

# Microeconometrics Task - Problem Set 2

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## 1 Setup

```
library(tidyverse)
library(glue)
library(broom)

library(knitr)
library(kableExtra)
```

Loading data:

```
data_lot <- haven::read_dta("ps2/base_lotteries.dta")
data_exam <- haven::read_dta("ps2/voluntary_exam.dta")
```

## 2 Question 1

First, we standardize the variables.

```
cols <- expand_grid(c("mt", "lp"), 7:9) %>%
  apply(1, \ (x) paste0(c("score", x), collapse = "_"))

data_lot <- data_lot %>%
  mutate(
    across(all_of(cols), function(col) {
      control <- col[won_lotteryA == 0]
      (col - mean(control)) / sd(control)
    }),
    across(sex:ever_failed_school, as.factor)
  ) %>%
  na.omit()
```

### 2.1 Item a)

The grades of the test are largely defined by the difficulty of the test. Without standardization, we would be capturing this effect, which would pollute the effect of the treatment between grades. When we standardize the scores, we are capturing the relative position of students, censored from the difficulty effect.

### 2.2 Item b)

The averages and standard deviations are expected to change with the treatment, such that we only want to consider the changes in difficulty of the counterfactual, that is, we want to standardize using the averages and standard deviation of the control group.

## 3 Question 2.

### 3.1 Items a), and c)

First, lets create dummies for each variable.

```
labels <- list(
  sex = c("male", "female"),
  race = c("white", "brown", "black", "yellow", "indigenous"),
  mother = c("l.t. 5", "5 to 9", "9 to HS", "HS to college", "college", "more", "unsure"),
  father = c("l.t. 5", "5 to 9", "9 to HS", "HS to college", "college", "more", "unsure"),
  failed = c("never", "once", "more")
) %>%
  imap(~ paste(.y, .x)) %>%
  reduce(c)

data_dummies <- fastDummies::dummy_cols(data_lot[2:6], remove_selected_columns = TRUE) %>%
  set_names(labels) %>%
  cbind(data_lot[-c(1:6)])
```

Now, we can create a function that makes the comparisons.

```
compare <- function(data, treat_ind, control_ind = !treat_ind) {
  imap_dfr(data, function(col, name) {
    control <- col[treat_ind]
    treat <- col[control_ind]

    test <- tryCatch(t.test(control, treat), error = \(e) list(p.value = NA))
    n <- c(length(control), length(treat))

    results <- c(
      mean(control),
      sd(control),
      mean(treat) - mean(control),
      sqrt((sd(control)^2 / n[1]) + (sd(treat)^2 / n[2])),
      test$p.value
    ) %>%
      round(3)

    tibble(
      Variable = name,
      Control = glue("{results[1]} ({results[2]})",
      Diff = glue("{results[3]} ({results[4]})",
      `P-value` = results[5],
      `Ajd. P-value` = p.adjust(`P-value`, method = "holm")
    )
  })
}
```

The results can be seen at the end of the question.

### 3.2 Items b) and c)

As with everything in inference, there is a chance of any unbalancedness to arise randomly, which wouldn't indicate a problem with the lottery. With lots of control variables, the probability of such random deviation is relevant.

But, if the difference in groups was not random, it can be an indication that the individuals are self selecting, or that the lottery is not fair. This would put in check the hypothesis of the exogeneity of the treatment.

To get further evidence, we could test if any unbalancedness is correlated with the treatment, with methods/tests such as Randomization Inference, Bonferroni, and Holm.

At the end, I present the results with the Hold p-value adjustment.

We can see that some variables present statistically significant differences, meaning that the evidence for balanced groups and lottery fairness is not good.

### 3.3 Item d)

Then, the hypothesis of the exogeneity of the treatment would be hard to defend, once that we have an indication that the individuals are self selecting, or that the lottery is not fair.

### 3.4 Item e)

Then, the comparison talked above would be valid, since the lottery would similarly divide the groups.

### 3.5 Results

Below I present the results from this question. They wouldn't fit in a horizontally doubled table with both comparisons, so I presented one table for each comparison.

```
comparison_treated <- select(data_dummies, `sex male`:`failed more`) %>%
  compare(data_dummies$won_lotteryA + data_dummies$won_lotteryB >= 1)

comparison_treated %>% kable() %>% kable_styling(latex_options = "HOLD_position")
```

Variable	Control	Diff	P-value	Ajd. P-value
sex male	0.405 (0.492)	-0.001 (0.046)	0.989	0.989
sex female	0.595 (0.492)	0.001 (0.046)	0.989	0.989
race white	0.265 (0.442)	-0.013 (0.041)	0.748	0.748
race brown	0.502 (0.501)	0.05 (0.046)	0.286	0.286
race black	0.191 (0.394)	-0.039 (0.035)	0.272	0.272
race yellow	0.019 (0.135)	0.013 (0.014)	0.355	0.355
race indigenous	0.023 (0.151)	-0.011 (0.012)	0.365	0.365
mother l.t. 5	0.07 (0.255)	0.038 (0.026)	0.146	0.146
mother 5 to 9	0.214 (0.411)	0.026 (0.039)	0.504	0.504
mother 9 to HS	0.153 (0.361)	-0.049 (0.031)	0.115	0.115
mother HS to college	0.298 (0.458)	0.026 (0.043)	0.542	0.542
mother college	0.107 (0.31)	-0.023 (0.027)	0.404	0.404
mother more	0.07 (0.255)	-0.014 (0.023)	0.545	0.545
mother unsure	0.088 (0.284)	-0.004 (0.026)	0.867	0.867
father l.t. 5	0.112 (0.316)	0 (0.029)	0.990	0.990
father 5 to 9	0.214 (0.411)	0.026 (0.039)	0.504	0.504
father 9 to HS	0.14 (0.347)	-0.048 (0.03)	0.113	0.113
father HS to college	0.251 (0.435)	0.017 (0.041)	0.680	0.680
father college	0.056 (0.23)	0.016 (0.023)	0.476	0.476
father more	0.019 (0.135)	-0.015 (0.01)	0.148	0.148
father unsure	0.209 (0.408)	0.003 (0.038)	0.943	0.943
failed never	0.712 (0.454)	0.012 (0.042)	0.768	0.768
failed once	0.2 (0.401)	0.02 (0.038)	0.598	0.598

failed more	0.088 (0.284)	-0.032 (0.024)	0.183	0.183
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```
comparison_ab <- select(data_dummies, `sex male`:`failed more`) %>%
  compare(data_dummies$won_lotteryA == 1, data_dummies$won_lotteryB == 1)

comparison_ab %>% kable() %>% kable_styling(latex_options = "HOLD_position")
```

Variable	Control	Diff	P-value	Ajd. P-value
sex male	0.432 (0.497)	-0.084 (0.071)	0.240	0.240
sex female	0.568 (0.497)	0.084 (0.071)	0.240	0.240
race white	0.24 (0.428)	0.079 (0.067)	0.238	0.238
race brown	0.514 (0.502)	-0.035 (0.073)	0.630	0.630
race black	0.192 (0.395)	-0.003 (0.058)	0.953	0.953
race yellow	0.021 (0.142)	-0.006 (0.019)	0.746	0.746
race indigenous	0.034 (0.182)	-0.034 (0.015)	0.025	0.025
mother l.t. 5	0.062 (0.241)	0.025 (0.04)	0.524	0.524
mother 5 to 9	0.212 (0.41)	0.005 (0.06)	0.933	0.933
mother 9 to HS	0.151 (0.359)	0.009 (0.053)	0.870	0.870
mother HS to college	0.308 (0.463)	-0.033 (0.066)	0.621	0.621
mother college	0.116 (0.322)	-0.029 (0.043)	0.497	0.497
mother more	0.068 (0.253)	0.004 (0.038)	0.916	0.916
mother unsure	0.082 (0.276)	0.019 (0.043)	0.656	0.656
father l.t. 5	0.11 (0.313)	0.006 (0.047)	0.892	0.892
father 5 to 9	0.247 (0.433)	-0.102 (0.056)	0.070	0.070
father 9 to HS	0.151 (0.359)	-0.035 (0.049)	0.478	0.478
father HS to college	0.226 (0.42)	0.078 (0.066)	0.236	0.236
father college	0.048 (0.214)	0.025 (0.036)	0.498	0.498
father more	0.021 (0.142)	-0.006 (0.019)	0.746	0.746
father unsure	0.199 (0.4)	0.033 (0.061)	0.586	0.586
failed never	0.678 (0.469)	0.105 (0.063)	0.101	0.101
failed once	0.212 (0.41)	-0.038 (0.057)	0.503	0.503
failed more	0.11 (0.313)	-0.066 (0.036)	0.067	0.067

## 4 Question 3

```
form_base <- score_mt_8 ~ won_lotteryA
mod_base <- lm(form_base, data_lot)

form_controls <- update.formula(form_base,
  . ~ . + sex + race + mother_schooling + father_schooling + ever_failed_school
)
mod_controls <- lm(form_controls, data_lot)

test_permutation <- function(f, data, n = 1000) {
  coef_true <- abs(coef(lm(f, data)))
  n_coef <- length(coef_true)

  coef_perm <- map_dfr(1:n, function(i) {
    data$score_mt_8 <- sample(data$score_mt_8)
```

```

  abs(coef(lm(f, data)))
})

sapply(1:n_coef, \(i) mean(coef_perm[,i] >= coef_true[i]))
}

```

#### 4.1 Item c)

Using averages differences does not account for the different variances in the potential outcomes, such that the test, while asymptotically valid, can underreject. That is why we used the adjustments.

#### 4.2 Item d)

```

test_wildboot <- function(f, data, n = 1000) {
  mod <- lm(f, data)
  res <- resid(mod)
  pred <- predict(mod)
  coef_true <- coef(mod)
  n_coef <- length(coef_true)

  coef_perm <- map_dfr(1:n, function(i) {
    y <- pred + res * sample(c(-1, 1), length(residuals), replace = TRUE)
    data$score_mt_8 <- y
    coef(lm(f, data))
  })

  sapply(1:n_coef, \(i) mean(coef_perm[,i] >= coef_true[i]))
}

```

#### 4.3 Results

```

summary(mod_base)$coef[,c(1,4)] %>%
  as_tibble(rownames = "Coefficient") %>%
  mutate(
    `Pr Perm` = test_permutation(form_base, data_lot),
    `Pr Wild` = test_wildboot(form_base, data_lot)
  ) %>%
  kable() %>%
  kable_styling(latex_options = "HOLD_position")

```

Coefficient	Estimate	Pr(>#124;t#124;)	Pr Perm	Pr Wild
(Intercept)	0.0008760	0.9873211	0.998	1.000
won_lotteryA	0.2389622	0.0154668	0.020	0.513

```

summary(mod_controls)$coef[,c(1,4)] %>%
  as_tibble(rownames = "Coefficient") %>%
  mutate(
    `Pr Perm` = test_permutation(form_controls, data_lot),
    `Pr Wild` = test_wildboot(form_controls, data_lot)
  ) %>%

```

```
kable() %>%
kable_styling(latex_options = "HOLD_position")
```

Coefficient	Estimate	Pr(> t )	Pr Perm	Pr Wild
(Intercept)	0.4046692	0.0444820	0.059	1.000
won_lotteryA	0.2479112	0.0123628	0.015	0.000
sex2	-0.0446908	0.6380350	0.656	0.000
race2	-0.0408518	0.7126682	0.726	1.000
race3	-0.2117029	0.1454232	0.181	0.000
race4	0.7114344	0.0170654	0.022	1.000
race5	0.0135123	0.9704270	0.966	0.000
mother_schooling2	-0.2296147	0.2294087	0.226	0.000
mother_schooling3	-0.0790496	0.7056870	0.710	1.000
mother_schooling4	-0.1592331	0.3976212	0.410	1.000
mother_schooling5	-0.0054524	0.9815636	0.980	1.000
mother_schooling6	-0.0452888	0.8596504	0.866	1.000
mother_schooling7	-0.3237400	0.1856243	0.205	1.000
father_schooling2	-0.0593496	0.7393442	0.752	1.000
father_schooling3	-0.1890603	0.3524776	0.364	0.000
father_schooling4	-0.0505090	0.7786279	0.775	0.000
father_schooling5	-0.1814210	0.4622589	0.464	0.000
father_schooling6	-0.0420376	0.9306210	0.946	0.506
father_schooling7	-0.1408316	0.4568370	0.474	0.000
ever_failed_school2	-0.5098885	0.0000103	0.000	1.000
ever_failed_school3	-0.0036747	0.9836599	0.975	1.000

## 5 Question 4

### 5.1 Item a)

Two options can be:

- Define a new, combined, dependent variable. For example, any weighted sum of the outcomes. In the most simple way, just the sum or mean of both.
- Do separate regressions, but jointly test the p-values using Bonferroni or Holm methods.

### 5.2 Item b)

I did both approaches from above. The results are in the next section.

```
mod_sum <- lm(
  score_mt_8 + score_lp_8 ~ won_lotteryA + sex + race + mother_schooling +
    father_schooling + ever_failed_school,
  data_lot
)
```

```
mod_mt <- lm(
  score_mt_8 ~ won_lotteryA + sex + race + mother_schooling +
    father_schooling + ever_failed_school,
  data_lot
)
mod_lp <- lm(
```

```

score_lp_8 ~ won_lotteryA + sex + race + mother_schooling +
  father_schooling + ever_failed_school,
data_lot
)

adj_pvalues <- p.adjust(
  c(summary(mod_mt)$coefficients[, 4], summary(mod_lp)$coefficients[, 4]),
  method = "holm"
)

```

### 5.3 Results

Again, all in one table wouldn't be very easy to see.

```

summary(mod_sum)$coef[,c(1,4)] %>%
  as_tibble(rownames = "Coefficient") %>%
  kable() %>%
  kable_styling(latex_options = "HOLD_position")

```

Coefficient	Estimate	Pr(>#124;t#124;)
(Intercept)	0.3411289	0.2367740
won_lotteryA	0.4055460	0.0043610
sex2	0.1257289	0.3561922
race2	-0.2444985	0.1247445
race3	-0.3436771	0.0994232
race4	0.4217956	0.3227434
race5	-0.3195906	0.5409690
mother_schooling2	-0.2172668	0.4275198
mother_schooling3	-0.1260763	0.6744632
mother_schooling4	-0.3208463	0.2347856
mother_schooling5	-0.0718971	0.8317221
mother_schooling6	-0.1179993	0.7480111
mother_schooling7	-0.8283897	0.0184300
father_schooling2	0.2774653	0.2783181
father_schooling3	-0.0813376	0.7801825
father_schooling4	0.1855781	0.4714731
father_schooling5	0.0077334	0.9825601
father_schooling6	-0.0188552	0.9782741
father_schooling7	0.1081930	0.6901004
ever_failed_school2	-0.5917364	0.0003394
ever_failed_school3	-0.0031021	0.9903802

```

summary(mod_mt)$coef[,c(1,4)] %>%
  as_tibble(rownames = "Coefficient") %>%
  mutate(`Pr Adj` = adj_pvalues[1:length(coef(mod_mt))]) %>%
  kable() %>%
  kable_styling(latex_options = "HOLD_position")

```

Coefficient	Estimate	Pr(>#124;t#124;)	Pr Adj
(Intercept)	0.4046692	0.0444820	1.0000000

won_lotteryA	0.2479112	0.0123628	0.5068754
sex2	-0.0446908	0.6380350	1.0000000
race2	-0.0408518	0.7126682	1.0000000
race3	-0.2117029	0.1454232	1.0000000
race4	0.7114344	0.0170654	0.6826161
race5	0.0135123	0.9704270	1.0000000
mother_schooling2	-0.2296147	0.2294087	1.0000000
mother_schooling3	-0.0790496	0.7056870	1.0000000
mother_schooling4	-0.1592331	0.3976212	1.0000000
mother_schooling5	-0.0054524	0.9815636	1.0000000
mother_schooling6	-0.0452888	0.8596504	1.0000000
mother_schooling7	-0.3237400	0.1856243	1.0000000
father_schooling2	-0.0593496	0.7393442	1.0000000
father_schooling3	-0.1890603	0.3524776	1.0000000
father_schooling4	-0.0505090	0.7786279	1.0000000
father_schooling5	-0.1814210	0.4622589	1.0000000
father_schooling6	-0.0420376	0.9306210	1.0000000
father_schooling7	-0.1408316	0.4568370	1.0000000
ever_failed_school2	-0.5098885	0.0000103	0.0004324
ever_failed_school3	-0.0036747	0.9836599	1.0000000

```
summary(mod_lp)$coef[,c(1,4)] %>%
  as_tibble(rownames = "Coefficient") %>%
  mutate(`Pr Adj` = adj_pvalues[1:length(coef(mod_lp))]) %>%
  kable() %>%
  kable_styling(latex_options = "HOLD_position")
```

Coefficient	Estimate	Pr(>#124;t#124;)	Pr Adj
(Intercept)	-0.0635403	0.7645948	1.0000000
won_lotteryA	0.1576348	0.1311373	0.5068754
sex2	0.1704197	0.0898444	1.0000000
race2	-0.2036467	0.0826321	1.0000000
race3	-0.1319742	0.3897353	1.0000000
race4	-0.2896389	0.3564862	0.6826161
race5	-0.3331029	0.3870123	1.0000000
mother_schooling2	0.0123479	0.9511576	1.0000000
mother_schooling3	-0.0470267	0.8315169	1.0000000
mother_schooling4	-0.1616132	0.4162259	1.0000000
mother_schooling5	-0.0664447	0.7897361	1.0000000
mother_schooling6	-0.0727105	0.7880761	1.0000000
mother_schooling7	-0.5046497	0.0509931	1.0000000
father_schooling2	0.3368149	0.0742731	1.0000000
father_schooling3	0.1077227	0.6157820	1.0000000
father_schooling4	0.2360871	0.2137992	1.0000000
father_schooling5	0.1891544	0.4679616	1.0000000
father_schooling6	0.0231823	0.9637367	1.0000000
father_schooling7	0.2490246	0.2130699	1.0000000
ever_failed_school2	-0.0818479	0.4979544	0.0004324



ever_failed_school3	0.0005726	0.9975887	1.0000000
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## 6 Question 5

In this question, i'll focus on the computational answers.

### 6.1 Item a)

```
data_join <- full_join(data_lot, data_exam, by = "student_code") %>%
  filter(lotteryA == 1) %>%
  mutate(
    did_test = !is.na(voluntary_exam_score),
    military = !(is.na(won_lotteryA) | won_lotteryA == 0)
  )

summary(lm(did_test ~ military, data_join))
```

```
##
## Call:
## lm(formula = did_test ~ military, data = data_join)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.450e-16 -3.450e-16 -3.450e-16  0.000e+00  1.098e-13
##
## Coefficients:
##              Estimate Std. Error    t value Pr(>|t|)
## (Intercept)  1.000e+00  2.861e-16  3.495e+15  <2e-16 ***
## militaryTRUE -3.452e-16  5.106e-16 -6.760e-01   0.499
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.11e-15 on 463 degrees of freedom
## Multiple R-squared:  0.5006, Adjusted R-squared:  0.4995
## F-statistic: 464.1 on 1 and 463 DF, p-value: < 2.2e-16
```

### 6.2 Item b)

```
data_dummies <- filter(data_join, did_test)[2:6] %>%
  fastDummies::dummy_cols(remove_selected_columns = TRUE) %>%
  set_names(labels) %>%
  cbind(data_lot[-c(1:6)]) %>%
  na.omit()

comparison_treated <- select(data_dummies, `sex male`:`failed more`) %>%
  compare(data_dummies$won_lotteryA == 1)

comparison_treated %>% kable() %>% kable_styling(latex_options = "HOLD_position")
```

Variable	Control	Diff	P-value	Ajd. P-value
sex male	0.432 (0.497)	-0.04 (0.049)	0.423	0.423

sex female	0.568 (0.497)	0.04 (0.049)	0.423	0.423
race white	0.24 (0.428)	0.027 (0.043)	0.537	0.537
race brown	0.514 (0.502)	0.022 (0.05)	0.656	0.656
race black	0.192 (0.395)	-0.032 (0.039)	0.409	0.409
race yellow	0.021 (0.142)	0.008 (0.015)	0.610	0.610
race indigenous	0.034 (0.182)	-0.025 (0.016)	0.123	0.123
mother l.t. 5	0.062 (0.241)	0.042 (0.026)	0.113	0.113
mother 5 to 9	0.212 (0.41)	0.023 (0.041)	0.583	0.583
mother 9 to HS	0.151 (0.359)	-0.035 (0.035)	0.318	0.318
mother HS to college	0.308 (0.463)	0.005 (0.046)	0.910	0.910
mother college	0.116 (0.322)	-0.032 (0.031)	0.304	0.304
mother more	0.068 (0.253)	-0.009 (0.025)	0.719	0.719
mother unsure	0.082 (0.276)	0.006 (0.028)	0.841	0.841
father l.t. 5	0.11 (0.313)	0.003 (0.031)	0.917	0.917
father 5 to 9	0.247 (0.433)	-0.027 (0.043)	0.525	0.525
father 9 to HS	0.151 (0.359)	-0.054 (0.034)	0.117	0.117
father HS to college	0.226 (0.42)	0.05 (0.043)	0.246	0.246
father college	0.048 (0.214)	0.024 (0.023)	0.293	0.293
father more	0.021 (0.142)	-0.014 (0.013)	0.258	0.258
father unsure	0.199 (0.4)	0.018 (0.04)	0.662	0.662
failed never	0.678 (0.469)	0.059 (0.046)	0.204	0.204
failed once	0.212 (0.41)	-0.002 (0.041)	0.955	0.955
failed more	0.11 (0.313)	-0.056 (0.029)	0.052	0.052

```
comparison_treated <- select(data_dummies, `sex male`:`failed more`) %>%
  compare(data_dummies$won_lotteryB == 1)

comparison_treated %>% kable() %>% kable_styling(latex_options = "HOLD_position")
```

Variable	Control	Diff	P-value	Ajd. P-value
sex male	0.348 (0.48)	0.066 (0.063)	0.294	0.294
sex female	0.652 (0.48)	-0.066 (0.063)	0.294	0.294
race white	0.319 (0.469)	-0.071 (0.061)	0.242	0.242
race brown	0.478 (0.503)	0.06 (0.066)	0.366	0.366
race black	0.188 (0.394)	-0.022 (0.051)	0.671	0.671
race yellow	0.014 (0.12)	0.013 (0.017)	0.428	0.428
race indigenous	0 (0)	0.02 (0.007)	0.005	0.005
mother l.t. 5	0.087 (0.284)	0.004 (0.037)	0.915	0.915
mother 5 to 9	0.217 (0.415)	0.012 (0.054)	0.820	0.820
mother 9 to HS	0.159 (0.369)	-0.038 (0.047)	0.422	0.422
mother HS to college	0.275 (0.45)	0.043 (0.059)	0.470	0.470
mother college	0.087 (0.284)	0.009 (0.037)	0.810	0.810
mother more	0.072 (0.261)	-0.012 (0.034)	0.725	0.725
mother unsure	0.101 (0.304)	-0.018 (0.039)	0.645	0.645
father l.t. 5	0.116 (0.323)	-0.005 (0.042)	0.909	0.909
father 5 to 9	0.145 (0.355)	0.097 (0.048)	0.044	0.044
father 9 to HS	0.116 (0.323)	-0.002 (0.042)	0.956	0.956
father HS to college	0.304 (0.464)	-0.052 (0.06)	0.389	0.389
father college	0.072 (0.261)	-0.009 (0.034)	0.783	0.783

father more	0.014 (0.12)	-0.004 (0.015)	0.775	0.775
father unsure	0.232 (0.425)	-0.025 (0.055)	0.653	0.653
failed never	0.783 (0.415)	-0.076 (0.055)	0.173	0.173
failed once	0.174 (0.382)	0.043 (0.05)	0.393	0.393
failed more	0.043 (0.205)	0.032 (0.028)	0.253	0.253

## 7 Item e)

```
leedata <- data_join %>%
  select(military, did_test, voluntary_exam_score) %>%
  setNames(c("treat", "selection", "outcome"))
```

```
leebounds::leebounds(leedata)
```

```
## $lower_bound
## [1] 0.2242981
##
## $upper_bound
## [1] 0.2242981
##
## $p0
## [1] 1
##
## $trimmed_mean_upper
## [1] 6.876583
##
## $trimmed_mean_lower
## [1] 6.876583
##
## $mean_no_trim
## [1] 6.652285
##
## $odds
## [1] 0.4576803
##
## $yp0
##      100%
## 9.779208
##
## $y1p0
##      0%
## 1.336305
##
## $s0
## [1] 1
##
## $s1
## [1] 1
##
## $prop0
## [1] 0.6860215
##
```

```
## $prop1  
## [1] 0.3139785
```