Demonstration Class 1

Preparing your workfile

We add the basic libraries needed for this week's work:

```
library(tidyverse)    # for almost all data handling tasks
library(readxl)       # to import Excel data
library(ggplot2)      # to produce nice graphiscs
library(stargazer)    # to produce nice results tables
library(haven)        # to import stata file
library(AER)          # access to HS robust standard errors
library(estimatr)     # use robust se
source("stargazer_HC.r")
```

Introduction

The data are an extract from the Understanding Society Survey (formerly the British Household Survey Panel).

Data Upload - and understanding data structure

Upload the data, which are saved in a STATA datafile (extension `.dta`). There is a function which loads STATA file. It is called `read_dta` and is supplied by the `haven` package.

```
data_USoc <- read_dta("20222_USoc_extract.dta")
data_USoc <- as.data.frame(data_USoc)    # ensure data frame structure
names(data_USoc)
```

```
##  [1] "pidp"    "age"     "jbhrs"   "paygu"   "wave"    "cpi"     "year"
##  [8] "region"  "urate"   "male"    "race"    "educ"    "degree"  "mfsize9"
```

Let us ensure that categorical variables are stored as `factor` variables. It is easiest to work with these in R.

```
data_USoc$region <- as_factor(data_USoc$region)
data_USoc$male <- as_factor(data_USoc$male)
data_USoc$degree <- as_factor(data_USoc$degree)
data_USoc$race <- as_factor(data_USoc$race)
```

The pay information (`paygu`) is provided as a measure of the (usual) gross pay per month. As workers work for dy we shall also adjust for increasing price levels (as measured`mutate` function. We call this variable `hrpay` and also calculate the natural log of this variable (`lnhrpay`).

```
data_USoc <- data_USoc %>%
              mutate(hrpay = paygu/(jbhrs*4)/(cpi/100)) %>%
              mutate(lnhrpay = log(hrpay))
```

We will also calculate a modified race variable

```
data_USoc %>% count(race)
```

```
## # A tibble: 6 x 2
##   race      n
##   <fct> <int>
## 1 white 99593
## 2 mixed  2057
## 3 asian 12994
## 4 black  6167
## 5 other  2078
## 6 <NA>  10383
```

We shall create a variable called `white` which re-groups this into two categories, white and non-white.

```
data_USoc <- data_USoc %>%
    mutate(white = fct_recode(race,
    "white"    = "white",    # new level = old level
    "non-white"  = "mixed",
    "non-white"  = "asian",
    "non-white"  = "black",
    "non-white"  = "other"))
```

Let's estimate a regression, allowing average hourly pay to differ between whites and non-whites

```
mod1 <- lm(lnhrpay~white,data = data_USoc)
stargazer_HC(mod1,type="text")
```

```
##
## ================================================
##                          Dependent variable:
##                      ---------------------------
##                                lnhrpay
## ------------------------------------------------
## whitenon-white               -0.053***
##                               (0.007)
##
## Constant                     2.293***
##                               (0.003)
##
## ------------------------------------------------
## Observations                  57,915
## R2                             0.001
## Adjusted R2                    0.001
## Residual Std. Error     0.631 (df = 57913)
## F Statistic          59.331*** (df = 1; 57913)
## ================================================
## Note:               *p<0.1; **p<0.05; ***p<0.01
```

Now we calculate inflation adjusted figures for gross monthly pay (`paygu`) and scale it to annual pay (`annualpay`).

```
data_USoc <- data_USoc %>%
              mutate(annualpay = paygu*12/(cpi/100))
summary(data_USoc$annualpay)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.      NA's
##      0.81   8695.65  15551.84  18761.59  24665.56 162454.87     74056
```

Now we look at estimating the following model

$$anualpay = \beta_0 + \beta_1\ age + v$$

```
mod1 <- lm(annualpay~age,data = data_USoc,subset=(degree == "first degree"))
mod2 <- lm(annualpay~age,data = data_USoc,subset=(degree == "no degree"))
stargazer(mod1,mod2, type = "text",
          column.labels = c("first degree","without degree"),omit.stat = "all")
```

```
##
## =====================================
##               Dependent variable:
##           --------------------------
##                     annualpay
##           first degree  without degree
##                (1)           (2)
## -------------------------------------
## age        270.314***     142.448***
##             (14.932)       (4.284)
##
## Constant 14,365.930***  9,437.297***
##             (607.774)     (185.646)
##
## =====================================
## =====================================
## Note:     *p<0.1; **p<0.05; ***p<0.01
```

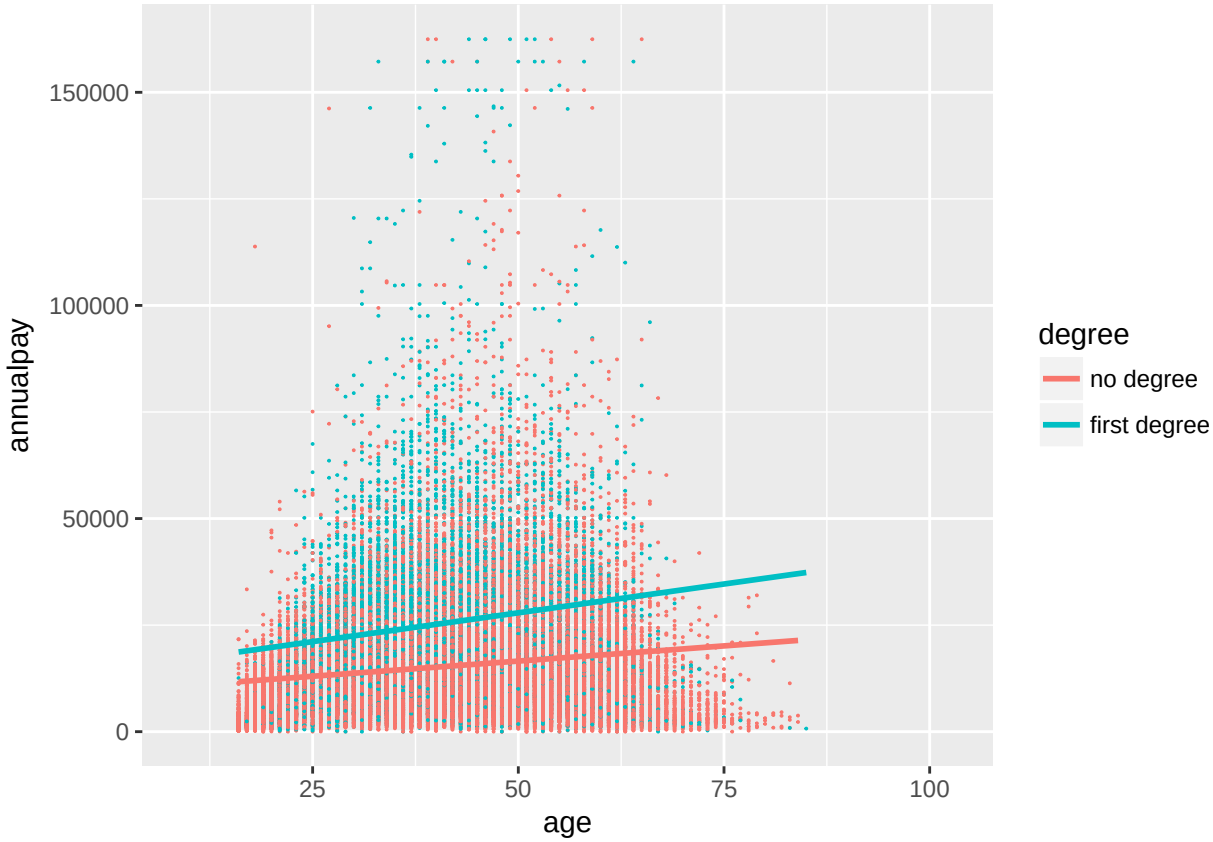
Now we use these models to predict annual wages at the age of 20 and 65 depending on whether someone has a degree or not.

```
# with degree, use mod1
y20_1 <- mod1$coefficients[1]+mod1$coefficients[2]*20
y65_1 <- mod1$coefficients[1]+mod1$coefficients[2]*65

# without degree, use mod2
y20_0 <- mod2$coefficients[1]+mod2$coefficients[2]*20
y65_0 <- mod2$coefficients[1]+mod2$coefficients[2]*65
```

Let's create a plot with the two fitted regression lines. But before we do that we create a temporary dataset which only contaisn obs with the two `degree` outcomes we consider here, i.e. "no degree" and "first degree".

```
temp <- data_USoc %>% filter(degree %in% c("no degree", "first degree"))
ggplot(temp, aes(x=age,y=annualpay,color = degree))+
  geom_point(size=0.01) +
  geom_smooth(method = "lm", se = FALSE)
```



To calculate the lifetime earnings premium for a graduate (earnings between 20 and 65) we calculate the lifetime earnings of a graduate and substract the lifetime earnings of a non-graduate.

```
L1 = (65-20)*(y20_1+y65_1)/2
L0 = (65-20)*(y20_0+y65_0)/2
D = L1 - L0
unname(L1)   # If you don't use unname then
```

```
## [1] 1163442
```

```
unname(L0)   # all these values will inherit the
```

```
## [1] 697109.9
```

```
unname(D)    # name "intercept" from coefficients
```

```
## [1] 466332
```

So this almost half a million pounds over a lifetime. Is that the value of a degree?