JACC study Milk intake and stroke mortality analysis

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Contents

1 Read in the data

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

```
## -- Attaching packages ------------------------------------------------------------------------

## v ggplot2 3.2.1     v dplyr   0.8.3
## v tibble  2.1.3     v stringr 1.4.0
## v tidyr   1.0.0     v forcats 0.4.0
## v purrr   0.3.3

## -- 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 object is masked from 'package:base':
##
##     date
```

```
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), "%"))
```

```
## # 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

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

3 define total stroke mortality

```
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), "%"))
```

```
## # 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), "%"))
```

```
## # 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), "%"))
```

```
## # 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), "%"))
```

```
## # 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), "%"))
```

```
## # 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

```
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: NAs introduced by coercion
```

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

```
## Warning: Factor `Mlkfre` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

```
## # 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%
```

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

```
## Warning: Factor `MlkLogi` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

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

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

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

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

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

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

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

## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion
```

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

```
## # 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)
```

```
## # 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)
```

```
## # 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)
```

```
## # 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)
```

```
## # 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)
```

```
## # 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)
```

```
## # 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)
```

```
## # 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()) %>%
```

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

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

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

```
## # 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%
```

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

```
## # 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%
```

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

```
## # 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%
```

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

```
## # 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%
```

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

```
## # 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%
```

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

```
## # 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%
```

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

```
## # 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%
```

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

```
## # 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%
```

```r
# 02-04 AREA 地区 (施設番号 + 地区番号)
# - 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

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

```
## # 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)
```

```
## # 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)
```

```
## # 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: NAs introduced by coercion

## Warning: NAs introduced by coercion
```

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

```
## # 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%
```

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

```
## # 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%
```

```r
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, Tot_Stroke, HemoStroke, IscheStroke, CHD, HeartF, MlkLogi,
         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

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

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

```
## # 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
```

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

```
## # 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
```

```r
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)
```

```r
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

## Loading required package: magrittr

##
## Attaching package: 'magrittr'

## The following object is masked from 'package:purrr':
##
##     set_names

## The following object is masked from 'package:tidyr':
##
##     extract
```

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

```r
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)
###################################################################################################
```

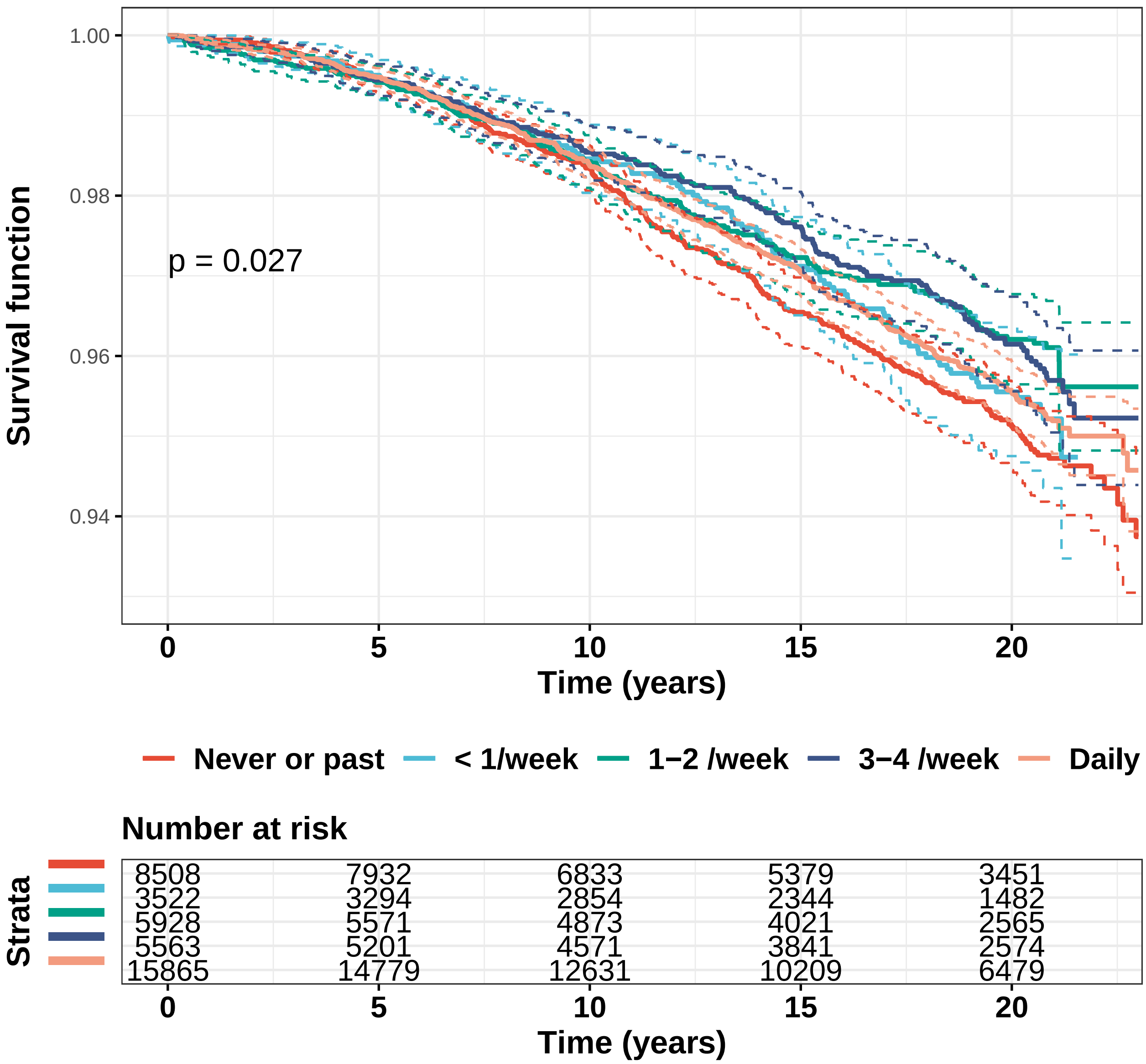

Figure 1: Kaplan-Meier survival curves for total stroke mortality by drinking frequency (P value was obtained from log-rank tests) in Men.

9 In Men

9.1 Model0

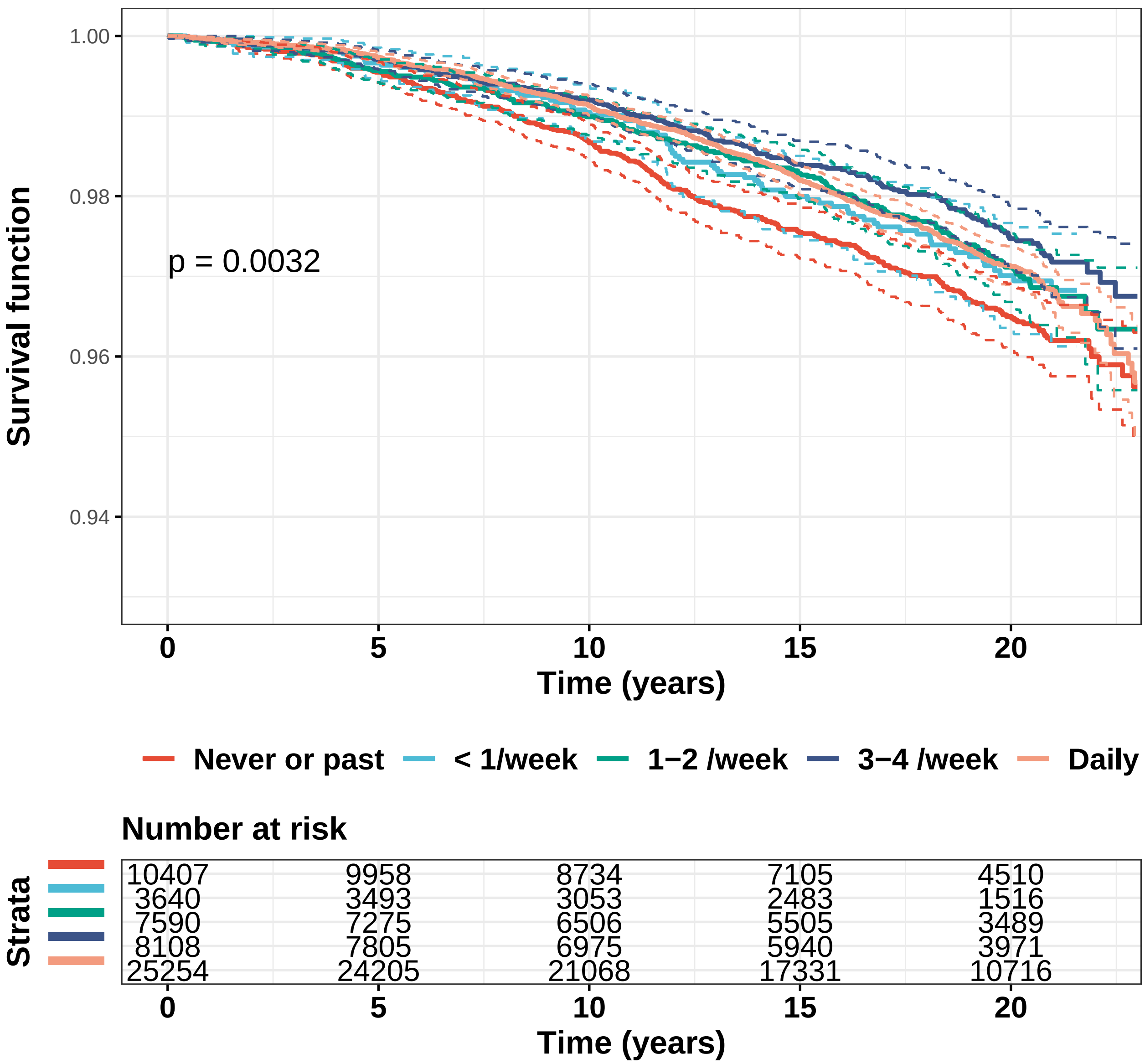

Figure 2: Kaplan-Meier survival curves for total stroke mortality by drinking frequency (P value was obtained from log-rank tests) in Women.

```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	0.8980399	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

9.2 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	0.9907616	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

9.3 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	1.0300683	0.1075649	0.2754162	0.7829965	0.8342700	1.2718194
MlkfreWek1_2	0.9061404	0.0938429	-1.0502765	0.2935910	0.7539044	1.0891175
MlkfreWek3_4	0.9628179	0.0951889	-0.3980606	0.6905855	0.7989493	1.1602968
MlkfreDaily	0.8734559	0.0730451	-1.8522475	0.0639903	0.7569459	1.0078992
Age	1.1384612	0.0105716	12.2666081	0.0000000	1.1151151	1.1622961
SmokingPast	0.9092779	0.0846937	-1.1229241	0.2614697	0.7702031	1.0734652
SmokingCurrent	1.3075884	0.0753798	3.5577787	0.0003740	1.1279963	1.5157739
Smokingunknown	1.2149551	0.1306811	1.4899405	0.1362399	0.9404252	1.5696260
Alc_Fre1-4 /week	1.1712398	0.1770038	0.8929911	0.3718620	0.8279038	1.6569590
Alc_FreDaily	1.2876971	0.1642444	1.5395075	0.1236805	0.9332729	1.7767191

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Alc_FreNever or past	1.3967678	0.1675560	1.9943231	0.0461168	1.0057737	1.9397606
Alc_Freunknown	1.6472841	0.1845000	2.7053004	0.0068243	1.1474184	2.3649131
BMIgrp[14,18.5)	1.5003884	0.0987751	4.1075518	0.0000400	1.2363065	1.8208797
BMIgrp[25,30)	1.0203389	0.0796094	0.2529201	0.8003300	0.8729328	1.1926365
BMIgrp[30,40)	1.4492199	0.2612867	1.4199934	0.1556096	0.8684136	2.4184769
BMIgrpunknown	1.3817305	0.1085374	2.9790350	0.0028916	1.1169562	1.7092694
DM_histTRUE	1.2836228	0.1041754	2.3967887	0.0165395	1.0465577	1.5743877
DM_histunknown	0.7349120	0.2150330	-1.4323589	0.1520411	0.4821686	1.1201387
HT_histTRUE	2.0048982	0.0628471	11.0680261	0.0000000	1.7725430	2.2677119
HT_histunknown	1.0581766	0.1591741	0.3552542	0.7223992	0.7745848	1.4455975
KID_histTRUE	1.0042507	0.1555771	0.0272641	0.9782491	0.7403118	1.3622900
KID_histunknown	1.1556749	0.1431050	1.0110374	0.3119985	0.8730206	1.5298430
LIV_histunknown	1.0081198	0.2277189	0.0355131	0.9716706	0.6451749	1.5752402
Exercise> 1h/w	0.8888327	0.0664392	-1.7737445	0.0761054	0.7803094	1.0124491
Exerciseunknown	0.9479967	0.1093089	-0.4885629	0.6251512	0.7651787	1.1744938
Slepgrp[6.9,7.9)	1.0683517	0.0924097	0.7154764	0.4743147	0.8913637	1.2804821
Slepgrp[7.9,8.9)	1.1667996	0.0865878	1.7815987	0.0748147	0.9846744	1.3826107
Slepgrp[8.9,23)	1.4173737	0.0980271	3.5582586	0.0003733	1.1696167	1.7176123
Slepgrpunknown	1.1695862	0.1490160	1.0512293	0.2931533	0.8733525	1.5662999
SpiOne2tw	0.8879411	0.1100452	-1.0800099	0.2801378	0.7156712	1.1016783
SpiThre4tw	0.8994989	0.1109290	-0.9548220	0.3396677	0.7237320	1.1179530
Spidaily	0.8884849	0.1098092	-1.0767551	0.2815897	0.7164408	1.1018432
Spiunknown	0.7855355	0.1538560	-1.5689320	0.1166638	0.5810364	1.0620092
FruOne2tw	0.9576372	0.0915918	-0.4725999	0.6364986	0.8002726	1.1459458
FruThre4tw	0.9459066	0.0960788	-0.5788107	0.5627169	0.7835485	1.1419068
Frudaily	0.8564286	0.0973184	-1.5925488	0.1112614	0.7077072	1.0364032
Fruunknown	0.8454586	0.1084428	-1.5480618	0.1216074	0.6835743	1.0456804
CofeThre3tw	0.9710044	0.0723145	-0.4068925	0.6840869	0.8426884	1.1188592
CofeNever	1.1891236	0.0703079	2.4636845	0.0137517	1.0360501	1.3648132
Cofeunknown	1.3526782	0.1679593	1.7985693	0.0720868	0.9732564	1.8800169
Educgrp[18,70)	0.8185838	0.0738148	-2.7119167	0.0066895	0.7083239	0.9460071
Educgrpunknown	1.0186215	0.0801000	0.2303397	0.8178278	0.8706259	1.1917744
GreteaThre3tw	0.9018289	0.1051730	-0.9824806	0.3258631	0.7338389	1.1082751
GreteaNever	1.1039716	0.1115240	0.8869319	0.3751155	0.8872142	1.3736854
Greteaunknown	1.0051178	0.1238702	0.0412106	0.9671280	0.7884579	1.2813136

10 In women

10.1 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

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreDaily	0.8126953	0.0710695	-2.918256	0.0035199	0.7070226	0.9341621

10.2 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

10.3 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	1.0467014	0.1247926	0.3657564	0.7145468	0.8195947	1.3367387
MlkfreWek1_2	1.1201783	0.0952611	1.1913348	0.2335222	0.9293959	1.3501238
MlkfreWek3_4	1.0102846	0.0975905	0.1048466	0.9164975	0.8344005	1.2232434
MlkfreDaily	0.9996588	0.0738354	-0.0046219	0.9963123	0.8649738	1.1553156
Age	1.1482663	0.0112234	12.3182668	0.0000000	1.1232831	1.1738052
SmokingPast	0.7785600	0.2331089	-1.0737866	0.2829183	0.4930256	1.2294609
SmokingCurrent	1.3300166	0.1234733	2.3097412	0.0209025	1.0441343	1.6941729
Smokingunknown	0.9301666	0.0997157	-0.7259793	0.4678515	0.7650372	1.1309384
Alc_Fre1-4 /week	0.9838100	0.1772855	-0.0920691	0.9266431	0.6950332	1.3925696
Alc_FreDaily	1.2608056	0.1939271	1.1950413	0.2320709	0.8621386	1.8438228
Alc_FreNever or past	1.0905128	0.1441253	0.6011990	0.5477074	0.8221500	1.4464735
Alc_Freunknown	1.3451436	0.1659978	1.7861726	0.0740713	0.9715632	1.8623713
BMIgrp[14,18.5)	1.9440536	0.0925427	7.1834450	0.0000000	1.6215702	2.3306697
BMIgrp[25,30)	1.1836198	0.0732828	2.3003690	0.0214273	1.0252596	1.3664402
BMIgrp[30,40)	1.4915614	0.1704111	2.3462295	0.0189644	1.0680386	2.0830290
BMIgrpunknown	1.5499423	0.0883179	4.9618198	0.0000007	1.3035844	1.8428582
DM_histTRUE	1.6029204	0.1191602	3.9596053	0.0000751	1.2690614	2.0246094
DM_histunknown	0.9933242	0.2062258	-0.0324798	0.9740895	0.6630577	1.4880953
HT_histTRUE	1.8212939	0.0630436	9.5100368	0.0000000	1.6095972	2.0608333
HT_histunknown	1.1165935	0.1459095	0.7558288	0.4497518	0.8388741	1.4862555
KID_histTRUE	1.1308567	0.1408644	0.8730064	0.3826596	0.8580322	1.4904300

term	estimate	std.error	statistic	p.value	conf.low	conf.high
KID_histunknown	1.1944264	0.1396201	1.2724967	0.2031967	0.9084783	1.5703781
LIV_histunknown	0.9199420	0.2180255	-0.3827288	0.7019208	0.6000353	1.4104059
Exercise> 1h/w	0.9641530	0.0724144	-0.5041158	0.6141800	0.8365785	1.1111821
Exerciseunknown	1.0288033	0.0967990	0.2933536	0.7692519	0.8510145	1.2437348
Slepgrp[6.9,7.9)	0.9437620	0.0820239	-0.7056632	0.4803976	0.8036068	1.1083613
Slepgrp[7.9,8.9)	1.1877371	0.0764556	2.2503248	0.0244283	1.0224480	1.3797469
Slepgrp[8.9,23)	1.3200220	0.0954417	2.9090893	0.0036248	1.0948158	1.5915536
Slepgrpunknown	1.0404227	0.1341486	0.2953970	0.7676906	0.7998754	1.3533100
SpiOne2tw	0.7553060	0.1221389	-2.2976488	0.0215818	0.5945085	0.9595945
SpiThre4tw	0.8809776	0.1194692	-1.0607171	0.2888185	0.6970637	1.1134155
Spidaily	0.7782482	0.1192466	-2.1024487	0.0355140	0.6160490	0.9831527
Spiunknown	0.7500660	0.1561738	-1.8414993	0.0655484	0.5522861	1.0186733
FruOne2tw	0.9005071	0.1072566	-0.9770699	0.3285345	0.7297769	1.1111793
FruThre4tw	0.8506338	0.1055080	-1.5332822	0.1252063	0.6917258	1.0460471
Frudaily	0.7375555	0.1016921	-2.9934854	0.0027581	0.6042745	0.9002336
Fruunknown	0.5994110	0.1191553	-4.2952989	0.0000174	0.4745692	0.7570942
CofeThre3tw	0.8460922	0.0775884	-2.1540193	0.0312387	0.7267321	0.9850563
CofeNever	1.0163001	0.0683542	0.2365420	0.8130121	0.8888711	1.1619973
Cofeunknown	1.0491755	0.1659541	0.2892643	0.7723791	0.7578578	1.4524745
Educgrp[18,70)	0.7838786	0.0857662	-2.8391273	0.0045237	0.6625894	0.9273702
Educgrpunknown	1.1213011	0.0756084	1.5142454	0.1299636	0.9668614	1.3004099
GreteaThre3tw	0.9216585	0.1045395	-0.7803800	0.4351672	0.7509065	1.1312386
GreteaNever	1.0261198	0.1080096	0.2387238	0.8113197	0.8303479	1.2680489
Greteaunknown	0.9870257	0.1183219	-0.1103701	0.9121159	0.7827313	1.2446414
MenopauseTRUE	0.5377835	0.2169379	-2.8593407	0.0042452	0.3515197	0.8227451

11 Cause specific: HemoStroke

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

12 In Men

12.1 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	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

12.2 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	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

12.3 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	1.1134015	0.1861324	0.5771147	0.5638619	0.7730643	1.6035704
MlkfreWek1_2	0.9449402	0.1668809	-0.3393658	0.7343342	0.6813261	1.3105499
MlkfreWek3_4	1.0062269	0.1696694	0.0365865	0.9708147	0.7215611	1.4031973
MlkfreDaily	0.9832157	0.1301855	-0.1300206	0.8965502	0.7617890	1.2690037
Age	1.0777785	0.0185111	4.0463314	0.0000520	1.0393764	1.1175995
SmokingPast	1.0101500	0.1598623	0.0631722	0.9496294	0.7384326	1.3818499
SmokingCurrent	1.5772291	0.1394669	3.2672238	0.0010861	1.1999975	2.0730474
Smokingunknown	1.1449340	0.2614826	0.5176138	0.6047277	0.6858136	1.9114143
Alc_Fre1-4 /week	1.2141812	0.3086607	0.6287483	0.5295139	0.6630572	2.2233918
Alc_FreDaily	1.3914300	0.2870213	1.1508970	0.2497746	0.7927721	2.4421613
Alc_FreNever or past	1.1796936	0.2978239	0.5548738	0.5789810	0.6580532	2.1148395
Alc_Freunknown	1.8929475	0.3238383	1.9705362	0.0487770	1.0034295	3.5710035
BMIgrp[14,18.5)	1.6674550	0.1753523	2.9158352	0.0035474	1.1824804	2.3513338
BMIgrp[25,30)	0.9304614	0.1420159	-0.5075113	0.6117961	0.7043917	1.2290867
BMIgrp[30,40)	0.8207613	0.5813293	-0.3397780	0.7340237	0.2626567	2.5647515
BMIgrpunknown	1.5642777	0.1952663	2.2913544	0.0219429	1.0668489	2.2936376
DM_histTRUE	1.1481046	0.1948149	0.7089417	0.4783606	0.7837088	1.6819311
DM_histunknown	0.6113172	0.3780974	-1.3016203	0.1930462	0.2913598	1.2826369
HT_histTRUE	1.7780869	0.1152353	4.9944612	0.0000006	1.4186150	2.2286477
HT_histunknown	0.8823975	0.2928417	-0.4272363	0.6692072	0.4970465	1.5665043
KID_histTRUE	1.3996573	0.2392006	1.4056296	0.1598342	0.8758179	2.2368129
KID_histunknown	1.2380224	0.2572768	0.8299050	0.4065925	0.7477116	2.0498538
LIV_histunknown	1.2593850	0.3985347	0.5786785	0.5628061	0.5766670	2.7503749
Exercise> 1h/w	0.9682060	0.1153437	-0.2801232	0.7793830	0.7723018	1.2138037
Exerciseunknown	0.5319369	0.2352731	-2.6829691	0.0072972	0.3354249	0.8435774
Slepgrp[6.9,7.9)	0.8611806	0.1514075	-0.9870778	0.3236045	0.6400530	1.1587042

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Slepgrp[7.9,8.9)	0.9822738	0.1415537	-0.1263490	0.8994557	0.7442894	1.2963531
Slepgrp[8.9,23)	0.9775126	0.1757417	-0.1294178	0.8970271	0.6926771	1.3794753
Slepgrpunknown	0.9215609	0.2753945	-0.2966160	0.7667597	0.5371651	1.5810306
SpiOne2tw	0.8537835	0.1781728	-0.8872149	0.3749632	0.6021252	1.2106226
SpiThre4tw	0.7694934	0.1846042	-1.4193772	0.1557891	0.5358824	1.1049439
Spidaily	0.7515458	0.1839380	-1.5528232	0.1204654	0.5240674	1.0777641
Spiunknown	0.9478997	0.2727461	-0.1961771	0.8444715	0.5553932	1.6177979
FruOne2tw	0.8904068	0.1547156	-0.7502593	0.4530985	0.6574977	1.2058205
FruThre4tw	0.7911651	0.1687246	-1.3883487	0.1650309	0.5683927	1.1012496
Frudaily	0.8317243	0.1667143	-1.1052102	0.2690685	0.5998905	1.1531527
Fruunknown	0.9440623	0.1871852	-0.3075197	0.7584478	0.6541364	1.3624888
CofeThre3tw	1.0381434	0.1283458	0.2916649	0.7705429	0.8072522	1.3350745
CofeNever	1.3908326	0.1239529	2.6615152	0.0077790	1.0908523	1.7733064
Cofeunknown	1.1266999	0.3206563	0.3720275	0.7098724	0.6009871	2.1122796
Educgrp[18,70)	0.9415033	0.1223844	-0.4925254	0.6223480	0.7407098	1.1967284
Educgrpunknown	0.8634590	0.1515303	-0.9688417	0.3326242	0.6415919	1.1620493
GreteaThre3tw	0.7235100	0.2050131	-1.5786357	0.1144196	0.4841022	1.0813143
GreteaNever	1.2481441	0.1869247	1.1858131	0.2356961	0.8652750	1.8004261
Greteaunknown	1.7690641	0.1998633	2.8542035	0.0043145	1.1956927	2.6173847

13 In women

13.1 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	0.7329251	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

13.2 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	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

term	estimate	std.error	statistic	p.value	conf.low	conf.high
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

13.3 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	0.8523110	0.2168453	-0.7369484	0.4611537	0.5572102	1.3036985
MlkfreWek1_2	1.2087347	0.1503743	1.2606816	0.2074236	0.9001858	1.6230421
MlkfreWek3_4	1.1301093	0.1524809	0.8021618	0.4224594	0.8381630	1.5237455
MlkfreDaily	1.0258900	0.1206184	0.2119123	0.8321755	0.8098978	1.2994853
Age	1.0863261	0.0173859	4.7625505	0.0000019	1.0499322	1.1239815
SmokingPast	0.6383644	0.4517490	-0.9935739	0.3204304	0.2633535	1.5473841
SmokingCurrent	1.8225964	0.1723866	3.4820703	0.0004976	1.3000343	2.5552077
Smokingunknown	0.9851802	0.1586694	-0.0940998	0.9250299	0.7218651	1.3445449
Alc_Fre1-4 /week	0.6640513	0.2444429	-1.6748122	0.0939711	0.4112742	1.0721900
Alc_FreDaily	0.8172757	0.2790388	-0.7231207	0.4696057	0.4729882	1.4121697
Alc_FreNever or past	0.7958204	0.1873558	-1.2189731	0.2228544	0.5512359	1.1489276
Alc_Freunknown	0.9091069	0.2317336	-0.4112163	0.6809139	0.5772487	1.4317491
BMIgrp[14,18.5)	2.4042129	0.1409511	6.2235962	0.0000000	1.8238753	3.1692077
BMIgrp[25,30)	1.0516113	0.1164995	0.4319636	0.6657679	0.8369329	1.3213560
BMIgrp[30,40)	0.7820537	0.3601086	-0.6826604	0.4948214	0.3861105	1.5840233
BMIgrpunknown	1.6019762	0.1528058	3.0839007	0.0020431	1.1873739	2.1613475
DM_histTRUE	1.0262080	0.2299845	0.1124880	0.9104365	0.6538412	1.6106403
DM_histunknown	1.1388221	0.3650284	0.3561215	0.7217496	0.5568563	2.3289952
HT_histTRUE	2.1598872	0.1011615	7.6121452	0.0000000	1.7714229	2.6335398
HT_histunknown	0.7796102	0.2402212	-1.0363835	0.3000233	0.4868564	1.2484011
KID_histTRUE	1.2167582	0.2142650	0.9156424	0.3598545	0.7995058	1.8517696
KID_histunknown	1.0510227	0.2292828	0.2170407	0.8281766	0.6705733	1.6473199
LIV_histunknown	1.0973036	0.3746108	0.2478731	0.8042326	0.5265717	2.2866310
Exercise> 1h/w	1.1623012	0.1122602	1.3397608	0.1803231	0.9327443	1.4483541
Exerciseunknown	1.2422318	0.1541718	1.4069341	0.1594469	0.9182720	1.6804823
Slepgrp[6.9,7.9)	1.0792731	0.1228908	0.6207768	0.5347465	0.8482551	1.3732076
Slepgrp[7.9,8.9)	1.1695672	0.1222299	1.2814687	0.2000291	0.9204134	1.4861663
Slepgrp[8.9,23)	1.0509384	0.1761699	0.2820201	0.7779281	0.7440826	1.4843397
Slepgrpunknown	1.1683948	0.2094594	0.7430121	0.4574744	0.7749924	1.7614965
SpiOne2tw	0.6798889	0.1875493	-2.0571967	0.0396673	0.4707558	0.9819293
SpiThre4tw	0.7479799	0.1847923	-1.5713814	0.1160941	0.5207083	1.0744480
Spidaily	0.7965040	0.1816674	-1.2524163	0.2104182	0.5578949	1.1371650
Spiunknown	0.6868033	0.2467738	-1.5224763	0.1278898	0.4234266	1.1140037
FruOne2tw	1.0772139	0.1674429	0.4441993	0.6568985	0.7758439	1.4956487
FruThre4tw	0.8906245	0.1690287	-0.6852821	0.4931659	0.6394655	1.2404297
Frudaily	0.6812614	0.1648204	-2.3286519	0.0198775	0.4931947	0.9410422
Fruunknown	0.6735045	0.1924663	-2.0536619	0.0400084	0.4618627	0.9821280

term	estimate	std.error	statistic	p.value	conf.low	conf.high
CofeThre3tw	0.7964819	0.1200031	-1.8962089	0.0579324	0.6295483	1.0076801
CofeNever	0.9900539	0.1090474	-0.0916659	0.9269635	0.7995350	1.2259708
Cofeunknown	0.8677467	0.3014628	-0.4705569	0.6379572	0.4806040	1.5667460
Educgrp[18,70)	0.7404118	0.1274145	-2.3588269	0.0183328	0.5767903	0.9504489
Educgrpunknown	0.9351974	0.1275887	-0.5251068	0.5995089	0.7282821	1.2009003
GreteaThre3tw	0.8022045	0.1688843	-1.3049866	0.1918974	0.5761433	1.1169652
GreteaNever	0.9872543	0.1711198	-0.0749626	0.9402445	0.7059462	1.3806592
Greteaunknown	0.7546384	0.2126032	-1.3241404	0.1854564	0.4974744	1.1447407
MenopauseTRUE	0.7246684	0.2628829	-1.2250364	0.2205615	0.4328854	1.2131253

14 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")
```

15 In Men

15.1 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	0.6545119	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

15.2 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	0.7296273	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

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Age	1.1908810	0.0170434	10.249906	0.0000000	1.1517574	1.2313337

15.3 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	0.7303037	0.1785211	-1.7605472	0.0783151	0.5146904	1.0362414
MlkfreWek1_2	0.6715428	0.1512266	-2.6329862	0.0084638	0.4992860	0.9032293
MlkfreWek3_4	0.7409258	0.1508224	-1.9881318	0.0467971	0.5513083	0.9957607
MlkfreDaily	0.6302994	0.1136080	-4.0627435	0.0000485	0.5044796	0.7874994
Age	1.1813267	0.0171802	9.6994181	0.0000000	1.1422106	1.2217824
SmokingPast	0.8526579	0.1338894	-1.1905112	0.2338455	0.6558552	1.1085153
SmokingCurrent	1.1974416	0.1198854	1.5029957	0.1328402	0.9466898	1.5146106
Smokingunknown	1.2732111	0.1957678	1.2338196	0.2172701	0.8674862	1.8686943
Alc_Fre1-4 /week	1.3985634	0.3060166	1.0961678	0.2730053	0.7677156	2.5477920
Alc_FreDaily	1.4325237	0.2874817	1.2502978	0.2111908	0.8154493	2.5165566
Alc_FreNever or past	1.7022079	0.2909702	1.8281125	0.0675327	0.9623618	3.0108342
Alc_Freunknown	2.1374495	0.3124477	2.4311697	0.0150502	1.1586171	3.9432270
BMIgrp[14,18.5)	1.4853426	0.1553511	2.5467824	0.0108721	1.0954474	2.0140106
BMIgrp[25,30)	1.0434390	0.1295405	0.3282524	0.7427208	0.8094722	1.3450306
BMIgrp[30,40)	1.8284387	0.3838893	1.5719698	0.1159576	0.8616149	3.8801419
BMIgrpunknown	1.3794339	0.1689716	1.9037120	0.0569477	0.9905400	1.9210107
DM_histTRUE	1.3546209	0.1640897	1.8497302	0.0643524	0.9820744	1.8684917
DM_histunknown	0.6126542	0.3418726	-1.4331496	0.1518151	0.3134822	1.1973412
HT_histTRUE	2.1212320	0.0998380	7.5321714	0.0000000	1.7442386	2.5797073
HT_histunknown	1.4143127	0.2583420	1.3418015	0.1796604	0.8524017	2.3466405
KID_histTRUE	0.8755882	0.2655242	-0.5003665	0.6168171	0.5203377	1.4733791
KID_histunknown	1.0760275	0.2258943	0.3243818	0.7456490	0.6911014	1.6753478
LIV_histunknown	0.9911336	0.3647097	-0.0244192	0.9805182	0.4849431	2.0256932
Exercise> 1h/w	0.8247533	0.1094280	-1.7607095	0.0782876	0.6655470	1.0220435
Exerciseunknown	1.1093185	0.1638314	0.6332476	0.5265720	0.8046420	1.5293603
Slepgrp[6.9,7.9)	1.3127116	0.1563744	1.7400219	0.0818552	0.9661914	1.7835097
Slepgrp[7.9,8.9)	1.3376281	0.1481472	1.9635739	0.0495795	1.0005349	1.7882923
Slepgrp[8.9,23)	1.6367531	0.1635147	3.0132735	0.0025845	1.1879529	2.2551068
Slepgrpunknown	1.4300069	0.2333532	1.5327804	0.1253300	0.9051228	2.2592733
SpiOne2tw	0.7564227	0.1775736	-1.5720522	0.1159384	0.5340891	1.0713107
SpiThre4tw	0.8195790	0.1764754	-1.1274343	0.2595589	0.5799288	1.1582625
Spidaily	0.7857216	0.1746744	-1.3805841	0.1674069	0.5579375	1.1065011
Spiunknown	0.6504042	0.2399908	-1.7924074	0.0730677	0.4063523	1.0410315
FruOne2tw	0.9867436	0.1541594	-0.0865663	0.9310163	0.7294299	1.3348273
FruThre4tw	1.0393080	0.1590030	0.2424801	0.8084081	0.7610281	1.4193445
Frudaily	0.9832703	0.1592206	-0.1059614	0.9156130	0.7196878	1.3433888
Fruunknown	0.9261831	0.1759501	-0.4358242	0.6629643	0.6560363	1.3075727
CofeThre3tw	0.9792461	0.1151794	-0.1820834	0.8555173	0.7813597	1.2272491

term	estimate	std.error	statistic	p.value	conf.low	conf.high
CofeNever	1.0442240	0.1149784	0.3763669	0.7066442	0.8335351	1.3081679
Cofeunknown	1.1110015	0.2797317	0.3762957	0.7066971	0.6421057	1.9223069
Educgrp[18,70)	0.9534358	0.1201091	-0.3969991	0.6913681	0.7534499	1.2065033
Educgrpunknown	1.2270916	0.1246967	1.6411567	0.1007649	0.9610256	1.5668197
GreteaThre3tw	1.0028034	0.1622111	0.0172580	0.9862308	0.7296951	1.3781298
GreteaNever	0.8603076	0.2006038	-0.7500617	0.4532176	0.5806300	1.2747002
Greteaunknown	0.8194409	0.2023699	-0.9840048	0.3251132	0.5511376	1.2183589

16 In women

16.1 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

16.2 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	1.2915128	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

16.3 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)
```

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

term	estimate	std.error	statistic	p.value	conf.low	conf.high
MlkfreMon1_2	1.2985583	0.1989801	1.3129690	0.1891934	0.8792033	1.9179336
MlkfreWek1_2	1.1829521	0.1628500	1.0317045	0.3022105	0.8597041	1.6277411
MlkfreWek3_4	0.8728178	0.1762848	-0.7716402	0.4403276	0.6178311	1.2330409
MlkfreDaily	0.9267683	0.1284726	-0.5919678	0.5538722	0.7204687	1.1921401
Age	1.2278541	0.0201946	10.1645008	0.0000000	1.1802040	1.2774280
SmokingPast	1.2079254	0.3101462	0.6090816	0.5424703	0.6577232	2.2183856
SmokingCurrent	1.3621103	0.2112804	1.4626778	0.1435556	0.9002644	2.0608885
Smokingunknown	0.8219028	0.1748899	-1.1214662	0.2620895	0.5833832	1.1579426
Alc_Fre1-4 /week	1.3218749	0.3393623	0.8222808	0.4109171	0.6797115	2.5707279
Alc_FreDaily	1.6148890	0.3641637	1.3160734	0.1881494	0.7909808	3.2970036
Alc_FreNever or past	1.3283422	0.2878218	0.9864843	0.3238955	0.7556411	2.3350940
Alc_Freunknown	1.7457337	0.3192538	1.7452414	0.0809429	0.9337458	3.2638283
BMIgrp[14,18.5)	1.5821029	0.1731207	2.6499143	0.0080512	1.1268709	2.2212390
BMIgrp[25,30)	1.4583792	0.1258912	2.9972353	0.0027244	1.1394929	1.8665055
BMIgrp[30,40)	2.3186959	0.2563626	3.2805288	0.0010361	1.4029027	3.8323049
BMIgrpunknown	1.7614769	0.1423614	3.9768688	0.0000698	1.3325966	2.3283872
DM_histTRUE	2.7853079	0.1689789	6.0620496	0.0000000	2.0000374	3.8788975
DM_histunknown	1.3101088	0.3198621	0.8444584	0.3984133	0.6999069	2.4523048
HT_histTRUE	1.4798633	0.1112369	3.5235573	0.0004258	1.1899715	1.8403764
HT_histunknown	1.1949795	0.2448690	0.7274463	0.4669526	0.7394820	1.9310491
KID_histTRUE	0.9713730	0.2613876	-0.1111177	0.9115230	0.5819591	1.6213604
KID_histunknown	1.1296597	0.2325356	0.5242917	0.6000757	0.7161649	1.7818957
LIV_histunknown	0.7982141	0.3472921	-0.6489592	0.5163648	0.4041139	1.5766489
Exercise> 1h/w	0.7984106	0.1312291	-1.7155674	0.0862412	0.6173393	1.0325918
Exerciseunknown	0.9019604	0.1649223	-0.6256559	0.5315406	0.6528379	1.2461480
Slepgrp[6.9,7.9)	0.7795343	0.1463529	-1.7017673	0.0887990	0.5851395	1.0385109
Slepgrp[7.9,8.9)	1.0434133	0.1308685	0.3247334	0.7453829	0.8073482	1.3485028
Slepgrp[8.9,23)	1.2167807	0.1561065	1.2568893	0.2087937	0.8960540	1.6523059
Slepgrpunknown	0.9501586	0.2224805	-0.2298013	0.8182462	0.6143563	1.4695079
SpiOne2tw	0.7968559	0.2167615	-1.0476094	0.2948186	0.5210413	1.2186739
SpiThre4tw	0.9804503	0.2111062	-0.0935234	0.9254878	0.6482337	1.4829262
Spidaily	0.7655606	0.2128046	-1.2553625	0.2093472	0.5044754	1.1617673
Spiunknown	0.8569925	0.2643260	-0.5838475	0.5593229	0.5104842	1.4387050
FruOne2tw	0.8368067	0.1937984	-0.9193168	0.3579299	0.5723526	1.2234513
FruThre4tw	0.8216662	0.1883682	-1.0427505	0.2970639	0.5680102	1.1885973
Frudaily	0.8186580	0.1783392	-1.1219561	0.2618811	0.5771649	1.1611950
Fruunknown	0.6705543	0.2032536	-1.9662665	0.0492678	0.4502194	0.9987198
CofeThre3tw	0.8069217	0.1371992	-1.5636288	0.1179048	0.6166621	1.0558825
CofeNever	0.8764203	0.1205735	-1.0940175	0.2739473	0.6919585	1.1100557
Cofeunknown	1.2492590	0.2512718	0.8856964	0.3757811	0.7634305	2.0442569
Educgrp[18,70)	0.8834768	0.1530873	-0.8092781	0.4183552	0.6544659	1.1926234
Educgrpunknown	1.2121692	0.1277467	1.5061952	0.1320171	0.9436806	1.5570460
GreteaThre3tw	0.9341911	0.1874390	-0.3631808	0.7164698	0.6469749	1.3489134
GreteaNever	1.0422318	0.1902987	0.2173656	0.8279234	0.7177642	1.5133761
Greteaunknown	1.1012543	0.1915347	0.5035630	0.6145685	0.7565767	1.6029584
MenopauseTRUE	0.3585526	0.4884617	-2.0998165	0.0357450	0.1376491	0.9339685

17 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")
```

18 In Men

18.1 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

18.2 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	0.9421510	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

18.3 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	0.9295763	0.1463973	-0.4988233	0.6179038	0.6977044	1.2385075
MlkfreWek1_2	0.8869141	0.1241245	-0.9668289	0.3336296	0.6953870	1.1311925
MlkfreWek3_4	0.8669820	0.1288328	-1.1079255	0.2678940	0.6735152	1.1160219
MlkfreDaily	0.8593248	0.0980577	-1.5461130	0.1220773	0.7090723	1.0414159
Age	1.1102452	0.0141586	7.3863636	0.0000000	1.0798590	1.1414864
SmokingPast	1.4217022	0.1250155	2.8144900	0.0048855	1.1127440	1.8164441
SmokingCurrent	2.0501174	0.1141833	6.2872329	0.0000000	1.6390255	2.5643172
Smokingunknown	1.9038967	0.1837541	3.5041541	0.0004581	1.3281025	2.7293243
Alc_Fre1-4 /week	1.1746340	0.2159304	0.7454096	0.4560241	0.7693116	1.7935061
Alc_FreDaily	1.0401151	0.2020266	0.1946844	0.8456401	0.7000290	1.5454209
Alc_FreNever or past	1.3563618	0.2060641	1.4791800	0.1390922	0.9056772	2.0313167
Alc_Freunknown	1.3613589	0.2331719	1.3229867	0.1858398	0.8619783	2.1500520
BMIgrp[14,18.5)	1.0636930	0.1594863	0.3871608	0.6986372	0.7781464	1.4540231
BMIgrp[25,30)	1.4634113	0.0930011	4.0942562	0.0000424	1.2195616	1.7560184
BMIgrp[30,40)	1.5589424	0.3376652	1.3149343	0.1885320	0.8042830	3.0216992
BMIgrpunknown	1.0632886	0.1670932	0.3672591	0.7134258	0.7663393	1.4753028
DM_histTRUE	1.9545616	0.1228228	5.4563640	0.0000000	1.5363933	2.4865449
DM_histunknown	2.0898072	0.3020077	2.4405731	0.0146640	1.1562103	3.7772490
HT_histTRUE	1.7971633	0.0875792	6.6934795	0.0000000	1.5137007	2.1337085
HT_histunknown	1.0174239	0.2086927	0.0827717	0.9340330	0.6758688	1.5315862
KID_histTRUE	0.8903249	0.2201448	-0.5276927	0.5977126	0.5783103	1.3706802
KID_histunknown	0.9856763	0.1901951	-0.0758550	0.9395344	0.6789533	1.4309640
LIV_histunknown	0.5860399	0.3358852	-1.5909225	0.1116270	0.3034039	1.1319656
Exercise> 1h/w	0.9377831	0.0894156	-0.7184047	0.4725078	0.7870307	1.1174114
Exerciseunknown	0.9103985	0.1517420	-0.6186344	0.5361572	0.6761896	1.2257293
Slepgrp[6.9,7.9)	0.8567192	0.1160837	-1.3321857	0.1827992	0.6823825	1.0755959
Slepgrp[7.9,8.9)	0.9485135	0.1091525	-0.4842701	0.6281942	0.7658306	1.1747739
Slepgrp[8.9,23)	1.1657273	0.1289702	1.1889973	0.2344407	0.9053518	1.5009859
Slepgrpunknown	0.9731586	0.1948283	-0.1396521	0.8889349	0.6642713	1.4256792
SpiOne2tw	0.8724617	0.1427423	-0.9558241	0.3391611	0.6595442	1.1541143
SpiThre4tw	0.9078033	0.1442515	-0.6705478	0.5025087	0.6842340	1.2044225
Spidaily	0.7801588	0.1465096	-1.6944810	0.0901739	0.5854284	1.0396622
Spiunknown	0.9623383	0.2008498	-0.1911343	0.8484204	0.6491785	1.4265644
FruOne2tw	0.9411443	0.1214061	-0.4996353	0.6173319	0.7418485	1.1939806
FruThre4tw	0.8637748	0.1286183	-1.1385882	0.2548749	0.6713059	1.1114261
Frudaily	0.7518807	0.1315714	-2.1674740	0.0301987	0.5809720	0.9730670
Fruunknown	0.7437689	0.1466171	-2.0190346	0.0434836	0.5580041	0.9913766
CofeThre3tw	0.7634694	0.0957247	-2.8193591	0.0048120	0.6328644	0.9210276
CofeNever	0.7922931	0.0990736	-2.3500097	0.0187729	0.6524605	0.9620939
Cofeunknown	0.8321171	0.2423148	-0.7584434	0.4481856	0.5175183	1.3379602
Educgrp[18,70)	0.9273232	0.0960265	-0.7857535	0.4320119	0.7682334	1.1193580
Educgrpunknown	1.1778856	0.1087228	1.5058566	0.1321040	0.9518271	1.4576330
GreteaThre3tw	1.3803857	0.1187399	2.7148652	0.0066303	1.0937771	1.7420960
GreteaNever	1.3514412	0.1428640	2.1081000	0.0350223	1.0213888	1.7881468
Greteaunknown	1.0608111	0.1672296	0.3530104	0.7240807	0.7643495	1.4722586

19 In women

19.1 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	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

19.2 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

19.3 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	1.3830104	0.1785758	1.8158255	0.0693971	0.9745888	1.9625895
MlkfreWek1_2	1.2242714	0.1441247	1.4039641	0.1603295	0.9229933	1.6238909
MlkfreWek3_4	0.8514313	0.1610690	-0.9985563	0.3180097	0.6209369	1.1674863
MlkfreDaily	1.1073774	0.1137715	0.8964860	0.3699932	0.8860398	1.3840065
Age	1.1547566	0.0171705	8.3800236	0.0000000	1.1165415	1.1942797
SmokingPast	1.1296635	0.3080987	0.3957167	0.6923140	0.6175825	2.0663467
SmokingCurrent	2.8687071	0.1446932	7.2834188	0.0000000	2.1603449	3.8093362
Smokingunknown	1.1656036	0.1445464	1.0601380	0.2890818	0.8780370	1.5473515
Alc_Fre1-4 /week	1.0814890	0.2568842	0.3049577	0.7603984	0.6536750	1.7892967
Alc_FreDaily	1.1010998	0.2962629	0.3250811	0.7451197	0.6160944	1.9679139

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Alc_FreNever or past	1.1259751	0.2112712	0.5615977	0.5743902	0.7442081	1.7035826
Alc_Freunknown	1.1784985	0.2432394	0.6752246	0.4995331	0.7316162	1.8983434
BMIgrp[14,18.5)	1.3744035	0.1545100	2.0582481	0.0395663	1.0153018	1.8605159
BMIgrp[25,30)	1.0444468	0.1136672	0.3825849	0.7020276	0.8358582	1.3050888
BMIgrp[30,40)	1.8251320	0.2284929	2.6331338	0.0084601	1.1662745	2.8561944
BMIgrpunknown	1.2828900	0.1368337	1.8205708	0.0686721	0.9811071	1.6774997
DM_histTRUE	2.6436469	0.1537245	6.3240372	0.0000000	1.9559283	3.5731724
DM_histunknown	1.0765105	0.2747913	0.2682939	0.7884731	0.6282254	1.8446803
HT_histTRUE	1.7012132	0.0976204	5.4429389	0.0000001	1.4049606	2.0599343
HT_histunknown	0.9061544	0.2117631	-0.4653578	0.6416753	0.5983415	1.3723196
KID_histTRUE	1.3008352	0.2033717	1.2932308	0.1959313	0.8731965	1.9379055
KID_histunknown	1.2236613	0.1984615	1.0170611	0.3091244	0.8293360	1.8054771
LIV_histunknown	1.0454774	0.2898904	0.1534152	0.8780709	0.5923242	1.8453119
Exercise> 1h/w	0.7904550	0.1169010	-2.0115027	0.0442724	0.6285949	0.9939932
Exerciseunknown	0.8601747	0.1510662	-0.9970448	0.3187428	0.6397331	1.1565768
Slepgrp[6.9,7.9)	0.7879789	0.1184376	-2.0118949	0.0442310	0.6247415	0.9938683
Slepgrp[7.9,8.9)	0.8461901	0.1136910	-1.4689925	0.1418348	0.6771642	1.0574063
Slepgrp[8.9,23)	1.0835767	0.1395395	0.5752305	0.5651354	0.8242965	1.4244129
Slepgrpunknown	0.8377186	0.2018445	-0.8772745	0.3803375	0.5640113	1.2442525
SpiOne2tw	0.8042105	0.1840240	-1.1840533	0.2363919	0.5606970	1.1534832
SpiThre4tw	0.7874964	0.1840711	-1.2978489	0.1943393	0.5489932	1.1296143
Spidaily	0.7179949	0.1825014	-1.8152898	0.0694794	0.5020834	1.0267549
Spiunknown	0.8736380	0.2304400	-0.5862227	0.5577259	0.5561355	1.3724054
FruOne2tw	1.1670913	0.1698171	0.9098883	0.3628814	0.8366740	1.6279963
FruThre4tw	1.0520905	0.1692520	0.3000212	0.7641610	0.7550671	1.4659551
Frudaily	0.7550155	0.1680391	-1.6723307	0.0944591	0.5431512	1.0495208
Fruunknown	0.8865868	0.1852127	-0.6499355	0.5157339	0.6166915	1.2746019
CofeThre3tw	0.9586122	0.1158236	-0.3649395	0.7151566	0.7639302	1.2029075
CofeNever	0.9631272	0.1073343	-0.3500261	0.7263191	0.7804058	1.1886303
Cofeunknown	1.2434744	0.2209786	0.9861105	0.3240789	0.8063795	1.9174948
Educgrp[18,70)	0.9033610	0.1284543	-0.7911999	0.4288273	0.7022970	1.1619885
Educgrpunknown	0.9316298	0.1197483	-0.5914052	0.5542490	0.7367386	1.1780760
GreteaThre3tw	1.0099941	0.1541155	0.0645264	0.9485511	0.7466817	1.3661620
GreteaNever	1.0517535	0.1637038	0.3082322	0.7579056	0.7630781	1.4496359
Greteaunknown	1.1233704	0.1640025	0.7093398	0.4781136	0.8145614	1.5492523
MenopauseTRUE	2.1236262	0.4325175	1.7412594	0.0816381	0.9097426	4.9572131

20 Cause specific: HeartF

```
# 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")
```

21 In Men

21.1 Model0

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

```r
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

21.2 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	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

21.3 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	1.1212800	0.1863526	0.6142705	0.5390366	0.7781986	1.615614
MlkfreWek1_2	1.0326576	0.1574580	0.2040905	0.8382828	0.7584516	1.405998
MlkfreWek3_4	1.0467268	0.1602453	0.2849880	0.7756534	0.7645966	1.432961
MlkfreDaily	1.0594232	0.1228612	0.4698356	0.6384725	0.8327024	1.347873
Age	1.1446770	0.0177936	7.5938949	0.0000000	1.1054448	1.185302
SmokingPast	0.9764990	0.1431931	-0.1660801	0.8680940	0.7375401	1.292879
SmokingCurrent	1.5862895	0.1269488	3.6345187	0.0002785	1.2368683	2.034424
Smokingunknown	1.5727764	0.2071353	2.1862163	0.0287998	1.0479803	2.360374
Alc_Fre1-4 /week	1.3644711	0.2869652	1.0829426	0.2788339	0.7774977	2.394581
Alc_FreDaily	1.1877656	0.2701521	0.6369518	0.5241562	0.6994825	2.016901
Alc_FreNever or past	1.7528764	0.2718058	2.0649228	0.0389303	1.0289393	2.986159
Alc_Freunknown	1.6034339	0.3025242	1.5606934	0.1185961	0.8862209	2.901083
BMIgrp[14,18.5)	1.6052530	0.1512708	3.1287023	0.0017558	1.1933876	2.159263

term	estimate	std.error	statistic	p.value	conf.low	conf.high
BMIgrp[25,30)	0.9614101	0.1389413	-0.2832436	0.7769901	0.7322201	1.262338
BMIgrp[30,40)	1.3843852	0.4522224	0.7192394	0.4719934	0.5705905	3.358840
BMIgrpunknown	1.5741754	0.1627649	2.7876498	0.0053092	1.1442143	2.165703
DM_histTRUE	1.1676032	0.1770965	0.8749644	0.3815933	0.8251834	1.652114
DM_histunknown	0.4322642	0.3051459	-2.7485810	0.0059854	0.2376887	0.786122
HT_histTRUE	1.5063275	0.1107939	3.6976265	0.0002176	1.2123037	1.871662
HT_histunknown	0.9814912	0.2456932	-0.0760390	0.9393881	0.6063900	1.588623
KID_histTRUE	1.2468396	0.2448986	0.9008298	0.3676788	0.7715294	2.014970
KID_histunknown	1.3688452	0.2143635	1.4646501	0.1430164	0.8992653	2.083631
LIV_histunknown	1.7308109	0.3234693	1.6959570	0.0898940	0.9181466	3.262776
Exercise> 1h/w	0.8166424	0.1144580	-1.7696802	0.0767804	0.6525369	1.022018
Exerciseunknown	1.0412105	0.1701475	0.2373467	0.8123878	0.7459483	1.453344
Slepgrp[6.9,7.9)	0.8861999	0.1512846	-0.7985794	0.4245344	0.6588068	1.192080
Slepgrp[7.9,8.9)	1.1362995	0.1366959	0.9347530	0.3499156	0.8692347	1.485418
Slepgrp[8.9,23)	1.2925389	0.1561792	1.6430379	0.1003751	0.9517077	1.755430
Slepgrpunknown	0.8070770	0.2520749	-0.8502880	0.3951650	0.4924344	1.322761
SpiOne2tw	0.8553443	0.1925117	-0.8116452	0.4169952	0.5865091	1.247404
SpiThre4tw	1.0645598	0.1889230	0.3311472	0.7405333	0.7351204	1.541635
Spidaily	0.8300871	0.1917194	-0.9713399	0.3313791	0.5700747	1.208692
Spiunknown	0.9174896	0.2490935	-0.3457098	0.7295608	0.5630829	1.494961
FruOne2tw	0.8044158	0.1583408	-1.3744974	0.1692873	0.5897944	1.097136
FruThre4tw	0.8406649	0.1631751	-1.0636553	0.2874849	0.6105595	1.157492
Frudaily	0.7954909	0.1642307	-1.3931367	0.1635785	0.5765564	1.097561
Fruunknown	0.7746391	0.1770266	-1.4424840	0.1491659	0.5475379	1.095935
CofeThre3tw	1.1436927	0.1165358	1.1521116	0.2492752	0.9101519	1.437159
CofeNever	1.1287845	0.1205253	1.0051116	0.3148431	0.8912914	1.429560
Cofeunknown	1.3117184	0.2606104	1.0411636	0.2977996	0.7870615	2.186113
Educgrp[18,70)	0.9448713	0.1252990	-0.4525699	0.6508585	0.7391251	1.207890
Educgrpunknown	1.1965802	0.1319037	1.3605963	0.1736413	0.9239856	1.549596
GreteaThre3tw	1.1433282	0.1583160	0.8460516	0.3975240	0.8383244	1.559300
GreteaNever	1.1913306	0.1791223	0.9773814	0.3283804	0.8386159	1.692394
Greteaunknown	0.7364382	0.2023297	-1.5120363	0.1305246	0.4953509	1.094863

22 In women

22.1 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	0.7934785	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

22.2 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

22.3 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	1.0994192	0.1811009	0.5233658	0.6007197	0.7709211	1.5678940
MlkfreWek1_2	0.9644743	0.1451427	-0.2492172	0.8031928	0.7256797	1.2818475
MlkfreWek3_4	0.7631415	0.1557873	-1.7351342	0.0827170	0.5623396	1.0356462
MlkfreDaily	0.9763110	0.1066068	-0.2248835	0.8220699	0.7922173	1.2031840
Age	1.1807904	0.0170754	9.7323751	0.0000000	1.1419267	1.2209768
SmokingPast	1.2487810	0.2746808	0.8088220	0.4186175	0.7289161	2.1394148
SmokingCurrent	1.7830829	0.1664761	3.4740357	0.0005127	1.2866690	2.4710199
Smokingunknown	0.8809917	0.1578696	-0.8026058	0.4222026	0.6465363	1.2004683
Alc_Fre1-4 /week	1.0215460	0.2768150	0.0770088	0.9386165	0.5937896	1.7574511
Alc_FreDaily	0.9792125	0.3168883	-0.0662904	0.9471466	0.5261882	1.8222701
Alc_FreNever or past	1.2758946	0.2226323	1.0943946	0.2737820	0.8247263	1.9738756
Alc_Freunknown	1.0699195	0.2621570	0.2577975	0.7965632	0.6400334	1.7885436
BMIgrp[14,18.5)	1.8431400	0.1331736	4.5915304	0.0000044	1.4197136	2.3928524
BMIgrp[25,30)	0.9692297	0.1167735	-0.2676430	0.7889742	0.7709549	1.2184971
BMIgrp[30,40)	1.3266946	0.2667928	1.0595883	0.2893320	0.7864597	2.2380275
BMIgrpunknown	1.3885727	0.1279438	2.5657859	0.0102942	1.0805943	1.7843275
DM_histTRUE	1.8705903	0.1664739	3.7618748	0.0001686	1.3498199	2.5922777
DM_histunknown	0.9008102	0.3064458	-0.3408783	0.7331952	0.4940673	1.6424057
HT_histTRUE	1.5134926	0.0935893	4.4280717	0.0000095	1.2598446	1.8182083
HT_histunknown	1.3339919	0.2305203	1.2501105	0.2112592	0.8490513	2.0959090
KID_histTRUE	1.4236902	0.1897974	1.8612069	0.0627150	0.9814307	2.0652437
KID_histunknown	0.8640625	0.1930762	-0.7567487	0.4492005	0.5918319	1.2615136
LIV_histunknown	0.9308700	0.3217310	-0.2226570	0.8238024	0.4954857	1.7488274
Exercise> 1h/w	1.0091925	0.1084098	0.0844066	0.9327331	0.8160099	1.2481093
Exerciseunknown	1.1045152	0.1413861	0.7030859	0.4820022	0.8371893	1.4572019
Slepgrp[6.9,7.9)	0.9983152	0.1244354	-0.0135513	0.9891879	0.7822544	1.2740524

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Slepgrp[7.9,8.9)	1.2007661	0.1157394	1.5807898	0.1139261	0.9570636	1.5065238
Slepgrp[8.9,23)	1.5163269	0.1363186	3.0538083	0.0022596	1.1608022	1.9807400
Slepgrpunknown	1.0333997	0.2002803	0.1640405	0.8696993	0.6978940	1.5301966
SpiOne2tw	0.6504087	0.1692688	-2.5412494	0.0110457	0.4667716	0.9062922
SpiThre4tw	0.5747576	0.1704497	-3.2490932	0.0011577	0.4115264	0.8027342
Spidaily	0.5601546	0.1670531	-3.4692114	0.0005220	0.4037495	0.7771480
Spiunknown	0.7652163	0.2115412	-1.2649861	0.2058763	0.5054987	1.1583730
FruOne2tw	0.8083564	0.1783653	-1.1927894	0.2329519	0.5698730	1.1466416
FruThre4tw	1.0799223	0.1655807	0.4643603	0.6423897	0.7806385	1.4939466
Frudaily	0.9930470	0.1596621	-0.0437005	0.9651431	0.7262149	1.3579208
Fruunknown	0.9745758	0.1794968	-0.1434733	0.8859164	0.6855319	1.3854905
CofeThre3tw	0.9169969	0.1173898	-0.7381488	0.4604241	0.7285267	1.1542245
CofeNever	1.0317877	0.1031324	0.3034245	0.7615664	0.8429540	1.2629226
Cofeunknown	1.3112762	0.2274730	1.1913538	0.2335147	0.8395929	2.0479510
Educgrp[18,70)	0.7735522	0.1326575	-1.9355276	0.0529256	0.5964463	1.0032469
Educgrpunknown	1.0590361	0.1132496	0.5064844	0.6125167	0.8482279	1.3222360
GreteaThre3tw	1.1175822	0.1501040	0.7406038	0.4589337	0.8327425	1.4998515
GreteaNever	1.1532497	0.1558854	0.9146708	0.3603645	0.8496371	1.5653564
Greteaunknown	0.9735653	0.1675266	-0.1599172	0.8729463	0.7010777	1.3519605
MenopauseTRUE	1.0217225	0.4746582	0.0452745	0.9638885	0.4029983	2.5903755