.1224238	2.9341822	0.0033443	1.1266713	1.8205889
BMIgrp[14,18.5)	1.7181910	0.0672303	8.0510116	0.0000000	1.5060691	1.9601891
BMIgrp[25,30)	1.0944983	0.0536179	1.6840654	0.0921690	0.9853158	1.2157793
BMIgrp[30,40)	1.4500152	0.1419216	2.6181648	0.0088404	1.0979150	1.9150336
BMIgrpunknown	1.4821973	0.0678322	5.8014559	0.0000000	1.2976786	1.6929531
DM_histTRUE	1.3971406	0.0761318	4.3927474	0.0000112	1.2034737	1.6219730
DM_histunknown	0.8579305	0.1072180	-1.4291654	0.1529567	0.6953252	1.0585618
HT_histTRUE	1.9031222	0.0441559	14.5732639	0.0000000	1.7453442	2.0751632
HT_histunknown	1.0818299	0.1032975	0.7614314	0.4463994	0.8835517	1.3246039
KID_histTRUE	1.0897829	0.1056799	0.8135746	0.4158887	0.8859008	1.3405867
KID_histunknown	1.4181243	0.1564492	2.2328979	0.0255557	1.0436251	1.9270106
LIV_histTRUE	1.1108379	0.0940274	1.1179142	0.2636037	0.9238775	1.3356325
LIV_histunknown	0.7705636	0.1597458	-1.6315494	0.1027744	0.5634205	1.0538634
Exercise> 1h/w	0.9157741	0.0488876	-1.7997501	0.0719001	0.8320993	1.0078632
Exerciseunknown	0.9972226	0.0719491	-0.0386562	0.9691645	0.8660618	1.1482470
Slepgrp[6.9,7.9)	0.9942201	0.0609644	-0.0950834	0.9242486	0.8822457	1.1204062
Slepgrp[7.9,8.9)	1.1641519	0.0569877	2.6671184	0.0076505	1.0411221	1.3017202
Slepgrp[8.9,23)	1.3692442	0.0674355	4.6601413	0.0000032	1.1997195	1.5627234
Slepgrpunknown	1.0828350	0.0994759	0.8000186	0.4237000	0.8910216	1.3159408

term	estimate	std.error	statistic	p.value	conf.low	conf.high
SpiOne2tw	0.8300652	0.0817118	-2.2793652	0.0226454	0.7072274	0.9742388
SpiThre4tw	0.8968118	0.0811024	-1.3428611	0.1793170	0.7650096	1.0513221
Spidaily	0.8360228	0.0806574	-2.2204950	0.0263852	0.7137767	0.9792055
Spiunknown	0.7927486	0.1080628	-2.1492054	0.0316181	0.6414344	0.9797577
FruOne2tw	0.9356948	0.0695562	-0.9555722	0.3392884	0.8164468	1.0723598
FruThre4tw	0.9018099	0.0708123	-1.4595137	0.1444238	0.7849454	1.0360734
Frudaily	0.8015204	0.0697585	-3.1715815	0.0015161	0.6990947	0.9189527
Fruunknown	0.7268547	0.0798191	-3.9968956	0.0000642	0.6215920	0.8499429
CofeThre3tw	0.8971033	0.0526211	-2.0635143	0.0390638	0.8091915	0.9945659
CofeNever	1.0867998	0.0488684	1.7032981	0.0885123	0.9875355	1.1960419
Cofeunknown	1.1759974	0.1173101	1.3819492	0.1669873	0.9344408	1.4799973
Educgrp[18,70)	0.7992093	0.0557003	-4.0239003	0.0000572	0.7165531	0.8914002
Educgrpunknown	1.0806599	0.0547909	1.4157812	0.1568396	0.9706239	1.2031703
GreteaThre3tw	0.9050048	0.0740807	-1.3473830	0.1778569	0.7826963	1.0464259
GreteaNever	1.0648226	0.0774925	0.8105072	0.4176488	0.9147776	1.2394785
Greteaunknown	0.9962006	0.0854295	-0.0445589	0.9644589	0.8426147	1.1777810

9.4 Model2 sex interaction

```r
SurvM3 <-  coxph(su_obj ~ Mlkfre*as.factor(tr_sex) + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
                 data = MData)

tidy(SurvM3, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0185253	0.1068442	0.1717994	0.8635952	0.8260871	1.2557921
MlkfreWek1_2	0.9093738	0.0933088	-1.0181145	0.3086235	0.7573869	1.0918602
MlkfreWek3_4	0.9593442	0.0943434	-0.4399392	0.6599812	0.7973871	1.1541963
MlkfreDaily	0.8729100	0.0717557	-1.8942454	0.0581924	0.7583871	1.0047268
as.factor(tr_sex)2	0.5422548	0.0919569	-6.6555002	0.0000000	0.4528241	0.6493476
Age	1.1399761	0.0075861	17.2693256	0.0000000	1.1231517	1.1570525
SmokingPast	0.8838568	0.0735300	-1.6790455	0.0931432	0.7652319	1.0208707
SmokingCurrent	1.2857447	0.0611798	4.1081876	0.0000399	1.1404556	1.4495428
Smokingunknown	1.0309604	0.0767976	0.3970272	0.6913474	0.8868939	1.1984288
Alc_Fre1-4 /week	1.0613281	0.1226028	0.4854782	0.6273372	0.8346222	1.3496134
Alc_FreDaily	1.1812997	0.1136124	1.4665237	0.1425057	0.9454815	1.4759346
Alc_FreNever or past	1.1978685	0.1090688	1.6553203	0.0978595	0.9673189	1.4833671
Alc_Freunknown	1.4315227	0.1224339	2.9300611	0.0033890	1.1261140	1.8197602
BMIgrp[14,18.5)	1.7158979	0.0672385	8.0301649	0.0000000	1.5040348	1.9576046
BMIgrp[25,30)	1.0955820	0.0536193	1.7024791	0.0886656	0.9862887	1.2169864
BMIgrp[30,40)	1.4489269	0.1419714	2.6119571	0.0090026	1.0969838	1.9137832
BMIgrpunknown	1.4823700	0.0678422	5.8023197	0.0000000	1.2978044	1.6931834
DM_histTRUE	1.3962696	0.0761492	4.3835554	0.0000117	1.2026825	1.6210171
DM_histunknown	0.8559841	0.1072391	-1.4500628	0.1470410	0.6937190	1.0562040
HT_histTRUE	1.9027341	0.0441594	14.5674952	0.0000000	1.7449763	2.0747542
HT_histunknown	1.0841053	0.1033025	0.7817335	0.4343712	0.8854014	1.3274029

term	estimate	std.error	statistic	p.value	conf.low	conf.high
KID_histTRUE	1.0878558	0.1056893	0.7967560	0.4255928	0.8843179	1.3382407
KID_histunknown	1.4139247	0.1563374	2.2155243	0.0267241	1.0407625	1.9208830
LIV_histTRUE	1.1122115	0.0940531	1.1307480	0.2581612	0.9249734	1.3373513
LIV_histunknown	0.7728481	0.1596789	-1.6136928	0.1065941	0.5651649	1.0568494
Exercise> 1h/w	0.9154322	0.0488876	-1.8073909	0.0707013	0.8317887	1.0074868
Exerciseunknown	0.9964640	0.0719462	-0.0492352	0.9607319	0.8654079	1.1473670
Slepgrp[6.9,7.9)	0.9943033	0.0609678	-0.0937044	0.9253440	0.8823137	1.1205075
Slepgrp[7.9,8.9)	1.1659685	0.0569959	2.6940891	0.0070581	1.0427299	1.3037726
Slepgrp[8.9,23)	1.3696927	0.0674380	4.6648208	0.0000031	1.2001064	1.5632430
Slepgrpunknown	1.0841264	0.0994765	0.8119958	0.4167941	0.8920832	1.3175118
SpiOne2tw	0.8286256	0.0817234	-2.3002823	0.0214322	0.7059848	0.9725712
SpiThre4tw	0.8957899	0.0811074	-1.3568353	0.1748335	0.7641302	1.0501345
Spidaily	0.8348200	0.0806690	-2.2380248	0.0252194	0.7127337	0.9778188
Spiunknown	0.7919712	0.1080606	-2.1583283	0.0309023	0.6408082	0.9787927
FruOne2tw	0.9370893	0.0695701	-0.9339736	0.3503175	0.8176412	1.0739874
FruThre4tw	0.9037809	0.0708429	-1.4280654	0.1532730	0.7866139	1.0384002
Frudaily	0.8023001	0.0697930	-3.1560854	0.0015990	0.6997275	0.9199087
Fruunknown	0.7293359	0.0798593	-3.9522132	0.0000774	0.6236649	0.8529114
CofeThre3tw	0.8973691	0.0526241	-2.0577632	0.0396129	0.8094264	0.9948666
CofeNever	1.0877401	0.0488649	1.7211184	0.0852293	0.9883967	1.1970685
Cofeunknown	1.1759087	0.1173116	1.3812892	0.1671901	0.9343677	1.4798898
Educgrp[18,70)	0.7991063	0.0556956	-4.0265559	0.0000566	0.7164673	0.8912770
Educgrpunknown	1.0795215	0.0547924	1.3965049	0.1625625	0.9695984	1.2019066
GreteaThre3tw	0.9049839	0.0740762	-1.3477765	0.1777303	0.7826851	1.0463925
GreteaNever	1.0636782	0.0774951	0.7966042	0.4256810	0.9137899	1.2381526
Greteaunknown	0.9960004	0.0854294	-0.0469118	0.9625835	0.8424456	1.1775440
MlkfreMon1_2:as.factor(tr_sex)2	1.0233331	0.1630348	0.1414728	0.8874964	0.7434324	1.4086157
MlkfreWek1_2:as.factor(tr_sex)2	1.2210755	0.1321899	1.5109479	0.1308017	0.9423718	1.5822049
MlkfreWek3_4:as.factor(tr_sex)2	1.0462821	0.1339951	0.3376470	0.7356292	0.8046221	1.3605223
MlkfreDaily:as.factor(tr_sex)2	1.1279491	0.1002322	1.2012205	0.2296657	0.9267694	1.3728001

```
SurvM <-  coxph(su_obj ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
                 data = MData)


anova(SurvM, SurvM3)
```

```
## Analysis of Deviance Table
##  Cox model: response is  su_obj
##  Model 1: ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre + BMIgrp + DM_hist + HT_hist + KID_his
##  Model 2: ~ Mlkfre * as.factor(tr_sex) + Age + strata(Agegrp) + Smoking + Alc_Fre + BMIgrp + DM_hist
##   loglik  Chisq Df P(>|Chi|)
## 1 -24155
## 2 -24115 79.945  5 8.617e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

10 In Men

10.1 Model0

```
SurvM0 <-  coxph(su_obj_men ~ Mlkfre,
               data = MData_men)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.8980399	0.1061906	-1.012715	0.3111962	0.7292997	1.1058219
MlkfreWek1_2	0.7703381	0.0927036	-2.814622	0.0048835	0.6423503	0.9238275
MlkfreWek3_4	0.7889043	0.0933746	-2.539345	0.0111060	0.6569672	0.9473379
MlkfreDaily	0.9024874	0.0700243	-1.465214	0.1428626	0.7867494	1.0352516

```
epiDisplay::tabpct(MData_men$Mlkfre, MData_men$Tot_Stroke, graph = FALSE)
```

```
##
## Original table
##                 MData_men$Tot_Stroke
## MData_men$Mlkfre  Alive/Censor  I60_9  other_death  Total
##           Never           5742    326         2440   8508
##           Mon1_2          2582    122          818   3522
##           Wek1_2          4292    181         1455   5928
##           Wek3_4          4044    177         1342   5563
##           Daily          10741    546         4578  15865
##           Total          27401   1352        10633  39386
##
## Row percent
##                 MData_men$Tot_Stroke
## MData_men$Mlkfre  Alive/Censor  I60_9  other_death  Total
##           Never           5742    326         2440   8508
##                         (67.5)  (3.8)       (28.7)  (100)
##           Mon1_2          2582    122          818   3522
##                         (73.3)  (3.5)       (23.2)  (100)
##           Wek1_2          4292    181         1455   5928
##                         (72.4)  (3.1)       (24.5)  (100)
##           Wek3_4          4044    177         1342   5563
##                         (72.7)  (3.2)       (24.1)  (100)
##           Daily          10741    546         4578  15865
##                         (67.7)  (3.4)       (28.9)  (100)
##
## Column percent
##                 MData_men$Tot_Stroke
## MData_men$Mlkfre  Alive/Censor       %  I60_9       %  other_death       %
##           Never           5742  (21.0)    326  (24.1)         2440  (22.9)
##           Mon1_2          2582   (9.4)    122   (9.0)          818   (7.7)
##           Wek1_2          4292  (15.7)    181  (13.4)         1455  (13.7)
```

```
##          Wek3_4          4044  (14.8)    177  (13.1)         1342  (12.6)
##          Daily          10741  (39.2)    546  (40.4)         4578  (43.1)
##          Total          27401   (100)   1352   (100)        10633   (100)
```

```
MData_men %>%
  group_by(Mlkfre) %>%
  summarise(TotPY = sum(followpy))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 5 x 2
##   Mlkfre    TotPY
##   <fct>     <dbl>
## 1 Never  135704.
## 2 Mon1_2  56551.
## 3 Wek1_2  97098.
## 4 Wek3_4  92153.
## 5 Daily  252364.
```

10.2 Model1

```
SurvM1 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp),
                 data = MData_men)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.9907616	0.1062427	-0.0873596	0.9303857	0.8045169	1.220122
MlkfreWek1_2	0.8409711	0.0927365	-1.8676357	0.0618129	0.7012029	1.008599
MlkfreWek3_4	0.8601705	0.0934625	-1.6116056	0.1070478	0.7161915	1.033094
MlkfreDaily	0.7599266	0.0701965	-3.9109300	0.0000919	0.6622475	0.872013
Age	1.1459568	0.0104664	13.0169169	0.0000000	1.1226884	1.169707

10.3 Model2

```
SurvM2 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
                 data = MData_men)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1__2	1.0301939	0.1075013	0.2767130	0.7820005	0.8344758	1.2718157
MlkfreWek1__2	0.9026104	0.0938561	-1.0917166	0.2749577	0.7509479	1.0849027
MlkfreWek3__4	0.9619867	0.0951280	-0.4073946	0.6837182	0.7983548	1.1591568
MlkfreDaily	0.8720239	0.0730211	-1.8753277	0.0607477	0.7557406	1.0061994
Age	1.1384038	0.0105709	12.2626843	0.0000000	1.1150605	1.1622359
SmokingPast	0.9048595	0.0847244	-1.1800096	0.2379964	0.7664142	1.0683134
SmokingCurrent	1.3049781	0.0753874	3.5309111	0.0004141	1.1257277	1.5127708
Smokingunknown	1.2176241	0.1307021	1.5064905	0.1319413	0.9424523	1.5731388
Alc_Fre1-4 /week	1.1717298	0.1769789	0.8954800	0.3705306	0.8282906	1.6575713
Alc_FreDaily	1.2849996	0.1642454	1.5267307	0.1268280	0.9313161	1.7730007
Alc_FreNever or past	1.3903808	0.1675301	1.9672744	0.0491516	1.0012255	1.9307927
Alc_Freunknown	1.6402229	0.1843912	2.6835993	0.0072834	1.1427436	2.3542739
BMIgrp[14,18.5)	1.5045324	0.0987714	4.1356308	0.0000354	1.2397301	1.8258955
BMIgrp[25,30)	1.0179723	0.0796142	0.2237382	0.8229611	0.8708999	1.1898815
BMIgrp[30,40)	1.4450890	0.2613161	1.4089101	0.1588617	0.8658884	2.4117222
BMIgrpunknown	1.3869654	0.1085498	3.0135299	0.0025823	1.1211606	1.7157872
DM_histTRUE	1.2653057	0.1020775	2.3052452	0.0211528	1.0358739	1.5455533
DM_histunknown	0.7391435	0.1571159	-1.9238232	0.0543767	0.5432397	1.0056944
HT_histTRUE	1.9957463	0.0624572	11.0638614	0.0000000	1.7658005	2.2556359
HT_histunknown	1.0663401	0.1526243	0.4208527	0.6738626	0.7906454	1.4381685
KID_histTRUE	0.9770167	0.1583241	-0.1468606	0.8832421	0.7163682	1.3325014
KID_histunknown	1.2040967	0.2228276	0.8335129	0.4045555	0.7780190	1.8635134
LIV_histTRUE	1.3006487	0.1163398	2.2594422	0.0238559	1.0354553	1.6337615
LIV_histunknown	0.9484960	0.2264099	-0.2335485	0.8153355	0.6085764	1.4782774
Exercise> 1h/w	0.8881456	0.0664493	-1.7851146	0.0742427	0.7796908	1.0116864
Exerciseunknown	0.9532648	0.1090945	-0.4387255	0.6608604	0.7697543	1.1805244
Slepgrp[6.9,7.9)	1.0713132	0.0924202	0.7453481	0.4560613	0.8938163	1.2840582
Slepgrp[7.9,8.9)	1.1712927	0.0866009	1.8257087	0.0678942	0.9884407	1.3879706
Slepgrp[8.9,23)	1.4240811	0.0980255	3.6064784	0.0003104	1.1751554	1.7257353
Slepgrpunknown	1.1728620	0.1490775	1.0695569	0.2848188	0.8756930	1.5708760
SpiOne2tw	0.8899407	0.1100651	-1.0593764	0.2894284	0.7172548	1.1042024
SpiThre4tw	0.9022968	0.1109569	-0.9265915	0.3541387	0.7259434	1.1214919
Spidaily	0.8910869	0.1098402	-1.0498284	0.2937970	0.7184953	1.1051371
Spiunknown	0.7962352	0.1530359	-1.4889358	0.1365043	0.5898981	1.0747459
FruOne2tw	0.9587735	0.0916097	-0.4595631	0.6458299	0.8011940	1.1473459
FruThre4tw	0.9447489	0.0960846	-0.5915218	0.5541708	0.7825805	1.1405222
Frudaily	0.8563906	0.0973298	-1.5928186	0.1112009	0.7076600	1.0363803
Fruunknown	0.8531078	0.1083502	-1.4662581	0.1425780	0.6898839	1.0549498
CofeThre3tw	0.9665556	0.0722978	-0.4705049	0.6379943	0.8388549	1.1136965
CofeNever	1.1844124	0.0702370	2.4096548	0.0159676	1.0320890	1.3592169
Cofeunknown	1.3504452	0.1672895	1.7958943	0.0725113	0.9729261	1.8744510
Educgrp[18,70)	0.8136946	0.0738470	-2.7918574	0.0052406	0.7040488	0.9404161
Educgrpunknown	1.0174627	0.0798818	0.2167201	0.8284265	0.8700074	1.1899098
GreteaThre3tw	0.8967798	0.1052014	-1.0355844	0.3003961	0.7296898	1.1021315
GreteaNever	1.0997244	0.1115352	0.8522828	0.3940571	0.8837814	1.3684308
Greteaunknown	1.0030227	0.1238779	0.0243639	0.9805623	0.7868025	1.2786621

11 In women

```r
epiDisplay::tabpct(MData_fem$Mlkfre, MData_fem$Tot_Stroke, graph = FALSE)
```

```
##
## Original table
##                 MData_fem$Tot_Stroke
## MData_fem$Mlkfre  Alive/Censor  I60_9  other_death  Total
##            Never          8322    300         1785  10407
##            Mon1_2         3065     84          491   3640
##            Wek1_2         6403    182         1005   7590
##            Wek3_4         6931    172         1005   8108
##            Daily         20951    585         3718  25254
##            Total         45672   1323         8004  54999
##
## Row percent
##                 MData_fem$Tot_Stroke
## MData_fem$Mlkfre  Alive/Censor  I60_9  other_death  Total
##            Never          8322    300         1785  10407
##                           (80)  (2.9)       (17.2)  (100)
##            Mon1_2         3065     84          491   3640
##                         (84.2)  (2.3)       (13.5)  (100)
##            Wek1_2         6403    182         1005   7590
##                         (84.4)  (2.4)       (13.2)  (100)
##            Wek3_4         6931    172         1005   8108
##                         (85.5)  (2.1)       (12.4)  (100)
##            Daily         20951    585         3718  25254
##                           (83)  (2.3)       (14.7)  (100)
##
## Column percent
##                 MData_fem$Tot_Stroke
## MData_fem$Mlkfre  Alive/Censor       %  I60_9       %  other_death       %
##            Never          8322  (18.2)    300  (22.7)         1785  (22.3)
##            Mon1_2         3065   (6.7)     84   (6.3)          491   (6.1)
##            Wek1_2         6403  (14.0)    182  (13.8)         1005  (12.6)
##            Wek3_4         6931  (15.2)    172  (13.0)         1005  (12.6)
##            Daily         20951  (45.9)    585  (44.2)         3718  (46.5)
##            Total         45672   (100)   1323   (100)         8004   (100)
```

```r
MData_fem %>%
  group_by(Mlkfre) %>%
  summarise(TotPY = sum(followpy))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 5 x 2
##   Mlkfre   TotPY
##   <fct>    <dbl>
## 1 Never  173222.
## 2 Mon1_2  59904.
## 3 Wek1_2 129233.
## 4 Wek3_4 139919.
## 5 Daily  418925.
```

11.1 Model0

```
SurvM0 <-  coxph(su_obj_fem ~ Mlkfre,
                 data = MData_fem)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.8256913	0.1235535	-1.550213	0.1210903	0.6481100	1.0519295
MlkfreWek1_2	0.8093525	0.0939774	-2.250762	0.0244006	0.6731998	0.9730416
MlkfreWek3_4	0.6993278	0.0956485	-3.739060	0.0001847	0.5797819	0.8435231
MlkfreDaily	0.8126953	0.0710695	-2.918256	0.0035199	0.7070226	0.9341621

11.2 Model1

```
SurvM1 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp),
                 data = MData_fem)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0083893	0.1236489	0.0675651	0.9461319	0.7913673	1.284927
MlkfreWek1_2	1.0659228	0.0941722	0.6779174	0.4978240	0.8862705	1.281992
MlkfreWek3_4	0.9382761	0.0959736	-0.6638386	0.5067936	0.7773879	1.132462
MlkfreDaily	0.8805198	0.0711912	-1.7873398	0.0738826	0.7658453	1.012365
Age	1.1568656	0.0108181	13.4695388	0.0000000	1.1325948	1.181657

11.3 Model2

```
SurvM2 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea + Menopause,
                 data = MData_fem)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0389119	0.1247821	0.3059244	0.7596622	0.8135120	1.3267633
MlkfreWek1_2	1.1129211	0.0952648	1.1230609	0.2614116	0.9233680	1.3413863
MlkfreWek3_4	1.0106748	0.0975701	0.1088264	0.9133402	0.8347561	1.2236670

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreDaily	0.9989912	0.0737776	-0.0136803	0.9890851	0.8644941	1.1544133
Age	1.1481406	0.0112211	12.3111041	0.0000000	1.1231653	1.1736713
SmokingPast	0.7786934	0.2330272	-1.0734279	0.2830792	0.4931891	1.2294747
SmokingCurrent	1.3322407	0.1234829	2.3230932	0.0201741	1.0458608	1.6970378
Smokingunknown	0.9393472	0.0997932	-0.6269978	0.5306607	0.7724707	1.1422740
Alc_Fre1-4 /week	0.9727935	0.1773238	-0.1555540	0.8763846	0.6871988	1.3770793
Alc_FreDaily	1.2554269	0.1938729	1.1733238	0.2406660	0.8585519	1.8357618
Alc_FreNever or past	1.0753869	0.1440978	0.5043830	0.6139923	0.8107902	1.4263332
Alc_Freunknown	1.3222065	0.1659011	1.6835452	0.0922696	0.9551774	1.8302674
BMIgrp[14,18.5)	1.9531668	0.0925536	7.2331268	0.0000000	1.6291368	2.3416453
BMIgrp[25,30)	1.1848014	0.0732829	2.3139797	0.0206688	1.0262828	1.3678048
BMIgrp[30,40)	1.4957963	0.1703782	2.3633235	0.0181119	1.0711402	2.0888085
BMIgrpunknown	1.5482474	0.0883271	4.9489160	0.0000007	1.3021355	1.8408761
DM_histTRUE	1.6148175	0.1149917	4.1674476	0.0000308	1.2889685	2.0230404
DM_histunknown	1.0081874	0.1474719	0.0552922	0.9559057	0.7551148	1.3460759
HT_histTRUE	1.8169004	0.0627024	9.5232730	0.0000000	1.6067886	2.0544874
HT_histunknown	1.1011630	0.1409620	0.6836375	0.4942041	0.8353424	1.4515725
KID_histTRUE	1.1971499	0.1420871	1.2664316	0.2053586	0.9061576	1.5815878
KID_histunknown	1.7763428	0.2222932	2.5846799	0.0097469	1.1489748	2.7462689
LIV_histTRUE	0.8476014	0.1604800	-1.0303137	0.3028627	0.6188577	1.1608939
LIV_histunknown	0.5929503	0.2289096	-2.2831932	0.0224190	0.3785908	0.9286807
Exercise> 1h/w	0.9652547	0.0724117	-0.4883648	0.6252914	0.8375389	1.1124457
Exerciseunknown	1.0461224	0.0962915	0.4682700	0.6395915	0.8662018	1.2634148
Slepgrp[6.9,7.9)	0.9427542	0.0820288	-0.7186463	0.4723589	0.8027409	1.1071884
Slepgrp[7.9,8.9)	1.1861538	0.0764784	2.2322123	0.0256009	1.0210394	1.3779692
Slepgrp[8.9,23)	1.3199055	0.0954653	2.9074463	0.0036439	1.0946686	1.5914868
Slepgrpunknown	1.0333982	0.1342006	0.2448023	0.8066095	0.7943939	1.3443102
SpiOne2tw	0.7528921	0.1221578	-2.3234965	0.0201525	0.5925866	0.9565633
SpiThre4tw	0.8786850	0.1194707	-1.0825148	0.2790238	0.6952477	1.1105212
Spidaily	0.7770322	0.1192647	-2.1152393	0.0344096	0.6150645	0.9816515
Spiunknown	0.7806248	0.1549009	-1.5988327	0.1098578	0.5762228	1.0575338
FruOne2tw	0.8988301	0.1072602	-0.9944163	0.3200202	0.7284127	1.1091177
FruThre4tw	0.8482477	0.1055220	-1.5596990	0.1188310	0.6897667	1.0431414
Frudaily	0.7360887	0.1016935	-3.0130205	0.0025866	0.6030711	0.8984457
Fruunknown	0.6110841	0.1188543	-4.1439046	0.0000341	0.4840966	0.7713827
CofeThre3tw	0.8486136	0.0775704	-2.1161593	0.0343313	0.7289235	0.9879570
CofeNever	1.0161670	0.0683436	0.2346629	0.8144704	0.8887731	1.1618211
Cofeunknown	1.0423002	0.1652623	0.2506924	0.8020519	0.7539131	1.4410012
Educgrp[18,70)	0.7850206	0.0857735	-2.8219116	0.0047738	0.6635451	0.9287346
Educgrpunknown	1.1324763	0.0754300	1.6492986	0.0990865	0.9768389	1.3129109
GreteaThre3tw	0.9244191	0.1045743	-0.7515201	0.4523397	0.7531043	1.1347044
GreteaNever	1.0277093	0.1080399	0.2529841	0.8002805	0.8315848	1.2700887
Greteaunknown	0.9740447	0.1185137	-0.2218988	0.8243927	0.7721468	1.2287342
MenopauseTRUE	0.5380063	0.2169547	-2.8572095	0.0042738	0.3516537	0.8231131

12 Cause specific: HemoStroke

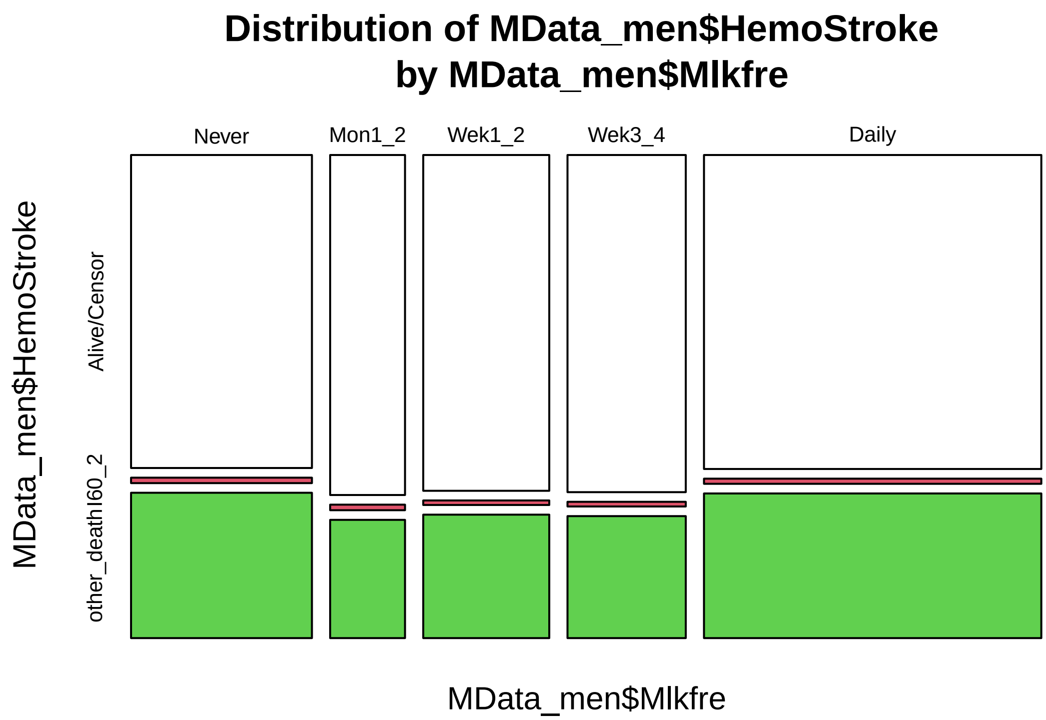
```
# in Men
su_obj_men <- Surv(MData_men$followpy, MData_men$HemoStroke == "I60_2")
```

```r
# in Women
su_obj_fem <- Surv(MData_fem$followpy, MData_fem$HemoStroke == "I60_2")
```

13 In Men

```r
epiDisplay::tabpct(MData_men$Mlkfre, MData_men$HemoStroke)
```

```
##
## Original table
##                  MData_men$HemoStroke
## MData_men$Mlkfre  Alive/Censor  I60_2  other_death  Total
##           Never           5742    100         2666   8508
##           Mon1_2          2582     42          898   3522
##           Wek1_2          4292     58         1578   5928
##           Wek3_4          4044     56         1463   5563
##           Daily          10741    176         4948  15865
##           Total          27401    432        11553  39386
##
## Row percent
##                  MData_men$HemoStroke
## MData_men$Mlkfre  Alive/Censor  I60_2  other_death  Total
##           Never           5742    100         2666   8508
##                         (67.5)  (1.2)       (31.3)  (100)
##           Mon1_2          2582     42          898   3522
##                         (73.3)  (1.2)       (25.5)  (100)
##           Wek1_2          4292     58         1578   5928
##                         (72.4)    (1)       (26.6)  (100)
##           Wek3_4          4044     56         1463   5563
##                         (72.7)    (1)       (26.3)  (100)
##           Daily          10741    176         4948  15865
##                         (67.7)  (1.1)       (31.2)  (100)
##
## Column percent
##                  MData_men$HemoStroke
## MData_men$Mlkfre  Alive/Censor       %  I60_2       %  other_death       %
##           Never           5742  (21.0)    100  (23.1)         2666  (23.1)
##           Mon1_2          2582   (9.4)     42   (9.7)          898   (7.8)
##           Wek1_2          4292  (15.7)     58  (13.4)         1578  (13.7)
##           Wek3_4          4044  (14.8)     56  (13.0)         1463  (12.7)
##           Daily          10741  (39.2)    176  (40.7)         4948  (42.8)
##           Total          27401   (100)    432   (100)        11553   (100)
```



13.1 Model0

```
SurvM0 <-  coxph(su_obj_men ~ Mlkfre,
                 data = MData_men)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0018664	0.1839174	0.0101387	0.9919107	0.6986490	1.436682
MlkfreWek1_2	0.8063903	0.1650585	-1.3037040	0.1923345	0.5835085	1.114406
MlkfreWek3_4	0.8187506	0.1669198	-1.1980353	0.2309033	0.5902952	1.135622
MlkfreDaily	0.9442372	0.1252492	-0.4581096	0.6468737	0.7387012	1.206962

13.2 Model1

```
SurvM1 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp),
                 data = MData_men)
```

```r
tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0771740	0.1840374	0.4039446	0.6862535	0.7509878	1.545037
MlkfreWek1_2	0.8593591	0.1651432	-0.9178000	0.3587236	0.6217338	1.187804
MlkfreWek3_4	0.8703379	0.1670434	-0.8313635	0.4057683	0.6273362	1.207467
MlkfreDaily	0.8463106	0.1255224	-1.3293948	0.1837177	0.6617361	1.082367
Age	1.0812843	0.0183013	4.2701629	0.0000195	1.0431862	1.120774

13.3 Model2

```r
SurvM2 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
                 data = MData_men)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.1192145	0.1860450	0.6053758	0.5449293	0.7772336	1.6116662
MlkfreWek1_2	0.9413956	0.1668670	-0.3619161	0.7174147	0.6787888	1.3055984
MlkfreWek3_4	1.0111939	0.1695524	0.0656534	0.9476538	0.7252891	1.4098006
MlkfreDaily	0.9816362	0.1301282	-0.1424323	0.8867386	0.7606506	1.2668230
Age	1.0777434	0.0185173	4.0432222	0.0000527	1.0393300	1.1175766
SmokingPast	0.9962426	0.1598873	-0.0235444	0.9812160	0.7282304	1.3628920
SmokingCurrent	1.5662326	0.1394688	3.2170143	0.0012953	1.1916266	2.0586016
Smokingunknown	1.1444925	0.2614628	0.5161778	0.6057302	0.6855757	1.9106029
Alc_Fre1-4 /week	1.2159298	0.3086196	0.6334952	0.5264103	0.6640657	2.2264142
Alc_FreDaily	1.3871519	0.2870404	1.1400927	0.2542477	0.7903051	2.4347437
Alc_FreNever or past	1.1712370	0.2978262	0.5307138	0.5956171	0.6533331	2.0996886
Alc_Freunknown	1.9031327	0.3235521	1.9888644	0.0467162	1.0093946	3.5882043
BMIgrp[14,18.5)	1.6719496	0.1753391	2.9314079	0.0033743	1.1856985	2.3576106
BMIgrp[25,30)	0.9240431	0.1420139	-0.5562596	0.5780334	0.6995355	1.2206037
BMIgrp[30,40)	0.8115847	0.5813688	-0.3590947	0.7195242	0.2597000	2.5362723
BMIgrpunknown	1.5790020	0.1952918	2.3390280	0.0193340	1.0768371	2.3153432
DM_histTRUE	1.1332264	0.1887523	0.6626082	0.5075815	0.7827994	1.6405253
DM_histunknown	0.7006223	0.2876239	-1.2369845	0.2160929	0.3987108	1.2311469
HT_histTRUE	1.7661605	0.1141660	4.9822902	0.0000006	1.4120560	2.2090646
HT_histunknown	0.9345055	0.2829621	-0.2393883	0.8108045	0.5366906	1.6271952
KID_histTRUE	1.3096525	0.2433636	1.1084723	0.2676579	0.8128391	2.1101220
KID_histunknown	1.3247181	0.3650028	0.7704042	0.4410602	0.6477875	2.7090335
LIV_histTRUE	1.7676636	0.1765629	3.2263785	0.0012537	1.2505729	2.4985624
LIV_histunknown	0.9783391	0.3708356	-0.0590531	0.9529099	0.4729699	2.0236959
Exercise> 1h/w	0.9675793	0.1153474	-0.2857274	0.7750869	0.7717962	1.2130270
Exerciseunknown	0.5322081	0.2359301	-2.6733369	0.0075101	0.3351640	0.8450951
Slepgrp[6.9,7.9)	0.8689875	0.1514615	-0.9271435	0.3538521	0.6457869	1.1693319
Slepgrp[7.9,8.9)	0.9943568	0.1416186	-0.0399609	0.9681243	0.7533491	1.3124664

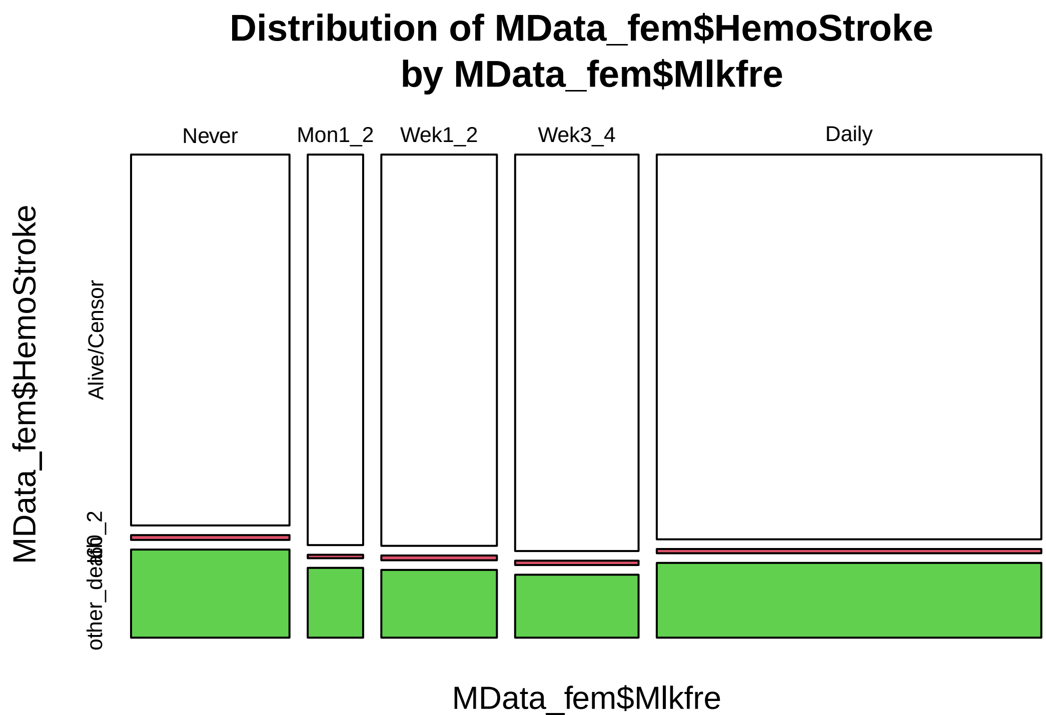
term	estimate	std.error	statistic	p.value	conf.low	conf.high
Slepgrp[8.9,23)	0.9892454	0.1757677	-0.0615177	0.9509469	0.7009552	1.3961042
Slepgrpunknown	0.9305784	0.2753308	-0.2613180	0.7938472	0.5424891	1.5963017
SpiOne2tw	0.8538625	0.1782405	-0.8863590	0.3754241	0.6021010	1.2108951
SpiThre4tw	0.7703085	0.1846724	-1.4131195	0.1576206	0.5363784	1.1062624
Spidaily	0.7541478	0.1840462	-1.5331309	0.1252436	0.5257703	1.0817250
Spiunknown	0.9516425	0.2728764	-0.1816421	0.8558636	0.5574437	1.6246007
FruOne2tw	0.8929252	0.1547788	-0.7317058	0.4643482	0.6592758	1.2093805
FruThre4tw	0.7885300	0.1687474	-1.4079312	0.1591515	0.5664743	1.0976309
Frudaily	0.8303061	0.1668244	-1.1147103	0.2649746	0.5987382	1.1514350
Fruunknown	0.9534187	0.1872995	-0.2546781	0.7989717	0.6604715	1.3763006
CofeThre3tw	1.0281739	0.1283098	0.2165406	0.8285664	0.7995563	1.3221602
CofeNever	1.3781840	0.1238151	2.5906903	0.0095784	1.0812237	1.7567050
Cofeunknown	1.1371933	0.3204434	0.4012042	0.6882698	0.6068374	2.1310629
Educgrp[18,70)	0.9322604	0.1223838	-0.5731403	0.5665497	0.7334389	1.1849786
Educgrpunknown	0.8601364	0.1512257	-0.9962877	0.3191104	0.6395047	1.1568868
GreteaThre3tw	0.7137950	0.2050236	-1.6444904	0.1000749	0.4775921	1.0668171
GreteaNever	1.2378380	0.1869449	1.1413328	0.2537314	0.8580963	1.7856305
Greteaunknown	1.7652332	0.1998473	2.8435855	0.0044609	1.1931410	2.6116344

14 In women

```r
epiDisplay::tabpct(MData_fem$Mlkfre, MData_fem$HemoStroke)
```

```
##
## Original table
##                     MData_fem$HemoStroke
## MData_fem$Mlkfre  Alive/Censor  I60_2  other_death  Total
##           Never           8322    108         1977  10407
##           Mon1_2          3065     27          548   3640
##           Wek1_2          6403     78         1109   7590
##           Wek3_4          6931     76         1101   8108
##           Daily          20951    231         4072  25254
##           Total          45672    520         8807  54999
##
## Row percent
##                     MData_fem$HemoStroke
## MData_fem$Mlkfre  Alive/Censor  I60_2  other_death  Total
##           Never           8322    108         1977  10407
##                           (80)    (1)         (19)  (100)
##           Mon1_2          3065     27          548   3640
##                         (84.2)  (0.7)       (15.1)  (100)
##           Wek1_2          6403     78         1109   7590
##                         (84.4)    (1)       (14.6)  (100)
##           Wek3_4          6931     76         1101   8108
##                         (85.5)  (0.9)       (13.6)  (100)
##           Daily          20951    231         4072  25254
##                           (83)  (0.9)       (16.1)  (100)
##
## Column percent
```

```
##                  MData_fem$HemoStroke
## MData_fem$Mlkfre  Alive/Censor        %  I60_2        %  other_death        %
##            Never          8322   (18.2)    108   (20.8)         1977   (22.4)
##           Mon1_2          3065    (6.7)     27    (5.2)          548    (6.2)
##           Wek1_2          6403   (14.0)     78   (15.0)         1109   (12.6)
##           Wek3_4          6931   (15.2)     76   (14.6)         1101   (12.5)
##            Daily         20951   (45.9)    231   (44.4)         4072   (46.2)
##            Total         45672    (100)    520    (100)         8807    (100)
```



14.1 Model0

```r
SurvM0 <-  coxph(su_obj_fem ~ Mlkfre,
                 data = MData_fem)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.7329251	0.2152953	-1.4431888	0.1489673	0.4806178	1.117685
MlkfreWek1_2	0.9656254	0.1486205	-0.2353601	0.8139292	0.7216103	1.292155
MlkfreWek3_4	0.8631136	0.1497347	-0.9831320	0.3255425	0.6435964	1.157504
MlkfreDaily	0.8894565	0.1166414	-1.0043148	0.3152269	0.7076840	1.117918

14.2 Model1

```r
SurvM1 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp),
                 data = MData_fem)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.8288805	0.2154022	-0.8712967	0.3835922	0.5434271	1.264278
MlkfreWek1_2	1.1565026	0.1489302	0.9762997	0.3289160	0.8637281	1.548518
MlkfreWek3_4	1.0356829	0.1501549	0.2334987	0.8153742	0.7716399	1.390077
MlkfreDaily	0.9155020	0.1167504	-0.7561665	0.4495494	0.7282512	1.150899
Age	1.0972778	0.0164735	5.6352378	0.0000000	1.0624152	1.133284

14.3 Model2

```r
SurvM2 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea + Menopause,
                 data = MData_fem)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.8446959	0.2167928	-0.7785251	0.4362595	0.5522885	1.2919174
MlkfreWek1_2	1.2019042	0.1503578	1.2231302	0.2212805	0.8951279	1.6138182
MlkfreWek3_4	1.1302578	0.1524458	0.8032085	0.4218542	0.8383308	1.5238410
MlkfreDaily	1.0240632	0.1205618	0.1972287	0.8436486	0.8085454	1.2970273
Age	1.0863001	0.0173927	4.7593119	0.0000019	1.0498931	1.1239696
SmokingPast	0.6345700	0.4516902	-1.0069016	0.3139820	0.2618184	1.5380094
SmokingCurrent	1.8272985	0.1723838	3.4970717	0.0004704	1.3033952	2.5617862
Smokingunknown	0.9991489	0.1587031	-0.0053652	0.9957192	0.7320519	1.3636991
Alc_Fre1-4 /week	0.6539700	0.2445440	-1.7366762	0.0824443	0.4049502	1.0561220
Alc_FreDaily	0.8092720	0.2789978	-0.7585013	0.4481510	0.4683939	1.3982276
Alc_FreNever or past	0.7805672	0.1874183	-1.3218268	0.1862258	0.5406044	1.1270443
Alc_Freunknown	0.8908720	0.2317829	-0.4985463	0.6180991	0.5656155	1.4031668
BMIgrp[14,18.5)	2.4174277	0.1409297	6.2634374	0.0000000	1.8339773	3.1864935
BMIgrp[25,30)	1.0522627	0.1165016	0.4372709	0.6619149	0.8374480	1.3221797
BMIgrp[30,40)	0.7791225	0.3601246	-0.6930571	0.4882737	0.3846512	1.5781360
BMIgrpunknown	1.6008477	0.1528090	3.0792250	0.0020754	1.1865301	2.1598384
DM_histTRUE	1.0598257	0.2238091	0.2596163	0.7951597	0.6834831	1.6433918
DM_histunknown	1.3899268	0.2439568	1.3496287	0.1771351	0.8616592	2.2420658
HT_histTRUE	2.1621869	0.1005763	7.6670166	0.0000000	1.7753441	2.6333218
HT_histunknown	0.7823757	0.2363099	-1.0385523	0.2990130	0.4923433	1.2432621
KID_histTRUE	1.3150234	0.2148802	1.2744518	0.2025033	0.8630325	2.0037328
KID_histunknown	1.9625949	0.3456969	1.9504588	0.0511215	0.9967195	3.8644560

term	estimate	std.error	statistic	p.value	conf.low	conf.high
LIV_histTRUE	0.8922214	0.2455241	-0.4644799	0.6423040	0.5514195	1.4436539
LIV_histunknown	0.4512268	0.3558283	-2.2364303	0.0253236	0.2246536	0.9063094
Exercise> 1h/w	1.1623879	0.1122527	1.3405151	0.1800779	0.9328277	1.4484407
Exerciseunknown	1.2725639	0.1532456	1.5728583	0.1157516	0.9424030	1.7183931
Slepgrp[6.9,7.9)	1.0785922	0.1228938	0.6156262	0.5381413	0.8477150	1.3723494
Slepgrp[7.9,8.9)	1.1703248	0.1222785	1.2862544	0.1983543	0.9209217	1.4872708
Slepgrp[8.9,23)	1.0526234	0.1762172	0.2910358	0.7710240	0.7452065	1.4868576
Slepgrpunknown	1.1562564	0.2095797	0.6927559	0.4884627	0.7667603	1.7436073
SpiOne2tw	0.6779586	0.1875842	-2.0719714	0.0382681	0.4693871	0.9792084
SpiThre4tw	0.7468264	0.1848019	-1.5796512	0.1141868	0.5198954	1.0728112
Spidaily	0.7962589	0.1816609	-1.2541550	0.2097857	0.5577303	1.1368007
Spiunknown	0.7263466	0.2445392	-1.3074711	0.1910527	0.4497714	1.1729947
FruOne2tw	1.0724700	0.1674666	0.4177815	0.6761069	0.7723913	1.4891313
FruThre4tw	0.8855280	0.1690364	-0.7192012	0.4720170	0.6357966	1.2333501
Frudaily	0.6782642	0.1648142	-2.3554907	0.0184983	0.4910308	0.9368909
Fruunknown	0.6912322	0.1917981	-1.9253545	0.0541850	0.4746408	1.0066601
CofeThre3tw	0.7992285	0.1199623	-1.8681569	0.0617402	0.6317697	1.0110743
CofeNever	0.9902983	0.1090095	-0.0894328	0.9287380	0.7997919	1.2261825
Cofeunknown	0.8713604	0.3008456	-0.4577085	0.6471619	0.4831896	1.5713686
Educgrp[18,70)	0.7420853	0.1274476	-2.3404990	0.0192580	0.5780564	0.9526590
Educgrpunknown	0.9490879	0.1269427	-0.4116330	0.6806084	0.7400356	1.2171954
GreteaThre3tw	0.8018607	0.1689567	-1.3069643	0.1912248	0.5758146	1.1166450
GreteaNever	0.9863021	0.1712131	-0.0805581	0.9357934	0.7051363	1.3795798
Greteaunknown	0.7404497	0.2130591	-1.4103951	0.1584231	0.4876849	1.1242214
MenopauseTRUE	0.7245142	0.2629075	-1.2257312	0.2202998	0.4327725	1.2129256

15 Cause specific: IscheStroke

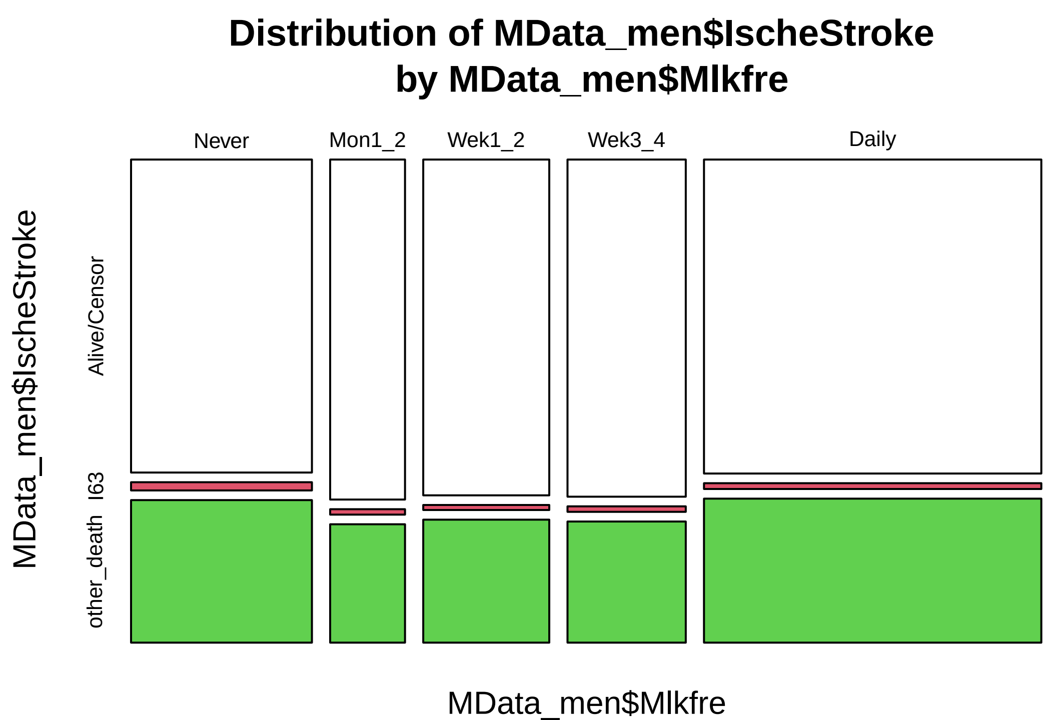
```
# in Men
su_obj_men <- Surv(MData_men$followpy, MData_men$IscheStroke == "I63")
# in Women
su_obj_fem <- Surv(MData_fem$followpy, MData_fem$IscheStroke == "I63")
```

16 In Men

```
epiDisplay::tabpct(MData_men$Mlkfre, MData_men$IscheStroke)
```

```
##
## Original table
##                 MData_men$IscheStroke
## MData_men$Mlkfre  Alive/Censor   I63  other_death  Total
##           Never           5742   151         2615   8508
##           Mon1_2          2582    41          899   3522
##           Wek1_2          4292    64         1572   5928
##           Wek3_4          4044    66         1453   5563
##           Daily          10741   198         4926  15865
```

```
##           Total          27401    520        11465  39386
##
## Row percent
##                 MData_men$IscheStroke
## MData_men$Mlkfre  Alive/Censor    I63  other_death  Total
##           Never           5742    151         2615   8508
##                         (67.5)  (1.8)       (30.7)  (100)
##           Mon1_2          2582     41          899   3522
##                         (73.3)  (1.2)       (25.5)  (100)
##           Wek1_2          4292     64         1572   5928
##                         (72.4)  (1.1)       (26.5)  (100)
##           Wek3_4          4044     66         1453   5563
##                         (72.7)  (1.2)       (26.1)  (100)
##           Daily          10741    198         4926  15865
##                         (67.7)  (1.2)         (31)  (100)
##
## Column percent
##                 MData_men$IscheStroke
## MData_men$Mlkfre  Alive/Censor       %  I63       %  other_death       %
##           Never           5742  (21.0)  151  (29.0)         2615  (22.8)
##           Mon1_2          2582   (9.4)   41   (7.9)          899   (7.8)
##           Wek1_2          4292  (15.7)   64  (12.3)         1572  (13.7)
##           Wek3_4          4044  (14.8)   66  (12.7)         1453  (12.7)
##           Daily          10741  (39.2)  198  (38.1)         4926  (43.0)
##           Total          27401   (100)  520   (100)        11465   (100)
```



16.1 Model0

```r
SurvM0 <-  coxph(su_obj_men ~ Mlkfre,
            data = MData_men)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.6545119	0.1762278	-2.405213	0.0161630	0.4633532	0.9245341
MlkfreWek1_2	0.5887414	0.1491731	-3.551365	0.0003832	0.4394892	0.7886803
MlkfreWek3_4	0.6356200	0.1475729	-3.070717	0.0021355	0.4759741	0.8488125
MlkfreDaily	0.7089936	0.1081102	-3.181093	0.0014672	0.5736127	0.8763265

16.2 Model1

```r
SurvM1 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp),
            data = MData_men)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.7296273	0.1763062	-1.787921	0.0737888	0.5164508	1.0307970
MlkfreWek1_2	0.6519601	0.1492176	-2.866765	0.0041469	0.4866388	0.8734444
MlkfreWek3_4	0.7039817	0.1477422	-2.375780	0.0175119	0.5269908	0.9404154
MlkfreDaily	0.5803523	0.1084025	-5.019440	0.0000005	0.4692662	0.7177350
Age	1.1908810	0.0170434	10.249906	0.0000000	1.1517574	1.2313337

16.3 Model2

```r
SurvM2 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
               BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
               Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
            data = MData_men)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.7308665	0.1784165	-1.7572617	0.0788732	0.5151926	1.0368274
MlkfreWek1_2	0.6690458	0.1512647	-2.6569498	0.0078851	0.4973924	0.8999380
MlkfreWek3_4	0.7413762	0.1507334	-1.9852739	0.0471140	0.5517396	0.9961922

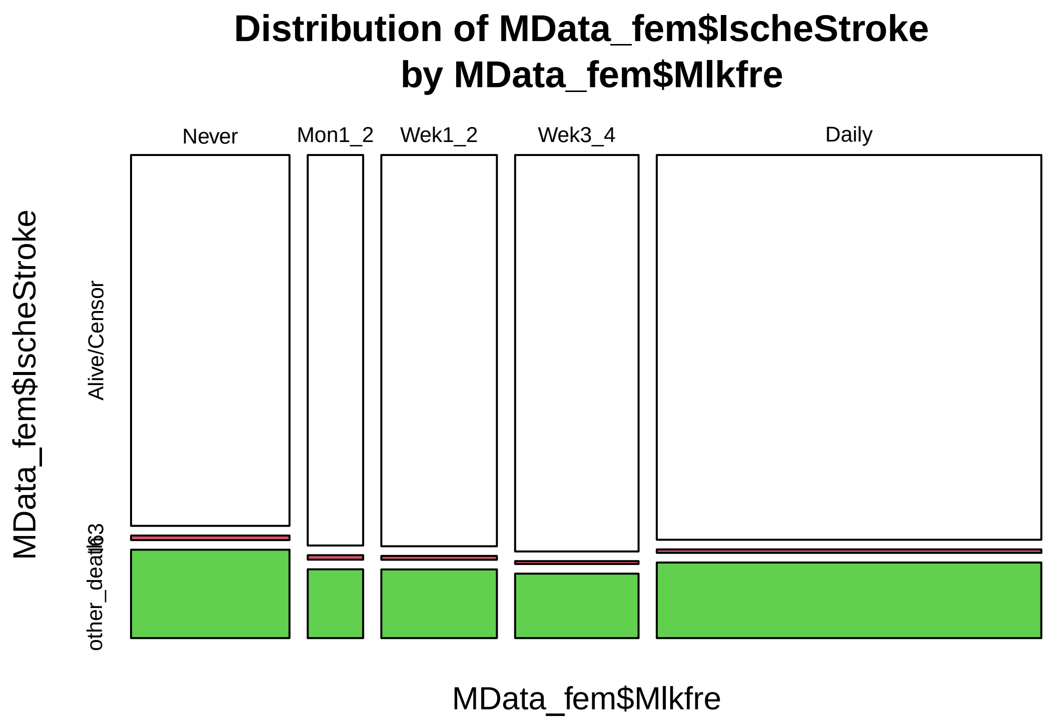
term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreDaily	0.6296329	0.1135882	-4.0727675	0.0000465	0.5039657	0.7866361
Age	1.1815084	0.0171806	9.7081379	0.0000000	1.1423854	1.2219713
SmokingPast	0.8487341	0.1339536	-1.2243747	0.2208109	0.6527549	1.1035528
SmokingCurrent	1.1958846	0.1198911	1.4920723	0.1356802	0.9454483	1.5126580
Smokingunknown	1.2685655	0.1958682	1.2145248	0.2245474	0.8641509	1.8622423
Alc_Fre1-4 /week	1.4000465	0.3059889	1.0997308	0.2714494	0.7685714	2.5503552
Alc_FreDaily	1.4335422	0.2874977	1.2527000	0.2103149	0.8160034	2.5184247
Alc_FreNever or past	1.7017833	0.2909498	1.8273833	0.0676422	0.9621602	3.0099630
Alc_Freunknown	2.1515683	0.3122896	2.4534826	0.0141480	1.1666317	3.9680441
BMIgrp[14,18.5)	1.4872080	0.1553496	2.5548859	0.0106223	1.0968264	2.0165340
BMIgrp[25,30)	1.0404402	0.1295552	0.3059997	0.7596049	0.8071226	1.3412035
BMIgrp[30,40)	1.8220788	0.3839016	1.5628435	0.1180894	0.8585974	3.8667380
BMIgrpunknown	1.3837814	0.1689732	1.9223157	0.0545660	0.9936586	1.9270711
DM_histTRUE	1.3338282	0.1606859	1.7926470	0.0730294	0.9734727	1.8275784
DM_histunknown	0.5936373	0.2536769	-2.0557122	0.0398103	0.3610696	0.9760035
HT_histTRUE	2.1177301	0.0992962	7.5566326	0.0000000	1.7432093	2.5727149
HT_histunknown	1.4034300	0.2441999	1.3878764	0.1651747	0.8696158	2.2649262
KID_histTRUE	0.8311575	0.2721091	-0.6796389	0.4967331	0.4875999	1.4167821
KID_histunknown	0.8711790	0.3842756	-0.3588773	0.7196869	0.4102149	1.8501348
LIV_histTRUE	1.2263508	0.1969653	1.0359333	0.3002333	0.8335997	1.8041467
LIV_histunknown	1.2863293	0.3892483	0.6468690	0.5177167	0.5998234	2.7585501
Exercise> 1h/w	0.8246979	0.1094532	-1.7609184	0.0782522	0.6654695	1.0220252
Exerciseunknown	1.1066720	0.1641844	0.6173385	0.5370114	0.8021673	1.5267676
Slepgrp[6.9,7.9)	1.3156453	0.1563922	1.7540979	0.0794137	0.9683169	1.7875578
Slepgrp[7.9,8.9)	1.3412424	0.1481770	1.9813891	0.0475477	1.0031797	1.7932292
Slepgrp[8.9,23)	1.6427006	0.1635044	3.0356475	0.0024002	1.1922937	2.2632554
Slepgrpunknown	1.4422615	0.2334087	1.5689746	0.1166539	0.9127800	2.2788823
SpiOne2tw	0.7584061	0.1776043	-1.5570361	0.1194619	0.5354572	1.0741845
SpiThre4tw	0.8230063	0.1765475	-1.1033372	0.2698808	0.5822716	1.1632704
Spidaily	0.7870662	0.1747147	-1.3704796	0.1705372	0.5588482	1.1084821
Spiunknown	0.6446885	0.2394108	-1.8336182	0.0667107	0.4032395	1.0307107
FruOne2tw	0.9885289	0.1542032	-0.0748196	0.9403582	0.7306870	1.3373569
FruThre4tw	1.0401743	0.1590346	0.2476714	0.8043886	0.7616152	1.4206158
Frudaily	0.9848343	0.1592727	-0.0959479	0.9235620	0.7207588	1.3456631
Fruunknown	0.9254432	0.1762516	-0.4396128	0.6602175	0.6551249	1.3073005
CofeThre3tw	0.9756304	0.1151712	-0.2142153	0.8303791	0.7784871	1.2226981
CofeNever	1.0417063	0.1148252	0.3558452	0.7219565	0.8317750	1.3046219
Cofeunknown	1.1133579	0.2785562	0.3854898	0.6998746	0.6449519	1.9219506
Educgrp[18,70)	0.9503338	0.1201960	-0.4238244	0.6716938	0.7508706	1.2027828
Educgrpunknown	1.2214737	0.1246054	1.6055327	0.1083766	0.9567970	1.5593673
GreteaThre3tw	1.0008792	0.1622358	0.0054167	0.9956781	0.7282598	1.3755519
GreteaNever	0.8570397	0.2006251	-0.7689521	0.4419217	0.5784003	1.2699110
Greteaunknown	0.8205442	0.2023857	-0.9772800	0.3284305	0.5518627	1.2200369

17 In women

```
epiDisplay::tabpct(MData_fem$Mlkfre, MData_fem$IscheStroke)
```

```
##
```

```
## Original table
##                 MData_fem$IscheStroke
## MData_fem$Mlkfre  Alive/Censor    I63  other_death  Total
##           Never           8322    102         1983  10407
##           Mon1_2          3065     35          540   3640
##           Wek1_2          6403     63         1124   7590
##           Wek3_4          6931     50         1127   8108
##           Daily          20951    187         4116  25254
##           Total          45672    437         8890  54999
##
## Row percent
##                 MData_fem$IscheStroke
## MData_fem$Mlkfre  Alive/Censor    I63  other_death  Total
##           Never           8322    102         1983  10407
##                           (80)    (1)       (19.1)  (100)
##           Mon1_2          3065     35          540   3640
##                         (84.2)    (1)       (14.8)  (100)
##           Wek1_2          6403     63         1124   7590
##                         (84.4)  (0.8)       (14.8)  (100)
##           Wek3_4          6931     50         1127   8108
##                         (85.5)  (0.6)       (13.9)  (100)
##           Daily          20951    187         4116  25254
##                           (83)  (0.7)       (16.3)  (100)
##
## Column percent
##                 MData_fem$IscheStroke
## MData_fem$Mlkfre  Alive/Censor       %  I63       %  other_death       %
##           Never           8322  (18.2)  102  (23.3)         1983  (22.3)
##           Mon1_2          3065   (6.7)   35   (8.0)          540   (6.1)
##           Wek1_2          6403  (14.0)   63  (14.4)         1124  (12.6)
##           Wek3_4          6931  (15.2)   50  (11.4)         1127  (12.7)
##           Daily          20951  (45.9)  187  (42.8)         4116  (46.3)
##           Total          45672   (100)  437   (100)         8890   (100)
```



17.1 Model0

```
SurvM0 <-  coxph(su_obj_fem ~ Mlkfre,
                 data = MData_fem)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0080356	0.1960744	0.0408184	0.9674407	0.6863996	1.4803851
MlkfreWek1_2	0.8230070	0.1602724	-1.2153721	0.2242242	0.6011452	1.1267502
MlkfreWek3_4	0.5973692	0.1726508	-2.9841731	0.0028435	0.4258751	0.8379218
MlkfreDaily	0.7628325	0.1231793	-2.1977466	0.0279672	0.5992096	0.9711349

17.2 Model1

```
SurvM1 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp),
                 data = MData_fem)
```

```r
tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.2915128	0.1962488	1.3035201	0.1923972	0.8791267	1.897344
MlkfreWek1_2	1.1502535	0.1605802	0.8717286	0.3833564	0.8396677	1.575722
MlkfreWek3_4	0.8559781	0.1731919	-0.8979082	0.3692345	0.6095951	1.201943
MlkfreDaily	0.8559983	0.1234132	-1.2598888	0.2077095	0.6720837	1.090241
Age	1.2344720	0.0196322	10.7294688	0.0000000	1.1878737	1.282898

17.3 Model2

```r
SurvM2 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea + Menopause,
                 data = MData_fem)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.2899646	0.1990376	1.2792297	0.2008162	0.8732864	1.905456
MlkfreWek1_2	1.1751012	0.1629161	0.9904135	0.3219720	0.8538879	1.617148
MlkfreWek3_4	0.8720469	0.1762686	-0.7767243	0.4373215	0.6173049	1.231913
MlkfreDaily	0.9248366	0.1283628	-0.6087292	0.5427039	0.7191218	1.189399
Age	1.2277167	0.0201929	10.1597960	0.0000000	1.1800758	1.277281
SmokingPast	1.2164614	0.3098992	0.6322899	0.5271974	0.6626918	2.232981
SmokingCurrent	1.3682134	0.2113073	1.4836483	0.1379022	0.9042504	2.070232
Smokingunknown	0.8246481	0.1751743	-1.1006094	0.2710667	0.5850056	1.162458
Alc_Fre1-4 /week	1.3070310	0.3393941	0.7889299	0.4301530	0.6720369	2.542019
Alc_FreDaily	1.6062748	0.3640031	1.3019604	0.1929299	0.7870092	3.278385
Alc_FreNever or past	1.3087641	0.2876705	0.9353871	0.3495888	0.7447248	2.299995
Alc_Freunknown	1.7129786	0.3190077	1.6872124	0.0915625	0.9166681	3.201045
BMIgrp[14,18.5)	1.5864817	0.1731641	2.6652104	0.0076940	1.1298935	2.227577
BMIgrp[25,30)	1.4606963	0.1258845	3.0100062	0.0026124	1.1413184	1.869447
BMIgrp[30,40)	2.3347896	0.2561992	3.3096188	0.0009342	1.4130924	3.857669
BMIgrpunknown	1.7604210	0.1423879	3.9719183	0.0000713	1.3317287	2.327112
DM_histTRUE	2.7405632	0.1645671	6.1261538	0.0000000	1.9849979	3.783725
DM_histunknown	1.1853612	0.2408590	0.7060044	0.4801854	0.7393177	1.900511
HT_histTRUE	1.4681418	0.1105938	3.4721440	0.0005163	1.1820352	1.823499
HT_histunknown	1.1409575	0.2320837	0.5681909	0.5699054	0.7239681	1.798123
KID_histTRUE	1.0126895	0.2663938	0.0473345	0.9622466	0.6007883	1.706991
KID_histunknown	1.3866763	0.3793436	0.8617774	0.3888100	0.6592911	2.916574
LIV_histTRUE	0.8192543	0.2896906	-0.6881853	0.4913361	0.4643374	1.445452
LIV_histunknown	0.7252437	0.3878526	-0.8282724	0.4075163	0.3391121	1.551046
Exercise> 1h/w	0.7996809	0.1312425	-1.7032786	0.0885159	0.6183053	1.034262
Exerciseunknown	0.9160223	0.1638564	-0.5353134	0.5924332	0.6644025	1.262935
Slepgrp[6.9,7.9)	0.7786207	0.1463649	-1.7096401	0.0873325	0.5844401	1.037318
Slepgrp[7.9,8.9)	1.0408647	0.1309002	0.3059718	0.7596261	0.8053261	1.345293

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Slepgrp[8.9,23)	1.2154238	0.1561432	1.2494483	0.2115012	0.8949905	1.650582
Slepgrpunknown	0.9447243	0.2225475	-0.2555057	0.7983325	0.6107623	1.461295
SpiOne2tw	0.7925103	0.2167859	-1.0727166	0.2833983	0.5181750	1.212086
SpiThre4tw	0.9761400	0.2111073	-0.1143932	0.9089261	0.6453827	1.476410
Spidaily	0.7635469	0.2128674	-1.2673652	0.2050248	0.5030866	1.158854
Spiunknown	0.8845474	0.2623100	-0.4676878	0.6400078	0.5289839	1.479108
FruOne2tw	0.8345912	0.1937954	-0.9330112	0.3508142	0.5708407	1.220205
FruThre4tw	0.8202347	0.1884142	-1.0517508	0.2929139	0.5669694	1.186633
Frudaily	0.8178442	0.1783520	-1.1274526	0.2595512	0.5765767	1.160070
Fruunknown	0.6814127	0.2029212	-1.8903261	0.0587144	0.4578080	1.014231
CofeThre3tw	0.8076362	0.1371786	-1.5574119	0.1193727	0.6172330	1.056775
CofeNever	0.8765676	0.1205849	-1.0925202	0.2746045	0.6920594	1.110267
Cofeunknown	1.2293333	0.2497299	0.8267813	0.4083610	0.7535276	2.005581
Educgrp[18,70)	0.8834467	0.1530876	-0.8094988	0.4182283	0.6544432	1.192584
Educgrpunknown	1.2216292	0.1275774	1.5691287	0.1166180	0.9513609	1.568677
GreteaThre3tw	0.9405057	0.1875051	-0.3271246	0.7435736	0.6512637	1.358207
GreteaNever	1.0446118	0.1903294	0.2293148	0.8186243	0.7193599	1.516923
Greteaunknown	1.0885017	0.1917214	0.4423198	0.6582578	0.7475419	1.584976
MenopauseTRUE	0.3587145	0.4884966	-2.0987426	0.0358396	0.1377019	0.934454

18 Cause specific: CHD

```
# in Men
su_obj_men <- Surv(MData_men$followpy, MData_men$CHD == "I20_5")
# in Women
su_obj_fem <- Surv(MData_fem$followpy, MData_fem$CHD == "I20_5")
```

19 In Men

19.1 Model0

```
SurvM0 <-  coxph(su_obj_men ~ Mlkfre,
                 data = MData_men)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.8697228	0.1447459	-0.9643162	0.3348874	0.6548969	1.1550180
MlkfreWek1_2	0.8053123	0.1226913	-1.7647955	0.0775981	0.6331831	1.0242345
MlkfreWek3_4	0.7580702	0.1267064	-2.1859930	0.0288161	0.5913666	0.9717669
MlkfreDaily	0.9060687	0.0940136	-1.0492112	0.2940809	0.7535926	1.0893957

19.2 Model1

```r
SurvM1 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp),
                 data = MData_men)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.9421510	0.1448316	-0.4114415	0.6807488	0.7093158	1.251415
MlkfreWek1_2	0.8671080	0.1227483	-1.1616598	0.2453737	0.6816943	1.102952
MlkfreWek3_4	0.8128123	0.1268234	-1.6342017	0.1022165	0.6339252	1.042180
MlkfreDaily	0.7806553	0.0942738	-2.6266201	0.0086238	0.6489531	0.939086
Age	1.1130282	0.0140503	7.6215160	0.0000000	1.0827958	1.144105

19.3 Model2

```r
SurvM2 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
                 data = MData_men)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.9227578	0.1463237	-0.5493881	0.5827391	0.6926865	1.2292457
MlkfreWek1_2	0.8859170	0.1241378	-0.9757860	0.3291705	0.6945871	1.1299504
MlkfreWek3_4	0.8631137	0.1288576	-1.1424150	0.2532816	0.6704775	1.1110965
MlkfreDaily	0.8575268	0.0980690	-1.5672929	0.1170462	0.7075730	1.0392599
Age	1.1103348	0.0141621	7.3902692	0.0000000	1.0799389	1.1415863
SmokingPast	1.4254345	0.1250461	2.8347691	0.0045859	1.1155984	1.8213218
SmokingCurrent	2.0491013	0.1142006	6.2819390	0.0000000	1.6381576	2.5631332
Smokingunknown	1.9098117	0.1837824	3.5204938	0.0004307	1.3321549	2.7379554
Alc_Fre1-4 /week	1.1635962	0.2158890	0.7018208	0.4827909	0.7621443	1.7765089
Alc_FreDaily	1.0349432	0.2020058	0.1700275	0.8649885	0.6965766	1.5376736
Alc_FreNever or past	1.3448947	0.2059660	1.4386633	0.1502459	0.8981931	2.0137560
Alc_Freunknown	1.3350476	0.2330151	1.2401213	0.2149305	0.8455786	2.1078491
BMIgrp[14,18.5)	1.0655214	0.1594763	0.3979544	0.6906638	0.7794993	1.4564939
BMIgrp[25,30)	1.4672813	0.0930050	4.1224797	0.0000375	1.2227773	1.7606757
BMIgrp[30,40)	1.5661228	0.3376698	1.3285255	0.1840046	0.8079802	3.0356444
BMIgrpunknown	1.0607713	0.1671015	0.3530566	0.7240460	0.7645127	1.4718339
DM_histTRUE	1.9025424	0.1232251	5.2196417	0.0000002	1.4943245	2.4222768
DM_histunknown	1.4355522	0.2009977	1.7987750	0.0720543	0.9681206	2.1286708
HT_histTRUE	1.7706344	0.0874452	6.5336701	0.0000000	1.4917479	2.1016596
HT_histunknown	0.9098469	0.1946224	-0.4854476	0.6273589	0.6213058	1.3323895
KID_histTRUE	0.8559087	0.2291744	-0.6789223	0.4971871	0.5462027	1.3412230
KID_histunknown	0.7376277	0.3229624	-0.9422647	0.3460571	0.3916797	1.3891314

term	estimate	std.error	statistic	p.value	conf.low	conf.high
LIV_histTRUE	0.8754137	0.1809092	-0.7354996	0.4620353	0.6140774	1.2479684
LIV_histunknown	1.2293623	0.3254186	0.6345536	0.5257196	0.6496554	2.3263589
Exercise> 1h/w	0.9381382	0.0894050	-0.7142554	0.4750693	0.7873452	1.1178113
Exerciseunknown	0.9203374	0.1502731	-0.5524268	0.5806560	0.6855424	1.2355486
Slepgrp[6.9,7.9)	0.8543405	0.1160743	-1.3562479	0.1750203	0.6805004	1.0725896
Slepgrp[7.9,8.9)	0.9456869	0.1091486	-0.5116301	0.6089099	0.7635542	1.1712642
Slepgrp[8.9,23)	1.1588673	0.1289432	1.1434727	0.2528424	0.9000716	1.4920740
Slepgrpunknown	0.9675866	0.1950403	-0.1689412	0.8658429	0.6601936	1.4181051
SpiOne2tw	0.8713344	0.1427376	-0.9649135	0.3345881	0.6586981	1.1526125
SpiThre4tw	0.9075135	0.1442481	-0.6727777	0.5010887	0.6840201	1.2040299
Spidaily	0.7788937	0.1465036	-1.7056281	0.0880773	0.5844860	1.0379640
Spiunknown	0.9847459	0.1988715	-0.0772941	0.9383896	0.6668751	1.4541323
FruOne2tw	0.9410595	0.1214017	-0.5003958	0.6167964	0.7417879	1.1938628
FruThre4tw	0.8645441	0.1286308	-1.1315558	0.2578212	0.6718873	1.1124433
Frudaily	0.7528409	0.1315695	-2.1578050	0.0309430	0.5817160	0.9743060
Fruunknown	0.7483318	0.1460548	-1.9849321	0.0471520	0.5620463	0.9963599
CofeThre3tw	0.7614295	0.0957734	-2.8458590	0.0044292	0.6311131	0.9186545
CofeNever	0.7882920	0.0990646	-2.4013296	0.0163356	0.6491771	0.9572184
Cofeunknown	0.8141584	0.2416512	-0.8508145	0.3948724	0.5070082	1.3073829
Educgrp[18,70)	0.9283780	0.0960593	-0.7736503	0.4391376	0.7690578	1.1207034
Educgrpunknown	1.1861164	0.1084472	1.5738937	0.1155120	0.9589961	1.4670259
GreteaThre3tw	1.3842486	0.1188026	2.7369550	0.0062011	1.0967032	1.7471858
GreteaNever	1.3538901	0.1428839	2.1204765	0.0339659	1.0231997	1.7914572
Greteaunknown	1.0605624	0.1671551	0.3517650	0.7250145	0.7642818	1.4716987

20 In women

20.1 Model0

```
SurvM0 <-  coxph(su_obj_fem ~ Mlkfre,
                 data = MData_fem)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0842463	0.1760247	0.4595100	0.6458679	0.7678837	1.5309482
MlkfreWek1_2	0.9060470	0.1421102	-0.6942784	0.4875076	0.6857823	1.1970580
MlkfreWek3_4	0.5832514	0.1583727	-3.4042290	0.0006635	0.4276108	0.7955416
MlkfreDaily	0.9015677	0.1094816	-0.9464620	0.3439130	0.7274571	1.1173500

20.2 Model1

```r
SurvM1 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp),
              data = MData_fem)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.3420048	0.1761838	1.6696464	0.0949893	0.9501368	1.895492
MlkfreWek1_2	1.2060974	0.1424235	1.3157225	0.1882672	0.9123285	1.594460
MlkfreWek3_4	0.7958769	0.1588814	-1.4369888	0.1507212	0.5829158	1.086641
MlkfreDaily	0.9856377	0.1096425	-0.1319415	0.8950306	0.7950408	1.221927
Age	1.1721849	0.0166594	9.5363440	0.0000000	1.1345291	1.211091

20.3 Model2

```r
SurvM2 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea + Menopause,
              data = MData_fem)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.3914373	0.1786367	1.8492125	0.0644271	0.9804101	1.9747834
MlkfreWek1_2	1.2302606	0.1441646	1.4374271	0.1505967	0.9274362	1.6319626
MlkfreWek3_4	0.8512400	0.1610953	-0.9997880	0.3174131	0.6207653	1.1672842
MlkfreDaily	1.1080047	0.1136850	0.9021490	0.3669777	0.8866919	1.3845558
Age	1.1547678	0.0171777	8.3771116	0.0000000	1.1165367	1.1943079
SmokingPast	1.1277332	0.3078083	0.3905340	0.6961417	0.6168782	2.0616422
SmokingCurrent	2.8661163	0.1446842	7.2776305	0.0000000	2.1584323	3.8058284
Smokingunknown	1.1553586	0.1447011	0.9979936	0.3182825	0.8700556	1.5342163
Alc_Fre1-4 /week	1.0887466	0.2568938	0.3309818	0.7406583	0.6580493	1.8013381
Alc_FreDaily	1.1020212	0.2962318	0.3279388	0.7429579	0.6166475	1.9694406
Alc_FreNever or past	1.1351281	0.2111376	0.6002982	0.5483075	0.7504543	1.7169811
Alc_Freunknown	1.1895878	0.2429170	0.7146756	0.4748095	0.7389672	1.9149958
BMIgrp[14,18.5)	1.3697689	0.1545670	2.0356350	0.0417870	1.0117649	1.8544493
BMIgrp[25,30)	1.0438761	0.1136801	0.3777333	0.7056287	0.8353803	1.3044086
BMIgrp[30,40)	1.8256610	0.2283928	2.6355568	0.0083999	1.1668415	2.8564618
BMIgrpunknown	1.2832459	0.1368321	1.8226181	0.0683613	0.9813822	1.6779601
DM_histTRUE	2.6249115	0.1475537	6.5403110	0.0000000	1.9656976	3.5051984
DM_histunknown	1.0604062	0.2028996	0.2890694	0.7725283	0.7124654	1.5782680
HT_histTRUE	1.7026461	0.0967383	5.5012686	0.0000000	1.4085769	2.0581082
HT_histunknown	0.9120635	0.2035278	-0.4522508	0.6510883	0.6120430	1.3591528
KID_histTRUE	1.2336541	0.2120434	0.9902717	0.3220413	0.8141450	1.8693262
KID_histunknown	0.9387788	0.3221110	-0.1961295	0.8445088	0.4993234	1.7649995
LIV_histTRUE	1.0777077	0.2312787	0.3235763	0.7462589	0.6849142	1.6957655
LIV_histunknown	1.4101721	0.3277886	1.0485775	0.2943726	0.7417507	2.6809348
Exercise> 1h/w	0.7897409	0.1169386	-2.0185832	0.0435306	0.6279807	0.9931686

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Exerciseunknown	0.8513409	0.1514346	-1.0627860	0.2878790	0.6327062	1.1455259
Slepgrp[6.9,7.9)	0.7884894	0.1184362	-2.0064492	0.0448083	0.6251479	0.9945096
Slepgrp[7.9,8.9)	0.8469026	0.1137158	-1.4612716	0.1439409	0.6777015	1.0583480
Slepgrp[8.9,23)	1.0826921	0.1395831	0.5691995	0.5692208	0.8235531	1.4233718
Slepgrpunknown	0.8420433	0.2017744	-0.8520593	0.3941812	0.5670009	1.2505042
SpiOne2tw	0.8047697	0.1839811	-1.1805515	0.2377810	0.5611341	1.1541881
SpiThre4tw	0.7888338	0.1840203	-1.2889863	0.1974029	0.5499804	1.1314200
Spidaily	0.7183372	0.1824587	-1.8131012	0.0698162	0.5023648	1.0271586
Spiunknown	0.8529214	0.2311062	-0.6883758	0.4912162	0.5422394	1.3416120
FruOne2tw	1.1672596	0.1698023	0.9108168	0.3623919	0.8368189	1.6281838
FruThre4tw	1.0535517	0.1692470	0.3082302	0.7579072	0.7561232	1.4679767
Frudaily	0.7551877	0.1680482	-1.6708832	0.0947448	0.5432654	1.0497788
Fruunknown	0.8741957	0.1859545	-0.7230320	0.4696602	0.6071890	1.2586165
CofeThre3tw	0.9566742	0.1157855	-0.3825386	0.7020619	0.7624428	1.2003858
CofeNever	0.9630977	0.1073518	-0.3502538	0.7261482	0.7803553	1.1886346
Cofeunknown	1.2427333	0.2197610	0.9888616	0.3227309	0.8078245	1.9117843
Educgrp[18,70)	0.9020740	0.1284404	-0.8023853	0.4223301	0.7013156	1.1603015
Educgrpunknown	0.9231619	0.1203712	-0.6642009	0.5065618	0.7291514	1.1687942
GreteaThre3tw	1.0084186	0.1541204	0.0543948	0.9566206	0.7455098	1.3640439
GreteaNever	1.0515360	0.1636835	0.3070070	0.7588381	0.7629508	1.4492782
Greteaunknown	1.1319825	0.1639190	0.7562915	0.4494745	0.8209404	1.5608737
MenopauseTRUE	2.1233148	0.4324051	1.7413727	0.0816183	0.9098096	4.9553952

21 Cause specific: HeartF

```r
# in Men
su_obj_men <- Surv(MData_men$followpy, MData_men$HeartF == "I50")
# in Women
su_obj_fem <- Surv(MData_fem$followpy, MData_fem$HeartF == "I50")
```

22 In Men

22.1 Model0

```r
SurvM0 <-  coxph(su_obj_men ~ Mlkfre,
                 data = MData_men)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.9275534	0.1836660	-0.4094658	0.6821979	0.6471457	1.329461
MlkfreWek1_2	0.8675740	0.1555403	-0.9132968	0.3610864	0.6396029	1.176800
MlkfreWek3_4	0.8749949	0.1570022	-0.8505435	0.3950230	0.6432281	1.190272
MlkfreDaily	1.0890675	0.1178539	0.7239628	0.4690886	0.8644450	1.372057

22.2 Model1

```
SurvM1 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp),
                 data = MData_men)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0150173	0.1837912	0.0811009	0.9353617	0.7079948	1.455180
MlkfreWek1_2	0.9521410	0.1556234	-0.3151332	0.7526605	0.7018340	1.291719
MlkfreWek3_4	0.9485807	0.1572220	-0.3357570	0.7370541	0.6970224	1.290928
MlkfreDaily	0.8888479	0.1182452	-0.9964815	0.3190163	0.7049803	1.120670
Age	1.1542319	0.0176620	8.1211207	0.0000000	1.1149597	1.194887

22.3 Model2

```
SurvM2 <-  coxph(su_obj_men ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea,
                 data = MData_men)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.1381516	0.1863578	0.6943929	0.4874359	0.7898999	1.6399408
MlkfreWek1_2	1.0328334	0.1574749	0.2051498	0.8374551	0.7585556	1.4062845
MlkfreWek3_4	1.0600132	0.1600575	0.3641275	0.7157628	0.7745868	1.4506160
MlkfreDaily	1.0615324	0.1228854	0.4859285	0.6270178	0.8343207	1.3506210
Age	1.1445845	0.0177788	7.5956404	0.0000000	1.1053873	1.1851716
SmokingPast	0.9643904	0.1432824	-0.2530599	0.8002219	0.7282671	1.2770713
SmokingCurrent	1.5841603	0.1268726	3.6261139	0.0002877	1.2353925	2.0313899
Smokingunknown	1.5346456	0.2074293	2.0647977	0.0389421	1.0219837	2.3044761
Alc_Fre1-4 /week	1.3788457	0.2869491	1.1195252	0.2629162	0.7857134	2.4197314
Alc_FreDaily	1.1990504	0.2701859	0.6718705	0.5016661	0.7060814	2.0361985
Alc_FreNever or past	1.7839865	0.2718012	2.1296832	0.0331978	1.0472104	3.0391292
Alc_Freunknown	1.7016800	0.3021155	1.7596447	0.0784681	0.9412754	3.0763737
BMIgrp[14,18.5)	1.6028967	0.1513058	3.1182705	0.0018192	1.1915542	2.1562408
BMIgrp[25,30)	0.9509386	0.1388990	-0.3621751	0.7172212	0.7243049	1.2484856
BMIgrp[30,40)	1.3669946	0.4521746	0.6913582	0.4893405	0.5634755	3.3163362
BMIgrpunknown	1.5876167	0.1627343	2.8404220	0.0045054	1.1540537	2.1840638
DM_histTRUE	1.2176698	0.1681594	1.1711448	0.2415406	0.8757739	1.6930396
DM_histunknown	0.5515295	0.2452777	-2.4260659	0.0152635	0.3410264	0.8919685
HT_histTRUE	1.5490688	0.1086478	4.0281919	0.0000562	1.2519575	1.9166899
HT_histunknown	1.1036044	0.2355254	0.4185601	0.6755376	0.6955588	1.7510276
KID_histTRUE	1.0934048	0.2569602	0.3475112	0.7282073	0.6607788	1.8092804
KID_histunknown	0.7505158	0.3739522	-0.7674633	0.4428061	0.3606211	1.5619550

term	estimate	std.error	statistic	p.value	conf.low	conf.high
LIV_histTRUE	1.3456468	0.2011606	1.4758098	0.1399950	0.9071996	1.9959942
LIV_histunknown	2.4322728	0.3751743	2.3691019	0.0178313	1.1659055	5.0741257
Exercise> 1h/w	0.8185188	0.1144465	-1.7498027	0.0801524	0.6540510	1.0243438
Exerciseunknown	1.0049933	0.1740434	0.0286187	0.9771687	0.7145246	1.4135435
Slepgrp[6.9,7.9)	0.8914905	0.1512983	-0.7591660	0.4477533	0.6627219	1.1992288
Slepgrp[7.9,8.9)	1.1400579	0.1367475	0.9585481	0.3377864	0.8720216	1.4904814
Slepgrp[8.9,23)	1.3098147	0.1561913	1.7279176	0.0840030	0.9644053	1.7789352
Slepgrpunknown	0.8360150	0.2517113	-0.7115642	0.4767347	0.5104545	1.3692133
SpiOne2tw	0.8598182	0.1925332	-0.7844583	0.4327712	0.5895519	1.2539818
SpiThre4tw	1.0695208	0.1889766	0.3556562	0.7220981	0.7384686	1.5489821
Spidaily	0.8320868	0.1917571	-0.9586010	0.3377598	0.5714059	1.2116929
Spiunknown	0.8197531	0.2537893	-0.7831382	0.4335459	0.4984909	1.3480590
FruOne2tw	0.8052702	0.1583943	-1.3673305	0.1715217	0.5903589	1.0984167
FruThre4tw	0.8428047	0.1631910	-1.0479746	0.2946503	0.6120946	1.1604739
Frudaily	0.7949486	0.1643092	-1.3966215	0.1625274	0.5760747	1.0969815
Fruunknown	0.7514406	0.1795194	-1.5918225	0.1114246	0.5285517	1.0683213
CofeThre3tw	1.1458493	0.1165069	1.1685664	0.2425784	0.9119197	1.4397873
CofeNever	1.1347459	0.1203174	1.0506275	0.2934297	0.8963637	1.4365242
Cofeunknown	1.3874954	0.2596357	1.2613835	0.2071707	0.8341213	2.3079897
Educgrp[18,70)	0.9492650	0.1253403	-0.4154073	0.6778437	0.7425020	1.2136048
Educgrpunknown	1.1640709	0.1330336	1.1419919	0.2534574	0.8968939	1.5108378
GreteaThre3tw	1.1429356	0.1582248	0.8443689	0.3984633	0.8381864	1.5584862
GreteaNever	1.1792222	0.1791191	0.9203660	0.3573815	0.8300977	1.6751824
Greteaunknown	0.7390853	0.2026334	-1.4920630	0.1356826	0.4968356	1.0994526

23 In women

23.1 Model0

```r
SurvM0 <-  coxph(su_obj_fem ~ Mlkfre,
                 data = MData_fem)

library("broom")
tidy(SurvM0, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	0.7934785	0.1782423	-1.297833	0.1943447	0.5595192	1.1252664
MlkfreWek1_2	0.6511954	0.1428941	-3.001841	0.0026835	0.4921298	0.8616741
MlkfreWek3_4	0.4879095	0.1529114	-4.693081	0.0000027	0.3615604	0.6584119
MlkfreDaily	0.7735712	0.1016797	-2.524964	0.0115710	0.6337972	0.9441700

23.2 Model1

```r
SurvM1 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp),
              data = MData_fem)

tidy(SurvM1, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0168809	0.1784145	0.0938266	0.9252469	0.7168089	1.4425697
MlkfreWek1_2	0.8984683	0.1431718	-0.7477998	0.4545809	0.6786326	1.1895175
MlkfreWek3_4	0.6934907	0.1533932	-2.3861381	0.0170264	0.5134192	0.9367187
MlkfreDaily	0.8637554	0.1019007	-1.4373375	0.1506221	0.7073800	1.0546996
Age	1.1980416	0.0166858	10.8288901	0.0000000	1.1594952	1.2378694

23.3 Model2

```r
SurvM2 <-  coxph(su_obj_fem ~ Mlkfre + Age + strata(Agegrp) + Smoking + Alc_Fre +
                   BMIgrp + DM_hist + HT_hist + KID_hist + LIV_hist + Exercise +
                   Slepgrp + Spi + Fru + Cofe + Educgrp + Gretea + Menopause,
              data = MData_fem)

tidy(SurvM2, exponentiate = TRUE, conf.int = TRUE) %>%
  knitr::kable(.)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.0970129	0.1811515	0.5111241	0.6092642	0.7691575	1.5646174
MlkfreWek1_2	0.9618579	0.1451719	-0.2678794	0.7887921	0.7236696	1.2784433
MlkfreWek3_4	0.7630279	0.1557788	-1.7361838	0.0825313	0.5622652	1.0354750
MlkfreDaily	0.9763177	0.1065134	-0.2250160	0.8219669	0.7923678	1.2029721
Age	1.1806768	0.0170732	9.7279741	0.0000000	1.1418217	1.2208542
SmokingPast	1.2516126	0.2743658	0.8180058	0.4133539	0.7310201	2.1429425
SmokingCurrent	1.7847883	0.1664787	3.4797223	0.0005019	1.2878929	2.4733961
Smokingunknown	0.8840400	0.1579904	-0.7801297	0.4353145	0.6486198	1.2049071
Alc_Fre1-4 /week	1.0158675	0.2768684	0.0568608	0.9546561	0.5904271	1.7478650
Alc_FreDaily	0.9815912	0.3168496	-0.0586410	0.9532381	0.5275065	1.8265582
Alc_FreNever or past	1.2674383	0.2226006	1.0646774	0.2870219	0.8193112	1.9606713
Alc_Freunknown	1.0605753	0.2620678	0.2244131	0.8224359	0.6345545	1.7726135
BMIgrp[14,18.5)	1.8473410	0.1332097	4.6073782	0.0000041	1.4228489	2.3984758
BMIgrp[25,30)	0.9706309	0.1167697	-0.2552803	0.7985066	0.7720751	1.2202496
BMIgrp[30,40)	1.3327139	0.2667909	1.0765635	0.2816753	0.7900309	2.2481731
BMIgrpunknown	1.3884235	0.1279478	2.5648666	0.0103215	1.0804698	1.7841497
DM_histTRUE	1.8711679	0.1608547	3.8952102	0.0000981	1.3651897	2.5646759
DM_histunknown	0.8853943	0.2206195	-0.5517290	0.5811340	0.5745728	1.3643582
HT_histTRUE	1.5104168	0.0930331	4.4326763	0.0000093	1.2586555	1.8125364
HT_histunknown	1.3132578	0.2188391	1.2452568	0.2130374	0.8552120	2.0166299
KID_histTRUE	1.4722580	0.1943670	1.9900353	0.0465870	1.0058620	2.1549115
KID_histunknown	1.0313979	0.3406645	0.0907494	0.9276917	0.5289956	2.0109460
LIV_histTRUE	0.8701804	0.2410696	-0.5768239	0.5640584	0.5425135	1.3957515
LIV_histunknown	0.7934548	0.3490770	-0.6627728	0.5074761	0.4003015	1.5727405
Exercise> 1h/w	1.0103870	0.1084143	0.0953145	0.9240650	0.8169686	1.2495975

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Exerciseunknown	1.1122835	0.1410326	0.7545427	0.4505234	0.8436617	1.4664345
Slepgrp[6.9,7.9)	0.9972530	0.1244423	-0.0221049	0.9823643	0.7814116	1.2727141
Slepgrp[7.9,8.9)	1.1979761	0.1157722	1.5602496	0.1187009	0.9547786	1.5031201
Slepgrp[8.9,23)	1.5148081	0.1363501	3.0457524	0.0023210	1.1595679	1.9788781
Slepgrpunknown	1.0302521	0.2003036	0.1487919	0.8817179	0.6957365	1.5256055
SpiOne2tw	0.6487578	0.1692544	-2.5564817	0.0105737	0.4656000	0.9039662
SpiThre4tw	0.5737271	0.1704223	-3.2601459	0.0011135	0.4108106	0.8012519
Spidaily	0.5594227	0.1670547	-3.4770037	0.0005071	0.4032207	0.7761351
Spiunknown	0.7760521	0.2114688	-1.1989267	0.2305565	0.5127295	1.1746094
FruOne2tw	0.8078987	0.1783695	-1.1959367	0.2317213	0.5695457	1.1460017
FruThre4tw	1.0791995	0.1656189	0.4602105	0.6453651	0.7800576	1.4930585
Frudaily	0.9931985	0.1596845	-0.0427387	0.9659098	0.7262939	1.3581876
Fruunknown	0.9818471	0.1795170	-0.1020500	0.9187170	0.6906192	1.3958831
CofeThre3tw	0.9182654	0.1173496	-0.7266222	0.4674574	0.7295919	1.1557300
CofeNever	1.0316730	0.1031331	0.3023444	0.7623896	0.8428591	1.2627841
Cofeunknown	1.3055927	0.2259188	1.1803225	0.2378720	0.8385042	2.0328726
Educgrp[18,70)	0.7740844	0.1326527	-1.9304128	0.0535557	0.5968623	1.0039277
Educgrpunknown	1.0661438	0.1133359	0.5651191	0.5719928	0.8537764	1.3313354
GreteaThre3tw	1.1217749	0.1501451	0.7653405	0.4440688	0.8357992	1.5055995
GreteaNever	1.1551957	0.1558668	0.9255961	0.3546559	0.8511017	1.5679408
Greteaunknown	0.9684336	0.1677351	-0.1912263	0.8483483	0.6970974	1.3453838
MenopauseTRUE	1.0224885	0.4747607	0.0468433	0.9626381	0.4032193	2.5928388