

# Problem Set 2

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## Problem 1

### Hansen 2.2

If  $\mathbb{E}[Y|X] = a + bX$ , we can do the following:

$$\mathbb{E}[Y] = \mathbb{E}[\mathbb{E}[Y|X]|X] = \mathbb{E}[X(a + bX)] \rightarrow \mathbb{E}[YX] = a\mathbb{E}[X] + b\mathbb{E}[X]^2$$

## Problem 2

### Hansen 2.5

#### Part A

$$\begin{aligned}\mathbb{E}[(Y - h(X))^2] &= \mathbb{E}[((Y - m(X)) + (m(X) - h(X)))^2] = \\ \mathbb{E}[(e + (m(X) - h(X)))^2] &= \mathbb{E}[e^2 + 2e(m(X) - h(X)) + (m(X) - h(X))^2] = \mathbb{E}[e^2]\end{aligned}$$

#### Part B

Predicting  $e^2$  is to estimate the amount of variation in the model in expectation. That is, it estimates  $\sigma^2$  which is present due to the potential omission of omni-present factors.

## Part C

Take a function  $h(X)$  which aims to minimize the mean squared error.  $\mathbb{E}[(e^2 - h(X))^2]$   
 $\mathbb{E}[e^4] - 2\mathbb{E}[e^2 h(X)] + \mathbb{E}[h(X)^2]$ . Next, to minimize, we want derivate w.r.t.  $X$ . We then get  
 $-2\mathbb{E}[e^2|X] + 2h(X) = 0$ . Then, we get that  $h(X) = \mathbb{E}[e^2|X] = e^2 = \sigma^2(X)$ .

## Problem 3

### Hansen 2.6

$var[Y] = var[\mathbb{E}[Y|X]] + \mathbb{E}[var(Y|X)]$   $var[Y] = var[m(X)] + \mathbb{E}[var(e|X)]$ . Since  
 $var(e|X) = \sigma^2(X)$ , we get that in expectation  $\mathbb{E}[\sigma^2(X)] = \sigma^2$ . This yields that  $var[Y] =$   
 $var[m(X)] + \sigma^2$ .

## Problem 4

### Hansen 2.10

This is true. We can use the law of iterated expectations to prove it.  $\mathbb{E}[X^2 e] = \mathbb{E}[\mathbb{E}[X^2 e|X]]$  We  
can then do some factoring to yield  $X^2 \mathbb{E}[e|X]$ . Because of the fact that  $\mathbb{E}[e|X] = 0$ , we can say  
that  $\mathbb{E}[X^2 e] = \mathbb{E}[0] = 0$

## Problem 5

### Hansen 2.11

This is false. Mainly, this is due to the fact that we are not given information of the error term's corre-  
lation to  $X$ . If we were to make  $X$  a binary variable, with equal possibility of equaling negative one  
or one,  $\mathbb{E}[Xe] = \mathbb{E}[X^2] = 1$ . This is a contradiction as, in this case, the equality is not zero.

## Problem 6

### Hansen 2.12

This is also false. The condition of  $\mathbb{E}[e|X] = 0$  implies zero-mean expectation, but not full independence.

## Problem 7

### Hansen 2.13

False. The condition of  $\mathbb{E}[Xe] = 0$  implies only expectationally zero correlation between  $X$  and the error term  $e$ . In reality, this is no guarantee of the zero mean assumption holding.

## Problem 8

### Hansen 2.14

Finally, this is also false. From the given conditions, we can assume that the error is homoskedastic, but nothing is given regarding independence.

## Problem 9

### Hansen 2.21

#### Part A

$\gamma_1 = \beta_1$  if and only if the quadratic term's  $\beta_2 = 0$ . This would imply that in the short term regression, there is no omitted variable bias, thus meaning the two parameters would be equivalent.

#### Part B

It is a similar case here in which the cubic term's  $\theta_2 = 0$  or in the case that  $\mathbb{E}[X^3X] = 0$ , or that  $X^3$  is uncorrelated with  $X$ .

## Problem 10

### Part A

Consider  $y_i = D_i y_i(1) + (1 - D_i) y_i(0)$ . In expectation, the average treatment effect would be such that  $ATE = \mathbb{E}[y(1) - y(0)]$

### Part B

In class, we derived that  $ATT = \mathbb{E}[y_i(1) - y_i(0) | D = 1]$ . This can be expanded as  $\mathbb{E}[y_i(1) | D = 1] - \mathbb{E}[y_i(0) | D = 1]$  Which can finally be simplified as  $y_i = y_i(0) + D_i[y_i(1) - y_i(0)]$ . In this case, the difference is that the difference in treated and untreated is scaled by  $D_i$ , allowing the treatment to be switched on and off depending on treated status of agent  $i$ .

### Part C

In the case described,  $\alpha$  is the effect of participation. The untreated potential outcomes model is used to delete the error term in expectation and homogeneity is used to discern the treatment effect  $\alpha$ .

### Part D

After identifying the ATT in class, we were left with the regression  $\mathbb{E}[y | x, D] = \alpha D + x^T \beta$ . This is the same as found in part (B), and once we plug in the given regression in (C), we would be left with the same regression as well. This occurs due to the given assumptions and same parameters.

## Problem 11

### Part A

```
library(Ecdat)
```

Loading required package: Ecfun

Attaching package: 'Ecfun'

The following object is masked from 'package:base':

sign

Attaching package: 'Ecdat'

The following object is masked from 'package:datasets':

Orange

```
library(dplyr)
```

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

filter, lag

The following objects are masked from 'package:base':

intersect, setdiff, setequal, union

```
data(Star,package="Ecdat")
str(Star)
```

```
'data.frame':  5748 obs. of  8 variables:
 $ tmathssk: int  473 536 463 559 489 454 423 500 439 528 ...
 $ treadssk: int  447 450 439 448 447 431 395 451 478 455 ...
 $ classk  : Factor w/ 3 levels "regular","small.class",...: 2 2 3 1 2 1 3 1 2 2 ...
 $ totexpk : int   7 21  0 16  5  8 17  3 11 10 ...
 $ sex      : Factor w/ 2 levels "girl","boy": 1 1 2 2 2 2 1 1 1 1 ...
 $ freelunk: Factor w/ 2 levels "no","yes": 1 1 2 1 2 2 2 1 1 1 ...
 $ race     : Factor w/ 3 levels "white","black",...: 1 2 2 1 1 1 2 1 2 1 ...
 $ schidkn  : int   63 20 19 69 79  5 16 56 11 66 ...
 - attr(*, "na.action")= 'omit' Named int [1:5850] 1 4 6 7 8 9 10 15 16 17 ...
 ..- attr(*, "names")= chr [1:5850] "1" "4" "6" "7" ...
```

This loads the required package and associated data into the program. Next, we will subset the data and perform the necessary actions to find the ATT

```
boys <- Star %>%
  filter(sex == "boy", classk %in% c("small.class","regular")) %>%
  mutate(small_class = ifelse(classk == "small.class", 1,0))
mean_score <- boys %>%
  group_by(small_class) %>%
  summarise(mean_score = mean(tmathssk, na.rm=TRUE), .groups="drop")
mean_small <- mean_score %>% filter(small_class == 1) %>% pull(mean_score)
mean_not <- mean_score %>% filter(small_class == 0) %>% pull(mean_score)
ATT_mean <- mean_small - mean_not
ATT_mean
```

```
[1] 13.67522
```

## Part B

```
Y <- as.matrix(boys$tmathssk)
X <- as.matrix(cbind(1,boys$small_class))
beta_hat <- solve(t(X) %*% X) %*% t(X) %*% Y
beta_hat
```

```
      [,1]
[1,] 476.69066
[2,]  13.67522
```

The effect of being in a small class is the same as in part (A). It also matches with the built in regression function.

## Part C

```
X_c <- as.matrix(cbind(1, boys$small_class, boys$totexpk, boys$freelunk))
beta_hat_c <- solve(t(X_c) %*% X_c) %*% t(X_c) %*% Y
beta_hat_c
```

```
      [,1]  
[1,] 505.2189955  
[2,]  13.4233260  
[3,]   0.5397799  
[4,] -22.4616584
```

In this case, the effect of a small class is slightly smaller. This makes sense as with more factors being taken into account, one would expect less “oomph” from a singular variable. With that said, parameter coefficients match with both matrix algebra and `lm`.